Restarting the Economy while saving lives under Covid-19

Carlo Favero[†] Andrea Ichino[‡] Aldo Rustichini[§]

ONLINE APPENDIX

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As a complement to Appendix A in the main text, this Online Appendix contains:

- In Part B: additional material and evidence that could not be included in the main text to save on space; the additional evidence is based on the same Covid-19 paramenters used in the main text, i.e. those taken from Ferguson et al. (2020).
- In Part C: a replication of the figures and tables in the main text, based on a different set of Covid-19 parameters, i.e. those estimated by the US Center for Diseases Control (CDC, see Garg (2020)).

[†]Bocconi University and CEPR; carlo.favero@unibocconi.it.
[‡]European University Institute, University of Bologna, CEPR, CESifo, and IZA; andrea.ichino@eui.eu.
[§]University of Minnesota; rusti001@umn.edu.

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Appendix B

Additional evidence based on Covid-19 parameters from Ferguson et al. (2020)

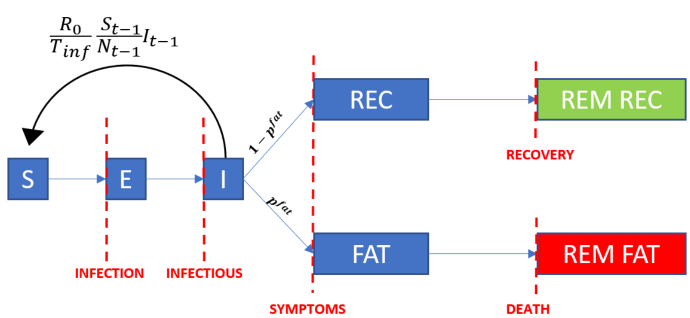
Appendix to Section 2: The SEIR-HC-SEC-AGE Model

In this appendix we characterize the basic epidemiological concepts on which the SEIR-HC-SEC-AGE model presented in the paper is constructed. We start with the basic SEIR model.

SEIR Model

The basic SEIR model (Allen, 2017) for the transmission dynamics of the virus (Figure B–1) for the transmission dynamics of the virus classifies individuals as: Susceptible, then Exposed, then Infectious, then Removed. Infectious are divided in three groups: Mild (no hospitalization is needed), Severe(hospitalization needed with a lag T_{shosp}), and Fatal (this condition has to be interpreted as a pre-assigned final outcome for that condition, after hospitalization, with a lag T_{shosp}). At the end of the process some subjects are removed as Recovered (REC) and the others are removed as fatalities (REM_FAT).

Figure B–1: Flowchart of the SEIR model



Note: Description of the possible dynamic transitions of a subject in the basic SEIR model (Allen, 2017)

Time is measured in days and is denoted by t. An initial total population of N_0 individuals is divided into the first infectious subject ($I_0 = 1$) and $S_0 = N_0 - 1$ susceptible subjects. The virus spreads via the interaction between Susceptible and Infectious individuals (visually illustrated in the graphical representation of the model by the black arrow)

In each subsequent day t some susceptibles become exposed. The daily quantity of new exposed that become new infectious after an incubation period is determined by the net reproduction number of the infection multiplied by the number of existing infectious. The net reproduction number is time varying and it depends on three components: the basic reproduction number (BRN) of the infection, R_0 (i.e. the number of secondary infections each infectious individual produces at the initial stage of the infection in absence of policies or behavioural responses), the average number of days in which a subject is infectious, $T_{\inf}$, and the fraction of susceptibles to the total population,$\frac{S_{t-1}}{N_{t-1}}$, so in each period we have:

$$NewE_t = \frac{R_t}{T_{\inf}} I_{t-1} \quad ; \quad R_t = R_0 \frac{S_{t-1}}{N_{t-1}}$$

The exposed, after an incubation period of T_{inc} days, become infectious. Therefore the outflow from the susceptibles is the inflow into the exposed in each period and, similarly, the outflow from the exposed is the inflow into the infectious, who fall into two categories: those whose destiny is recovery and those whose destiny is to become a fatality. The allocation to these two groups is controlled, respectively by the two probabilities: $1 - p^{fat}$ and p^{fat}. Those who survive the infection are then removed as recovered, REM_REC_t, after a period of T_{srec} days from symptoms to recovery. Those who become instead fatalities are removed as fatalities, REM_FAT_t, after a period of T_{sd} days from symptoms to death.

Some comments are necessary to understand the extensions of this basic model that will be presented later. First, a feature of the model is that the lethality of the virus, as measured by

$$\lambda_t^{seir} = \frac{REM\_FAT_t}{E_t + I_t + REM\_REC_t + REM\_FAT_t},$$

always converges eventually to the Case Fatality Rate which is the exogenously fixed probability with which an Exposed individual eventually dies. If $R_0 \leq 1$ the virus diffusion is inhibited and the share of the total population that dies goes to zero as λ_t^{seir} goes to the CFR. If instead $R_0 > 1$, the share of the total population that dies converges to the CFR as λ_t^{seir} converges to p^{fat}, and all individuals become eventually Exposed. In this second case, the total number of victims will be the same independently of the size of R_0, which determines only the speed at which the asymptotic number of victims is reached.

The full model dynamics is described as follows:

$$
\begin{aligned}
\Delta S_t &= \left(-\frac{R_0}{T_{\inf}}\frac{I_{t-1}}{N_{t-1}}\right) S_{t-1} \\
\Delta E_t &= \left(\frac{R_0}{T_{\inf}}\frac{I_{t-1}}{N_{t-1}}\right) S_{t-1} - \left(\frac{1}{T_{inc}}\right) E_{t-1} \\
\Delta I_t &= \left(\frac{1}{T_{inc}}\right) E_{t-1} - \left(\frac{1}{T_{\inf}}\right) I_{t-1} \\
\Delta REC_t &= (1-p^{fat}) \left(\frac{1}{T_{\inf}}\right) I_{t-1} - \left(\frac{1}{T_{rec}}\right) REC_{t-1} \\
\Delta FAT_t &= p^{fat} \left(\frac{1}{T_{\inf}}\right) I_{t-1} - \left(\frac{1}{T_{sd}-T_{shosp}}\right) FAT_{t-1} \\
\Delta REM\_FAT_t &= \left(\frac{1}{T_{sd}-T_{shosp}}\right) FAT_{t-1} \\
\Delta REM\_REC_t &= \left(\frac{1}{T_{rec}}\right) REC_{t-1} \\
N_t &= N_{t-1} - \Delta REM\_FAT_t
\end{aligned}
$$

From the basic SEIR to the SEIR-HC-AGE-SEC model

As discussed in the main text our SEIR-HC-AGE model extends the basic SEIR model along several dimensions:

1. **Multi-risk and multi-activity** Populations is divided into 9 age-brackets (from 0-9 to 80+) of which 5 are in working age (20-69 yers old). The working cohorts are allocated to two-production sectors, characterized by different levels of coworkers proximity, or inactivity imposed by a containment policy. We have therefore 19 groups with different probabilities of infection, hospitalization and fatality that vary with age, sector and age-specific labor force participation.

2. **Intervention Policies and Behavioural Responses** In our model to basic reproduction number of homogenous agents model will be substituted by a basic reproduction matrix,$R(a, b; \alpha)$, that describes the number of agents of type (a) that are infected by an agent of type (b) for a level of activity α, (for example, a worker in the high-risk sector does not infect many people if he is not active). The virus dynamics will be affected not only by the containment policy adopted by the government and reflected in the choices of Activity Levels but also by the behavioural response of individuals to the development of the virus.

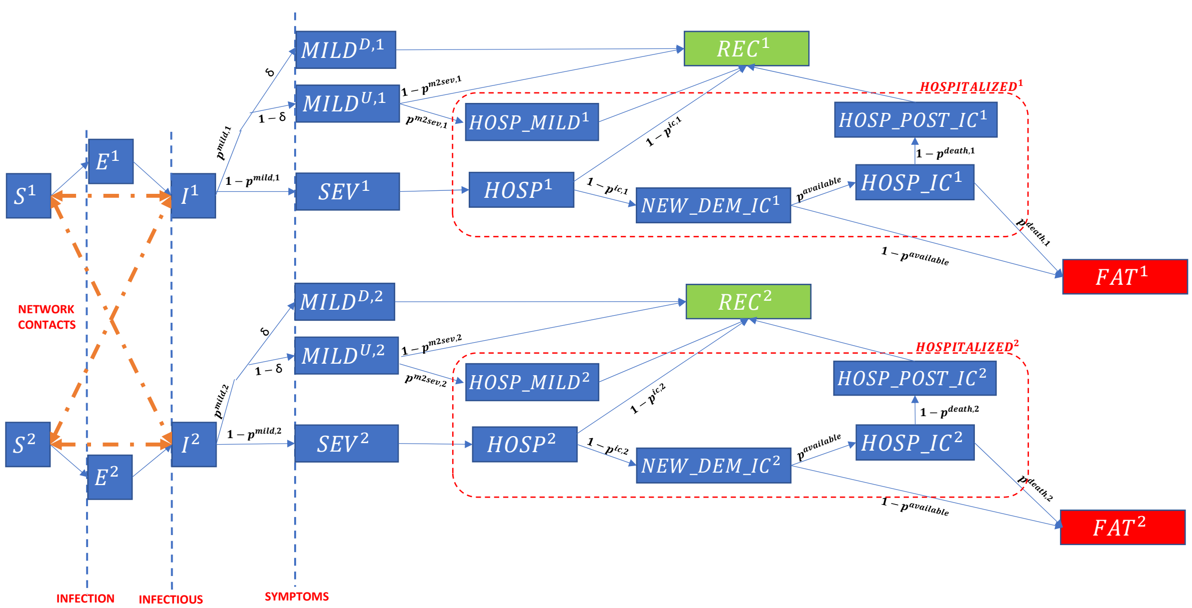
3. **Time-Varying death probability** The probability of death is time-varying and it can become higher than the constant CFR (Case Fatality Rate) of COVID-19. The

Probability of death is modelled to increase progressively with the saturation of hospitals and to reach a critical point when the available supply of intensive care beds is fully saturated.

4. **Management of Hospital Flows** With our specification of the probability of death management of the hospital flows becomes an important policy to reduce mortality. Extensive testing, early detection of the infectious, their placement in domestic quarantine paired with administering medicines can prevent them to reach the stage of symptoms that need hospitalization.

The dynamics in the SEIR-HC-AGE model (Figure B–2) is much richer than that of the basic SEIR model. To evaluate the impact of the extensions on the model dynamics, we describe how the compartmental dynamics evolves at the different stages of the model.

Figure B–2: Flowchart of Multiple-Risk SEIR-HC-SEC-AGE Model



Note: Solid lines show the flows from one state to another. Dashed lines emphasize interactions that take place across risk groups.

1. **The Dynamics of Susceptible and Exposed**

The core equations describing the dynamics of the virus are reported in the following interaction of Susceptible and Exposed, in each of our 19 groups of agents:

$$\begin{aligned}
\Delta S_t(a) &= -\frac{1}{T_{Inf}}\frac{\beta(m_{t-1})}{\beta(m_0)}\sum_{b\in A}\frac{I_{t-1}(b)Pr(V_t \geq v_t^*|b)}{N_{t-1}}R(b,a;\alpha)S_{t-1}(a)Pr(V_t \geq v_t^*|a) \\
\Delta E_t(a) &= -\Delta S_t(a) - \frac{1}{T_{Inc}}E_{t-1}(a)
\end{aligned}$$

The number of susceptible that each infectious infect, depends on the activation policy for each sector of the working population, described by α, on the probability of contamination $\beta(m_{t-1})$ (This probability may evolve over time with the spreading of the virus as it is affected by precaution, such as wearing masks, and mutation of the virus aggressiveness that might be related to a number of different factors, such as temperature and humidity) and on the probabilities with which susceptibles and infectious agents are active, $Pr(V_t \geq v_t^*|a)$. Note that, as the model features quadratic matching, what matters for the virus dynamics is the product of probabilities of being active for susceptible and infectious agents. These probabilities reflect both the average response of agents to policies and their behavioural response to the spreading of the virus and they vary over time.

In standard single-agent SEIR models the diffusion of the virus in each period depends on the basic reproduction number r_t, which is the product of the basic reproduction number r_0 and the share of susceptible individuals in the total population at time t. A virus starts to implode when r_t goes below unity. "Herd immunity" is reached when the share of susceptible individuals in the total population goes below $1/r_0$. We emphasize the r_0 used here is the reproduction number at initial pre-epidemic conditions, when no precautionary measure of any type is taken, so the number of infected contracts even if no such measure is taken.

The same concepts apply to our model except that the basic reproduction number becomes a basic initial reproduction matrix. $R_t(a, b, \alpha)$ depends on the share of susceptible individuals in the total population, the evolution over time of the probability of contracting the virus for a susceptible given a contact with an infectious, and the product of the probabilities of activation of susceptible and infectious agents. The

$R_t(a, b, \alpha)$ element of the matrix will evolve according to:

$$R_t(a, b; \alpha) = \frac{S_{t-1}(b)}{N_{t-1}} \frac{\beta(m_{t-1})}{\beta(m_0)} Pr(V_t \geq v_t^*|a) Pr(V_t \geq v_t^*|b) R(a, b; \alpha)$$

In the current multi-risk model, $Pr(V_t \geq v_t^*)$ is a 19 dimensional vector that describes the probability with which agents in each group become active. As explained in Section 3 of the main paper each of the elements of this vector is given by:

$$Pr(V_t \geq v_t^*|a) = \frac{(\overline{V} - K_t(a))\,(1 + \psi * TEMP_t)}{I_t + \overline{V}\,(1 + \psi * TEMP_t)}$$

To determine $K_t(a)$ we use the estimates of the behavioural response of grocery moves in the first column of Table 3 of Section 3. We pick the parameter estimates for grocery because they refer to an activity that can be chosen more freely by an individual, differently than workplace and transportation activities that may be constrained by the legal possibility to work or by interruptions of transportation services during Lockdown or the Phase 2. Indeed grocery was never prohibited, provided that a minimum distance could be maintained between individuals inside the shops or in their vicinity. For agents that are activated and go to school and work we set $K_t(a) = 0$, as their choice of being active depends only on the behavioural reaction and no lockdown policy is imposed to them. For agents that are inactive we use the estimation results and set

$$K_t(a) = 199.87 Lock + 55.36 Phase2.$$

where Lock and Phase2 are defined in foonote 10 of the main paper. Agents in the first two groups are activated when schools are opened and inactive otherwise. For agents in group 3,...12 (the ten groups constructed by considering the share of agents in working age employed in high risk and low risk sectors) a share α is active and the complement to one is inactive. Finally, agents in groups, 13,...19 are all inactive.

2. **From Infectious to Mild and Severe**

   Infectious do not initially feel symptoms, but unlike the period in which they were just exposed, they spread the virus for a period that lasts T_{inf} days. After this period they suffer symptoms, that can be mild or severe. Severe patients (SEV) never revert to a state of MILD. MILD patients without proper medical care may turn into Severe. This process occurs after T_{inf} days, in which both infected and infectious have very mild symptoms, and thus do not avoid contacts. Within this framework, we introduce testing, which leads to domestic quarantine of the infectious with mild symptoms. Domestic quarantine, paired with pharmacological treatment, can stop them from reaching a stage requiring hospitalization. The dynamics of the Infectious in daily data is as follows:

$$\begin{aligned}
\Delta I_t(a) &= \left(\frac{1}{T_{inc}}\right) E_{t-1}(a) - (1-\delta)\left(\frac{1}{T_{\inf}}\right) I_{t-1}(a) - \delta\left(\frac{1}{T_{\inf_0}}\right) I_{t-1}(a) \\
\Delta MILD_t^U(a) &= p^{mild}(a)\,(1-\delta)\left(\frac{1}{T_{\inf}}\right) I_{t-1}(a) - \left(\frac{1}{T_{srec,U}}\right) MILD_{t-1}^U(a) \\
&\quad -p^{M2Sev,U}(a)\left(\frac{1}{T_{shosp,U}}\right) MILD_{t-1}^U(a) \\
\Delta MILD_t^D(a) &= p^{mild}(a)\delta\left(\frac{1}{T_{\inf_0}}\right) I_{t-1}(a) - \left(\frac{1}{T_{srec,D}}\right) MILD_{t-1}^D(a) \\
&\quad -p^{M2Sev,D}(a)\left(\frac{1}{T_{shosp,D}}\right) MILD_{t-1}^D(a) \\
\Delta SEV_t(a) &= \left(1 - p^{mild}(a)\right)\left((1-\delta)\left(\frac{1}{T_{\inf}}\right) + \delta\left(\frac{1}{T_{\inf_0}}\right)\right) I_{t-1}(a) - \left(\frac{1}{T_{shosp}}\right) SEV_{t-1}(a)
\end{aligned}$$

Exposed enter the compartment of the infectious as those with mild symptoms, $MILD_t(a)$, and those with severe symptoms, $SEV_t(a)$. The allocation to these groups is controlled by two probabilities: $p^{mild}(a)$ and $\left(1 - p^{mild}(a)\right)$. Testing allows to detect a share δ of those destined to become MILD; they thus become detected, $MILD_t^D(a)$ while $(1-\delta)$ become undetected, $MILD_t^U(a)$. Detection and associated medical care reduces the length of the period in which agents are infectious from $T_{\inf}$ to $T_{\inf_0} < T_{\inf}$. The same applies to the infectious who are destined to become Severe. As a consequence of the severity of symptoms, there are no Severe undetected after $T_{\inf}$ days in which they are virtually asymptomatic.

3. **Hospitalization,ICU needs and endogenous mortality**

The mild infected either recover – after periods of duration respectively of $T_{srec,U}$ and ($T_{srec,D}$) days – or their condition becomes severe and they require hospitalization, after a period of duration $T_{shosp,U}$ ($T_{shosp,D}$) days. The probability of becoming severe is higher for the undetected than for the detected: $p^{M2Sev,U}(a) > p^{M2Sev,D}(a)$. With testing and early detection, patients are cared at home and hospitals congestion is reduced. MILD patients who become severe and are hospitalized recover after a period of $(T_{shd,U} - T_{shosp,U})$ days. All severe patients become hospitalized after T_{shosp} days. Severe hospitalized either recover after $(T_{shd,U} - T_{shosp,U})$ days with probability $p^{ic}(a)$ or they worsen with probability $(1 - p^{ic}(a))$ and require intensive care after $T_{hosp-ic}$ days. Patients needing ICU may die or recover. When ICU is available and there is no hospital congestion mortality is determined by the CFR, $p^{fat}(a)$. However, mortality in ICU increases with hospital congestion. This increase is modelled by a logistic function of total hospitalization. The parameter k in the logistic is calibrated in such a way that the endogenous mortality probability is zero under normal conditions and it increases with hospital saturation. When ICU is fully saturated, mortality explodes as all patients in need of ICU who do not find availability succumb. Those patients in ICU who recover, leave ICU after $(T_{shd} - T_{hosp-ic})$. Those who do not recover die after $(T_{sd} - T_{shosp-ic})$. Those who need ICU and do not find it available, die immediately. The dynamics of hospitalization is determined as follows:

$$
\begin{aligned}
\Delta HOSP\_MILD_t(a) &= p^{M2Sev,D}(a)\left(\frac{1}{T_{shosp,D}}\right) MILD^D_{t-1}(a) + p^{M2Sev,U}(a)\left(\frac{1}{T_{shosp,U}}\right) MILD^U_{t-1}(a) \\
&\quad - \left(\frac{1}{T_{shd} - T_{shosp,U}}\right) HOSP\_MILD_{t-1}(a) \\
\Delta HOSP_t(a) &= \left(\frac{1}{T_{shosp}}\right) SEV_{t-1}(a) - p^{ic}(a)\left(\frac{1}{T_{hosp-ic}}\right) HOSP_{t-1}(a) \\
&\quad -(1-p^{ic}(a))\left(\frac{1}{T_{shd} - T_{shosp}}\right) HOSP_{t-1}(a) \\
p^{death}(a) &= \left(p^{fat-ic}(a)\right) + \left(1 - p^{fat-ic}(a)\right)\left(\frac{1}{1 + e^{-k_0(HOSP\_MILD_t + HOSP_t - k_1)}}\right) \\
NEW\_DEM\_IC_t(a) &= p^{ic}(a)\left(\frac{1}{T_{hosp-ic}}\right) HOSP_{t-1}(a) \\
p^{av} &= \min\left\{1, \frac{ICC_t - \sum_a HOSP\_IC_{t-1}(a)}{\sum_a NEW\_DEM\_IC_t(a)}\right\} \\
\Delta HOSP\_IC_t(a) &= p^{av} NEW\_DEM\_IC_t(a) - p^{death}(a)\left(\frac{1}{T_{sd} - T_{hosp-ic} - T_{shosp}}\right) HOSP\_IC_{t-1}(a) \\
&\quad -(1 - p^{death}(a))\left(\frac{1}{T_{shd} - T_{hosp-ic} - T_{shosp}}\right) HOSP\_IC_{t-1}(a) \\
\Delta HOSP\_POST\_IC_t(a) &= (1 - p^{death}(a))\left(\frac{1}{T_{shd} - T_{hosp-ic} - T_{shosp}}\right) HOSP\_IC_{t-1}(a) \\
&\quad - \left(\frac{1}{T_{ic-rec}}\right) HOSP\_POST\_IC_{t-1}(a)
\end{aligned}
$$

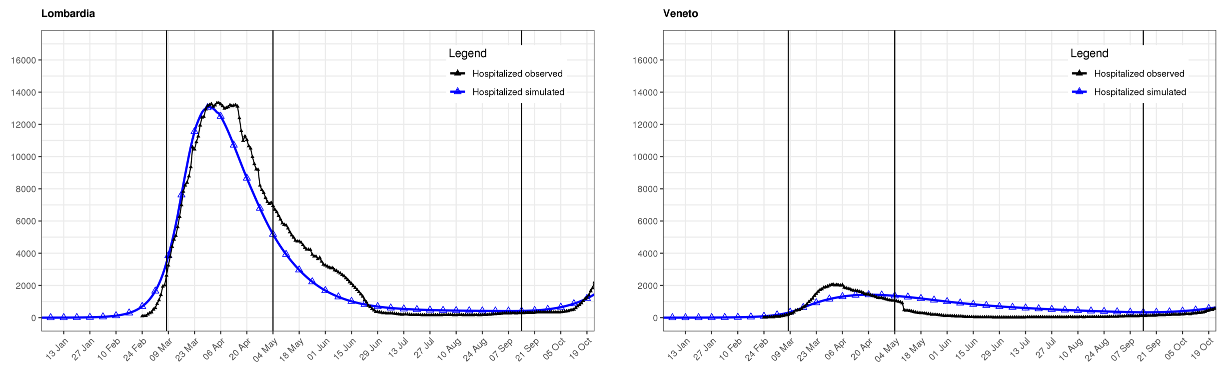
4. **Recoveries and Fatalities**

At the end of each day the population decreases because of fatalities, while the stock of recovered grows by the amount of those who survive having had mild or severe symptoms, with or without the need of IC.

$$
\begin{aligned}
\Delta FAT_t(a) &= (1 - p^{available}) NEW\_DEM\_IC_t(a) + p^{death}(a)\left(\frac{1}{T_{sd} - T_{hosp-ic} - T_{shosp}}\right) HOSP\_IC_{t-1}(a) \\
\Delta REC_t(a) &= \left(\frac{1}{T_{ic-rec}}\right) HOSP\_POST\_IC_{t-1}(a) + (1 - p^{ic}(a))\left(\frac{1}{T_{shd} - T_{shosp} - T_{shosp}}\right) HOSP_{t-1}(a) \\
&\quad + \left(\frac{1}{T_{srec,U}}\right) MILD^U_{t-1}(a) + \left(\frac{1}{T_{srec,D}}\right) MILD^D_{t-1}(a) + \left(\frac{1}{T_{shd} - T_{shosp,U}}\right) HOSP\_MILD_{t-1}(a) \\
\Delta N_t &= -\sum_{a \in A} \Delta FAT_t(a)
\end{aligned}
$$

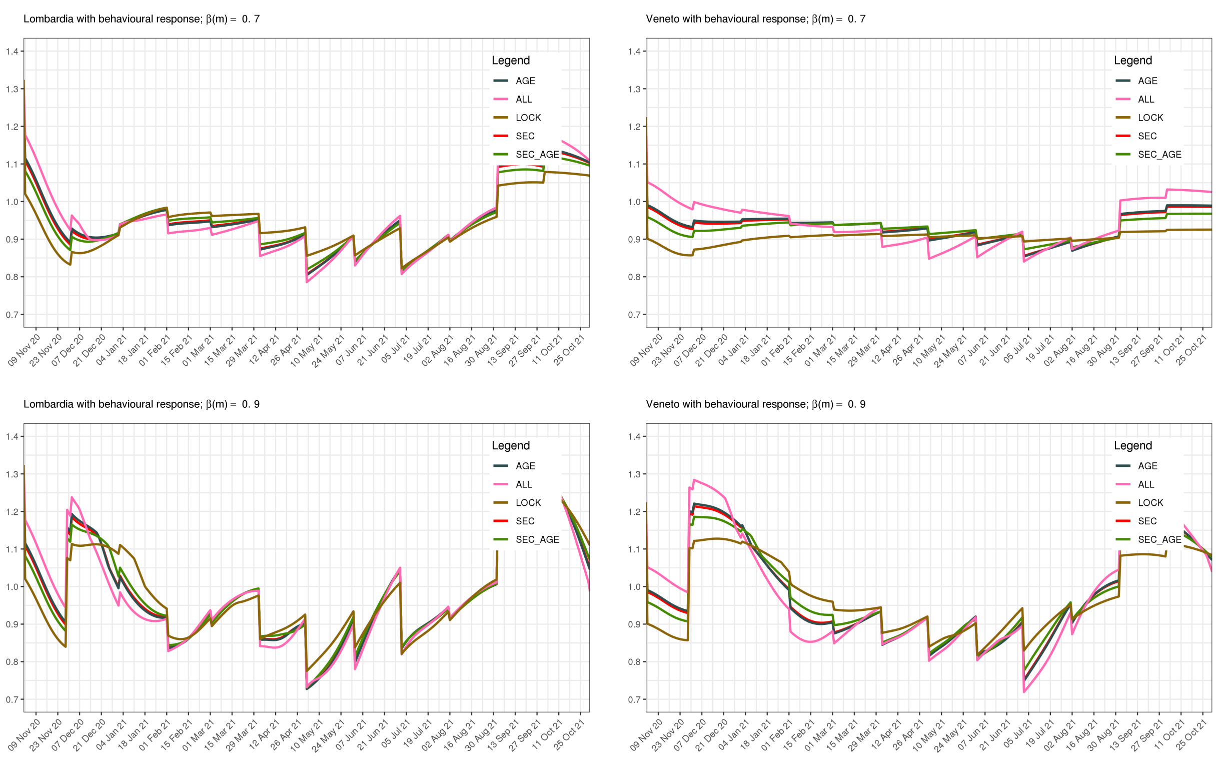
Appendix to Section 6.6: Calibration Results

Figure B–3: Simulated and observed daily hospitalization with parameters from Ferguson et al. (2020)



Note: the figure reports, respectively for the two regions, the simulated and observed numbers of daily hospitalized due to Covid-19.The vertical bars indicate the start of the lockdown (March 8), the start of the phase 2 (May 4) and the start of the new school year (September 14). Source: The simulated values are from the SEIR-HC-SEC-AGE model. The observed series were downloaded from `https://github.com/pcm-dpc/COVID-19`.

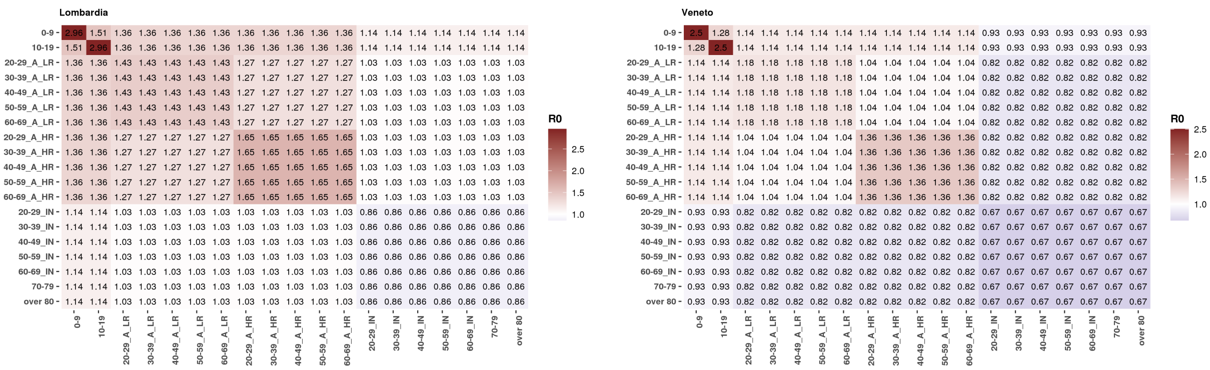
Figure B–4: Simulated daily R_t with parameters from Ferguson et al. (2020)



Note: The figure reports, for both Lombardia (left panels) and Veneto (right panels), the average R_t during the simulation period under the 5 representative policies that we consider with behavioral response. The upper panels refer to $\beta(m) = 0.7$ while the lower panels refer to $\beta(m) = 0.9$. The jumps are due to the change of temperature from months to months.

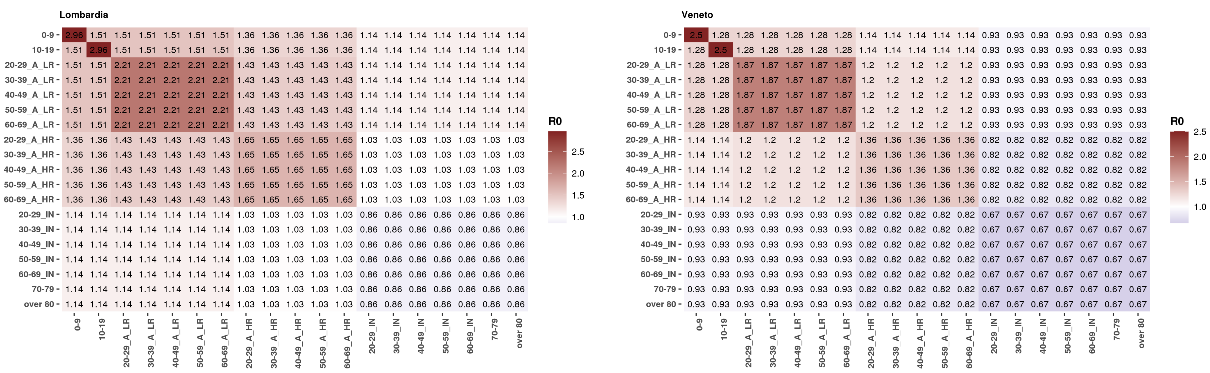
Appendix to Section 7.1: The BRM under alternative policies

Figure B–5: Equivalent Basic Reproduction Matrices post-Lockdown for Policy LOCK



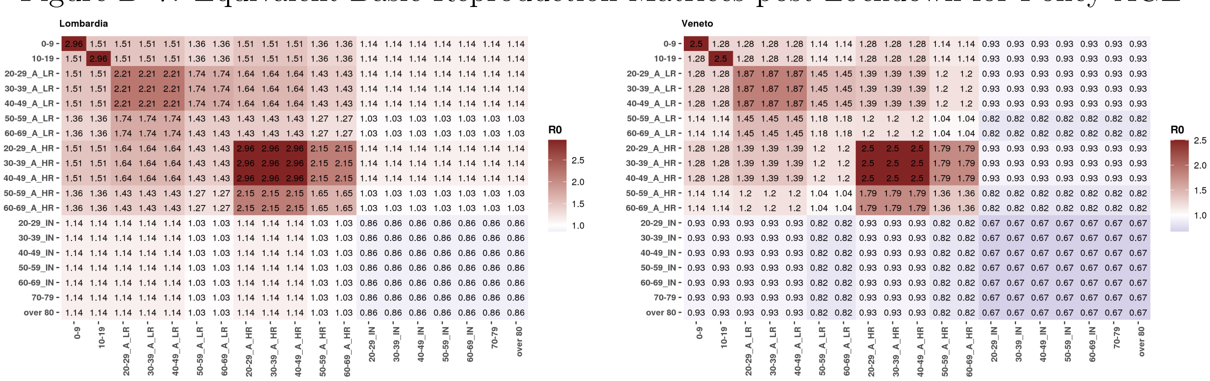
Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

Figure B–6: Equivalent Basic Reproduction Matrices post-Lockdown for Policy SEC



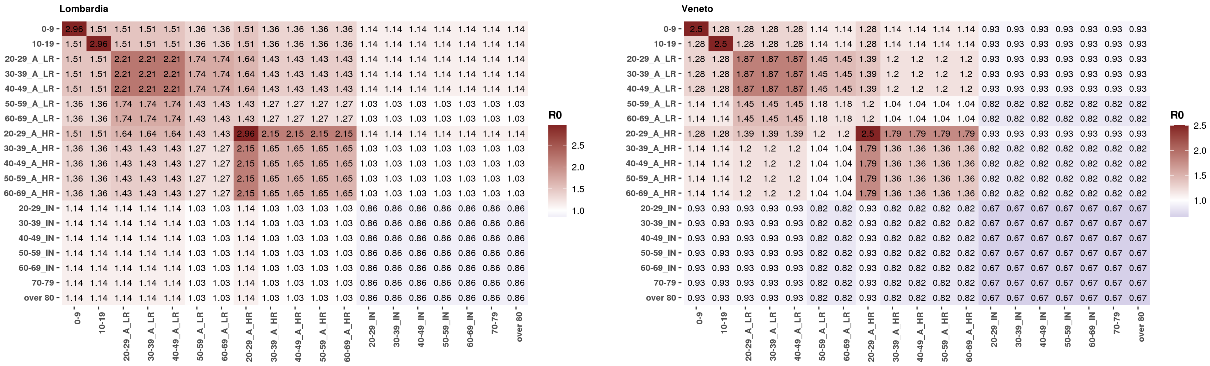
Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

Figure B–7: Equivalent Basic Reproduction Matrices post-Lockdown for Policy AGE



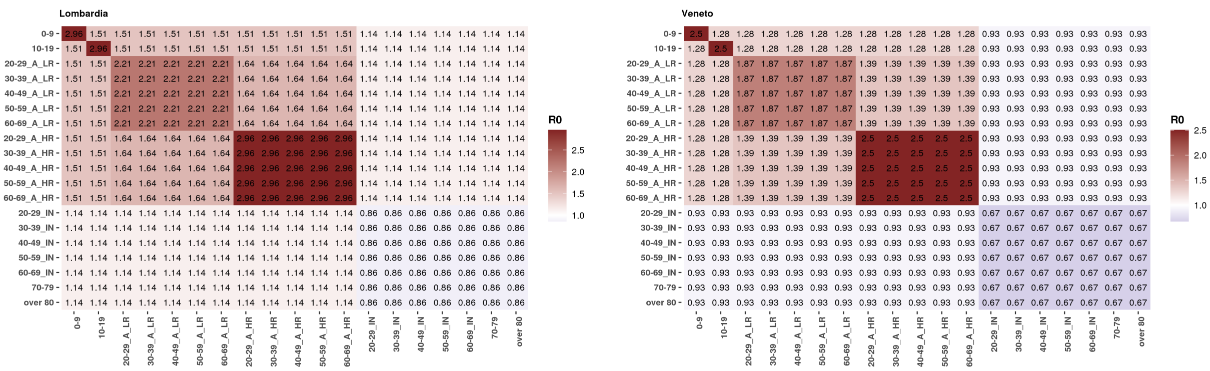
Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

Figure B–8: Equivalent Basic Reproduction Matrices post-Lockdown for Policy AGE-SEC



Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

Figure B–9: Equivalent Basic Reproduction Matrices post-Lockdown for Policy ALL



Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

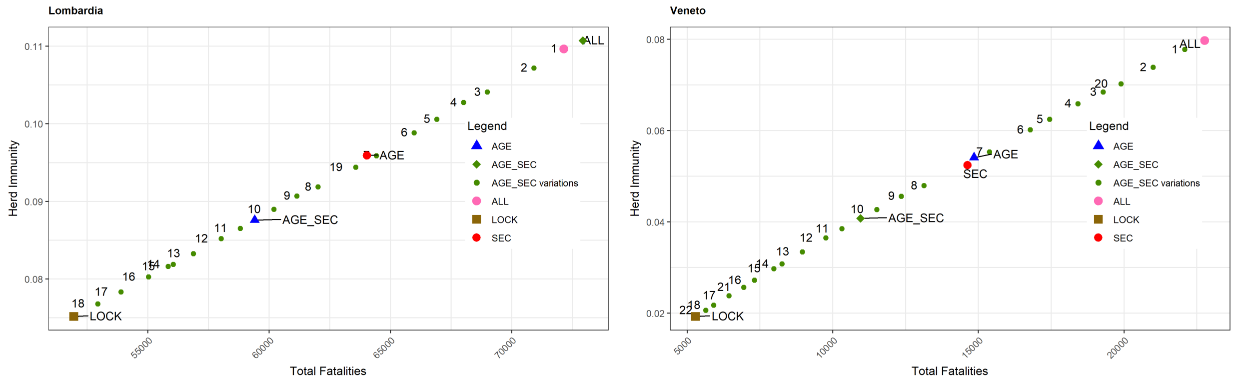
Appendix to Section 7.2: The Simulation of the Effects of Different Policies

Table B–1: Worker activation vector of the efficient policies in Lombardia and Veneto with behavioural response amd $\beta(m) = 0.9$

	Low-Risk sector Age brackets					High-Risk sector Age brackets				
Policy	20-29	30-39	40-49	50-59	60-65	20-29	30-39	40-49	50-59	60-65
Efficient AGE_SEC policies common to both regions										
$p =$ ALL	1	1	1	1	1	1	1	1	1	1
$p = AGE\_SEC_1$	1	1	1	1	1	1	1	1	1	0.6
$p = AGE\_SEC_2$	1	1	1	1	1	0.6	1	1	1	0.6
$p = AGE\_SEC_3$	1	1	1	1	1	1	1	1	0.6	0.6
$p = AGE\_SEC_4$	1	1	1	1	1	0.6	1	1	0.6	0.6
$p = AGE\_SEC_5$	1	1	1	1	0.6	0.6	1	1	0.6	0.6
$p = AGE\_SEC_6$	1	1	1	1	0.6	1	0.6	1	0.6	0.6
$p = AGE\_SEC_7$	1	1	1	1	0.6	1	1	0.6	0.6	0.6
$p = SEC\_SEC_8$	1	1	1	1	0.6	0.6	1	0.6	0.6	0.6
$p = AGE\_SEC_9$	0.6	1	1	1	0.6	1	1	0.6	0.6	0.6
$p = AGE\_SEC_{10}$	0.6	1	1	1	0.6	0.6	1	0.6	0.6	0.6
$p = AGE\_SEC_{11}$	1	1	1	0.6	1	1	1	0.6	0.6	0.6
$p = AGE\_SEC_{12}$	1	1	1	0.6	0.6	1	1	0.6	0.6	0.6
$p = AGE\_SEC_{13}$	1	1	1	0.6	0.6	0.6	1	0.6	0.6	0.6
$p = AGE\_SEC$	1	1	1	0.6	0.6	1	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{14}$	1	1	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{15}$	0.6	1	1	0.6	0.6	1	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{16}$	1	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{17}$	1	0.6	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{18}$	1	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{19}$	0.6	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{20}$	1	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p =$ LOCK	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
Efficient AGE_SEC policies for Veneto only										
$p = AGE\_SEC_{22}$	1	1	1	1	1	1	0.6	1	1	0.6
$p = AGE\_SEC_{23}$	1	1	1	1	1	1	1	1	0.6	1
$p = AGE\_SEC_{24}$	1	1	1	1	1	1	0.6	1	0.6	0.6
Other representative policies close to the efficient contour										
$p = AGE$	1	1	1	0.6	0.6	1	1	1	0.6	0.6
$p = SEC$	1	1	1	1	1	0.6	0.6	0.6	0.6	0.6

Note: This table reports the labor force activation vector for all the efficient and representative policies.

Figure B–10: The trade off between herd immunity and fatalities



Note: This figure describes the trade off betweeen fatalities and herd immunity which is defined as the ratio between total recoveries and population in the last period of the simulation. Source: our simulations of the SEIR-HC-SEC-AGE model.

Table B–2: Lombardia and Veneto: final main outcome with $\beta(m) = 0.9$

	Policies				
	LOCK	SEC	AGE	SEC_AGE	ALL
Lombardia					
Total fatalities	31518	39512	40095	36993	45632
GDP loss	0.26	0.104	0.094	0.148	0
Final immunity share	0.074	0.087	0.089	0.083	0.098
Average R_t	0.991 (0.775-1.324)	0.991 (0.727-1.324)	0.992 (0.727-1.324)	0.992 (0.732-1.324)	0.991 (0.733-1.333)
Veneto					
Total fatalities	11661	17936	18234	15858	22756
GDP loss	0.26	0.104	0.097	0.150	0
Final immunity share	0.051	0.071	0.073	0.065	0.087
Average R_t	0.981 (0.818-1.225)	0.985 (0.751-1.225)	0.986 (0.749-1.225)	0.985 (0.776-1.225)	0.987 (0.719-1.284)

Note: The table reports the main outcomes of the five policies in Lombardia and Veneto, for the scenario with behavioural response and $\beta(m) = 0.9$, measured over the year between November 1, 2020 and October 31, 2021. Final immunity share is calculated at the end of the simulation period taking into account the total exposed from January 1, 2020. The numbers in the parentheses indicate the minimum and maximum Average R_t during the simulation period (they do not define a confidence interval.

Appendix C

Evidence based on Covid-19 parameters from CDC (Garg, 2020)

This section evaluate the robustness of results using Covid-19 parameters estimated for the U.S. by the Center of Deseases Control (CDC (Garg, 2020)) . The next two tables report this different set of parameters.

Table C–3: Health effects of Covid-19 by age bracket (Garg (2020))

	Age brackets								
	0-9	10-19	20-29	30-39	40-49	50-59	60-69	70-79	80+
p^{sev}	0.001	0.003	0.012	0.032	0.049	0.102	0.166	0.243	0.273
p^{ic}	0.05	0.05	0.05	0.05	0.063	0.122	0.274	0.432	0.709
p^{fat}	0.00002	0.00006	0.0003	0.0008	0.0015	0.006	0.022	0.051	0.093

Note: the table reports for each age bracket the probability of hospitalization, p^{sev}, the probability of needing intensive care if hospitalized, p^{ic} and the probability of death p^{fat} for a subject exposed to Covid-19 infection. Source: Garg (2020).

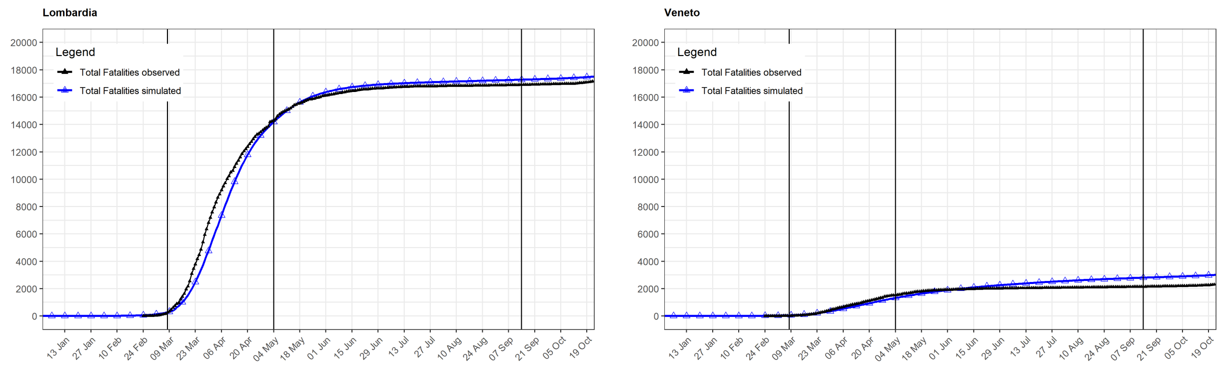
Table C–4: Calibrated parameters

Lombardia				Veneto			
k_0	k_1	$\delta_{1:68}$	$\delta_{68:609}$	k_0	k_1	$\delta_{1:609}$	γ
0.0008	2000	0.3	0.7	0.0008	800	0.7	0.1

Note: k_1 and k_2 are the parameters of the logistic function that affects the endogenous mortality $\left(\frac{1}{1+e^{-k_0(HOSP\_MILD_t+HOSP_t-k_1)}}\right)$. δ_t and γ are consistent with the higher hospitalization rate implied by parameters from Garg (2020).

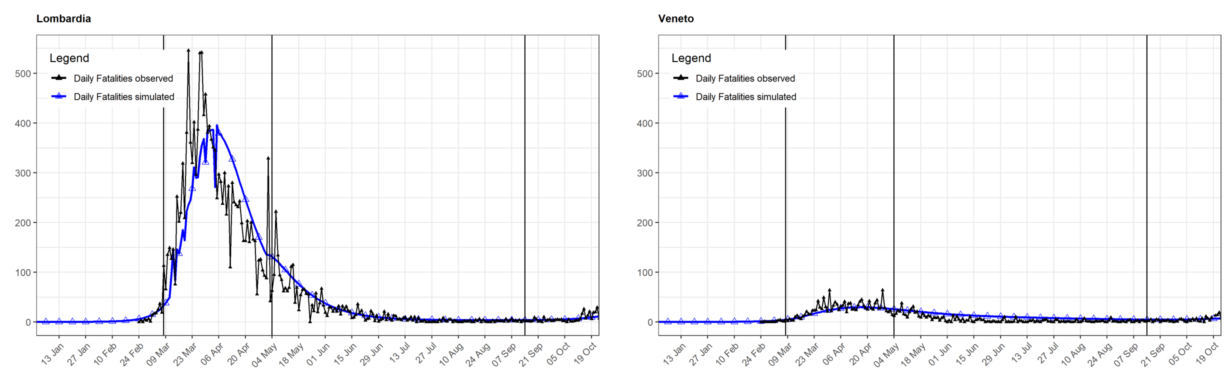
Appendix to Section 6.6: Calibration Results

Figure C–11: Simulated and observed total fatalities with parameters from Garg (2020).



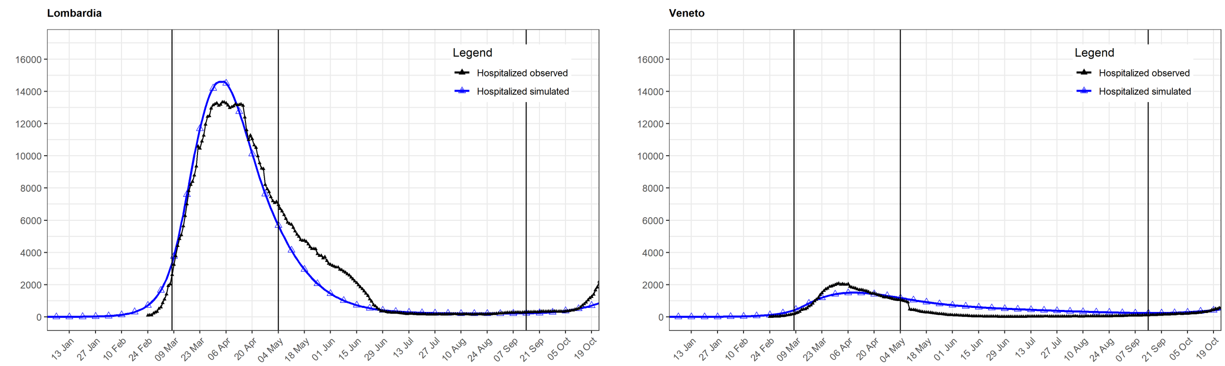
Note: The figure reports, respectively for the two regions, the simulated and observed numbers of daily hospitalized due to Covid-19.The vertical bars indicate the start of the lockdown (March 8), the start of the phase 2 (May 4) and the start of the new school year (September 14). Source: The simulated values are from the SEIR-HC-SEC-AGE model. The observed series were downloaded from `https://github.com/pcm-dpc/COVID-19`.

Figure C–12: Simulated and observed daily fatalities with parameters from Garg (2020).



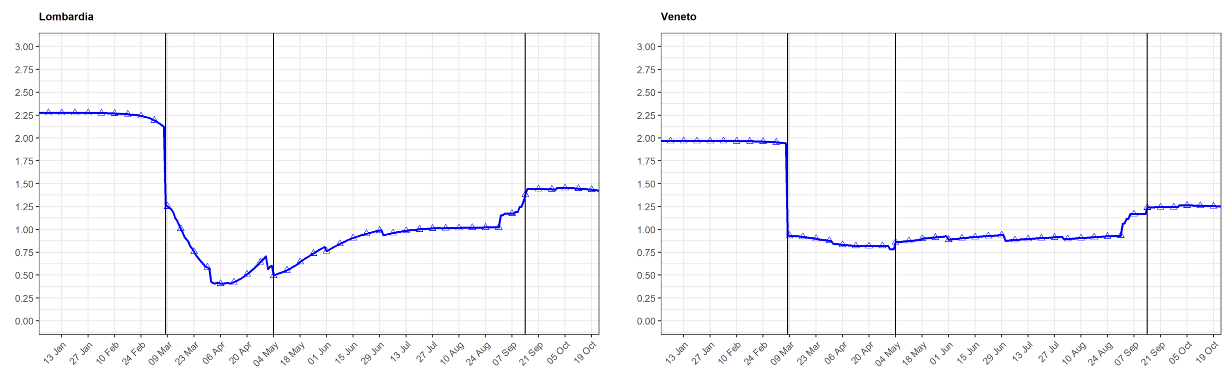
Note: The figure reports, respectively for the two regions, the simulated and observed numbers of daily fatalities due to Covid-19. The vertical bars indicate the start of the lockdown (March 8), the start of the phase 2 (May 4) and the start of the new school year (September 14). Source: The simulated values are from the SEIR-HC-SEC-AGE model. The observed series were downloaded from `https://github.com/pcm-dpc/COVID-19`.

Figure C–13: Simulated and observed daily hospitalization with parameters from Garg (2020).



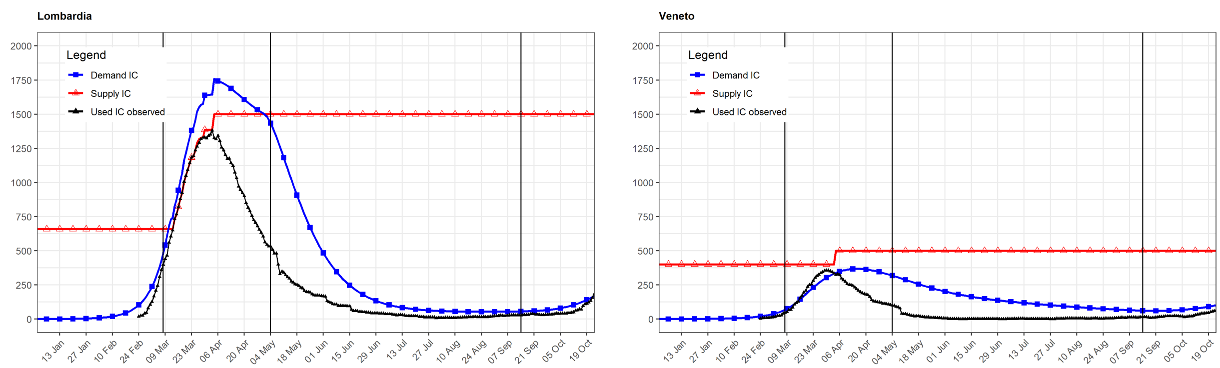
Note: the figure reports, respectively for the two regions, the simulated and observed numbers of daily hospitalized due to Covid-19. The vertical bars indicate the start of the lockdown (March 8), the start of the phase 2 (May 4) and the start of the new school year (September 14). Source: The simulated values are from the SEIR-HC-SEC-AGE model. The observed series were downloaded from `https://github.com/pcm-dpc/COVID-19`.

Figure C–14: Simulated average R_t with CDC parameters with parameters from Garg (2020).



Note: The figure reports, respectively for the two regions, the average R_t, weighted to take into account the population structure. The vertical bars indicate the start of the lockdown (March 8), the start of the phase 2 (May 4) and the start of the new school year (September 14).

Figure C–15: The IC availability constraint in Lombardia and Veneto with parameters from Garg (2020).



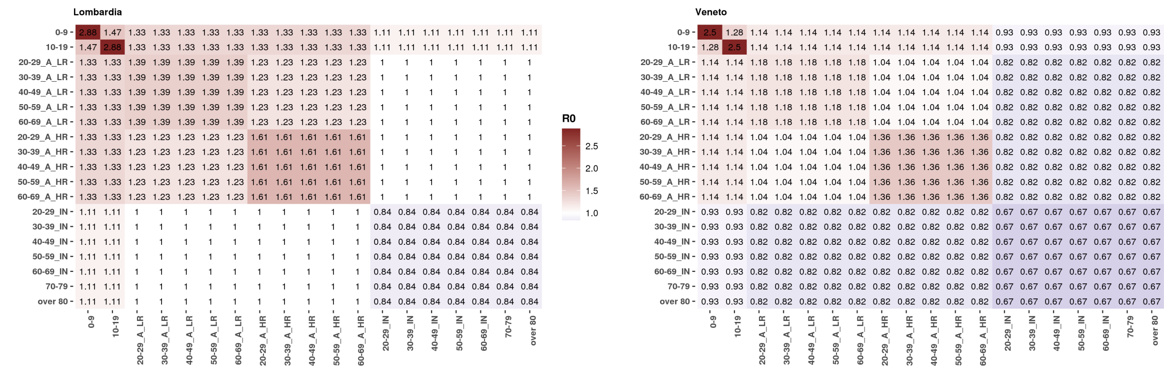
Note: The figure reports, respectively for the two regions, the simulated demand for IC beds due to Covid-19, the observed number Covid-19 patients in IC and the observed number of patients that were effectively hospitalized in IC. The vertical bars indicate the start of the lockdown (March 8), the start of the phase 2 (May 4) and the start of the new school year (September 14). Source: the demand for IC is simulated by our SEIR-HC-SEC-AGE model. The observed series were downloaded from `https://github.com/pcm-dpc/COVID-19` for the used IC and from `https://www.dropbox.com/s/skabm9ct71qud32/ICU%20beds%20statistics.xlsx?dl=0` for the supply of IC.

Figure C–16: Simulated daily R_t with parameters from Garg (2020).

Note: The figure reports, for both Lombardia (left panels) and Veneto (right panels), the average R_t during the simulation period under the 5 representative policies that we consider with behavioral response. The upper panels refer to $\beta(m) = 0.7$ while the lower panels refer to $\beta(m) = 0.9$. The jumps are due to the change of temperature from months to months.

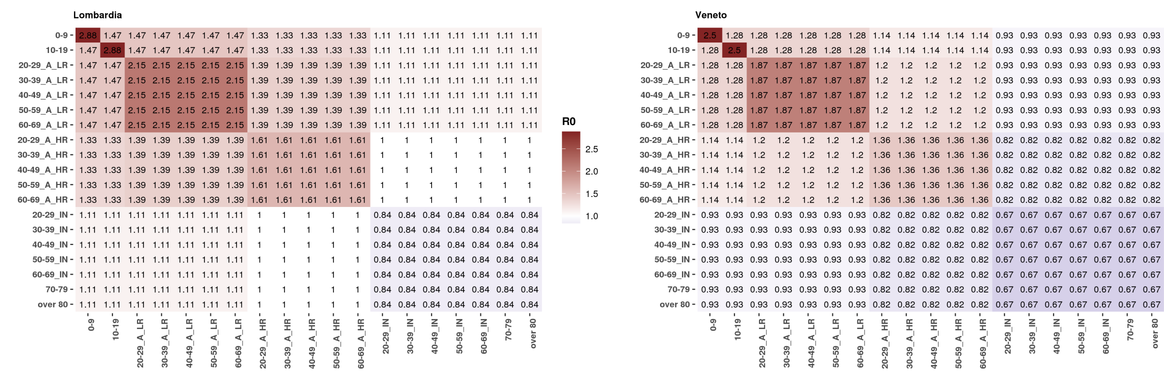
Appendix to Section 7.1: The BRM under alternative policies

Figure C–17: Equivalent Basic Reproduction Matrices post-Lockdown for Policy LOCK with parameters from Garg (2020).



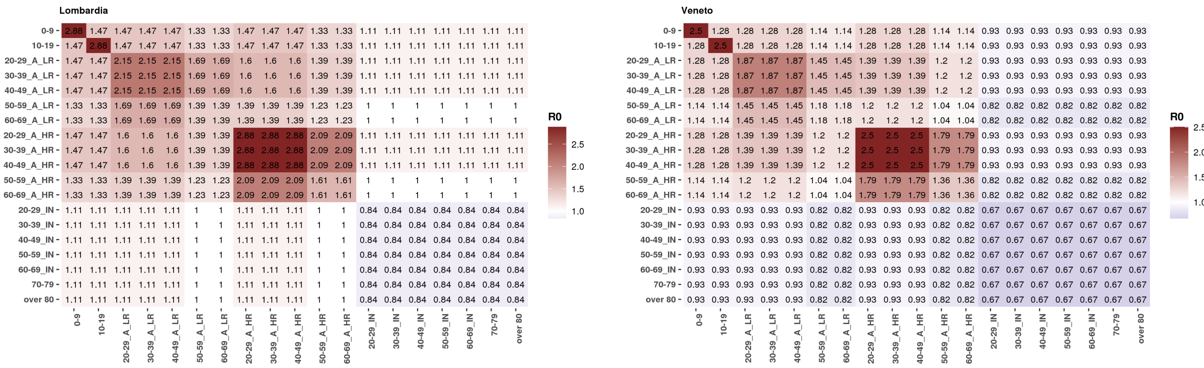
Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

Figure C–18: Equivalent Basic Reproduction Matrices post-Lockdown for Policy SEC with parameters from Garg (2020).



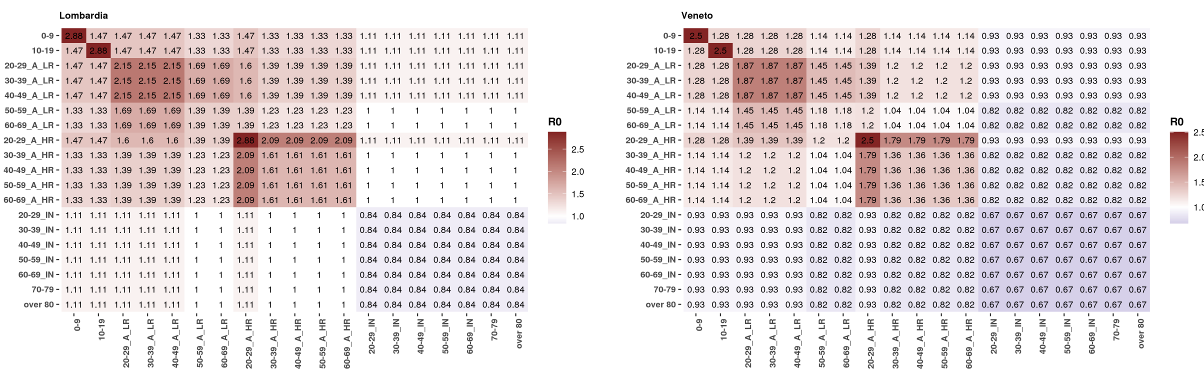
Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

Figure C–19: Equivalent Basic Reproduction Matrices post-Lockdown for Policy AGE with parameters from Garg (2020).



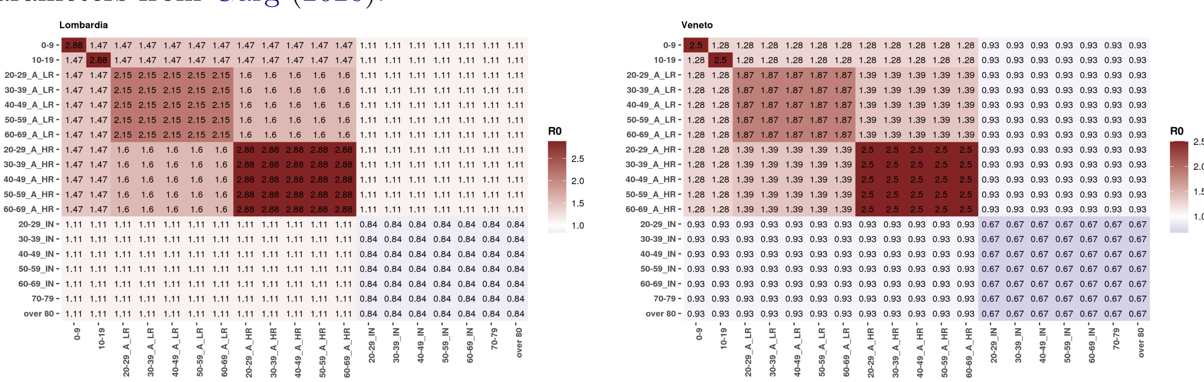
Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

Figure C–20: Equivalent Basic Reproduction Matrices post-Lockdown for Policy AGE-SEC with parameters from Garg (2020).



Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

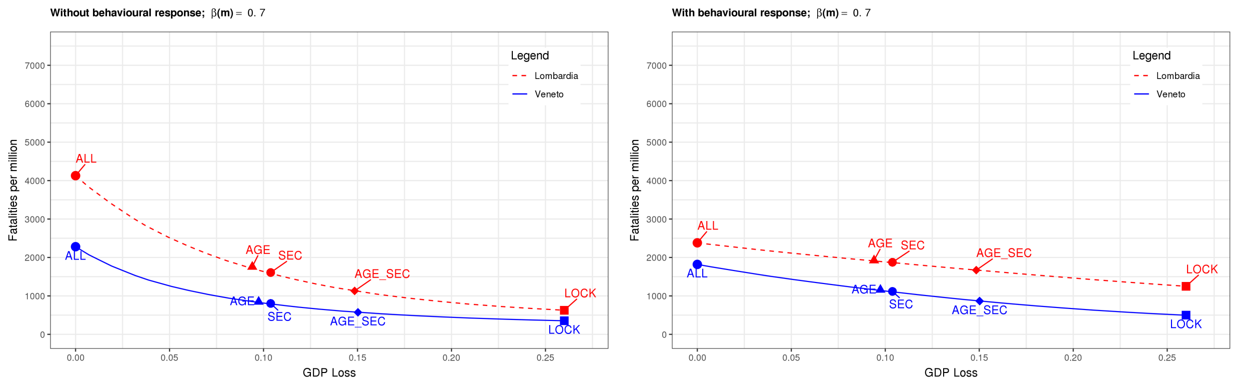
Figure C–21: Equivalent Basic Reproduction Matrices post-Lockdown for Policy ALL with parameters from Garg (2020).



Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

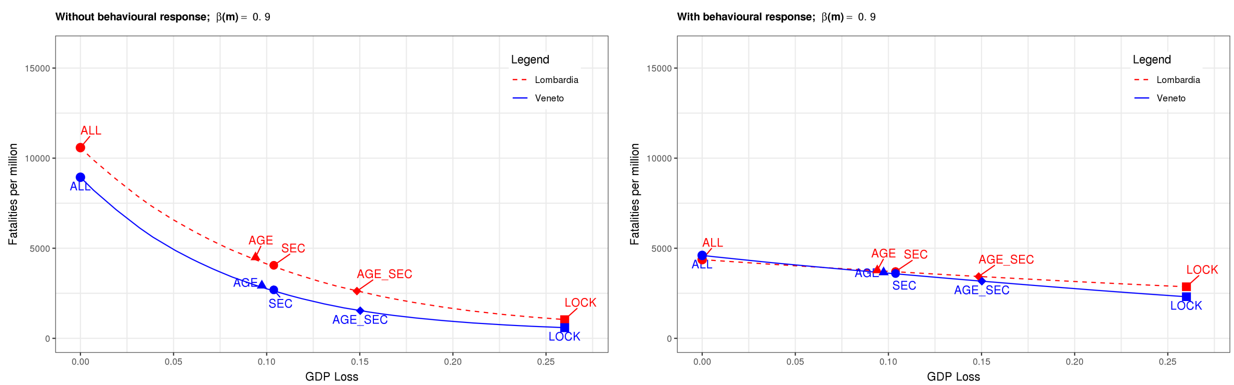
Appendix to Section 7.2: The Simulation of the Effects of Different Policies

Figure C–22: The efficient frontier in the two regions with $\beta(m) = 0.7$



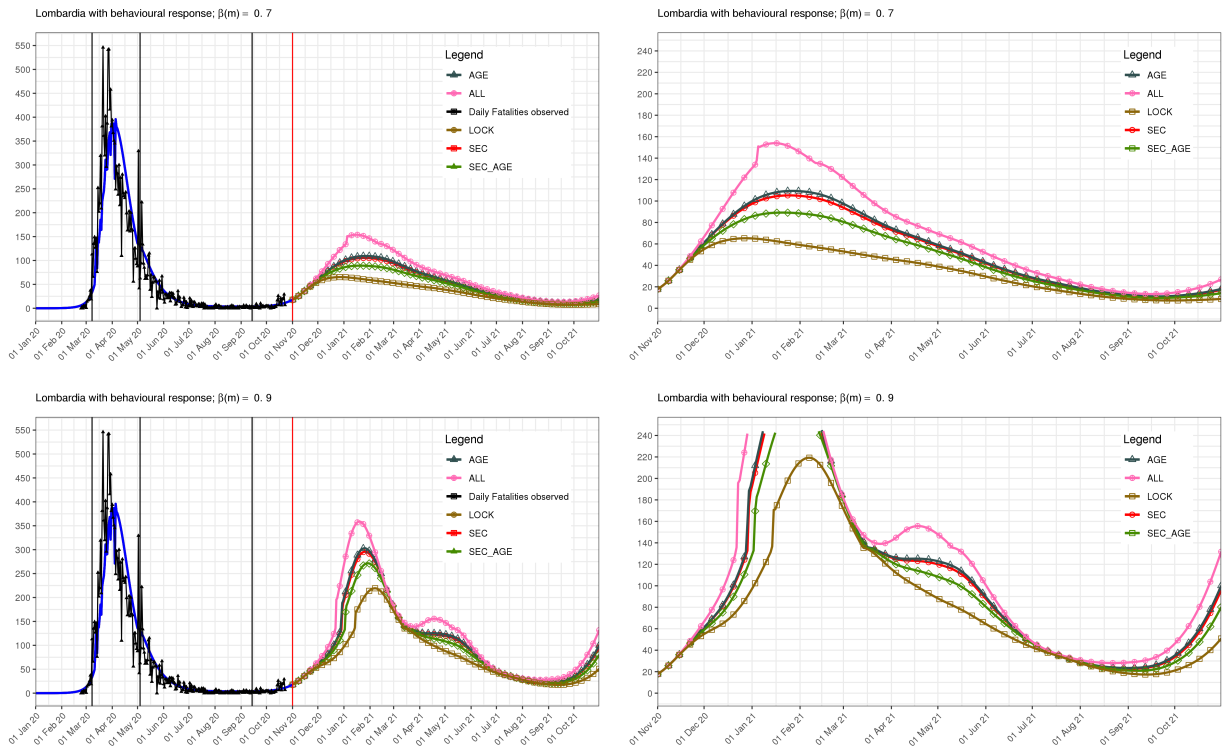
Note: In each panel, the two curves report the efficient frontiers for outcomes occurring between November 1, 2020, and October 31, 2021. Each point shows the GDP loss and the number of fatalities per million individuals associated to the policies that are efficient (as defined in the text). The representative policies are displayed in the same way. GDP losses are defined as relative to the GDP implied by the policy ALL.

Figure C–23: The efficient frontier in the two regions with $\beta(m) = 0.9$



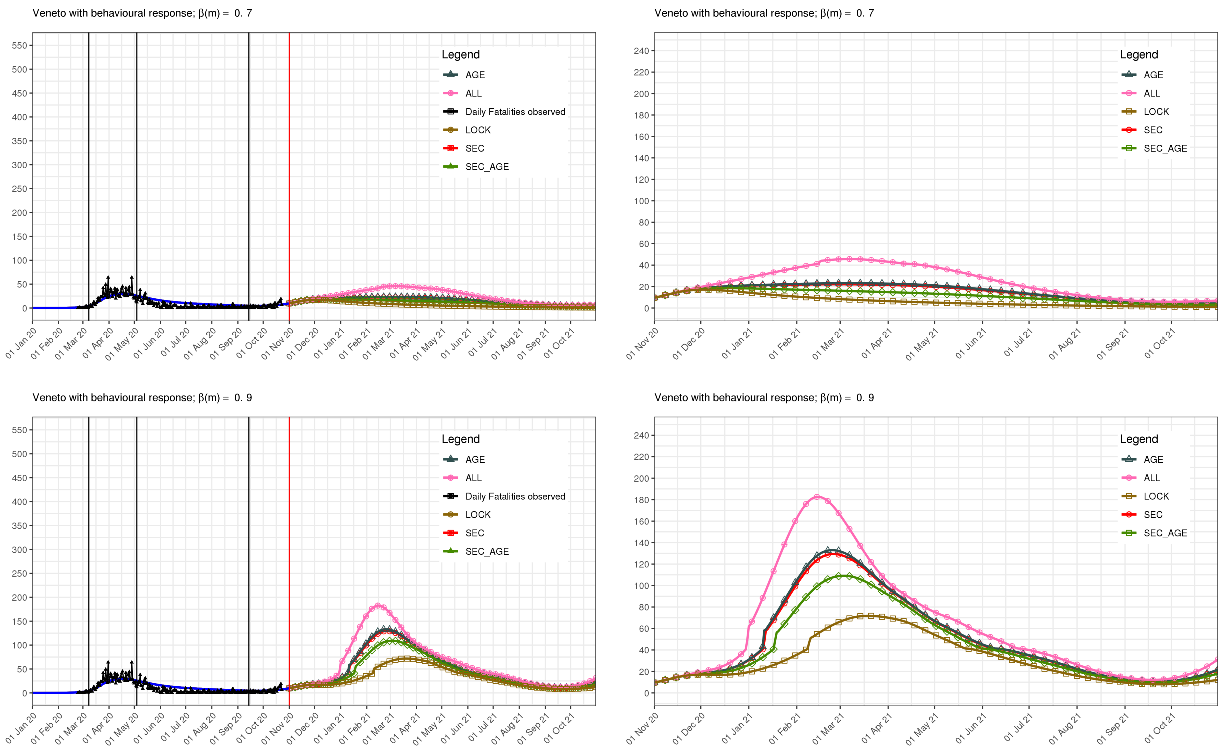
Note: In each panel, the two curves report the efficient frontiers for outcomes occurring between November 1, 2020, and October 31, 2021. Each point shows the GDP loss and the number of fatalities per million individuals associated to the policies that are efficient (as defined in the text). The representative policies are displayed in the same way. GDP losses are defined as relative to the GDP implied by the policy ALL.

Figure C–24: Daily fatalities under the different policies in Lombardia with parameters from Garg (2020).



Note: The figure reports, for Lombardia, the daily fatalities due to Covid-19 under the 5 representative policies that we consider, for the scenario with behavioural response and $\beta(m) = 0.7$. The left panel covers the entire period from January 1, 2020 to October 31, 2021. The right panel zooms into the year of simulation starting on November 1 in order to better highlight the differences between the fatalities associated to each policy.

Figure C–25: Daily fatalities under the different policies in Veneto with parameters from Garg (2020).



The figure reports, for Veneto, the daily fatalities due to Covid-19 under the 5 representative policies that we consider, for the scenario with behavioural response and $\beta(m) = 0.7$. The left panel covers the entire period from January 1, 2020 to October 31, 2021. The right panel zooms into the year of simulation starting on November 1 in order to better highlight the differences between the fatalities associated to each policy.

Table C–5: Lombardia and Veneto: final main outcome with parameters from Garg (2020) and $\beta(m) = 0.9$

	Policies				
	LOCK	SEC	AGE	SEC_AGE	ALL
Lombardia					
Total fatalities	28621	37066	37745	34702	43702
GDP loss	0.26	0.104	0.094	0.148	0
Final immunity share	0.058	0.070	0.071	0.066	0.079
Average R_t	1.004	1.008	1.009	1.008	1.009
	(0.771-1.397)	(0.737-1.397)	(0.732-1.397)	(0.756-1.397)	(0.700-1.409)
Veneto					
Total fatalities	11311	17634	17956	15540	22556
GDP loss	0.26	0.104	0.097	0.150	0
Final immunity share	0.039	0.055	0.057	0.050	0.068
Average R_t	0.983	0.991	0.991	0.989	0.996
	(0.772-1.239)	(0.740-1.254)	(0.739-1.260)	(0.753-1.239)	(0.732-1.334)

Note: The table reports the main outcomes of the five policies in Lombardia and Veneto, for the scenario with behavioural response and $\beta(m) = 0.9$, measured over the year between November 1, 2020 and October 31, 2021. Final immunity share is calculated at the end of the simulation period taking into account the total exposed from January 1, 2020. The numbers in the parentheses indicate the minimum and maximum Average R_t during the simulation period (they do not define a confidence interval.

Table C–6: Lombardia and Veneto: final main outcome with parameters from Garg (2020) and $\beta(m) = 0.7$

	Policies				
	LOCK	SEC	AGE	SEC_AGE	ALL
Lombardia					
Total fatalities	12504	18748	19244	16714	23808
GDP loss	0.26	0.104	0.094	0.148	0
Final immunity share	0.038	0.046	0.047	0.044	0.053
Average R_t	0.953	0.964	0.965	0.962	0.971
	(0.813-1.397)	(0.791-1.397)	(0.790-1.397)	(0.799-1.397)	(0.770-1.397)
Veneto					
Total fatalities	2435	5473	5673	4249	8915
GDP loss	0.26	0.104	0.097	0.150	0
Final immunity share	0.015	0.024	0.025	0.020	0.033
Average R_t	0.914	0.938	0.940	0.935	0.947
	(0.844-1.239)	(0.820-1.239)	(0.816-1.239)	(0.850-1.239)	(0.783-1.239)

Note: The table reports the main outcomes of the five policies in Lombardia and Veneto, for the scenario with behavioural response and $\beta(m) = 0.7$, measured over the year between Novbember 1, 2020 and October 31, 2021. Final immunity share is calculated at the end of the simulation period taking into account the total exposed from January 1, 2020. The numbers in the parentheses indicate the minimum and maximum Average R_t during the simulation period (they do not define a confidence interval.

Table C–7: Worker activation vector of the efficient policies in Lombardia and Veneto with behavioural response, $\beta(m) = 0.7$ and parameters from Garg (2020)

	Low-Risk sector Age brackets					High-Risk sector Age brackets				
Policy	20-29	30-39	40-49	50-59	60-65	20-29	30-39	40-49	50-59	60-65
Efficient AGE_SEC policies common to both regions										
$p = ALL$	1	1	1	1	1	1	1	1	1	1
$p = AGE\_SEC_1$	1	1	1	1	1	1	1	1	1	0.6
$p = AGE\_SEC_2$	1	1	1	1	1	0.6	1	1	1	0.6
$p = AGE\_SEC_3$	1	1	1	1	1	1	1	1	0.6	1
$p = AGE\_SEC_4$	1	1	1	1	1	1	1	1	0.6	0.6
$p = AGE\_SEC_5$	1	1	1	1	1	0.6	1	1	0.6	0.6
$p = AGE\_SEC_6$	1	1	1	1	1	1	0.6	1	0.6	0.6
$p = AGE\_SEC_7$	1	1	1	1	0.6	1	1	0.6	0.6	0.6
$p = AGE\_SEC_8$	1	1	1	1	0.6	0.6	1	0.6	0.6	0.6
$p = AGE\_SEC_9$	1	1	1	0.6	1	0.6	1	0.6	0.6	0.6
$p = AGE\_SEC_{10}$	1	1	1	0.6	0.6	0.6	1	0.6	0.6	0.6
$p = AGE\_SEC$	1	1	1	0.6	0.6	1	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{11}$	0.6	1	1	0.6	0.6	1	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{12}$	0.6	1	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{13}$	1	0.6	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{14}$	1	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{15}$	0.6	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{16}$	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
Efficient AGE_SEC policies for Lombardia only										
$p = AGE\_SEC_{17}$	1	1	1	1	1	1	1	0.6	0.6	0.6
Efficient AGE_SEC policies for Veneto only										
$p = AGE\_SEC_{18}$	1	1	1	1	0.6	1	0.6	1	0.6	0.6
$p = AGE\_SEC_{19}$	0.6	1	1	1	0.6	1	1	0.6	0.6	0.6
$p = AGE\_SEC_{20}$	0.6	1	1	1	0.6	0.6	1	0.6	0.6	0.6
$p = AGE\_SEC_{21}$	1 1	1	0.6	1	1	1	0.6	0.6	0.6	
$p = AGE\_SEC_{22}$	1	1	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6
Other representative policies close to the efficient contour										
$p = AGE$	1	1	1	0.6	0.6	1	1	1	0.6	0.6
$p = SEC$	1	1	1	1	1	0.6	0.6	0.6	0.6	0.6

Note: This table reports the labor force activation vector for all the efficient and representative policies.

Table C–8: Worker activation vector of the efficient policies in Lombardia and Veneto with behavioural response, $\beta(m) = 0.9$ and parameters from Garg (2020)

	Low-Risk sector Age brackets					High-Risk sector Age brackets				
Policy	20-29	30-39	40-49	50-59	60-65	20-29	30-39	40-49	50-59	60-65
Efficient AGE_SEC policies common to both regions										
$p = ALL$	1	1	1	1	1	1	1	1	1	1
$p = AGE\_SEC_1$	1	1	1	1	1	1	1	1	1	0.6
$p = AGE\_SEC_2$	1	1	1	1	1	0.6	1	1	1	0.6
$p = AGE\_SEC_3$	1	1	1	1	1	1	1	1	0.6	1
$p = AGE\_SEC_4$	1	1	1	1	1	1	1	1	0.6	0.6
$p = AGE\_SEC_5$	1	1	1	1	1	0.6	1	1	0.6	0.6
$p = AGE\_SEC_6$	1	1	1	1	1	1	1	0.6	0.6	0.6
$p = AGE\_SEC_7$	1	1	1	1	0.6	1	1	0.6	0.6	0.6
$p = AGE\_SEC_8$	1	1	1	0.6	1	0.6	1	0.6	0.6	0.6
$p = AGE\_SEC_9$	1	1	1	0.6	0.6	0.6	1	0.6	0.6	0.6
$p = AGE\_SEC$	1	1	1	0.6	0.6	1	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{10}$	0.6	1	1	0.6	0.6	1	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{11}$	0.6	1	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{12}$	1	0.6	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{13}$	1	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{14}$	0.6	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{15}$	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
Efficient AGE_SEC policies for Lombardia only										
$p = AGE\_SEC_{16}$	1	1	1	1	1	1		1 0.6	0.6	1
$p = AGE\_SEC_{17}$	1	1	1	1	0.6	0.6	1	0.6	0.6	0.6
$p = AGE\_SEC_{18}$	0.6	1	1	1	0.6	0.6	1	0.6	0.6	0.6
Efficient AGE_SEC policies for Veneto only										
$p = AGE\_SEC_{19}$	1	1	1	1	1	1	0.6	1	0.6	0.6
Other representative policies close to the efficient contour										
$p = AGE$	1	1	1	0.6	0.6	1	1	1	0.6	0.6
$p = SEC$	1	1	1	1	1	0.6	0.6	0.6	0.6	0.6

Note: This table reports the labor force activation vector for all the efficient and representative policies.

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