# Fighting the spread of Covid-19: was the Swiss lockdown worth it?*

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July 2021

**Abstract**

The implementation of lockdowns to control the Covid-19 pandemic has led to a strong economic and political debate. To shed light on the actual benefits of such policy, we focus on the Swiss lockdown during the first wave of infections and estimate the number of potentially saved lives. To predict the number of deaths in absence of restrictive measures, we develop a novel age-structured SIRDC model which accounts for age-specific endogenous behavioral responses and for seasonal patterns in the spread of the virus. Including the additional fatalities due to the potential shortage of healthcare resources, our estimates suggest that the lockdown prevented more than 11,200 deaths between March and the beginning of September 2020. Using the value of statistical life, we compute the corresponding monetary benefits, which exceed 32 billion francs (4.34% of the Swiss GDP) and are mainly concentrated among people older than 65.

**Keywords**: Covid-19; lockdown; benefit-cost; behavioral responses; intergenerational inequality.

**JEL codes**: H12; I18; D63; D91.

*We thank the Swiss Federal Office of Public Health (FOPH) for providing the data and Fabrizio Mazzonna, Marius Brülhart, Sara Rellstab, Paolo Campli and the participants to the USI Brown Bag Seminars for valuable feedbacks.

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# 1 Introduction

Since the end of 2019, all countries in the world have experienced a rapid spread of the Covid-19 epidemic, which has required the fast development of appropriate policy responses to face the increasing number of infections, hospitalizations and deaths. The majority of governments have therefore introduced different types of measures to reduce contacts among people. Such interventions have included bans on public events and gatherings of people, closures of national and regional borders, as well as school closures and the interruption of all non-essential business activities. However, these lockdown policies have been at the center of a heated debate, mainly due to their high economic and social costs.

A lockdown may have substantial negative effects on economic activities, leading to business disruption, job losses and earnings reductions, especially among younger generations. Recent surveys reveal that at least 42% of young people experienced a deterioration of their career prospects and serious income losses (ILO, 2020). Such detrimental consequences in terms of learning outcomes and disposable income are also reverberated in lower levels of wellbeing and worse mental health conditions (OECD, 2020b; Cutler and Summers, 2020). In light of these costs, which may even induce an exacerbation of intergenerational inequalities, a question might arise concerning the appropriateness of lockdown policies.

The first aim of this paper is to evaluate the monetary benefits of a lockdown in terms of saved lives. Given the high economic costs implied by this policy, a reliable estimate of benefits is crucial to understand whether its adoption is actually optimal (Gros, 2020). Since young generations shoulder most of the economic and social costs, our analysis also studies the distributional impact of lockdown policies, determining which groups of individuals benefit most from these measures. In order to address our research questions, we examine the lockdown adopted in Switzerland in response to the first wave of Covid-19 infections. To the best of our knowledge, the existing literature has not provided yet an estimate of the monetary benefits of the Swiss lockdown implemented in spring 2020.

Taking advantage of a unique dataset about the individuals who tested positive for the disease, we estimate the number of potentially saved lives by developing a novel SIRDC model. This model not only allows us to predict the number of daily infections and deaths for different age groups in absence of lockdown accounting for seasonal patterns characterizing the spread of the disease, but also to include age-specific endogenous behavioral responses (Cochrane, 2020). In particular, we assume that not only individuals respond to changes in the death rate of their age group, but they are also *altruistic* and care about the well-being of other subjects. A basic SIR model, instead, would lead to overstate the impact of the policy right because it does not consider that citizens spontaneously reduce their contacts even in absence of government interventions. To obtain a reliable estimate of saved lives, we also take into account potential *overflow* deaths due to hospital overcrowding. This is particularly relevant if we consider that the impossibility of providing proper hospital treatments, especially in intensive care units, results in a higher mortality risk also for younger subjects.

Our SIRDC model which incorporates endogenous behavioral responses suggests that the absence of any policy intervention in Switzerland would have resulted into approximately 11,500 deaths by September $1^{st}$, plus 1,500 additional casualties due to the lack of available beds in intensive care units. Relying on a basic SIR model, instead, we would have predicted roughly 65,000 deaths, plus 62,000 fatalities due to the limited availability of healthcare resources. Such results are in line with the simulations by the Imperial College Covid-19 Response Team. Neglecting hospital overcrowding, behavioral responses and seasonality, indeed, Flaxman et al. (2020) conclude that Switzerland would have reached 54,000 deaths by May $4^{th}$. The only reason why we estimate a higher amount of deaths by means of a basic SIR model is that we consider a time horizon which goes beyond May $4^{th}$, reaching the end of May, when the contagion finally fades out.

Exploiting the age group-specific value of statistical life (VSL), we compute the monetary benefits related to such avoided deaths. According to our SIRDC model, these benefits amount to at least 32 billion francs, a value which corresponds to 4.34% of the GDP and is actually likely to represent a *lower bound*. The VSL, indeed, tends to underestimate the willingness to pay of older individuals, namely the most vulnerable subjects who benefit from large reductions in risk (e.g., Viscusi, 2012; Colmer, 2020)[1]. Assuming that the VSL does not depreciate any more after age 65, benefits would exceed 11% of the GDP.

Comparing the results obtained from the SIR and SIRDC models, the former would clearly lead to a higher amount of monetary benefits as a result of more predicted

[1]The value of statistical life reflects the willingness to pay of a worker to achieve a *marginal* reduction in the probability of death. When considering old individuals, however, a lockdown may reduce their probability of dying from Covid-19 quite *substantially*.

deaths. However, in the SIRDC model the achievement of herd immunity in the counterfactual scenario turns out to be postponed by several months, as people self-regulate their behavior. The resulting period of uncertainty due to the fear of new waves of infections would make the economic consequences of the pandemic even more serious, with a further depression of labor market outcomes (ILO, 2020). Hence, in absence of containment measures, the monetary costs which would not be attributed to additional deaths in the SIRDC model might translate, at least partially, into the costs of a slower economic recovery.

Our work is related to a growing literature concerning the impact of the restrictive measures adopted to limit the spread of an epidemic, especially after the outbreak of Covid-19. For instance, Zhang et al. (2020) show that contacts among people were reduced by more than seven times in China thanks to physical distancing policies, while Fang et al. (2020) document that the lockdown in Wuhan reduced the number of potential infections by almost 65%. As far as the monetary benefits of saved lives are concerned, Greenstone and Nigam (2020) show that a mitigation policy would have saved up to 1.7 million lives over seven months in the US, which is worth more than one third of the American GDP (see also Thunström et al., 2020). However, their analysis relies on the simulations about the impact of containment measures on mortality and health care demand performed by Ferguson et al. (2020), who take advantage of limited early mortality data (Verity et al., 2020).

This work contributes to the current literature about the Covid-19 pandemic from both a methodological and an empirical point of view. First, we develop a novel age-structured SIRDC model that accounts for age-specific endogenous behavioral responses, including both an egoistic and an altruistic component. Second, we are able to provide reliable estimates of the severity of Covid-19 by exploiting rich data concerning the entire period of the first wave of infections in Switzerland. Indeed, the infection fatality rates estimated so far rely on early limited data and do not reflect properly the characteristics of the Swiss population. Third, to the best of our knowledge, this is the first estimate of the monetary benefits associated to the lives saved by the lockdown implemented in Switzerland in spring 2020. Our findings are also relevant from a policy perspective, as we document that such monetary benefits are actually substantial.

The rest of the paper is organized as follows. Section 2 introduces the Swiss context and the policies implemented in response to the epidemic during the first wave of the pandemic, between March and the beginning of September. Section 3 describes the data. Section 4 presents our model and the estimates of the potential number of deaths in absence of containment measures. Section 5 focuses on the *overflow* deaths due to hospital overcrowding. Section 6 discusses the monetary benefits of *lockdown* measures and their distributional consequences. Finally, Section 7 concludes.

## 2 Background

After the outbreak of the Covid-19 epidemic in China and in several European countries, at the end of February 2020 Switzerland started facing the spread of the virus, with an increasing number of infections. As a consequence, massive public health Non Pharmaceutical Interventions became the only viable strategy to limit the spread of the disease.

Switzerland is a Confederation made up of 26 independent and sovereign cantons, so interventions can be planned and implemented both at national and cantonal level. Indeed, some restrictive measures were already introduced, cancelling several public events, on February $26^{th}$ in the cantons at the border with Italy and France, where the first Covid-19 cases were reported.[2] Meanwhile, the first containment measure adopted at national level by the federal government on February $28^{th}$ was the banning of any event involving more than 1,000 participants.

However, because of the rapidly increasing number of infections throughout the country, the Swiss federal government intervened with more stringent measures. In particular, on March $17^{th}$ schools and non-essential economic activities were closed, while gatherings of more than five people were forbidden starting from March $20^{th}$. Nevertheless, differently from other countries like Italy, Switzerland did not opt for a *strict* lockdown, with the general requirement to stay at home.

The introduction of restrictive measures was not a straightforward decision. The implied economic losses, in fact, were expected to be severe also in a country like Switzerland, which exhibits one of the largest values of GDP per capita in the world[3] and an extremely high score regarding the *Human Development Index*[4]. However,

[2] The first Covid-19 case in Switzerland was reported on February $25^{th}$ in Ticino, the most southern canton at the border with Italy.

[3] See https://www.worldometers.info/gdp/gdp-per-capita and Section 3 for more details.

[4] This index is computed by the United Nations to measure the development of a country, not only in terms of economic growth, but also considering quality of life. More information is available at http://hdr.undp.org/en/countries/profiles/CHE

policy makers had the primary objective of trying to avoid an unsustainable burden in terms of infections and lost lives, a concern which was particularly reasonable considering that the Swiss population has increasingly aged over the last decades and more than 20% of people are older than 65, hence far more likely to develop serious illnesses or eventually die from Covid-19. In light of the limited availability of healthcare facilities, moreover, Switzerland, with its 3.6 hospital beds for acute care per 100,000 people[5], aimed at avoiding a scenario in which access to life-saving treatments would have been denied to patients in need.

After reaching a peak during the first half of April, the number of infections and, consequently, deaths started to exhibit a decreasing pattern. As a result, lockdown measures were progressively loosened. On April 27$^{th}$ several shops opened again, while schools restarted on May 11$^{th}$ and the activities in the majority of offices and facilities could take place again from June 8$^{th}$.

# 3 Data

Our analysis is based on individual-level data released by the *Federal Office of Public Health* (FOPH) about the universe of individuals who tested positive for Covid-19 in Switzerland between February 24$^{th}$ and May 15$^{th}$, during the first wave of the epidemic[6]. For each positive case in a specific Swiss canton on a certain day, this dataset contains information about age and gender, as well as the date of the onset of the first symptoms. Furthermore, these data also report whether and when an individual was hospitalized, specifying if intensive care was required and providing the exact days on which the patient entered and left the intensive care unit. Finally, we know whether and when the person eventually died. Table 1 summarizes these data.

In spite of relevant testing efforts, however, during the first wave of the pandemic asymptomatic cases were largely undetected. Because of the limited availability of resources, only people with severe symptoms were tested, in line with the criteria defined by the federal government. This is the reason why we derive information about seroprevalence from the study conducted in Geneva by Stringhini et al. (2020). In this way, it is possible to understand the extent to which younger subjects, who tend to be underrepresented in the official data, were actually affected by the spread of the disease.

[5] See `https://data.oecd.org/healtheqt/hospital-beds.htm` and Section 3 for more details.
[6] In addition, we exploit the number of deaths in each age group by the first week of September.

Table 1: DESCRIPTIVE STATISTICS BY AGE GROUP (BY MAY, $15^{th}$)

| | Age Groups | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 0–9 | 10–19 | 20–29 | 30–39 | 40–49 | 50–64 | 65–79 | 80+ | Total |
| **Positive Cases** | | | | | | | | | |
| Number of Cases | 153 | 862 | 3801 | 4106 | 4768 | 8318 | 4393 | 4059 | 30460 |
| Share of Total Cases | 0.50% | 2.83% | 12.48% | 13.48% | 15.65% | 27.31% | 14.42% | 13.33% | 100% |
| Share of Women | 47.02% | 58.58% | 59.73% | 57.20% | 57.19% | 50.29% | 44.81% | 60.70% | 54.30% |
| **Hospitalizations and ICU** | | | | | | | | | |
| Hospitalizations | 26 | 33 | 110 | 136 | 258 | 866 | 1275 | 1187 | 3891 |
| Hospitalizations/Cases | 16.99% | 3.83% | 2.89% | 3.31% | 5.41% | 10.41% | 29.02% | 29.24% | 12.77% |
| ICU | 1 | 1 | 5 | 15 | 27 | 132 | 239 | 78 | 498 |
| ICU/Cases | 0.65% | 0.12% | 0.13% | 0.36% | 0.57% | 1.59% | 5.44% | 1.92% | 1.63% |
| Average Days in ICU | - | - | - | 4.33 | 10.50 | 16.25 | 11.41 | 8.66 | 11.30 |
| **Deaths** | | | | | | | | | |
| Number of Deaths | 0 | 0 | 0 | 5 | 4 | 71 | 403 | 1112 | 1,595 |
| Deaths/Cases | 0.00% | 0.00% | 0.00% | 0.12% | 0.08% | 0.85% | 9.17% | 27.39% | 5.24% |
| Share of Women | 0.00% | 0.00% | 0.00% | 40.00% | 25.00% | 25.35% | 31.27% | 47.48% | 42.32% |

These data are complemented by the yearly cantonal statistics provided by the *Federal Statistical Office* about the population and the weekly number of deaths by age. The Federal Statistical Office is also the source for economic indicators, such as the annual Swiss GDP, and for the gender-specific value of life expectancy at different ages in the country. The average value of statistical life (VSL) for the Swiss population is derived from the estimates released by the Federal Office for Spatial Development (2019)[7]. However, we need to obtain an age-specific VSL and, according to the most advanced literature (Aldy and Viscusi, 2008), it should exhibit a hump-shaped relationship with age. Indeed, the VSL not only reflects life expectancy, but also other age-dependent characteristics including education and career prospects. Hence, after initially increasing with age, the VSL starts declining when the individual turns approximately 30. To compute an age-specific VSL that mirrors such characteristics, we rescale the estimates obtained by Murphy and Topel (2006) in the US by means of the Swiss average value[8]. The values for Switzerland are actually higher than those for the US, reflecting a generally higher quality of life.

As far as the healthcare supply in Switzerland is concerned, we rely on several sources. The *Organization for Economic Cooperation and Development* (OECD) provides indicators about the number of total and acute care hospital beds per 1,000 inhabitants, and the latest statistics available for Switzerland are for year 2018 (OECD, 2020a). We also refer to Rhodes et al. (2012), who estimated the number of intensive care beds in several European countries including Switzerland, expressing them as a percentage of total acute care beds. Besides, we rely on the information released by the *Swiss Society of Intensive Care Medicine* about the percentage of healthcare resources which could be exclusively allocated to Covid-19 patients. In order to derive the number of daily available beds, finally, we need statistics about the average length of stay in hospital and intensive care for Covid-19 patients. To this purpose, we exploit the FOPH dataset to compute the average number of days spent in ICU by these patients. In the case of individuals who were hospitalized but did not enter ICU, instead, FOPH data provide only the day of entrance, so we take advantage of the statistics available in Pellaud et al. (2020) about hospitalizations related to Covid-19 in Fribourg.

[7]The most updated value refers to year 2017 and amounts to 6.7 million Swiss francs. More information about the Swiss value of statistical life is provided by Ecoplan (2016).

[8]An alternative way to compute an age-specific VSL would be to multiply the average value of a life year lost (VYLY), which amounts to 222'000 Swiss francs (see Ecoplan, 2016, p. 46), by life expectancy. Such approach, however, would lead to a monotonically decreasing relationship between VSL and age, contradicting the studies mentioned above.

To estimate the number of overflow deaths due to hospital overcrowding, we finally need information about the mortality rates associated with being admitted to or rejected from hospital or ICU. While FOPH data allow to compute mortality rates for Covid-19 patients who received appropriate care, the corresponding estimates for rejected individuals will be taken from the literature (Greenstone and Nigam, 2020; Rojas, 2020), since Switzerland never faced the problem of overcrowded hospitals during the first wave of the pandemic.

## 4 An estimate of potential *direct* deaths

The present section describes our estimates of the potential number of avoided *direct* deaths thanks to containment measures in Switzerland. The term *"direct"* refers to the fact that these estimates do not include the additional potential deaths due to hospital overcrowding, which will be computed in the next section. We now proceed with the following steps. First, we focus on the initial phase of the epidemic, when the growth of infections was not influenced yet by any restriction, to determine the parameters which allow to predict the subsequent spread of the contagion in a counterfactual scenario without mitigation policies. Second, we develop a novel SIRDC model to estimate the potential number of infections and the corresponding deaths between March and the beginning of September. To this purpose, we use an age-specific *imputed* infection fatality rate derived from the data.[9]

However, before proceeding with our analysis, we need to address a preliminary issue, which requires an adjustment of the data. Indeed, older people, who are more likely to exhibit severe symptoms, tend to be over-represented, while younger (and often asymptomatic) cases are systematically under-reported. Therefore, the total number of predicted infections in the *counterfactual* scenario cannot be attributed to the different age groups on the basis of the shares retrieved from the original data.

To circumvent this issue, we exploit the results obtained by Stringhini et al. (2020) from the seroprevalence tests conducted in Geneva. They not only estimate the overall seroprevalence in the population in each of the five weeks between April $6^{th}$ and May $9^{th}$, but they also compute how the relative risk varies depending on age. After computing the average value of seroprevalence over the five weeks, using the

[9] In order to check the robustness of our results, we also estimate the age-specific infection fatality rate of Covid-19 using an alternative approach based on a Bayesian model (See Appendix B).

number of observations in each week as a weight, we exploit the specific relative risks to obtain the shares of people belonging to different age groups who have been actually infected in Geneva.

At this point, for each age group we compute the ratio between the actual share of infected people in Geneva and the corresponding share of infected individuals in our data. Such ratio represents an age group-specific factor $k_a$ measuring the extent to which each age group in the canton of Geneva is underrepresented in the data (see Table 2). Since testing criteria in Switzerland are defined centrally by the Federal Office of Public Health, it is reasonable to assume that the factor $k_a$ computed for Geneva can be applied to all the other cantons. Hence, after multiplying the number of reported cases in each age group by the corresponding adjustment factor $k_a$, the issue of over- or under-representation of different groups is overcome (Table 3).

Table 2: Adjustment Factors

| Age group | Estimated Seroprevalence | Adjustment Factor $k_a$ |
|---|---|---|
| 0–9 | 0.02808 | 44.908633 |
| 10–19 | 0.07546 | 30.858332 |
| 20–49 | 0.08774 | 7.7625095 |
| 50–64 | 0.06931 | 5.0841335 |
| 65+ | 0.04387 | 3.0066347 |

## 4.1 Estimating $R_0$ during the early stage of the epidemic

As a first step, we estimate the *basic reproduction number* ($R_0$) of the disease, which reveals the number of individuals who are infected by a single positive person during the initial phase of the epidemic[10], when the population consists almost exclusively of susceptible individuals and the cumulative number of cases grows exponentially until some containment measures are introduced (Muggeo et al., 2020; Daddi and Giavalisco, 2020; Massad et al., 2005).

The starting date of the epidemic is identified as the first day when an incidence of at least 20 cases of Covid-19 per 100,000 people is registered after the adjustment described above. The length of the initial phase, before any effect of containment measures, is computed by estimating when the linear growth of the *logarithm* of the cumulated number of infections changes slope. In practice, we estimate a *hockey*

[10]Note that, indeed, if $R_0 = 1$ the number of infected people remains constant, if $R_0 < 1$ the number of infected people decreases and if $R_0 > 1$ the number of infected people increases.

Table 3: DESCRIPTIVE STATISTICS BY AGE GROUP AFTER ADJUSTING THE DATA (BY MAY, $15^{th}$)

| | Age Groups | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 0–9 | 10–19 | 20–29 | 30–39 | 40–49 | 50–64 | 65–79 | 80+ | Total |
| **Positive Cases** | | | | | | | | | |
| Number of Cases | 6871 | 26507 | 29366 | 31733 | 36911 | 42203 | 13181 | 12189 | 198961 |
| Share of Total Cases | 3.45% | 13.32% | 14.76% | 15.95% | 18.55% | 21.21% | 6.63% | 6.13% | 100% |
| **Hospitalizations and ICU** | | | | | | | | | |
| Hospitalizations | 26 | 33 | 110 | 136 | 258 | 866 | 1275 | 1187 | 3891 |
| Hospitalizations/Cases | 0.38% | 0.12% | 0.37% | 0.43% | 0.70% | 2.05% | 9.67% | 9.74% | 1.96% |
| ICU | 1 | 1 | 5 | 15 | 27 | 132 | 239 | 78 | 498 |
| ICU/Cases | 0.01% | 0.00% | 0.02% | 0.05% | 0.07% | 0.31% | 1.81% | 0.64% | 0.25% |
| Average Days in ICU | - | - | - | 4.33 | 10.50 | 16.25 | 11.41 | 8.66 | 11.30 |
| **Deaths** | | | | | | | | | |
| Number of Deaths | 0 | 0 | 0 | 5 | 4 | 71 | 403 | 1112 | 1,595 |
| Deaths/Cases | 0.00% | 0.00% | 0.00% | 0.02% | 0.01% | 0.17% | 3.06% | 9.12% | 0.80% |
| Share of Women | 0.00% | 0.00% | 0.00% | 40.00% | 25.00% | 25.35% | 31.27% | 47.48% | 42.32% |

*stick* regression model that allows to identify the *breakpoint* at which the slope of this linear relationship changes[11], as also displayed in Figure 1:

$$log\mathbb{E}[Y_t] = \beta_0 + \beta_1 t \tag{1}$$

where $Y_t$ is the cumulative number of infections at day $t = 1, 2, ..., n$, after we have normalized the first day of the epidemic as day 1.

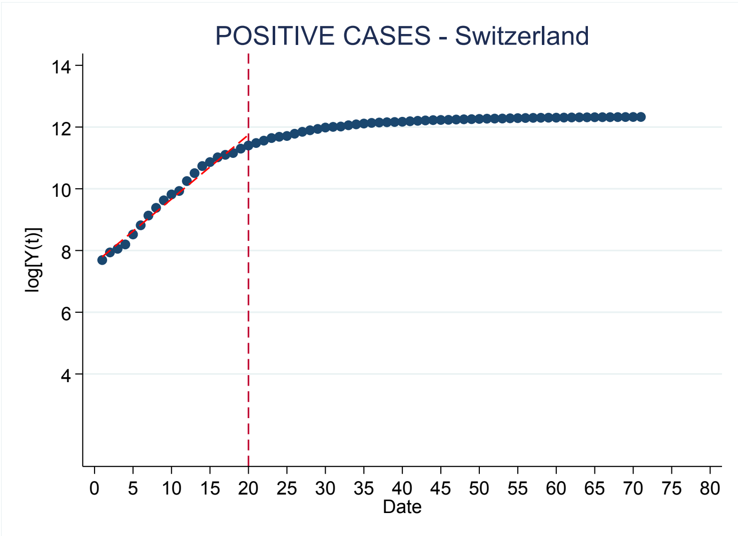



Figure 1: (Log) number of cumulative positive cases.

Table 4 reports the breakpoint dates estimated both for Switzerland and its seven macro-regions. Since the federal lockdown was announced on March $16^{th}$, its effects are expected to be observed at most ten days later, considering that the incubation period for Covid-19 amounts to 5 days and other 4.5 days pass on average between the onset of the first symptoms and the test. This timing is exactly reflected in our estimates, with an anticipated effect in French cantons and in Ticino, where some restrictive measures were introduced even earlier.

In light of the results obtained so far, it is finally possible to compute the value of $R_0$ using the following equation (Massad et al., 2005; Daddi and Giavalisco, 2020):

$$Y_b = Y_1 * e^{(R_0 - 1)\gamma t} \tag{2}$$

Here, $Y_b$ is the cumulative number of infections on the breakpoint date, $Y_1$ is the

[11]Indeed, if the cumulative number of infections grows exponentially during the early stage of the epidemic, the *log* of the cumulative number of infections exhibits a linear growth over time.

cumulative number of infections on the first day, while $\gamma$ represents the *resolving* rate, so that $\frac{1}{\gamma}$ is the average infectious period during which an individual can transmit the virus to others. Such period can be expected to be similar to the incubation period and, indeed, according to Almeshal et al. (2020), it amounts to 5.8 days. Exploiting this value, we derive the estimates of $R_0$ reported in Table 4. Given that the basic reproduction number $R_0$ is defined as the product between the contact rate $\beta$ and the average infectious period $1/\gamma$, we can finally retrieve the value of $\beta$, which captures how the infection is transferred.

Table 4: ESTIMATES OF $R_0$ DURING THE EARLY PHASE OF THE EPIDEMIC.

| Region | Starting Date | Breakpoint date | $R_0$ | $\beta$ |
|---|---|---|---|---|
| Lake Geneva | $6^{th}$ March | $23^{rd}$ March | 2.2939 | 0.3955 |
| Espace Mittelland | $6^{th}$ March | $26^{th}$ March | 1.9005 | 0.3277 |
| Northwestern Switzerland | $5^{th}$ March | $25^{th}$ March | 1.9528 | 0.3367 |
| Zurich | $8^{th}$ March | $24^{th}$ March | 2.1808 | 0.3760 |
| Eastern Switzerland | $7^{th}$ March | $24^{th}$ March | 2.0553 | 0.3544 |
| Central Switzerland | $5^{th}$ March | $25^{th}$ March | 1.8601 | 0.3207 |
| Ticino | $3^{rd}$ March | $22^{nd}$ March | 2.1577 | 0.3720 |
| **Switzerland** | $5^{th}$ **March** | $24^{th}$ **March** | **2.0859** | **0.3596** |

Table 4 reveals the existence of remarkable differences across Swiss regions in the intensity of the spread of the epidemic, which can also be explained by cultural heterogeneity (Mazzonna, 2020). A separate analysis of regions, however, would not allow to take into account the possibility that the contagion also spreads from one region to another, an aspect of key importance in a country where the degree of mobility is extremely high. Hence, in order to avoid underestimating the potential effects of lockdown measures, in the following sections of the paper we will rely on the number of infections and deaths estimated at the national level.

## 4.2 Imputed infection fatality rates

The most widely used measure for the severity of a disease is the infection fatality rate (IFR), which indicates the proportion of deaths among all infected individuals, including those who are asymptomatic or undiagnosed. After adjusting the data in light of seroprevalence results, we can actually estimate the whole number of cases in each age group. Hence, by taking the ratio between the number of reported deaths and the number of cases within each age group, we obtain an age group-specific *imputed* infection fatality rate $IFR_a$ for Covid-19[12]. These estimates will now be exploited to fit our model and derive the potential number of *direct* deaths in absence of restrictive measures.

## 4.3 Direct deaths in absence of restrictions

### 4.3.1 An age-structured SIRDC model with endogenous behaviors

The values of $R_0$ and $\beta$ determined above can be now exploited to fit a model which allows to simulate the spread of the Covid-19 epidemic in Switzerland in absence of any mitigation policy. In particular, our aim is to improve the estimates which could be derived from a basic SIR model (see Appendix A) by considering a more realistic counterfactual scenario in which people tend to reduce spontaneously their contacts also in absence of any government intervention. Furthermore, following Atkeson (2021), we are also including in the model an additional component which accounts for seasonal variation in the spread of the virus. Indeed, as documented by the epidemiological literature (e.g., Park et al., 2020), the transmissibility of the virus changes during the year, reaching a peak towards the end of January.

As far as the time horizon of our predictions is concerned, we focus on the 180 days between March $5^{th}$ and September $1^{st}$. Indeed, the present analysis is meant to estimate the benefits associated to the lockdown implemented in response to the first wave of infections. Moreover, such focus allows us to avoid a potential bias in our estimates arising from factors which changed after summer and led to the insurgence of the second wave of infections.

We start from a simple SIRDC model (Fernández-Villaverde and Jones, 2020), in which individuals can be in one of five possible states: Susceptible (S), Infectious (I), Resolving (R), Dead (D) and reCovered (C). Since we are interested in estimating how the number of potential infections and deaths varies with age, we distinguish eight age groups (i.e., 0–9; 10–19; 20–29; 30–39; 40–49; 50–64; 65–79; 80+)[13].

Excluding vital dynamics (i.e., neglecting births and deaths that are unrelated to the epidemic, see Rowthorn and Maciejowski, 2020) and taking into account that the contagion may spread also across age groups, the model is described by the

[12] The value of $IFR_a$ is null if no deaths are reported for age group $a$. The youngest individual who officially died from Covid-19 in Switzerland by May $15^{th}$ is aged 31.

[13] To implement this model, we have followed Deforche (2020), but identifying eight different age groups rather than only two. See Appendix A for more details.

following system of five ordinary differential equations:

$$\frac{dS_a}{dt} = -\frac{\beta_0 \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a \tag{3}$$

$$\frac{dI_a}{dt} = \frac{\beta_0 \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a - \gamma I_a \tag{4}$$

$$\frac{dR_a}{dt} = \gamma I_a - \theta R_a \tag{5}$$

$$\frac{dD_a}{dt} = \delta_a \theta R_a \tag{6}$$

$$\frac{dC_a}{dt} = (1 - \delta_a)\theta R_a \tag{7}$$

with $a$ indicating one of the eight age groups, $a \in \{1, ..., 8\}$. $N_a$ represents the total population belonging to a given age group, while $N$ represents the total population, which does not vary over time since vital dynamics are here neglected.

The number of subjects in each compartment varies over time, but the stock across the five states remains constant:

$$\sum_{a=1}^{8} S_a(t) + \sum_{a=1}^{8} I_a(t) + \sum_{a=1}^{8} R_a(t) + \sum_{a=1}^{8} D_a(t) + \sum_{a=1}^{8} C_a(t) = \sum_{a=1}^{8} N_a(t) = N(t) = N$$

The rate at which susceptible individuals in each age cohort $a$ become infectious is $-\frac{\beta_0 \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a = -\frac{\beta_0 IS}{N}$. Hence, it depends on the share of infections subjects in the total population, on the value of the contact rate $\beta_0$, which mirrors the speed of the transmission of the disease, and on the amount of individuals who are still susceptible. Infectiousness resolves at rate $\gamma$. Once individuals are no longer in the state in which they can infect others, they move to the resolving state. In each period $t$, then, a constant fraction of individuals ($\theta$) in every considered age group leaves the resolving compartment, ending in one of the two final stages: either dead (with probability $\delta_a$) or recovered (with probability $(1-\delta_a)$)[14]. These last two states are permanent, that is, once in them, people can no longer change compartment We set $\beta_0 = 0.3596$ and $\gamma = 0.1724$, while $\delta_a$ indicates age-specific mortality rates[15].

The system of differential equations can be recursively estimated to predict the daily number of people in each compartment. Since the analysis is performed at national level, the initial conditions are represented by the individuals in each age

[14] Note that this dynamics collapses to that of a basic SIR model if we aggregate $R_a$, $D_a$ and $C_a$.
[15] Age-specific mortality rates are the imputed IFRs described in Section 4.2.

group and compartment on March $5^{th}$ (see Appendix C). More in detail, the initial number of susceptible people in each age group is the number of individuals who had not been infected by March $5^{th}$. Since the infectious period $1/\gamma$ is assumed to be 5.8 days on average, the initial number of infectious individuals is represented by the number of new infections occurred during the 5.8 days before March $5^{th}$[16]. The initial number of people in the resolving state is given by all the subjects who were infected previously[17]. Only one person aged 72 had officially died from Covid-19 before March $5^{th}$, while no subjects had recovered yet on this date. Finally, dividing these values by the total population, we obtain the shares of individuals who initially belong to each age group and compartment[18].

At this point, following Cochrane (2020), we introduce in this framework an endogenous behavioral response common to all age groups. In other words, we suppose that when individuals start getting infected and dying, the contact rate $\beta$ becomes lower, as people try to avoid the disease. Hence, we model the behavioral response as a function of the current death rate, according to the following equation:

$$log(\beta_t) = log(\beta_0) - \alpha_D \frac{\Delta D_t}{N} \tag{8}$$

where $D_t = \sum_{a=1}^{8} D_{a,t}$ and $N = \sum_{a=1}^{8} N_a$.

We calibrate $\alpha_D$ as in Cochrane (2020). Using equation 8, we assign values to $\beta_0$, $\beta_t$, and $\Delta D_t$ to obtain the parameter $\alpha_D$, which measures people's sensitivity to changes in the death rates. $\beta_0$ is the baseline contact rate ($\beta_0 = 0.3596$), while $\beta_t$ is the lowest value of $\beta$ which is observed. Thus, the calculations based on our data reveal that $\beta_t = 0.173$[19]. The peak in the variation of the daily number of deaths in Switzerland is 25 deaths, so $\Delta D_t = 25$. Finally, $N$ is the total Swiss population in 2020. We recover $\alpha_D = 108697.16$.

However, we know that there is striking heterogeneity in mortality rates across age groups. If people's behavior is affected by their perceived personal risk, behavioral responses could greatly vary by age and imposing a common differential equation

[16] The initial number of infectious individuals on March $5^{th}$ includes the infections registered between March $1^{st}$ and March $5^{th}$, plus 80% of the infections occurred on February $29^{th}$.

[17] Hence, individuals infected before February $28^{th}$, plus 20% of those infected on February $29^{th}$.

[18] The adjustment based on seroprevalence results described before is meant to obtain reliable values at this stage of the analysis, avoiding an over-representation of older individuals.

[19] We recovered the lowest observed value for $\beta$ from $R_{0t}$. Indeed, we first estimate the daily value for $R_{0t}$, and we recover the corresponding $\beta_t$ from the relationship $R_{0t} = \frac{\beta_t}{\gamma}$

for $\beta$ could be an unrealistic assumption. Thus, we adapt the behavioral differential equation to introduce age-specific responses. We model the behavioral response of each age group as a function of both the death rate for that particular age group and a fraction of the death rates registered for the other age groups (introducing both an *egoistic* and an *altruistic* component).

First of all, we assume that individuals care to the maximum possible level (= 1) to the death rate of people belonging to their own age group, so we keep a one-to-one relationship between $\frac{d\beta_a}{dt}$ and $\frac{dD_a}{dt}$. Second, we assume that individuals are, at least partially, altruistic, and adjust their behavior also in response to changes in the death rates of other age groups. However, they weight other people's well-being less than their own, with an *altruism factor* equal to 0.27 (Long and Krause, 2017). Third, we assume that people do not give the same importance to the death rates of all the other age cohorts, but rather they adopt a societal perspective. In other words, individuals give more weight to the death rates of those age groups that have a higher value of statistical life. Therefore, if we consider the perspective of age cohorts $0-9$, $10-19$, $30-39$, $40-49$, $50-64$, $65-79$ and 80+, and we normalize their VSL by giving value 1 to the highest VSL (i.e., that of the age group $20-29$), we obtain the coefficients reported in column (1) of Table 5.

Table 5: Normalization: Coefficients for VSL by age group

| Age groups | Normalized coefficients<br>$20-29$ *reference group*<br>(1) | Normalized coefficients<br>$30-39$ *reference group*<br>(2) |
|---|---|---|
| 0 - 9 | $0.91261336 = \phi_{1,3}$ | $0.93025210 = \phi_{1,4}$ |
| 10 - 19 | $0.95136026 = \phi_{2,3}$ | $0.96974790 = \phi_{2,4}$ |
| 20 - 29 | $1 = \phi_{3,3}$ | - |
| 30 - 39 | $0.98103875 = \phi_{4,3}$ | $1 = \phi_{4,4}$ |
| 40 - 49 | $0.85572960 = \phi_{5,3}$ | $0.87226891 = \phi_{5,4}$ |
| 50 - 64 | $0.59356966 = \phi_{6,3}$ | $0.60504202 = \phi_{6,4}$ |
| 65 - 79 | $0.27287716 = \phi_{7,3}$ | $0.27815126 = \phi_{7,4}$ |
| 80 + | $0.09398186 = \phi_{8,3}$ | $0.09579832 = \phi_{8,4}$ |

When we adopt the perspective of individuals in group $20-29$, we have slightly different normalized coefficients, since, excluding the VSL of that group, the highest VSL becomes that of the cohort aged $30-39$. Normalizing it to 1, we obtain the coefficients displayed in column (2) of Table 5.

Following Atkeson (2021), we finally include in equation 8 a parameter $\psi(t)$ that captures seasonal patterns affecting the transmissibility of the virus:

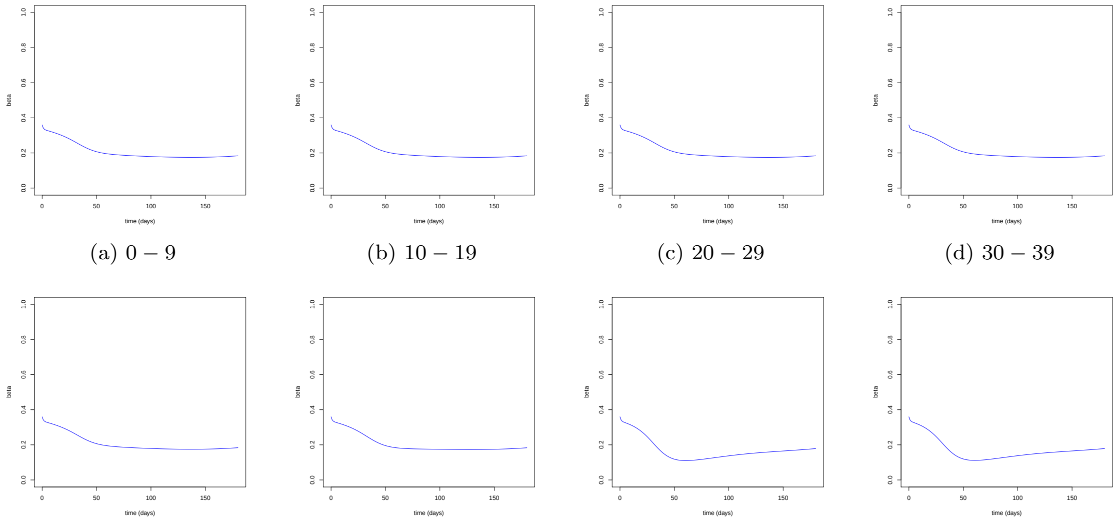
$$\psi(t) = \omega * (cos((t + \tau) * 2\pi/365) - 1)/2 \tag{9}$$

where $\omega$ measures the amplitude of seasonal fluctuations and is set equal to 1, while $\tau$ identifies the peak in the transmission of the virus on January, $31^{st}$, thus $\tau = 33$.

Putting everything together, we now have age-specific differential equations for the behavioral responses which can be included in the age-structured SIRDC model:

$$\frac{dS_a}{dt} = -\frac{\beta_a \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a$$
$$\frac{dI_a}{dt} = \frac{\beta_a \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a - \gamma I_a$$
$$\frac{dR_a}{dt} = \gamma I_a - \theta R_a$$
$$\frac{dD_a}{dt} = \delta_a \theta R_a$$
$$\frac{dC_a}{dt} = (1 - \delta_a)\theta R_a$$
$$\frac{d\beta_a}{dt} = \frac{\beta_0}{exp(\alpha_D * (\frac{dD_a}{dt} + 0.27 * (\sum_{i=1,i\neq a}^{8} \phi_{i,3} * \frac{dD_i}{dt})) - \psi)} - \beta_a \quad \text{for } a \in \{1,2,4,5,6,7,8\}$$
$$\frac{d\beta_a}{dt} = \frac{\beta_0}{exp(\alpha_D * (\frac{dD_a}{dt} + 0.27 * (\sum_{i=1,a\neq 3}^{8} \phi_{i,4} * \frac{dD_i}{dt})) - \psi)} - \beta_a \quad \text{for } a \in \{3\}$$

These equations imply an immediate reduction of contact rates for older individuals, while younger people tend to reduce their interactions more slowly since the death rate for their age group is low or even null. Figure 2 shows the evolution over time of the contact rates by age cohort. As before, $N$ is normalized to 1, so that $S_a$, $I_a$, $R_a$, $D_a$, $C_a$ represent the shares of population in each age group and compartment. As already mentioned, we consider a time horizon of 180 days. Therefore, instead of looking directly at the results for state $D_a$ on September $1^{st}$, direct deaths are obtained by applying the IFR to the cumulative number of infections predicted in each age group by that day. This allows to take into account the additional deaths which would have materialized in the first weeks of September. Figure 3 reports the evolution over time of the variables considered in our SIRDC model after aggregating the different age groups.



(a) 0 − 9 (b) 10 − 19 (c) 20 − 29 (d) 30 − 39

(e) 40 − 49 (f) 50 − 64 (g) 65 − 79 (h) 80+

Figure 2: Contact Rate by age group over time

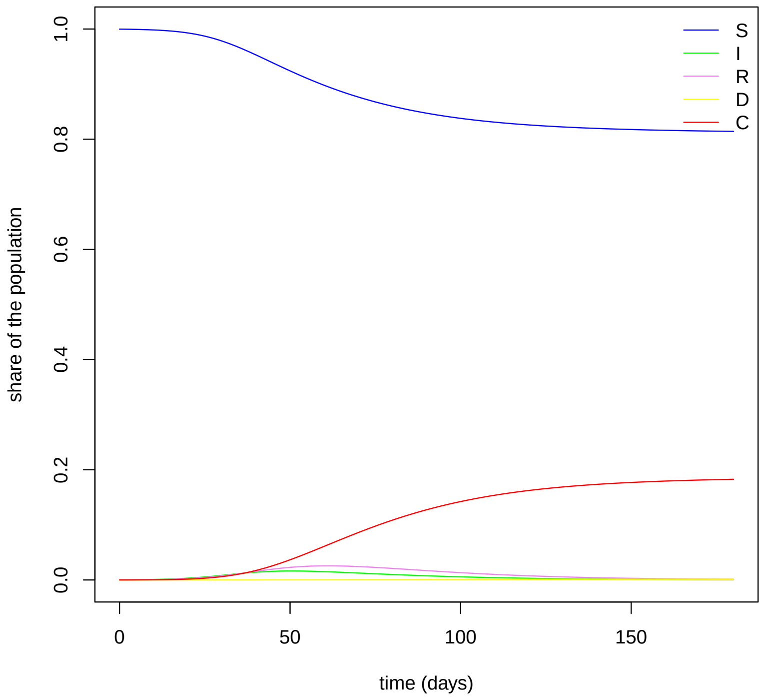



Figure 3: SIRDC model

### 4.3.2 Results

Table 6 shows our estimates of the potential number of *direct* deaths[20] in absence of restrictive measures.

Table 6: Direct deaths (infections until September, $1^{st}$)

| | | SIR Model | | | SIRDC Model | | |
|---|---|---|---|---|---|---|---|
| Age | Pop | Cases | $IFR_a$ | Deaths | Cases | $IFR_a$ | Deaths |
| 0–9 | 871,211 | 712,403 | 0.0000% | 0 | 172,233 | 0.0000% | 0 |
| 10–19 | 844,092 | 690,167 | 0.0000% | 0 | 166,857 | 0.0000% | 0 |
| 20–29 | 1,045,160 | 854,592 | 0.0000% | 0 | 206,098 | 0.0000% | 0 |
| 30–39 | 1,228,988 | 1,004,847 | 0.0158% | 159 | 242,444 | 0.0158% | 38 |
| 40–49 | 1,198,240 | 979,793 | 0.0108% | 106 | 236,544 | 0.0108% | 26 |
| 50–64 | 1,810,157 | 1,480,214 | 0.1682% | 2,490 | 345,460 | 0.1682% | 581 |
| 65–79 | 1,152,223 | 942,376 | 3.0574% | 28,812 | 162,498 | 3.0574% | 4,968 |
| 80+ | 453,828 | 371,150 | 9.1148% | 33,830 | 64,411 | 9.1148% | 5,871 |
| | 8,603,899 | 7,035,542 | | 65,397 | 1,596,545 | | 11,484 |

According to our SIRDC model which accounts for citizens' behavioral responses and for seasonal patterns, the spread of the virus in absence of any government intervention would have caused almost 11,500 deaths within six months from the beginning of the pandemic, especially among older age groups. Robustness evidence for these estimates will be presented in Appendix B, where we discuss an alternative approach to derive the infection fatality rates.

# 5 An estimate of potential *overflow* deaths

The present section is dedicated to estimate the overflow deaths which would have occurred in a counterfactual scenario without lockdown measures. These fatalities would have resulted from hospitals reaching their capacity and being unable to serve some Covid-19 patients. In order to estimate them, we first need to quantify daily demand for specialized healthcare and daily supply of acute care and intensive care beds in Switzerland. Second, we need to assign mortality probabilities for cases requiring hospitalization or intensive care, when appropriate care is provided or denied.

[20]Note that $IFR_a$ is null for the two of the three youngest age groups, as no deaths are reported in the official data. The youngest individual who has officially died because of Covid-19 in Switzerland is aged 31.

## 5.1 Healthcare demand

The SIRDC model presented in Section 4.3.1 (as the basic SIR model discussed in Appendix A) allows us to compute the daily number of new cases within each age group. On each day $t$, in fact, the share of new cases in age group $a$ can be computed as $NC_{a,t} = (I_{a,t} - I_{a,t-1}) + (R_{a,t} - R_{a,t-1}) + (D_{a,t} - D_{a,t-1}) + (C_{a,t} - C_{a,t-1})$ in the SIRDC model[21]. The actual number of cases is then obtained multiplying $NC_{a,t}$ by the total Swiss population. In order to derive the demand for healthcare services by Covid-19 patients, we exploit our data to compute the share of infected individuals within each age group who were hospitalized or needed intensive care treatment[22].

## 5.2 Healthcare supply

As the survival probability of Covid-19 patients depends crucially on the provision of specialized care, we need precise information about the total number of available hospital and ICU beds In Switzerland. According to the OECD, in 2018 there were 3.6 acute care hospital beds per $1,000$ inhabitants in the country. Considering the population in 2020, the stock of curative hospital beds over the entire country turns out to be about $30,982$ beds. According to Rhodes et al. (2012), then, 3.1% of these acute care beds are for intensive care, giving us a stock of 960 beds in Switzerland. This figure is in line with the estimate provided by the Swiss Society of Intensive Care Medicine, which set the stock between 950 and 1000 beds in the 82 intensive care units present on the Swiss territory. For the moment, we do not consider the possibility to improve health care supply, although there is some evidence that the total stock of ICU beds could be increased by 50%[23].

However, healthcare resources cannot be allocated only to Covid-19 patients and, indeed, before the spread of the virus, the daily average occupation rate of hospital and ICU beds was, respectively, 74% and 75%[24] [25]. We assume that 50% of the stock of acute care beds can be allocated to the treatment of Covid-19 patients and, following the Swiss Society of Intensive Care Medicine, we fix the available stock of ICU beds for individuals affected by Covid-19 at 56%.

[21]On each day $t$, the share of new cases in age group $a$ can be computed as $NC_{a,t} = (I_{a,t} - I_{a,t-1}) + (R_{a,t} - R_{a,t-1})$ in a basic SIR model.

[22]We distinguish between people needing a hospital bed, but not intensive care, on one side, and people needing intensive care on the other side.

[23]https://icumonitoring.ch/. Last checked: 10.11.2010

[24]https://www.bfs.admin.ch/bfs/it/home/statistiche/salute/rilevazioni/ms.html

[25]https://www.esicm.org/resources/coronavirus-public-health-emergency/

The daily availability of beds depends also on the length of stay in hospital and intensive care for the average patient. Hence, we exploit the data released by the FOPH to calculate the average number of days spent by a Covid-19 patient in ICU, obtaining an estimate of 11.3 days. Some of the individuals admitted to the ICU spend some time before in acute care beds, for an average of 1.9 days. We notice in the data that when the patients pass through the hospitalization phase before receiving intensive care, the date of the test assessing whether they have contracted the virus or not is subsequent to the hospitalization date. We can speculate that these 120 people are first admitted to the hospital and then moved to ICU once confirmed to be positive for Covid-19.

With regard to patients who do not need ICU, instead, we cannot apply the same procedure described above to obtain the figure for hospitalizations, since we know when an individual enters the hospital, but the exit date is not available in the dataset. Therefore, we rely on Pellaud et al. (2020), who calculate several metrics in a retrospective cohort study about 196 hospitalized individuals with confirmed cases of Covid-19 in the Fribourg area. The average length of stay for Covid-19 patients who require hospitalization but not intensive care is 7 days.

Finally, daily supply is obtained dividing the stock of hospital and ICU beds which could be allocated to Covid-19 patients by the respective length of stay, obtaining an estimate of $0.5 * \frac{(30{,}982-960)}{7} = 2144.43$ daily hospital beds and $0.56 * \frac{960}{11.3} = 47.58$ daily places available in ICU.

## 5.3 Mortality rates

In order to estimate the number of *overflow* deaths, then, we need mortality rates for the cases in which people are admitted or not to the hospital or ICU. The individual data released by the FOPH also allow us to calculate the probability of death when patients receive appropriate care: indeed, the problem of overcrowding was never faced by Switzerland over the period covered by these data. In light of these data, the probability of dying for admitted patients is 17.9% in case of hospitalization and 52% in case of intensive care. These results are in line with those presented in international literature (Rojas, 2020; Greenstone and Nigam, 2020).

Since we cannot directly calculate the corresponding probabilities when the demand for healthcare cannot be accommodated, we follow Rojas (2020), who assumes that mortality increases threefold when a patient is rejected from a hospital (i.e., 53.7%

in Switzerland). For ICU cases, we assume a survival probability of 10%, which is derived from the existing literature (Greenstone and Nigam, 2020; Ferguson et al., 2020). It is worth remarking that such assumptions imply that the mortality rates do not change depending on the age of the potential patient. This situation leads to a considerable number of overflow deaths also among younger people, explaining why these overflow deaths, compared to direct ones, are significantly higher in those categories. However, we do expect that reached a certain level of criticality, even younger people will face a significant risk of dying if left without proper healthcare interventions.

## 5.4 Overflow deaths

Exploiting the daily demand and supply of hospital beds computed above, we can now predict the daily number of deaths due to the shortage of healthcare resources. More in detail, on days when $demand \leq supply$, all people in need can receive appropriate care, and, therefore, survival probabilities are those estimated using FOPH data. When, instead, $demand > supply$ and facilities reach their capacity (Greenstone and Nigam, 2020), for the individuals who do not receive healthcare we apply the mortality probabilities of 53.7% and 90% for hospitalization and intensive care respectively.

Following the literature, we assume that age does not affect the probability of being rejected or admitted to healthcare facilities. In other words, the share of patients in each age group who do not receive appropriate care stays constant. For instance, if 20% of the cumulative number of patients cannot obtain a hospital bed on day $t$, that day 20% of patients belonging each age group are assumed not to have received the needed care. We obtain the total number of overflow deaths over the considered time period by summing up across all days.

As reported in Table 7, our SIRDC model allows to predict slightly more than 1,500 overflow deaths by September $1^{st}$, all imputable to overcrowded ICUs. Such estimate is significantly lower in comparison to the one obtained by means of a basic SIR model. Endogenous individual responses and seasonal patterns, in fact, lead to a slower spread of the virus, flattening the number of new cases. As a result, since the fraction of new cases requiring hospitalization or intensive care remains constant, hospitals avoid reaching their maximum capacity.

Table 7: OVERFLOW DEATHS (INFECTIONS UNTIL SEPTEMBER, $1^{st}$)

| | SIR Model | | | SIRDC Model | | |
|---|---|---|---|---|---|---|
| Age | Hospital | ICU | Total | Hospital | ICU | Total |
| 0 - 9 | 772 | 256 | 1,028 | 0 | 19 | 19 |
| 10 - 19 | 140 | 57 | 197 | 0 | 4 | 4 |
| 20 - 29 | 799 | 194 | 993 | 0 | 14 | 14 |
| 30 - 39 | 967 | 669 | 1,636 | 0 | 49 | 49 |
| 40 - 49 | 1,549 | 889 | 2,438 | 0 | 66 | 66 |
| 50 - 64 | 2,856 | 4,743 | 7,599 | 0 | 336 | 336 |
| 65 - 79 | 16,083 | 17,888 | 33,971 | 0 | 858 | 858 |
| 80 + | 10,729 | 3,680 | 14,409 | 0 | 178 | 178 |
| Total | 33,895 | 28,376 | 62,271 | 0 | 1,524 | 1,524 |

# 6 The monetary benefits of lockdown measures

Having estimated the potential number of deaths in absence of any policy measure, it is now possible to derive the monetary value associated to these saved lives. To this purpose, we rely on the age-specific values of statistical life (VSL) computed by Murphy and Topel (2006) for American individuals and we rescale them on the basis of the Swiss average VSL (cfr. Section 3). These age-specific values are then aggregated into age groups by computing their weighted average, using the values of the resident population by age as weights.

As reported in Table 8, we compute the potential excess deaths by subtracting the actual registered deaths from the total predicted fatalities within each age group[26]. This number of saved lives is then multiplied by the corresponding VSL.

According to our SIRDC model, the monetary benefits associated to the lives saved thanks to the lockdown implemented in Switzerland amount to approximately 32 billion francs, namely 4.34% of the GDP in 2019[27]. However, this value is likely to represent a *lower bound* for the actual benefits, which can be expected to be higher after considering some factors leading to an underestimation.

[26] The imputed IFR used to predict the direct number of deaths in the first age group (0–9) is null (see Table 6) because no deaths were registered in our daily data by May $15^{th}$. However, we are now considering the cumulative number of fatalities until the first week of September $1^{st}$ and there is one casualty which occurred later in that age group.

[27] The value of the Swiss GDP in 2019 at current prices amounts to 726,921 millions of Swiss francs (https://www.bfs.admin.ch/bfs/en/home/statistics/national-economy/national-accounts/gross-domestic-product.html.)

Table 8: MONETARY BENEFITS OF LOCKDOWN (BY SEPTEMBER, $1^{st}$)

| | | | SIR Model | | SIRDC Model | |
|---|---|---|---|---|---|---|
| Age | Actual Deaths | VSL *(mln. CHF)* | Excess Deaths | Benefits *(bln. CHF)* | Excess Deaths | Benefits *(bln. CHF)* |
| 0–9 | 1 | 11.07 | 1,027 | 11.3689 | 18 | 0.1993 |
| 10–19 | 0 | 11.54 | 197 | 2.2734 | 4 | 0.0462 |
| 20–29 | 0 | 12.13 | 993 | 12.0451 | 14 | 0.1698 |
| 30–39 | 5 | 11.90 | 1,790 | 21.3010 | 82 | 0.9758 |
| 40–49 | 6 | 10.38 | 2,538 | 26.3444 | 86 | 0.8927 |
| 50–64 | 90 | 7.20 | 9,999 | 71.9928 | 827 | 5.9544 |
| 65–79 | 455 | 3.31 | 62,328 | 206.3057 | 5,371 | 17.7780 |
| 80+ | 1,215 | 1.14 | 47,024 | 53.6074 | 4,834 | 5.5108 |
| | 1,772 | | 125,896 | 405.2387 | 11,236 | 31.5270 |

A first reason why benefits are expected to be larger is related to the limitations implied by the value of statistical life. As documented by Colmer (2020), indeed, the VSL underestimates the real willingness to pay of older individuals to reduce the mortality related to Covid-19. On one side, in fact, the VSL reflects *marginal* reductions in the risk of dying, while in this context the reduction in the mortality risk is bigger. In addition, older individuals, who are not only the most vulnerable ones, but also those with more economic resources available, are likely to exhibit a willingness to pay which is much higher than that reflected by their VSL, whose value depreciates over time because of the progressive reductions in life expectancy.

In order to speculate about the magnitude of the potential downward bias induced by such questionable depreciation of the VSL, we verify how our estimates would change if the VSL did not decrease any more after age 65, remaining constant at 7.2 million francs. In this case, the overall benefits would reach 82 billion francs[28], which correspond to more than 11% of the GDP. It is worth underlining here that benefits should even include further aspects which go beyond the number of saved lives. For instance, avoiding hospital overcrowding allows to improve the quality of health care also for patients with issues unrelated to Covid-19.

Furthermore, when people self-regulate their behaviors in response to the reported number of cases and deaths, herd immunity is postponed by several months or even years in the counterfactual scenario, with detrimental effects on economic activities.

[28] Benefits for age groups 65-79 and 80+ increase to, respectively, 38.6712 and 34.8048 bln. CHF.

In a context dominated by the uncertainty due to the fear of new waves of infections, in fact, the economic consequences of the pandemic become more serious, with a further depression of labor market outcomes (ILO, 2020). Hence, the monetary costs which would not be attributed any more to additional deaths might translate, at least partially, into the costs of a slower economic recovery.

In light of all these considerations, the estimates derived from a basic SIR model, which are likely to suffer from an upward bias, may represent an *upper bound* for the overall monetary benefits of lockdown measures. According to these estimates, benefits may reach 405 billion Swiss francs, which correspond to 56% of the value of the Swiss GDP in 2019.

Our results also show that older age groups are those taking more advantage from the lockdown. Approximately 74% of the monetary benefits, in fact, can be attributed to individuals older than 65. However, benefits are not negligible also for younger age groups, especially for people aged 50-64.

In order to confirm the reliability of our estimates, we finally perform a further sensitivity check by computing the monetary benefits by means of an alternative measure of the value of statistical life. We obtain it by multiplying the age-specific value of life expectancy and the the average value of one life year lost (see Section 3)[29]. This alternative approach leads to a monotonically decreasing relationship between the VSL and age, since the VSL depends only on life expectancy. Interestingly, the monetary benefits of the lockdown do not vary substantially when we attribute this new VSL to the lives saved according to our SIRDC model. Indeed, benefits amount to roughly 37 billion Swiss francs, namely 5.13% of the Swiss GDP in 2019.

# 7 Conclusions

The introduction of lockdown measures to limit the spread of the Covid-19 pandemic has been at the center of a heated economic and political debate in the majority of countries worldwide. These policies, in fact, while preventing several deaths, are often claimed to be responsible for economic losses which may compromise the stability of a country. This is the reason why several studies have attempted an evaluation of the benefits associated to the measures adopted to face the epidemic.

[29] In this case, the VSL for the different age groups amounts to 17.93 (0–9), 15.82 (10–19), 13.58 (20–29), 11.45 (30–39), 9.28 (40–49), 6.76 (50–64), 3.91 (65–79) and 1.73 million CHF (80+).

The present research is meant to shed light on the monetary benefits of the lockdown implemented in Switzerland to deal with the first wave of infections. Our results suggest that an uncontrolled spread of the disease would have implied a large cost in terms of lost lives, also because of the limited availability of healthcare resources. After quantifying the monetary benefits of lockdown measures, we also draw the attention on their distributional impact. Benefits, in fact, tend to be remarkably concentrated among elderly individuals.

Exploiting a rich dataset concerning the universe of positive cases in Switzerland, we have predicted the evolution of the epidemic in absence of restrictive policies. To this purpose, we have fitted a SIRDC model which incorporates both individual endogenous behavioral responses and seasonal patterns in the spread of the virus. According to our estimates, the absence of any policy intervention in Switzerland would have led to approximately 11,500 *direct* deaths and 1,500 *overflow* fatalities due to hospital overcrowding within six months from the beginning of the pandemic. The corresponding monetary benefits turn out to exceed at least 32 billion CHF, namely 4.4% of the Swiss GDP in 2019. This value is quite substantial, especially considering that benefits are estimated over the first six months after the beginning of the pandemic, a limited time horizon that includes the summer months, when the transmissibility of the virus lowers drastically. This value is likely to represent a lower bound for the overall benefits even because the VSL is likely to underestimate the willingness to pay of old individuals to achieve a reduction in their probability of dying from Covid-19.

Finally, our results are also relevant from a policy perspective. Indeed, they show that lockdown measures are crucial to deal with the spread of a pandemic like the Covid-19 one. For instance, during the second wave of infections in autumn 2020, Switzerland implemented a series of sectoral restrictive measures, avoiding a new lockdown until January 2021. This may contribute to explain why more than 6,000 deaths were registered between October and December, whereas the first wave of infections led to roughly 1,800 deaths.

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# A An age-structured SIR model

The values of $R_0$ and $\beta$ determined in Section 4.1 can be exploited to fit a *susceptible-infected-recovered* (SIR) model which allows to simulate the evolution of the spread of the epidemic in Switzerland if containment measures had not been implemented. Since we are interested in estimating the number of potential infections which would have occurred in each age group, we build an age-structured SIR model following Deforche (2020), but letting the age groups be eight (i.e., 0–9; 10–19; 20–29; 30–39; 40–49; 50–64; 65–79; 80+) rather than only two.

According to this model, which allows contacts between all age groups $a$, at any time each individual can be either Susceptible (S), Infectious (I) or Recovered (R). The last compartment not only includes those subjects who are not infectious any more, but also those who died because of the disease. Excluding vital dynamics (i.e., neglecting births and deaths that are unrelated to the epidemic, see Rowthorn and Maciejowski, 2020), the model is described by the following system of ordinary differential equations:

$$\frac{dS_a}{dt} = -\frac{\beta_0 \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a \tag{10}$$

$$\frac{dI_a}{dt} = \frac{\beta_0 \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a - \gamma I_a \qquad \text{for } a \in \{1, ..., 8\} \tag{11}$$

$$\frac{dR_a}{dt} = \gamma I_a \tag{12}$$

The rate at which susceptible individuals in each age group $a$ become infectious $\left(\frac{\beta_0 \sum_{a=1}^{8} I_a}{\sum_{a=1}^{8} N_a} * S_a\right)$ depends on the share of infectious subjects in the total population, on the value of the contact rate $\beta_0$, which mirrors the speed of the transmission of the disease, and on the remaining stock of susceptible individuals.

As previously mentioned, $\gamma$ represents the rate at which infectiousness resolves: individuals who are no longer infectious move to the resolving state and cannot change compartment any more (Eksin et al., 2019; Toxvaerd, 2020). At each point in time, the cumulative stock of individuals across states remains constant: $\sum_{a=1}^{8}(S_a + I_a + R_a) = \sum_{a=1}^{8} N_a = N$, where $N$ is the total population. Normalizing $N$ to 1, $S_a$, $I_a$ and $R_a$ are interpreted as the shares of the population belonging to each compartment.

At this point, the system of differential equations can be recursively estimated to predict the daily number of people in each compartment after the beginning of the epidemic. Since the analysis is performed at national level, the initial conditions are represented by the individuals in each age group and compartment on March $5^{th}$. We exploit the values of $\beta_0$ and $\gamma$ discussed before ($\beta_0 = 0.3596$; $\gamma = 0.1724$ ).

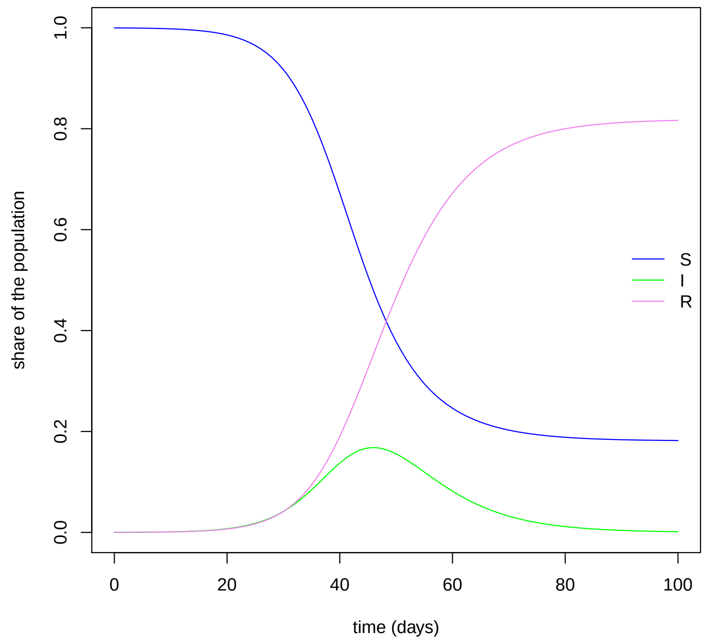


Figure A.1: SIR MODEL

Figure A.1 plots the evolution over time of the predicted share of individuals who belong to each compartment when age groups are aggregated. It is interesting to observe that, when herd immunity is reached[30], the epidemic continues to spread at a slower rate, since each person infects less than one other person. Thanks to this model, therefore, we can estimate the total number of infected people by the end of the pandemic, who correspond to the amount of people in state $R$ when the number of susceptible individuals does not decrease any more and nobody else contracts the disease[31]. At this point, having predicted the total number of infections in each age group, the corresponding number of potential deaths can be derived through the infection fatality rate computed from the data.

[30] Herd immunity is reached 46 days after March $5^{th}$, i.e., on April $20^{th}$.

[31] Quite reassuringly, it is also possible to observe that the cumulated number of infections predicted by the model during the first days after March $5^{th}$, when containment measures were not in place yet, are actually in line with those observed in the data.

# B An alternative estimate of the IFR

Considering that several approaches have been proposed so far in the literature to estimate the infection fatality rate of Covid-19, we now back up the imputed IFR discussed in Section 4.2 by estimating the severity of the disease with an alternative methodology. More specifically, we follow the approach proposed by Rinaldi and Paradisi (2020), which relies on the use of administrative data concerning death counts and demographic information.

A potential concern regarding the *imputed* IFR reported in Table 6, indeed, is represented by the fact that official data about Covid-19 cases may misrepresent the actual number of deaths related to the spread of the virus. FOPH deaths data may present a downward bias because people might die at home (because of Covid-19) or in other non-medical facilities, and remain untested. This situation can be present if individuals decide not to go to the hospital, or they are not in a position to go. At the same time, official Covid-19 deaths data can present un upward bias since a fractions of those who died because of the pandemic where already severely-ill individuals, who might have died over the following few weeks or months without the virus. Thus, Covid-19 has simply slighly anticipated their death.

In the attempt to correct for these biases, we use weekly administrative data about the deaths recorded between 2000 and 2020[32] by the Federal Statistical Office, which also provides demographic information at cantonal level[33]. We then elaborate these data to identify eight age groups (0–9; 10–19; 20–29; 30–39; 40–49; 50-64; 65–79; 80+) in the seven major Swiss regions (Lake Geneva, Espace Mittelland, North-West Switzerland, Zurich Region, Eastern Switzerland, Central Switzerland and Ticino).

Exploiting such information, we build a Bayesian model which fits age-stratified mortality and demographic data for the seven regions between 2000 and 2020 over the weeks 11-19, namely those characterized by the Covid-19 outbreak. Specifically, starting from a simple standard binomial mortality mode, we assume that deaths are binomially distributed and in weeks affected by Covid-19 the baseline lethality rate is augmented by a factor that indicates the interaction between the IFR and the infection rate of Covid-19. Further, we assume that mortality is not correlated between different age groups. The model is described with the following binomial

[32]Data provide information about gender, age-group (5 years bin) and cantonal residence.
[33]Data provide information on the total population, by gender and age.

equations:

$$D_{i,a,y} \sim \text{Binomial}(\delta_a,\ N_{i,a,y}) \qquad \text{for } y \in \{2000, ..., 2019\} \tag{13}$$

$$D_{i,a,2020} \sim \text{Binomial}(\delta_a + \delta_a^{Covid} * \theta_i,\ N_{i,a,2020}) \tag{14}$$

where $i$ denotes the macro-region, $y$ the year, and $a$ one of the eight age groups $(0-9; 10-19; 20-29; 30-39; 40-49; 50-64; 65-79; 80+)$. $D_{i,a,y}$ and $N_{i,a,y}$ are, respectively, the total deaths and population in macro-region $i$, year $y$, and age range $a$.
The baseline lethality rates $\delta_a$ are assumed to be constant across macro-regions and years, but can vary across age groups. Before 2020, the infection fatality rates $\delta_a^{Covid}$ are assumed to be equal to zero, while in 2020, they are heterogenous across age ranges and fixed in the other dimensions. Finally, the infection rates $\theta_i$ are region-specific but constant across age groups.

The identifying assumption is that in the absence of the Covid-19 outbreak, the weekly deaths recorded in 2020 would have been the same on average as the ones in the previous twenty years. We provide visual evidence (Figure B.1) about the extent to which this assumption is satisfied. Indeed, over the first 10 weeks of 2020, excess mortality (calculated as the number of deaths in 2020 versus the average value of deaths over the years between 2000 - 2019) is substantially null. However, we can not check whether the composition of the typologies of deaths changes over time and particularly in 2020, given that statistics on the causes of deaths are not available.

Using Markov Chain Monte Carlo procedures, we estimate an overall Infection Fatality Ratio for Covid-19 of 1.087123% (95% confidence interval 0.2899833% – 2.038417%), with striking heterogeneity across age groups (see Table B.1).

As required with a Bayesian model, we specify priors for all the parameters we are interested in monitoring, i.e., $\delta_a, \delta_a^{Covid}, \theta_i$. We choose uninformative priors for all parameters:

$$\delta_a \sim \text{Uniform}[0,\ 0.1] \tag{15}$$

$$\delta_a^{Covid} \sim \text{Uniform}[0,\ 0.3] \tag{16}$$

$$\theta_i \sim \text{Uniform}[0,\ 0.2] \tag{17}$$

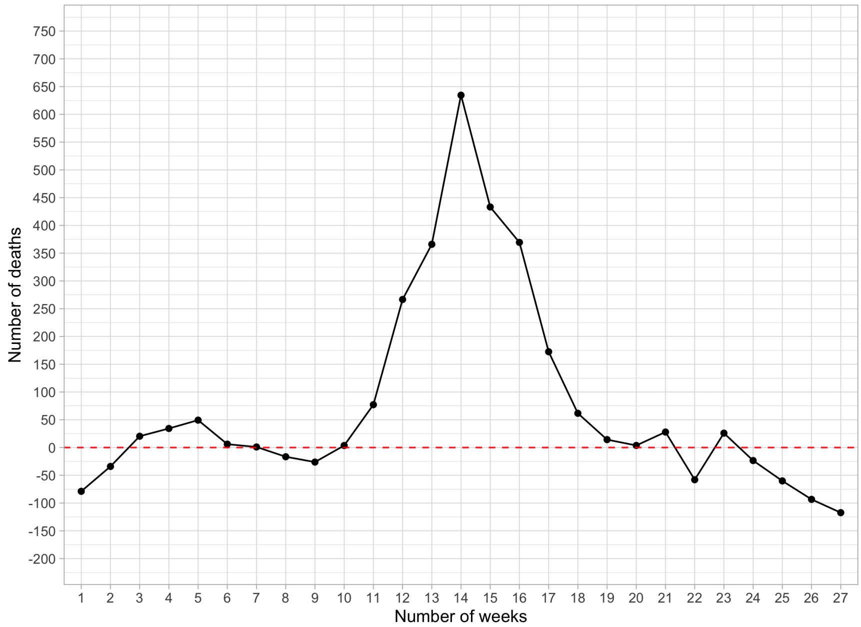


Figure B.1: Excess mortality 2020 vs mean 2000-2019

*Notes:* The Figure B.1 plots the weakly difference between 2020 deaths counts and respective mean values over the years between 2000 and 2019. In the first ten weeks, excess mortality is in expectation about zero, while during the phase of the pandemic outbreak (weeks 11-19) excess mortality is significantly positive.

Table B.1: Infection Fatality Rates by age group

| Age groups | Median | Confidence interval |
|---|---|---|
| 0 - 9 | 0.00016 | (0.0000056 - 0.00110) |
| 10 - 19 | 0.00023 | (0.0000089 - 0.00130) |
| 20 - 29 | 0.00014 | (0.0000045 - 0.00094) |
| 30 - 39 | 0.00019 | (0.0000064 - 0.00120) |
| 40 - 49 | 0.00023 | (0.0000078 - 0.00150) |
| 50 - 64 | 0.00023 | (0.0000076 - 0.00160) |
| 65 - 79 | 0.01300 | (0.0031 - 0.03000) |
| 80 + | 0.17000 | (0.047 - 0.29000) |

To derive point estimates and respective 95% confidence intervals for the parameters of interest, we employ a Markov Chain Monte Carlo procedure, that allows us to calculate the median and the CIs of the posterior distributions of $\delta_a$, $\delta_a^{Covid}$, and $\theta_i$, using as model equations (6) and (7) [34]. We draw 100,000 samples from the joint

[34]The likelihood function is composed of 5 equations for each combination macro-region - age group, for a total of $21 * 7 * 8 = 1176$ equations

posterior distribution and use 50 independent chains. The burn in interval is fixed at 20000, and the thinning interval is 30. Convergence is checked (and satisfied) visually with Gelman-Rubin diagnostic. Our estimates are robust to the definitions of alternative distributions of the priors.

Table B.2 shows our estimates of the potential number of *direct* deaths in absence of restrictive measures (both for SIR and SIRDC models), when we use the infection fatality rates estimated through this Bayesian approach. As previously mentioned, this approach leads to higher infection fatality rates, which result in more potential *direct* deaths, also among younger age groups. It is worth underlining here that such differences in the infection fatality rates are also reverberated in the slight discrepancies between the number of cases predicted by the SIRDC model reported in Tables 6 and B.2. According to our SIRDC model, indeed, individual behavioral responses depend on the number of daily deaths. Hence, changes in the fatality rate imply differences in the intensity of reduction of the contact rate $\beta_a$ and, as a consequence, in the number of predicted infections.

Table B.2: Direct deaths (infections until September, $1^{st}$)

| | | **SIR Model** | | | **SIRDC Model** | | |
|---|---|---|---|---|---|---|---|
| Age | Pop | Cases | $IFR_a$ | Deaths | Cases | $IFR_a$ | Deaths |
| 0–9 | 871,211 | 712,403 | 0.016% | 114 | 159,980 | 0.016% | 26 |
| 10–19 | 844,092 | 690,167 | 0.023% | 159 | 154,907 | 0.023% | 36 |
| 20–29 | 1,045,160 | 854,592 | 0.014% | 120 | 191,341 | 0.014% | 27 |
| 30–39 | 1,228,988 | 1,004,847 | 0.019% | 191 | 225,456 | 0.019% | 43 |
| 40–49 | 1,198,240 | 979,793 | 0.023% | 225 | 219,719 | 0.023% | 51 |
| 50–64 | 1,810,157 | 1,480,214 | 0.023% | 340 | 331,345 | 0.023% | 76 |
| 65–79 | 1,152,223 | 942,376 | 1.300% | 12,251 | 181,062 | 1.300% | 2,354 |
| 80+ | 453,828 | 371,150 | 17.00% | 63,095 | 51,367 | 17.00% | 8,732 |
| | 8,603,899 | 7,035,542 | | 76,495 | 1,515,177 | | 11,345 |

Since an alternative infection fatality rate leads to a different number of predicted infections, in Table B.3 we report the corresponding overflow deaths due to the lack of available beds in intensive care units, which are now different in the case of the SIRDC model Table B.4, then, reports the monetary benefits associated to saved lives when the alternative IFR is exploited. It is worth mentioning that now also very young individuals seem to benefit from lockdown measures. Indeed, the Bayesian estimates of the IFR for these age groups are no longer exactly zero.

Table B.3: Overflow deaths (infections until September, 1$^{st}$)

| | SIR Model | | | SIRDC Model | | |
|---|---|---|---|---|---|---|
| Age | Hospital | ICU | Total | Hospital | ICU | Total |
| 0 - 9 | 772 | 256 | 1,028 | 0 | 18 | 18 |
| 10 - 19 | 140 | 57 | 197 | 0 | 4 | 4 |
| 20 - 29 | 799 | 194 | 993 | 0 | 14 | 14 |
| 30 - 39 | 967 | 669 | 1,636 | 0 | 47 | 47 |
| 40 - 49 | 1,549 | 889 | 2,438 | 0 | 63 | 63 |
| 50 - 64 | 2,856 | 4,743 | 7,599 | 0 | 333 | 333 |
| 65 - 79 | 16,083 | 17,888 | 33,971 | 0 | 1,032 | 1,032 |
| 80 + | 10,729 | 3,680 | 14,409 | 0 | 138 | 138 |
| Total | 33,895 | 28,376 | 62,271 | 0 | 1,649 | 1,649 |

Table B.4: Monetary Benefits of Lockdown (by September, 1$^{st}$)

| | | | SIR Model | | SIRDC Model | |
|---|---|---|---|---|---|---|
| Age | Actual Deaths | VSL *(mln. CHF)* | Excess Deaths | Benefits *(bln. CHF)* | Excess Deaths | Benefits *(bln. CHF)* |
| 0–9 | 1 | 11.07 | 1,141 | 12.6309 | 43 | 0.4760 |
| 10–19 | 0 | 11.54 | 356 | 4.1082 | 40 | 0.4616 |
| 20–29 | 0 | 12.13 | 1,113 | 13.5007 | 41 | 0.4973 |
| 30–39 | 5 | 11.90 | 1,822 | 21.6818 | 85 | 1.0115 |
| 40–49 | 6 | 10.38 | 2,657 | 27.5797 | 108 | 1.1210 |
| 50–64 | 90 | 7.20 | 7,849 | 56.5128 | 319 | 2.2968 |
| 65–79 | 455 | 3.31 | 45,767 | 151.4888 | 2,931 | 9.7016 |
| 80+ | 1,215 | 1.14 | 76,289 | 86.9695 | 7,655 | 8.7267 |
| | 1,772 | | 136,994 | 374.4724 | 11,222 | 24.2925 |

The estimates of monetary benefits do not vary substantially with respect to Table 8. They are only slightly lower because there are now more fatalities in the age group 80+, characterized by a lower VSL, and fewer fatalities in the age group 65-79, for which the VSL is higher.

# C Details - SIR and SIRDC Models

The initial values used to fit the SIR and SIRDC models are reported in the following tables. The first subscript indicates the age group. These shares are calculated on March $5^{th}$, 2020.

Table C.1: Initial values - SIR model

| Susceptibles | Infectious | Recovered |
|---|---|---|
| $S_{1,0} = \frac{871031}{8603899}$ | $I_{1,0} = \frac{90}{8603899}$ | $R_{1,0} = \frac{90}{8603899}$ |
| $S_{2,0} = \frac{843844}{8603899}$ | $I_{2,0} = \frac{242}{8603899}$ | $R_{2,0} = \frac{6}{8603899}$ |
| $S_{3,0} = \frac{1044880}{8603899}$ | $I_{3,0} = \frac{197}{8603899}$ | $R_{3,0} = \frac{83}{8603899}$ |
| $S_{4,0} = \frac{1228592}{8603899}$ | $I_{4,0} = \frac{334}{8603899}$ | $R_{4,0} = \frac{62}{8603899}$ |
| $S_{5,0} = \frac{1197959}{8603899}$ | $I_{5,0} = \frac{246}{8603899}$ | $R_{5,0} = \frac{35}{8603899}$ |
| $S_{6,0} = \frac{1809807}{8603899}$ | $I_{6,0} = \frac{323}{8603899}$ | $R_{6,0} = \frac{27}{8603899}$ |
| $S_{7,0} = \frac{1152211}{8603899}$ | $I_{7,0} = \frac{69}{8603899}$ | $R_{7,0} = \frac{12}{8603899}$ |
| $S_{8,0} = \frac{453792}{8603899}$ | $I_{8,0} = \frac{36}{8603899}$ | $R_{8,0} = \frac{0}{8603899}$ |

Table C.2: Initial values - SIRDC model

| Susceptibles | Infectious | Resolving | Dead | ReCovered |
|---|---|---|---|---|
| $S_{1,0} = \frac{871031}{8603899}$ | $I_{1,0} = \frac{90}{8603899}$ | $R_{1,0} = \frac{90}{8603899}$ | $D_{1,0} = \frac{0}{8603899}$ | $C_{1,0} = \frac{0}{8603899}$ |
| $S_{2,0} = \frac{843844}{8603899}$ | $I_{2,0} = \frac{242}{8603899}$ | $R_{2,0} = \frac{6}{8603899}$ | $D_{2,0} = \frac{0}{8603899}$ | $C_{2,0} = \frac{0}{8603899}$ |
| $S_{3,0} = \frac{1044880}{8603899}$ | $I_{3,0} = \frac{197}{8603899}$ | $R_{3,0} = \frac{83}{8603899}$ | $D_{3,0} = \frac{0}{8603899}$ | $C_{3,0} = \frac{0}{8603899}$ |
| $S_{4,0} = \frac{1228592}{8603899}$ | $I_{4,0} = \frac{334}{8603899}$ | $R_{4,0} = \frac{62}{8603899}$ | $D_{4,0} = \frac{0}{8603899}$ | $C_{4,0} = \frac{0}{8603899}$ |
| $S_{5,0} = \frac{1197959}{8603899}$ | $I_{5,0} = \frac{246}{8603899}$ | $R_{5,0} = \frac{35}{8603899}$ | $D_{5,0} = \frac{0}{8603899}$ | $C_{5,0} = \frac{0}{8603899}$ |
| $S_{6,0} = \frac{1809807}{8603899}$ | $I_{6,0} = \frac{323}{8603899}$ | $R_{6,0} = \frac{27}{8603899}$ | $D_{6,0} = \frac{0}{8603899}$ | $C_{6,0} = \frac{0}{8603899}$ |
| $S_{7,0} = \frac{1152211}{8603899}$ | $I_{7,0} = \frac{69}{8603899}$ | $R_{7,0} = \frac{11}{8603899}$ | $D_{7,0} = \frac{1}{8603899}$ | $C_{7,0} = \frac{0}{8603899}$ |
| $S_{8,0} = \frac{453792}{8603899}$ | $I_{8,0} = \frac{36}{8603899}$ | $R_{8,0} = \frac{0}{8603899}$ | $D_{8,0} = \frac{0}{8603899}$ | $C_{8,0} = \frac{0}{8603899}$ |