Restarting the Economy while saving lives under Covid-19

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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)).

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Appendix B

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

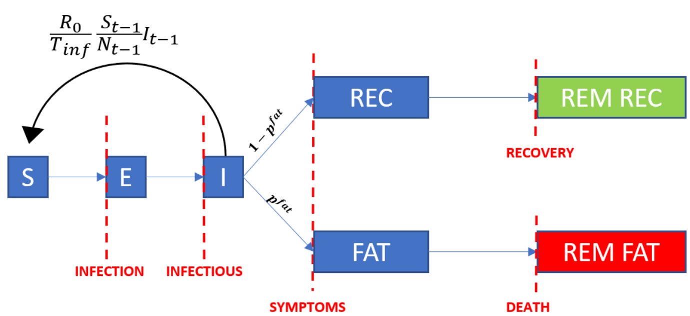
Appendix to Section 2: The Epi-nomics Model

In this appendix we characterize the basic epidemiological concepts on which the Epi-nomics 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 Epi-nomics model

As discussed in the main text our Epi-nomics 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.

5. **Economic Structure.** Finally, we complement the epidemiological framework with a simple economic structure to model production in the two regions.

Model Overview

We describe the model dynamics reporting only the main equations. The full specification of the model along is reported and illustrated in details in the Online Appendix. We adopt a compartmental model for the daily dynamics of the population. The population is divided into 19 groups with different age, sector and age-specific labor force participation, and thus with different probabilities of infection, hospitalization and fatality. The are 9 age-brackets. Population in working age (belonging to the five brackets between 20 and 69 years of age) is split into three separate groups. The first two groups include individuals who work respectively in the low-risk or in the high-risk sectors; the third group includes individuals in working age that are not part of the labor force, either voluntarily or because of containment policies. Thus we have 15 different groups of working age population.

In addition there are two age groups of inactive under 20 and 2 age groups of inactive over 69. Denoting these groups with generic terms $a, b \in \{1, \ldots, 19\}$, the model for the transmission dynamics of the virus classifies individuals in ten compartments as Susceptible $S_t(a)$, Exposed $E_t(a)$, Infectious $I_t(a)$, Mildly symptomatic $MILD_t(a)$, Severely symptomatic $SEV_t(a)$, Hospitalized with mild symptoms, $HOSPMILD_t(a)$, Hospitalized with severe symptoms $HOSP_t(a)$, Hospitalized needing Intensive Care $HOSPICU_t(a)$, Fatalities $FAT_t(a)$ and Recovered $REC_t(a)$.

Model Dynamics

The epidemiological dynamics is described by 228 equations (19 groups and 12 compartments). The compartmental structure of a simplified (only two groups) version is illustrated in Figure B–2.

Susceptible individuals become Exposed through contacts with Infectious. They stay exposed, without symptoms and being not infectious, for an incubation period T_{inc}. Once incubation has elapsed, Exposed become Infectious and suffer symptoms, that can be mild or severe. Severe patients (SEV) never revert to a state of MILD. MILD patients do not show symptoms initially, but without proper medical care may turn into Severe. This process occurs after T_{inf} days.

Within this framework, we introduce testing, which leads to domestic quarantine of the infectious with mild symptoms. Domestic quarantine has two effects. First, it reduces the spread of the virus by reducing the number of contacts in which some infectious agents are allowed to interact with susceptible agents. Second, paired with pharmacological treatment, it can prevent patients from reaching a stage requiring hospitalization.

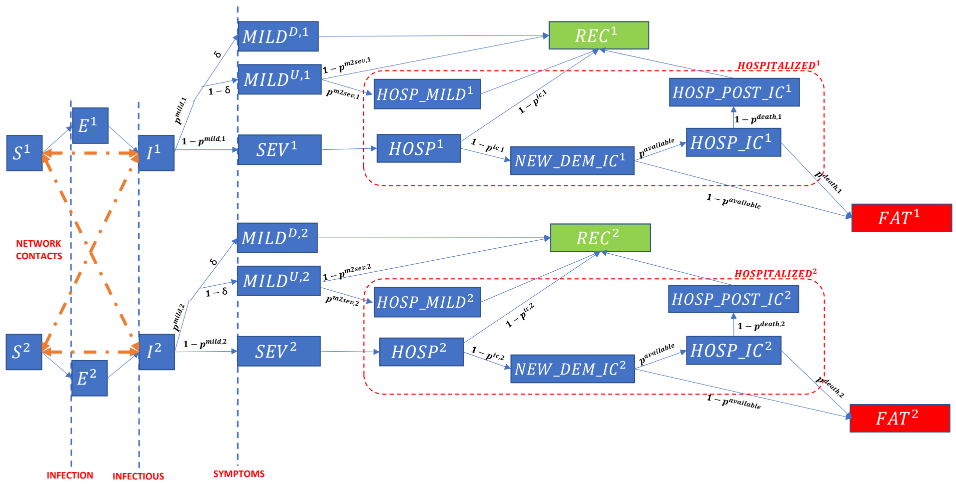
The mild infected either recover or their condition becomes severe and they require hospitalization. The probability of becoming severe is higher for the undetected than for the detected. With testing and early detection, patients are cared at home and hospitals congestion is reduced. All severe patients become hospitalized. Severe hospitalized either recover or they worsen and require intensive care (IC). Patients needing IC may die or recover. When IC is available and there is no hospital congestion mortality is determined by the CFR. However, mortality in IC increases with hospital congestion. When IC units are fully saturated, mortality explodes as all patients in need of IC and who cannot receive it succumb. 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. The cycle starts again in the next day. We close the model by summarizing the economic effects via a production function.[1]

The Dynamics of Susceptible and Exposed individuals

We denote by $R_t(a, b; \alpha)$ the element (a, b) of the reproduction matrix at day t corresponding to the total number of Susceptible in group a that an infectious agent in group b contaminates, under policy α to be defined below. So, $\frac{R_t(a,b;\alpha)}{T_{Inf}}$ is the number of daily infections. The core equations describing the dynamics of the virus for Susceptible and Exposed individuals are, for each a of our 19 groups of agents:

[1] We are fully aware that a complete characterization of the economic costs of the Covid–19 pandemic would require a more sophisticated and detailed dynamic macroeconomic model, which we leave for future extensions of this project.

Figure B–2: Flowchart of the Multi-Groups Epi Model



Note: Solid lines show the flows between states. Dashed lines emphasize interactions that take place across risk groups.

$$\begin{aligned} \Delta S_t(a) &= -\frac{1}{T_{Inf}} \sum_{b \in A} I_{t-1}(b) R_t(a,b;\alpha) \\ \Delta E_t(a) &= -\Delta S_t(a) - \frac{1}{T_{Inc}} E_{t-1}(a). \end{aligned}$$

Note that the Infectious do not initially feel symptoms as T_{inc} is the average number of days of incubation before becoming symptomatic.

$R_t(a,b;\alpha)$ is best understood by tracking its evolution over time. At time 0, in the initial period of the pandemic, we have:

$$R_0(a,b;\alpha) = \frac{N_0(a)}{N_0} R(a,b;\alpha) = \frac{N_0(a)}{N_0} \beta(m_0) M(a,b;\alpha) \tag{B–1}$$

At this initial stage, the entire population, N_0, is susceptible, so that $S_0(a) = N_0(a)$. Moreover, the probability of interacting with other agents, which is initially equal to one for every group, is not reduced by lockdown policies or by behavioural responses to the virus and all workers are active. Finally, only the non-employed do not go to work and do not interact with other workers. The number of susceptible agents of type a that are infected by an agent of type b depends on the number of meetings between the agents, $M(a,b;\alpha)$, and on the probability of contagion given that a meeting takes place, $\beta(m_0)$.

In subsequent periods, as the virus spreads across the population, the number of susceptible decreases, the probability of contagion is affected by policies such as wearing masks or social distancing, the probability of interaction among agents becomes smaller than one as a consequence of legally imposed or voluntary chosen reduction in mobility, and the number of active workers can be reduced by NPIs.

The number of Susceptible individuals that each infectious infect, depends on the probability of infection, denoted as $\beta(m_{t-1})$,[2] on the probabilities with which susceptible and infectious agents interact and on the activation policy for the working population, described by α. Quadratic matching implies that the probability of two people interacting is in turn given by the product of the two probabilities with which each one of them enters into an activity. This event occurs if their utility V_t is higher than an optimally chosen threshold v_t^* , denoted by $Pr(V_t \geq v_t^*|a)$. This probability reflect both the average response of agents to policies and their behavioural response to the spreading of the virus. Therefore, $R_t(a, b; \alpha)$ will evolve according to:

$$R_t(a, b; \alpha) = \frac{S_{t-1}(a)}{N_{t-1}} \frac{\beta(m_{t-1})}{\beta(m_0)} Pr(V_t \geq v_t^*|a) Pr(V_t \geq v_t^*|b) R(a, b; \alpha) \tag{B–2}$$

Modelling $R_t(a, b; \alpha)$

In our model the population is divided into 9 age-brackets. Each age bracket between 20 and 69 years of age is split into three separate groups. The first two groups include individuals who work respectively in the low-risk or in the high-risk sectors; the third and last group include individuals in working age that are not part of the labor force. Thus we have: 5 age groups of active in the low-risk sector, 5 age groups of active in the high-risk sector, and 5 age groups of inactive. In addition to these 15 groups there are two age groups of inactive under 20 and 2 age groups of inactive over 69. The resulting 19 groups constitute the set $\{1, 2, \ldots, 19\}$, with generic term a, b, that we have already introduced. Workers correspond to the elements $\{3, \ldots, 12\}$ with $\{3, \ldots, 7\}$ in the low-risk sector and $\{8, \ldots, 12\}$ in the high-risk sector. The set $\{13, \ldots, 17\}$ indicates the inactive groups in the five active age brackets. The number of age groups of workers is $L = 5$, and so $3L = 15$ is the number of classes of workers as distinct by age, risk sector and activation.

In this framework the basic reproduction number of single-agent standard epidemiological models will be replaced by a matrix, with entries that differ among the 19 groups. For workers, this number may depend on the level of activity. For example, a worker in the high-risk sector does not infect many people if he is not active. To model the effects of policies that restrict the access to work of particular categories of workers we specify how each entry in the basic reproduction matrix depends on the level of activity.

[2]This probability may evolve over time with the spreading of the virus, as it is affected by imposed precaution, such as wearing masks, and by mutations of the virus aggressiveness.

We will first focus on the sub-matrix defining the reproduction rates within the workforce, that is the sub-matrix that describes how many infected workers of class b are induced by workers of type a; here a and b are generic elements of the set of workers. We denote the level of activity as $\alpha : \{3, \ldots, 17\} \to [0, 1]$, with $\alpha(a)$ indicating the level of activity of group a: for example, $\alpha(9) = 0.5$ indicates that half of the individuals of age 30 to 39 in the high-risk sector are active. We denote α_{min} the minimum level of activity of each active class, and with $\mathbf{1}$, a vector of 1's, the vector of activity corresponding to normal conditions. Iso is a fixed number (independent of the group); intuitively, this describes the number of infected when a person is isolated. Thus we define the Basic Reproduction Matrix (BRM) at level α of activity, for every a and b in the set of workers:

$$R(a, b; \alpha) = R(a, b; \mathbf{1})\alpha(a)\alpha(b) + Iso(1 - \alpha(a)\alpha(b)) \tag{B–3}$$

To simplify the description of the BRM, we denote $r(a)$ the (high, low or inactive) risk sector of class a; for instance $r(3) = Low$, $r(10) = High$; and we introduce two numbers, $Risk(r)$ for $r \in Low, High$ to indicate the level of risk (in number of infected). We assume:

1. $R(a, b; \mathbf{1}) = Risk(r(a))$ if $r(a) = r(b)$;
2. $R(a, b; \mathbf{1}) = Tr$ if $r(a) \neq r(b)$.

The first condition requires that the BRM of a on b when both are active and in the same sector only depends on the sector (and not on the age of a and b): so $Risk(L)$ for the low-risk sector and $Risk(H)$ for the high-risk sector. The second condition requires the value to be the same for any two active workers who are working in different sectors. Tr is suggestive of the means of transportation that they share when going to work even if the do not affect each other during work.

The value of α for the inactive is constrained to reflect the inactivity condition:

$$\text{for all } a \in \{13, \ldots, 17\}, \alpha(a) = 0. \tag{B–4}$$

In view of the constraint (B–4), in the description of the calibration of parameters and policies we focus on the $2L$ levels of activity of the workforce. The reduction in activation of agents during lockdown is modeled by choosing an appropriate level of minimum activity, which reflects institutional constraints.

We then assume that the values of the reproduction matrix for the inactive workers is equal to a common value:

$$Risk(In) = Iso \tag{B–5}$$

The description of the BRM is completed by considering the four non-working groups. For the first two age groups and the last two age groups we have, for all b, $R(1, b; \mathbf{1}) = R(2, b; \mathbf{1}) = R(18, b; \mathbf{1}) = R(19, b; \mathbf{1}) = Iso$, with two exceptions: before the lockdown and after Phase II we set $R(1, 1; \mathbf{1}) = R(2, 2; \mathbf{1}) = Risk(High)$. The parameters we have introduce are collected into a vector $\rho \equiv (Risk(L), Risk(H), Risk(In), Tr, Iso)$.

Modelling probabilities of activity

In this section we see how the interaction of policy and behavioural responses to the virus dynamic affects the probability, $Pr(V_t \geq v_t^*)$, with which an agent enters into a generic activity. We choose the time unit, denoted Δt, to be "short enough" so that a person only meets another person within that time unit. When we re-scale the process and set the time unit to one day, then the number of matches in that longer time unit will be:

$$M = \frac{1}{\Delta t}. \tag{B–6}$$

For simplicity, we now consider a single period model and omit time subscripts in this section. Each individual's value of the activity, indicated by V, is distributed according to a continuous cumulative distribution function F, the same for all consumers. We assume that (i) whether the activity occurs or not does not affect the agent's utility in the next period; (ii) the distribution F over the value drawn is independent of the health condition of the agent (i.e. on whether he/she is S, E, I or REM).

People are randomly matched. We are interested in the matches in which one of the two individuals is I and the other is S. The meeting of an I and an S person result in the S-type being infected with probability $\beta(m)$, which is influenced by biological factors, and preventive measures (m) imposed on the agents (m is mnemonic for masks). In our specification agents do not take any decision that affects $\beta(m)$, in line with the evidence on COVID–19 rules compliance in northern Italy.[3]

The number of individuals an active person meets is determined by the maximization of her utility derived from the activity. She may choose to be *inactive*, thus getting a given fixed utility value, which we normalize to zero. Or she may choose to be *active* (for example, to go out of the house in pursuit of some activity), getting the (random) value V, minus the expected cost of the potential infection. The solution of this simple maximization problem is described by a threshold in value space: those with a draw of V higher than a threshold v^*, to be determined endogenously, decide to be active.

This behavioral response depends on the behavior of others as well as on the policy being implemented. We examine later – see equations (B–11) and (B–12) – how different policies

[3] See, for example, Durante et al. (2020).

affect the response. Let C be the cost of being infected for a subject. The threshold v^* solves:[4]

$$v^* = \frac{I}{N}\beta(m)Pr(V \geq v^*)C. \tag{B–7}$$

We consider the case in which F is a uniform distribution on $[0, \overline{V}]$, so $F(x) = \frac{x}{\overline{V}}$, for $x \in [0, \overline{V}]$. If we denote the probability of being infected as

$$p \equiv \frac{I}{N}\beta(m) \tag{B–8}$$

then

$$v^* = \frac{pC}{\overline{V} + pC}\overline{V} \tag{B–9}$$

so that substituting the value of v^* gives:

$$Pr(V \geq v^*) = \frac{\overline{V}}{\overline{V} + pC} \tag{B–10}$$

Similar arguments extend to the period after administrative measures (enforced by fines or other penalties) are taken to limit movements (as in lockdown). If we call K the expected non-negative cost of measures to control the spread of the virus, then we have:

$$v^* = \overline{V} \min\left\{\frac{pC + K}{pC + \overline{V}}, 1\right\} \tag{B–11}$$

and therefore:

$$P(V \geq v^*) = \max\left\{\frac{\overline{V} - K}{pC + \overline{V}}, 0\right\}. \tag{B–12}$$

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

[4] Note that this equation omits a measure of population density acting as a determinant of the number I of infectious, because of our choice of the time scale. Garibaldi et al. (2020) note the similarity of this assumption with the one behind the "matching function" of labor models.

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.

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:

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

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.

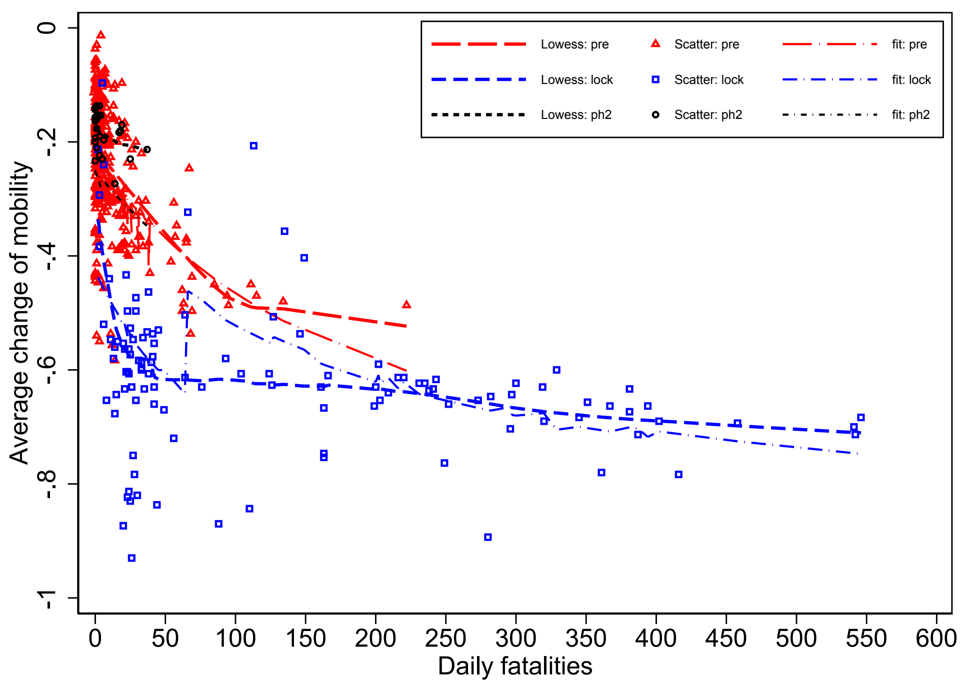
$$
\begin{aligned}
\Delta FAT_t(a) &= (1 - p^{available})NEW\_DEM\_IC_t(a) + p^{death}(a)\left(\frac{1}{T_{sd} - T_{hosp-ic} - T_{shosp}}\right) HOSP\_IC_{t-1}(a) \\
\Delta REC_t(a) &= \left(\frac{1}{T_{ic-rec}}\right) HOSP\_POST\_IC_{t-1}(a) + (1 - p^{ic}(a))\left(\frac{1}{T_{shd} - T_{shosp} - T_{shosp}}\right)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

Appendix to Section 4: Estimation and Calibration

Appendix to Section 4.1: Parameters determining the probability of activity

This result of our non-linear estimation of behavioural responses reported in Table 2 is graphically illustrated by B–3 which is based on the estimates for the average mobility measure. The figure displays the scatter plot of daily fatalities and average mobility. The different markers of the scatter plot identify the three periods for which we have data: Pre-lockdown, Lockdown and Phase 2. The figure also plots predictions from locally weighted regressions as well as predictions based on the estimates in column 2 of Table 2.

Figure B–3: Behavioural responses to news and policies



Note: the figure displays the scatter plot of daily fatalities and the average of the Google mobility measures for workplace, transportation and grocery. For each type of mobility, the measure is the change of the number of moves on a given day relative to the same day-of-the-week in the reference period defined as January, 6 – February, 3, 2020. The different markers of the scatter plot identify the three periods for which we have data: Pre-lockdown, Lockdown and Phase2. The figure also plots predictions from locally weighted regressions obtained with the "lowess" Stata command (dashed lines; bandwith=0.8) as well as the predicted values of obtained with the non-linear least square estimates for working days reported in column 4 of Table **??** (dashed-dotted lines).

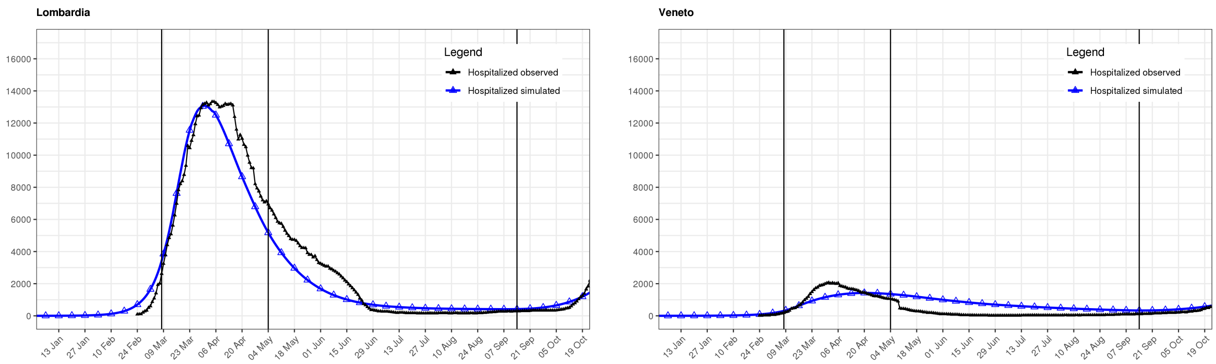
Within each of the three phases we cannot reject that the relationship between mobility and daily fatalities is negative and convex as predicted by the model. This negative and convex relationship within each phase is the behavioural response of subjects to the variation of the contagion risk, in the absence of policies.[5]

The parallel downward shift between the circles and the squares is the effect of the Lockdown, which has reduced mobility for any level of fatalities. The upward shift from the squares to the triangles is instead the effect of the softening of restrictions during the Phase 2 with respect to the Lockdown. While it is evident that policies were effective, this Figure clearly shows that the hypothesis of an endogenous response to the number of infectious cannot be dismissed and it is quantitatively important. Of course, the short time horizon on which these estimates are computed does not guarantee that in the long run this behavioural effect would maintain the same intensity, as individuals may become used to the presence of Covid-19 and less responsive to news related to the effects of the disease.

[5] Cochrane (2020) for example states that, as a consequence of the omission of this response, "the SIR model has been completely and totally wrong". Durante et al. (2020) also find that after the virus outbreak mobility declined in Italy, but significantly more in areas with higher civic capital, both before and after a mandatory national lockdown. Civic capital is however likely to be irrelevant for our analysis since all available measures suggest the absence of significant differences in this variable between Lombardia and Veneto.

Appendix to Section 5: Model Fit

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

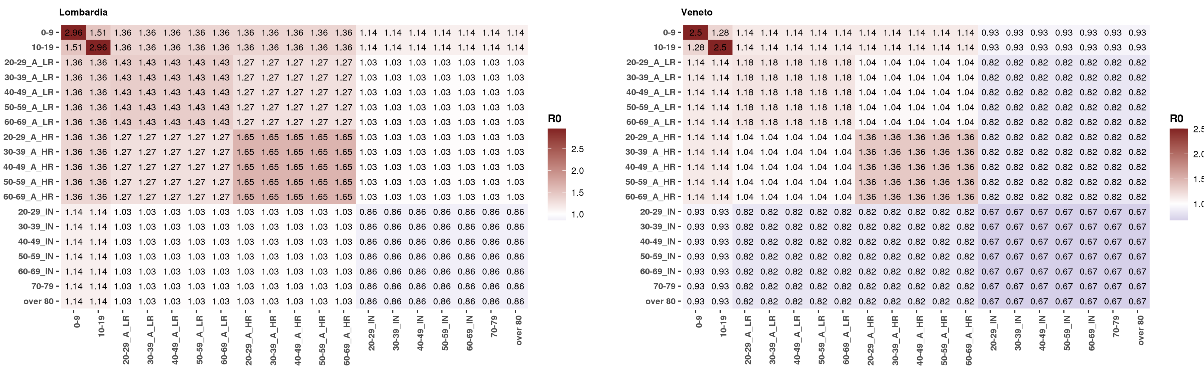


Note: the figure reports, respectively for the two regions, the simulated and observed numbers of daily hospitalized due to Covid-19.The vertical bars indicate the start of the lockdown (March 8), the start of the phase 2 (May 4) and the start of the new school year (September 14). Source: The simulated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

Appendix to Section 6: Policy Simulations

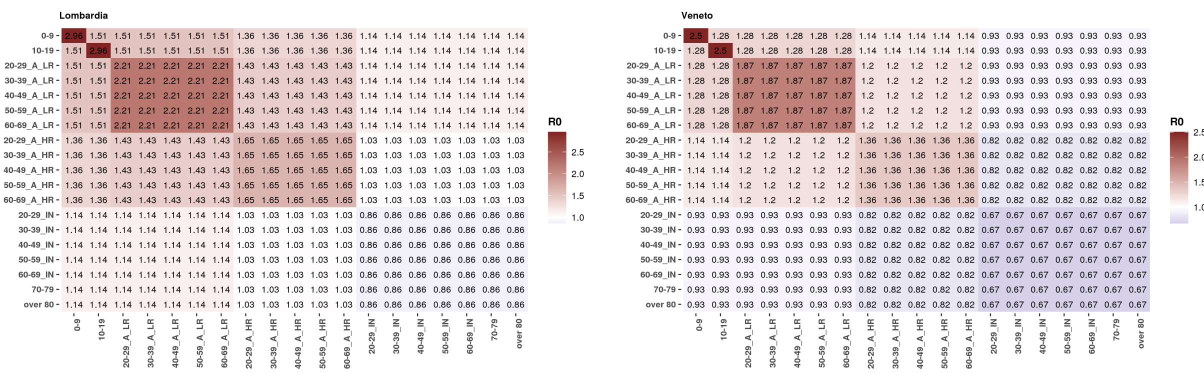
The BRM under alternative policies

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



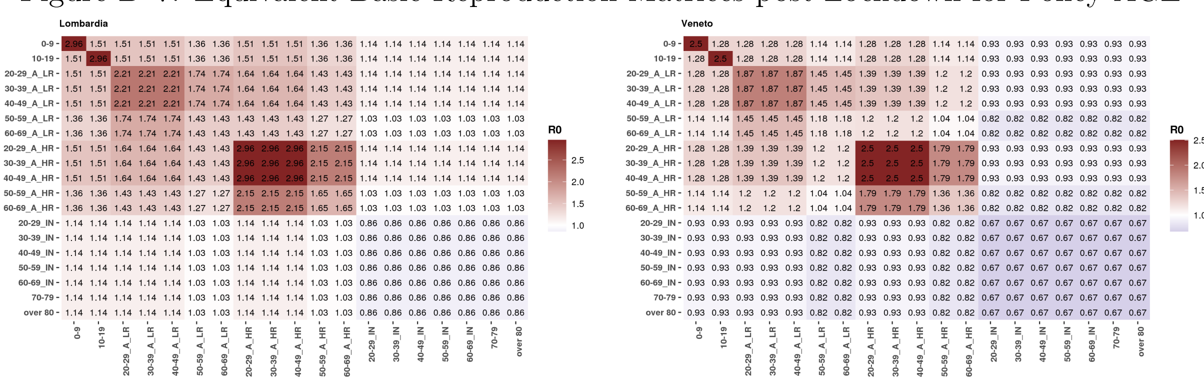
Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

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



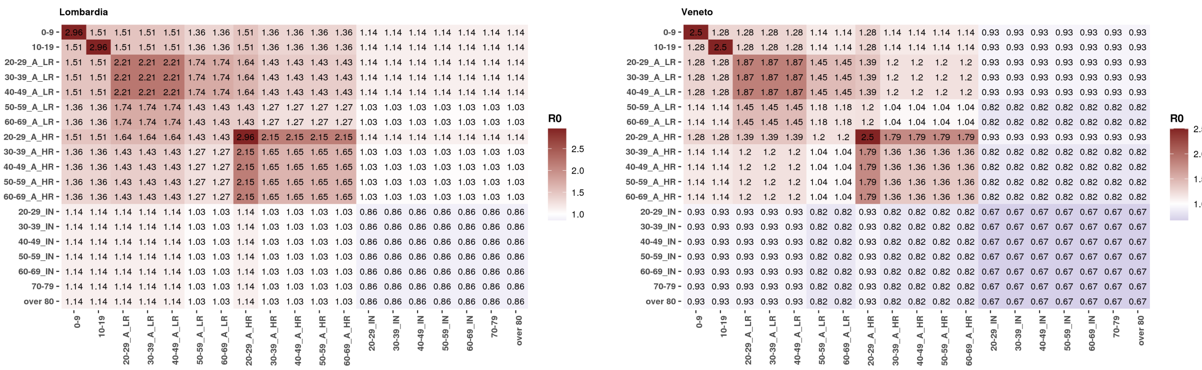
Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

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



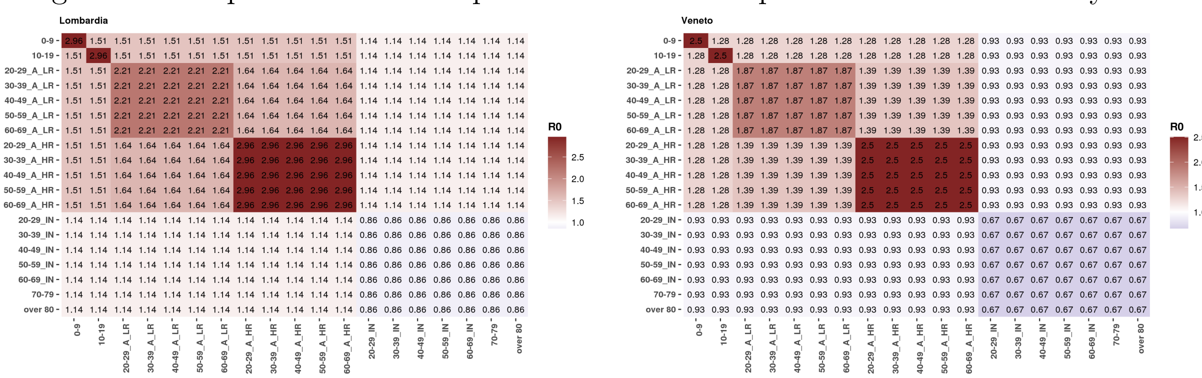
Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

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.

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

	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										
$p = \text{ALL}$	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
$p = \text{LOCK}$	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

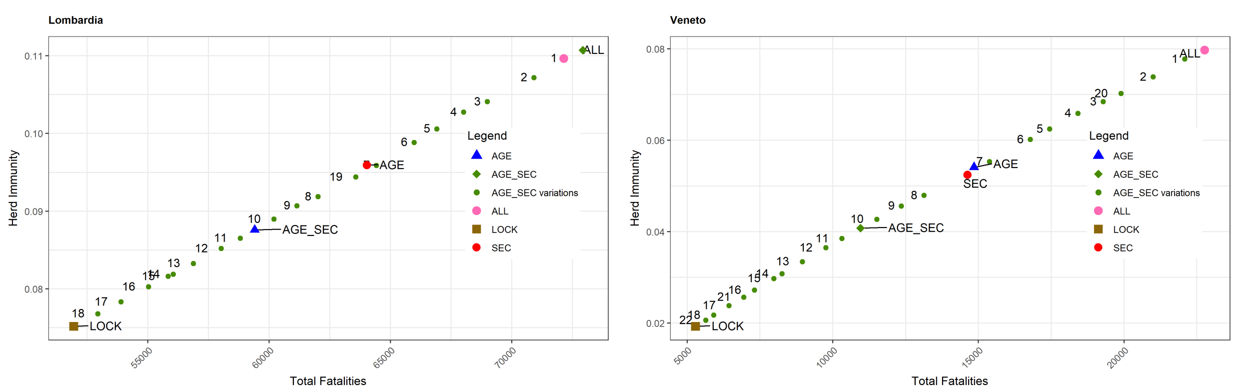
Note: This table reports the labor force activation vector for all the efficient and representative policies.

Table B–2: Lombardia and Veneto: main outcomes with behavioural response and $\beta(m) = 0.7$

	Policies				
	LOCK	SEC	AGE	SEC_AGE	ALL
Lombardia					
Total fatalities	15198	21422	21894	19400	26393
GDP loss	0.26	0.104	0.094	0.148	0
Final immunity share	0.050	0.059	0.061	0.057	0.068
Veneto					
Total fatalities	5557	8681	8891	7339	12311
GDP loss	0.26	0.104	0.097	0.150	0
Final immunity share	0.023	0.035	0.036	0.031	0.045

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 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 and excluding reinfection. The numbers in parentheses indicate the minimum and maximum Average R_t during the simulation period (they do not define a confidence interval).

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 Epi-nomics model.

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).

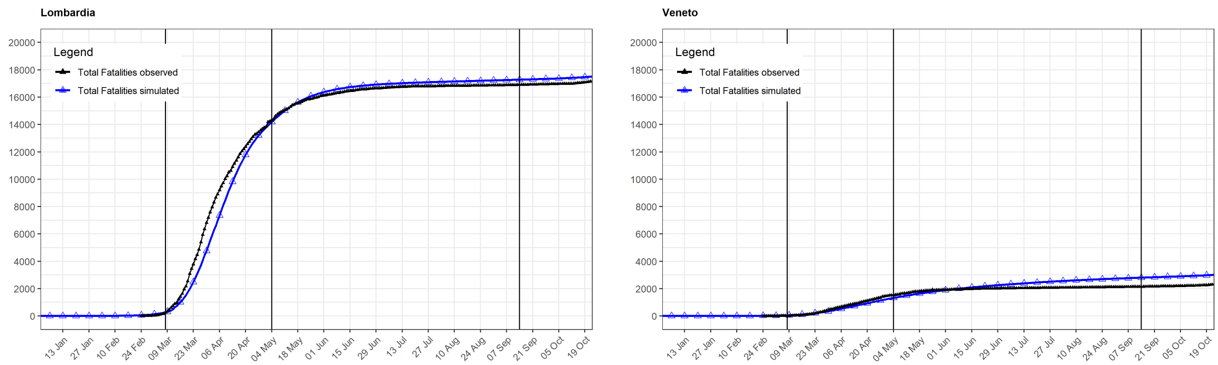
Table C–4: Calibrated parameters

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).

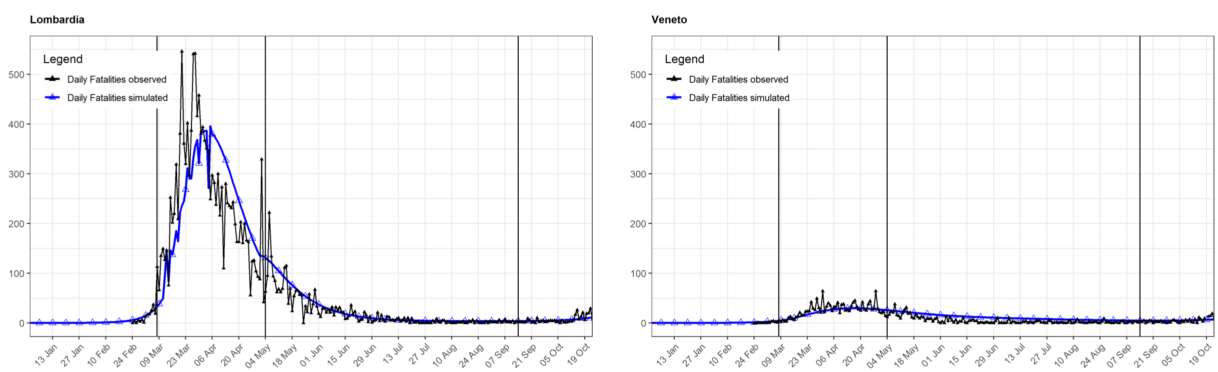
Appendix to Section 5: Model Fit

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



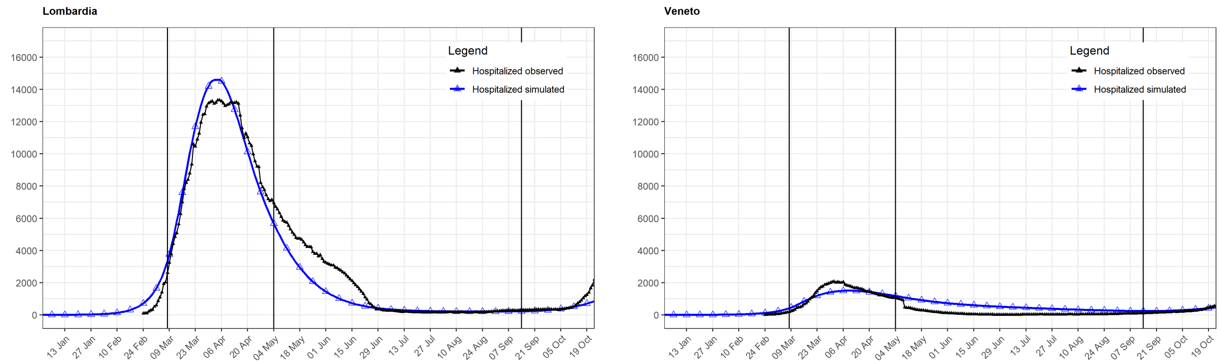
Note: The figure reports, respectively for the two regions, the simulated and observed numbers of daily hospitalized due to Covid-19.The vertical bars indicate the start of the lockdown (March 8), the start of the phase 2 (May 4) and the start of the new school year (September 14). Source: The simulated values are from the Epi-nomics 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).



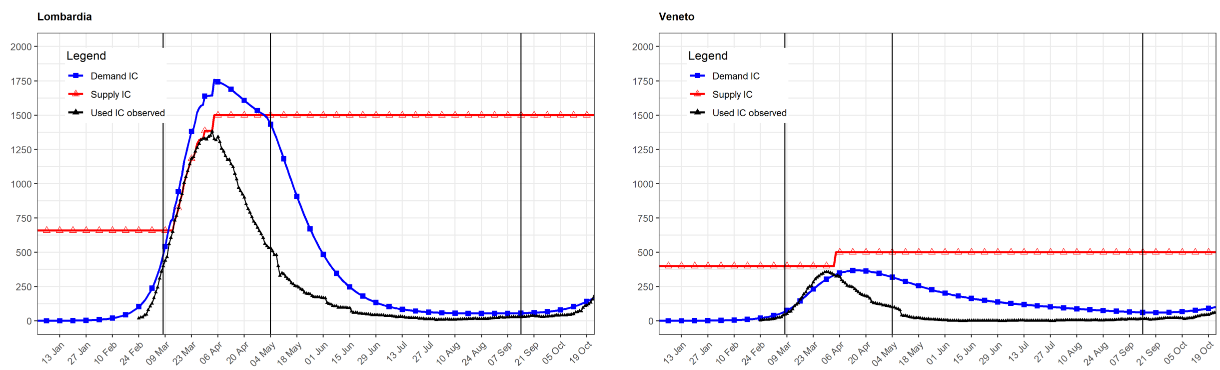
Note: The figure reports, respectively for the two regions, the simulated and observed numbers of daily fatalities due to Covid-19. The vertical bars indicate the start of the lockdown (March 8), the start of the phase 2 (May 4) and the start of the new school year (September 14). Source: The simulated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

Figure C–14: The IC availability constraint in Lombardia and Veneto with parameters from Garg (2020).

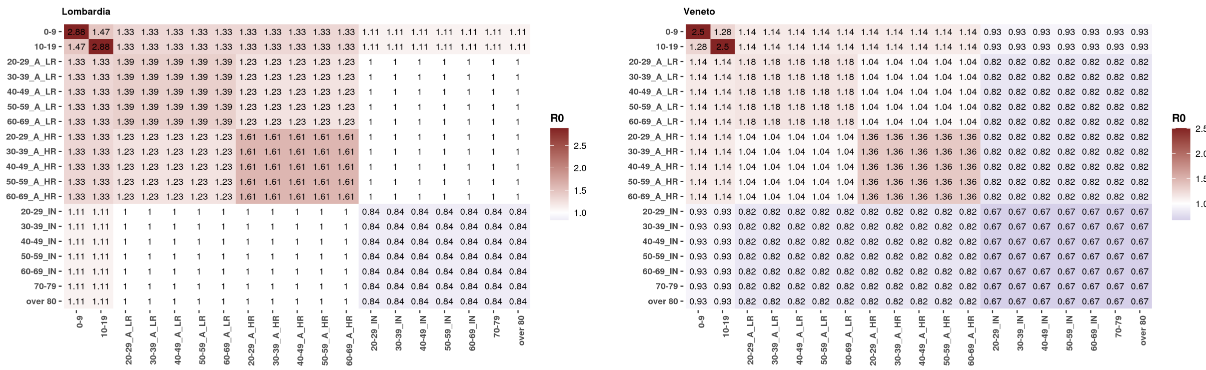


Note: The figure reports, respectively for the two regions, the simulated demand for IC beds due to Covid-19, the observed number Covid-19 patients in IC and the observed number of patients that were effectively hospitalized in IC. The vertical bars indicate the start of the lockdown (March 8), the start 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 Epi-nomics 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.

Appendix to Section 6: Policy Simulations

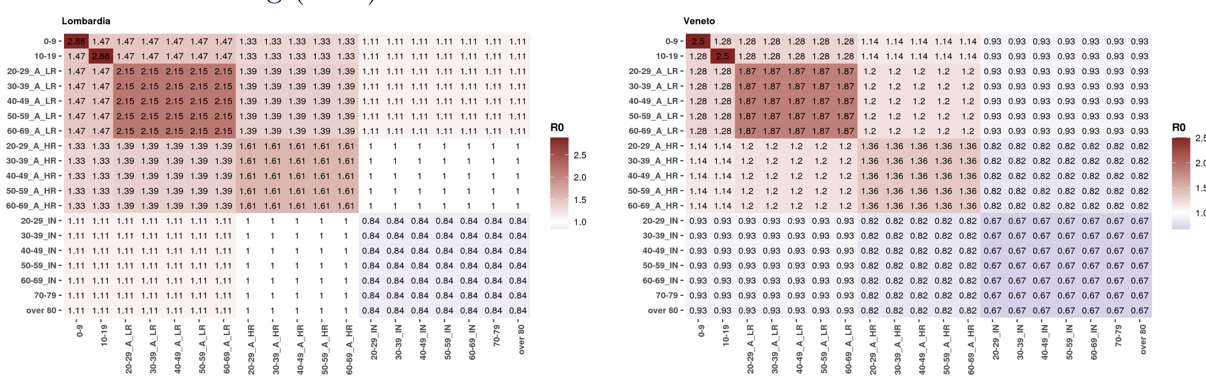
Appendix to Section 7.1: The BRM under alternative policies

Figure C–15: Equivalent Basic Reproduction Matrices post-Lockdown for Policy LOCK with parameters from Garg (2020).



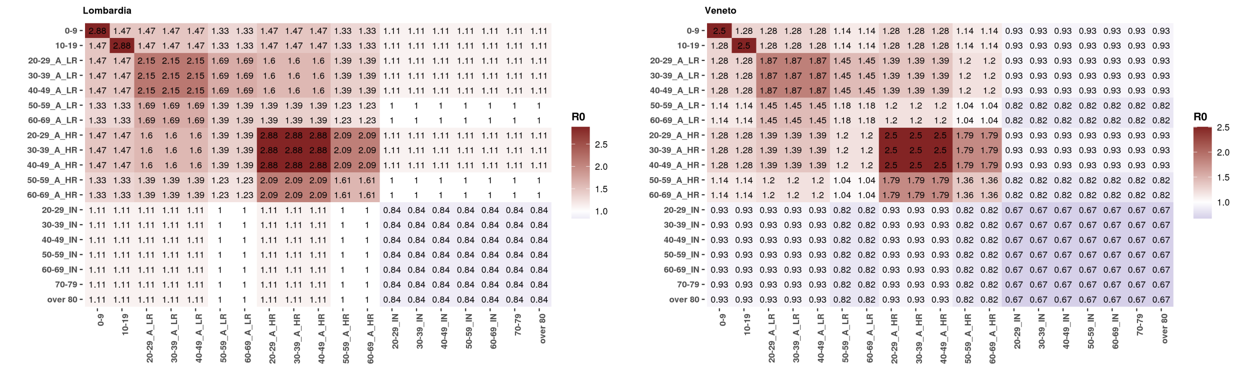
Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

Figure C–16: Equivalent Basic Reproduction Matrices post-Lockdown for Policy SEC with parameters from Garg (2020).



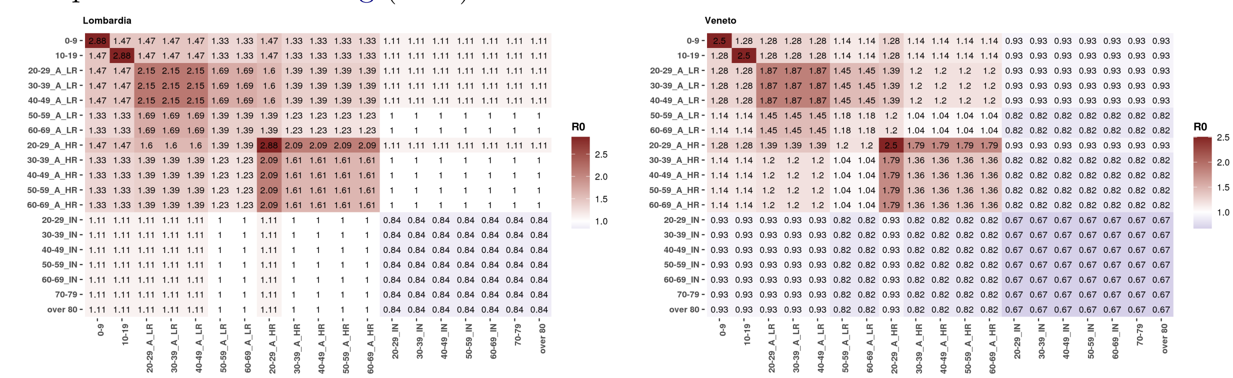
Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

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



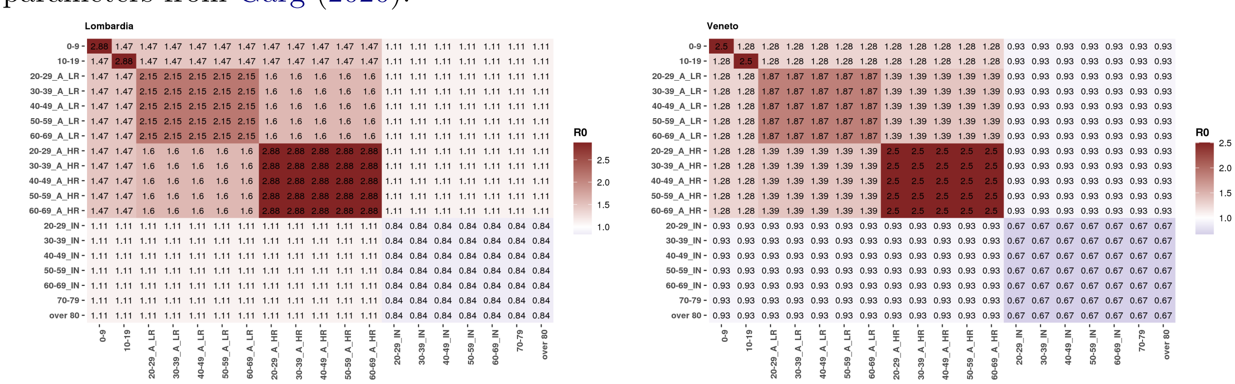
Note: Each cell in the table reports the R_0, eq with $\beta(m) = 0.9$ for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

Figure C–18: 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.

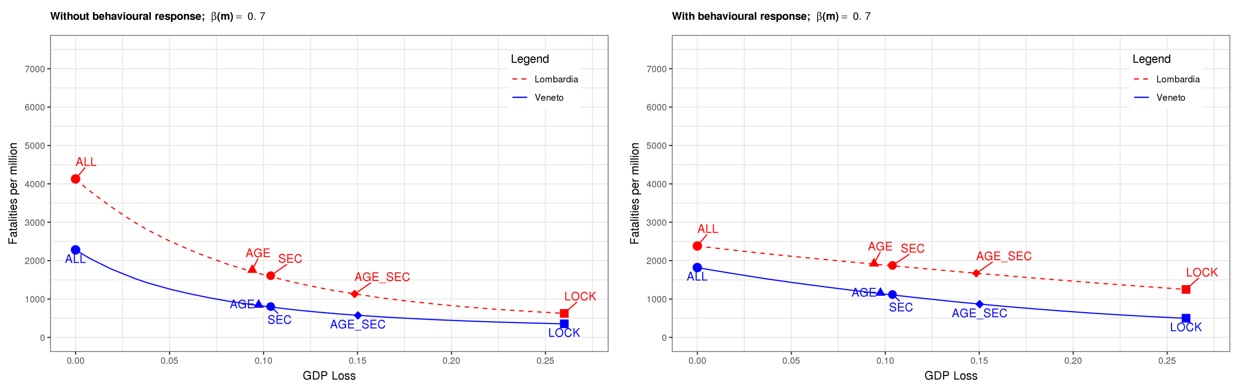
Figure C–19: Equivalent Basic Reproduction Matrices post-Lockdown for Policy ALL with parameters from Garg (2020).



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.

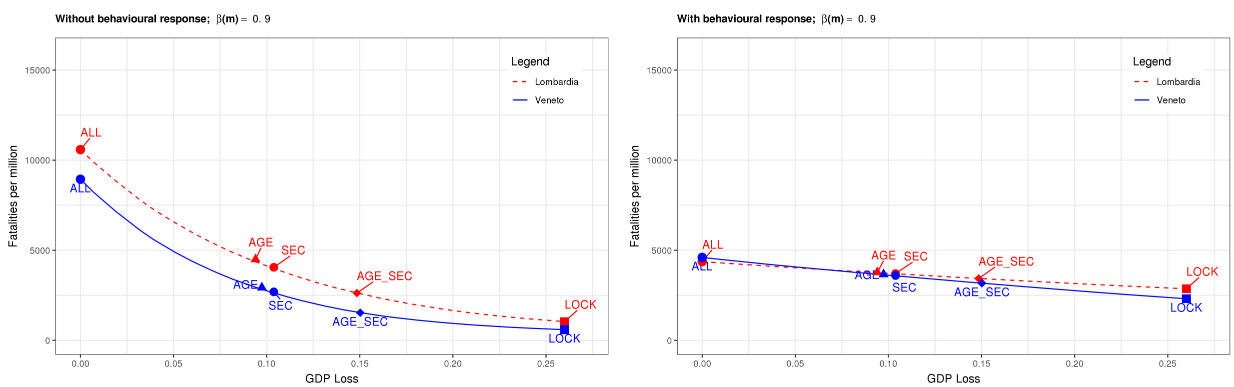
Efficient frontiers and Virus dynamics

Figure C–20: The efficient frontier in the two regions with $\beta(m) = 0.7$



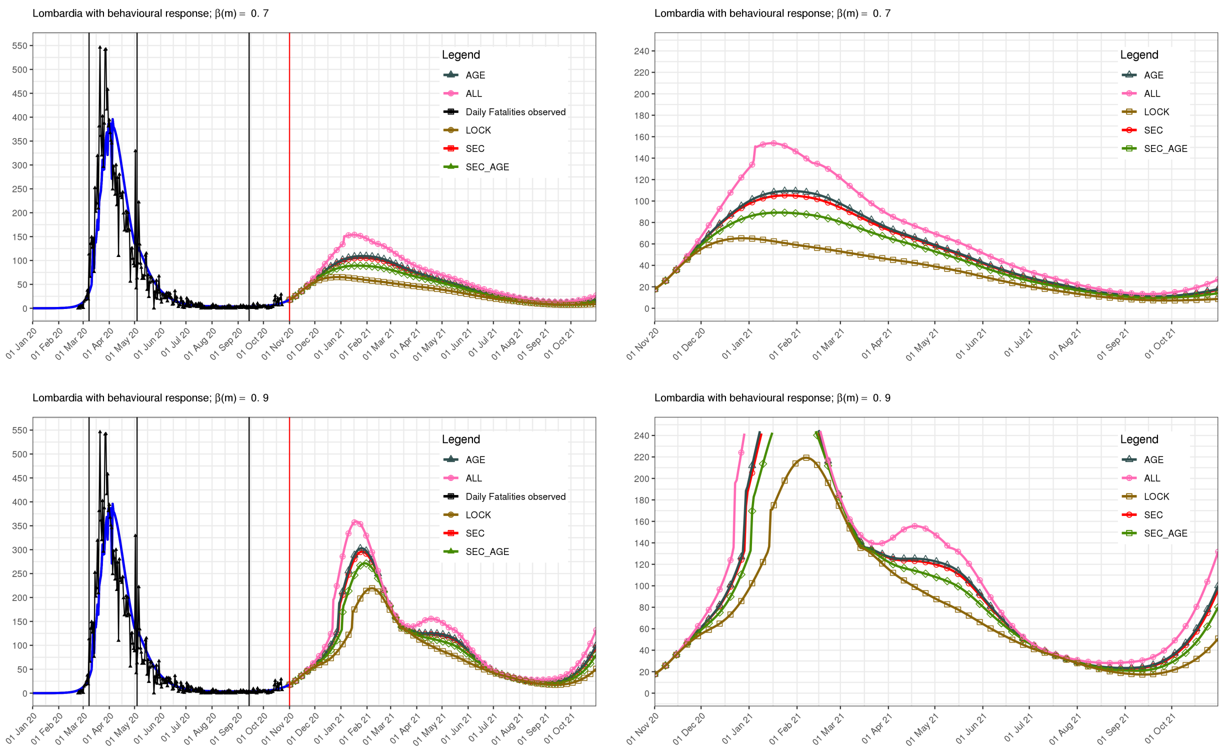
Note: In each panel, the two curves report the efficient frontiers for outcomes occurring between November 1, 2020, and October 31, 2021. Each point shows the GDP loss and the number of fatalities per million individuals associated to the policies that are efficient (as defined in the text). The representative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

Figure C–21: The efficient frontier in the two regions with $\beta(m) = 0.9$



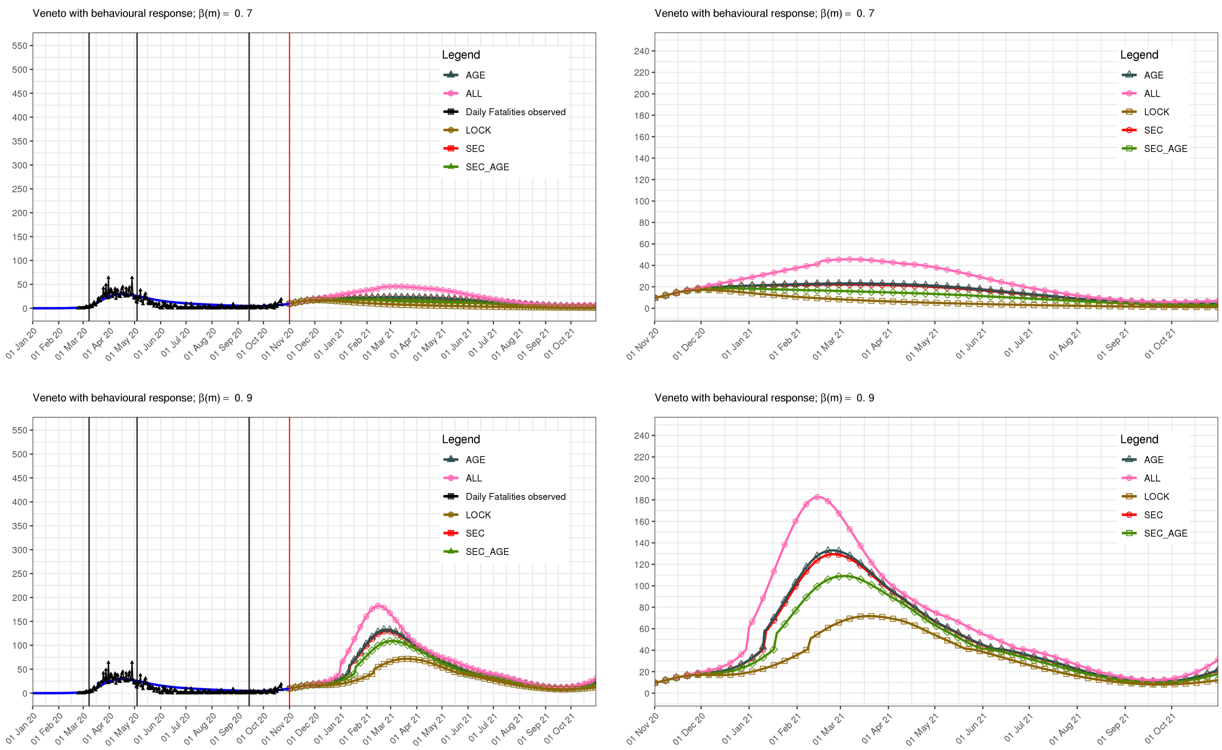
Note: In each panel, the two curves report the efficient frontiers for outcomes occurring between November 1, 2020, and October 31, 2021. Each point shows the GDP loss and the number of fatalities per million individuals associated to the policies that are efficient (as defined in the text). The representative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

Figure C–22: 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–23: 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)

Policy	Low-Risk sector Age brackets 20-29	30-39	40-49	50-59	60-65	High-Risk sector Age brackets 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.

References

Allen, L.J., 2017. A primer on stochastic epidemic models: Formulation, numerical simulation, and analysis. Infectious Disease Modelling 2, 128–142.

Cochrane, J., 2020. A SIR model with behaviour. Technical Report. https://johnhcochrane.blogspot.com/2020/05/an-sir-model-with-behavior.html.

Durante, R., Gulino, G., Guiso, L., 2020. Asocial capital: Civic culture and social distancing during COVID-19. Technical Report. CEPR Discussion Paper No. DP14820.

Ferguson, N.M., Daniel, L., Gemma, N.G., Imai, N., Kylie, A., Marc, B., Sangeeta, B., Adhiratha, B., Zulma, C.c., Gina, C.D., Amy, D., Ilaria, D., Han, F.a., 2020. Impact of non-pharmaceutical interventions (npis) to reduce covid-19 mortality and healthcare demand. Imperial College Covid-19 Response Team 2, 60–66.

Garg, S., 2020. Hospitalization rates and characteristics of patients hospitalized with laboratory-confirmed coronavirus disease 2019—covid-net, 14 states, march 1–30, 2020. MMWR. Morbidity and mortality weekly report 69.

Garibaldi, P., Moen, E.R., Pissarides, C.A., 2020. Modelling contacts and transitions in the sir epidemics model. Covid Economics Vetted and Real-Time Papers, CEPR .