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JEL Classification: I12, I18, D6, H84

Keywords: COVID19, SEIR model, post lockdown policies

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Restarting the economy while saving lives under Covid-19*

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April 24, 2020

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1 Introduction

The main question all countries are facing throughout the world is how to restart the economy while saving lives once the initial diffusion of Covid-19 has been put under control, thanks to emergency lock down measures, and the so called “Phase 2” can begin. We present simulations that answer this question based on data for two emblematic Italian regions: Lombardia and Veneto. These contiguous areas in the north of the country were the first in Italy to be hit by the Covid-19 outbreak (at about the same time) but experienced very different evolutions of the infection. While in Lombardy, with a population of about 10 ml people, at least 12213 (official data from Protezione Civile) persons died because of Covid-19 between February 24 and April 19, 2020, in Veneto, with a population of 4.9 ml, the same happened to only 1087 persons.

A simulation of the effects of different Phase 2 strategies in these two regions is instructive for a wider audience because Lombardia and Veneto capture well the dichotomy of Covid-19 experiences that is emerging throughout the world, between areas hit very severely and areas hit more mildly by the pandemic. The two main factors determining this dichotomy are the presence of delays in reacting correctly to the early phase of the infection together with constraints in the number of intensive care places in hospitals (HC). The simulations that we present are based on an innovative version of the $SEIR$ model (Allen, 2017) specifically designed to capture these factors. The basic compartmental model of diseases divides the population in three compartments with homogeneous characteristics: Susceptible, Infected, and Recovered or Removed, from which the acronym SIR (Kermack and McKendrick, 1927). The $SEIR$ model extends the standard dynamics as for many important infections there is a significant incubation period in which individuals are Exposed, i.e. infected but not yet infectious. Since this is an essential feature of the current virus infection, using $SEIR$ instead of SIR is crucial to insure that the estimates are quantitatively and not only qualitatively correct.

A second substantial innovation is allowing a differentiation of the population by sectors (SEC) and ages (AGE), and thus generalizing the concept of basic reproduction number (R_0) to a matrix. Specifically, our SEIR-HC-SEC-AGE model has two sectors characterized respectively by a low and a high risk of infection, which are calibrated on the basis of the information on workers' proximity contained in Boeri et al. (2020) and Barbieri et al. (2020). As for age, we consider 9 brackets, which are calibrated to match the initial distribution of age in the population of the two regions, and that are characterized by age specific labor force participation rates (taken from national statistics) and by age specific lethality, hospitalization and intensive care (IC) rates due to Covid-19 (taken from Ferguson et al., 2020). This model can be easily calibrated to evaluate the option of letting different geographic areas to restart at different times (as currently considered by the Italian government), depending on when the virus appeared in the area or depending on the area specific age, labor force participation and sector risk characteristics.

Our goal is to contrast the economic and public health effects (GDP loss vs. saved lives) of five possible policies to be implemented as of May 4, 2020. The GDP loss induced by the interaction between the pandemic and the different policies is assumed to be proportional to the number of days in which the policies are in place and to the corresponding fraction of the workforce that is unproductive. In future research we plan to improve on this measure in various ways, particularly with the goal of capturing more long term economic effects of the pandemic. It is likely, however, that the measure of GDP loss we currently use is a lower bound to the total economic cost of the different policies. The number of Covid-19 fatalities associated to the different strategies is predicted by the SEIR-HC-SEC-AGE model.[1]

Leaving details for later, the five policies that we consider are:

1. *LOCK – Prolonged lockdown:*
   to continue the lockdown, in which only a strictly needed minimum number of workers is actively employed, until the vaccine arrives or until herd immunity is reached.

2. *SEC – Some sectors go back to work:*
   to allow workers of all ages to go back to work in the low-risk sector, while only the strictly needed minimum number resume activities in the high-risk sector (which include health workers). The rest of the population remains isolated in the current lockdown setting.

[1]The Matlab and R code to replicate our simulations are available from the authors.

3. *AGE – Young go back to work:*

   to allow only young workers in the 20-49 age bracket to resume activities in all sectors, while only the strictly needed minimum number of older workers is employed in the high-risk sector. The rest of the population remains isolated in the current lockdown setting.

4. *AGE-SEC – Young go back to work in specific sectors:*

   to allow young workers in the 20-49 age bracket to go back to work in the low-risk sectors, while only workers in the 20-29 age bracket are employed in the high-risk sector; the rest of the population remains isolated in the current lockdown setting.

5. *ALL – Workers of all ages and sectors can go back to work:*

   to allow all active workers to go back to work independently of their age or sector. The rest of the population remains isolated in the current lockdown setting.

The trade-off between saved lives and GDP losses that characterizes "age based" and "sector based" strategies is not immediately obvious, and its description is our main contribution. The two extreme policies LOCK and ALL provide useful benchmark against which to evaluate the intermediate ones. Our main results are reported in the next section.

1.1 Evaluation of the policies

a) If we take the continuation of the current policy of lockdown as reference, we see that a sequence of policies of immediate return to work for a large fraction of the labor force are possible, that have a moderate cost in terms of fatalities. While we are well aware that each single death due to the current epidemic is a tragedy, we are also keenly aware that the social, mental, and even health implications of a prolonged inactivity are also tragic. Thus, we consider the exploration of these combinations an intellectual duty.

b) This flat section of the frontier of possible combinations makes possible a containment of the *GDP* loss within values that are *one fifth* of the loss incurred with the continuation of the lockdown.

c) Further containment is possible, but it is *extremely* costly in terms of human lives. The cost associated with an unconstrained return to work is several orders (approximately four times) larger that what is needed to bring the GDP loss close to the 5-10 per cent mark. There is a clear kink in the set of possible efficient outcomes, at which the health costs become substantially larger, that should be very clear and present in the current discussion. This kink is due, in final analysis, to the very different dynamic and health outcomes according to age. Bringing older workers back to work is very costly.

d) The policies that make this relatively safe return to work possible are a combination of one that has been discussed (return to work taking into account the risk specific to each productive sectors) and another one which instead has received less attention (differentiation depending on the age of the worker). We think the debate should consider carefully both, and the public should be aware and able to discuss openly both.

e) Some of the policies that are currently under discussion (for example, the return to work according to sectors) are close to the kink; a policy *criterion* that we consider essential (age differentiation) has so far however been ignored, and in our opinion it should not.

f) Since these conclusions are robust to parameter specification, the relative merits of the policies are the same when we extend these policies to other regions in the country, thus are of immediate interest for national policy making.

This research project is obviously related to the large amount of inspiring research that is currently conducted throughout the world on the Covid-19 Pandemic.[2] We differ, however, from this literature because we do not aim at suggesting an optimal policy based on some welfare function. Our goal is to measure as precisely as possible in a specific geographic context the policy trade off between economic and public health costs of the pandemic so that

[2]Without aiming for an exhaustive review of the literature, some of the most relevant related papers are: Atkeson (2020), Berger et al. (2020), Eichenbaum et al. (2020), Fang et al. (2020), Glover et al. (2020), Greenstone and Nigam (2020), Hall et al. (2020) and Piguillem and Shi (2020)

politicians and the public opinion can make an informed choice. Of course our code can be applied to different geographic context, with the appropriate corresponding parametrization.

The rest of the paper is organized as follows. In Section 2, we describe the SEIR-HC-SEC-AGE model. Section 3 describes the calibration of the parameters designed to capture the situation of Lombardia and Veneto and to characterize the different policies. Section 4 presents the results, which are discussed in Section 5 together with an analysis of the limits of our simulation exercise.

2 The SEIR-HC-SEC-AGE model for Covid-19

Our model for the dynamics of the virus extends the basic SEIR (Susceptible, Exposed, Infectious, Removed) model to a SEIR-HC-SEC-AGE specification that follows subjects in their patterns of hospitalization, endogeneizing the lethality of the virus. Lethality becomes endogenous when the model dynamics generates an excess demand for intensive car beds that cannot be accommodated at the available supply level. In this case the observed lethality becomes higher than that implied by the exogenous case fatality ratio (CFR) of COVID-19. In addition, the model divides the population in two production sectors characterized by different levels of coworkers proximity and thus by different infection risks and in 9 age brackets (from 0-9 to 80+), characterized by fatality and hospitalization rates that increase with age and by age specific labor force participation preferences.

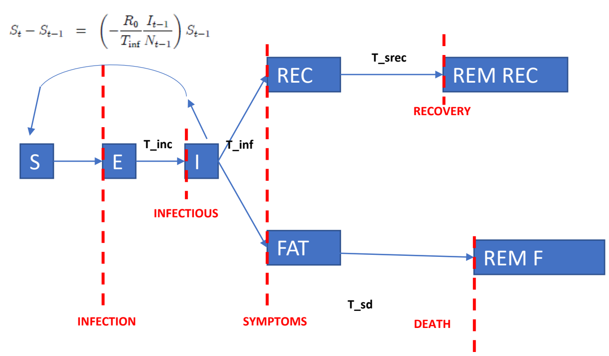
2.1 The basic SEIR model

The basic SEIR model (Allen, 2017) is described in Figure 1 and its formal representation is in Appendix 6.1. 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. In each subsequent day t some Susceptibles become Exposed. Their daily quantity E_t is determined by the basic reproduction number of the infection, R_0 (i.e. the number of secondary infections each infected individual produces), divided by the average number of days in which a subject is infectious, T_{inf}, and multiplied by the probability with which the

Susceptibles meet the Infectious, $\frac{I_{t-1}}{N_{t-1}}$.

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.

Figure 1: Flowchart of the SEIR model



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

An important feature of the model is that the lethality of the virus, as measured by

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

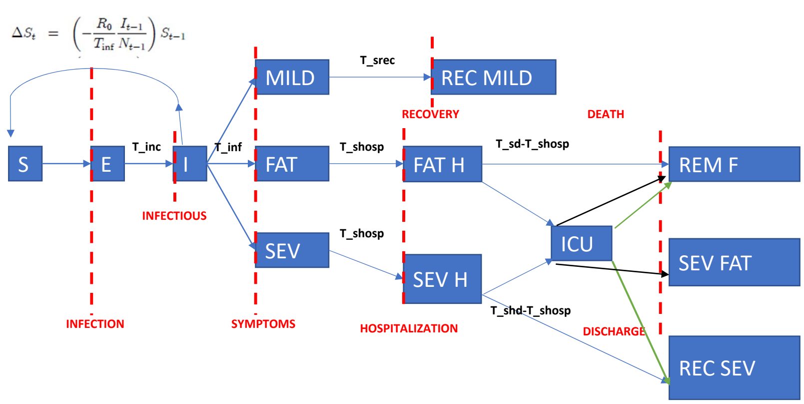
converges to two possible values only. If $R_0 \leq 1$ the virus diffusion is inhibited and λ_t^{seir} goes to zero. If instead $R_0 > 1$, λ_t^{seir} converges to p^{fat}, which is fixed exogenously. In this second case, the total number of victims will be the same independently of the size of R_0, which determines only the speed at which the asymptotic number of victims is reached.

2.2 The SEIR-HC model

Starting from the basic SEIR model, we introduce the possibility of a constraint in the availability of intensive care units that endogenizes the lethality index. This modification delivers the SEIR-HC model (Favero, 2020) described in Figure 2 and in Appendix 6.2. In this model, that continues to feature only one age bracket and one production sector, the dynamics from the Susceptibles to the Exposed and the Infectious is unaltered but the Infectious fall into three groups: those with mild symptoms, $MILD_t$, those with severe symptoms, SEV_t and those with fatal symptoms FAT_t. The allocation to these groups is controlled by three probabilities: $\left(1 - p^{sev} - p^{fat}\right)$, p^{sev}, and p^{fat}.

The daily change in the number of patients with mild symptoms is determined by an inflow equal to the share $(1 - p^{sev} - p^{fat})$ of those who leave the group of Infectious, and by an outflow consisting in those who recover, which is determined by the average period of T_{srec} days from symptoms to recovery for mild patients.

Figure 2: Flowchart of the SEIR-HC model



Note: Description of the possible dynamic transitions of a subject in the SEIR-HC model (Favero, 2020).

Patients with severe and fatal symptoms, instead, become Hospitalized, after a period of T_{shosp} days between the moment in which they begin to develop symptoms and the moment in which they enter the hospital. The daily change in the number of Fatal patients is determined by an inflow equal the share p^{fat} of those who leave the group of Infectious and by an outflow corresponding to the share of Fatal subjects who are hospitalized. Even if they find place in intensive care (IC), patients with fatal symptoms succumb after an average period of T_{sd} days from the onset of symptoms to the moment of death. The daily change in the number of Severe patients is determined by an inflow, which is the share p^{sev} of those who leave the group of Infectious and by an outflow determined by the share of Severe who have to be admitted in hospital.

Hospitalized patients, independently of their initial status of Severe or Fatal, require intensive care with probability p^{ic}. Patient with severe symptoms either Recover or become Fatal. The Severe who recover, with a mean duration from the onset of symptoms to hospital discharge of T_{shd} days, are those who do not need IC and those who need it and find a place in IC. The patients with severe symptoms that need IC but do not find a place become fatal. At the end of each day the population decreases because of the Fatalities, while the stock of Recovered grows because of those who survive having had mild or severe symptoms without need of IC. The cycle starts again in the next day.

The crucial difference between the SEIR and the SEIR-HC model is that in the latter the lethality rate of the virus has two determinants. The first one, is the same lethality rate λ_t^{seir} of the basic SEIR model, which applies if there is enough space in IC for all the patients who need it. In this case, also the lethality rate in the SEIR-HC model converges to the exogenous value p^{fat}. However, if the number of IC units is not sufficient, a second endogenous component of the lethality rate kicks in, which depends on the difference between the (endogenous) number of patients who need IC and the number of available places in IC. When R_0 is high, causing many infections, the number of patients needing IC is more likely to go above the level of available IC units and this causes a dramatic increase in the number of fatalities.

2.3 The SEIR-HC-SEC-AGE model

To build our final SEIR-HC-SEC-AGE model, we extend the structure of the SEIR-HC model to allow for 9 age brackets of ten-years groups, from 0–9, 10–19 ... to 80+ years of age, and for two sectors in which subjects between age 20 and 65 have the possibility to work.[3] The two sectors differ because of the risk of becoming infected faced by the workers who operate in them. In this extended model the dynamics of transitions of patients that are exposed to the virus is qualitatively the same as the one of the SEIR-HC model described in Figure 2. The crucial difference is that in the extended model the reproduction number of the virus, R_0, is not the same for the entire population and varies instead with the age, the employment status and the sector of the infectious subject and of the subjects that become exposed to her/him.

2.3.1 Extension to an heterogeneous population

Specifically, 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. This amounts to 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. Thus, we have in total 19 groups, $A \equiv \{1, 2, \ldots, 19\}$, with generic term $a \in A$. 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. Thus, 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 and sector, $\{L, H, I\}$ for low-risk, high-risk and inactive. The basic reproduction number, R_0, must be allowed to differ among these groups and as a function of the level of activity of the corresponding workers (for example, a worker in the high-risk sector does not infect many people if he is not active). This is a crucial feature of the extended model.

We indicate $\sigma_c \equiv \frac{1}{T_{Inc}}$ and $\sigma_f \equiv \frac{1}{T_{Inf}}$. The equation for the number of exposed in a

[3] As explained below in Section 3.3, these are the age brackets for which Ferguson et al. (2020) estimate biological and epidemiologial parameters of Covid-19, and these is why we adopt the same categorization. Labor participation rates are allowed to change in these age brackets in line with available statistics for the two regions as explained in Section 3.2.

homogeneous population (e.g., in the $SEIR$ model) has the form:

$$E(t+dt) = E(t) - \sigma_c E(t)dt + \sigma_f \frac{I(t)}{N(t)} R_0 S(t)dt$$

If we ignore for the moment the level of activity, we denote by $R(b,a)$ the number of individuals of group a that a person in group b infects, and call R the *basic reproduction matrix*, BRM. The equation for the exposed is then a system of equations for each age group $a \in A$ of the form:

$$E(a,t+dt) = E(a,t) - \sigma_c E(a,t)dt + \sigma_f \sum_{b \in A} \frac{I(b,t)}{N(t)} R(b,a) S(a,t)dt \tag{1}$$

Similarly, the equation for the infected becomes the system:

$$I(a,t+dt) = I(a,t) + (\sigma_c E(a,t) - \sigma_f I(a,t))\, dt \tag{2}$$

and that for the susceptible individuals:

$$S(a,t+dt) = S(a,t) - \sigma_f \sum_{b \in A} \frac{I(b,t)}{N(t)} R(b,a) S(a,t)dt \tag{3}$$

The formal specification of the complete SEIR-HC-SEC-AGE model is reported in Appendix 6.3 for the simpler case of two sectors and two age brackets.

2.3.2 Extension to different levels of activity

To model the effects of policies that restrict the access to work of specified categories of workers we need to model how the basic reproduction matrix depends on the level of activity. We will focus in the following on the sub-matrix defining the reproduction rates within the workforce, that is the sub-matrix that describes how many infected workers of class a are induced by workers of type b; here a and b are generic elements of the set of workers, indexed in the set $\{1, 2, , \ldots, 3L\}$.

We denote $\alpha : \{1, 2, \cdots, 3L\} \times \{0, 1\} \to [0, 1]$ the level of activity, with $\alpha(a, 1)$ the level of activity of class a (for example, $a = 9$ indicates individuals of age 30 to 39 in the high-risk sector); the fraction of workers allowed to work and not add to 1: $\alpha(a, 0) = 1 - \alpha(a, 1)$. We also denote $R(a, b; i, j)$ with $a, b, \in \{3, \ldots, 12\}$ and $i, j \in \{0, 1\}$ the number of workers of type b that a worker of type a infects when a is i-active (that is, active if $i = 1$ and not active if $i = 0$) and b is j-active. Finally we denote $S(a)$ the (high, low or inactive) risk sector of the class a; for instance $S(3) = Low$, $S(10) = High$. Thus we define the basic reproduction matrix at level α of activity as:

$$R(a, b; \alpha) = \sum_{(i,j) \in \{0,1\}^2} R(a, b; i, j)\alpha(a, i)\alpha(b, j) \tag{4}$$

We assume:

1. $R(a, b; i, j) = Risk(S(a))$ if $S(a) = S(b)$ and $(i, j) = (1, 1)$

2. $R(a, b; i, j) = Tr$ if $S(a) \neq S(b)$ and $(i, j) = (1, 1)$

3. $R(a, b; i, j) = Iso$ if $(i, j) \neq (1, 1)$

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 two active workers, but 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 third condition requires that if one of the two workers is not active (no matter who that is among the two) then the BRM value is equal to a common value Iso which is suggestive of isolation.

Under these conditions the matrix $R(a, b; \alpha)$ is a very simple combination of the $3L \times 3L$ activation matrix $M(\cdot; \alpha)$:

$$M(a, b; \alpha) \equiv \alpha(a, 1)\alpha(b, 1) \tag{5}$$

and the five-values parameter $\rho \equiv (Risk(L), Risk(H), Risk(In), Tr, Iso)$. For example it is equal to $Risk(H)M(a, b; \alpha)$ when $S(a) = S(b) = High$.

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

$$\text{for all } a \in \{13, \dots, 17\}, \alpha(a, 0) = 1. \tag{6}$$

In view of the constraint (6), in the description of the calibration of parameters and policies we focus on the $2L$ levels of activity of the workforce. We denote α_{min} the minimum level of activity of each active class, and with **1** the vector of activity corresponding to normal conditions.

In the calibration of the parameter ρ, we set the level of activity corresponding to normal and minimum activity as:

$$R_{normal} = R(a, b; \mathbf{1}); R_{lock} = R(a, b; \alpha_{min}) \tag{7}$$

We assume that the values of the reproduction matrix for the inactive is the same as the one between workers in different sectors:

$$Risk(In) = Tr \tag{8}$$

Given the parameter restriction and the model, we calibrate parameters to match the number of fatalities in a given region (for instance, Lombardia or Veneto) at the March 7 and April 4 dates. Details are in section 3 below.

2.4 Adding Economics to SEIR-HC-SEC-AGE model

For given demographic and epidemiological parameters, the SEIR-HC-SEC-AGE model described in the previuos section produces a set of public health effects of Covid-19 that depend on the age brackets and sectors that are allowed to go back to work according to the post lockdown policy that the authority will decide to implement. Our goal is to compare public health effects and economic effects of different possible policies.

A policy p is formally defined as a vector with ten elements, each one corresponding to one of the five potentially active age brackets in each of the two sectors. Each element of this vector specifies the fraction of the workforce that is allowed to go back to work in the corresponding age bracket/sector. Table 1 describes five of these policies in which we are specifically interested.

Defining with t^* the day in which the authority intends to possibly change the current lock down status (e.g., May 4 for Italy as of today), Policy "LOCK" is defined as prolonging after t^* the lock down with the minimum set of workers that is currently employed, which is on average equal to about 60% of the labor force according to Barbieri et al. (2020). Policy

Table 1: A set of possible post lock down policies

	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
$p =$ LOCK	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p =$ SEC	1	1	1	1	1	0.6	0.6	0.6	0.6	0.6
$p =$ AGE	1	1	1	0.6	0.6	1	1	1	0.6	0.6
$p =$ AGE_SEC	1	1	1	0.6	0.6	1	0.6	0.6	0.6	0.6
$p =$ ALL	1	1	1	1	1	1	1	1	1	1

"SEC" is based on sending back to work after t^* all the labor force of the low-risk sector, and only the strictly needed minimum in the sector, which incidentally includes health and education workers according to Barbieri et al. (2020). Policy "AGE" uses only age as the criterion to decide who is allowed to resume activities after t^*: under this policy all workers between 20 and 49 years of age go back to work independently of the sector, while only 60% of the older workers is allowed to be productive in both sectors. Policy "SEC_AGE" is representative of what a mixed policy could look like, using both the age and the sector criteria: all workers under 50 in the low-risk sector and under 30 in the high-risk sector resume activities, while 40% of the older workers in all sectors has to stay home. Finally, Policy "ALL" sends back to work all those who were working before the Covid-19 outbreak. Note that schools, even if they are part of the risky sector, are assumed to reopen with at least the minimum set of workers allowed by each policy. Of course, many more policies can be defined in a similar way, but these are the main ones in which we are interested, because they capture those currently under consideration in the political debate. Our framework could be easily adjusted to consider also policies differentiate by geographic area.

Using the SEIR-HC-SEC-AGE model described in Section 2.3 we can associate to every policy p its public health effects which we summarize with the total number of fatalities in the first year after t^*:

$$M_{rp} = \sum_{t=t^*}^{t^*+365} REM\_FAT_{tp} \tag{9}$$

As for the economic effects, we summarize them as a function of the fraction of the labor force that is not allowed to work under a given policy p. 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. For the time being, given the urgency of comparing the economic effects of different post lockdown strategies, we believe that estimating these consequences as a function of the fraction of the labor force that cannot work is sufficiently informative at least about the orders of magnitude. Specifically we assume that the GDP of region r, denoted as Y_r, is a Cobb Douglas function of labor L_r and capital K_r,

$$Y_r = AK_r^{1-\beta} L_r^{\beta},$$

so that the percent GDP change induced, ceteris paribus, by a variation dL_r of the employed labor force is

$$\Delta Y_r \approx \frac{dY_r}{Y_r} = \beta \frac{dL_r}{L_r} \tag{10}$$

which is a negative number if $dL_r < 0$. Each post lockdown policy p will produce a decline dL_{rp} of the employed labor force and thus a corresponding percent GDP loss ΔY_{rp} according to equation (10). This GDP loss is the measure of the economic effects of the interaction between policy p and Covid-19 that we consider.

Within this framework we aim at making two contributions. First, we want to characterize an efficient set of policies. Second, we want to compare between themselves and against the efficient frontier the five stereotypical post lockdown policies described in Table 1.

3 Calibration of the model for Lombardia and Veneto

The calibration of the SEIR-HC-SEC-AGE model requires giving values to different sets of parameters that are described in this section.

3.1 Relevant dates for the simulation

The relevant dates for the simulation are described in Table 2:

Table 2: Relevant dates for the simulation

	Observed Past				Simulated Future	
	Appearance of the virus	Beginning of observed data	Beginning of the lock down	Peak of fatalities	Start of post lock down policies $= t^*$	End of simulation $= t^* + 365$
Date	January 1 2020	February 24 2020	March 8 2020	April 4 2020	May 4 2020	May 3 2021

We assume that in both region the virus SARS-Cov-2 arrived at the beginning of 2020 so that the first infectious subjects is observed on January 1, 2020. The available data on the diffusion of Covid-19 in Italy, published by the Protezione Civile, are available from February 24, 2020 and are continuously updated.[4] The first lock down has been introduced by the Italian government on March 8, 2020. As explained below in more detail, we calibrate the basic reproduction numbers of the virus before the lock down, by age, sector and type of interactions, in order to match the simulated and observed numbers of fatalities around March 7, 2020. The analogous reproduction numbers for the lock down period are calibrated instead to match the number of fatalities at their peak, which occurred in both regions around April 4, 2020.

As of today, the intention of the government is to modify the lockdown policy on May 4, 2020, and we therefore simulate the effects of the possible post lockdown policies starting with this date. We end the simulation after one year, on May 3, 2021, given the expectation that a vaccine should become available at about that time.

[4] The data can be downloaded from https://github.com/pcm-dpc/COVID-19.

Table 3: Fraction of the population and labor force participation in each age bracket

	Age brackets								
	0-9	10-19	20-29	30-39	40-49	50-59	60-69	70-79	80+
Lombardia									
Population	0.088	0.094	0.098	0.118	0.158	0.156	0.118	0.099	0.071
Participation			0.494	0.771	0.832	0.804	0.235		
Veneto									
Population	0.085	0.096	0.098	0.112	0.156	0.161	0.121	0.100	0.071
Participation			0.497	0.751	0.826	0.794	0.236		

Note: The table report the fraction of the population in each age bracket and the labor force participation rates for the brackets between age 20 and age 69 in Lombardia and Veneto. The SEIR-HC-SEC-AGE assumes, in line with the available evidence, no significant labor force participation in the other age brackets. The total population is 10 ml. in Lombardia and 4.9 ml. in Veneto Source: ISTAT.

3.2 Demographic parameters and labor share

The distribution of the population and of the labor force participation rate in the nine age brackets[5] that we consider for the two regions is taken from ISTAT and is reported in Table 3. As expected Lombardia and Veneto have a similar distributions, with a slightly higher fraction of over-50 in Veneto (45.3%) than in Lombardia (44.4%). The total population of the two regions is instead significantly different: 10 ml. in Lombardia and 4.9 ml. in Veneto.

In order to compute the GDP loss using equation (10) we need to calibrate the parameter β that represents the labor share, and thus the coefficient that maps the loss of employment due to Covid-19 into a GDP loss. We take this parameter from Torrini (2016), who estimate $\beta = 0.65$ for the Italian economy. In the absence of specific information about this parameter for the two regions that we consider, we use this estimate for both Lombardia and Veneto.

3.3 Covid-19 parameters

There are two sets of relevant parameters defining the health consequences of Covid-19 for an exposed subject. We take both these sets from Ferguson et al. (2020). An obvious caveat

[5]See Footnote 3.

in considering these parameters is that they are estimated on the basis of data from China adjusted to predict US and Great Britain targets. We cannot exclude that the corresponding values for Lombardia and Veneto are different. However, the estimates of Ferguson et al. (2020) have been confirmed by follow up research for different regions in the world. We hope to be able to improve this parameter estimates if and when reliable data based on random testing for these two regions will become available. In any case, we do not expect that the comparison of the effects of the different policies should be particularly sensitive to reasonable changes of these parameters, at least in terms of first order consequences.

Table 4: Health effects of Covid-19 by age bracket

	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: Ferguson et al. (2020).

The first set of Covid-19 parameters defines the probability of hospitalization, p^{sev}, the probability of needing intensive care if hospitalized, p^{ic}, and the probability of death p^{fat} by age bracket and is described in Table 4. The values of all these probabilities clearly indicates that Covid-19 is considerably more dangerous for the old, with a pronounced increase of risks for subjects with an age greater than 49.

The second set of Covid-19 parameters that we need describes the lags of the transitions between states of the disease and are described in Table 5.

As by now well known, a characteristics that makes SARS-Cov-2 particularly nasty is the number of days in which a subject may be infectious without showing symptoms, which is on average $T_{inf} = 2.9$. $T_{inc} = 5.2$ is instead the average number of days of incubation before showing symptoms. The period going from the day in which the first symptoms appear to the

Table 5: Transition lags in the evolution between illness states of Covid-19

	Infectious without symptoms T_{inf}	Incubation without symptoms T_{inc}	Symptoms to recovery T_{srec}	Symptoms to death T_{sd}	Symptoms to entry in hospital T_{shosp}	Symptoms to discharge from hospital T_{shd}
Days	2.9	5.2	11.1	17.8	5	22.6

Note: the table reports the number of days for each transition between illness states of Covid-19. Source: Ferguson et al. (2020).

day of recovery is usually of $T_{srec} = 11.1$ days for a Covid-19 patient, while in case of death, this event occurs $T_{sd} = 17.8$ days after the appearance of symptoms. Hospitalization, if it is needed, occurs typically $T_{shosp} = 5$ days after symptoms, while the period from symptoms to hospital discharge in case of hospitalization is of $T_{shd} = 22.6$ days.

3.4 Availability of beds in intensive care

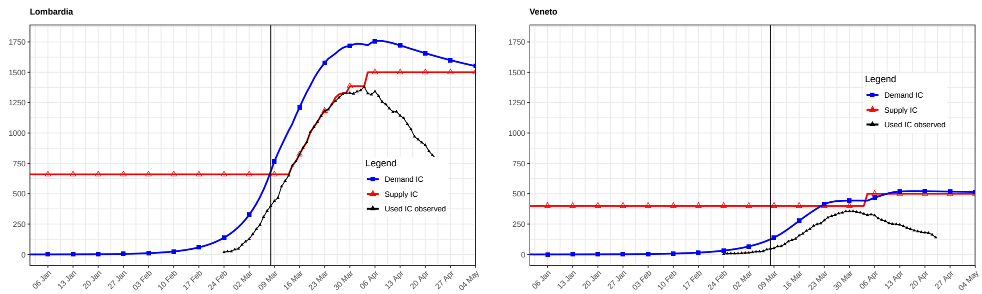
A crucial feature of the SEIR-HC-SEC-AGE model is to endogeneize the constraint in the availability of IC beds. When this constraint is binding, all subjects who need intensive care and do not find it become fatalities. Figure 3 illustrates how the constraint has operated in the two regions during the period between February 24 and May 4, 2020.

In Lombardia (left panel), given the initial very fast diffusion of the virus and the number of available IC beds, the constraint started to bite very quickly. These facts are responsible for the explosion of fatalities in this region which is displayed in the left panel of Figure 5. Even if Lombardia made a major effort to increase the supply of IC beds, the constraint continued to bite for a long time. In Veneto instead, the demand of IC is simulated to be higher than the supply in only two relative brief periods.

3.5 The basic reproduction number of Covid-19 by age and sector

It is well known that every variant of the SEIR model is very sensitive to the basic reproduction number R_0. In the case of the SEIR-HC-SEC-AGE extension that we have designed, the calibration of R_0 is further complicated by the need to set different values for different

Figure 3: The IC availability constraint in Lombardia and Veneto



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 bar indicate the start of the lockdown. 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.

combinations of age, sector and working status of an infectious subject and of the susceptible subjects that enter in contact with him/her.

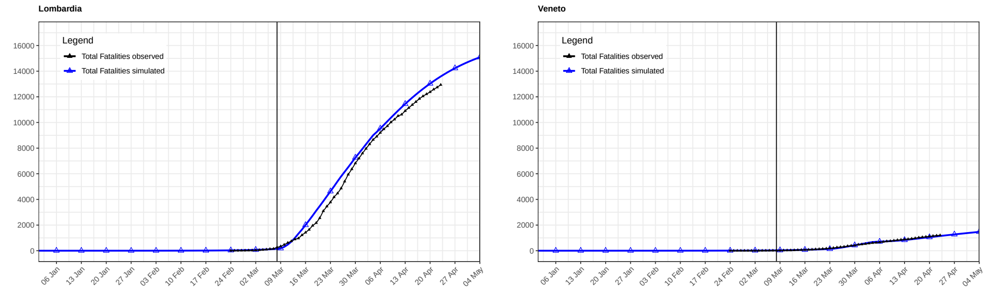
As explained in Section 2.3, we therefore need to calibrate different 19×19 basic reproduction matrices, BRM, for three periods: the period before the lockdown, the period of the lockdown until t^*, and the period after t^* in which the policies are introduced. Moreover, in this last period we have a different BRM for each policy. This task is simplified by the fact that these matrices are divided in blocks that are characterized by the same R_0 because they refer to subjects with similar types of interactions from the viewpoint of the Covid-19 diffusion. The values of R_0 in the various blocks are determined by the combination of the activation matrix $M(a, b; \alpha)$ with the basic reproduction numbers in the vector $\rho \equiv (Risk(L), Risk(H), Risk(In), Tr, Iso)$ that are relevant in each specific period and type of interaction.

Before describing in detail our calibration procedure, which is crucial for the validity of the simulation exercise, we show in Figures 4 and 5 that this calibration produces a very good match between simulated and observed fatalities.

3.5.1 Basic reproduction matrix before the lockdown

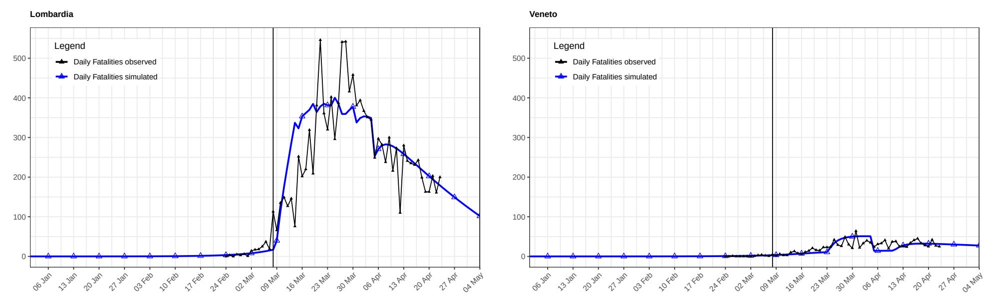
For the period before the lock down, in which subjects with age between 20 and 65 are allowed to work, only three values of the ρ vector need to be calibrated. The R_0 for the interactions

Figure 4: Simulated and observed total fatalities



Note: The figure reports, respectively for the two regions, the simulated and observed numbers of total fatalities due to Covid-19 The vertical bar indicate the start of the lockdown. 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 5: Simulated and observed daily fatalities



Note: The figure reports, respectively for the two regions, the simulated and observed numbers of daily fatalities due to Covid-19 The vertical bar indicate the start of the lockdown. 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.

between workers in the low- and in the high-risk sectors ($Risk(L)$ and $Risk(H)$ respectively) and the R_0 of all the other normal interactions involving at least one non-working subject in the population, Tr.

We discipline the calibration of these parameters using the evidence in Barbieri et al. (2020) who report an index of proximity for workers operating in different sectors of the Italian economy. Sectors with higher proximity are sectors in which R_0 is likely to be higher. Based on the evidence in their Table 3, we compute the proximity index for the sectors above and below the mean proximity index. We then assume that the percent difference between $Risk(H)$ and Tr is equal to the percent difference between the proximity index for sectors above the mean index and the mean index itself. This difference is equal to 18%. Similarly for the percent difference between Tr and $Risk(L)$, which is equal to 12%. In this way, we reduce the multiplicity of parameters to be calibrated because now by setting Tr we set also $Risk(H)$ and $Risk(L)$.

Table 6: Lombardia: basic reproduction matrix before the lockdown

	Kids	Active low-risk	Active high-risk	Inactive	Old
Kids	2.33	2.33	2.33	2.33	2.33
Active low-risk	2.33	2.05	2.33	2.33	2.33
Active high-risk	2.33	2.33	2.75	2.33	2.33
Inactive	2.33	2.33	2.33	2.33	2.33
Old	2.33	2.33	2.33	2.33	2.33

Note: Each cell in the table reports the R_0 for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

Finally, we calibrate Tr so that the number of cumulated fatalities simulated by the SEIR-HC-SEC-AGE model for March 7, 2020 (the last day before the lockdown) is as close as possible to the observed fatalities in the same day. As shown in Figures 4 and 5, the calibration just for this day delivers a fairly good match between simulated and observed mortality in the entire pre-lockdown period.

The building blocks of the BRMs that result from this procedure for Lombardia and Veneto are displayed in Tables 6 and 7.

As expected, given how these numbers were calibrated, in each region the R_0 for interactions among workers in the low-risk sector is smaller than the interactions involving non-active subjects and even smaller than the R_0 of the high-risk sector. More interestingly, to match the observed mortality in the two regions, in each pair of corresponding blocks of the two matrices the relevant R_0 must be set to a considerably higher value for Lombardia. In this type of model such difference in R_0 can generate outcomes that are very dissimilar.

Table 7: Veneto: basic reproduction matrix before the lockdown

	Kids	Active low-risk	Active high-risk	Inactive	Old
Kids	2.10	2.10	2.10	2.10	2.10
Active low-risk	2.10	1.85	2.10	2.10	2.10
Active high-risk	2.10	2.10	2.48	2.10	2.10
Inactive	2.10	2.10	2.10	2.10	2.10
Old	2.10	2.10	2.10	2.10	2.10

Note: Each cell in the table reports the R_0 for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

3.5.2 Basic reproduction matrix during the lockdown

We followed a similar procedure for the calibration of the BRM during the lock down, i.e. between March, 8 and $t^* =$ May 4, 2020. In this case the additional term $Risk(In)$ of the vector ρ becomes relevant. This is the R_0 for a population in isolation. Maintaining the other elements of ρ that were calibrated for the pre-lockdown period in order to match the pre-lockdown total mortality of March 7, we have calibrated $Risk(In)$ to match total mortality at its peak, which occurred around April 4 in both regions. Moreover, as already mentioned, during the lockdown only 60% of the Italian Labor force was allowed to work (see Barbieri et al., 2020). This modifies the activation matrix with respect to the pre-lockdown period, with the effect of reducing the R_0 of the interactions between those who continue to work in the two sectors. Once again, note in Figures 4 and 5 that, just by calibrating these two dates in the different periods, the simulated and observed mortalities (both total and daily) are very similar.

The corresponding building blocks of the BRMs for the lockdown period are reported in Tables 8 and 9. In Lombardia, the R_0 for interactions in isolation, $Risk(In)$, is calibrated to be equal to 0.75, and it is lower than the analogous parameter for Veneto which is equal to 0.90. A possible interpretation of this finding is that given the gravity of the situation in Lombardia, social distancing was observed with greater attention in this region. The R_0

Table 8: Lombardia: basic reproduction matrix during the lockdown

	Kids	Active low-risk	Active high-risk	Inactive	Old
Kids	0.75	0.75	0.75	0.75	0.75
Active low-risk	0.75	1.22	1.32	0.75	0.75
Active high-risk	0.75	1.32	1.47	0.75	0.75
Inactive	0.75	0.75	0.75	0.75	0.75
Old	0.75	0.75	0.75	0.75	0.75

Note: Each cell in the table reports the R_0 for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

parameters for the interactions of workers within and between the two sectors are instead almost identical in the two regions.

3.5.3 Basic reproduction matrix post lockdown

We now abandon the period for which observed data exists and move to the simulation of the effects of the policies that could be adopted in the two regions as of $t^* =$ May 4, 2020. We run the simulation for 365 days, under the assumption (hope?) that by May 4, 2021 a vaccine or a therapy for Covid-19 will be available.

Since each policy has its own workers activation vector, also the corresponding BRMs differ between policies. We also assume that during at least part of the post lockdown period schools will re-open and that the interaction between students in the same class, given the adoption of protection measures, will imply a $R_0 = 1.80$. Note that workers in the education sectors (teachers and assistants) are classified by Barbieri et al. (2020) as operating in a high-risk sector an are treated accordingly in our simulation model, as a function of their age. Moreover we assume that, after t^*, particular attention will be devoted to reducing the spread of the virus within and between subjects of the two old age brackets who stay in isolation at home. Therefore, for interactions involving these subjects $R_0 = 0.5$.

Table 10 reports for Lombardia the values of the relevant R_0 parameters corresponding

Table 9: Veneto: basic reproduction matrix during the lockdown

	Kids	Active low-risk	Active high-risk	Inactive	Old
Kids	0.90	0.90	0.90	0.90	0.90
Active low-risk	0.90	1.24	1.33	0.90	0.90
Active high-risk	0.90	1.33	1.47	0.90	0.90
Inactive	0.90	0.90	0.90	0.90	0.90
Old	0.90	0.90	0.90	0.90	0.90

Note: Each cell in the table reports the R_0 for the interaction between an infectious subject of the category of the corresponding row and exposed subjects in the category of the corresponding column.

to each policy and type of interaction. The same is done for Veneto in Table 11. The last column in both tables report the mean R_0 parameter for each policy, obtained as an average of the policy/interaction specific R_0 parameters, weighted by the size of the corresponding population. As expected, for each policy the R_0 parameters grows with a combination of age, activity and riskiness of the sector (in case of activity). Most interactions (in particular those involving active subjects) have an R_0 greater than one but, taking into account the population weights, the mean R_0 corresponding to each policy (last column) is smaller than 1 except for policy ALL in which all active workers are allowed to resume activities. As we will show in the next section this is the only policy that would produce a second explosion of the infection, precisely because its R_0 is greater than 1. Interestingly, the R_0 of policy LOCK is equal to 0.8, which is the same value announced on April 18 by Franco Locatelli, president of *Consiglio Superiore di Sanità* for the lockdown condition.

4 Results of the policy simulations

Our main results are described in Figures 6 and 7: the top panel of Figure 6, refers to Lombardia, the bottom one to Veneto. In both panels, a marker indicates the GDP loss (horizontal axis) and the total number of fatalities (vertical axis), associated to the policies

Table 10: Lombardia: Relevant R_0 parameters for the different policies

	1	2	3	4	5	6	7	8	9	10	11	12	mean
$p =$ LOCK	0.5	0.75	1.80	1.47	1.47	1.32	1.32	1.47	1.32	1.22	1.22	1.22	0.825
$p =$ SEC	0.5	0.75	1.80	1.47	1.47	1.70	1.70	1.74	1.70	2.05	2.05	2.05	0.912
$p =$ AGE	0.5	0.75	1.80	2.75	1.95	2.33	1.70	1.47	1.32	2.05	1.53	1.22	0.929
$p =$ AGE_SEC	0.5	0.75	1.80	*	**	***	****	1.47	1.32	2.05	1.53	1.22	0.886
$p =$ ALL	0.5	0.75	1.80	2.75	2.75	2.33	2.33	2.75	2.33	2.05	2.05	2.05	1.003

Note: For each policy indicated in a row, the columns of this table report the R_0 for Lombardia corresponding to the following interactions:

1. any interaction involving subjects with age greater than 69 at home;
2. all subjects with subjects under 70 in isolation at home;
3. students with students in the same class;
4. young active high-risk with young active high-risk;
5. young active high-risk with old active high-risk;
6. young active high-risk with young active low-risk;
7. young active high-risk with old active low-risk;
8. old active high-risk with old active high-risk;
9. old active high-risk with old active low-risk;
10. young active low-risk with young active low-risk;
11. young active low-risk with old active low-risk;
12. old active low-risk with old active low-risk;

The last column reports, for each policy, the average R_0 in the population, obtained as an average of the R_0 for each type of interaction weighted by the size of the population involved.
* Given the structure of the policy there are 3 different values for this class: 2.75 for 20-29 to 20-29, 1.95 for 30-49 to 20-29 and vice versa, and 1.47 for 30-49 to 30-49.
** Given the structure of the policy there are 2 different values for this class: 1.95 for 20-29 to 50-69 and 1.47 for 30-49 to 50-69.
*** Given the structure of the policy there are 2 different values for this class: 2.33 for 20-29 to 20-49 and 1.7 for 30-49 to 20-49.
**** Given the structure of the policy there are 2 different values for this class: 1.7 for 20-29 to 50-69 and 1.32 for 30-49 to 50-69.

that are efficient, i.e. those yielding combinations of fatalities and GDP losses that are located on the lowest south-west convex envelope of the set of outcomes induced by all feasible policies. The representative policies described in Table 1 are displayed in the same fashion and appear to be close or on the frontier. Both the GDP loss and the total number of fatalities are computed over the post-lockdown period of one year between May 4, 2020 and May 3, 2021.

As expected, Policy ALL, that sends back to work all the active population, avoids any GDP loss but causes the maximum number of yearly fatalities in both regions (41,446 in

Table 11: Veneto: Relevant R_0 parameters for the different policies

	1	2	3	4	5	6	7	8	9	10	11	12	mean
$p =$ LOCK	0.5	0.9	1.80	1.47	1.47	1.33	1.33	1.47	1.33	1.24	1.24	1.24	0.918
$p =$ SEC	0.5	0.9	1.80	1.47	1.47	1.62	1.62	1.47	1.62	1.85	1.85	1.85	0.981
$p =$ AGE	0.5	0.9	1.80	2.48	1.85	2.1	1.62	1.47	1.33	2.85	1.47	1.24	0.992
$p =$ AGE_SEC	0.5	0.9	1.80	*	**	***	****	1.47	1.33	1.85	1.47	1.24	0.962
$p =$ ALL	0.5	0.9	1.80	2.48	2.48	2.1	2.1	2.48	2.1	1.85	1.85	1.85	1.049

Note: For each policy indicated in a row, the columns of this table report the R_0 for Veneto corresponding to the following interactions:

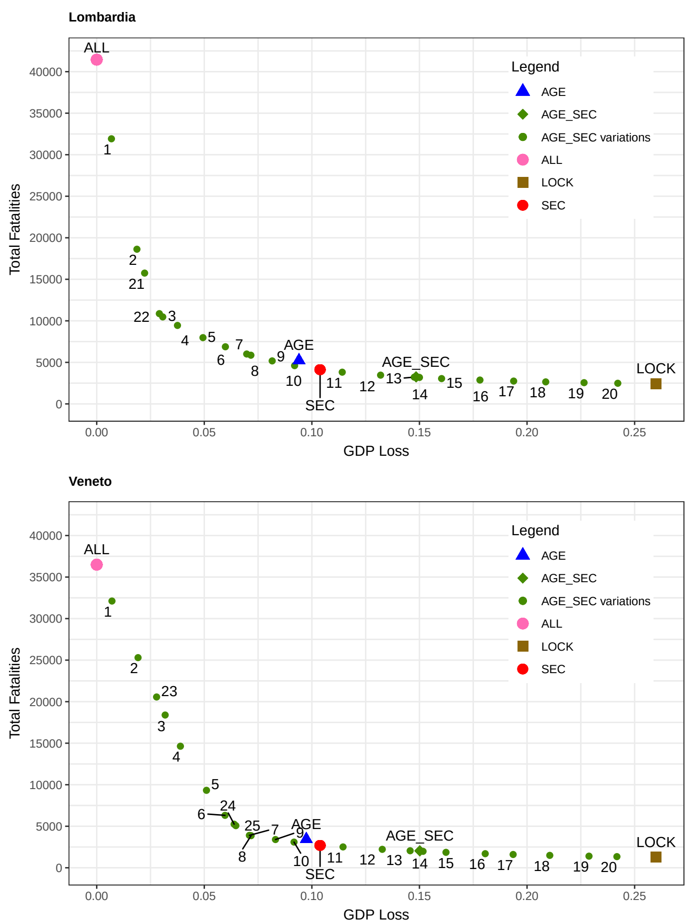
1. any interaction involving subjects with age greater than 69 at home;
2. all subjects with subjects under 70 in isolation at home;
3. students with students in the same class;
4. young active high-risk with young active high-risk;
5. young active high-risk with old active high-risk;
6. young active high-risk with young active low-risk;
7. young active high-risk with old active low-risk;
8. old active high-risk with old active high-risk;
9. old active high-risk with old active low-risk;
10. young active low-risk with young active low-risk;
11. young active low-risk with old active low-risk;
12. old active low-risk with old active low-risk;

The last column reports, for each policy, the average R_0 in the population, obtained as an average of the R_0 for each type of interaction weighted by the size of the population involved.
* Given the structure of the policy there are 3 different values for this class: 2.48 for 20-29 to 20-29, 1.85 for 30-49 to 20-29 and vice versa, and 1.47 for 30-49 to 30-49.
** Given the structure of the policy there are 2 different values for this class: 1.85 for 20-29 to 50-69 and 1.47 for 30-49 to 50-69.
*** Given the structure of the policy there are 2 different values for this class: 2.1 for 20-29 to 20-49 and 1.62 for 30-49 to 20-49.
**** Given the structure of the policy there are 2 different values for this class: 1.62 for 20-29 to 50-69 and 1.33 for 30-49 to 50-69.

Lombardia and 36,497 in Veneto, as indicated respectively in Tables 13 and 14).

The number of fatalities is similar in the two regions but, taking into account that Lombardia has twice the population of Veneto, this fact indicates that Policy ALL is much more costly in terms of fatalities in the latter. This is, from the point of view of policy evaluation, a crucial difference between the two regions, and it is highlighted in Figure 7, where (differently from Figure 6) we report on the vertical axis the number of fatalities *per million individuals* in the region. While the two frontiers are close for *GDP* losses larger than 5 per cent, they are substantially different for less conservative policies (defined here to be those with GDP losses smaller than 5 per cent, so conservative refers to fatalities), indicating that the price in fatalities of these policies is substantially higher for Veneto. The reason for this difference is the difference in the per-capita supply of IC units, which is currently much lower in Veneto (500 over 4.9 ml. instead of 1500 over 10 ml. as indicated in Figure 3), causing deaths to increase drastically for policies that put a larger number of subjects at risk of having severe symptoms.

Figure 6: Frontier of the efficient policies in Lombardia and Veneto

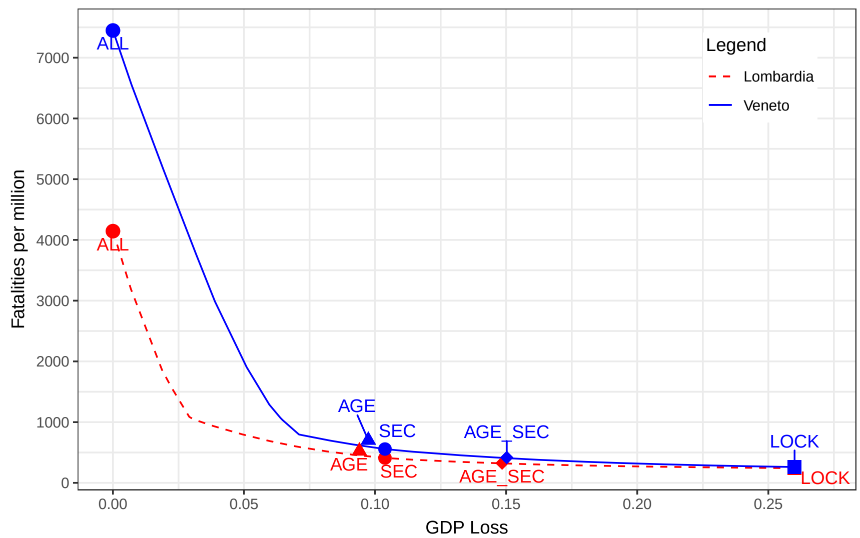


Note: In this figure, respectively for Lombardia and Veneto and for the year between May 4, 2020 and May 3, 2021, each marker shows the GDP loss and the total number of fatalities associated to the policies that are efficient (as defined in the text). The representative policies described in Table 1 are displayed in the same way. The precise workers activation vector of these efficient policies is described in Table 12 for Lombardia and Veneto.

There exist, however, a number of efficient mixed strategies based on the age and sector criteria, that would reduce dramatically the total number of fatalities with relatively minor

GDP losses until the threshold of approximately a 5 percent loss. Mixed policies that cause a GDP loss of about this size are associated to about 5000 total fatalities in both regions (or less than one thousand per million). Trying to reduce fatalities beyond this level causes a huge increase in the size of GDP losses. Prolonging the lock down for a full year after t^* (Policy LOCK) would cause a probably unsustainable GDP loss of almost 25 per cent.

Figure 7: The efficient frontier in the two regions, in terms of fatalities per million individuals



Note: The two curves (dashed for Lombardia and solid for Veneto) report the efficient frontiers of outcomes occurring between May 4, 2020 and May 3, 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, described in Table 1, are displayed in the same way.

The exact characterization of the workers activation vectors for these efficient policies is provided in Table 12. These vectors provide suggestions for alternative policies. The top part lists the 23 efficient policies that are common to both regions, ordered from the one that maximizes fatalities and minimizes the GDP loss (ALL) to the one associated with the opposite effects (LOCK).

Table 12: Worker activation vector of the efficient policies in Lombardia and Veneto

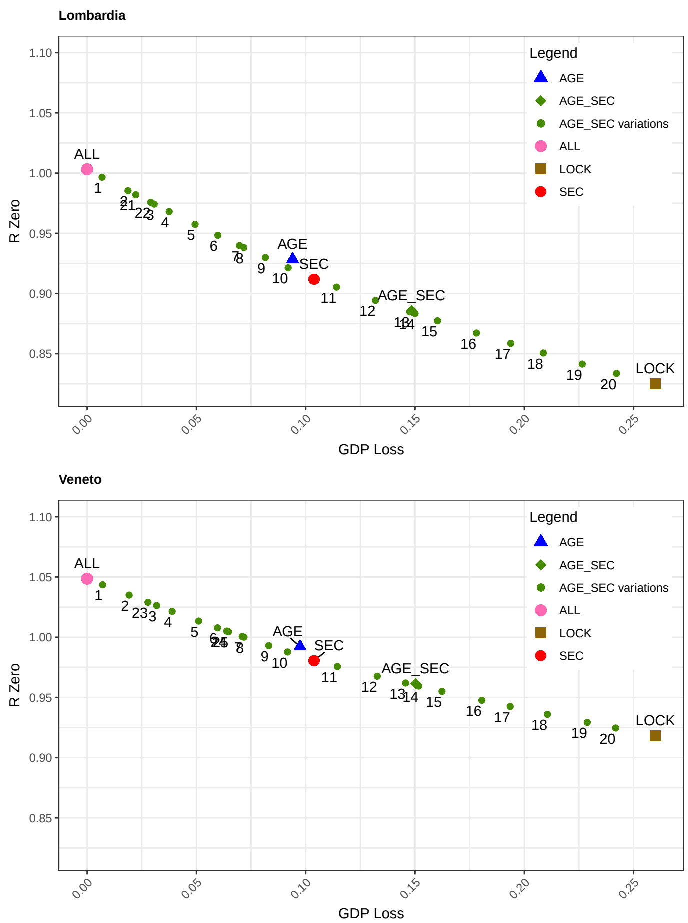
	Low-Risk sector Age brackets					High-Risk sector Age brackets				
Policy	20-29	30-39	40-49	50-59	60-65	20-29	30-39	40-49	50-59	60-65
Efficient AGE_SEC policies common to both regions										
$p =$ ALL	1	1	1	1	1	1	1	1	1	1
$p = AGE\_SEC_1$	1	1	1	1	1	1	1	1	1	0.6
$p = AGE\_SEC_2$	1	1	1	1	1	0.6	1	1	1	0.6
$p = AGE\_SEC_3$	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	1	1	1	0.6	0.6	0.6
$p = AGE\_SEC_8$	1	1	1	1	1	0.6	0.6	1	0.6	0.6
$p = AGE\_SEC_9$	1	1	1	1	1	0.6	1	0.6	0.6	0.6
$p = AGE\_SEC_{10}$	1	1	1	1	1	1	0.6	0.6	0.6	0.6
$p =$ SEC	1	1	1	1	1	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{11}$	1	1	1	1	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{12}$	0.6	1	1	1	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{13}$	1	0.6	1	1	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{14}$	1	1	1	0.6	1	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{15}$	1	1	1	0.6	0.6	0.6	0.6	0.6	0.6	0.6
$p = AGE\_SEC_{16}$	0.6	1	1	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	0.6	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 Lombardia only										
$p = AGE\_SEC_{21}$	1	1	1	1	1	1	0.6	1	1	1
$p = AGE\_SEC_{22}$	1	1	1	1	1	1	0.6	1	1	0.6
Efficient AGE_SEC policies for Veneto only										
$p = AGE\_SEC_{23}$	1	1	1	1	1	1	0.6	1	1	0.6
$p = AGE\_SEC_{24}$	1	1	1	1	1	1	1	0.6	0.6	1
$p = AGE\_SEC_{25}$	1	1	1	1	1	0.6	0.6	1	0.6	1
Other representative policies close to the efficient contour										
$p =$ AGE	1	1	1	0.6	0.6	1	1	1	0.6	0.6
$p = AGE\_SEC_0$	1	1	1	0.6	0.6	1	0.6	0.6	0.6	0.6

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

The general pattern is clear: starting from policy ALL, in order to move down along the efficient contour it is necessary to progressively inactivate (i.e. allow only the minimum

60% of the labor force to be active) workers in the high-risk sector, beginning with those belonging to a higher age bracket, until LOCK is reached in which case all age brackets and sectors are inactivated. Some policies slightly deviate from this pattern, like for example AGE_SEC_{12} and AGE_SEC_{13}, because labor force participation rates are not the same in all age brackets. The next two panels in the table describe policies that are efficient only in Lombardia (2) or Veneto (3), respectively.

Figure 8: The trade off between R_0 and GDP loss



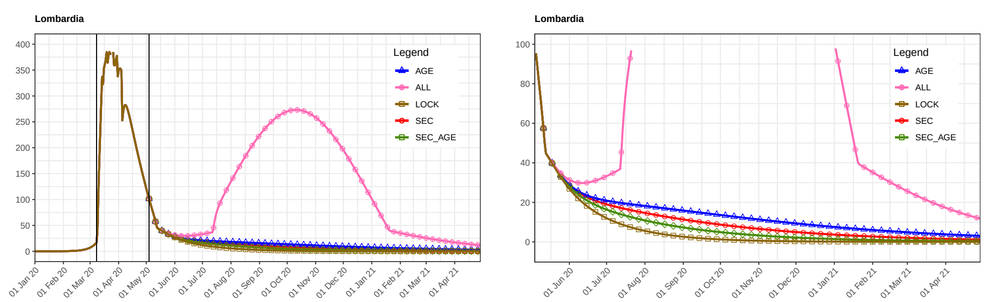
Note: The figure reports the trade-off between the average basic reproduction number R_0 and the GDP loss over the year after May 4, 2020. The average R_0 is computed as the expected value of the basic reproduction matrix with respect to the existing frequency in the population. Source: our simulations of the SEIR-HC-SEC-AGE model.

It is remarkable that, despite the different pre-t^* experiences of Lombardia and Veneto, the vast majority of the prudent efficient policies (i.e., those implying GDP losses higher than 5%) are common to both regions and only few are region specific. While SEC is in the set of efficient policies common to both regions, the representative policies AGE and AGE_SEC$_0$, in the last panel, are not on the efficient contour but are located very close to it, as shown in Figure 6.

The choice of which one of these specific efficient policies should be adopted depends of course on the weight society wants to give to fatalities or GDP losses in the aggregate welfare function, but our guess is that the optimal choice should fall on one of the mixed policies that produce a GDP loss of about 5% and a total number of fatalities equal to about one thousand per million. It is also clear that mixed policies relying on both an AGE and a SECTOR criteria offer a wider set of efficient options.

Figure 8 shows the trade off between the average R_0 and the total number of fatalities of the efficient policies for the two regions, which appears remarkably linear. As already noted, under lock down the average R_0 is about 0.8, as estimated by others.[6] However, a very important finding of our simulations is that in both regions all the efficient policies except one have an R_0 lower than 1. This is crucially important because it means that it will be feasible to resume activities, with one of these efficient policies, without risking a second explosion of the infection.

Figure 9: Daily fatalities under the different policies in Lombardia



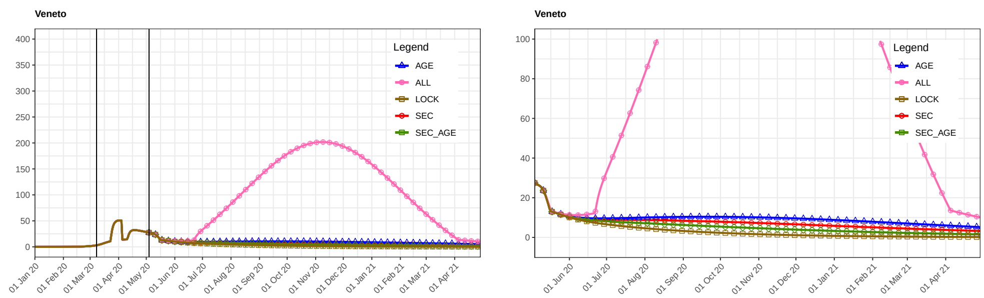
Note: The figure reports, for Lombardia, the daily fatalities due to Covid-19 under the 5 representative policies that we consider. The left panel covers the entire period from January 1, 2020 to May 4, 2021. The right panel zooms into the post-lockdown year of simulation in order to better highlight the differences between the fatalities associated to each policy. Source: our simulations of the SEIR-HC-SEC-AGE model.

The only strategy that features an average R_0 greater than 1 in both regions is the policy ALL that sends back to work the entire active population. Adopting this policy would

[6] See for example the estimates reported by the Italian COVID-19 policy group https://www.medrxiv.org/content/10.1101/2020.04.08.20056861v1.full.pdf.

necessarily imply a second explosion of the infection in both regions, as shown in Figure 9 and 10. The same figure also shows that the other four representative policies are associated to a relatively low and declining evolution of the associated daily mortality, precisely because their R_0 is lower than 1.

Figure 10: Daily fatalities under the different policies in Veneto.



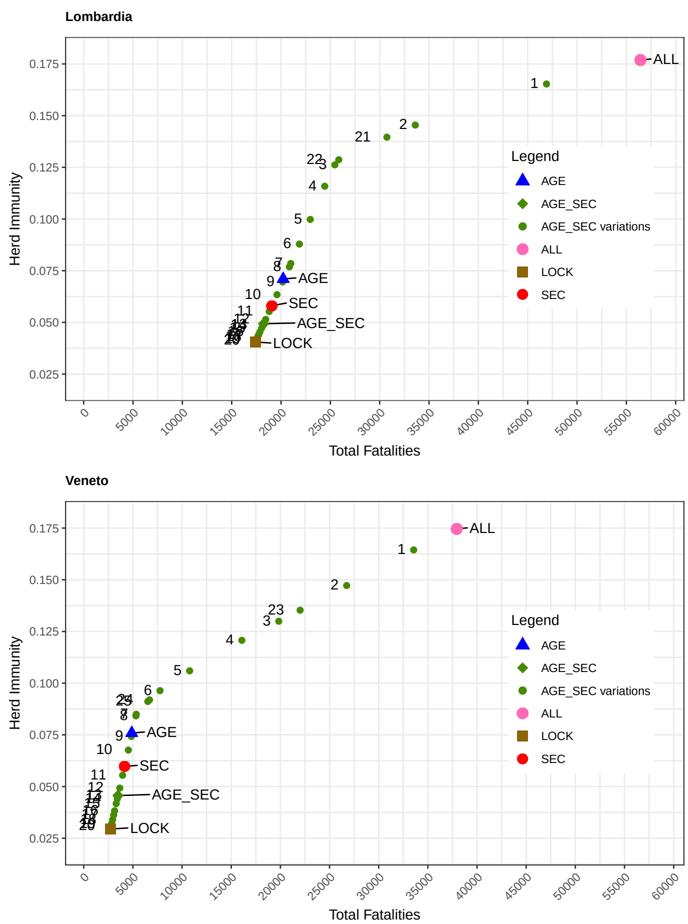
The figure reports, for Veneto, the daily fatalities due to Covid-19 under the 5 representative policies that we consider. The left panel covers the entire period from January 1, 2020 to May 4, 2021. The right panel zooms into post-lockdown year of simulation in order to better highlight the differences between the fatalities associated to each policy. Source: our simulations of the SEIR-HC-SEC-AGE model.

The other side of the coin of a reduced number of fatalities is the smaller degree of immunity in the population. This is also an additional very important trade-off, as long as a vaccine or an effective pharmacological remedy are not yet available. Figure 11 displays the trade off between fatalities and herd immunity in the two regions. A remarkable finding is that it seems very hard to reach a sufficient level of herd immunity with the efficient policies, precisely because they manage to keep under control the diffusion of the infection by inducing a low average R_0. According to these estimates, unless a vaccine arrives we will always be under the threat of a recurrence of the virus epidemic even after May 4, 2021. Note that herd immunity is computed by taking the ratio between the model simulated number of recovered and the total population. The average probability of having a mild version of the disease has been calibrated to 0.89, therefore the majority of the recovered are those recovered after mild symptoms and the model based measure of total recovered subjects include also those who did not need hospitalization and those who did not report to health authorities. The model based measure of recovered is much higher than the recovered from hospital in the official data (”dimessi guariti” in the data file made available by Protezione Civile). This variable is instead closely matched by the recovered from hospital in the simulated data.

The effective level of herd immunity could be higher than the one indicated by our model simulation only in the case in which the observed number of asymptomatic patients were higher than the model based “mild” patients.

Tables 13 and 14 display some summary statistics for the representative policies.

Figure 11: 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 13: Lombardia: final main outcomes

	Policies				
	LOCK	SEC	AGE	SEC_AGE	ALL
Total fatalities	2420	4104	5237	3246	41446
GDP loss	0.26	0.104	0.094	0.148	0
Final herd immunity	0.041	0.058	0.071	0.049	0.177
Total recoveries	404898	579587	708739	492804	1759042
Total exposed	2	468	1360	108	4399

Note: The table reports the main outcomes of the five policies for Lombardia, measured over the year between May 4, 2020 and May 3, 2021.

Table 14: Veneto: final main outcomes

	Policies				
	LOCK	SEC	AGE	SEC_AGE	ALL
Total fatalities	1277	2725	3438	2040	36497
GDP loss	0.260	0.104	0.097	0.150	0
Final herd immunity	0.030	0.060	0.076	0.046	0.175
Total recoveries	144309	292485	371450	223441	848977
Total exposed	71	1465	2384	672	3804

Note: The table reports the main outcomes of the five policies for Veneto, measured over the year between May 4, 2020 and May 3, 2021.

5 Conclusions: Estimating Tradeoffs in an Epidemic

Compared to existing work in the rapidly growing field of economics of a pandemic, this paper has several important distinctive features.

Quantitative Realism in Modeling. First of all, we have tried to make the model directly empirically relevant, aiming to provide precise (as much as possible) estimates and predictions of future developments. We are not interested here in providing qualitative regularities that can organize our thinking about the phenomenon: we want to provide a tool that measures consequences in terms of the most important outcomes (such as number of fatalities, loss of GDP, development of herd immunity in the population), and thus offers precise estimates of the tradeoffs between the values of these variables that follows specific, implementable, realistic policies. We want to provide a tool for the decision makers and the informed public opinion.

To achieve this objective of quantitative realism, we build, relying on Favero (2020), a model extending the classical $SEIR$ (which is the relevant epidemiological model in the case the Covid-19 epidemic, as opposed for instance to SIR models) taking into account two broad orders of factors. The first is the constraints of Intensive Care Units availability. This constraint is a crucial specific characteristic of the current epidemic, and explains many of the puzzling phenomena that have emerged (one instance is the difference of the spread of the epidemic in the two regions of Lombardia and Veneto). The second is the specific dynamic of the epidemics across different types of individuals and clinical conditions. This in turn allows us to take into due account the differences in fundamental biological parameters across ages. Only because we do this in a realistic way we can then calibrate the crucial parameters and provide an accurate estimate of policies differentiating the intervention depending on the age of the individuals.

Identification of Efficient Policies. Second, in line with our main aim, we have not tried to derive estimation of policies on the basis of a welfare function or the utility of a representative agent in a competitive economy with a public sector. Our main conclusions, when we evaluate policies, have been formulated as two main groups of findings. First, we want to identify the policies that are efficient, that is policies for which there is no other feasible policy that induces a better final outcome in all relevant outcomes. We think that public opinion and informed discussion should choose among these. We offer the preliminary analysis necessary to avoid policy mistakes. Second, we allow the comparison between any two of these policies to be reduced to a comparison between estimated specific values of the relevant outcomes. When the public is considering the shift from a policy to another, we are offering here an estimate of the costs and benefits of the two policies. We have no illusion that the numbers we offer are the true numbers: we are however convinced that having some estimate reasonably close to the truth is better that having only qualitative, sometimes obvious, statements.

The results presented in Figure 6 illustrate one of the main tools we offer to the public debate. The figure presents the values of possibly the two most important variables (total number of fatalities and GDP loss over one year period) that our model associates to a menu of policy choices determining the number and groups of workers that are allowed back to work. In line with our efficiency criterion, we only provide the values associated with the policies that are not dominated by other feasible ones. The results are presented for two regions, that are emblematic of two very different evolutions of the current epidemic in Italy, Lombardia and Veneto. As expected, the precise trade-offs depend on the estimated underlying parameters, that are very different as anyone acquainted with the current debate in Italy knows. In spite of this, precise conclusions common to both cases can be drawn, which are therefore robust to the parameter specification. The most important ones, because directly relevant for the evaluation of the policies, have been reported in section 1.1.

Extensions. We have not explicitly considered, in this version of the paper, policies that are different according to regions (or macro regions, such as North and South). This extension is feasible, indeed easy within our framework, since it requires a calibration of the key parameters, as well as the number of Infectious I in the initial period. Also, we have not modelled the impact of policies on the capital side of the production function and we have not considered fiscal policy interventions and their consequences to workers, firms and the sustainability of public debt. We plan to extend the simple macroeconomic structure adopted here to address all these issues in future work.

Costs and benefits of alternative policies that are widely discussed have not been considered explicitly, but can be easily adjusted within the current framework. For instance:

1. Increasing the number of IC units and training the personnel necessary to manage them has a financial cost, and a benefit in terms of fatalities. These unitary costs can be estimated, and the effect of the policy estimated.

2. Testing, of all types, has clear costs, and benefits that can be formulated as reduction of the corresponding entries of the basic reproduction matrix. Testing of workers can substantially reduce the R_0 within the risk class (low and high risk); and it can reduce the risk across risk classes (for instance affecting the contagion in mass transportation)..

3. Measures to reduce the spread during traveling affect the Tr parameter.

4. Pharmacological remedies change the basic "biological" parameters, such as the p^{sev}, p^{ic} and p^{fat}.

In summary on this point, the purpose of the paper is to provide a method that is rich enough but tractable to quantify the benefits of alternative policies.

6 Appendix

6.1 The basic SEIR Model

There are three stages: Susceptible, then Exposed, then Infectious. Infectious is 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 pre-assigned final outcome for that condition, after hospitalization, with a lag T_{shosp}).

$$
\begin{aligned}
S_t - S_{t-1} &= \left(-\frac{R_0}{T_{\inf}}\frac{I_{t-1}}{N_{t-1}}\right) S_{t-1} \\
E_t - E_{t-1} &= \left(\frac{R_0}{T_{\inf}}\frac{I_{t-1}}{N_{t-1}}\right) S_{t-1} - \left(\frac{1}{T_{inc}}\right) E_{t-1} \\
I_t - I_{t-1} &= \left(\frac{1}{T_{inc}}\right) E_{t-1} - \left(\frac{1}{T_{\inf}}\right) I_{t-1} \\
\Delta MILD_t &= \left(1 - p^{fat} - p^{sev}\right)\left(\frac{1}{T_{\inf}}\right) I_{t-1} - \left(\frac{1}{T_{rec}}\right) MILD_{t-1} \\
\Delta SEV_t &= p^{sev}\left(\frac{1}{T_{\inf}}\right) I_{t-1} - \left(\frac{1}{T_{shd} - T_{shosp}}\right) SEV_{t-1} \\
\Delta FAT_t &= p^{fat}\left(\frac{1}{T_{\inf}}\right) I_{t-1} - \left(\frac{1}{T_{sd} - T_{shosp}}\right) FAT_{t-1} \\
\Delta REM\_FAT_t &= \left(\frac{1}{T_{sd} - T_{shosp}}\right) FAT_{t-1} \\
\Delta RECOVERED_t &= \left(\frac{1}{T_{rec}}\right) MILD_{t-1} + \left(\frac{1}{T_{shd} - T_{shosp}}\right) SEV_{t-1} \\
N_t &= N_{t-1} - \Delta REM\_FAT_t
\end{aligned}
$$

In the following sections we will write for any variable X:

$$\Delta X_t \equiv X_t - X_{t-1}$$

6.2 The SEIR-HC Model

$$
\begin{aligned}
\Delta S_t &= \left(-\frac{R_0}{T_{\inf}}\frac{I_{t-1}}{N_{t-1}}\right) S_{t-1} \\
\Delta E_t &= \left(\frac{R_0}{T_{\inf}}\frac{I_{t-1}}{N_{t-1}}\right) S_{t-1} - \left(\frac{1}{T_{inc}}\right) E_{t-1} \\
\Delta I_t &= \left(\frac{1}{T_{inc}}\right) E_{t-1} - \left(\frac{1}{T_{\inf}}\right) I_{t-1} \\
\Delta MILD_t &= p^{mild}\left(\frac{1}{T_{\inf}}\right) I_{t-1} - \left(\frac{1}{T_{srec}}\right) MILD_{t-1} \\
\Delta REC\_MILD_t &= \left(\frac{1}{T_{srec}}\right) MILD_{t-1} \\
\Delta SEV_t &= p^{sev}\left(\frac{1}{T_{\inf}}\right) I_{t-1} - \left(\frac{1}{T_{shosp}}\right) SEV_{t-1} \\
\Delta SEV\_H_t &= \left(\frac{1}{T_{shosp}}\right) SEV_{t-1} - \left(\frac{1}{T_{shd}-T_{shosp}}\right) SEV\_H_{t-1} - \Delta SEV\_FAT_t \\
\Delta SEV\_FAT_t &= \mathbb{I}_t\left(EDIC_t\right) EDIC_t \frac{SEV\_H_t}{HOSP_t} \\
\Delta REC\_SEV_t &= \left(\frac{1}{T_{shd}-T_{shosp}}\right) SEV\_H_{t-1} \\
\Delta FAT_t &= p^{fat}\left(\frac{1}{T_{\inf}}\right) I_{t-1} - \left(\frac{1}{T_{shosp}}\right) FAT_{t-1} \\
\Delta FAT\_H_t &= \left(\frac{1}{T_{shosp}}\right) FAT_{t-1} - \left(\frac{1}{T_{sd}-T_{shosp}}\right) FAT\_H_{t-1} \\
\Delta REM\_FAT_t &= \left(\frac{1}{T_{sd}-T_{shosp}}\right) FAT\_H_{t-1} \\
HOSP_t &= SEV\_H_t + FAT\_H_t \\
EFF\_FAT_t &= REM\_FAT_t + SEV\_FAT_t \\
RECOVERED_t &= REC\_MILD_t + REC\_SEV_t \\
\Delta N_t &= -\Delta EFF\_FAT_t \\
I_t^{ICCS}\left(EDIC_t\right) &= \left\{\begin{array}{c} 1 \;\; if \;\; EDIC_t > 0 \\ 0, \;\; otherwise \end{array}\right\} \\
EDIC_t &= p^{ic} SEV\_H_t + p^{ic} FAT\_H_t - ICC_t
\end{aligned}
$$

6.3 The SEIR-HC-AGE-SEC

In this simplified version we illustrate the model for two age groups, denoted by $i \in \{\text{young}, \text{old}\}$ and two sectors denoted by $j \in \{\text{low-risk}, \text{high-risk}\}$ In the high-risk sector there is high proximity between workers and thus high risk of infection. The opposite holds in the low-risk sector

$$
\begin{aligned}
\Delta S_t^{i,j} &= -\sum_{i,j}\left(\frac{R_0^{i,j}}{T_{\inf}}\frac{I_{t-1}^{i,j}}{N_{t-1}}\right)S_{t-1}^{i,j} \\
\Delta E_t^{i,j} &= \sum_{i,j}\left(\frac{R_0^{i,j}}{T_{\inf}}\frac{I_{t-1}^{i,j}}{N_{t-1}}\right)S_{t-1}^{i,j} - \left(\frac{1}{T_{inc}}\right)E_{t-1}^{i,j} \\
\Delta I_t^{i,j} &= \left(\frac{1}{T_{inc}}\right)E_{t-1}^{i,j} - \left(\frac{1}{T_{\inf}}\right)I_{t-1}^{i,j} \\
\Delta MILD_t^{i,j} &= \left(1 - p^{fat,ij} - p^{sev,ij}\right)\left(\frac{1}{T_{\inf}}\right)I_{t-1}^{i,j} - \left(\frac{1}{T_{rec}}\right)MILD_{t-1}^{i,j} \\
\Delta REC\_MILD_t^{i,j} &= \left(\frac{1}{T_{srec}}\right)MILD_{t-1}^{i,j} \\
\Delta SEV_t^{i,j} &= p^{sev,ij}\left(\frac{1}{T_{\inf}}\right)I_{t-1}^{i,j} - \left(\frac{1}{T_{shosp}}\right)SEV_{t-1}^{i,j} \\
\Delta SEV\_H_t^{i,j} &= \left(\frac{1}{T_{shosp}}\right)SEV_{t-1}^{i,j} - \left(\frac{1}{T_{shd} - T_{shosp}}\right)SEV\_H_t^{i,j} - \Delta SEV\_FAT_t^{i,j} \\
\Delta FAT_t^{i,j} &= p^{fat,ij}\left(\frac{1}{T_{\inf}}\right)I_{t-1}^{i,j} - \left(\frac{1}{T_{shosp}}\right)FAT_{t-1}^{i,j} \\
\Delta FAT\_H_t^{i,j} &= \left(\frac{1}{T_{shosp}}\right)FAT_{t-1}^{i,j} - \left(\frac{1}{T_{sd} - T_{shosp}}\right)FAT\_H_{t-1}^{i,j} \\
HOSP_t &= \sum_{i,j} SEV\_H_t^{i,j} + \sum_{i,j} FAT\_H_t^{i,j}
\end{aligned}
$$

$$
\begin{aligned}
ICCD_t &= p^{ic,y} \sum_j \left(SEV\_H_t^{y,j} + FAT\_H_t^{y,j} \right) \\
&\quad + p^{ic,o} \sum_j \left(SEV\_H_t^{o,j} + FAT\_H_t^{o,j} \right) \\
EDIC_t &= ICCD_t - ICCS_t \\
\Delta SEV\_FAT_t^{ij} &= \mathbb{I}_t \left(EDIC_t \right) * EDIC_t * \frac{p^{ic,ij} SEV\_H_t^{i,j}}{ICCD_t} \\
\Delta REM\_FAT_t^{i,j} &= \left(\frac{1}{T_{sd} - T_{shosp}} \right) FAT_{t-1}^{i,j} \\
EFF\_FAT_t &= \sum_{i,j} REM\_FAT_t^{i,j} + \sum_{i,j} SEV\_FAT_t^{i,j} \\
RECOVERED_t &= \left(\frac{1}{T_{rec}} \right) sum_{i,j} MILD_{t-1}^{i,j} + \\
&+ \left(\frac{1}{T_{shd} - T_{shosp}} \right) \sum_{i,j} SEV\_H_t^{i,j} \\
N_t &= N_{t-1} - \Delta EFF\_FAT_t
\end{aligned}
$$

6.4 Basic Reproduction matrices during the policy

6.4.1 Lombardia

Figure 12: BRM for Lombardia, post-lock down: Policy LOCK

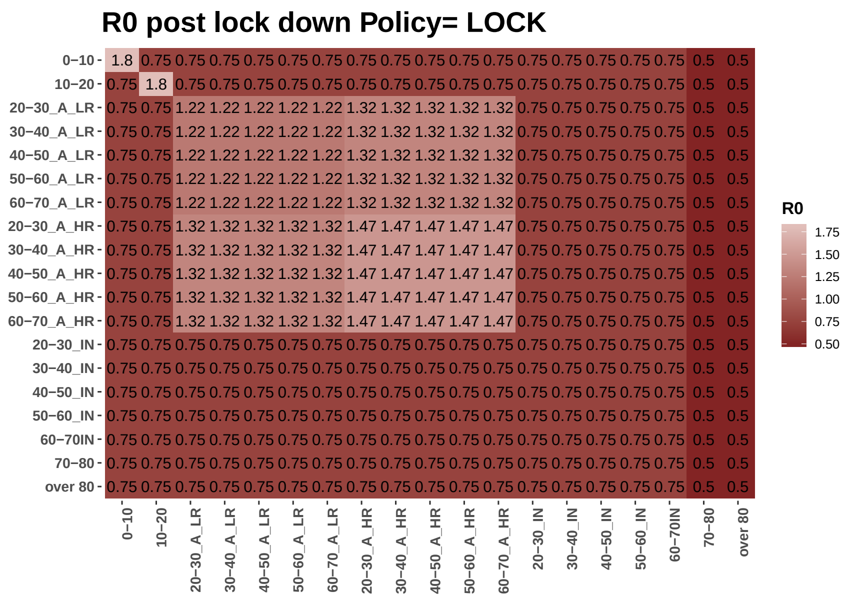


Figure 13: BRM for Lombardia, post-lock down: Policy SEC

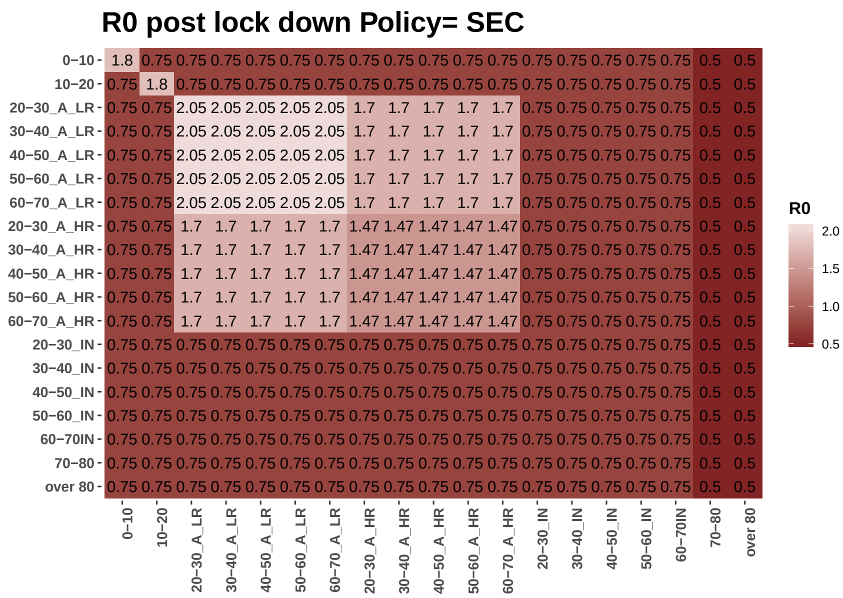


Figure 14: BRM for Lombardia, post-lock down: Policy AGE

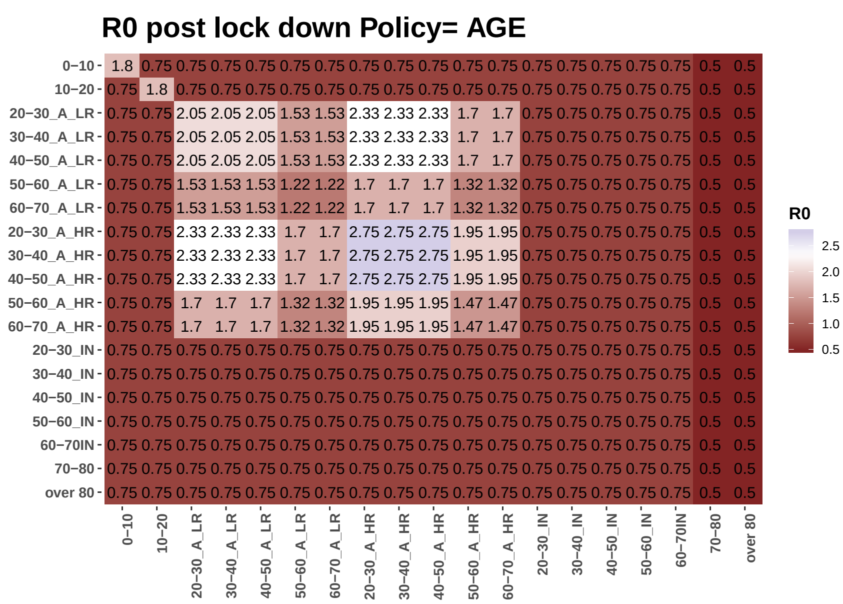


Figure 15: BRM for Lombardia, post-lock down: Policy AGE-SEC

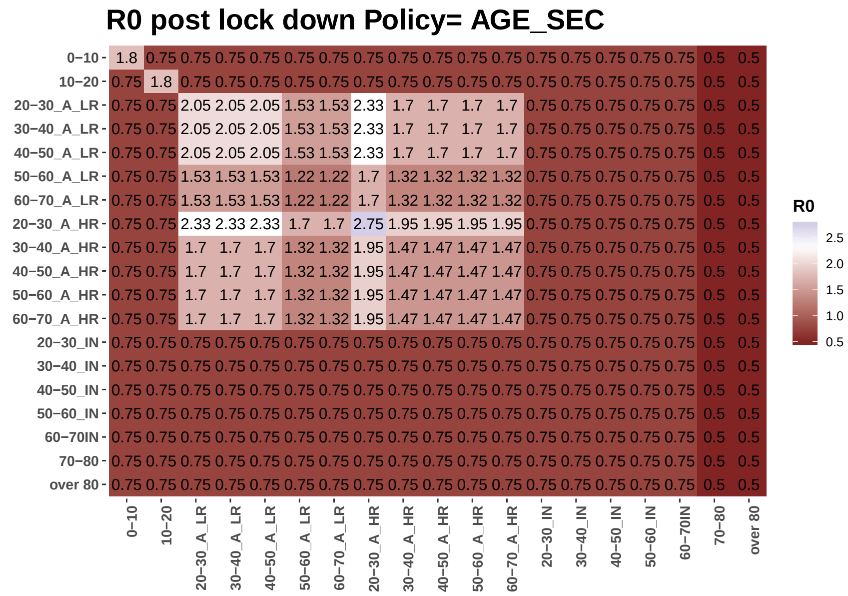
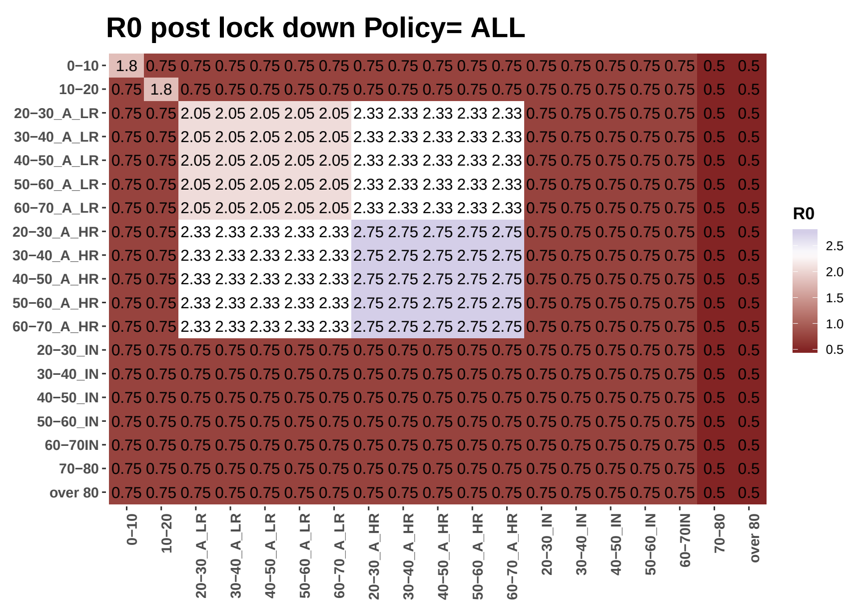


Figure 16: BRM for Lombardia, post-lock down: Policy ALL



6.4.2 Veneto

Figure 17: BRM for Veneto, post-lock down: Policy LOCK

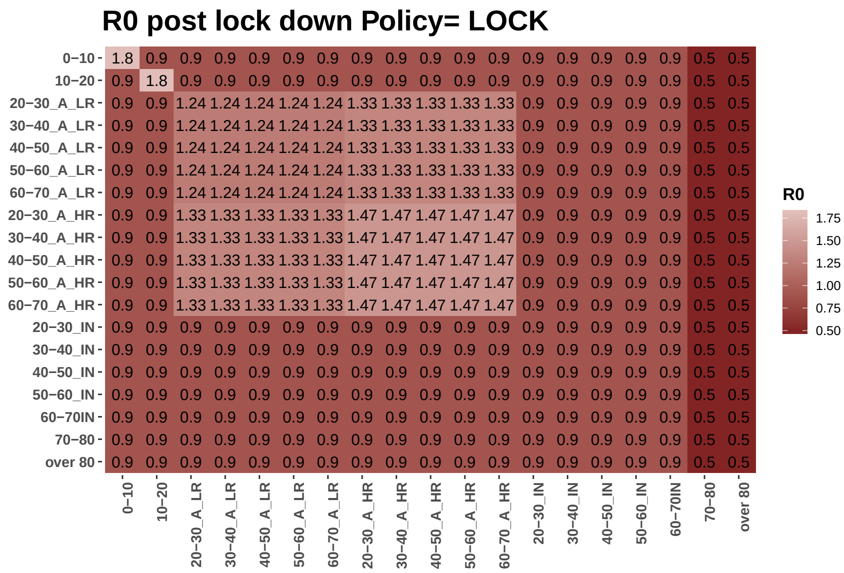


Figure 18: BRM for Veneto, post-lock down: Policy SEC

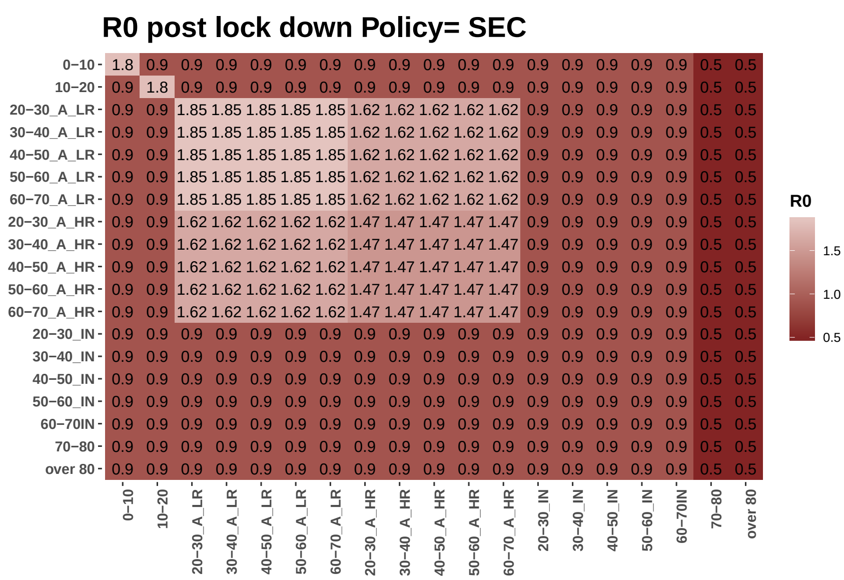


Figure 19: BRM for Veneto, post-lock down: Policy AGE

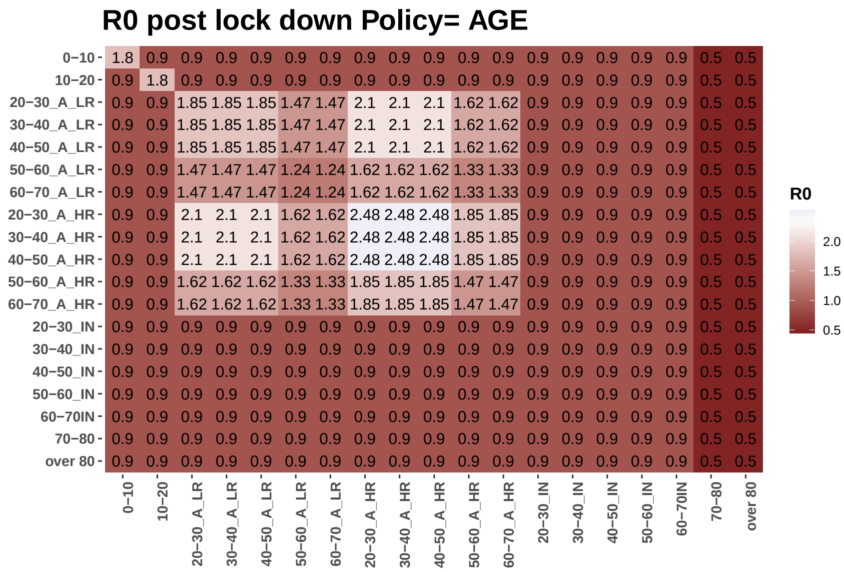


Figure 20: BRM for Veneto, post-lock down: Policy AGE-SEC

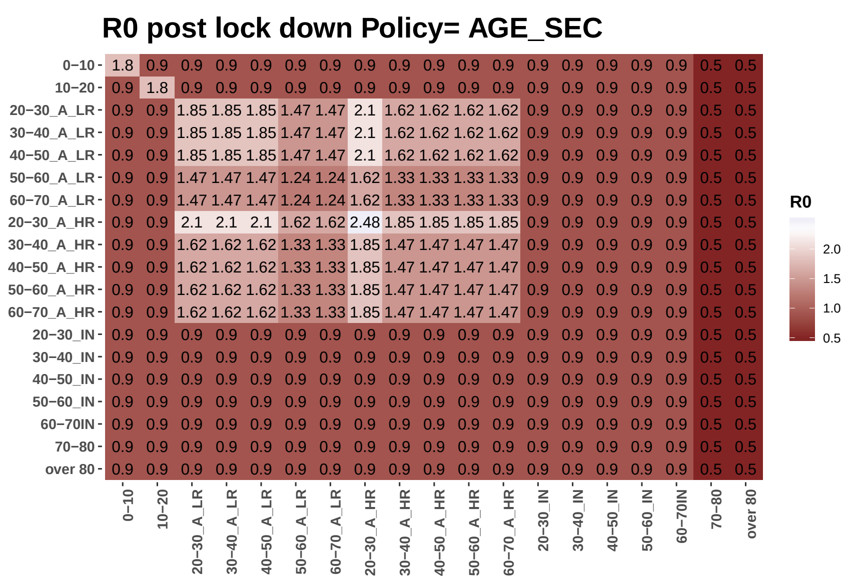
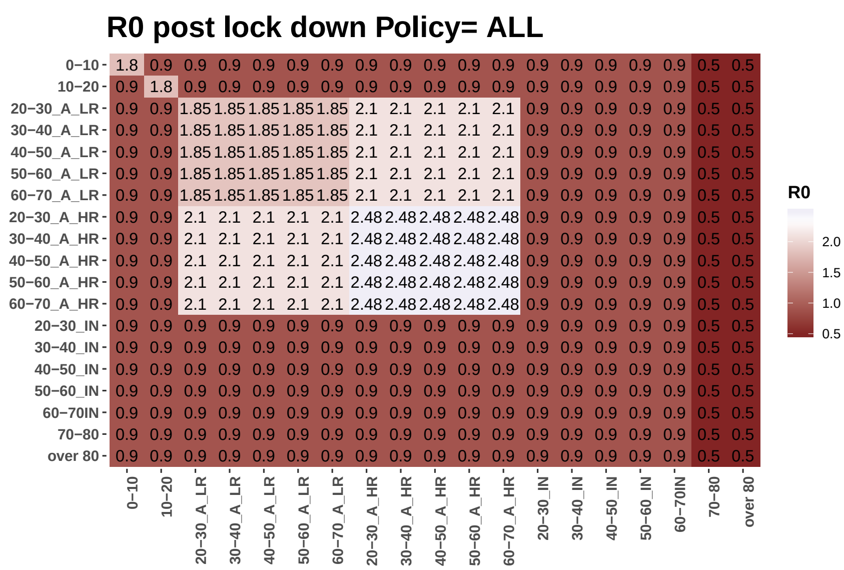


Figure 21: BRM for Veneto, post-lock down: Policy ALL



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