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INTERNSHIP REPORT

« COVID-19 Risk Mitigation »

NON CONFIDENTIAL REPORT

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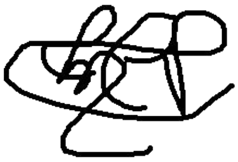
Internship dates: May 4 to August 31, 2020

Declaration of Academic Integrity

Hereby I, Martin Cepeda, confirm that:

1. The results presented in this report are my own work.
2. I am the author of this report.
3. I have not used the work of others without clearly acknowledging it, and quotations and paraphrases from any source are clearly indicated.

Martin Cepeda on September 2, 2020,

Signature 

Abstract

We present the current COVID-19 evolution in a country level as a theoretical Markov Decision Process framework with an underlying SEIR-derived epidemiological evolution, which allows to formulate a ``pandemic response game'' as an episodic RL task, which can be expanded to efficient policy design for future pandemics. We show that it is possible to map measures taken by a country to the disease evolution's internal parameters, which allows to perform a counter-factual analysis on different strategies.

Link to repository: `https://github.com/cepedus/COVID19-Risk-Mitigation`

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1 Introduction

Following the ongoing COVID-19 pandemics across the world, policy-design and decision-making has been a key aspect to reduce the prevalence of the disease in a country's population, mainly due to the absence of a known effective treatment and/or cure to treat infected individuals.

In this sense, the measures taken to reduce the number of deaths via decreasing the number of infected people (in order to avoid the overflow of treatment-seeking people in health facilities) and prevent a strong economic recession have been at the center of the debate for governments, resulting in several approaches in different countries, ranging from a kind of "COVID-negationism" to strict and long-lasting lockdowns.

In order to cope with the inherent trade-of between enforcing strict distancing policies (thus reducing contacts but heavily impacting commerce and workforce production) and continuing a "pre-pandemic" population dynamic (thus leading to a very high number of infections, overflowing health facilities and a very high number of deaths), we present in this report the current state of a country-based simulation model to assess the impact of social distancing measures both on the number of deaths and on the value production from different work sectors.

1.1 Current approaches

COVID-19 has been a very active topic of research during the last months. Ranging from modelling the disease, studying the medical evolution of it to long-term effects on different aspects of society, there have been roughly 200.000 research papers published about COVID-19 (as end of July 2020) [2], number which is six times the quantity of research papers in March 2020 [3], only three months ago.

In this vast scenario, modelling the evolution (in order to make predictions) of COVID-19 has been proposed via several approaches. in particular, death and infection forecasting models have been a key component in lockdown policy making. Among this kind of models, we can retrieve the following basal methods:[1]

- Differential equation, epidemiological-based models [4] (SIR, SEIR, SIS and others)
- Stochastic agent-based modelling (ABM) [5]
- Parametric estimation[2]
- Regression-based [6]
- Deep learning[3]

At the same time as COVID-19 mortality and bed occupancy of the different countries' health facilities has been an important concern of governments and their responses, the economic consequences of such measures (in particular those affecting the closure of stores and factories and the mobility reduction of workers, known broadly as "lockdown") have also been a major concern.

[1]Used in the United States by the Centers of Disease Control and Prevention (CDC) and also present across literature

[2]`http://rwalraven.com/COVID19/Model`

[3]`https://www.cc.gatech.edu/~badityap/covid.html`

In this sense, a global recession is reportedly in place [7] and we have seen since the beginning of the current pandemic a stock market crash[4] and peaks of unemployment claims [8] that will have an impact markedly on macro-economic factors such as production [9] and more in general the Gross Domestic Product (GDP).

The macro-effects of external disruptions in the economy are currently modelled by so-called Dynamic stochastic general equilibrium (DGSE) models, which are used to make economic growth forecasts at a national and continental level [10] [11] [12], taking into account policy interventions.

A basic idea behind policy evaluation (understood in the macro-economic sense as the monetary policy driven by a central bank and the fiscal policy driven by the government) used in DGSE modelling is its effect on future expectations of supply and demand [13] and thus conditioning their decisions. This framework includes also utility functions for each of the main economic actors (supply, demand and government), all of them susceptible to external shocks.

Parallel to general macro-economic modelling made by institutions such as central banks and the International Monetary Fund, COVID-19 has motivated the inclusion of a pandemic externality. In this sense, utility-based models (as it is usual in economic modelling) have been proposed in order to forecast and measure the specific effect of COVID-19 within economies, which can be grouped in the following categories:

- Economic actors' utility over SIR-like death evolution [14] [15]
- Expected losses estimation based on country-wise parameters [16] [17]
- Extrapolation from past pandemic scenarios [18] [19]

1.2 Relevant aspects in pandemic modelling

Both from the economic and the epidemiological side of COVID-19 (or more generally, a pandemic) modelling, we can list the following "ingredients" that prove to be essential when it comes to a rolling scenario simulation at a country level:

1. A timescale that allows to measure both kinds of effects (EPI and ECO)
2. An evolutionary dynamic on the case of infected and/or dead and/or non-infected individuals
3. A reward/utility decreasing on the number of dead/infected as well as on the lost production with respect to a non-pandemic scenario

Although there exist mixed EPI-ECO approaches across literature, very few of them focus on strategy proposal (by enforcing lockdowns, social distancing, economic help, etc.) [20] and in this line the main guidelines have been given only from an EPI point of view [21] [22].

1.3 Policy design

Policy evaluation using on-line data remains a more or less open subject due to the novelty of this problem, this is the global impact of the current pandemic compared to previous ones [23]. A notable example of this subject is a data-driven a policy effect forecast [24] offering a

[4] https://www.fool.com/investing/2020/03/10/stock-market-crash-2020-everything-you-need-to-kno.aspx

counterfactual analysis framework for different countries, which is also one of the motivations for this project: rather than having only a simulation model based on the unfolding COVID-19 scenario, something much more interesting is try to separate the observable evolution of a pandemic from some of its causes (e.g. lockdowns) [25].

In this sense, data availability plays a central role but also tricks the mixing between 2 separate areas such as epidemiological models and macroeconomic analysis. From one side, the long-term approach of GDP forecasting, alongside with the sparsity of general economic indicators (which are available at least at a monthly rate) makes impossible to "plug in" rapid-evolving externalities such as an ongoing pandemic and to see its immediate effects (by the nature itself of macro-economic models), whereas these short-term effects are a major concern of policy makers (e.g. unemployment claims, school closures, transport reduction). From another side, daily-available data such as stock market value, does not necessarily correlates with production and growth,[5] [6] which motivates looking for other ways to measure economic impact at a (relatively) instantaneous rate as the one COVID-19 evolves at, which is the gap our model plans to fill.

1.4 Project objectives

Develop a country-wise model to:

1. Simulate a pandemic scenario at a daily basis
2. Include effects of government interventions in the economy of that country and the evolution of the disease
3. Measure the impact of such measures

With this model in hand, considering the step-like behaviour of the simulation and the presence of a performance (policy impact) measure, optimize the intervention strategy to adopt considering the country' specific features (e.g. population, economy production distribution, available spending resources) under a Markov Decision Process framework.

2 Our contribution

Reducing deaths as a result of a "good" crisis response is not only a public health concern. Reduced morbidity and access to good healthcare facilities not only correlates to GDP growth [26] [27], but more generally an increase in adult morbidity leads to a fall of economic growth [28]. For this reason, considering deaths from a) COVID-19 and b) estimates from secondary sources such as psychological fatigue [29] during a pandemic scenario, untreated preexisting conditions due to health facilities being prioritized for COVID-19, among other sources [30] [31]; would give us a fair view over future performance in the economy at the same time as permitting a daily change dynamics.

With this in mind and what was presented in section 1.1, we will work with the following hypotheses:

1. Rolling pandemic of only one disease
2. No re-infection of recovered individuals is possible

[5] https://fivethirtyeight.com/features/the-economy-is-a-mess-so-why-isnt-the-stock-market/

[6] https://www.reuters.com/article/us-health-coronavirus-markets-disconnect/resurgent-wall-street-disconnected-from-reality-on-the-ground-idUSKBN22039D

3. Each state (e.g. susceptible, infected, recovered, etc.) is mutually exclusive
4. Each economic sector is independent and there's no transport between them
5. Available data is representative (i.e. we do dot include case testing uncertainties, unreported deaths, etc.)

These hypotheses come from a) the existing approaches of modelling infectious diseases [4] and b) the stability of production sector distribution in a country. This last aspect is founded mainly on the short-term side of our modelling, which cannot give significant insight on macro changes in production. In this sense, we aim for an indirect measurement of economic damage of a crisis via pandemic-related and secondary deaths and the cost of putting in place disease-mitigation measures such as social distancing, lockdowns and so on.

2.1 Model specification

A given theoretical country (of size N individuals) is divided in n economic sectors (e.g. Agriculture, Construction, Services, etc. and non-occupied): $N = \sum_i N_i$ where each sector i has:

- A population of N_i individuals with statuses statuses $S_i(t), E_i(t), I_i(t), R_i(t), D_i(t), F_i(t)$ corresponding to Susceptible, Exposed, Infectious, Recovered, Dead-COVID and Dead-non-COVID individuals (we have then $N_i = S_i + E_i + I_i + R_i + D_i + F_i$ for all t)
- An effective stringency $s_i(s) \in [0, 1]$ representing the expected proportion of workers available under social distancing based on a country-based policy s (e.g. $s_{\text{agriculture}} \ll s_{\text{services}}$)

This theoretical country is subject to an ongoing infectious disease with the following parameters:

- β the transmission rate (expected number of contacts between Infectious and Susceptible individuals
- σ incubation rate of an Exposed individual to become Infectious
- γ recovery rate of Infectious individuals
- μ morbidity rate of Infectious individuals
- ν excess morbidity rate (not by contracting the disease)

The evolution of the disease follows a SEIR-inspired [32] [33] dynamic described by the following equations per sector i:

$$\dot{S}_i(t) = -\beta_i(t, s_i)S_i(t) - \nu_i(t, s_i)S_i(t) \tag{1}$$
$$\dot{E}_i(t) = \beta_i(t, s_i)S_i(t) - \sigma E_i(t) \tag{2}$$
$$\dot{I}_i(t) = \sigma E_i(t) - (\gamma(t) + \mu_i(t))I_i(t) \tag{3}$$
$$\dot{R}_i(t) = \gamma(t)I_i(t) \tag{4}$$
$$\dot{D}_i(t) = \mu_i(t)I_i(t) \tag{5}$$
$$\dot{F}_i(t) = \nu_i(t, s_i)S_i(t) \tag{6}$$

Where we have added the excess morbidity ν_i due to non-COVID causes and made to capture long term, social distancing related deaths. We note that ν_i, β_i are time-stringency dependant *per economic sector* whereas μ is only time dependant.

At a country level, the relevant values are then the sum over all economic sectors:

$$S = \sum_i S_i \qquad E = \sum_i E_i \qquad \cdots \qquad F = \sum_i F_i \qquad N = S + E + I + R + D + F \tag{7}$$

Which are fitted to real data. A summary of the model is presented in table 1.

Table 1: Model "cheatsheet" (from section 2.1)

Variable	Description	Available from data?
Model dynamics		
S_i	Susceptible individuals of sector i	No
E_i	Exposed individuals of sector i	No*
I_i	Infected individuals of sector i	Yes*
R_i	Recovered individuals of sector i	Yes†
D_i	Dead from COVID-19 individuals of sector i	Yes†
F_i	Excess dead individuals of sector i	No
β_i	Transmission rate of sector i	No
μ_i	Morbidity rate of sector i	No
ν_i	Excess morbidity rate of sector i	No
σ	Disease's incubation rate	No
γ	Disease's recovery rate i	No
Interventions		
s	Stringency of a country's response measures	Yes
s_i	Stringency of measures affecting sector i	No

2.2 Policy effects

Over this evolution, a planifying agent/decision maker can act enforcing a general, country-based stringency index s based on policies such as containment/closures, economic responses, health system, etc. [1]. In order to compute this index, "data is collected from publicly available sources such as news articles and government press releases and briefings. These are identified via internet searches by a team of over one hundred Oxford University students and staff" into the following categories:

*But hidden by the number and extent of testing and tracing (not considered in our approach)
†But hidden by non-hospital recorded deaths and recoveries (not considered in our approach)

Table 2: OxCGRT Indicators (copied from [1])

ID	Name	Type	Targeted/General?
Containment and closure			
C1	School closing	Ordinal	Geographic
C2	Workplace closing	Ordinal	Geographic
C3	Cancel public events	Ordinal	Geographic
C4	Restrictions on gathering size	Ordinal	Geographic
C5	Close public transport	Ordinal	Geographic
C6	Stay at home requirements	Ordinal	Geographic
C7	Restrictions on internal movement	Ordinal	Geographic
C8	Restrictions on international travel	Ordinal	No
Economic response			
E1	income support	Ordinal	Sectoral
E2	debt/contract relief for households	Ordinal	No
E3	fiscal measures	Numeric	No
E4	giving international support	Numeric	No
Health systems			
H1	Public information campaign	Ordinal	Geographic
H2	testing policy	Ordinal	No
H3	contact tracing	Ordinal	No
H4	emergency investment in healthcare	Numeric	No
H5	investment in Covid-19 vaccines	Numeric	No
Miscellaneous			
M1	Other responses	Text	No

Depending on the composition of the country's economy, this general stringency value s affects differently the economic sectors depending on a set of modulating factors Ψ (e.g. easiness to telecommute or the fraction of open business during lockdown). For each sector i, the effective stringency s_i is computed as:

$$s_i = s \prod_{x \in \Psi} x_i \tag{8}$$

The stringency value per economic sector (in $[0, 1]$ where 1 represents absolute lockdown for every activity and strong economic help for households) can also be seen as a proxy of the fraction of available workers in an economic sector. In this sense, measuring the effects (or rather the variation) of s_i over parameters such as β_i, ν_i captures this "collateral damage" of enforcing social distancing or lockdown measures.

As defined in Oxford COVID-19 Government Response Tracker (OxCGRT) [1], there are several areas where decision-makers can act in the context of an ongoing pandemic. in particular, for COVID-19 there's a distinction on 3 main areas: Containment and closure, Economic response and Health systems. These measures are summarized in the above-defined policy stringency value s, which is expected to reduce the contagion rate and subsequently reduce COVID-19 related deaths. As presented in eq. 8, the current intervention stringency does not affect all economic sectors in the same way.

2.3 How "good" is a policy

Equipped with the presented SEIRDF-stringent model (lacking a better name), the whole stake of designing appropriate mitigation policies for COVID-19 taking into account the economic and production-related losses lies on the definition of a reward function to be used in the context of a Markov Decision Process [34].

One key aspect of dealing with a pandemic due to an infectious disease such as COVID-19 is the number of deaths. These deaths can come from an infectious episode or dues to collateral reasons (eqs. 5, 6) and are the main component of reward penalty.

Another aspect of policy assessment is the reduction of transmission and mortality rates with respect to an initial epidemic outbreak. These rates are affected by the policy stringency thus subject to an economic sector-wise dependence. This is precisely the economic side of the model: the policy impact across the different economic sectors of a country.

We do not specify a direct (cash) cost of the form $f(s) = \text{cost}_s \in \mathbb{R}$ of implementing such measures because of:

a) the inherent sparsity of macro-economic data (which is both necessary for policy design in a broad sense [35] but impossible to have at a daily basis)

b) the indirect effect s has over the transmission and morbidity rates, where a reduction in mobility directly correlates to a decrease in production [17]

For these reasons, we define the instant reward function of COVID-19 response policy in a country of n economic sectors as:

$$r(t) = -\sum_{i=1}^{n} [D_i(t) + F_i(t)] - c_s \sum_{i=1}^{n} s_i(t) \tag{9}$$

And the cumulative reward over a simulation episode as:

$$R(T) = \sum_{t=0}^{T} r(t) = -\sum_{t=0}^{T}\sum_{i=1}^{n} [D_i(t) + F_i(t)] - c_s \sum_{t=0}^{T}\sum_{i=1}^{n} s_i(t) \tag{10}$$

The importance of the coefficient c_s is fundamental: on one side, they balance the trade-off between the number of deaths and the agent's strategy effect on each sector's effective stringency and conversely, they represent a specific country's relative capacity to put in place economic relief packages, health system capacity and efficiency (see table 2). This coefficient must adjusted or imposed at a country scale, which can lead to additional constraints over an individual country's response problem.

Out of the instantaneous reward function (eq. 9), it is possible to specify a country's response problem as an constrained minimization problem, or rather four variants of it depending on how we pose the problem of "fighting" COVID-19:

$$\begin{cases} \min \sum_{t=0}^{T} \sum_{i=1}^{n} s_i(t) \\ \text{s.t.} \\ \sum_{t=0}^{T} \sum_{i=1}^{n} [D_i(t) + F_i(t)] < \theta \end{cases} \tag{11}$$

$$\begin{cases} \min \sum_{t=0}^{T} \sum_{i=1}^{n} [D_i(t) + F_i(t)] \\ \text{s.t.} \\ \sum_{t=0}^{T} \sum_{i=1}^{n} s_i(t) < \theta \end{cases} \tag{12}$$

$$\begin{cases} \min \sum_{t=0}^{T} \sum_{i=1}^{n} s_i(t) \\ \text{s.t.} \\ \max_t \sum_{i=1}^{n} [D_i(t) + F_i(t)] < \theta \end{cases} \tag{13}$$

$$
\begin{cases}
\min \max_t \sum_{i=1}^{n} [D_i(t) + F_i(t)] \\
\text{s.t.} \\
\sum_{t=0}^{T} \sum_{i=1}^{n} s_i(t) < \theta
\end{cases} \tag{14}
$$

We observe that the first two variants (eqs. 11 and 12) lead to a cumulative reward function of the form presented in eq. 10, which is the problem of minimizing total deaths subject to a hard constraint on the cost of measures (or similarly minimizing the cost of measures subject to a hard constraint on the number of deaths).

The latter variants (eqs. 13 and 14) represent a min-max optimization problem: minimize the cost of measures subject to a hard constraint on the peak deaths value (or similarly minimize the peak value of deaths subject to a hard constraint on the cost of measures). This problem posing leads to the following reward function:

$$
R(t) = -\sum_{t=0}^{T} \sum_{i=1}^{n} s_i(t) - c_\theta \max_t \sum_{i=1}^{n} [D_i(t) + F_i(t)] \tag{15}
$$

The four presented variants can be viewed as the possible problem setups for decision makers: is the strategy trying to minimize deaths over costs (eq. 12)? the other way around (eq. 11)? is it an anti-health system collapse strategy (eq. 14)? In any case, the simplified reward-maximization framework we present allow to model the decision process that e.g. a government must face in a pandemic such as COVID-19.

2.4 Data modelling

We will be working with the evolution of COVID-19 in France. For this country, we have access (at a country level) to the daily confirmed cases, deaths due to COVID-19 and the OxCGRT stringency index [36], as well as daily hospitalizations and recovered cases from hospitals [37] and total number of deaths [38].

For time dependance of β_i and μ we consider a "sigmoid step" function f parametrized by $C_0^f > 0$, $|L^f| \leq C_0^f$, $k^f > 0$ and $t_0^f \geq 0$, which has the advantage of modelling a smooth transition between two values. :

$$
f(t) = C_0^f + \frac{L^f}{1 + e^{-k^f (t - t_0^f)}} \tag{16}
$$

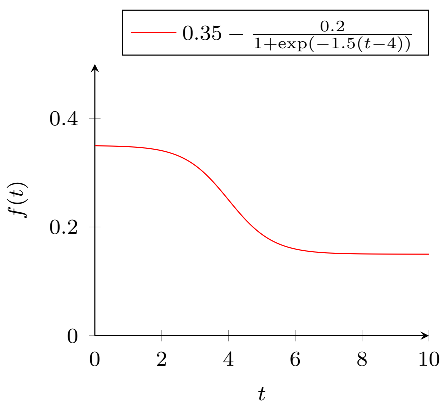

Figure 1: The sigmoid step defined in eq. 16 where C_0^f, L^f, k^f, t_0^f must be fitted to data.

As for decision makers in a country, the measures taken to cope with an ongoing pandemic are captured by the time series of s (at a country level), which can be parametrized by three key factors: when stringent measures were enforced $t_0^s > 0$, for how long they were maintained $t_1^s > 0$ and what was the stringency of such measures $C_s < 100$. We consider a boxcar window function for this purpose (defined using H the Heaviside step function):[7]

$$\sqcap_s(t) = C_s[H(t - t_0^s) - H(t - (t_0^s + t_1^s))] \tag{17}$$

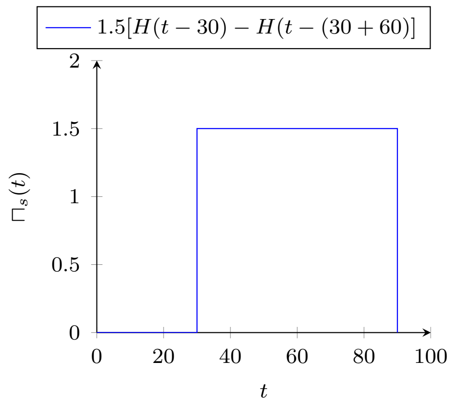

Figure 2: The measure strategy window defined in eq. 17 where t_0^s, t_1^s and C_s depend on a country's strategy.

In order to map the above parameters to s_i, we look in particular for the moment where the stringency reaches a so-called critical threshold to effectively reduce the transmission rate (influence on t_0^β) and also the time where $s_i(t)$ remained above this threshold in order to keep β_i controlled (influence on L^β). This is a first approach to later being able to map $s_i(t)$ onto $\beta_i(t, s_i)$, which has been pointed (in a more general fashion) as the "lockdown effect" [39] [40].

An important aspect when dealing with $\sqcap_s$ is that we must keep into account that the decision process when dealing with a pandemic rolls in an online fashion (i.e. information is discovered in temporal steps). This affects how the risk of a certain strategy is perceived, in particular, without knowing the full extent and consequences of a pandemic it's difficult to compare losses due to deaths without acting vs. losses from containment measures that will eventually slow the spread of the pandemic. We can characterize this aspect by a decreasing perceived cost of t_0^s.

The advantage of this model is to include a more versatile and general definition of policy measures (as detailed in section 2.2) which can effectively change across the economic setup of a theoretical country. Disease's parameters are initialized from previous similar region-based simulations [41] and then optimized via a Levenberg-Marquardt algorithm [42] on the difference of S, D and F series (from eq. 7) to data. This gives a total of $4 + 8n$ parameters to be fitted, where n is the number of economic sectors.

On a more general level, on a rolling scenario of length T, at a given time $t_i,\ i \in \{0, ..., T\}$, the agent perceives a cost of implanting stringent measures $C(t_i, t_0^s)$ and an estimate of the cumulative reward $\hat{R}(R(T))$. These two values condition whether a country acts early or not, and whether the actions (response measures) are stringenet or not.

3 Results

In order to run the presented model in the context of an MDP framework, we must first try to separate the observed pandemic evolution from the measures taken for, in a second time,

[7] `https://mathworld.wolfram.com/HeavisideStepFunction.html`

abstract the model to perform a counterfactual analysis. By using a simplified version of the model (only one economic sector with "sigmoid steps" for transmission and morbidity rates) we observe already a good fit to infected and dead reported cases of COVID-19 in France:

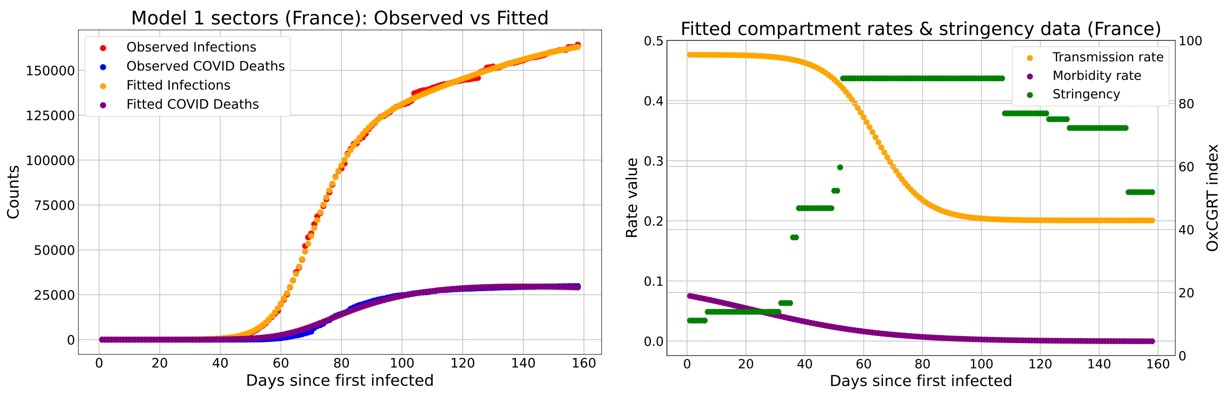

Figure 3: Data and fitted model in France from 25 January 2020 to 1 July 2020. At left, Infected and Dead compartments and at right, fitted $\beta_1(t)$ and $\mu(t)$ compared with the value of the stringency of measures [1]

We observe in figure 3 an effective decrease in both the transmission rate and the morbidity rate at the same time as more stringent measures were put into place and maintained across time. At the right we can observe the phenomenon described in section 2.4: a sufficiently high, sufficiently long stringency in the imposed measures to cope with COVID-19 can lead to an early and/or important decrease in the transmission rate. See appendix A for other countries' fits and evolution of rates, where the mean quantity of data points is 148. The model is then robust to different country setups.

We obtain also the following mean fitted disease parameters (see table 1 and section 2.4 for their descriptions):

Table 3: Mean fitted parameters (1 sector) over data in France, Italy, Germany, United Kingdom, United States, China, Russia, India, Japan, Brazil and Chile

Parameter	Mean Value	Value for France
σ	1.29	1.34
γ	0.09	0.19
C_1^β	0.58	0.47
L_1^β	-0.47	-0.26
C_1^μ	0.13	0.104
L_1^μ	-0.13	-0.10

From these parameters, in particular we can compute the so-called reproduction number $R_0 = \beta/\gamma$ (simplified for a SIR scenario [43]) evolution in France. We have that at the initial and final states of the epidemic, $R_{0i} = \frac{C_1^\beta}{\gamma} = 2.47$ and $R_{0f} = \frac{C_1^\beta + L_1^\beta}{\gamma} = 1,11$ which are in the range of previously found values [44] [45].

We will discuss now a key aspect of modelling, specially in disease forecasting and simulation: validation. Due to the nature of data and the extent of the current COVID-19 pandemic, it is impossible (and highly unethical[8]) to set-up certain scenarios to have differ-

[8] `https://history.nih.gov/display/history/Nuremburg+Code`

ent time series of an contagious disease spreading. Also, disease modelling has ambiguous validation criteria [46] and proposed strategies to achieve this include examining: 1) the process of model development, 2) the performance of a model, and 3) the quality of decisions based on the model [47] [48].

On a more "classical" approach, we evaluate the robustness of our model over the number of Infected and Dead individuals at a national scale. Considering data from France between January the 25$^{\text{th}}$ 2020 to July the 1$^{\text{st}}$ 2020 (158 data points), the baseline fitting errors are:

Table 4: Fitting error for France (1 sector)

Quantity	MAE	RMSE
Infected (I)	552.73	837.73
Dead (D)	280.94	404.53

We observe a close fit to data (errors are in the same unit as the quantity, see also figure 3). This comes from one part of the choice of the base SEIR model that inspires our contribution (particularly, the existence of an *Exposed* state justified by an important incubation period [49]) and mostly the variation in time of both the infection rate and the morbidity rate. For hidden data points, we have the following error curves:

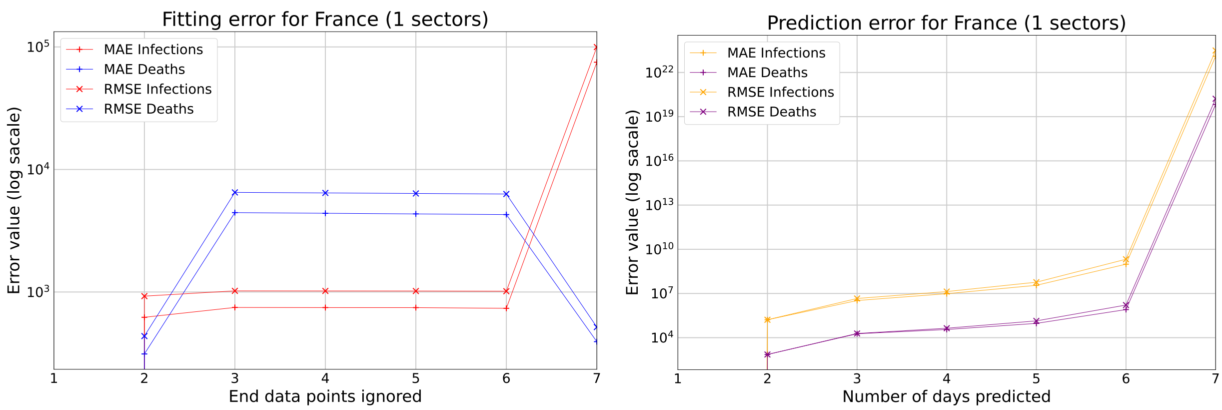

Figure 4: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) for forecasting for fitting and forecasting. The x values represent the number of most recent data points removed prior to fitting and the errors are computed on the last x points.

We observe a very poor forecasting performance of our model beyond a window of 2 days, which highlights the trade-off of the simplistic approach compared to specialized forecasting methods[9]. Nevertheless, considering the goal of designing better policy strategies, the focus of our approach is to generate a plausible scenario given the government's intervention to tackle the effects of an ongoing pandemic. In order to do so, we will analyze now the relation between the measures put in place and, in particular, the evolution of the transmission rate.

3.1 Modelling transmission rate

By proceeding similarly on the countries presented in appendix A (countries where the model had a good fit), we study now the relation between putting stringent measures and reducing the transmission rate of COVID-19:

[9] https://www.cdc.gov/coronavirus/2019-ncov/covid-data/forecasting-us.html

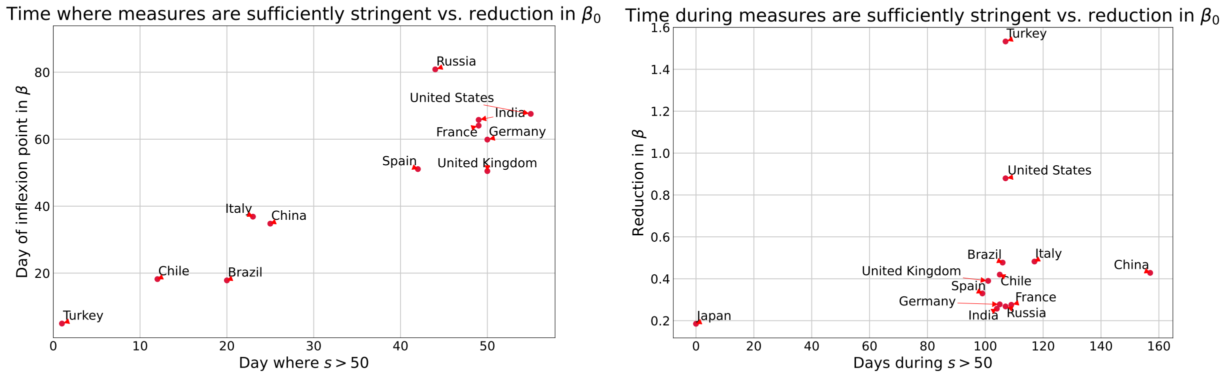

Figure 5: Scattering of a) the time of measures being sufficiently stringent t_0^s (eq. 17) according to OxCGRT [1] vs. the time of inflection t_0^β of the sigmoid step (eq. 16); and b) the length of sufficiently stringent measures vs. the reduction L^β in the transmission rate.

We see in the left scattering a crucial relationship, yet completely expected: there is a positive correlation between the time (since an outbreak of COVID-19) when countries decide to enforce stringent measures and the time when the transmission rate decreases. This result is also important because the time series of the government's strategy (shown in figure 3 at right) was not used at all for fitting the model, and it represents the action space (see table 2) of an agent in a Markov Decision Process framework. The explainability of t_0^β by t_0^s allows to decouple internal epidemic variables from external actions, for instance, by doing a linear regression we have that $\hat{t}_0^\beta = 1.21 t_0^s + 3.70$ with a RMSE of 8.84 days.

For the amount of the reduction in transmission rate (figure 5 at right), we can say that there's a less direct relation but there appears to be a minimum period of approximately 100 days (modelled as t_1^s from eq.17) of maintaining stringent measures so a reduction in β materializes. This can be interpreted as the observed delay between the time when measures were put in place and the mobility reduction [50] and more generally as the "behavioral inertia" of the population when lockdowns were put in place [51].

As for the variability between different countries' period of stringent measures and quantitative reduction in β (see for example Turkey vs. India), we take a look at country features that can have a role in the effectiveness of stringency measures (figure 6). In this case, the relation is less clear between individual country features and the reduction they achieved in the transmission rate, although extreme poverty levels seem to be positively related.

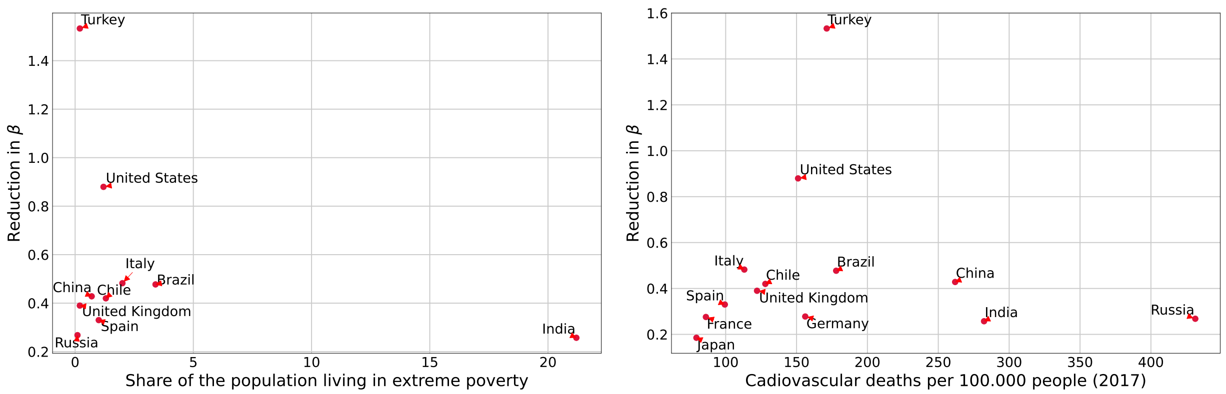

Figure 6: Scattering of a) the extreme poverty levels in different countries and b) cardiovascular deaths incidence vs. reduction L^β in the transmission rate. See appendix B for more country attributes.

A similar analysis can be performed on the modelling of μ the morbidity rate (see appendix C).

4 Conclusion

The presented results show a promising path to decouple a country's features and actions from an infectious disease evolution (in our case, COVID-19). The case for the moment where the transmission is reduced as a product of enforcing stringent measures is very clear, whereas the coupled impact of a country's context and attributes needs further studies.

A central aspect of the approach presented in section 2.4 is that it only considers a "first wave" scenario i.e. the effect of measures and the evolution on infectiousness and morbidity as the one we've seen until the end of June 2020 in France (as a country example). This is mainly due to the modelling choice of β, μ (eq. 16) and s (eq. 17), but the behaviour of a second wave of infections/deaths and a second set of measures can be extended from the presented model by the sum of two (or more) sigmoid steps/stringency windows.

With a mapping from s to β, μ it is possible to "plug-in" a previously characterized disease within a country's situation and simulate the evolution of an epidemic episode. Here in this project we provide the framework to such a model to then study the effect of disease-response measures in different economic sectors (section 2.2) and a way to measure the mixed epidemiological and economical cost of those measures (section 2.3). A possible path in defining the cost of measures c_s (from eq. 9) is by the current estimations from the International Monetary Fund[10]

The versatility of the presented environment can be later refined with secondary deaths not dues to a COVID-19 infection (represented by the compartment F_i introduced in section 2.1) which at the current state of data availability it is not possible to grasp. Similarly, the specific per-sector effect is yet to be defined as well as the chosen optimization statement (section 2.3) of the "policy design game".

We are conscious that the assumptions made in section 2 do not adjust completely the modelling framework to reality, as the current pandemic of COVID-19 has had an impact in several spheres of society: government, economics, media, education and so on. This set of factors a) is very difficult to track with openly available data and b) its effects are subtle and most of the time inter-coupled between them. In this line, this model must be taken with caution to gain qualitative insight in policy design. Nevertheless, with the presented framework of policy design as an MDP it is possible to perform a counter-factual analysis of a pandemic episode.

[10] https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19

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Appendix A: Model fits and rate evolutions

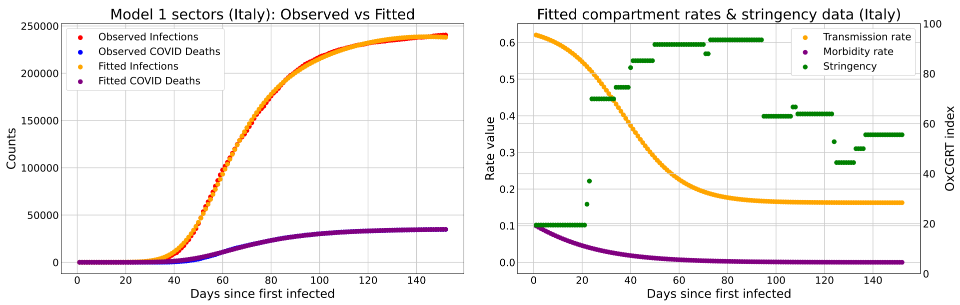

Figure 7: Data and fitted model in Italy until July 1st 2020.

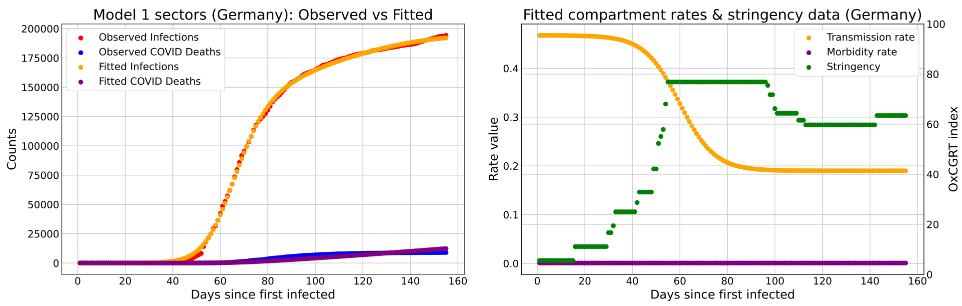

Figure 8: Data and fitted model in Germany until July 1st 2020.

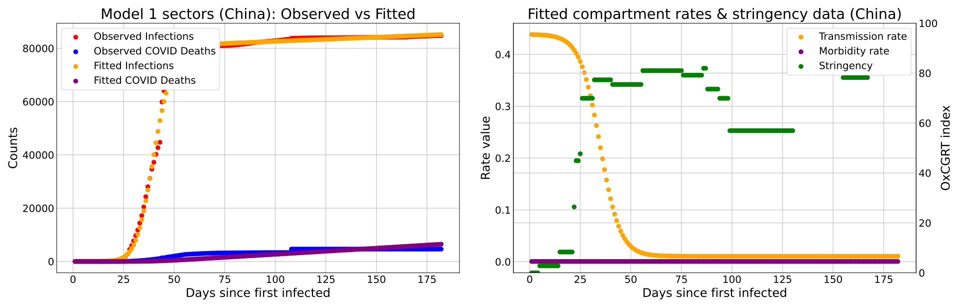

Figure 9: Data and fitted model in China until July 1st 2020.

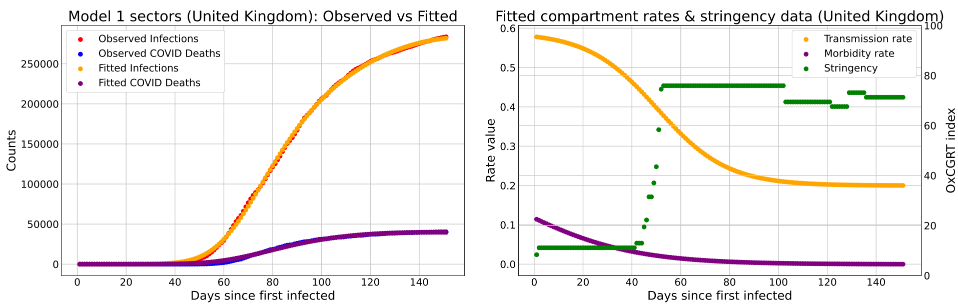

Figure 10: Data and fitted model in United Kingdom until July 1st 2020.

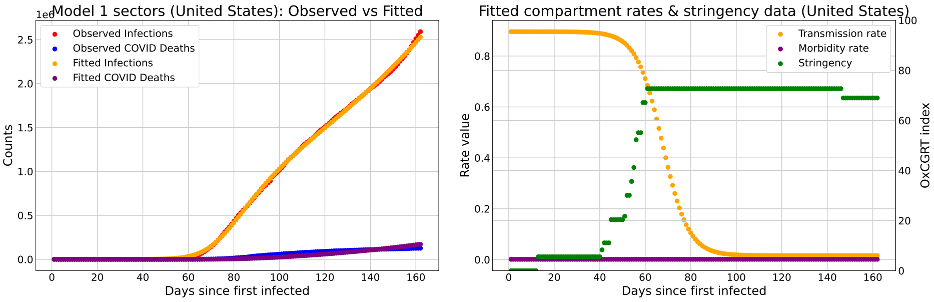

Figure 11: Data and fitted model in United States until July 1st 2020.

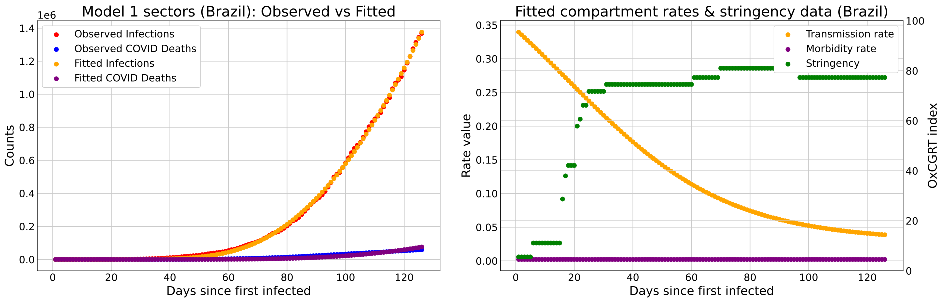

Figure 12: Data and fitted model in Brazil until July 1st 2020.

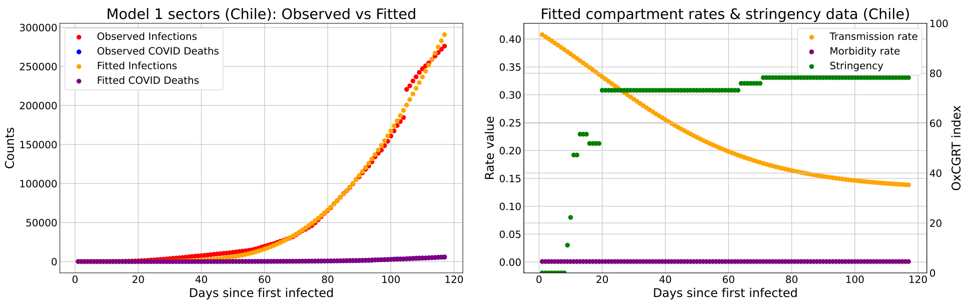

Figure 13: Data and fitted model in Chile until July 1st 2020.

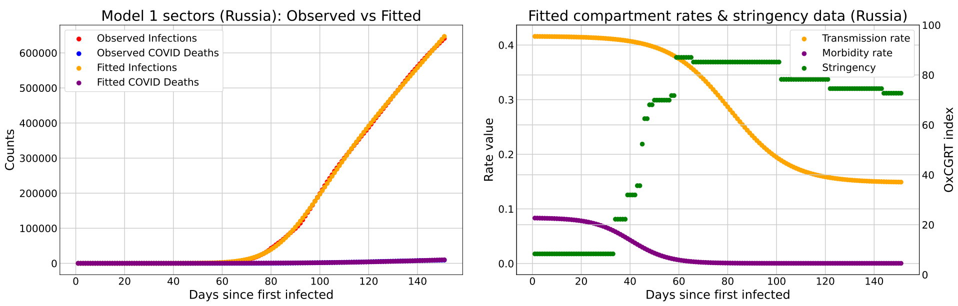

Figure 14: Data and fitted model in Russia until July 1st 2020.

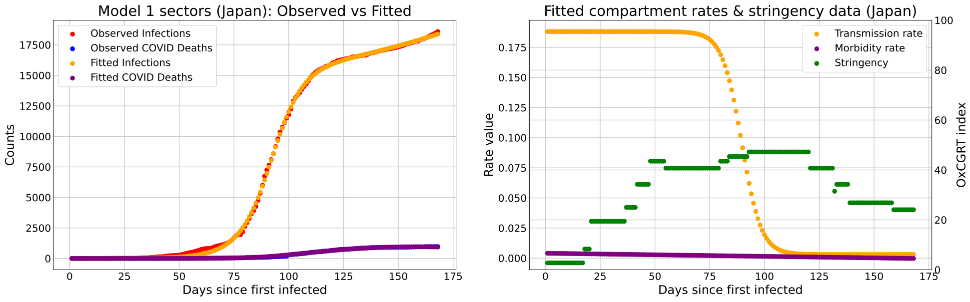

Figure 15: Data and fitted model in Japan until July 1st 2020.

Appendix B: Country attributes and reduction in transmission rate

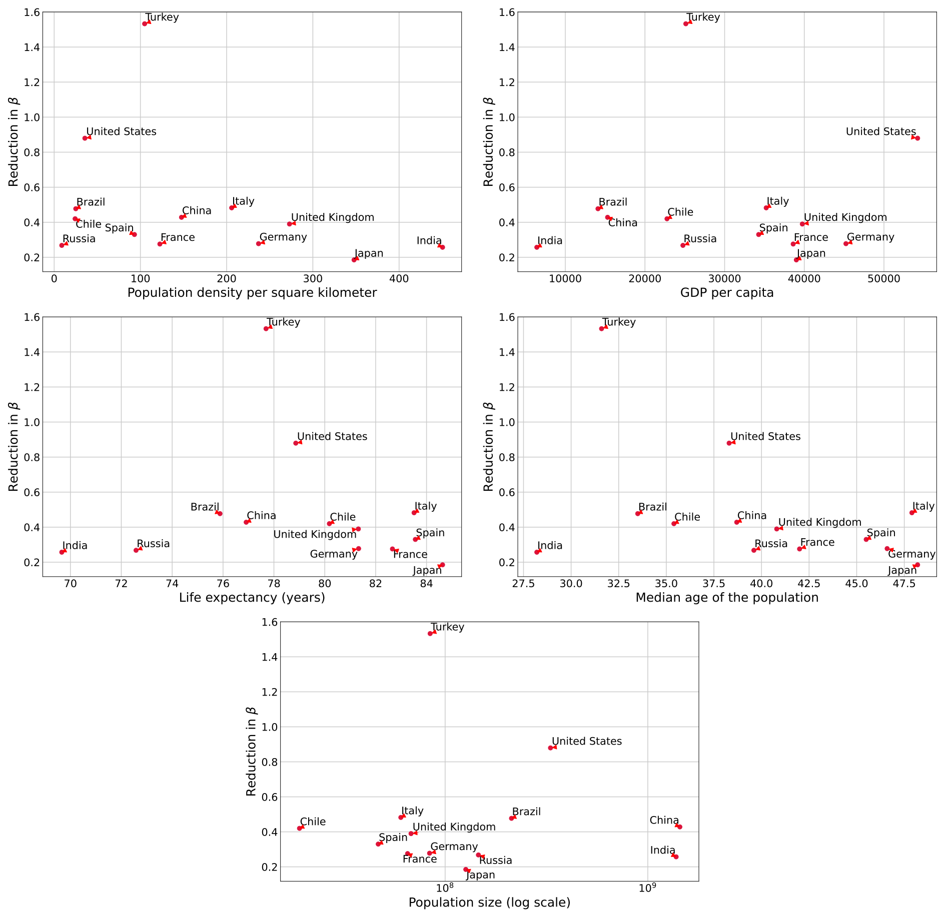

Figure 16: Different country attributes vs. reduction magnitude in transmission rate

Appendix C: Time of stringent measures, country attributes and reduction in morbidity rate

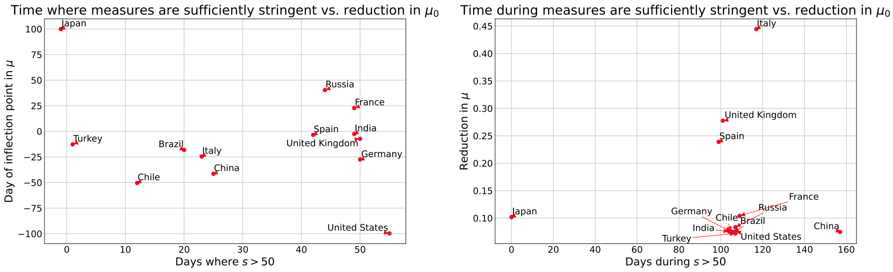

Figure 17: Scattering of a) the time of measures being sufficiently stringent t_0^s (eq. 17) according to OxCGRT [1] vs. the time of inflection t_0^μ of the sigmoid step (eq. 16); and b) the length of sufficiently stringent measures vs. the reduction L^μ in the transmission rate.

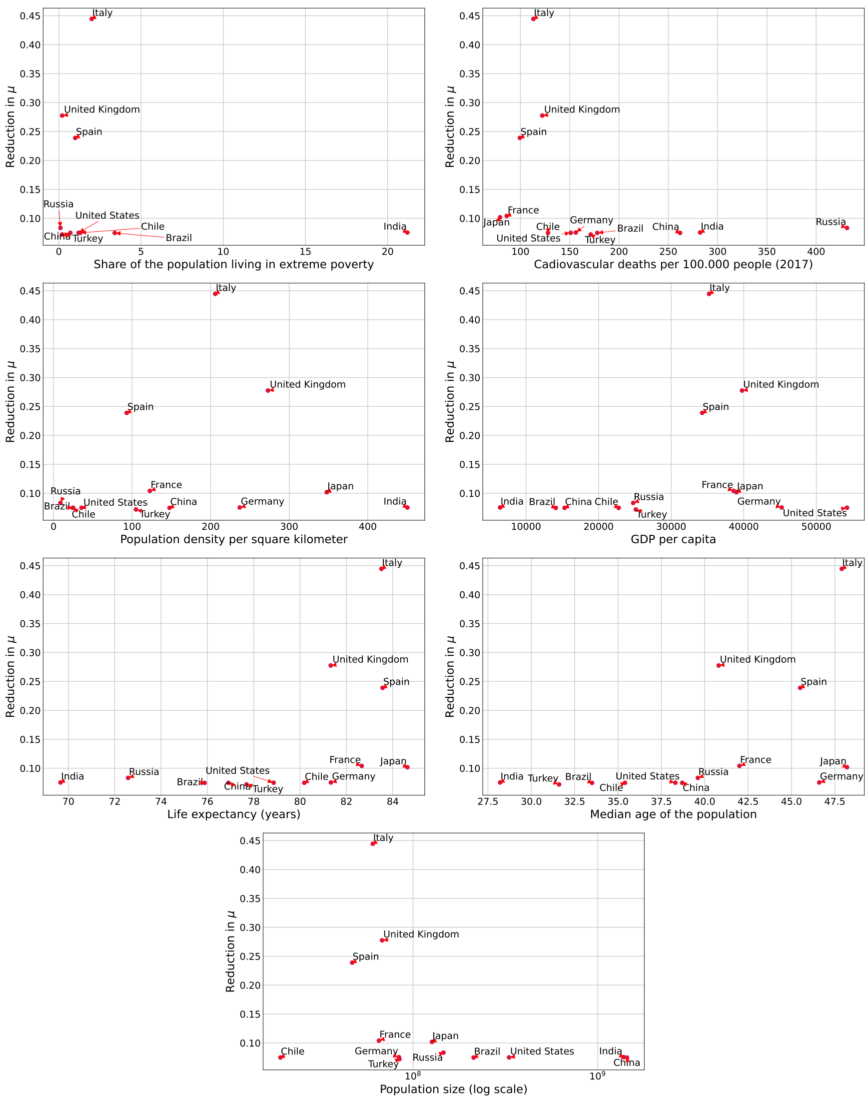

Figure 18: Different country attributes vs. reduction magnitude in morbidity rate