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André de Palma, Nathalie Picard, Stef Proost

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SCARE: when Economics meets Epidemiology with COVID-19, first wave

André de Palma[1], Nathalie Picard[2], Stef Proost[3]

(1) CY Cergy Paris Université, ThEMA, France, andre.de-palma@cyu.fr
https://orcid.org/0000-0003-4364-3068

(2) Unistra, BETA and CY Cergy Paris Université, ThEMA, France, nathalie.picard@cyu.fr
https://orcid.org/0000-0003-1552-8484

(3) KU Leuven, BELGIUM and CES-IFO
https://orcid.org/0000-0003-3731-4532

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Abstract

We develop an epidemic model to explain and predict the dynamics of the SARS-CoV-2 virus and to assess the economic costs of lockdown scenarios. The standard epidemic three-variable model, SIR (Susceptible, Infected and Removed) is extended into a five-variable model SCARE: Susceptible, Carrier, Affected (i.e. sick), Recovered and Eliminated (i.e. dead). Using WHO and Oxford data on cases and deaths, we rely on indirect inference techniques to estimate the parameters of SIR and SCARE. We consider different observation rates and stringencies of lockdown. Both models are estimated for five countries and provide predictions on the number of cases, the number of deaths, and the basic reproduction number, R_0. SCARE is used to test the impact of lockdown policies on economic costs for the well-documented Belgium case. Economic assessments of epidemic results on hospital, morbidity and mortality together with macro-economic impacts show that the total net benefits of the Belgian lockdown policy is negative for low valuations of life years lost. The gains of extending the Belgian lockdown policy are negative even for high valuation of life.

Introduction

Most of the literature that combines epidemiological and economic data starts from the standard SIR model and relies on aggregate estimates of economic loss. SIR parameters are then borrowed from the epidemiological literature and economic losses are either limited to the value of statistical life lost or to the expected loss in production capacity. There remains a large uncertainty on both the epidemic development and economic effects, which has led modelers to opt for different modelling strategies discussed below.

We contribute to the COVID-19 literature in three ways: by adapting the standard epidemiologic model to the COVID-19; by estimating all the parameters from the available aggregate data in five countries; and finally by extending the scope of the assessment of the economic consequences.

A recent survey [1] distinguishes two primary approaches for modelling the spread of a disease: “Mechanistic”, mainly using exogenous parameters to calibrate the model and “Phenomenological”, where more emphasis is put on deriving parameters from the available aggregate reported case and mortality data. The SIR model has been extended mainly in two dimensions: use of social networks to model the spread of the disease and introduction of agents’ heterogeneity along vulnerability and behavior. Our model focusses on the malleability of an extended version of the SIR model with homogenous agents to estimate its parameters of interest using available data. Very few ancillary parameters are calibrated rather than estimated: some observation rates, and number and date of initial cases.

A major issue also mentioned in [1] is data uncertainty. As there is a high asymptomatic infection rate, it is difficult to know whether changes in reported cases are due to a spread of infection or to reporting bias. Moreover, the number of reported deaths is often biased. For example, COVID-19 deaths outside the hospitals (elderly homes etc.) are not always reported as COVID-19 deaths. Reported case mortality rates (i.e. deaths divided by confirmed cases) range from 0.1% to 22% according to [1]. Exogenous estimates of the number of asymptomatic cases vary between 30% and 86% and lead to very different policies and very different outcomes [2]. The SIR model provides poor prediction of the timing of the epidemic: a high initial number of active cases and a low death rate give the same predictions for the evolution of the number of deaths in the early stages of the pandemic as a low initial number of active cases and a high fatality rate [3]. Our results confirm that SIR provides less accurate predictions than SCARE near the peak of the epidemic in Belgium (see also Fig. 3).

Our starting point is the canonical three-variable SIR model that describes the transmission of a disease [4]. There are three groups in SIR: Susceptible, Infected and Removed. Before the start of the epidemic, all individuals are susceptible to contract the disease. At the start, an exogenous fraction of Susceptible is Infected. At any time, a Susceptible may be Infected by a contact with an Infected, and after some time becomes Removed. Susceptible can only get Infected, while Infected can only become Removed. Over time, the fraction of Susceptible monotonically decreases and the fraction of Removed monotonically increases, while the fraction of Infected first increases and then decreases. The process reaches a stationary solution with no more Infected, and some fraction (between 0 and 1) of Susceptible and Removed. The deterministic dynamics of this model is described by a system of three differential equations. For a stochastic approach, see [5]. At time t, we denote the densities of Susceptible by $s(t)$, of Infected by $i(t)$, and of Removed by $r(t)$, with $s(t)+i(t)+r(t)=1$. We use the notation

$\dot{s}(t) \equiv ds(t)/dt \approx s(t+1) - s(t)$, where time increment is one day. The three differential equations of the SIR model are:

$$\dot{s}(t) = -\beta s(t) i(t); \quad \dot{i}(t) = \beta s(t) i(t) - \gamma i(t); \quad \dot{r}(t) = \gamma i(t),$$

where β measures the strength of contamination from Susceptible to Infected and γ measures the Removed (recovery and death) transition rate. Each Infected generates $\beta s(t)$ new infected per day. See top of **Fig. 1**.

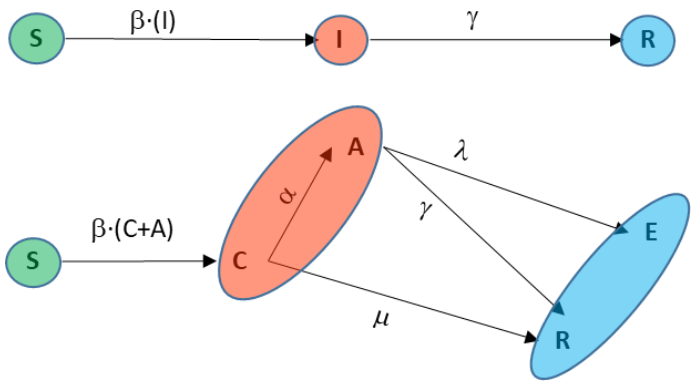

Fig. 1. Transitions in SIR (top) and SCARE (bottom) models

We extend SIR into SCARE model, which is more amenable to explain COVID-19 data. In SCARE, Infected are split into "Carriers" (contagious, but asymptomatic) and "Affected" (sick, i.e. contagious and symptomatic). Similarly, Removed are split into "Recovered" (no more contagious nor symptomatic) and "Eliminated" (dead). A Carrier transits to Affected (with daily probability α) or to Recovered (with daily probability μ). An Affected transits to Recovered (with daily probability γ) or to Eliminated (with daily probability λ). Each Carrier or Affected generates $\beta s(t)$ new Carriers per day. The total number of Susceptible contaminated by a Carrier all over the epidemic defines the *basic reproduction number*, R_0. Transitions in SCARE are presented in the bottom of **Fig. 1**.

The fractions of Susceptible, Carrier, Affected, Removed and Eliminated are: $s(t)$, $c(t)$, $a(t)$, $r(t)$, and $e(t)$. They sum to 1. The key parameter β depends on the lockdown policy (which varies over time), while the recovery rate γ depends on the health conditions, on the intensity of medical care and on the available logistics. These parameters suggest the coupling between epidemic and economic dimensions. The corresponding dynamics of SCARE is:

$$\begin{cases} \dot{s}(t) = -\beta s(t) \cdot \left[c(t) + a(t) \right]; \dot{c}(t) = -\dot{s}(t) - (\alpha + \mu) c(t); \\ \dot{a}(t) = \alpha c(t) - (\gamma + \lambda) a(t); \dot{r}(t) = \mu c(t) + \gamma a(t); \dot{e}(t) = \lambda a(t). \end{cases}$$

SCARE collapses to SIR if $\lambda+\gamma=\mu$ (see SI for details). This condition is strongly rejected empirically for the five countries studied. Useful output of SCARE includes final death rate and other fatality rates (for cases, Affected and Carrier), number of Recovered, daily and cumulative number of cases, deaths and days in hospital, the different transition probabilities, and the basic reproduction number, R_0.

Our aim is to estimate SCARE parameters using directly reported data rather than estimates drawn in the literature for different countries and different diseases. There are two reasons for that: our model has a different parameter structure than the SIR model;

we wish to build a unified tool, which can be fed continuously with published data in order to compare, on equal grounds, the lockdown (and other policies) implemented in various countries. We illustrate the method on five countries (Belgium, France, Germany, Italy and USA).

We compare three policies: no lockdown, long lockdown, and an eight-week lockdown followed by gradual relaxation of the lockdown (actual policy). The epidemic model is complemented with economic cost and benefit analysis.

International comparison of the epidemic

Table 1 illustrates that the SCARE parameters are country-specific and can be estimated simultaneously for each country. It uses data uploaded from [8] on June, 20. For each parameter, when relevant, the most (least) favorable value is highlighted in green (red).

The contagion parameter β was particularly large in Italy before lockdown, and then decreased more sharply because the Italian lockdown policy was the most severe among the four European countries. It increased again after the lockdown in all five countries but remained at a lower level than before the lockdown. In all countries, after lockdown, a Carrier or an Affected contaminates about 0.5 Susceptible daily. Note that β_{after} could be biased upwards by the import of new cases after the opening of the frontiers.

The transition probabilities from Carrier to Affected or Removed are not precisely estimated because they depend on unknown observation rates, and Carriers are not observed.

The transition probabilities from Affected to Removed or Eliminated are less relevant per se than the cumulated fatality rate for Affected. Germany has the lowest fatality rate for affected, thanks to the best (among the five countries) availability and quality of health infrastructure. This can also explain the very low final death rate in Germany. By contrast, Italy faced strong capacity constraints in hospital during the peak of the epidemic. This results in the highest fatality rate. In addition, the estimated value of the daily death rate for affected, λ more than doubled during the peak of the epidemic in Italy (2.152% from March, 10 to April, 1st).

In USA, lockdown policy was less strict and shorter. As a result, the final death rate is the highest among the five countries. Data show that the number of new cases on June, 19 (last observation date available on June, 20) is not yet decreasing as in the other four countries.

Parameter, statistic \ Country	Belgium	France	Germany	Italy	USA
# daily transmissions /C or A before β^0	0.544	0.577	0.569	0.726	0.536
# daily transmissions /C or A during β^1	0.393	0.377	0.400	0.277	0.305
# daily transmissions /C or A after β^2	0.517	0.549	0.511	0.476	0.498
Daily Transition probability C→A α	1.051%	0.498%	0.238%	0.140%	0.568%
Daily Transition probability C→R μ	29.1%	16.6%	30.0%	15.2%	22.5%
Daily Transition probability A→R γ	17.00%	9.76%	4.54%	10.21%	13.58%
Daily Transition probability A→E λ	0.879%	0.591%	0.125%	1.036%	0.858%
Cumulated fatality rate for Affected $\lambda/(\lambda+\gamma)$	4.916%	5.711%	2.684%	9.211%	5.944%
Cumulative # days sick / inhabitant	0.108	0.104	0.097	0.063	0.123
Max % inhabitants simultaneously sick	0.255%	0.236%	0.183%	0.137%	0.176%
Final % population immune	55.5%	59.8%	57.7%	79.8%	71.9%
Final death rate	0.095%	0.061%	0.012%	0.080%	0.105%
Average relative squared error	0.0781	0.0835	0.0356	0.0428	0.1006
Check SIR model : $(\lambda+\gamma)/\mu$	0.614	0.379	0.156	0.739	0.642

Table 1. Estimated parameters and aggregate results in 5 countries, SCARE

The SIR condition ($\lambda+\gamma=\mu$) is far from being met for any of the five countries: the daily probability that a Carrier directly recovers (μ) is always larger than the daily probability that an Affected recovers or dies ($\lambda+\gamma$).

Basic reproduction number R_0

SCARE allows for an approximate analytical expression of the basic reproduction number, R_0 (see details in SI). There are two cases. (a) The Carrier recovers after a random number of days, T, without ever being Affected; s/he contaminates $\beta\, s(t) \approx \beta\, s(t_0)$ Susceptibles each day t between t_0 and t_0+T, so s/he contaminates in total approximately $T\beta\, s(t_0)$ Susceptibles. (b) The Carrier becomes Affected after a random number of days, T_1, and can then recover or be Eliminated after another T_2 days, after contaminating approximately $\beta\,(T_1+T_2)\, s(t_0)$ Susceptible.

As shown in SI, the average number of Susceptible who will contract the virus from an individual who became carrier at time t_0, $R_0(t_0)$, is approximated by:

$$R_0(t_0) \approx \frac{\beta}{\alpha+\mu} s(t_0)\left\{1+\frac{\alpha}{\gamma+\lambda}\right\}.$$

For SIR, $\gamma+\lambda=\mu$, and we obtain $R_0^{SIR}(t_0) \approx (\beta/\mu)\, s(t_0)$, which is independent of α. This formula stresses the role of collective immunity ($R_0(t_0)$ depends on $s(t_0)$) in determining the condition for the epidemic to regress ($R_0(t_0)<1$). The condition for the epidemic to regress also depends on the contagion parameter, β. The two steps for each country in **Fig. 2** highlight the effect of lockdown policies on β and, thus, on the basic reproduction number. For a given lockdown policy, $R_0(t_0)$ decreases over time, like $s(t_0)$.

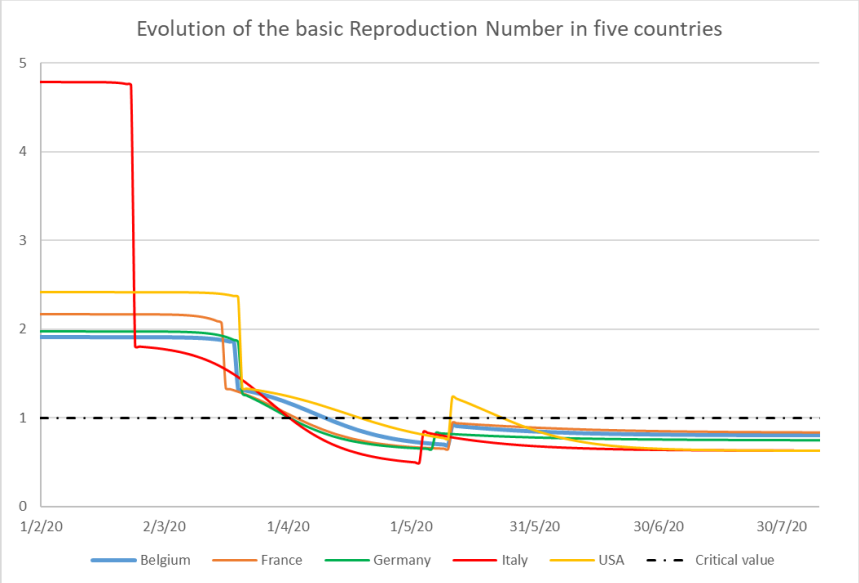

Fig. 2. Evolution of the basic reproduction number $R_0(t_0)$ in five countries

We have assumed here that when an individual is Recovered, he will never be infected again. This hypothesis is optimistic but plausible, since there is no clear evidence, in the case of Covid-19, that a Recovered individual can be infected again.

All $R_0(t_0)$ decrease over time when lockdown is implemented. At the end of the lockdown, $R_0(t_0)$ increases again, but remains less than the critical value of one (i.e. the epidemic is mastered) after the lockdown in most countries. Two comments are in order. First, the value of $R_0(t_0)$, is extremely high at the beginning of the epidemic in Italy. This is because Italy was the first of the five countries to face the epidemic with a large number of cases probably imported from China. Second, the value of $R_0(t_0)$, after the lockdown in the US was for a while larger than one, which suggests that USA removed the lockdown too early. Of course, there is also an economic cost of the lockdown ignored so far. We discuss below the cost-benefit of the lockdown of Belgium.

Focus on epidemic in Belgium (SIR and SCARE)

Fig. 3 compares, for SIR and SCARE, the daily numbers reported in Oxford data and their equivalent in the simulations. See Data and Methods and SI for details. The average relative squared error reported in Table 2 shows that SCARE fits data better than SIR. As shown in **Fig. 3**, the simulation results of SCARE and SIR differ mainly at the beginning/central part of the peak period, and after lockdown. In addition, SCARE explains better than SIR when the maximum number of required beds in hospital and ICU occurs.

According to the last four lines of Table 2, the public policy evaluation of the lockdown differs substantially between the two models. SIR model suggests erroneously that contagion is far from being finished just after the lockdown. By contrast, according to SCARE, the epidemic was virtually finished by the end of the lockdown.

Parameter, statistic	SIR			SCARE			
	Actual Policy	Long Lock-down	No Lock-down	Actual Policy	Long Lock-down	No Lock-down	No lock-down Exog. death rate
# daily contamin. /C or A before	0.478			0.544			
# daily contamin. /C or A during	0.229			0.393			
# daily contamin. /C or A after	0.234			0.517			
Daily Transition probability C→A	0.451%			1.051%			2.311%
Daily Transition probability A→R	17.000%			17.00%			
Daily Transition probability A→E	1.784%			0.879%			1.934%
Daily Transition probability C→R	18.784%=17.000%+1.784%			29.1%			
Average relative squared error	0.1003			0.0781			
Cumul. # days sick / inhabitant	0.0537	0.0533	0.114	0.108	0.101	0.1530	0.3089
Max % inhabitants simult. Sick	0.106%	0.106%	0.511%	0.255 %	0.255 %	0.682 %	1.408%
Final % population immune	42.93%	42.67%	90.88%	55.49 %	51.67 %	78.44 %	78.975%
Final death rate	0.096%	0.095%	0.203%	0.095 %	0.089 %	0.134 %	0.597%

Table 2. Parameters and statistics for Belgium in different scenarios, SIR and SCARE

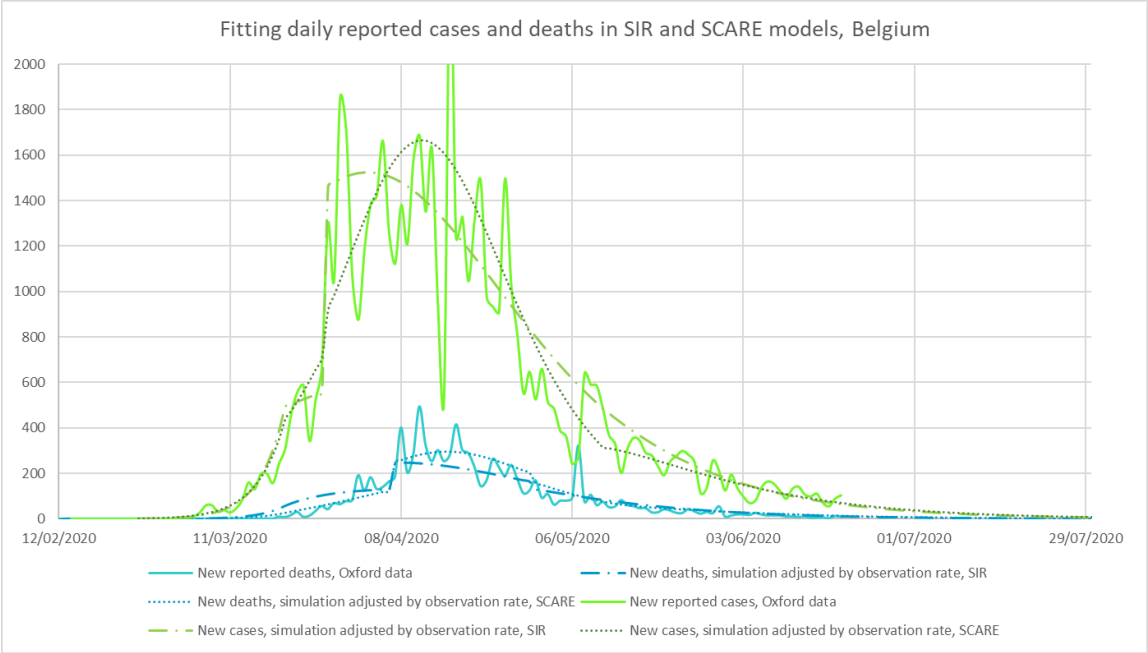

Fig. 3. Fitting daily reported cases and deaths in the SIR and SCARE models

In order to assess the usefulness of both models, we consider different scenarios. In the long lockdown scenario, the parameter β^2 (after) holds twelve (rather than eight) weeks after the beginning of the lockdown. In the No-Lockdown scenario, the parameter β^0 (estimated before lockdown) holds all over the epidemic period. We also analyze the effect of introducing exogenous parameters from other studies into the model. For example, the death rate of the pandemic in big cities in China or on the Diamond Princess cruise ship is often used in epidemiological models such as [6]. However, the argument of [7] suggests that the death rate observed in an overcrowded environment strongly *overestimates* the death rate expected in a normal population. First, on board or in an overcrowded city, a Carrier will meet several Carriers or Affected before his natural defenses can become effective, thus increasing the daily probability that s/he becomes Affected (α). Second, on board promiscuity or high urban density increase the concentration of virus attacks against passengers or urban residents Affected, thus increasing the severity of the disease and the probability that they become Eliminated (λ).

Table 2 compares the SIR and SCARE parameters for three lockdown scenarios. The actual policy is a nearly eight-week lockdown (March, 19 to May, 10), while the epidemic is almost over at the end of the (twelve-week) long lockdown. The last column ("exogenous death rate") illustrates the No Lockdown scenario combined with an exogenous death toll based on Diamond Princess and/or the Chinese pandemic. In this scenario, the parameter β_0 holds all over year 2020, and the α and λ parameters are calibrated (multiplied by 2.2) to reach the 0.6% exogenous mortality rate typically assumed in the early literature. The first six columns show that SIR and SCARE models generate sometimes very different outputs for the same input data. The last column shows the danger of relying on exogenous outputs when calibrating and simulating the model.

Economic costs and benefits

We have estimated how different lockdown strategies affect the spread of the virus. Optimal lockdown strategies strike the right balance between costs and benefits.

The policy measures for a country *i* (lockdown, protection, health infrastructure, macro-economic policy) are represented by the vector x_i and those for the rest of the world by x_{-i}. The policy measures generate three types of changes: loss in macro-economic activity, denoted by Δ GDP(x_i, x_{-i}), in health related costs, denoted by Δ HC(x_i) and in the value of the years of life lost, denoted by Δ YLL(x_i). It is expected that an increase in policy stringency (x_i) increases the macro-economic costs and decreases the health-related costs as well as years of life lost. It is also expected that the GDP reduction in country *i*, Δ GDP(x_i,x_{-i}) increases in policy stringency abroad (x_{-i}), but that the effect of other countries policy measures can be neglected for the other health and life years lost. The global benefit to opt for stricter measures increases when other countries already opted for stricter policies because the economic activity is already slowed down by reduced international trade. This may explain why countries waited for some time to adopt stricter lockdown policies.

In **Table 3**, we compare policies using the sum Δ GDP(x_i,x_{-i}) + Δ HC(x_i) + Δ YLL(x_i), expressed in % of the GDP of 2018. The best policy has the lowest overall % total loss. This % loss can also be used to compare the full cost of policies across countries.

To operationalize our concepts, we distinguish two types of health-related costs and benefits: willingness to pay to avoid COVID morbidity (psychic costs) and additional hospital costs (see details in SI). Economists value the years of life lost not by the loss of production of the individual but by the willingness to pay for a reduction of the risk of death. This corresponds to the willingness to pay for a *statistical* number of years of life lost. It is estimated by different methods. The Europeans [9] and the OECD [10] tend to prefer an estimation approach based on stated preference methods, while the US favor an approach via the wage versus risk approach [11]. This explains why the values used in the US are typically three times larger than the European values.

The EC recommends for use in transport related decisions on environment and safety, values that are of the order of 3 million € for the loss of a statistical life and a value of 70 000 € per year of life lost [11]. Using Belgian data on COVID fatality rates by age and mortality tables, the expected number of years of life lost of a COVID fatality is about 7.87 years so the cost of an expected statistical COVID death is 0.55 million €. Since patients with comorbidities run the highest risk, the number of years of life lost is probably overestimated.

For the macro-economic costs, most of the literature uses the loss of GDP as a proxy. The GDP loss can be estimated by a pure supply approach, where the loss of workforce (due to lockdown) reduces output. This is the simplest approach to link lockdown to economic losses. Here we rely on an alternative macro-economic approach that combines demand shortfall and supply reduction. It is probably more reliable because the analyses based on the loss of the available workforce lacks the demand, saving and investment effects. Our GDP loss estimate for Belgium is based on a combination of two macro-economic studies: a Belgian macro analysis [12] and an analysis for the EU [13]. The economic costs are measured as a one-off cost: it is the sum of the costs borne in 2020, 2021 and 2022. From 2023 onwards, we assume that one reaches again the normal activity levels.

Full costs of different lockdown scenarios

We summarize the SCARE model results for Belgium in **Table 3** using scenarios that are defined by a combination of lockdown policy in Belgium (x_i) and a mild lockdown in other countries (x_{-i}) as defined in [13]. All effects are measured in % loss of the GDP of 2018. For the value of the years of life lost, we use a "European" value but we also use [in brackets] a "US" value that is three times larger.

Belgium policy	**Actual policy**	**Long Lockdown in 2020**	**No lockdown**	**No lockdown Exogenous. Death rate**
Δ GDP(x_i , x_{-i})	21.80%	34.90%	10.00%	10.00%
Δ HC(x_i)	0.085%	0.079%	0.119%	0.241%
Δ YLL(x_i)	1.47%	1.37%	2.58%	9.22%
[Δ YLL(x_i) ×3]	[4.40%]	[4.10%]	[7.73%]	[27.65%]
TOTAL LOSS	23.35%	36.35%	12.70%	19.46%
[with Δ YLL(x_i) ×3]	[26.29%]	[39.08%]	[17.85%]	[37.89%]

Table 3. Costs & benefits of lockdown scenarios in Belgium, % 2018 GDP, mild lockdown abroad

We draw four lessons from **Table 3**.

First, the two dominant costs that are traded off when a lockdown policy is chosen are the loss of economic output and the value of life years lost. This is also the case in most other economic analyses of the lockdown ([14, 15, 16, 17, 18] among others). The saving of hospital costs and psychic costs of illness plays a minor role (less than 1% of GDP)

Second, the comparison of Columns 1 and 3 shows that, for EU values of life lost, the actual policy in Belgium has higher costs than no lockdown (23.35% instead of 12.70%). For US value of years of life lost, the loss of the actual lockdown policy (26.29%) comes closer to the loss of the no lockdown policy (17.85%). Note that no lockdown in Belgium still implies important macro-economic costs as long as lockdown policies are implemented in the rest of the world.

Third, the comparison of Columns 1 and 2 shows that the actual mild lockdown policy always dominates a very long lockdown (23.35%<36.35%), even with a high value of years of life lost (26.29%<39.08%). The main reason is that the lockdown started at about the right moment in Belgium and after 2 months, the additional savings in terms of years of life lost of a long lockdown are small.

Fourth, we use in Column 4 the higher exogenous death toll as model parameter. Comparing Columns 3 and 4 illustrates the importance of relying on country specific death rates that can be estimated provided enough data is available (which is now the case here). On the other hand, as in March 2020 the high exogenous death rate was often the reference, one can understand that one starts a lockdown policy even if, later, the economic costs turn out to be high.

Table 3 only analyzed aggregate lockdown policies using a homogenous SCARE model. Any more fine-tuned lockdown scenario exploiting the difference in death toll and productivity of different age classes, as suggested by [14] and [16] allows to reduce strongly the economic output losses and will dominate the simple lockdown scenarios

presented here at the cost of being unable to estimate parameters from data, as we do here. Clearly, a combination of the two approaches will be preferred.

Conclusions

We generalize the SIR model into SCARE and estimate its parameters for five countries using aggregate country data (cases and deaths). The main advantage of SCARE is that it is more flexible, and better explains and predicts data. Contrarily to most approaches, we do not transplant parameter estimates from one model to another. SCARE's estimates are used to assess the epidemic effects of different lockdown scenarios and their economic costs and benefits. Overall, SIR overestimates the mortality associated to the no lockdown policy, and thus the benefit of the lockdown. We have based our economic analysis on GDP and value of life years lost, which have been widely criticized, but remain at the centre of economic analyses.

Currently, SCARE is formulated as a deterministic model. However, it can be reformulated in stochastic terms; heterogeneous population groups (in particular for age, gender and spatial location) should be envisaged with accurate enough data. These extensions will allow further refinement of the scenarios and more complete evaluation of policies, especially concerning spatial and socio-economic equity.

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Appendix

From SCARE model to WHO daily situation reports: partial observations

WHO [19] reports daily the numbers of new cases, cumulative cases, new Deaths and cumulative Death for a given country *i* affected by COVID-19. For various reasons, reported numbers usually underestimate, or sometimes over-estimate, real numbers of cases and deaths. Deaths at home are not always reported, cases at the hospital neither, and if they are, there may be a delay in the transmission to WHO. In Belgium, for a while, all fatalities in retirement homes were attributed to the COVID-19, while no fatalities in retirement homes were attributed to COVID-19 in France in other periods. We convert the reported number of cases and deaths into actual number of cases and deaths, using observation rates that may vary over time.

The parameters of interest of the SCARE model are β, α; γ; λ; and μ. Additional (ancillary) parameters refer to the observation rates for Cases and Deaths, the number of cases initially introduced, and when they were introduced. In SI, we discuss how these parameters vary across countries and over time, and how they can be estimated simultaneously or calibrated using Oxford data on stringency indices and testing policies.

The parameters of the SCARE model are country-specific, and thus indexed by *i*. A new Case occurring day *t* corresponds to an individual who transits from Carrier to Affected (sick) during day *t*. However, only a fraction of them, corresponding to the *observation rate* $\varsigma_i(t)$ is reported. The daily number of reported Cases is $\omega_i^o(t) \equiv \varsigma_i(t)\alpha_i C_i(t)$ and the reported cumulative number of Cases is $\Omega_i^o(t) \equiv \sum_{\tau=1}^{t} \varsigma_i(\tau)\alpha_i C_i(t)$.

Similarly, only a fraction, denoted by $\xi_i(t)$ of actual New Deaths is reported. The daily number of reported Deaths is thus $\phi_i^o(t) = \xi_i(t)\lambda_i A_i(t)$ and the reported cumulative Deaths is $\Phi_i^o(t) \equiv \sum_{\tau=1}^{t} \xi_i(t)\lambda_i A_i(t)$.

The SIR and SCARE parameters are estimated minimizing the distance between reported and simulated daily and cumulative Deaths and Cases. Since the simulated data are non-linear numerical functions of the parameters of interest and the series to fit are not directly observed, such distance minimization corresponds to indirect inference. The distance is defined as the sum (over days) of squared relative difference between actual and simulated series for daily figures (using difference equations) and for cumulative figures. Since the daily figures more noisy than the cumulative figures, we attribute double weight to cumulative w.r.t. daily series.

The observation rates (very sensible politically) were estimated when possible, or calibrated. The observation rates for Belgium are: 25% cases reported until March, 26, 30% after; 60% deaths reported until April, 7, 95% after April, 30, and 115% in-between (some deaths in nursing homes wrongly attributed to COVID-19); 50 Carriers were imported on February, 12, 2020.

The Oxford data: indices and adjustment of ancillary parameters

Various policies have been implemented in different countries. Oxford data provide a very useful synthesis of the policies by computing a “stringency” index, which proposes on a day-to-day basis a weighted average of policy indicators of government responses, for containment, closure and restrictions on movement [8]. Other indices, which also vary

over time and across countries, refer to macro-economic, health and testing policies. These indices, along with discussions with public authorities, make it possible to validate the data. We use this combination of information as a guideline to calibrate the ancillary parameters of the SCARE model. For example, the objective of testing policies is to improve the observation of cases and deaths, implying that the observation rates $\varsigma_i(t)$ and $\xi_i(t)$ should increase when the testing policy index increases. We relied on the evolution of the Oxford index of testing policy to determine time periods during which the observation rates can be supposed constant. We then estimated the value of observation rates for some period-country combinations, and calibrated them for the other combinations.

Similarly, our estimates confirm that the contagion parameter $\beta_i(t)$ decreases when the stringency index increases.

The first cases were assumed to be introduced on February, 12 except in the countries where another date led to a better fit or more plausible parameter estimates. The initial number of cases was estimated together with the parameters of interest, whenever possible or assumed to represent a similar fraction of the population in the other cases.

Oxford data also contains information on cumulative cases and deaths, which coincide with WHO data, up to a few exceptions. We thus mainly rely on Oxford data to estimate the SCARE model.

From SIR to SCARE

We recall the SCARE model:

$$\begin{cases} \dot{s}(t) = -\beta s(t)\cdot\left[c(t)+a(t)\right]; \\ \dot{c}(t) = -\dot{s}(t) - (\alpha+\mu)c(t); \quad \dot{a}(t) = \alpha c(t) - (\gamma+\lambda)a(t); \\ \dot{r}(t) = \mu c(t) + \gamma a(t); \qquad\qquad \dot{e}(t) = \lambda a(t). \end{cases}$$

Let $i(t) = c(t) + a(t)$. Then $\dot{i}(t) = -\dot{s}(t) - \mu c(t) - (\gamma+\lambda)a(t) = -\dot{s}(t) - \mu i(t)$, when $\gamma+\lambda = \mu$, like in SIR. In addition, $\dot{r}(t) + \dot{e}(t) = \mu c(t) + (\gamma+\lambda)a(t) = \mu i(t)$, which corresponds to the "Removed" of SIR model. To sum up, SIR model is a special case of SCARE.

From daily transition probabilities to cumulative transition probabilities

We provide the computation of the cumulative transition probabilities, and their numerical values for Belgium. First, consider the transition from Affected to Recovered. The daily transition probability from *A* to *R* is γ, and the competing event occurs with daily probability λ. So, the cumulative transition probability from *A* to *R*, for an individual initially in state *A* is (all figures below are for Belgium):

$P(A \to R) = \gamma + (1-\gamma-\lambda)\gamma + ... + (1-\gamma-\lambda)^{\tau}\gamma + ... = \gamma/(\gamma+\lambda)$ = 95.08%. Similarly, the fatality rate for the Affected is: $P(A \to E) = \lambda/(\gamma+\lambda)$ =4.92%. The probability that a Carrier is ever affected is: $P\left(C \underset{ever}{\to} A\right) = \alpha/(\alpha+\mu)$ =3.48%. Therefore probability that a

Carrier is finally Eliminated is: $P(C \to E) = P\left(C \underset{ever}{\to} A\right) P(A \to E) = \frac{\alpha}{\alpha+\mu}\frac{\lambda}{\gamma+\lambda}$ = 0.17%.

The probability to directly recover without ever being affected is: $P\left(C \underset{direct}{\to} R\right) = 1 - P\left(C \underset{ever}{\to} A\right)$ = 96.52%.

Finally, the total probability for a Carrier to Recover, either directly or after being Affected, is:

$$P\left(C \underset{total}{\to} R\right) = P\left(C \underset{direct}{\to} R\right) + P\left(C \underset{ever}{\to} A\right) P(A \to R) = \frac{1}{\alpha+\mu}\left(\mu + \frac{\alpha\gamma}{\gamma+\lambda}\right).$$

Computation and decomposition of R_0

A carrier has two ways to contaminate a Susceptible, either directly and by first becoming Affected. In both cases, an individual (either Carrier or Affected) stops to contaminate when s/he becomes Eliminated or Recovered. The average time being carrier is denoted by: $E(T) = E(T_1) = \frac{1}{\alpha+\mu}$ and being affected is: $E(T_2) = \frac{1}{\gamma+\lambda}$. In all cases, the expected time spent in a state is equal to the inverse daily probability to leave this state.

We have:

$$R_0 \approx \beta s(t_0)\left[E(T) P\left(C \underset{direct}{\to} R\right) + E(T_1 + T_2) P\left(C \underset{ever}{\to} A\right)\right].$$

This is approximation is an upper bound for the exact basic reproduction number because it neglects the variation (decrease) of $s(t)$ during the contagious period. Using the value of $P\left(C \underset{direct}{\to} R\right)$ and $P\left(C \underset{ever}{\to} A\right)$, we get the required result.

Estimation of the parameters of interest

The first parameters to estimate are α; γ; λ; and μ, which are country-specific but independent of time. The contagion parameter, β is also country-specific, but it is time dependent, with typically three periods: (a) before lockdown, with little measure, (b) during lockdown with stringent measures, and (c) after lockdown, which is a regime intermediary between the first two regimes. We rely on the evolution of the Oxford stringency index to determine the frontiers between the three time periods (before, during and after the epidemic). We assume that the contagion parameter $\beta_i(t)$ is constant within a period, but varies across periods.

Additional deaths due to overcrowding of Intensive Care Units (ICU) beds

For the SIR and SCARE scenarios without lockdown, the ICU capacity will be insufficient during certain days, which will increase the death rate as follows.

This was the case in Italy, and our estimates show that that the case fatality rate raised from 1.051 in normal times to 2.152 during hospital capacity constraints.

We thus assume, for the scenarios without lockdown in Belgium, that the case fatality rate doubles for the excess demand for ICU beds. As a result, mortality increases proportionally to excess demand for ICU beds.

The overcrowding is based on the lack of ICU beds, that are more difficult to expand than a regular hospital bed. The capacity limit was set at 1,864 beds in ICU [23].

The demand for ICU beds is based on the ratio between ICU days (reported by [23]) and the number of Affected in the Scare output. The average ratio, computed for the period March 15 to May 23, 2020, is 50,537/1,127,000=0.048. This implies that ICU beds are insufficient when the number of Affected exceeds 1,864/0.0448=41,568.

In the no lockdown scenario, overcrowding in ICU would occur from March, 31 to April, 18 according to SCARE, and from March, 31 to April, 18 according to SIR. The cumulated excess would represent 24.2% of total days sick according to SCARE, and 11.3% according to SIR. The additional deaths would represent the same fraction (24.2% for SCARE, 11.3% for SIR).

For the exogenous death rate scenario, this correction was not applied since it is already included in the exogenous death rate.

Value of avoiding COVID morbidity and Additional costs of hospital treatment

We could not find estimates in the literature for psychic costs specific for COVID morbidity. We use an estimate of [24] for the health problems associated with air pollution. The highest estimate reports a WTP equal to 2.3 times the cost of illness+ the loss of income. For a 2-week sickness, we can use the loss of average gross income times 2.3, which gives 4.091 € or 292 €/day of sickness.

We use a value of 567 €/day for full costs of a regular hospital day (update of [21]), and 1,601 € per day for Intensive Care costs (update of [22]).

Macro-economic loss estimates

For Belgium, we rely on two main sources: the study of the Belgian Federal Planning Office [12] and a study for the European Economy [13]. The macro-economic cost used in column 1 (actual policy) is taken from [12]. The estimates of column 2 and 3 are our extrapolations based on a combination of [12] and [13] study. All scenarios assume mild lockdown scenario for the rest of the world.

Column 1: Actual policy for Belgium

BFP [12] estimates the cost of 8 weeks lockdown with a gradual relaxation to a loss of 10.5% of GDP in 2020, followed by a 8.2% recovery in 2021 and a recovery of 3.3% in 2022. From 2023 onwards, one returns to the normal growth rate of 1.3%. We compute the total undiscounted decrease in GDP level compared to the normal growth rate over the period 2020-2023 and express this in % of the 2018 GDP level. This is a 21.8% loss in gross domestic production and this can be seen as a loss in national income. It is 21.8% and not 10.5% observed for 2020 because we compare with the normal growth rate and there the decrease in activity of 2020 is not fully recovered in 2021 and 2022.

Column 2: Long lockdown for Belgium

We assumed that this generates a 50% deeper dip in 2020 (-15.5% instead of -10%), followed by growth rates in 2021 and 2022 that are identical to the actual policy scenario. This generates a loss in GDP of 34.9%.

Columns 3+4: No lockdown in Belgium (still mild lockdown in rest of Europe and the world)

The macro-economic costs of this hypothetical scenario are difficult to estimate as there are no macro-economic model estimates available for Belgium. One can expect a lower

level of economic activity because of two reasons. First there will be a lower level of international demand for Belgian products (e.g. beer). Second, the lockdown in the rest of the EC will create interruptions in the supply of essential imported inputs for the value chain in Belgium (e.g. parts for car assembly lines). If one uses input-output coefficients for the export demand multiplier (0.56) and for the import (0.429) taken from [20] and applies this to the “in-between” 8 weeks scenario of the EC [13] with an approximate GDP loss of 15% (11.5% in 2020 + 3.5% in 2021), one obtains a GDP loss for 2020+2021 of 14.8%. Using rigid input and output coefficients for the export multiplier and for the essential import coefficients neglects possible export and import substitution. We took therefore a GDP loss of 10% rather than 14.8%.