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STUDY OF EFFECTIVENESS OF POLICIES MITIGATING HEALTH AND ECONOMIC EFFECTS OF COVID-19 PANDEMIC

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STUDY OF EFFECTIVENESS OF POLICIES MITIGATING HEALTH AND ECONOMIC EFFECTS OF COVID-19 PANDEMIC

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Declaration

I, Rustam Bozorov, declare that this thesis titled, “STUDY OF EFFECTIVENESS OF POLICIES MITIGATING HEALTH AND ECONOMIC EFFECTS OF COVID-19 PANDEMIC” and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed: ______________________________

Date: ______________________________

Abstract

The COVID-19 pandemic is having a large social and economic impact worldwide. At the present stage, in this project, I will use publicly available data to assess strategies undertaken by governments to mitigate impacts while preserving the health of the population. This paper consists of two parts connected with a current state of data taken from open public sources. In the first part, I implement D models to the real data to forecast a future state of death numbers in Spain. In the second part, I use Oxford COVID-19 Government Response Tracker with the real data to evaluate the effects of different policies on death numbers and daily new cases. I will show that the most effective policies to mitigate the effects of COVID-19 will be restrictions on gathering policy, facial mask protection policy and stay at home policy. Overall, this paper suggests that the government anti-pandemic responses have substantial effects on preserving the health of the population.

Resumen

La pandemia de COVID-19 está teniendo un gran impacto social y económico en todo el mundo. En este proyecto, utilizaré los datos disponibles públicamente para evaluar las estrategias emprendidas por gobiernos para mitigar los impactos y preservar la salud de la población. Este documento consta de dos partes relacionadas con el estado actual de los datos tomados de fuentes públicas abiertas. En la primera parte, implemento ≪D modelos≫ a los datos reales para evaluar un estado futuro de numeros de muertes en España. En la segunda parte, uso ≪Oxford COVID-19 Government Response Tracker≫ con los datos reales para evaluar los efectos de diferentes políticas en las cifras de muertes y los nuevos casos diarios. Demostraré que las políticas más efectivas para mitigar los efectos del COVID-19 serán las restricciones en la política de recolección, la política de protección de mascarillas y la política de confinamiento en casa. En general, este documento sugiere que las respuestas gubernamentales antipandémicas tienen efectos sustanciales en la preservación de la salud de la población.

Sommario

La pandemia COVID-19 sta avendo un grande impatto sociale ed economico in tutto il mondo. Nella fase attuale, in questo progetto, utilizzero i dati disponibili al pubblico per valutare le strategie intraprese da governi per mitigare gli impatti preservando la salute della popolazione. Questo documento si compone di due parti connesse con lo stato attuale dei dati presi da fonti pubbliche aperte. Nella prima parte, implemento ≪modelli D≫ ai dati reali per prevedere uno stato futuro dei numeri di morte in Spagna. Nella seconda parte, utilizzo ≪Oxford COVID-19 Government Response Tracker≫ con i dati reali per valutare gli effetti delle diverse politiche sui numeri di morte e sui nuovi casi quotidiani. Mostrero che le politiche più efficaci per mitigare gli effetti di COVID-19 saranno la politica sulla restrizioni di riunioni, la politica di protezione con la maschera facciale e la politica del confinamento a casa. In generale, questo documento suggerisce che le risposte anti-pandemiche del governo hanno effetti sostanziali sulla conservazione della salute della popolazione.

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CHAPTER 1

Introduction. Objectives and scope of thesis.

The year 2020 was full of historical events, but the name of main event goes to a rapid COVID-19 pandemic outburst and spread. This pandemic has gotten a huge media attention not only for its population health consequences, but also for its economic and social effects. In 2020, the population of Earth learned what are "social distancing", "confinement", a remote work, "Zoom calls".

At the same time, tremendous economic costs of pandemic are going to be much worse since second World War, even not mentioning over 80 million infected patients and more than one million people died because of this virus and/or its consequences worldwide.

As it is said that a history fluctuates over time, the population of Earth had a very similar experience almost 100 years ago - 1918-1920 "Spanish flu" (influenza) pandemic. That pandemic allegedly infected around 500 million of population, almost one third of the population at that time, leading to 20 to 50 million of deaths according to different estimations. As an additional information, Spain involved in name of pandemic for its free media permission around 1918 year[1], where the news about the disease appeared first.

This study [Hatchett et al., 2020] shows that public health interventions and government restrictions that were implemented properly and at the right moment reduced the death toll of "Spanish flu" pandemic. The authors show in an example of Philadelphia and St. Louis that the public health responses to the pandemic in Philadelphia and St. Louis differed very much - St.Louis immediately implemented strong restrictions; in Philadelphia, in the other hand, it was

[1][Barry, John M (20 January 2004). "The site of origin of the 1918 influenza pandemic and its public health implications". Journal of Transnational Medicine. 2 (1): 3. doi:10.1186/1479-5876-2-3. ISSN 1479-5876.]

not even canceled a big parade. As a result, death rates differed in a consequential manner, with Philadelphia having one of the highest rates in the U.S., and St. Louis one of the lowest rates of death from pandemic.

Governments around the world have learned their "lessons", however, with different levels of an enthusiasm. To lower all COVID-19 infections and deaths in the pandemic, they have responded with a number of interventions. Among others, non-pharmaceutical interventions (including border restrictions,a quarantine and an isolation, social distancing, and changes in population behavior - less use of public transport, remote work and study, less public gatherings) were associated with reduced transmission of COVID-19.

Another curious aspect of studies about ongoing pandemic can be the possibility of "predicting" the evolution of pandemic, its consequences, future death numbers to prepare health care system against sudden spikes or overcrowds. In the work of [Amaro et al., 2020], the authors simplified classical SIR model up to D and D' models to match one and half beginning months of COVID-19 death numbers to their semi-empirical models. They have demonstrated that even small amount of data can be used to model a simple epidemiological forecast.

Taking into account all previous considerations, in this thesis I am going to pursue two objectives that are related to each other with a current state of data that was chosen as a frontier of this studies - first 300 days of COVID-19 pandemic spread in Spain.

1. I am going to implement official death numbers from COVID-19 in Spain to extend D models for 10 month time interval and forecast future death numbers for next two months (until 31.12.2020) with simple semi-empirical methods;

2. Then, I study the relation between Spanish government anti-coronavirus responses in terms of containment and closure, economic, health system measures with respect to daily death cases and daily new cases numbers for ten months of time period of 2020.

All the official data is taken from official public sources and their respective repositories are provided. Moreover, all the R statistic programming language codes necessary to create models and analysis will be given in the GitHub repository form: `https://github.com/RustamBozorov/Master-thesis.git`. The other chapters of this thesis work are developed as following:

- in chapter 2, I will provide a literature review on early studies of COVID-19 pandemic, I will list all possible non medical actions that a population can implement against the virus spread;

- in chapter 3, at first I will briefly cite the D models from the work [Amaro et al., 2020], with more mathematical explanation in A.2, then I will examine the effects of all semi-empirical coefficients that I am going to use in D models, with respective graphs provided through the examination and explanation;

- in chapter 4, I use previous chapter models to find coefficients for D models for Spain in 300 days period for death cases, and I will predict using these models next two months death numbers with two different models separately. In the end of chapter, I try to compare those predictions between themselves and against the real data obtained through official sources to qualify the accuracy of predictions done by simple epidemiological models;

- in chapter 5, I will introduce all types of government anti-pandemic responses in accordance to the Universal Government Response Tracker, which is created and is being continued to develop by University of Oxford;

- in chapter 6, I will provide data, its sources and methodology to achieve our second objective - the study of relation between death numbers and new cases numbers in Spain for ten months of 2020 and Spanish anti-pandemic policies. I will implement a generalized regression analysis using R program (source code will also be provided);

- in chapter 7, I will provide with results of analysis for different models with discussions on each of them in more detail;

- in chapter 8, I will conclude the thesis.

CHAPTER 2

Earlier studies of the COVID-19 effects on an economy and social life

2.1. Social distancing

If there was a quiz asking about the most used words for 2020, "social distancing" would be in one of the highest places for sure. Everywhere from media to public announcements we heard this phrase when we were talking about COVID-19 pandemic.

Surprisingly, this term is not newly created. This term takes its roots from XIX centuries memoirs about Napoleon and was defined as it is now as early as the beginning of the XX century in the work of a sociologist Emory Bogardus, who studied this phenomenon in the University of South Carolina.

However, it was used in a meaning of a social distancing between classes. Only after the AIDS spread and especially after the first SARS epidemic in 2003-2004, the Center for Control Disease (CDC of USA) started to use this term in the sense of counter action to an air-borne disease. Only a very huge spread of pandemic and social network connections made the term "social distancing" available for the entire world.

Social distancing was the most effective preventive action that people could take against the spread of the disease and it will still be the most useful and easy action, taking into account that the vaccination against COVID-19 is not widespread yet, the vaccination started only in late December,2020 in UK, USA and European Union. Russian Federation and People's Republic of China are also have started vaccination a population with their own vaccines, which are not officially confirmed by the World Health Organization yet.

Social distancing slows down the spread - "**Flattens the Curve**" - and saves thousands of lives (and of course, it has saved already), however it comes with a huge cost and pressure on an economy.

From the early days of the pandemic spread, the governments all around the world imposed differently scaled, yet however unseen actions to restrict the spread of the virus: from total lockdowns to local movement restrictions depending on the severity of the spread. Schools, universities, and daycare centers have temporarily ceased operations, playgrounds and other public spaces have been sealed off, cultural events have been canceled, tourist attractions have closed, and national sports leagues have suspended or canceled their seasons. Further, federal governments have imposed travel restrictions to reduce external exposure to the virus.

In the work of [Thunström et al., 2020], the authors studied the effect of the social distancing on economy, more specifically in the USA, by taking into account the difference of the numbers of two scenarios: without and with social distancing rule implications. Their studies showed the difference of total 100 million less infected individuals with the social distancing measures which resulted in more than $ 5.16 trillion net savings just in the USA. At the same time, after almost six months of time, we should be more critical to results, especially taking into account the limitations of the previous study regarding distributional effects to the groups in the different layers of the society. With saying net savings in the overall systems, authors acknowledged that the most vulnerable classes would be impacted the most by this pandemic.

In the alternative approach of studying the effects of social distancing - [Greenstone and Nigam, 2020],the authors from the University of Chicago tried to examine monetary effects of a social distancing. As authors indicated they examined two options:

- A mitigation scenario - combining a home isolation of suspected cases,a home quarantine of those living in the same household as suspect cases, and social distancing of the elderly and others at most risk of severe diseases that lasts for 3-4 months;
- No policy scenario.

They also implemented following assumptions:

- USA cannot stop the spread of virus entirely in this year(2020) - it turned out to be true;
- No reasonable vaccine will be developed - a vaccine is developed, but it is not widespread in 2020;
- "Overflow" deaths will appear (deaths occurring because of overcrowded hospitals, intensive care units and lack of personal protection equipment etc.).

They have concluded that more than 630,000 lives could be saved from "overflow" deaths and so, $ 8 trillion annually can be saved as well. Even if a robustness check would lead a bit lower amount of money, this study showed that how effective a social distancing could be in terms of monetary savings.

2.2. Non-pharmaceutical interventions (NPI)

In broader terms, social distancing is only one of the most implemented NPIs - non-pharmaceutical interventions - where individuals and society as a whole can slow down the spread of a disease without any help of chemical medicine and/or vaccine.

In the report by [Ferguson et al., 2020], a large number of authors studied the effects of different non-pharmaceutical interventions that governments around the world can implement against the disease. They highlighted several types of NPIs:

1. **CI** - *(Case isolation in the home)*- Symptomatic cases stay at home for 7 days, reducing non-household contacts by 75% for this period. Household contacts remain unchanged. Assume 70% of household comply with the policy;

2. **HQ** - *(Voluntary home quarantine)* - Following identification of a symptomatic case in the household, all household members remain at home for 14 days. Household contact rates double during this quarantine period, contacts in the community reduce by 75%. Assume 50% of household comply with the policy;

3. **SDO** - *(Social distancing of those over 70 years of age)* - Reduce contacts by 50% in workplaces, increase household contacts by 25% and reduce other contacts by 75%. Assume 75% compliance with policy;

4. **SD** - *(Social distancing of entire population)* - All households reduce contacts outside household, school or workplace by 75%. School contact rates unchanged, workplace contact rates reduced by 25%. Household contact rates assumed to increase by 25%;

5. **PC** - *(Closure of schools and universities)* - A closure of all schools, 25% of universities remain open. Household contact rates for student families increase by 50% during closure. Contacts in the community increase by 25% during closure.

From the today's perspective, we can understand that different countries implemented different types of NPIs. If we take Spain as an example, in the nine months of time line, the government implemented a mix of interventions depending on the severity of a situation.

Also, the authors listed two types of responses to the pandemic:

- **Suppression** - reducing new case numbers, eventually eliminating human-to-human transmission;
- **Mitigation** - focusing on slowing down but not necessarily stopping epidemic spread – reducing peak health care demand while protecting those who most at risk of severe disease from an infection. In this type of response, population(namely, herd) immunity builds up through the epidemic, leading to an eventual rapid decline in case numbers and transmission dropping to low levels. (example: Swedish experiment)

The authors pointed out risks for both responses, stating that a suppression brings with itself enormous social and economic costs which may themselves have a significant impact on health and well-being of the population in the short and longer term. Mitigation will never be able to completely protect those at risk from severe disease or death and the resulting mortality may therefore still be high (which was exactly the case with Sweden).

Their result showed that only implementing population-wide measures would help to achieve the largest impact, any half-implementing will not provide any substantial change. As they quote:

> Once interventions are relaxed from September on-wards(which occurred more or less even before - July-August), infections begin to rise, resulting in a predicted peak epidemic later in the year. The more successful a strategy is at temporary suppression, the larger the later epidemic is predicted to be in the absence of vaccination, due to lesser build-up of herd immunity.

Now, at the end of year 2020, their predictions mostly realized with a little exceptions in the actual numbers, but behavioral changes and governmental implementations, as well as, predicted "the second wave" of pandemic is happening as predicted.

2.3. Partial lockdown and other governmental responses

In the report by [di Porto et al., 2020], authors investigated the effects of partial lockdown in a social and economical life of Italy for the period beginning from 22nd March. They tried to estimate the cost of allowing a partial continuation of the economic activity on health care system and overall mortality. Their work included the suggestions from the article [Goodman-Bacon and Marcus, 2020], which shows the methodology of using difference-in-differences to clearly identify causal effects of coronavirus pandemic.

They have used, as a main measure of the presence of essential workers in the provinces of Italy, the density of essential workers, measured as the number of workers in essential sectors per built square kilometers, which accounts for both the local numbers of these workers and their concentration. The authors have concluded that a stronger presence of essential activities led to a higher number of new contagions: an additional 100 workers per square kilometer in essential sectors(essential jobs that were allowed to continue functioning also in lockdown times) lead to an about *0.27* additional daily cases.

In the article by [Dergiades et al., 2020], the authors introduced the notion of "'earlier' government response" along with strength of the that particular policy. They have shown that the greater a strength of government interventions at an *early* stage, the more effective they are in slowing down or reversing the growth rate of deaths. They have concluded that government decisiveness in taking early action is very crucial to control the virus spread.

2.4. Twelve lessons learned from novel coronavirus pandemic

In the article by authors [Forman et al., 2020], the authors tried to look into after life of coronavirus pandemic in terms of future pandemic responses. They have looked into data from different countries in the world, comparing them with government and societal actions and came up with twelve aspects of actions, which should be implemented more in the future to reduce the tremendous economic and social costs of pandemic. Namely, they are:

1. Transparency;
2. Decisive leadership;
3. Unified responses to pandemics rather than diverse disconnected strategies;
4. Effective communication at the highest political levels;
5. Regional blocs should assume a greater health care role;
6. Global solidarity;
7. The World Health Organization should focus on its activities, expand its remit and enhance its operational capacity;
8. Existing global insurance institutions and policies require significant changes and improvements;
9. Develop vaccines and treatments together;
10. Responsiveness and resilience of health systems should be tested and make changes and improvements based on the results;
11. Accountability is critical for building trust and for sound, inclusive decision making;
12. Opportunities to introduce newest technologies to fight against the pandemics.

And now it has become clear that this pandemic will contribute a lot in future changes of all health care system of countries around the world.

CHAPTER 3

SIR and D models

3.1. Basic SIR and D models

Every easily spreading, a contagious epidemic can be quite challenging to model due to the lack of the information, a huge number of unknowns that can affect the dynamics of epidemic and the errors of estimations of data. As a good way to base the modeling will be so-called "mass-action" principle. Mass - action principle by its own is used in a wide range of sciences and studies, however, in the epidemiological (disease) models, assuming the "law of mass action" means assuming that individuals are homogeneously mixed and every individual is about as likely to interact with every other individual. This is the most basic assumption that leads to SIR model.

SIR model, or [**S**usceptible, **I**nfectious, or **R**ecovered] model - mathematical modeling that was introduced in the famous work of [Kermack and McKendrick., 1927], based on the assumption of mass-action and dividing the entire population(which could potentially get infected by disease) into three categories:

- Susceptible - at time 0, all the population is in that category;
- Infectious - at any given time, it represents the number of population who get the disease;
- Recovered(Death) - shows the number of the recovered patients(or the worst case, the number of death).

As described in [Amaro et al., 2020], the authors based their assumptions on the classic work of [Kermack and McKendrick., 1927], they got following equations as beginning conditions:

$$\frac{dS}{dt} = -\lambda SI \tag{3.1}$$

$$\frac{dI}{dt} = \lambda SI - \beta I \tag{3.2}$$

$$\frac{dR}{dt} = \beta I \tag{3.3}$$

where

- $\lambda > 0$ - transmission or spreading rate. The higher the λ, the faster the increase of $I(t)$ and faster the decrease of susceptible individuals (minus sign in the equation A.3). λ also called "Flattening The Curve" coefficient - because the smaller it is, the smaller the overall number of infectious individuals;

- $\beta > 0$ - removal rate. The rate in which infectious individuals are recovering.

For the D model(D stands here for death), the main assumption will be

$$R(t) = 0$$

and system of equations became as

$$\frac{dI}{dt} = \lambda(N - I)I \tag{3.4}$$

This is the first degree ordinary differential equation, which as shown in the Appendix (A.1), can be solved in he time interval $[0; t]$ and putting $I(0) = I_0$. Solving this equation gives

$$I(t) = \frac{I_0 \cdot e^{N\lambda(t-t_0)}}{1 - \frac{I_0}{N} + \frac{I_0}{N}e^{N\lambda(t-t_0)}} \tag{3.5}$$

Then, authors used time lag notion to get $D(t)$ function out of equation 3.5 (all the meanings of the coefficients and authors other contributions are given in a simplified and shorter form in Appendix A.2):

$$D(t) = \mu I(t - \tau)$$

Final simplifications gave the **basic D model formula**:

$$D(t) = \frac{ae^{(t-t_0)/b}}{1 + ce^{(t-t_0)/b}} \tag{3.6}$$

The most useful aspect of the equation (3.6) is the possibility of choosing empirically the coefficients a, b, c to replicate the actual data. Other coefficients that were introduced until the reaching equation (3.6) are embedded in the defining formulas of a, b, c, so we do not really need to know beforehand all the conditions of pandemic initiation and development in depth.

If we want to define meanings of the latest coefficients, we can show that

- a - theoretical value of death at time(day) $t = 0$; can be also interpreted as expected value of deaths that day;

- b -characteristic evolution time, number of days to the number of deaths increase exponentially;
- c - inverse death factor. The lesser it is, the more death numbers asymptotically the function will reach eventually.

a, b and c correspond to the an average values over time, they are quite sensitive to external effects of pandemic evolution. The stochastic processes will easily change their values over time.

My analysis of D models will start from an equation 3.6. First, I will examine the coefficients effect on D function and later on elaborate a similar analysis for D' and D_n models.

3.2. Dependence of D model from its coefficients

The actual effects of all coefficients in the equation

$$D(t) = \frac{ae^{(t-t_0)/b}}{1 + ce^{(t-t_0)/b}}$$

can be examined by changing one coefficient at a time and comparing to default values, assuming default values are $a = 1, b = 1, c = 1, t_0 = 0$

In figure 3.1 we can see that D(t) increases very rapidly, then goes almost horizontally, reaching asymptotically the value a/c. If the value of a is increaed 10 times, the graph will look like in the figure 3.2. a will increase the value of a function, as it could be interpreted expected value of death.

If we compare default value graph with the value $b = 5$ line, we can notice that a growth of the line slowed down as in the figure 3.3. The reason behind shifting can be explained by the fact that the coefficient b represents the number of days to increase exponentially. The higher the value of b, the more days are needed to grow rapidly to reach maximum amounts.

If the value $c = 0.1$ is set (ten times lesser), the change resembles the change of $a = 10$, as it is shown in the figure 3.4. However, the effect in the beginning is different: the grow of the function not as rapid as in the first case. Eventually, the function goes to the same limits as in the previous case.

Setting $t_0 \neq 0$ shifts the graph to the right,as in the figure 3.5, meaning that start of the spread has some time lag as compared to a default case.

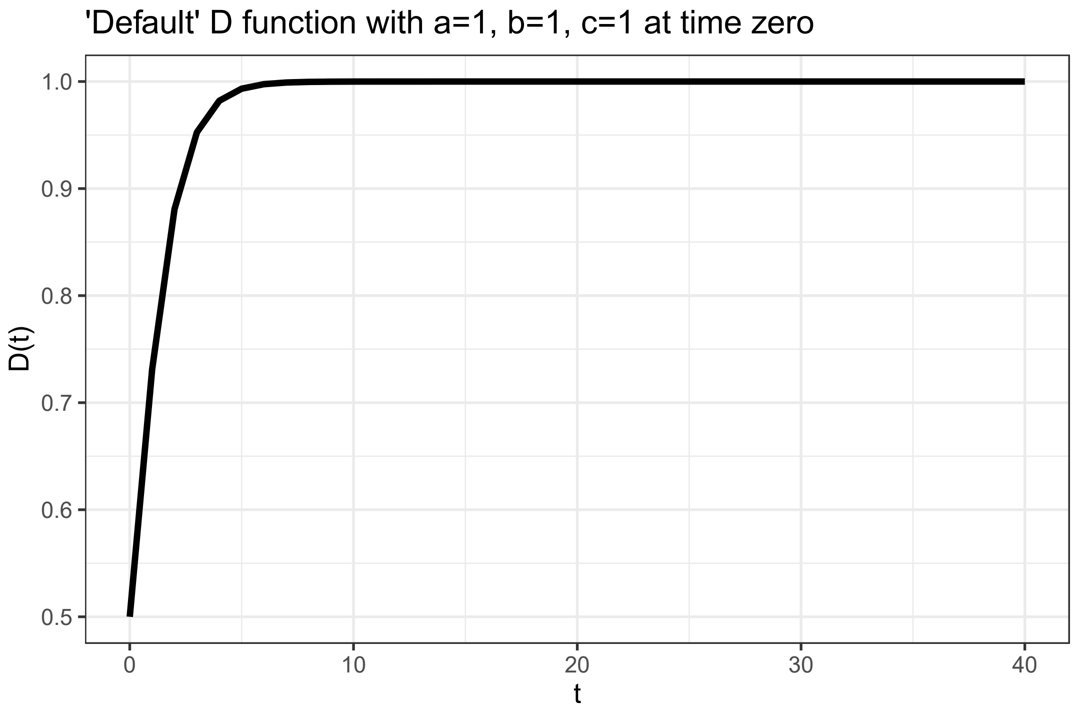

Figure 3.1: $D(t)$ graph with default values

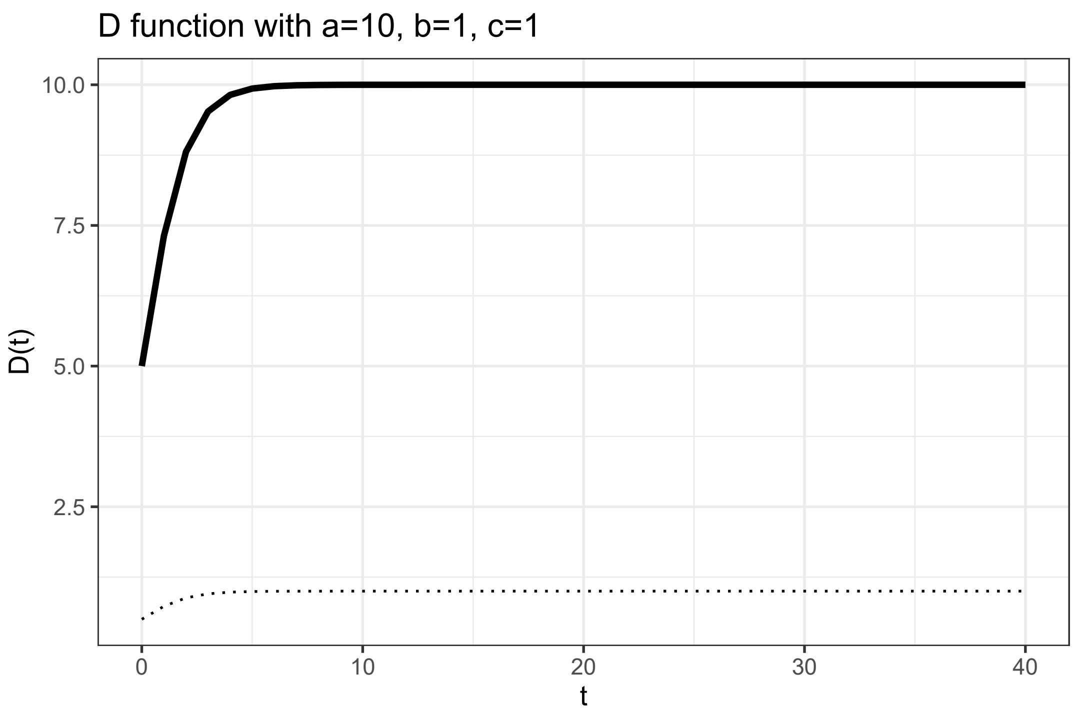

Figure 3.2: $D(t)$ graph with a value $a = 10$ as compared to default graph

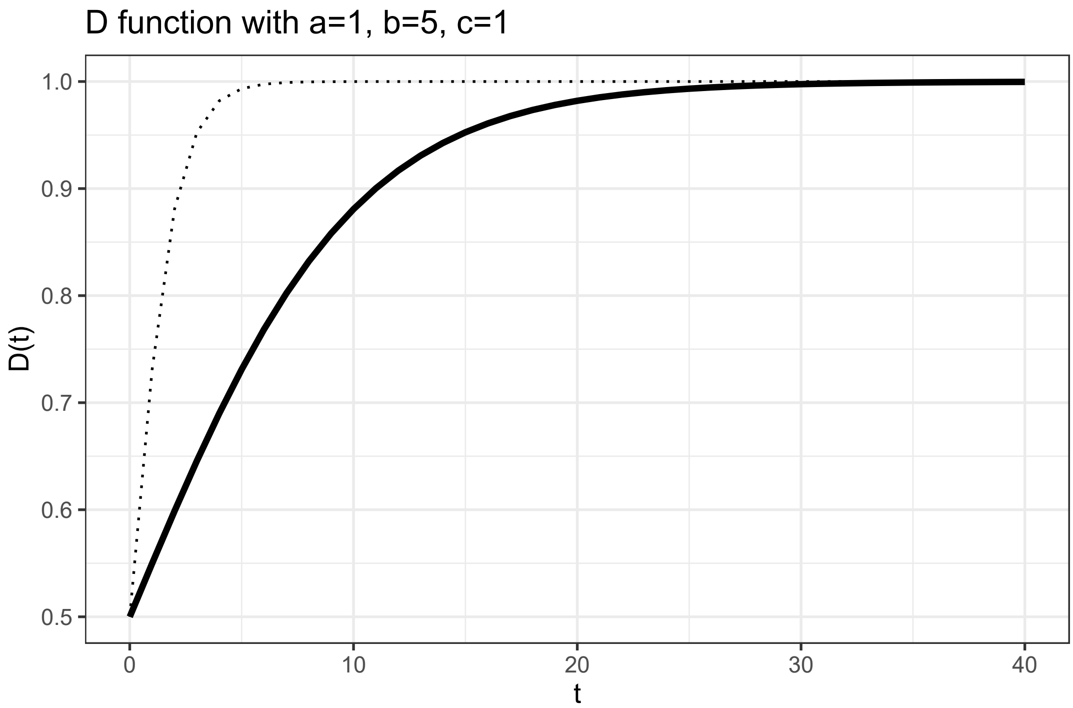

Figure 3.3: $D(t)$ graph with $b = 5$

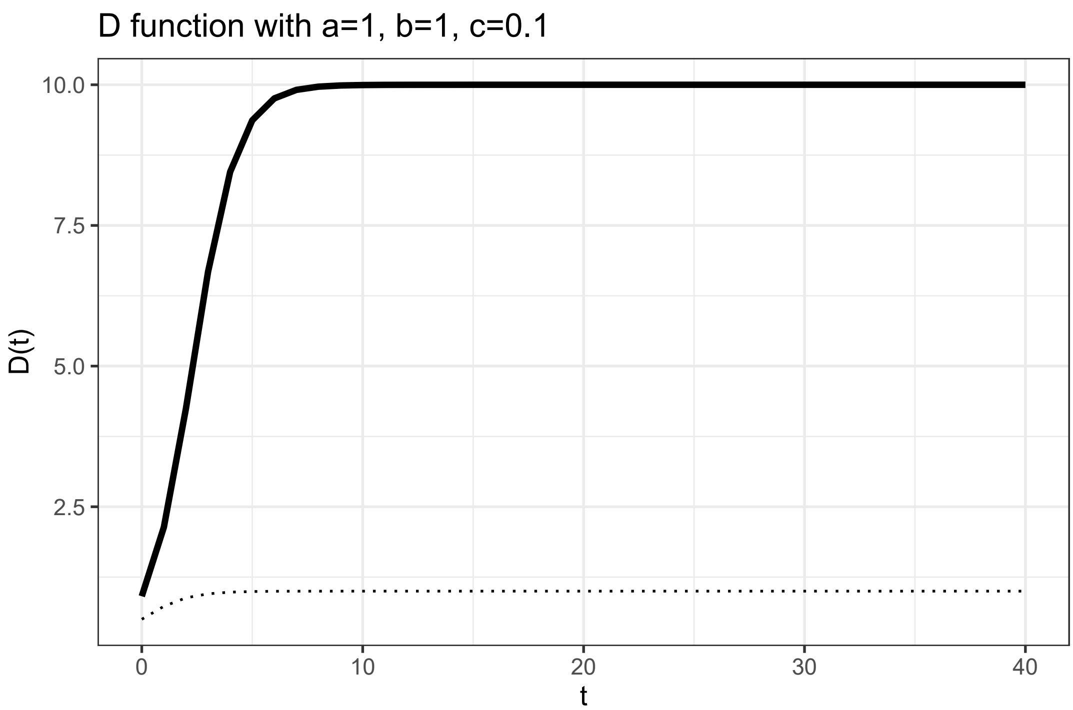

Figure 3.4: $D(t)$ graph with the change of value $c = 0.1$

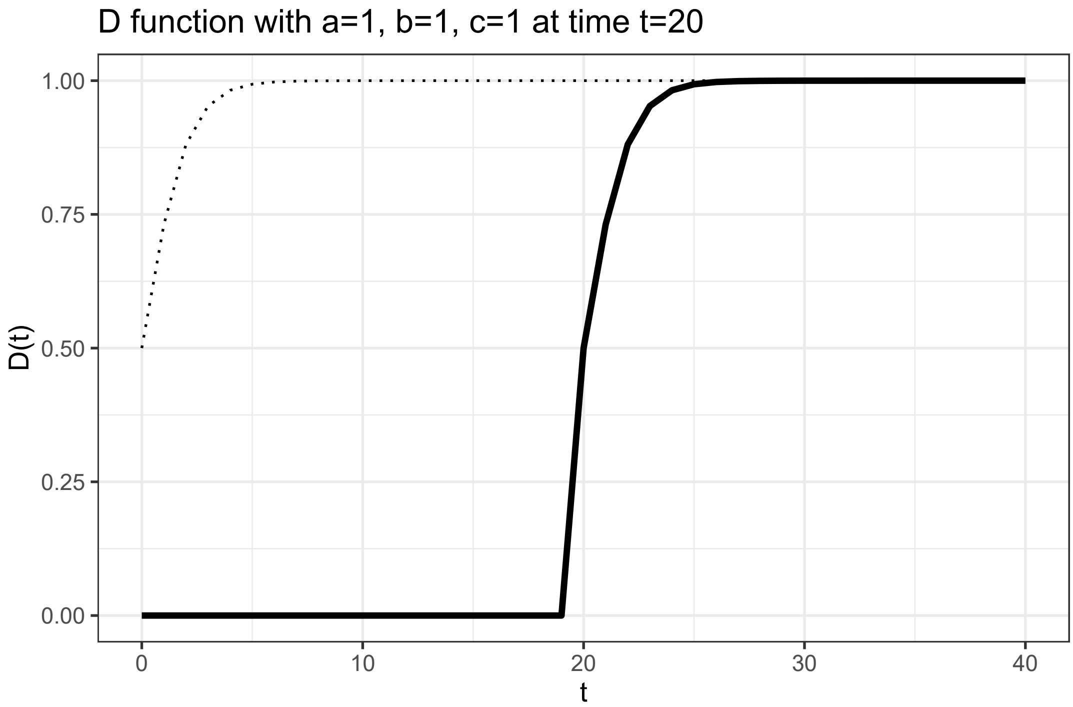

Figure 3.5: $D(t)$ graph with different start time

3.3. D′ model

After obtaining D model formulation, our model can be expanded further. For this reason, as it was suggested in [Amaro et al., 2020], I can introduce **D′ model** by taking the first derivative of the D model:

$$D'(t) = \left(\frac{ae^{(t-t_0)/b}}{1+ce^{(t-t_0)/b}}\right)' = a \cdot \left(\frac{\frac{1}{b}e^{(t-t_0)/b}(1+ce^{(t-t_0)/b}) - e^{(t-t_0)/b}(\frac{c}{b}e^{(t-t_0)/b})}{\left(1+ce^{(t-t_0)/b}\right)^2}\right) =$$
$$= \frac{\frac{a}{b}\cdot\left(e^{(t-t_0)/b} + c\cdot e^{2(t-t_0)/b} - c\cdot e^{2(t-t_0)/b}\right)}{\left(1+ce^{(t-t_0)/b}\right)^2} = \frac{\frac{a}{b}\cdot e^{(t-t_0)/b}}{\left(1+ce^{(t-t_0)/b}\right)^2} =$$
$$= \frac{a\cdot e^{(t-t_0)/b}}{b\cdot\left(1+ce^{(t-t_0)/b}\right)^2} \tag{3.7}$$

$$D'(t) = \frac{a\cdot e^{(t-t_0)/b}}{b\cdot\left(1+c\cdot e^{(t-t_0)/b}\right)^2} \tag{3.8}$$

As it was said earlier, D model allows a semi-empirical study of phenomenon and by choosing a, b and c the actual data can be replicated. However, these coefficients depend on many unknown stochastic variables at the same time, so, for D' model its coefficients are NOT necessarily the same as the D model.

The meaning of D' model can be obtained by the first degree approximation:

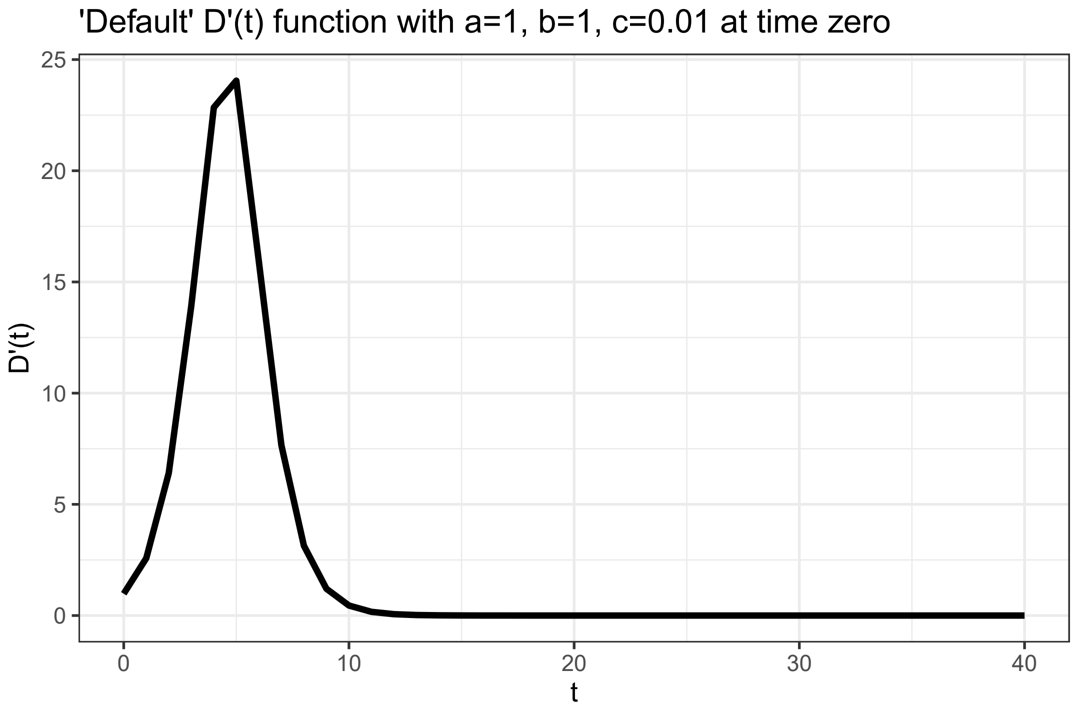

Figure 3.6: $D'(t)$ graph with default values

$$D(t) - D(t-1) \approx D'(t) \cdot \Delta t \tag{3.9}$$

If it is considered as $\Delta t \approx 1$ day, then, D' model shows the **DAILY NEW NUMBER OF DEATHS**. However, we should have been aware that D' has large fluctuations - both statistically and systematically with respect to the real collected data.

3.4. Dependence of D' model from its coefficients

The dependence of all coefficients in the equation

$$D'(t) = \frac{a \cdot e^{(t-t_0)/b}}{b \cdot \left(1 + c \cdot e^{(t-t_0)/b}\right)^2}$$

can be examined by changing one coefficient at a time and comparing to default values, assuming default values are $a = 1, b = 1, c = 0.01, t_0 = 0$. This time it is iven a value $c = 0.01$ to be able to notice more clearly the behavior of a graph.

In the figure 3.6 we can see that $D'(t)$ increases very rapidly until some time, then goes down almost in a similar manner, reaching asymptotically the value zero. If the value of a is increased 10 times, the graph will look like in the figure 3.7. a will increase the value of a function, as it could be interpreted as an expected value of death numbers per day.

If we compare graph with default values with the value $b = 5$ line, we can notice that the growth

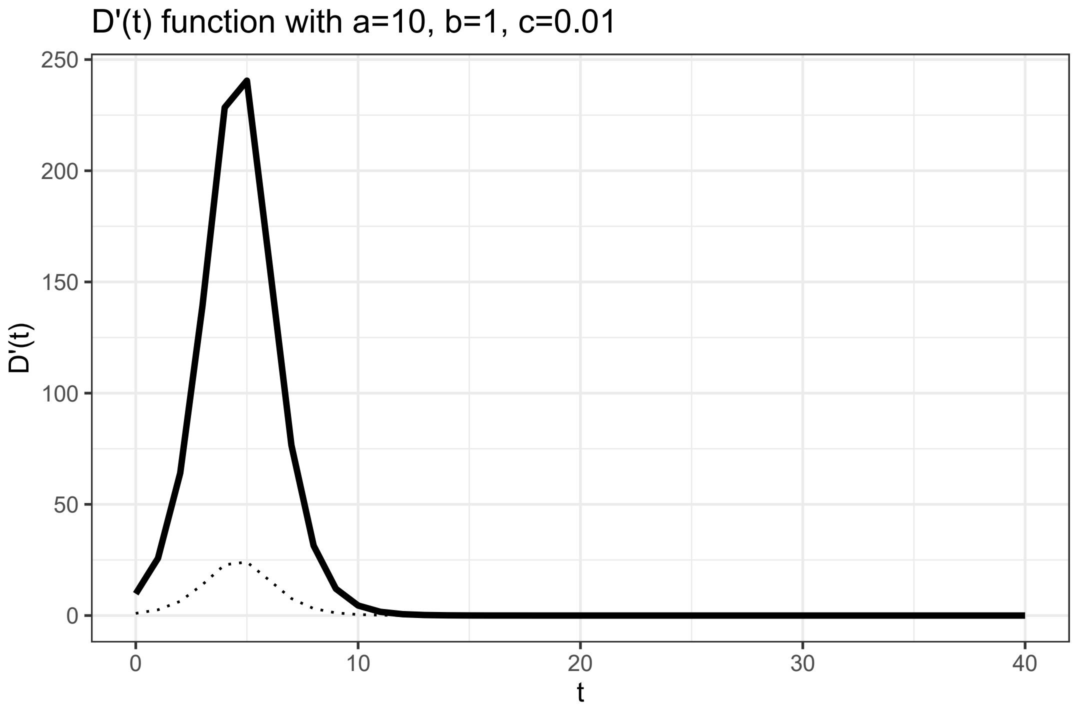

Figure 3.7: $D'(t)$ graph with a value $a = 10$ as compared to default graph

of a line slowed down as in the figure 3.8. This graph is the most "famous" of all graphs: it is so-called "**Flattening the COVID curve**". The graph will reach the maximum five times less in the value in a long period of time. The reason behind shifting can be explained as before by the fact that the coefficient b represents the number of days necessary to increase exponentially. The higher the value of b, the more days are needed to grow rapidly to reach maximum amounts.

If the value $c = 0.001$ is set (ten times less), the change resembles the change of $a = 10$, as it is shown in the figure 3.9.

However, the effect in the beginning is different: the grow of the function not as rapid as in the first case, it needs more time to reach a limit. Eventually, the function is going to show the same behavior as in the previous case.

Setting $t_0 \neq 0$ shifts the graph to the right,as in the figure 3.10, meaning that start of the spread and the growth of the function has some time lag as compared to a default case.

3.5. D_n model

D model was obtained with the assumption that we do not have recovered individuals (for example, at the beginning of the pandemic). That is the reason why at the beginning the actual data resembles the model. However, after some amount time actual data will deviate more and more from model values - due to stochastic processes, unknown factors and real time changes.

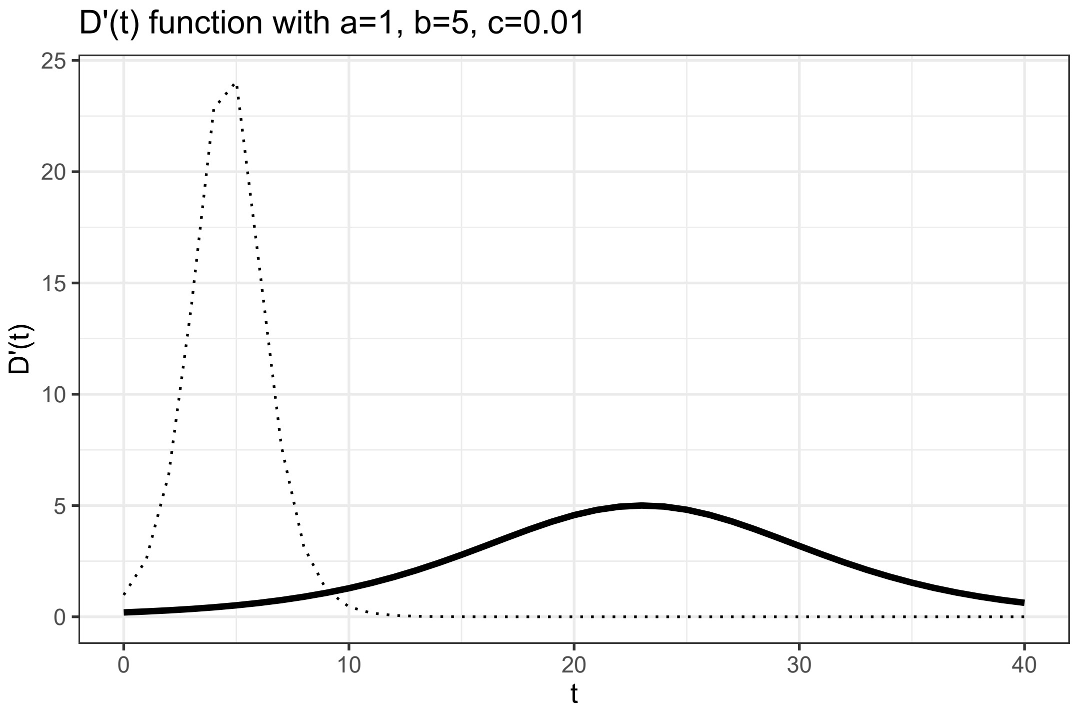

Figure 3.8: $D'(t)$ graph with $b = 5$; ***Flattening the curve***

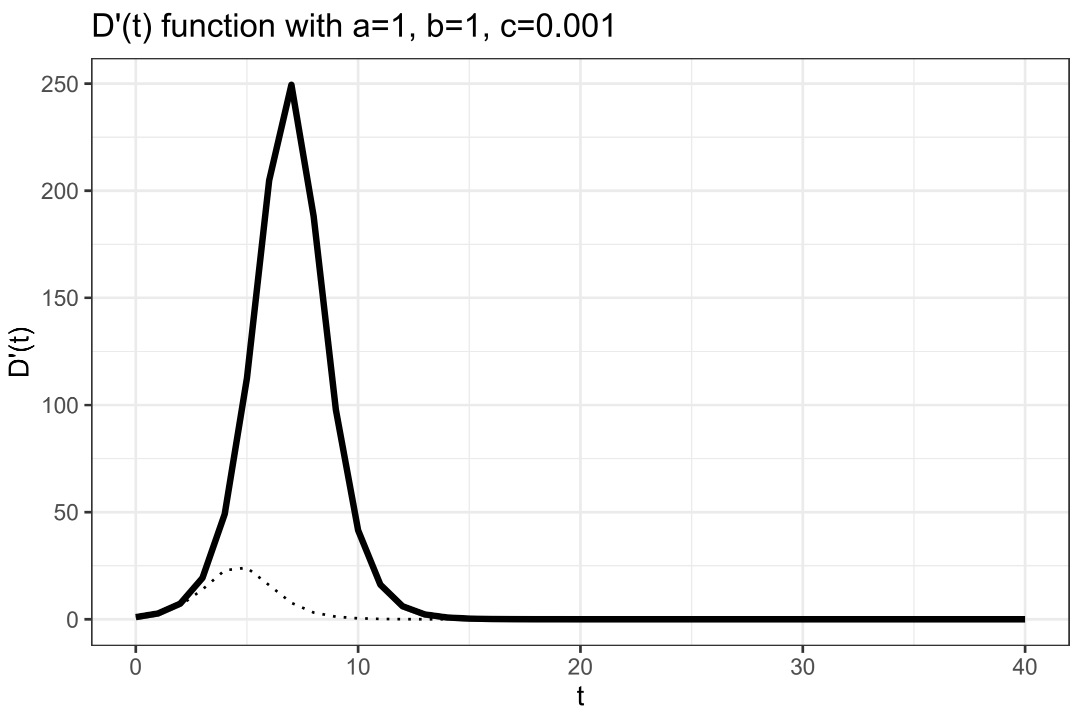

Figure 3.9: $D'(t)$ graph with the change of value $c = 0.001$

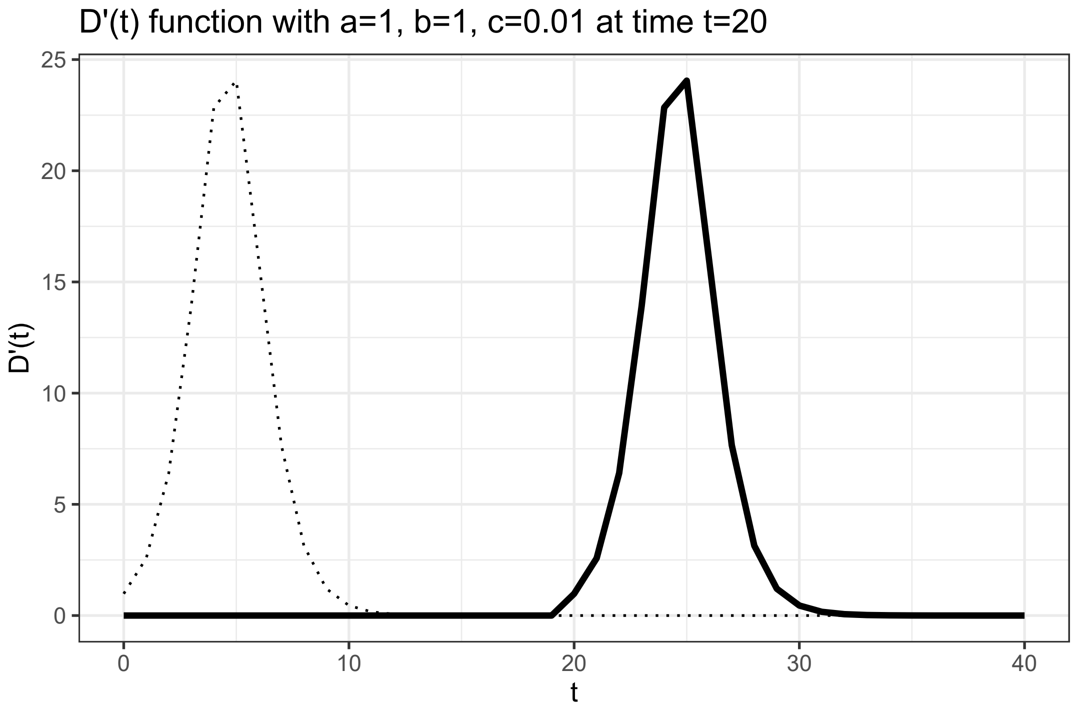

Figure 3.10: $D'(t)$ graph with different start time

To reflect the reality with the help of D models, an epidemic evolution can be viewed as a sum of independent (local) events that each of those events have their properties and features. So, each part of the modeling will have different (independent) coefficients. This modeling in general can be called as D_n model, as authors suggested:

$$D_n = D(a_1, b_1, c_1) + D(a_2, b_2, c_2) + \cdots + D(a_n, b_n, c_n) \tag{3.10}$$

or

$$D'_n = D'(a_1, b_1, c_1) + D'(a_2, b_2, c_2) + \cdots + D'(a_n, b_n, c_n) \tag{3.11}$$

The easiest form of D_n model will be D_2 model:

$$D_2 = D(a_1, b_1, c_1) + D(a_2, b_2, c_2) \tag{3.12}$$

or

$$D'_2 = D'(a_1, b_1, c_1) + D'(a_2, b_2, c_2) \tag{3.13}$$

Examples of the graphs for the equations 3.12 and 3.13 are given in the figures 3.11 and 3.12 respectively. In both cases, graphs are shown for $t_0 = 0$ condition.

3.6. Comments on using D model

In [Amaro et al., 2020], the authors introduce so-called "Extended SIR model", which is essentially extended D model, where primary assumption about zero Recovered individuals was

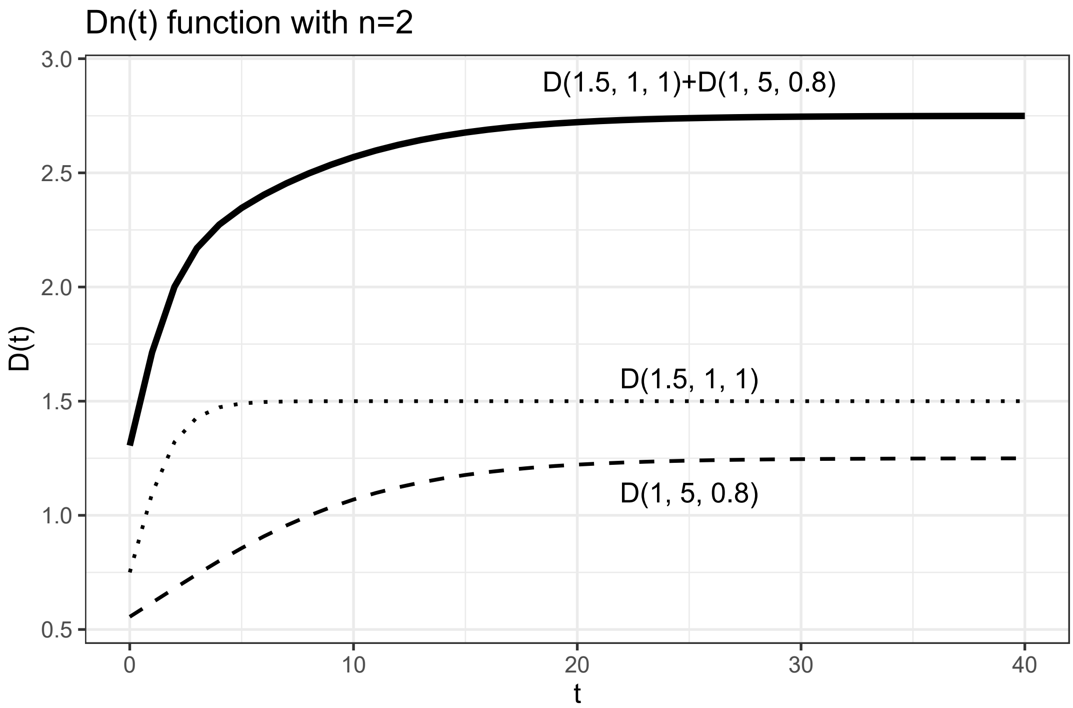

Figure 3.11: Example of $D_2(t)$ function

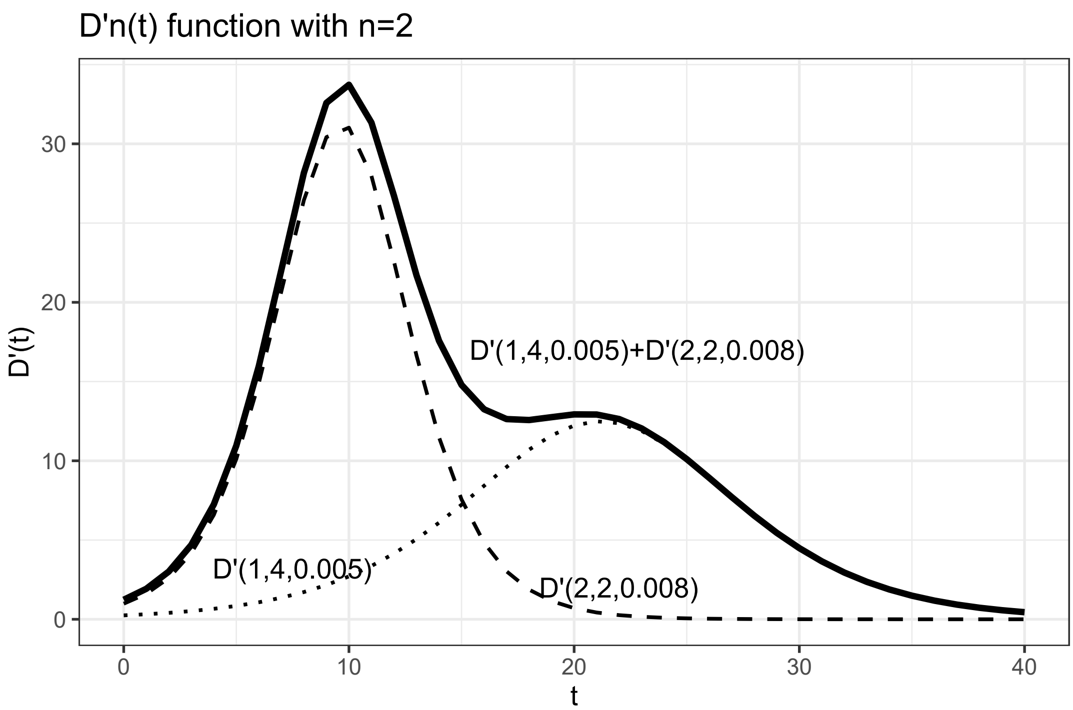

Figure 3.12: Example of $D_2'(t)$ function

released. After solving the system of differential equations it was shown that the most reliable solution has the form of D model - coefficients a, b, c that permit to solve an equation semi-empirically.

For this reason, I can use simpler D and D' models for a convenient modeling of pandemic spreading. They are SIR inspired - works well not only at the beginning, but also at advanced stages of the pandemics. To replicate the reality more correctly, I may use D_n models - a sum of independent D models with different widths and heights and centered at the different time intervals.

A healthy skepticism should be focused on the facts that no model is REALLY able to predict changes over time for that kind of complex evolution correctly, especially when properties of the physical causes of spreading are not included directly in the equations of a model. There will be always some uncertainty presented in the assumptions and calculations. The values of the model parameters are only well defined when the disease spread is coming to the end and time changes in the parameters have little impact. Observing the spread of COVID-19, now it has become obvious that the pandemic is not going to end soon, even the vaccination has already started.

Another point is that although different countries around the world may show similar trends of disease spread, statistical fluctuations in the daily data do not result in a nice universal behavior - for every country as a whole we will have to use different D models with different coefficients.

The last but not the least part of discussion should be the ability of models in terms of prediction of models from partial data. Can models truly predict from empirical findings and assumptions? Even if this question seems impossible to answer, in case of faster and comparably reliable numbers, the D model (especially D_n model) works pretty satisfactory.

CHAPTER 4

Implementation of D models with a real data in Spain

4.1. Overall cases in Spain

COVID-19 started spreading in the late December 2019, first cases in Europe were registered in January-February 2020, rising a concern only in the late February. One of the first and most affected countries was Italy, which had to implement total lockdown in 22nd February. Experts in Spain were urging the government of Spain to implement similar measures also in Spain, but lack of data, lack of compromise, the heavy relation of economy of Spain to tourism and international trade halted this decision for additional three weeks.

Only from 14th of March 2020, the government of Spain issued the regulation about the lockdown. It could be done earlier, however, it was better than implementing nothing. At that time, the spread and so-called the first wave of disease was already happening (as we will show later) lockdown effects could be observed from the second half of April.

As an official source of data about Covid-19 cases, I will use European Center for Disease Prevention and Control(An agency of the European Union) datasets[1]. All those data is open-source; data wrangling and analysis codes in R language will be presented in a GitHub repository in `https://github.com/RustamBozorov/Master-thesis.git`.

Let's take a look at the first 300 days of 2020 data for Spain in the figure 4.1.

Two aspects of situation will appear when the data is examined:

[1] (https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide)

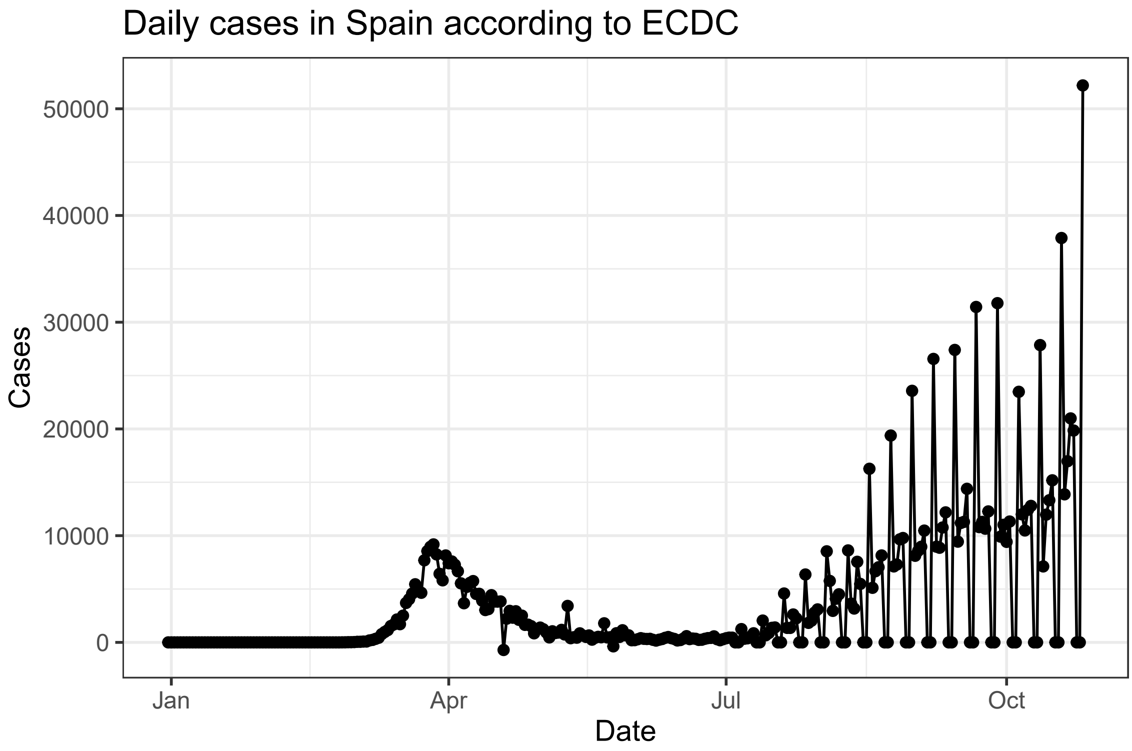

Figure 4.1: Daily cases from 31.12.2019 to 26.10.2020 in Spain according to ECDC

- There are some corrections along dateline in the cases, more specifically in the 19th April and 25th of May the numbers are negative. These should be taken into consideration;
- Starting from July, Spanish authorities published the official data only for five days in the week, weekend data was published together in Monday. That's why graph in the figure 4.1 represents those spikes. I will correct also those number by regularizing the numbers according to increase rate of that particular week data.

If all data is corrected from irregularities and regularized,I will obtain the following graph in the figure 4.2.

Even if the regression line in the figure 4.2 doesn't exactly represents the numbers, it is showing main highlights of the data - in April there was a pick of daily cases in Spain for the first wave, until August there was a decrease in daily cases, however, starting from August and especially, from the autumn the cases rose again very rapidly. The increase in the October was named as the beginning of the second wave, which in one form or another, returned the government restrictions in the Spanish autonomies.

To understand an increase of speed, I can sum up the daily cases and draw total cases in Spain according to each day of data, which is shown in figure 4.3. This graph clearly shows the exponential increase of cases in Autumn, which returned worries about implementing the second

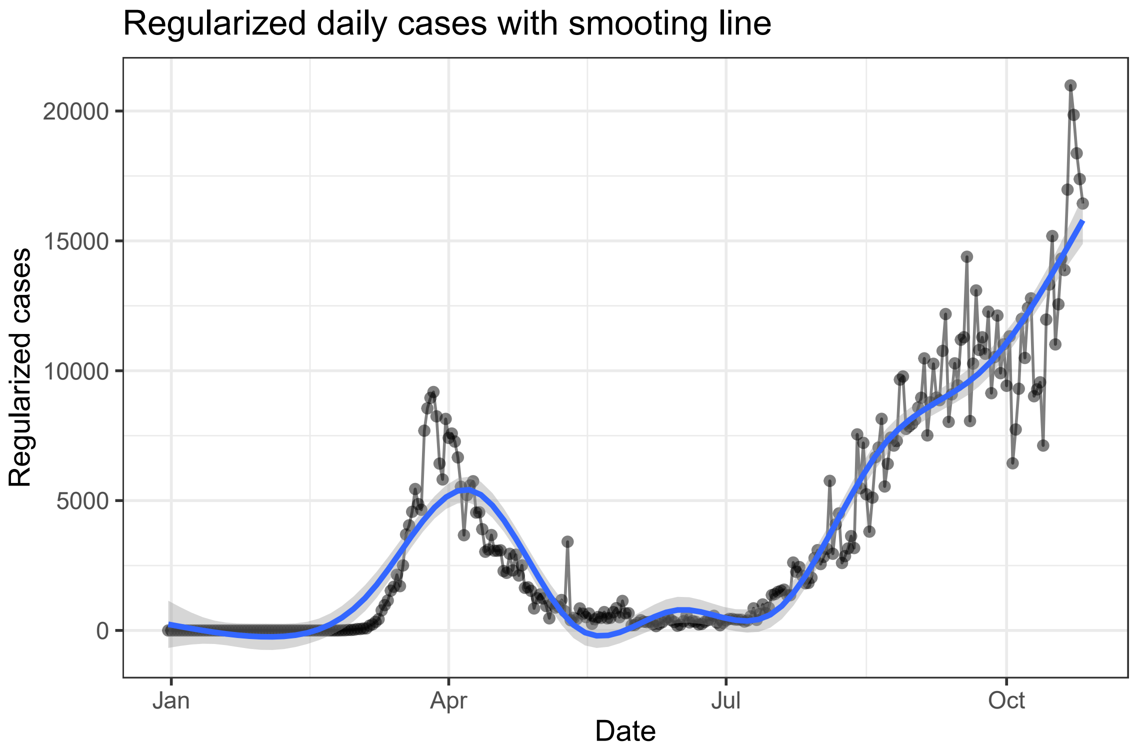

Figure 4.2: Daily regularized cases from 31.12.2019 to 26.10.2020 in Spain

total lockdown.

In the late October,2020, Spain has become the fifth country that surpass more than a million total Covid-19 cases worldwide, after USA, India, Brazil and Russian Federation.

4.2. D' model implementation

In this section I will look into other data that is provided in the data set - daily number of deaths. If a raw data is examined, the numbers look like in the figure 4.4 given.

Initial observation of data tells that there were several corrections of data in both upward and downward directions in May and June. Also, similar reporting pattern for weekend information from July that was implemented for daily cases, can be observed here too.

If I get rid of irregularities and apply the same regularization technique for the part of the data after July, 2020, the next graph can be observed in the figure 4.5.

The smoothing line here represents the main idea of the data: there was a pick of increase in April, followed by relatively small numbers in the summer, which afterwards in Autumn started to rose steadily again.

Now, the equation 3.9 in the chapter 3 can be implemented, as the regularized data is given

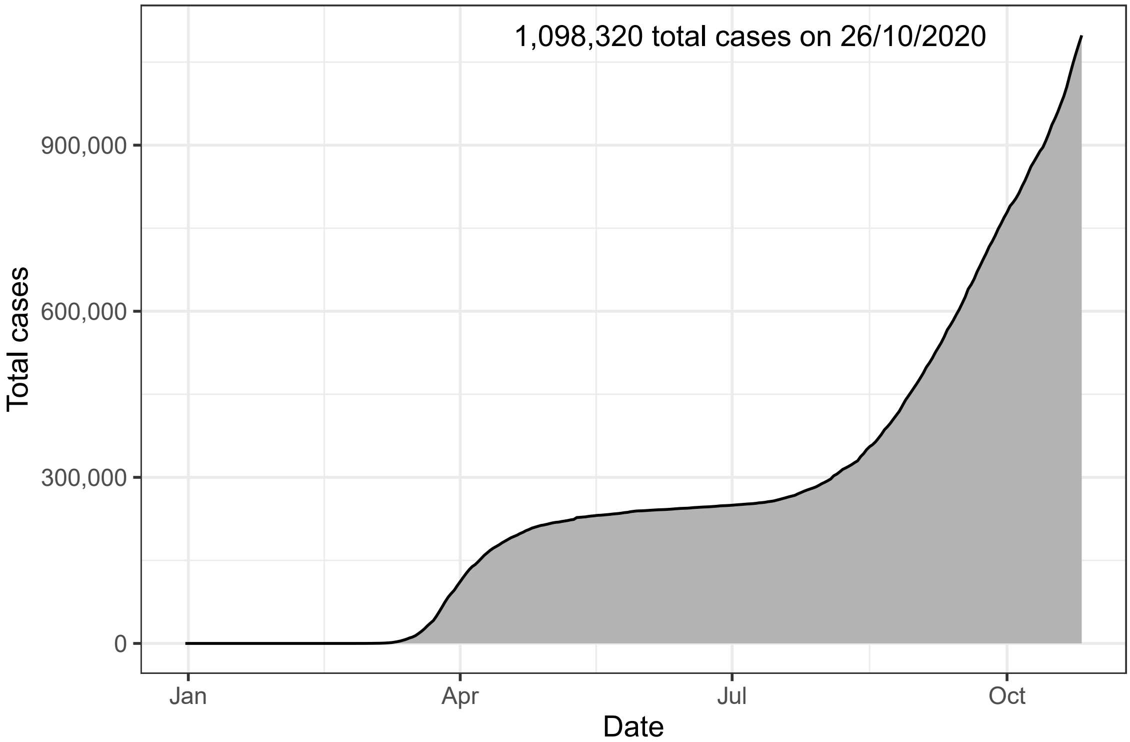

Figure 4.3: Total cases in Spain

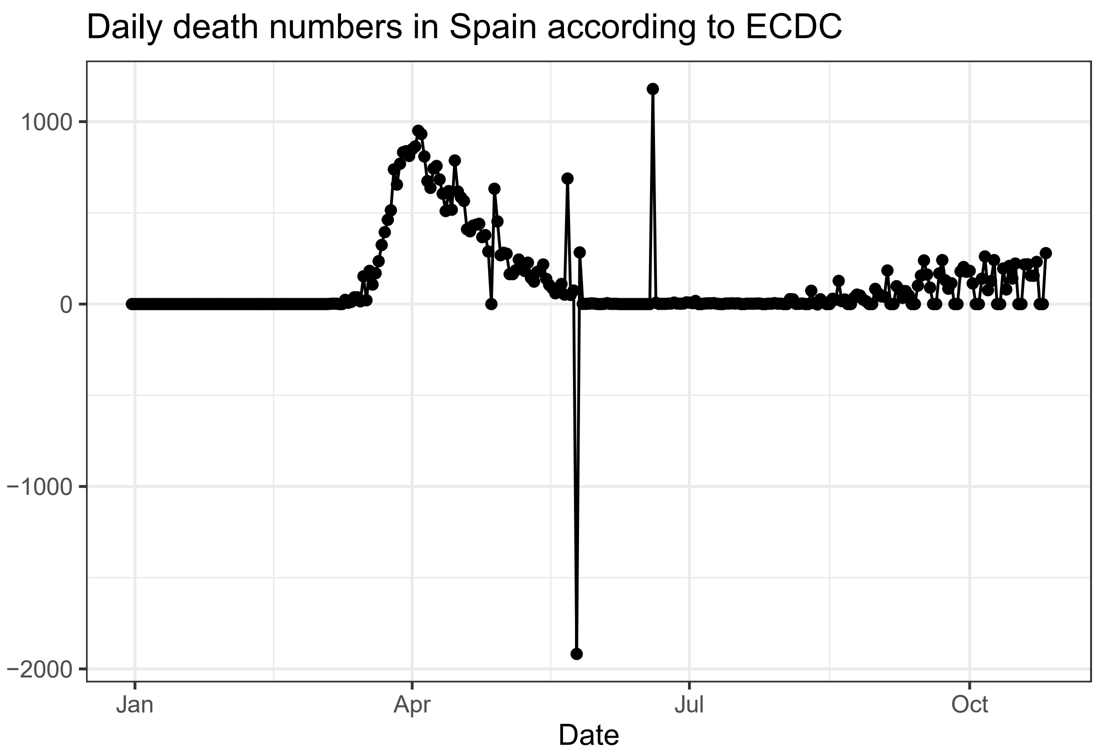

Figure 4.4: Daily cases of death from COVID-19 in Spain

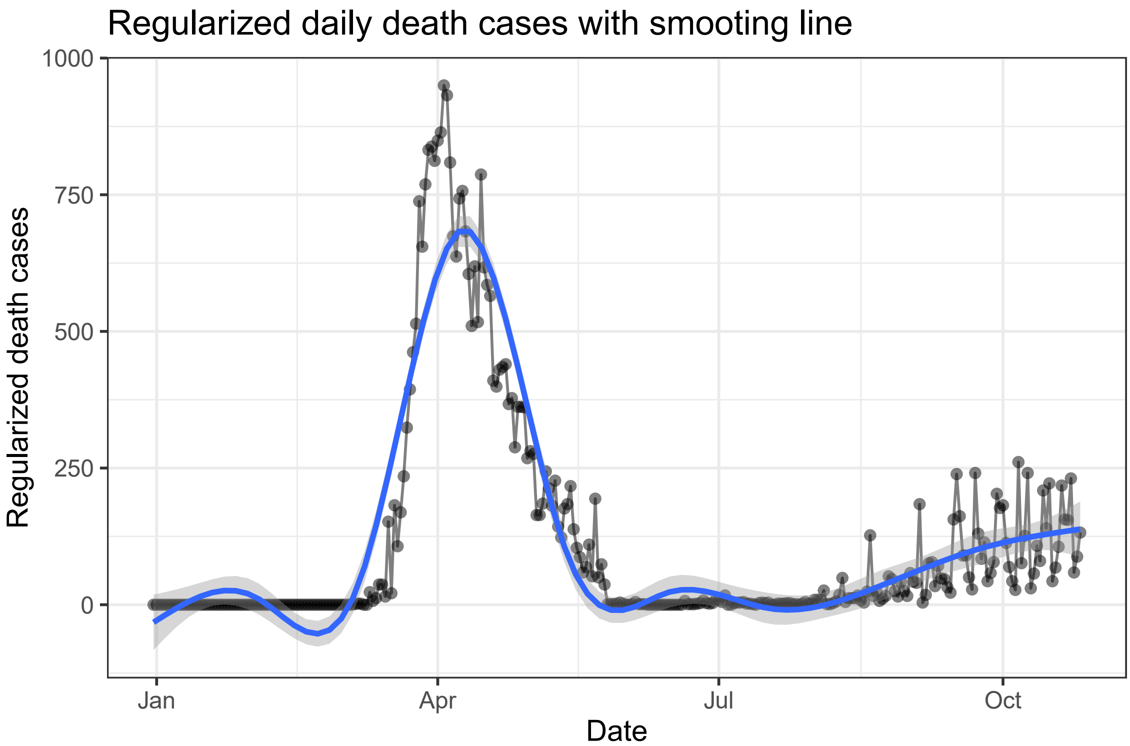

Figure 4.5: Regularized daily cases of death in Spain in the first 300 days of 2020

-	D'_{21}	D'_{22}
a	1950	950
b	8.85	42
c	0.0645	0.0065
t_0	75	215
Date for t_0	14-03-2020	01-08-2020

Table 4.1: The coefficients for D'_2 model for Spain case

for $\Delta t = 1$ day, we would have D' model. However, taking into consideration the evolution of pandemic, I should use D'_2 model as it was shown in the equation 3.13:

$$D'_2 = D'(a_1, b_1, c_1, t_1) + D'(a_2, b_2, c_2, t_2) = D'_{21} + D'_{22}$$

After semi-empirical method of finding of coefficients of equation 3.13 and plotting the resulting model graph, the following graph is obtained as it is shown in the figure 4.6. The corresponding coefficients are given in the table 4.1

4.2.1. Additional comments on the coefficients and plausibility check

The coefficients obtained in a table 4.1 demonstrate following properties:

- First of all, they are semi-empirical values, they could not be exact numbers, for example,

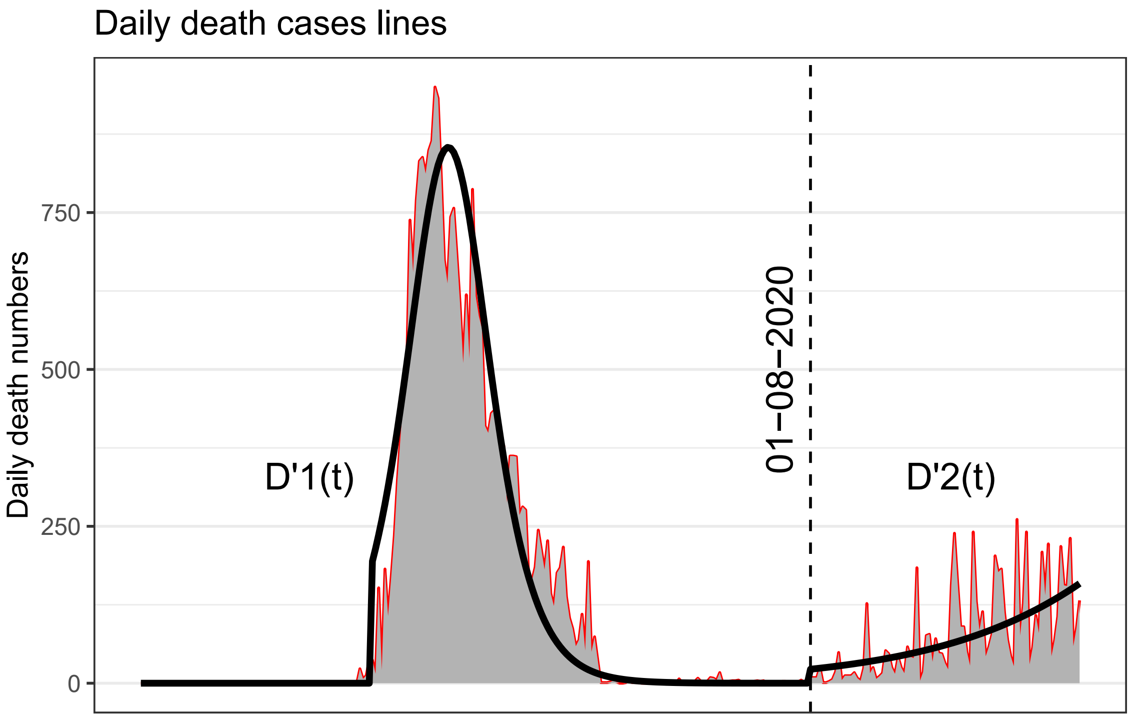

Figure 4.6: D'2 model for regularized daily cases of death in Spain

in the case of a coefficients in a table. However, they give a very easy possibility to check and quite exact description of the pandemic evolution;

- Coefficient a in the second part of D' model almost twice lesser than the first part of the model. This indicates that expected value of death decreased more than 50 %. This phenomenon can be explained by preparedness of the health-care system, better training of health-care workers and obligatory face mask regime in the whole country;
- Coefficient b in the second part of the equation as almost five times bigger than that of the first part of an equation. This represents the flattening the curve effect - lockdown, face mask regime, social distancing contributed to this change;
- Coefficient c in the second part as almost ten times smaller - which by the end of the year contributes to an increase of death numbers very significantly, as c was inverse death factor;
- t_0 time line represents the beginning point of increase in death numbers - not essentially the same dates as a beginning of "waves":
  - First increase started at 14th March - it coincides with the implementing strong restrictions in Spain;

- Second increase started roughly at the beginning of August, month later than a termination of first strong restrictions. Also numbers of deaths were increasing slowly, but very steadily from then on.

One more remark: the coefficients in D' model are not essentially the same as in D model, so when referring to the D model, it can be obtained (semi empirically) another values for all those coefficients.

Now, I can evaluate the accuracy of the results obtained by D' model and actual data. To accomplish this task I use simple integration of model over time. Before performing calculations, there are some simplifications:

1. D' model was obtained by differentiating D model - so, integrating D' model goes back to its initial function - D model itself;
2. Two parts of formula can be integrated apart, then added up;
3. Time limits for integrating intervals and coefficients used for calculating will be different, depending on the part of equation respectively. For the first part time line is for $t \in [75; 301]$ and for the second part of equation it will be $t \in [215; 301]$.

A calculation of area under a figure 4.6 (integrating over time line) follows like this:

$$Area = \int_0^{301} D'(t)dt = \int_{75}^{301} \left(\frac{a_1 e^{(t-t1_0)/b_1}}{1 + c_1 e^{(t-t1_0)/b_1}} \right)' dt + \int_{215}^{301} \left(\frac{a_2 e^{(t-t2_0)/b_2}}{1 + c_2 e^{(t-t2_0)/b_2}} \right)' dt =$$
$$= \left. \frac{a_1 e^{(t-75)/b_1}}{1 + c_1 e^{(t-75)/b_1}} \right|_{75}^{301} + \left. \frac{a_2 e^{(t-215)/b_2}}{1 + c_2 e^{(t-215)/b_2}} \right|_{215}^{301} = \frac{1950 \cdot e^{(301-75)/8.85}}{1 + 0.0645 \cdot e^{(301-75)/8.85}} - \frac{1950}{1 + 0.0645} +$$
$$+ \frac{950 \cdot e^{(301-215)/42}}{1 + 0.0065 \cdot e^{(301-215)/42}} - \frac{950}{1 + 0.0065} = [30232.558 - 1831.845] + [7008.909 - 943.865] =$$
$$\approx 28400 + 6065 = 34465 \quad (4.1)$$

As it is demonstrated in the next section, total number of an official COVID-19 deaths until 26th October(300 days of data) in Spain is **35031**. This model's error is less than 2 %:

$$\epsilon = \frac{|34465 - 35031|}{35031} = 0.01616 = 1.616\% \quad (4.2)$$

Even if we have used empirical numbers, overall result from model was pretty close to an actual data.

Having all coefficients can become handy when we want to "predict" possible numbers for the future days. The D' model coefficients will allow to forecast a near future numbers. If we want to predict what will happen by the end of this year in terms of total death numbers, we can use $t = 366$ as an upper limit for integrating (as 2020 has 366 days, 29th February included). The predicted number will be

$$\int_0^{366} D'(t)dt = \int_{75}^{366} \left(\frac{a_1 e^{(t-t1_0)/b_1}}{1+c_1 e^{(t-t1_0)/b_1}}\right)' dt + \int_{215}^{366} \left(\frac{a_2 e^{(t-t2_0)/b_2}}{1+c_2 e^{(t-t2_0)/b_2}}\right)' dt =$$

$$= \frac{a_1 e^{(t-75)/b_1}}{1+c_1 e^{(t-75)/b_1}}\Bigg|_{75}^{366} + \frac{a_2 e^{(t-215)/b_2}}{1+c_2 e^{(t-215)/b_2}}\Bigg|_{215}^{366} = \frac{1950 \cdot e^{(366-75)/8.85}}{1+0.0645 \cdot e^{(366-75)/8.85}} - \frac{1950}{1+0.0645} +$$

$$+ \frac{950 \cdot e^{(366-215)/42}}{1+0.0065 \cdot e^{(366-215)/42}} - \frac{950}{1+0.0065} = [30232.558 - 1831.845] + [27978.910 - 943.865] =$$

$$\approx 28400 + 27035 = 55435 \quad (4.3)$$

This number - 55435 - is quite high and bothering; that's why Spanish government is imposing new restrictions from November, 2020[2].

4.3. D model implementation

In the previous section, I have worked with an official data that was provided in the format that I could apply exactly to one of our models. For implementing D model - which represents the cumulative number of death until that particular time period, I should add up regularized data numbers to obtain new usable data (I will use regularized data to avoid sudden spikes and downfalls of original data set). As a result, the following graph in the figure 4.7 can be obtained.

This figure shows very clearly that after first quarantine measures, in the beginning of summer, death numbers almost didn't increase as compared to April numbers. However, from September, total number of deaths started to increase in slower rate than in spring, but very steadily, reaching the value of 35031 on 300th finished day of 2020 (26/10/2020).

Now, I can semi-empirically apply equation 3.12 for modeling the total death cases. For cumulative cases and randomness of disease spread, as it was also discussed in a chapter 3, the D model coefficients will differ from D' model coefficients which were shown in the table 4.1.

The D model in the manner of equation 3.12 will look like this(for these coefficients I will use different subscripts to distinguish them from D' model coefficients):

$$D_2 = D(a_3, b_3, c_3, t_3) + D(a_4, b_4, c_4, t_4) = D_{21} + D_{22}$$

The corresponding values are given in the table 4.2.If I draw the D model, the following in the figure 4.8 can be obtained.

[2]Those restrictions have given a positive result - according to official numbers, the number of death cases for Spain on 31st December,2020 was 50387 (5000+ less numbers than that of predicted by the model)

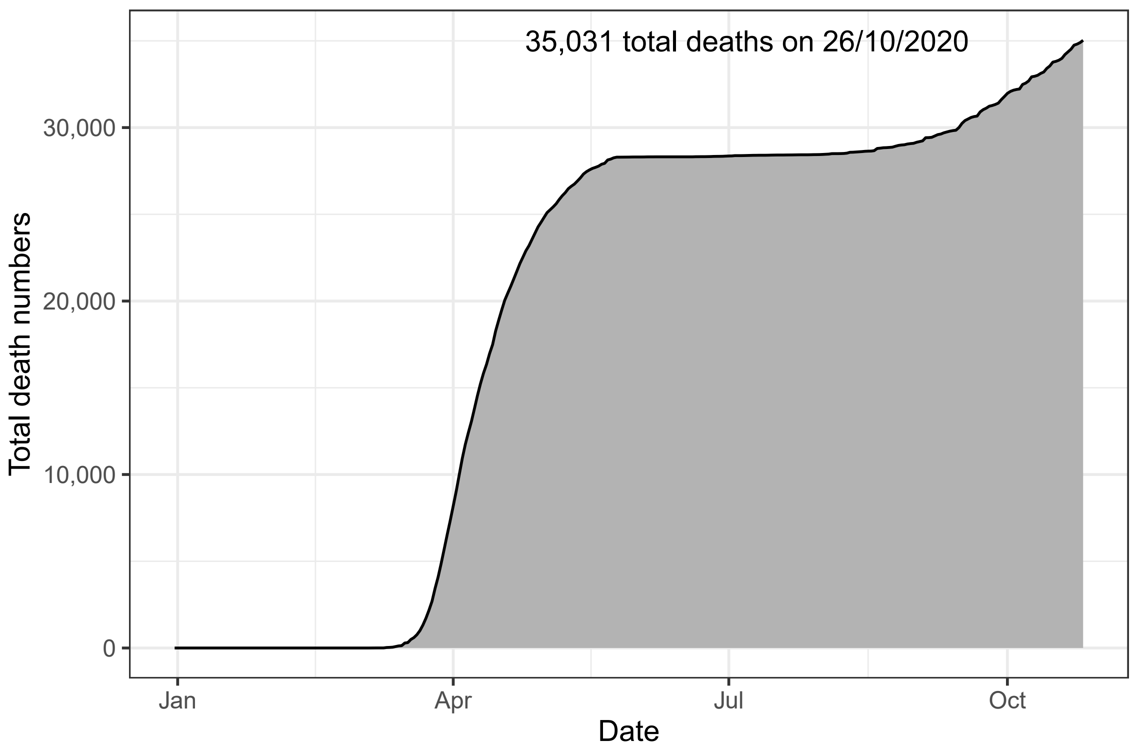

Figure 4.7: Total death numbers in Spain until 26.10.2020

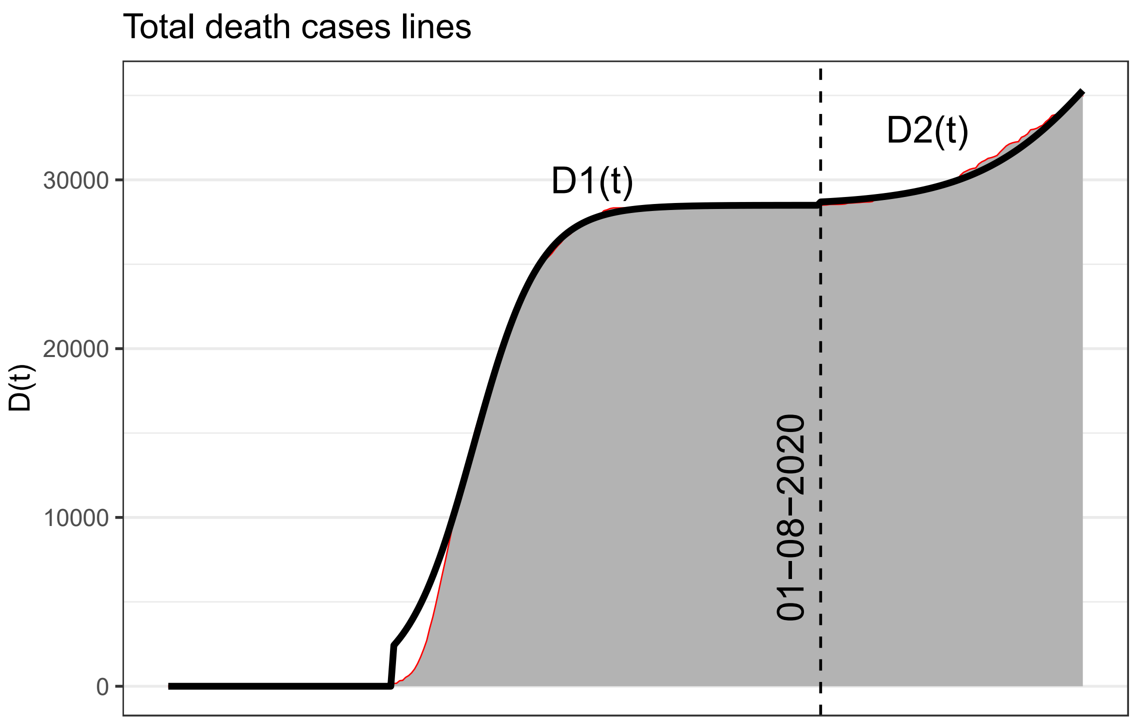

Figure 4.8: Total death numbers in Spain according to D model.

-	D_{21}	D_{22}
a	2650	200
b	11	21.5
c	0.093	0.0111
t_0	75	215
Date for t_0	14-03-2020	01-08-2020

Table 4.2: The coefficients for D_2 model for Spain total death cases

4.3.1. Additional comments on the coefficients of D model

The coefficients obtained in the table 4.2 demonstrate properties that resembles the previous model properties, in particular:

- They are also all semi-empirical values, they are not exact numbers. However, they give a very easy possibility to check and a quite exact description of the pandemic evolution;
- Coefficient a in the second part of D model less than the first part of the model. This phenomenon can be explained by preparedness of the health-care system, better training of health-care workers and obligatory face mask regime in the whole country;
- Coefficient b in the second part of the equation is twice bigger than that of the first part of an equation. This represents the flattening the curve effect - lockdown, face mask regime, social distancing contributed to this change. However, this is increase is not the same as it was in the previous model;
- Coefficient c in the second part as almost nine times smaller - which by the end of the year contributes to an increase of death numbers very significantly, as c was inverse death factor. This property is very similar to the first case;
- t_0 time line represents the beginning point of increase in death numbers - and they are the same dates as in D' model:
  - First increase started at 14th March - coincides with the implementing strong restrictions in Spain;
  - Second increase started roughly at the beginning of August, month later than a termination of first strong restrictions. And numbers of death were increasing slowly, but very steadily from then on.

Now, I can evaluate an accuracy of the results obtained by D model and actual data. Now, rather than integrating, I will simply put corresponding t values in the model equation A.18):

$$D_2(t = 301) = \left(\frac{a_3 e^{(t-t3_0)/b_3}}{1 + c_3 e^{(t-t3_0)/b_3}} + \frac{a_4 e^{(t-t4_0)/b_4}}{1 + c_4 e^{(t-t4_0)/b_4}} \right) \approx [28494] + [6799] = 35293 \quad (4.4)$$

The model's error is less than 1 % in this case:

$$\epsilon_2 = \frac{|35293 - 35031|}{35293} = 0.00748 = 0.748\% \quad (4.5)$$

Even if I have used empirical numbers, an overall result from model was pretty close to an actual data. However, we should be aware that our coefficients in this case very data related and they can predict future cases different than D' model forecast. If I want to predict what will happen by the end of this year in terms of total death numbers, I can use $t = 366$ as a time limit. The predicted number with the D model will be

$$D_2(t = 366) = \left(\frac{a_3 e^{(t-t3_0)/b_3}}{1 + c_3 e^{(t-t3_0)/b_3}} + \frac{a_4 e^{(t-t4_0)/b_4}}{1 + c_4 e^{(t-t4_0)/b_4}} \right) \approx [28494] + [16679] = 45173 \quad (4.6)$$

45173 is ten thousand less previous model forecast - 55435; this means D model coefficients will predict more optimistic outcome than D' model ones[3]. It should be taken a great care with taking that numbers as granted, because coefficients were chosen by "past" outcome and they will constantly change their behavior depending on the amount of data that we will introduce, as days go by.

[3]And it was optimistic - actual number turned out to be 50387

CHAPTER 5

Government anti-pandemic policy responses

As COVID-19 outbreak happened, the governments around the world started to implement different anti-pandemic policies to slow down the spread, save the health of population and at the same time, to keep going an economy in a working condition. However, the situation in the different countries in the different continents were totally different at the first time of pandemic spread. Also, the government responses differed in the sense of their stringency, duration, type of actions taken. If we consider that Sweden's response was out of common actions, all other countries implemented one or other type of restrictions (Side note: even Sweden admitted that their first reaction to pandemic spread did not covered all possible scenarios, and they also started to implement some restrictions and strong recommendations).

To study the response of countries (and Spain also) I will use the Universal Government Response Tracker, which is created and is being continued to develop by University of Oxford[1]. The Oxford COVID-19 Government Response Tracker (OxCGRT shortly),as shown by authors [Thomas et al., 2020], gathers information on several different common policy responses that governments have taken to respond to the pandemic. They are in an open public source [2] with everyday update of information and explanation.

Here, I will provide shortly all the common policies and their meanings. Whole explanation of policies with their value explanations can be found in a respective codebook for OxCGRT[3].

The main types of implemented government policies can be grouped into three categories:

[1]https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker

[2]https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker#data

[3]https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/codebook.md

- Containment and Closure policies;
- Economic policies;
- Health system policies.

Each category, at the same time, can be subdivided more into specific subcategories:

1. Containment and Closure policies:

    - School closings - closure of schools, high schools, universities (private and/or public) and other educative centers. Closure can be total or partly;
    - Workplace closing - can vary from recommendations, suggestions to change to remote work; partly remote work; total remote work; partly closure or even, total closure of workplaces that cannot comply with health and safety regulations, imposed by the government;
    - Cancellation of public events - can vary between recommendations, suggestions to cancel and total cancellations. For example, the cancellations of cultural events, sport activities, expositions etc;
    - Restrictions on gatherings - The restriction number ranged very largely, at the beginning being up 10-15 people, changing to 2-6 people at the public place. Also, some countries restricted gatherings only for family members and only living at the same house. In Autumn, 2020, in most part of Spain public gatherings were allowed maximum 6 people;
    - Restrictions of public transport - these restrictions have different level of stringency: a mild version of it can be the recommendation of using less public transport, changing working times, cancel some routes. As higher level of restrictions, it can be restricted most of the routes, it can be applied specific permissions to move around in public transport up to total restriction of it;
    - Stay-at-home requirements - range from recommendations not to leave a house; a possibility of leaving houses in certain hours; leaving a house only for doing sport and buying necessities; only going to supermarkets and pharmacies are allowed; only extreme cases can be a reason to leave house; total lockdown(previously gathering all necessary products for specific time period) - an example can be the first month of China regularities in Wuhan, China;
    - Restrictions on an internal movement - range from recommendations not to leave

living region, city to prohibitions to leave living district in town, cities;

- International travel restrictions/controls - at the beginning of pandemic, there were hardly ever any restrictions to an international travel except for China and other first disease spread countries. With the evolution of COVID-19, countries had imposed different type of restrictions depending on situation with spread, part of tourism in the overall economy and incoming country citizens. Those restriction/controls can be screening of entrance, asking for negative test for disease, compulsory 10-14 days of self-isolation, cancellation of some arrivals, ban to any entrance, total closure of country borders(except for the citizens of that particular country).

2. Economic policies:

   - Income support - Some governments have payed for the most vulnerable layer of workers monthly allowances; other countries payed some part of salaries (60-80%) so that businesses and factories kept the personnel in the pandemic times. Also, economic help differed from discounts to direct cash payments;

   - Debt/contract relief (for households) - as well as economic help, governments implemented tax relaxation in the period of pandemic spread and total lockdown of non-essential small and middle size businesses.

3. Health system policies:

   - Public information campaigns - from the beginning of restrictions, there were different approaches for informing public about new disease and the means to prevent from getting one - mostly on the television, Internet and public gathering places, tourist information centers, educational centers etc;

   - Testing policy - when testing equipment was scarce, testing was done only for people with symptoms and met specific requirements to be tested with a priority. With a large access to new tests in a quantitative way, testing was broadened for more layers of society from being compulsory for some workers to almost unlimited number of retaking the test for asymptomatic cases;

   - Contact tracing - when a discovery about the way of spread of disease was announced, more precisely, from person to person, most governments invested in the contact tracing systems. After a user of such system tests positive, system warns all the contacts of that patient for last 14 days. Most systems work as an application for a cellphone based on GPS, Bluetooth or QR code technologies. Also, unified databases of all cases were created to study the effect of person to person transition rates;

- Facial coverings - probably the most implemented, advertised and still up to now, the most useful actions. Different countries took different actions in that matter. However, we can identify main five variations of this policy:

  a) No such policy, even in public gatherings or closed spaces;

  b) Recommended to wear facial coverings, however no sanctions applied for not wearing;

  c) Required in some specified shared/public spaces outside the home with other people present, or some situations when social distancing not possible. Non compliance could infer penalties/fines;

  d) Required in all shared/public spaces outside the home with other people present or all situations when social distancing not possible. For more strict quarantining periods;

  e) Required outside the home at all times regardless of location or presence of other people. Most strict one, also with the highest possible fines for not complying this policy.

The Oxford COVID-19 Government Response Tracker provides some insight into an implementation and severity of each subcategory provided. In the next chapter, those data with relation to death and cases numbers in the Spain will be examined, that I developed in the chapter 4.

CHAPTER 6

Data and methodology

6.1. Data

The data consists of database of 18 overall indexes, of which 5 of them or about extreme financial interventions or miscellaneous indexes that in reality does not represent day by day change of policies. For this reason I fully use other indexes with their values. Those used variables are:

1. Containment and Closure policies:

   a) C1_ School closings;

   b) C2_ Workplace closing;

   c) C3_ Cancel public events;

   d) C4_ Restrictions on gatherings;

   e) C5_ Close public transport;

   f) C6_ Stay at home requirements;

   g) C7_ Restrictions on internal movement;

   h) C8_ International travel controls.

2. Economic policies:

   a) E1_ Income support (for households);

   b) E2_ Debt/contract relief.

# of j	Indicators	Maximum value(N_j) (all values)	Flag? (F_j)
1	C1	3 (0, 1, 2, 3)	yes=1
2	C2	3 (0, 1, 2, 3)	yes=1
3	C3	2 (0, 1, 2)	yes=1
4	C4	4 (0, 1, 2, 3, 4)	yes=1
5	C5	2 (0, 1, 2)	yes=1
6	C6	3 (0, 1, 2, 3)	yes=1
7	C7	2 (0, 1, 2)	yes=1
8	C8	4 (0, 1, 2, 3, 4)	no=0
9	E1	2 (0, 1, 2)	yes=1
10	E2	2 (0, 1, 2)	no=0
11	H1	2 (0, 1, 2)	yes=1
12	H2	3 (0, 1, 2, 3)	no=0
13	H3	2 (0, 1, 2)	no=0
14	H6	4 (0, 1, 2, 3, 4)	yes=1

Table 6.1: Indexes with their flag and maximum values

3. Health system policies:

   a) H1_ Public information campaigns;

   b) H2_ Testing policy;

   c) H3_ Contact tracing;

   d) H6_ Facial Coverings.

These variables can take values from 0 up to 4 depending on the level of strictness of policy. Meanwhile, most of values have additional "FLAG" binary indicator, which can take values 0 or 1, showing the application of policies only to some part of society, geographical region, day time or full application of it. Flag values with value equal to one is stricter than no flag policy. All indexes (j) with their maximum values (N_j) and flag existence (F_j) are shown in the table 6.1.

If I have null values for any policy value for some days, I will consider them 0 for consistency. This proposition is also true for flag values.

6.2. Methodology

For normalizing the values of indexes for country in the given time period, I will use the equation 6.1:

$$I_{j,t} = 100 \cdot \frac{v_{j,t} - 0.5(F_j - f_{j,t})}{N_j} \tag{6.1}$$

The meaning of coefficients:

- $I_{j,t}$ - normalized value of any index j at any given date t;
- $v_{j,t}$ - value of index j in the given day t;
- F_j - flag value of overall index j;
- $f_{j,t}$ - flag value at the given day t for the index j;
- N_j - maximum value of index j.

As it was emphasized before, for values $v_{j,t} = 0$ I will consider also $f_{j,t} = 0$; in which case I will consider normalized index value $I_{j,t} = 0$, even if by equation 6.1 theoretically it could happen that the result will be in the range of negative values.

Moreover, to give an overall effect of some types of policies all together, as containment, economic, health policies all united, simple averages of different indexes are also calculated by equation 6.2:

$$index = \frac{1}{k} \cdot \sum_{j=1}^{k} I_j \tag{6.2}$$

It is calculated 4 types of summarizing indexes by this formula:

1. Government response index;
2. Containment and health index;
3. Stringency index;
4. Economic support index.

The number k and types of indexes chosen (I_j) are given in this table 6.2

6.2.1. Assumptions for regression analysis

By computing all equations for all indexes I will get additional independent variables for regression analysis. For performing regression analysis, I will use some assumptions:

Index name	Government response index	Containment and health index	Stringency index	Economic support index
k	14	12	9	2
C1	√	√	√	
C2	√	√	√	
C3	√	√	√	
C4	√	√	√	
C5	√	√	√	
C6	√	√	√	
C7	√	√	√	
C8	√	√	√	
E1	√			√
E2	√			√
H1	√	√	√	
H2	√	√		
H3	√	√		
H6	√	√		

Table 6.2: Number k and respective chosen indexes

- For estimating relationship between independent variables and daily death numbers, I will use regularized death numbers, as was shown in the chapter 4. The reason behind this to smooth out the sudden fluctuations of data caused by artificial corrections of numbers;

- The same assumption is also applicable for daily new cases values;

- I will use death numbers from 08-03-2020, one week before implementing total lockdown in Spain, when numbers were high enough, but there were no conversation about lockdown because of COVID yet;

- But policy indexes values for analysis I will use will be even one week before the starting day of consideration of death numbers: 01-03-2020 - I assume that policies will start to give a result after a week of implementation. In this setting, 01-03-2020 policy indexes are linked to 08-03-2020 data for death numbers(regularized) and so on. Our time lag is 7 days;

- In this manner, I will have 233 days of studies until 300th day of 2020, which was the frontier day of this study;

- Dependent variables in both cases will be count variables, as they are non negative, and also whole numbers throughout the analysis. That's why I will use generalized linear modeling with Poisson distribution generalization - negative binomial model. Because negative binomial distribution converges to the Poisson distribution and with its coefficient controlling the deviation from the Poisson distribution;

- Using generalized linear model can be achieved by "Mass" package of R program language, [R Core Team, 2020];
- All necessary codes and data files will be presented as a GitHub repository in `https://github.com/RustamBozorov/Master-thesis.git`

CHAPTER 7

Results and discussion

7.1. The results of linear regression analysis for death numbers

After I have listed the data, indexes and methodology and assumptions, I will begin to present the results of applied statistical models. But before going into details of each model, I should present two further simplifications.

First,our indexes should be checked for zero variability case - in which variables have no variance, and I cannot make any hypothesis between possible correlation between dependent and independent variables. The check shows that two variables, H1_ Public information campaign and H3_ Contact tracing do not have variance, they are unchanged over whole period of study. It means that public information campaign and contact tracing policies were at the same level over last 8 months, and they cannot be taken into account, when modeling our linear regressions.

Secondly, there is no direct correlation between economic policies and death numbers. This assumption will be also true for new daily cases and economic policies alone. To prove our assumption, I can model a simple generalized linear model with only E1_ economic support and E2_ Debt release as a variable, as Economic Policy Index is a simple average of two variables(I do not have to use it in a modeling). This simple model can be written as in equation 7.1:

$$\log(death233) \approx \beta_0 + \beta_{E1}E1 + \beta_{E2}E2 \tag{7.1}$$

Results are shown in the table 7.1.

In this model, null hypothesis was the possibility of being equal to zero of all coefficients. Even is significance level, p values and z values suggest that there is a correlation between variables, the real connection between them can be explained in a reverse way. To put it in another way, it is false to say that economic support (E1) contributed in an increase of the number of death and

Coefficients:	Estimate	Std. Error (SE)	z value	p value	95 % CI
β_0	5.0131	0.02017	248.6	<2e-16 ***	(4.9733, 5.0524)
β_{E1}	0.0449	0.000389	115.4	<2e-16 ***	(0.0441, 0.0456)
β_{E2}	-0.0361	0.000242	-149.3	<2e-16 ***	(-0.0366, -0.0356)

*Table 7.1: Results for model in the equation 7.1. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

Coefficients:	exp(Estimate)	exp(Lower limit)	exp(Upper limit)	
β_0	150.3696867	144.5044632	156.3920531	***
β_{E1}	1.0458746	1.0450791	1.0466725	***
β_{E2}	0.9645398	0.9640834	0.9649979	***

*Table 7.2: Incident rate for model in the equation 7.1. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

debt release (E2) contributed in a decrease of the number of death; it is another way round: the government implemented income support (E1) policy when the numbers were very high and stopped doing that when numbers decreased and changed to the debt release policy and continued doing this, even if death numbers very low.

To understand better the meaning of log counts, incident rate ratios of the coefficients and 95 % confidence interval values can be demonstrated . To do this, I will use exponential function for the respective values.

As shown in table 7.2, for one unit increase of policy E2_ debt relief, the number of death incidence rate is approximately 3.5% decrease. And model suggests that one unit increase of E1_ Income support policy increased incident rate of death numbers for 4.5%, which have already been mentioned, should be viewed in a reverse direction.

The same type of explanations can be given for the non existence of direct correlation between economic values only and new daily cases (cases233), therefore, I will not consider that in future. Also, an explanation of reverse link between death numbers first and then policy implementation gives an insight and fair amount of skepticism for next models that are going to be developed.

7.1.1. Death numbers in relation to containment and closure policies

The analysis of death numbers and possible correlations with government policies will start with containment and closure policies. I use all 8 possible containment and closure policies in the

Coefficients:	Estimate	Std. Error (SE)	z value	p value	95 % CI
β_0	2.514	0.3097	8.117	4.76e-16 ***	(2.009 , 3.091)
β_{C1}	0.0091	0.0061	1.614	0.10645	(-0.0004, 0.0213)
β_{C2}	0.0736	0.0053	13.858	< 2e-16 ***	(0.064, 0.0834)
β_{C3}	0.0549	0.0094	5.813	6.15e-09 ***	(0.0343, 0.0752)
β_{C4}	-0.034	0.0037	-9.113	< 2e-16 ***	(-0.0406,-0.0278)
β_{C5}	-0.0108	0.0081	-1.337	0.18117	(-0.0287, 0.0073)
β_{C6}	-0.0150	0.0053	-2.830	0.00465 **	(-0.0280, -0.0014)
β_{C7}	-0.0048	0.0052	-0.920	0.35783	(-0.0154, 0.0055)
β_{C8}	-0.0537	0.0101	-5.295	1.19e-07 ***	(-0.0740, -0.0333)

*Table 7.3: Results for model in the equation 7.2. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

model as in equation 7.2:

$$\log(death233) \approx \beta_0 + \beta_{C1}C1 + \beta_{C2}C2 + \beta_{C3}C3 + \beta_{C4}C4 + \beta_{C5}C5 + +\beta_{C6}C6 + \beta_{C7}C7 + \beta_{C8}C8 \quad (7.2)$$

Results are shown in the table 7.3. Discussion of results:

- Not all the variables here have high significance levels of importance, some policies have better correlations with log number of death cases;
- The coefficients cannot give exact number of saved people due to themselves, but they can insight about effectiveness of policies compared among themselves;
- This model shows that policies C4_ Restrictions on gatherings and C8_ International travel restrictions have the most negative correlations and high significance levels;
- Then, it is followed by the policy C6_ Stay at home, which also has quite high significance level. An increase of one unit for Stay at home policy has reduced -0.0150 of log value for count variable - death numbers daily;
- Even if the policies C5_ Closure of public transport and C7_ Restrictions on internal movement have negative coefficients, their significance level in this model setting is quite low;
- The policy C2_ Workplace closing has a high significance and positive coefficient. It can be explained by the fact that in the spike of death numbers not all the works were shut down, numerous workplaces were labeled as an essential workplaces with essential workers.

To understand better the effects of coefficients, we will look at the incident rate ratios of the coefficients and 95 % confidence interval values. To do this, exponential function for the re-

Coefficients:	exp(Estimate)	exp(Lower limit)	exp(Upper limit)	
β_0	12.34907	7.45489	21.99496	***
β_{C1}	1.00997	0.99955	1.02155	
β_{C2}	1.07635	1.06613	1.08703	***
β_{C3}	1.05639	1.03486	1.07807	***
β_{C4}	0.96652	0.96017	0.97258	***
β_{C5}	0.98925	0.971643	1.00729	
β_{C6}	0.98511	0.97237	0.99851	**
β_{C7}	0.99522	0.984703	1.00556	
β_{C8}	0.94774	0.92866	0.96721	***

*Table 7.4: Incident rate for model in the equation 7.2. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

spective values will be used, which are shown in the table 7.4. As it shown in the table 7.4, one unit increase of C8_ International travel restrictions reduced more than 5.2% the daily death numbers. C4_ Restrictions on gathering has reduced more than 3.3% of death numbers.

At the same time, workplace closing did not increase the death numbers - one unit increase of C2_ Workplace closing policy was implemented in the average 7.63% daily increase of death numbers. And C1_ School closure did not led to very significant changes in death numbers, however its incident rate is slightly bigger than one by this model.

This table shows that first model can give some insight into the efficiency if some policies in comparison with other containment policies. However, the model can be filled with more variables for the next sections. I should also have to look at containment policies with health system policies together to get more variables and data involved, which I will proceed doing it in the next model.

7.1.2. Death numbers in relation to containment and closure policies with health system policies together

In this model, I take a look into two types of policies and the model for containment and health policies can be written as in equation 7.3:

$$\log(death233) \approx \beta_0 + \beta_{C1}C1 + \beta_{C2}C2 + \beta_{C3}C3 + \beta_{C4}C4 + \\ + \beta_{C5}C5 + \beta_{C6}C6 + \beta_{C7}C7 + \beta_{C8}C8 + \beta_{H2}H2 + \beta_{H6}H6 \quad (7.3)$$

Results are shown in the table 7.5. Discussion of results of this model:

- This time we get more clear and explanatory model;
- Only two policies are not significant enough to able to discussed in more detail: they are

Coefficients:	Estimate	Std. Error (SE)	z value	p value	95 % CI
β_0	2.7573	0.4269	6.458	1.06e-10 ***	(2.035, 3.519)
β_{C1}	0.0138	0.0059	2.314	0.0206 *	(0.0031, 0.0254)
β_{C2}	0.0679	0.0051	13.162	< 2e-16 ***	(0.0585, 0.0774)
β_{C3}	0.0378	0.0099	3.802	0.0001 ***	(0.0171, 0.0583)
β_{C4}	-0.0284	0.0037	-7.570	3.74e-14 ***	(-0.0353, -0.0216)
β_{C5}	-0.0225	0.0079	-2.847	0.0044 **	(-0.0395, -0.0052)
β_{C6}	-0.0261	0.0054	-4.840	1.30e-06 ***	(-0.0386, -0.0131)
β_{C7}	0.0042	0.0054	0.783	0.4333	(-0.0062, 0.0145)
β_{C8}	-0.0291	0.0109	-2.647	0.0081 **	(-0.0506, -0.0079)
β_{H2}	-0.0050	0.0083	-0.602	0.5474	(-0.0189, 0.0093)
β_{H6}	-0.0173	0.0043	-3.967	7.29e-05 ***	(-0.0251, -0.0095)

*Table 7.5: Results for model in the equation 7.3. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

C7_ Restrictions on internal movement of containment policies and H2_ Testing policy of health system. They have very least correlation significance with daily death numbers;

- The policies that have the most negative numbers are those which already discussed in the previous model, like C4_ Restrictions on gatherings, C5_ Public transport closure, C8_ International travel restrictions and C6_ Stay at home policies. One unit increase of them decreased log value of death numbers by around 0.02;

- H6_ Facial coverings of health system policy has also negative value and high significance in the model. Each unit increase of facial covering strictness has decreased the log value of death numbers by 0.0173;

- First three policies have positive coefficients which only can be explained by reverse causal relationship: they were strictest in the peak of numbers, but by the time, they have been relaxed more than other policies, so that schools, workplaces and public events could be reopen, holding social distancing and facial mask rulings in place.

To understand better the effects of coefficients, I will look at the incident rate ratios of the coefficients and 95 % confidence interval values. To do this, I can use exponential function for the respective values, which are shown in the table 7.6.

Table 7.6 shows that two containment policies - C4_ Restrictions on gatherings and C8_ International travel restrictions have the most downward impact on daily death numbers: each unit increase of them decreases approximately 2.8% of daily death numbers. Health system policy - H6_ Facial mask requirement also has high significance - each unit increase of it decreased

Coefficients:	exp(Estimate)	exp(Lower limit)	exp(Upper limit)	
β_0	15.75855	7.65020	33.78188	***
β_{C1}	1.01393	1.00318	1.02577	*
β_{C2}	1.07027	1.06028	1.08054	***
β_{C3}	1.03853	1.01729	1.06007	***
β_{C4}	0.97199	0.96524	0.97858	***
β_{C5}	0.97773	0.961200	0.994806	**
β_{C6}	0.97418	0.96205	0.98699	***
β_{C7}	1.00428	0.99376	1.01468	
β_{C8}	0.97131	0.95057	0.99210	**
β_{H2}	0.99498	0.98122	1.00934	
β_{H6}	0.98277	0.97519	0.99051	***

*Table 7.6: Incident rates for model in the equation 7.3. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

1.72% of daily death numbers. First three policies were the strictest in the increase of death numbers and they were relaxed before other containment policies - to continue to work, study in times of pandemics. Their unit increase has correlations with "increase" of death numbers - 1.3% , 7%, 3.85% respectively. Therefore, these effects of increase should be interpreted with care.

7.1.3. Death numbers in relation with all coefficients - final model

In a final model, I take a look into all types of policies - containment and closure, economic and health system policies. Even if I do not use explicitly H1_ Public In formation policy and H3_ Contact tracing policies in the model, because of their zero variance, - other policies of health system policies will be included in the final model.

The final model for can be written as in equation 7.4.

$$\log(death233) \approx \beta_0 + \beta_{C1}C1 + \beta_{C2}C2 + \beta_{C3}C3 + \beta_{C4}C4 + \beta_{C5}C5 + \beta_{C6}C6 + \beta_{C7}C7 + \\ + \beta_{C8}C8 + \beta_{E1}E1 + \beta_{E2}E2 + \beta_{H2}H2 + \beta_{H6}H6 \quad (7.4)$$

Results are shown in the table 7.7.

Discussion of results of final model:

- This final model gathers all singular policies together to get even more clear and explanatory model;
- However, not all of them are significant in 1% or 5% error intervals;

Coefficients:	Estimate	Std. Error (SE)	z value	p value	95 % CI
β_0	2.8468	0.4310	6.605	3.98e-11 ***	(2.1148, 3.6123)
β_{C1}	0.0136	0.0059	2.299	0.021496 *	(0.0031, 0.0251)
β_{C2}	0.0669	0.0052	12.739	< 2e-16 ***	(0.0575, 0.0764)
β_{C3}	0.0384	0.0103	3.712	0.000206 ***	(0.0182, 0.0584)
β_{C4}	-0.0307	0.0064	-4.728	2.27e-06 ***	(-0.0418, -0.0188)
β_{C5}	-0.0190	0.0084	-2.261	0.023776 *	(-0.0366, -0.0013)
β_{C6}	-0.0256	0.0054	-4.724	2.31e-06 ***	(-0.0381, -0.0127)
β_{C7}	0.0050	0.0065	0.772	0.440168	(-0.0071, 0.0171)
β_{C8}	-0.0371	0.0126	-2.928	0.003413 **	(-0.0606, -0.0136)
β_{E1}	0.0066	0.0080	0.830	0.406308	(-0.0077, 0.0199)
β_{E2}	0.0041	0.0101	0.412	0.680573	(-0.0144, 0.0208)
β_{H2}	-0.0082	0.0085	-0.963	0.335311	(-0.0226, 0.0067)
β_{H6}	-0.0177	0.0053	-3.334	0.000856 ***	(-0.0269, -0.0085)

*Table 7.7: Results for model in the equation 7.4. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

- The unit increase of policy C1_ School closure has a correlation of 0.0136 unit log "increase" of daily death numbers. This positive correlation can be explained by the fact that schools were not closed completely, especially beginning and mid schools. Higher schools and universities were transferred to remote studies. As death numbers dropped, schools were also open to face to face lessons;

- The policy C2_ Workplace closing has the most positive correlation with log death number. It is related with the fact that essential jobs were not closed at all even in the peak times, not all jobs could be transferred to remote regime. And also, we can use reverse correlation - every decrease of 0.0669 log unit of death numbers led to one unit decrease of strictness of workplace closures - more jobs and businesses were let to be opened;

- The policy C3_ Canceling public events has also positive correlation with log count number of daily deaths. It also can be explained by reverse correlation - every 0.0384 unit of log decrease of death number is related to one unit decrease of strictness of public event cancellation policy;

- C4_ Restrictions on gathering and C8_ International travel restrictions have the most negative correlation with log count of daily death numbers. These policies have been implemented for a long time and one or another way are kept implementing unchanged, with no relation to actual peak changes of death numbers;

- The policy C6_ Stay at home has also great significance and every unit increase of this

Coefficients:	exp(Estimate)	exp(Lower limit)	exp(Upper limit)	
β_0	17.23330	8.28810	37.05463	***
β_{C1}	1.01377	1.00316	1.02546	*
β_{C2}	1.06920	1.05919	1.07947	***
β_{C3}	1.03916	1.01837	1.06022	***
β_{C4}	0.96975	0.95898	0.98137	***
β_{C5}	0.98117	0.96410	0.99866	*
β_{C6}	0.97468	0.96261	0.98741	***
β_{C7}	1.00510	0.99288	1.01723	
β_{C8}	0.96355	0.94115	0.98644	**
β_{E1}	1.00672	0.99231	1.02015	
β_{E2}	1.00417	0.98566	1.02106	
β_{H2}	0.99176	0.97758	1.00676	
β_{H6}	0.98240	0.97342	0.99144	***

*Table 7.8: Incident rates for model in the equation 7.4. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

policy has a correlation with 0.0256 decrease of log unit of death numbers;

- C5_ Public transport closure has also negative correlation with log count even if public transport was never closed down completely because of not closing essential jobs and mid school levels;
- The policy C7_ Restrictions on internal movement has a very little significance in terms of decrease of log count of death numbers;
- The same insignificance levels have both economic policies. They show positive correlation, because these policies were implemented during the peak numbers of death toll and were less used later on;
- H2_ Testing policy of health system policies has a negative correlation, but very low significance level;
- H6_ Facial coverings of health system policy is also one of the most significant policies to reduce death numbers. Each unit increase of facial coverings decrease for 0.0177 log unit of daily death numbers.

To understand better the effects of coefficients, I will look at the incident rate ratios of the coefficients and 95 % confidence interval values. To do this, I can use exponential function for the respective values, which are shown in the table 7.8.

Coefficients:	Estimate	Std. Error (SE)	z value	p value	95 % CI
β_0	3.2776	0.5796	5.655	1.56e-08 ***	(2.1905, 4.5819)
β_{GRI}	0.0263	0.0088	2.980	0.00288 **	(0.0067, 0.0432)

*Table 7.9: Results for model in the equation 7.5. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

As it can be seen from table 7.8, C4_ Restrictions on gathering one unit increase has a correlation with more than 3% decrease of daily death numbers. C6_ Stay at home and C8_ International travel restrictions has more than 2% decrease effect, economic policies have very little effect and significance level to the change of daily death numbers.

7.1.4. Death numbers and average indexes relationship

Before going into results for daily new cases numbers and policies, we can try to answer the question - how fast the government response was against the spread of pandemic? And can we find a correlation between single index and daily death numbers? To answer this, I will build one more model, where death233 variable will be dependent to only average of all indexes - Government response index, as it was shown in the table 6.2.

This model will look like this equation 7.5:

$$\log(death233) \approx \beta_0 + \beta_{GRI} GovernmentResponseIndex \tag{7.5}$$

Results are given in the table 7.9.

The significance level of government response index is quite high, so there can be relationship between him and daily death numbers. This correlation can be explained as reverse way - on average, 0.0263 log unit increase of death numbers triggered the government to increase one unit of its anti-coronavirus response. To better understanding, I will also find exponential of these coefficients and get 1.026718, or the speed of one unit increase of government response is corresponds to on average 2.67% increase of daily death numbers.

The same modeling and reasoning can be also done for other average indexes in the table 6.2. If I proceed until finding exponential values of those corresponding coefficient values, I get for stringency index - 1.050176, or 5.01% increase of death numbers; for containment and health index 1.044744, or 4.47% increase of death numbers for each unit increase of coefficient. From this I can conclude that government response was faster in all system policies all together rather than only containment or health system policies implementation.

Coefficients:	Estimate	Std. Error (SE)	z value	p value	95 % CI
β_0	6.9475	0.1540	45.093	< 2e-16 ***	(6.6622, 7.2607)
β_{C1}	0.0084	0.0031	2.719	0.00655 **	(0.0019, 0.0152)
β_{C2}	0.0372	0.0020	18.336	< 2e-16 ***	(0.0334, 0.0409)
β_{C3}	0.0192	0.0043	4.425	9.64e-06 ***	(0.0098, 0.0285)
β_{C4}	-0.0258	0.0017	-14.678	< 2e-16 ***	(-0.0291, -0.0227)
β_{C5}	-0.0220	0.0032	-6.688	2.26e-11 ***	(-0.0287, -0.0153)
β_{C6}	-0.0145	0.0025	-5.724	1.04e-08 ***	(-0.0197, -0.0094)
β_{C7}	0.0322	0.0022	14.033	< 2e-16 ***	(0.0279, 0.0366)
β_{C8}	-0.0273	0.0041	-6.621	3.58e-11 ***	(-0.0359, -0.0187)

*Table 7.10: Results for model in the equation 7.6. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

7.2. The results of linear regression analysis for daily new case numbers

To study a possible correlation between daily new cases and indexes in data, I will use the same models for cases (cases233). For reasons explained before, I will not consider the model that depends on just economic indexes. Other models will be listed in following sections.

7.2.1. New cases numbers in relation to containment and closure policies

The analysis of new cases numbers and possible correlations with government policies will start with containment and closure policies.

The model for containment and closure can be written as in equation 7.6:

$$\log(cases233) \approx \beta_0 + \beta_{C1}C1 + \beta_{C2}C2 + \beta_{C3}C3+ \\ + \beta_{C4}C4 + \beta_{C5}C5 + \beta_{C6}C6 + \beta_{C7}C7 + \beta_{C8}C8 \quad (7.6)$$

Results are shown in the table 7.10.

Discussion of results:

- All the variables here have high significance levels of importance, some policies have better correlation with log number of new cases;
- The coefficients cannot give exact number of saved people due to themselves, but they can insight about effectiveness of policies compared among themselves;
- This model shows that policies C4_ Restrictions on gatherings and C8_ International travel restrictions have the most negative correlations and high significance levels. This is very

Coefficients:	exp(Estimate)	exp(Lower limit)	exp(Upper limit)	
β_0	1040.5613	782.2412	1423.2728	***
β_{C1}	1.0085	1.0019	1.0153	**
β_{C2}	1.0379	1.0339	1.0418	***
β_{C3}	1.0194	1.0098	1.0289	***
β_{C4}	0.9745	0.9713	0.9776	***
β_{C5}	0.9782	0.9717	0.9848	***
β_{C6}	0.9855	0.9805	0.9907	***
β_{C7}	1.0328	1.0283	1.0373	***
β_{C8}	0.9730	0.9647	0.9814	***

*Table 7.11: Incident rate for model in the equation 7.6. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

similar to the death and containment indexes model case;

- Then, it is followed by the policy C6_ Stay at home, which also has quite high significance level. An increase of one unit for Stay at home policy has reduced -0.0145 of log value for dependent variable - daily new cases numbers;
- The policy C5_ Closure of public transport has negative value and high significance level, which is different from the death model case. In death model, public transport closure was not significant enough. It could be suggested that closure of public transport correlated with reduction of cases directly;
- And C7_ Restrictions on internal movement has a positive coefficient, that can be explained by the fact that when cases numbers reduced, government opened internal borders and model also represents reverse link between reduction of numbers and reduction of strictness of C7_ Restrictions on internal movement policy;
- The policy C2_ Workplace closing has a high significance and positive coefficient. It can be explained by the fact that in the spike of death numbers not all the works were shut down, numerous workplaces were labeled as an essential workplaces with essential workers;
- C1_ School closure has a less effect on cases numbers increase than other policies.

To understand better the effects of coefficients, I will look at the incident rate ratios of the coefficients and 95 % confidence interval values. To do this, I can use exponential function for the respective values, which are shown in the table 7.11.

As it shown in the table 7.11, one unit increase of C8_ International travel restrictions reduced more than 2.7% the daily death numbers. C4_ Restrictions on gathering has reduced more than

Coefficients:	Estimate	Std. Error (SE)	t value	p value	95 % CI
β_0	6.5048	0.2178	29.856	< 2e-16 ***	(6.0603, 6.9580)
β_{C1}	0.0112	0.0030	3.716	0.000203 ***	(0.0047, 0.0179)
β_{C2}	0.0366	0.0020	18.009	< 2e-16 ***	(0.0327, 0.0404)
β_{C3}	0.0131	0.0046	2.820	0.004798 **	(0.0023, 0.0240)
β_{C4}	-0.0262	0.0017	-14.578	< 2e-16 ***	(-0.0295, -0.0229)
β_{C5}	-0.0245	0.0033	-7.323	2.43e-13 ***	(-0.0317, -0.0174)
β_{C6}	-0.0173	0.0026	-6.591	4.38e-11 ***	(-0.0227, -0.0118)
β_{C7}	0.0349	0.0024	14.507	< 2e-16 ***	(0.0303, 0.0395)
β_{C8}	-0.0220	0.0047	-4.610	4.03e-06 ***	(-0.0327, -0.0112)
β_{H2}	0.0144	0.0043	3.344	0.000827 ***	(0.0053, 0.0240)
β_{H6}	-0.0093	0.0021	-4.259	2.06e-05 ***	(-0.0141, -0.0046)

*Table 7.12: Results for model in the equation 7.7. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

2.55% of death numbers.

At the same time, workplace closing did not increase the death numbers - one unit increase of C2_ Workplace closing policy was implemented in the average 3.79% daily increase of death numbers. And C1_ School closure did not led to very significant changes in death numbers, however its incident rate is slightly bigger than one by this model.

This table shows that first model can give us some insight into the efficiency if some policies in comparison with other containment policies. However, the model can be filled with more variables for the next sections. I should also have to look at containment policies with health system policies together to get more variables and data involved, which I will proceed doing it in the next model.

7.2.2. New cases numbers in relation to containment and closure policies with health system policies together

In this model, I take a look into two types of policies and the model for containment and health policies can be written as in equation 7.7:

$$\log(cases233) \approx \beta_0 + \beta_{C1}C1 + \beta_{C2}C2 + \beta_{C3}C3 + \beta_{C4}C4 + \beta_{C5}C5 + \\ + \beta_{C6}C6 + \beta_{C7}C7 + \beta_{C8}C8 + \beta_{H2}H2 + \beta_{H6}H6 \quad (7.7)$$

Results are shown in the table 7.12.

Discussion of results of this model:

- In this section we get more clear and explanatory model;

Coefficients:	exp(Estimate)	exp(Lower limit)	exp(Upper limit)	
β_0	668.3647	428.5229	1051.5303	***
β_{C1}	1.0113	1.0047	1.0181	***
β_{C2}	1.0373	1.0333	1.0412	***
β_{C3}	1.0133	1.0023	1.0243	**
β_{C4}	0.9741	0.9709	0.9773	***
β_{C5}	0.9757	0.9688	0.9827	***
β_{C6}	0.9828	0.9776	0.9882	***
β_{C7}	1.0355	1.0308	1.0403	***
β_{C8}	0.9782	0.9678	0.9888	***
β_{H2}	1.0146	1.0053	1.0243	***
β_{H6}	0.9907	0.9860	0.9954	***

*Table 7.13: Incident rates for model in the equation 7.7. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

- Almost all policies have very high significance levels, which is different from the model of death numbers;
- The policies that have the most negative numbers are those which already discussed in the previous model, like C4_ Restrictions on gatherings, C5_ Public transport closure, C8_ International travel restrictions and C6_ Stay at home policies. One unit increase of them decreased log value of new cases numbers by around 0.02-0.262;
- H6_ Facial coverings of health system policy has also negative value and high significance in our model. But it does not have as much value as it was in death model case. Each unit increase of facial covering strictness has decreased the log value of death numbers by 0.0093;
- First three policies have positive coefficients which only can be explained by reverse causal relationship: they were strictest in the peak of numbers, but by the time, they have been relaxed more than other policies, so that schools, workplaces and public events could be reopen, holding social distancing and facial mask rulings in place.

To understand better the effects of coefficients, I will look at the incident rate ratios of the coefficients and 95 % confidence interval values. To do this, I can use exponential function for the respective values, which are shown in the table 7.13.

Table 7.13 shows that three containment policies - C4_ Restrictions on gatherings, C5_ Public transport closure and C8_ International travel restrictions have the most downward impacts on daily death numbers: each unit increase of them decreases approximately 2.2-2.6 % of daily new cases numbers. Health system policy - H6_ Facial mask requirement also has slightly downward - each unit increase of it decreased 1% of daily new cases numbers. First three policies were the strictest in the increase of pandemic spread and they were relaxed before other containment policies - to continue to work, study in times of pandemics. Their unit increase has correlations with "increase" of new cases numbers - 1.13% , 3.73%, 1.33 % respectively.

Also, H2_ Testing policy shows interesting values: more tests - more daily new cases. Each unit increase of testing capacity policy has a correlation of 1.46 % increase of daily new cases, which is drastically new and different result compared to previous death model. Therefore, these effects of increase should be interpreted with care.

7.2.3. New cases numbers in relation with all coefficients

In the final model, I take a look into all types of policies - containment and closure, economic and health system policies. Even if I do not use explicitly H1_ Public In formation policy and H3_ Contact tracing policies in the model, because of their zero variance, - other policies of health system policies will be included in the final model.

The final model for can be written as in equation 7.8.

$$\log(cases233) \approx \beta_0 + \beta_{C1}C1 + \beta_{C2}C2 + \beta_{C3}C3 + \beta_{C4}C4 + \beta_{C5}C5 + \beta_{C6}C6 + \beta_{C7}C7 + \\ + \beta_{C8}C8 + \beta_{E1}E1 + \beta_{E2}E2 + \beta_{H2}H2 + \beta_{H6}H6 \quad (7.8)$$

Results are shown in the table 7.14.

Discussion of results of the final model:

- Almost all singular policies have significance levels, except for E2_ Income support policy;
- The unit increase of policy C1_ School closure has a correlation of 0.0107 unit log "increase" of daily new cases numbers. This positive correlation can be explained by the fact that schools were not closed completely, especially beginning and mid schools. Higher schools and universities were transferred to remote studies. As new cases dropped in August, schools were also open to face to face lessons;
- The policy C2_ Workplace closing has the most positive correlation with log cases number. It is related with the fact that essential jobs were not closed at all even in the peak times, not all jobs could be transferred to remote regime. And also, we can use reverse correlation - every decrease of 0.0354 log unit of cases numbers led to one unit decrease of strictness of workplace closures - more jobs and businesses were let to be opened;
- The policy C3_ Canceling public events has also positive correlation with log count number

Coefficients:	Estimate	Std. Error (SE)	z value	p value	95 % CI
β_0	6.6232	0.2130	31.092	< 2e-16 ***	(6.2044, 7.0503)
β_{C1}	0.0107	0.0029	3.684	0.000230 ***	(0.0045, 0.0171)
β_{C2}	0.0354	0.0019	17.809	< 2e-16 ***	(0.0315, 0.0391)
β_{C3}	0.0149	0.0045	3.256	0.001131 **	(0.0048, 0.0249)
β_{C4}	-0.0270	0.0032	-8.408	< 2e-16 ***	(-0.0324, -0.0217)
β_{C5}	-0.0216	0.0033	-6.485	8.86e-11 ***	(-0.0284, -0.0148)
β_{C6}	-0.0174	0.0025	-6.865	6.67e-12 ***	(-0.0225, -0.0122)
β_{C7}	0.0350	0.0029	11.938	< 2e-16 ***	(0.0297, 0.0404)
β_{C8}	-0.0298	0.0050	-5.964	2.46e-09 ***	(-0.0400, -0.0194)
β_{E1}	0.0125	0.0040	3.089	0.002006 **	(0.0060, 0.0187)
β_{E2}	-0.0015	0.0050	-0.307	0.758862	(-0.0097, 0.0064)
β_{H2}	0.0103	0.0043	2.394	0.016648 *	(0.0017, 0.0192)
β_{H6}	-0.0091	0.0025	-3.559	0.000373 ***	(-0.0141, -0.0043)

*Table 7.14: Results for model in the equation 7.8. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

of daily new cases. It also can be explained by reverse correlation - every 0.0149 unit of log decrease of cases number is related to one unit decrease of strictness of public event cancellation policy;

- C4_ Restrictions on gathering and C8_ International travel restrictions have the most negative correlation with log count of daily cases numbers. These policies have been implemented for a long time and one or another way are kept implementing unchanged, with no relation to actual peak changes of death numbers;

- The policy C6_ Stay at home has also great significance and every unit increase of this policy has a correlation with 0.0174 decrease of log unit of death numbers;

- C5_ Public transport closure has also negative correlation with log count even if public transport was never closed down completely because of not closing essential jobs and mid school levels;

- The policy C7_ Restrictions on internal movement has controversially high positive coefficients. From the modeling point of view, the efficiency of this policy should be carefully studied in broader sense. Because restrictions for short period of time had opposite effect on both cases and death numbers;

- The lowest significance levels have both economic policies. Their first policy shows positive correlation, because these policies were implemented during the peak numbers of death

Coefficients:	exp(Estimate)	exp(Lower limit)	exp(Upper limit)	
β_0	752.3561	494.9194	1153.1814	***
β_{C1}	1.0108	1.0045	1.0172	***
β_{C2}	1.0361	1.0320	1.0399	***
β_{C3}	1.0150	1.0048	1.0252	**
β_{C4}	0.9733	0.9681	0.9785	***
β_{C5}	0.9786	0.9720	0.9853	***
β_{C6}	0.9827	0.9777	0.9879	***
β_{C7}	1.0356	1.0301	1.0412	***
β_{C8}	0.9706	0.9608	0.9808	***
β_{E1}	1.0126	1.0060	1.0189	**
β_{E2}	0.9985	0.9903	1.0065	
β_{H2}	1.0104	1.0017	1.0194	*
β_{H6}	0.9909	0.9860	0.9957	***

*Table 7.15: Incident rates for model in the equation 7.8. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

toll and were less used later on;

- H2_ Testing policy of health system policies has a positive correlation, that was explained in the previous model;
- H6_ Facial coverings of health system policy was also one of the most significant policies to reduce death numbers. But in the cases model, it has very little downward effect. Each unit increase of facial coverings decrease for just 0.0091 log unit of daily death numbers.

To understand better the effects of coefficients, I will look at the incident rate ratios of the coefficients and 95 % confidence interval values. To do this, I can use exponential function for the respective values, which are shown in the table 7.15.

As we can see from table 7.15, C8_ International travel restrictions one unit increase has a correlation with almost 3% decrease of daily new cases. C5_ Public transport closure C6_ Stay at home and C4_ Restrictions on gathering has around 2% decrease effect, economic policies have very little effect and significance level to the change of daily new cases numbers.

7.2.4. New case numbers and average indexes relationship

And now I can try to answer the question - how fast the government response was against the spread of pandemic? And can we find a correlation between single index and daily new case numbers? To answer this, I will build one more model, where cases233 variable will be dependent to only average of all indexes - Government response index, as it was shown in the

Coefficients:	Estimate	Std. Error (SE)	z value	p value	95 % CI
β_0	7.2201	0.3700	19.514	< 2e-16 ***	(6.4241, 8.1625)
β_{GRI}	0.01900	0.00565	3.363	0.000771 ***	(0.0046, 0.0313)

*Table 7.16: Results for model in the equation 7.9. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

table 6.2.

This model will look like this equation 7.9:

$$\log(cases233) \approx \beta_0 + \beta_{GRI} GovernmentResponseIndex \tag{7.9}$$

Results are given in the table 7.16.

The significance level of government response index is quite high, so there can be relationship between him and daily new cases numbers. This correlation can be explained as reverse way - on average, 0.019 log unit increase of new cases numbers triggered the government to increase one unit of its anti-coronavirus response. To better understanding, I can also find exponential of these coefficients and I get 1.0191, or the speed of one unit increase of government response is corresponds to on average 1.91% increase of daily new cases numbers. To compare, for death model it was 2.67% increase of daily death numbers. The difference can be explained by two components: a) new cases increased faster than death numbers, b) the government based on its decisions about containment and health system policies mostly on cases numbers' evolution.

The same modeling and reasoning can be also done for other average indexes in the table 6.2. If I proceed until finding exponential values of those corresponding coefficient values, I get

- For stringency index = 1.000952, or 0.095% increase of new cases, but very low p value - new cases numbers do not have a direct correlation with stringency index;
- For containment and health index = 1.0231 , or 2.31% increase of new cases numbers for each unit increase of this coefficient.

From this I can conclude that government response was faster in all system policies all together rather than only containment or health system policies implementation also for new cases numbers as it was for daily death numbers.

CHAPTER 8

Conclusions

In this work, I tried to pursue following tasks:

- Taking the current state of numbers of COVID-19 and evolution of pandemic, and using D models and D' models, try to forecast the number of deaths from COVID-19 in Spain for recent future time (30-45 days);
- Secondly, taking the current numbers for deaths and daily new cases of COVID-19, elaborate on the effect of government responses through containment and closure policies, economic policies and health system policies on the evolution of pandemic in Spain;
- Try to give numeric quantity for government anti-pandemic response implementation speed.

As it was shown in Chapter 4, obtaining real data from official sources and elaborating on D and D' models, permit to semi-empirically choose the coefficients to formulate simple epidemiological models. Those models not only reflect the real situation with the daily and cumulative death numbers, but also let us to predict the near future numbers. As two models have different coefficients, the predicted numbers for the end of 2020 for Spain also differ and they have different efficiency compared to real official numbers, which were obtained later.

In both models, I have used only available data to choose coefficients, and more data I had, the more accurate would be the predictions. In any case, those predicted numbers can give us two extreme scenarios of a possible evolution of numbers in near future, and can be used for robust forecast future conditions - number of fatal cases, possible resources needed, guidance to implement stricter government anti-pandemic responses or release some restrictions to boost the economic activities in a society.

In chapter 7, I have shown many models of analysis for government response efficiency. More inclusive models were the ones with more policies' variables included for both daily death and daily new cases numbers.

The most efficient policy for reducing the numbers of deaths and new cases was C8_ International travel restrictions of containment and closure policies. Each unit increase of this policy decreased death and new cases daily numbers for 3.6 and 3 % respectively.

Other useful policies were C4_ Restrictions on gathering, C6_ Stay at home, C5_ Public transport closure policies for death number reducing. Their unit increases in strictness was correlated with 2-3% reduction of daily death numbers. For the model of daily new case numbers, first four most useful policies are the same, only the policy C5_ Public transport closure showed more efficiency in reducing cases numbers rather than death numbers.

Other containment policies were implemented in the time interval of rise of COVID-19 numbers and as soon as numbers were down, they were released in strictness. Or some other restrictions never were implemented in full strictness. Because of these aspects, some containment policies have shown positive correlation with daily death and new cases numbers; in order of increase they are C1_ School closure, C3_ Canceling public events and C7_ Restrictions on internal movement. It is worth to mention that the policy C7_ Restrictions on internal movement has a very low significance in relation with death numbers directly, whereas it has a higher significance level for new cases numbers.

The least strictly implemented policy from containment and closure policies was C2_ Workplace closing - in which case, essential job places were never closed, not all workplaces could be transferred to remote regime and hospitals themselves as workplaces with very importance were never affected by this policy. Results can be interpreted in a reverse way: workplaces were closed(or advised to restrict the number of stuff, remote work options if possible) only when the numbers were very high. As numbers were down, more and more workplaces were permitted to reopen.

Two of economic policies did not have any direct impact to daily death numbers. For the model of daily new cases, only E1_ Income support policy has shown enough significance level to be considered. However, the correlation can be explained in a reverse way: only when daily numbers for new cases were high, this policy was implemented and this resulted in a positive correlation number in incidence of new cases.

The H2_ Testing policy of health system response did not show any direct correlation for death numbers, at the same time it showed very logical and consequential correlation for daily new cases numbers: each unit increase of strictness of testing policy has resulted in +1.26% increase of daily new cases.

H6_ Facial coverings of health system policy was one of most important policies that government could implement. This policy had a high significance level for both death and daily new cases numbers and in both cases, it has negative correlation number: each unit increase in strictness of facial mask requirement policy decreased 1.8% of death numbers and approximately 1% of daily new case numbers.

Use of overall government response index versus dependent variables has shown that each unit increase of government response index had a correlation with +2.67% increase of death numbers and +1.91% increase of daily new cases numbers.

The results of models represent the relationship between each type policies and consequences of pandemic spread, and can give justifications and further improvements on government anti-pandemic responses. Some suggestions are:

- International travel restrictions play huge role in decreasing numbers, even if tourism will be affected the most. That's why inner tourism should be promoted with all precautions;
- Restrictions on gathering is the one of the most useful anti pandemic responses that can reduce both death and new case numbers as well as stay at home policies;
- Public transport should be carefully restricted as not all schools and workplaces are closed;
- Public events can be held only if previous policy rules can be implemented; however there should be strong incentive not to held large public gatherings;
- Workplaces should be correctly given an incentive to reduce physical interactions as much as possible;
- Economic policies do not have direct correlations with dependent variable, however, they are crucial in enhancing the population and businesses for the pandemic crisis times;
- Even if a strong testing policy increases the daily new number cases (if it works as intended - to find new cases), this health system policy is very crucial to find patients (especially with no symptoms) earlier so that they can be isolated as fast as possible;
- And finally, facial mask requirement is necessary to fight against spread of pandemic, and especially, is useful to reduce the number of deaths.

APPENDIX A

Extended calculations and proofs

A.1. D models formulas

I will start from equation (A.9):

$$\frac{dI}{dt} = \lambda(N-I)I$$
$$\frac{dI}{(N-I)I} = \lambda dt \tag{A.1}$$

For the simplification of a fraction in the left part of the equation I will use the method of unknown coefficients, with the help of which we can break down the expression into simpler ratios:

$$\frac{1}{(N-I)I} = \frac{\alpha}{N-I} + \frac{\beta}{I}$$

From which we get:

$$\alpha I + \beta N - \beta I = 1$$

$$\begin{cases} \alpha - \beta = 0 \\ \beta N = 1 \end{cases}$$

$$\begin{cases} \alpha = \dfrac{1}{N} \\ \beta = \dfrac{1}{N} \end{cases}$$

Putting these coefficients back to a equation (A.1), we get

$$\left(\frac{\frac{1}{N}}{N-I} + \frac{\frac{1}{N}}{I} \right) dI = \lambda dt$$

$$\left(\frac{1}{N-I} + \frac{1}{I} \right) dI = N\lambda dt$$

By integrating previous equation in the time interval $t \in [0;t]$ and taking into account $I(0) = I_0$, we get

$$\int_0^t \left(\frac{1}{N-I} + \frac{1}{I}\right) dI = \int_0^t N\lambda dt$$

$$(-\ln(N-I) + \ln I)\Big|_0^t = \ln \frac{I}{N-I}\Big|_0^t = N\lambda t\Big|_0^t$$

$$\ln \frac{I(t)}{N-I(t)} - \ln \frac{I_0}{N-I_0} = N\lambda(t-t_0)$$

$$\ln \frac{I(t)}{N-I(t)} = \ln \frac{I_0}{N-I_0} + N\lambda(t-t_0)$$

$$\exp\left(\ln \frac{I(t)}{N-I(t)}\right) = \exp\left(\ln \frac{I_0}{N-I_0} + N\lambda(t-t_0)\right)$$

$$\frac{I(t)}{N-I(t)} = \frac{I_0}{N-I_0} e^{N\lambda(t-t_0)}$$

$$I(t) = [N-I(t)] \cdot \left(\frac{I_0}{N-I_0} e^{N\lambda(t-t_0)}\right)$$

$$I(t)\left(1 + \frac{I_0}{N-I_0} e^{N\lambda(t-t_0)}\right) = N \cdot \left(\frac{I_0}{N-I_0} e^{N\lambda(t-t_0)}\right)$$

$$I(t) = \frac{N I_0 e^{N\lambda(t-t_0)}}{N - I_0 + I_0 e^{N\lambda(t-t_0)}}$$

$$I(t) = \frac{I_0 \cdot e^{N\lambda(t-t_0)}}{1 - \frac{I_0}{N} + \frac{I_0}{N} e^{N\lambda(t-t_0)}}$$

A.2. Mathematical formulation of SIR and D models

Here is given short explanations with formulations and calculations from the work of [Amaro et al., 2020] concerning D models.

It is consider only three states of population, with the total number of N and

- $S(t)$ - Susceptible individuals at any given time t;
- $I(t)$ - Infectious individuals at any given time t;
- $R(t)$ - Recovered individuals at any given time t

With this setting, the first equation can be obtained:

$$S(t) + I(t) + R(t) = N \tag{A.2}$$

Notice that N - number of population doesn't depend on the time, we accept the constant number for a time interval given.

Based on assumptions in [Kermack and McKendrick., 1927], which were about constant rate of spreading disease(at least in the beginning of the pandemics), I have another three set of ordinary differential equations that describes the SIR model:

$$\frac{dS}{dt} = -\lambda SI \tag{A.3}$$

$$\frac{dI}{dt} = \lambda SI - \beta I \tag{A.4}$$

$$\frac{dR}{dt} = \beta I \tag{A.5}$$

where

- $\lambda > 0$ - transmission or spreading rate. The higher the λ, the faster the increase of $I(t)$ and faster the decrease of susceptible individuals (minus sign in the equation A.3). λ also called "flattening the curve" coefficient - because the smaller it is, the smaller the overall number of infectious individuals;
- $\beta > 0$ - removal rate. The rate in which infectious individuals are recovering.

This system of differential can be solved, if only I am given initial boundary conditions and known coefficients of α, β. However, that is not the case for ongoing pandemics, where stochastic processes are occurring and those coefficients may change at any time. Nevertheless, these equations can be reduced, so that easier analysis can be performed. More advanced theories and calculations on exponential growth of infectious diseases can be found in the article by [Ma, 2020].

For the D model(D stands here for death), the main assumption will be

$$R(t) = 0$$

At the time being, this assumption can be considered at least for the beginning of the pandemic. As of now, we still do not have clear information about the antibodies durability and we had the second time infected patients, for the purpose of this study, I can assume that recovered patients will not have infinite defense from virus, and they will become again as a part o susceptible patients, making $R(t) \approx 0$.

If we put our assumption back to the equations (A.2),(A.4), (A.5), a simpler system of equations is obtained:

$$S(t) + I(t) = N \tag{A.6}$$

$$\frac{dS}{dt} = -\lambda SI \tag{A.7}$$

$$\frac{dI}{dt} = \lambda SI \tag{A.8}$$

From equations (A.6),(A.8), it is obtained:

$$\frac{dI}{dt} = \lambda(N - I)I \tag{A.9}$$

This is the first degree ordinary differential equation, which as shown in the Appendix (A.1), can be solved in he time interval $[0; t]$ and putting $I(0) = I_0$. Solving this equation gives

$$I(t) = \frac{I_0 \cdot e^{N\lambda(t-t_0)}}{1 - \frac{I_0}{N} + \frac{I_0}{N} e^{N\lambda(t-t_0)}} \tag{A.10}$$

Then, it is introduced the notions

$$C = \frac{I_0}{N} \text{ where } C \ll 1 \tag{A.11}$$

and

$$b = \frac{1}{N\lambda} \tag{A.12}$$

By inserting equations (A.11, A.12) into equation (A.10), we get simplified version of infectious individuals in some given time t:

$$I(t) = \frac{I_0 \cdot e^{\frac{t-t_0}{b}}}{1 + C \cdot e^{\frac{t-t_0}{b}}} \tag{A.13}$$

In order to predict the number of death D out of the infectious individuals, it is introduced the idea of death rate - $0 < \mu < 1$ and proportionality of the death numbers to the $I(t)$ but with some time lag τ. Because the death occurs after some τ time individual gets infected:

$$D(t) = \mu I(t - \tau)$$

Using equation (A.13), we obtain:

$$D(t) = \mu \cdot \frac{I_0 \cdot e^{(t-\tau-t_0)/b}}{1 + C \cdot e^{(t-\tau-t_0)/b}} \tag{A.14}$$

$$D(t) = \frac{\mu I_0 e^{(-\tau)/b} \cdot e^{(t-t_0)/b}}{1 + Ce^{(-\tau)/b} \cdot e^{(t-t_0)/b}} \tag{A.15}$$

For further simplification, all coefficients that do not depend on the time t, is simplified by introducing

$$a = \mu I_0 e^{(-\tau)/b} \tag{A.16}$$

and

$$c = Ce^{(-\tau)/b} = \frac{I_0}{N} \cdot e^{(-\tau)/b} \tag{A.17}$$

Putting a and c into equation(A.15) results in the **basic D model formula**:

$$D(t) = \frac{ae^{(t-t_0)/b}}{1 + ce^{(t-t_0)/b}} \tag{A.18}$$

The most useful side of the equation (A.18) is the possibility of choosing empirically the coefficients a, b, c to replicate the actual data. Other coefficients that were introduced until the reaching equation (A.18) are embedded in the defining formulas of a, b, c, so we do not really need to know beforehand all the conditions of pandemic initiation and development.

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