Working Paper Series

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ECINEQ 2024 662

ECINEQ 2024 662
2024 January
www.ecineq.org

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Keyword: Cost-benefit analysis, Social welfare function, COVID-19, wellbeing, trust, policy evaluation

JEL Cassification: D61, I18, I38

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*Universitat de Girona, Department of Economics, Girona, Spain. E-mail: enza.simeone@udg.edu.

1 Introduction

The infectious COVID-19 disease was discovered in Wuhan (China) in December 2019 and spread worldwide, affecting several aspects of people's lives, such as health status, education, labour, economy, and other socio-demographic aspects.
Since the first wave of the pandemic, in all countries, the government has implemented several non-pharmaceutical interventions (i.e., suppression and mitigation policies) to reduce the transmission of the virus.
Several policy questions have emerged in this context: How long should policies be implemented to respect social distancing and limit economic activity? When should schools and non-essential businesses be reopened? To evaluate the balance between reducing fatalities and morbidity and associated socioeconomic costs, two frameworks can be used: cost-benefit analysis (CBA or BCA) for non-tax policies and social welfare function approach (SWF) for tax policies.
Our work aims at evaluating the impact of COVID-19 pandemic policies on wellbeing, specifically focusing on using the social welfare function (SWF) framework for non-tax policies and considering the effects on different age and income groups. To achieve this, we follow the work done by Adler et al. (2020), who conducted a comparative analysis of suppression and control policies using the COVID-19 pandemic simulator developed by Fleurbaey et al. (2020). On February 29th, 2020, there were 85,403 confirmed cases and 2,838 deaths worldwide due to the virus, causing significant increases in mortality, morbidity, and economic loss. In almost 80% of the infected cases, the symptoms were mild (e.g., headache, congestion, or a loss of taste and smell). However, the population mainly affected was the elderly and people with health problems. The fatality rate is lower than in past epidemics (e.g., SARS-COV-1[1] and MERS-COV[2]), but the virus spreads more rapidly.
The World Trade Organization (WTO) and the Organization for Economic Cooperation and Development (OECD) have declared the COVID-19 pandemic as the biggest threat to the global economy since the financial crisis of 2008-2009.
Indeed, as reported by Ferranna et al. (2021), the pandemic led to an expected 4.4% world economy contraction in 2020 compared to the 0.1% one caused by the 2009 global financial crisis.
An important trade-off emerged between women and men because women were more

[1] The 2002–2004 outbreak of SARS, caused by severe acute respiratory syndrome coronavirus (SARS-CoV-1), infected over 8,000 people from 29 countries and territories, and resulted in at least 774 deaths worldwide. The outbreak was first identified in Foshan, Guangdong, China, in November 2002 and became a global alert in March 2003 (Wikipedia (2022a)).

[2] Middle East respiratory syndrome (MERS) is a viral respiratory infection caused by Middle East respiratory syndrome–related coronavirus (MERS-CoV). The first case was identified in June 2012 in Jeddah, Saudi Arabia, but its risk to the global population was considered quite low (Wikipedia (2022b)).

affected by the pandemic due to job loss and were under more psychological stress due to childcare, domestic responsibilities and teleworking conditions.
Therefore, as highlighted by Gaspar et al. (2021)pp. 6, the coronavirus pandemic allows us *the opportunity to identify important factors to promote the resilience of people, professionals, and organizations and consequently raise awareness of the need to promote healthy workplaces and health and robust professionals from both an environmental and a biopsychosocial perspective.*
As summarised by Ferranna et al. (2021), during the pandemic the income among the employed has reduced with an impact on the overall levels of consumption and demand that decreased, leading to unemployment, especially in essential sectors with high individual contact.
The remainder of the work is organised as follows. In Section 2, a literature review is described. Section 3 describes the cost-benefit analysis and the social welfare function, and Section 4 describes the case study applying the two methodologies explained in Section 3. Section 5 shows the extension made by our work considering the impact of individual in the pandemic simulator, and Section 6 offers some conclusions and further extensions.

2 Literature review

The coronavirus pandemic is the latest but not the last pandemic globally. According to Tandon (2020), pandemics spread due to inadequate response capacity of the State to infectious diseases (because antibiotics are not effective against all infections), poverty, and underdevelopment. However, the coronavirus does not respect borders and unequally affects individuals, also in developed countries. Tandon (2020) highlights the relevance of the relationship existing between infectious diseases and human development. Indeed, the pandemic has reversed progress in health and reduced life expectancy, with 90% of countries reporting one or more disruptions to essential healthcare services.
Other relevant factors that led to the rapid diffusion of the pandemic across countries are the following:

- the ecological changes related to the new technology's development, construction of new irrigation channels, dams, deforestation, migration, high population density, globalisation of food and international travel;
- the impact of climate change on the environment and human development;
- some actions implemented by States (e.g., fiscal resources availability, resilience, autonomy, and legitimacy) that led to the economic declines;
- the closure of several industrial sectors within a month of the onset of the pandemic;
- changes in the supply chain from China to other countries that affected industrial production with negative effects on trade and tourism (Verschuur et al. (2021)).

The COVID-19 pandemic had an impact not only on the health of people but also on education, labour, economy and other socio-demographics aspects, exacerbating the pre-existing inequalities due to the disproportionate impact of infections, sickness, and deaths among disadvantaged populations and an inappropriate redistribution system.
On the one hand, health impacts on individuals' wellbeing generate treatment and other costs, intensive care units' overcrowding with delay issues of medical and health services, and out-of-pocket health expenditures. On the other hand, non-health impacts involve income loss due to unemployment or sickness. Gaspar et al. (2021) show how home working increased psychosocial risks due to isolation, confusing boundaries between work and family, increasing risk of conflicts and domestic violence and so forth. Job insecurity also increases due to fear of losing own job, wage cuts, and layoffs, with a relevant impact on mental health. A relevant concern was managing these risks thanks to the actions by organisations to avoid stress, productivity reduction and physical health problems of individuals (e.g., low motivation, low mood, headaches, changes in sleeping habits, addictive behaviour). On the one side, people sometimes consider the teleworking solution a positive experience thanks to the reduced travelling time/traffic jams, higher autonomy, and greater flexibility, but its success depends, for instance, on technological literacy and team cohesion maintenance. On the other hand, telecommuting was considered negative due to reduced physical activity, communication with colleagues, and adjusted work hours, especially when children were present at home.
A significant impact of the coronavirus pandemic is the less attention given to non-COVID patients whose health problems were serious (e.g., cardiovascular, obesity, hypertension) but whose access to the healthcare system was reduced.
Several studies (Lahav (2020)) find a relevant impact of the COVID-19 pandemic on the level of stress and distress mainly for younger who are women, not in a relationship, have low income, have low education, have health problems, living alone and with poor health status. Individuals with low socioeconomic status, large households, and poor working conditions other than low air quality face increased disease susceptibility.
To reduce the pandemic diffusion across countries, a reduction of people interactions is required through the adoption of non-pharmaceutical interventions (NPI hereafter), such as non-essential businesses' closure, sheltering in place, school closings, and lockdown orders whose enforcement depends on the government's capabilities and resistance.[3]
Yglesias (2020) defines that the control policies were divided into suppression and mitigation. The former includes policies related to the "Stay-at-home" orders and economic lockdowns, which aim to keep the number of infection cases as close to zero as possible as long as these policies are in place. The second type of policies, instead, includes contact

[3] Figure 1 in the study of Ferranna et al. (2021), pp. 9, displays the number of daily cases over time with and without NPI and projected rationing, to understand better how the infection curve changes.

tracing, quarantine for positive cases, and social distancing of more affected people (e.g., the elderly), aiming to mitigate the number of cases within the healthcare system capacity, without definitely suppressing the infection cases. Mitigation policies are less invasive as they permit controlled outbreaks. However, they require testing and contact tracing to curb the spread of the pandemic. The healthcare system must also be equipped to adopt an aggressive suppression policy in case the pandemic gets out of control (Ferranna et al. (2021)).[4] According to a study conducted by Maloney and Taskin (2020), there is a correlation between Non-Pharmaceutical Interventions (NPI) and mobility. The study found that in low-income countries (LICs), NPI had a limited effect on mobility and there was no voluntary component for reducing mobility due to reluctance to abandon sources of livelihood. On the other hand, in advanced countries like the USA, NPIs were effective in increasing social distancing, and there was a spontaneous component that directly impacted economic activity, even before NPI adoption. However, after the implementation of NPIs, mobility and economic activity may respond slowly in advanced countries. Some studies (Engle et al. (2020), Brzezinski et al. (2020)) find that in the USA, a "Stay-at-home" order has reduced mobility by 7.87%.

A workplace-related mobility proxy has been used to measure social distancing, and its impact on an economic activity affected by mandatory closures of non-essential businesses has been analyzed in several studies. Lower mobility is a signal about the likelihood of a serious negative impact on the health outcome of individuals.

Maloney and Taskin (2020) find a clear downward-sloping relationship between reported infectious cases and mobility in the USA, independently of NPI restrictions, indeed lower mobility lowers the number of infectious cases.

Globally, beyond the non-essential workplaces' closure, other relevant measures adopted are school closing, restrictions on internal mobility with a shut-down of public transportation, and public information campaigns to raise mobility information and trust by individuals.

In addition, all the NPI and the historical and anecdotal evidence, may be considered coordination devices rather than repressive measures if all people coordinate their actions. Verschuur et al. (2021) analyse the economic implications of NPI adoption, looking at the cost-benefit of the different NPIs to define a set of policies as many countries enter further waves of the pandemic. In this regard, it is difficult to monitor the extent of the economic disruption on a global scale due to the seasonality of the traditional macroeconomic indicators, which are published at several months of delay as aggregate indicators that do not allow specific analysis, and their limited availability in low-income countries than middle-upper one.

[4] To understand better the health-income trade-offs and how they are analysed during the pandemic control, we suggest seeing Ferranna et al. (2021), pp. 11-13.

Several high-frequency data (HFD), such as electricity consumption, air pollution, and human mobility, were used to track the global pandemic evolution in a country. For instance, Fezzi and Fanghella (2020) use daily electricity consumption data finding that a reduction of almost 30% of Italy's national GDP is due to three weeks of severe lockdown policy.

Further, other studies (Deb et al. (2020)) highlight how the non-essential workplaces' closure and "Stay-at-home" orders generated the greatest economic costs among the NPI measures.

Verschuur et al. (2021) highlight how real-time indicators of economic activity, like maritime trade, can be useful to monitor economic disruptions.

Two methodological frameworks can be adopted to evaluate the control policies' impact on individual wellbeing: Cost-benefit analysis (CBA or BCA hereafter) and Social welfare function approach (SWF hereafter). The former converts the policy's effects into monetary equivalents and sums them up, while the second defines the policy's effects on individual wellbeing by using an aggregation formula for the entire population.[5]

The COVID-19 measures work if accepted by the community; therefore, it is important to analyse the factors that impact the perception of risks and the measures' acceptability. Some authors (Siegrist et al. (2021)) find less acceptability of pandemic measures by people with an individualistic cultural worldview (i.e., general beliefs and value orientations), high general interpersonal trust (i.e., the conviction that people are trustworthy), low political trust (i.e., probability of unbiased information by the government) and low risks perception (measured through people's fears related to COVID-19). In Switzerland, a decline in the number of infected people over time leads to a reduction in the measures' acceptability due to a lower perception of risks and a higher social trust by people who thought that other risks were neglected.

Several types of trust (i.e., in science, in government, in other people) may have a different impact on the acceptability of the measures. During the early stages of a pandemic, the public risk perception is high, and a fast government response is necessary. During the pandemic, the risk perceptions might be reduced because people would become more familiar with the virus, and public acceptance becomes important, looking not only at the risk perceptions but also at the beliefs and cultural worldviews.

Woelfert and Kunst (2020) show how political trust (related to respondents' confidence in core political institutions) and social trust (related to the trust in most of the people who meet in daily life) interacted with each other and may affect social distancing tendencies. High social trust is associated with the low political trust of respondents, which leads to low social distancing trends. Among the existing studies, political trust was analysed by looking at the association with law compliance and with factors of well-functioning

[5] A detailed description of these two methodologies is reported in Section 3.

democracies, without paying much attention to the confidence in one's health care system. Political trust is positively related to people's behaviour against the recommendation (i.e., vaccination intentions) during the pandemic. Concerning social trust, social distancing measure has an impact on citizens' mental health due to social isolation. However, this measure can produce good results only if most people adopt this behaviour. Social trust is connected with better health, happiness, long life, a sense of social belonging and altruistic behaviour. Regarding health behaviour, a high level of social trust is associated with a non-smoking attitude, adequate sleep duration, and lower alcohol consumption. During the pandemic, the relationship between social trust and health policies received less attention, and the existing studies placed more burden on the association between social trust and the intent to accept vaccination (a measure not immediately available in the first part of the pandemic), without considering the role of social distancing. The study of Woelfert and Kunst (2020) aims to address this shortcoming, finding that more social trust means more extroversion, less social distancing behaviour, and more mobility during the COVID-19 crisis. In this regard, political trust may have a regulation function because socially trusting people would follow the trend of frequently socialising with other people if there is little political trust. Through a study, the authors investigated if a country's national-level political trust scores and/or social trust scores would be related to and interactively predict its citizens' social distancing behaviour.
The first aim of our work is to compare the methodologies used for evaluating tax and non-tax policies to highlight the advantages and disadvantages of these approaches in the COVID-19 era. Finally, the study aims to investigate the relationship between trust, social distancing behavior, and the spread of COVID-19. To achieve this, we modify the infection rate equation created by Fleurbaey et al. (2020), taking into account people's trust in various individuals and institutions responsible for preventing the spread of the virus, as well as their compliance with non-pharmaceutical interventions (NPIs) and other preventive measures.

3 Methodology

3.1 Cost-benefit analysis (CBA)

For governmental practice, the main approach used for the ex-ante policy evaluation is the Cost-benefit analysis (CBA or BCA hereafter). The dominant rule of this approach is firstly to define for each person a counterfactual monetary variation related to the impact of a certain choice by policymakers on the wellbeing of the individual. Then, to sum monetary equivalents whose value will be positive if the policy makes an individual better off than the baseline scenario, and will be negative if the policy makes her worse

off than the baseline scenario.[6] In a certainty scenario, each new policy generates some outcome x_1 as the counterpart of a baseline outcome x_b without new policy implementation. The monetary equivalent of individual i for any other outcome x_1 (i.e., $ME_i(x_1)$) is determined as the amount that, when summed to an initial endowment[7] of a person i in the baseline scenario, leads the person to be indifferent between x_b and x_1. Further, following the preference-based theory of individual wellbeing, if the individual i prefers x_1 to x_b, $ME_i(x_1)$ will be positive, whereas if x_b is preferred to x_1 by the individual i, $ME_i(x_1)$ will be negative. The sum of $ME_i(x_1)$ for the population of interest is the CBA valuation value assigned to x_1.[8]
Alternatively, the monetary equivalent theory can be expressed in terms of "willingness to pay" (WTP) and "willingness to accept" (WTA). If x_1 is preferred to x_b by individual i, then $ME_i(x_1)$ represents the "willingness to accept" (i.e., the minimum value accepted) of individual i in exchange for choosing to leave in place the x_b instead of implementing x_1. On the contrary, if x_b is preferred to x_1 by individual i, then $ME_i(x_1)$ is the "willingness to pay" (i.e., the maximum value paid) of individual i in exchange for the choice to leave in place the x_b.
The CBA approach aims to determine the monetary value of preventing fatality by using the average population's "value of statistical life" (VSL) as a measure of willingness to pay to increase survival chances (Hammitt (2000), Kniesner and Viscusi (2019)). *VSL is derived from the rate at which people are willing to trade off small changes in their income against small changes in their risk of death (Adler et al. (2020)*.[9] This monetary measure can depend on age, income, wealth and the overall risk level faced by individuals. A shortcoming of this approach is that the better-off's interests matter more than those of the worse-off because the former is likely to place a higher monetary value on risk reduction than the latter. The population average measure is used instead of the individual-specific ones to deal with this issue. However, people of different age groups must be treated differently in this case, hence the "value of a statistical life year" (VSLY) can be used as

[6] Generally speaking, for the population of interest and adopting the preference-based theory of individual wellbeing, to have a choice that is better than the baseline, the sum of monetary equivalents needs to be positive.

[7] A general term that can refer to a person's income, her consumption, her wealth and so forth in a one-period model.

[8] Given two outcomes, x_1 and x_2, $x_1 \succeq x_2$ if and only if the sum across the population of $ME_i(x_1)$ is at least as large as the sum of $ME_i(x_2)$. In terms of policies, given two policies, P_1 and P_2, $P_1 \succeq P_2$ if and only if the sum across the population of $ME_i(P_1)$ is at least as large as the sum of $ME_i(P_2)$.

[9] For example, for an annual mortality risk Ω_i reduction by 0.1%, an individual would accept a reduction in her income $\$y$ of at most USD 1,000 per year. Her monetary value of statistical life (VSL) is $\frac{\Delta \$ y}{\Delta \Omega_i} = \frac{1{,}000}{0.001} = 1,000,000$. Then, considering 1,000 identical individuals, they would be willing to pay an equal share of USD 1,000,000 for an intervention that decreases the expected deaths in a year by one. In the pandemic simulator by Fleurbaey et al. (2020), the VSL is equal to 150 times the Gross Domestic Product (GDP) per capita.

a monetary measure (Hammitt (2020a)). This value is obtained by dividing the VSL by the average life expectancy at the point of death and no time discounting is used when summing up the value of life years lost.[10] If a particular age cohort is considered, the VSL is defined as the product of VSLY and the life expectancy remaining for the cohort. However, VSL and VSLY are based on the marginality assumption[11] (Ferranna et al. (2021)), but the pandemic may lead to a non-marginal fatality risk. Hammitt (2020b) argues how the individuals' willingness to pay for a non-marginal rise in the likelihood of survival is an increasing and concave function of the variation in the likelihood of survival. Then, with a more significant increment, the willingness to pay of an individual to exchange wealth for less mortality risk reduces.[12] Therefore, neither VSL nor VSLY consider the quality of life. The "quality-adjusted life years" (QALYs) measure is used in the pandemic simulator to determine the value of life saved based on its remaining length, quality, and health conditions. This measure ranges from 0 to 1, and it assumes that every infected individual survives for three weeks at the calculated QALY parameter level.[13] Further, every life-year lost due to death counts for the loss of a full QALY. The value of living with an impaired health status is derived from people's preferences. To avoid more burdens on people with good health, assigning specific values to enhancements in the length and quality of life of those who are worse off is necessary.

Finally, estimates of the VSL and VSLY vary among countries mainly due to differences in income per capita. Similar variation is observed by looking at the monetary costs to obtain one QALY, defined by dividing the VSL by the average remaining QALYs.[14]

The CBA approach is *welfarist-consequentialist*, thus two outcomes are equally ethically good if individual i is as well off in x_b as he/she is in x_1.[15]

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[10] For example, in the U.S., considering a VSL equal to USD 10,000,000 and the number of years that an individual can be expected to live, if he/she does not die now, equal to 33 years of life (i.e., life expectancy obtained as $(e^{max} - e^l)$ where e^{max} is the maximum years of life achievable (85 or 88) and e^l is the age in the current year l), the VSLY is equal to $\frac{VSL}{(e^{max}-e^l)} = \frac{10{,}000{,}000}{33} = 303,030$ approximately. In the pandemic simulator developed by Fleurbaey et al. (2020), the VSLY and the willingness to pay for a life year are equal to three times the GDP per capita.

[11] Indeed, VSL is the marginal rate of substitution between wealth and the likelihood of survival.

[12] The concavity of the willingness to pay of an individual for the size of the less mortality risk is caused by the individual's ability reductions to spend because the opportunity cost of spending rises the more the person has already increased her likelihood of survival. For example, Adler (2020) displays that, considering a fatality rate of 1% of the population as a non-marginal risk, the willingness to pay of an individual to remove this risk is half the amount of VSL. This means that the VSL value tends to overestimate the value that people assign on saving lives, for high death's prevention likelihoods.

[13] For the USA, the value for one QALY is between USD 100,000 and USD 150,000 (ICER (2020)).

[14] In the simulator, the data about QALYs over life by quintile come from McIntosh et al. (2009) who define them for Canada and are applied to the U.S. in the simulator, while for all other countries the data used derived from Love-Koh et al. (2015) who define them for the UK.

[15] Like in the sum of monetary equivalent CBA test where a person i is indifferent between x_1 and x_2 with $ME_i(x_1) = ME_i(x_2)$ both with respect to x_b, and CBA ranks x_1 and x_2 as equally good.

Further, CBA is multidimensional because it also considers non-income dimensions of individual wellbeing (e.g., health, longevity, leisure and so forth), and the policy impact on their changes appears in an individual's monetary equivalent.
The CBA framework that we report in the Appendix A defines monetary equivalents in terms of changes to consumption (or income used as a proxy) and in the equivalent-variation purpose, following the model defined by Adler (2019), pp.289-290.[16]

3.2 Social welfare function analysis (SWF)

Individuals' wellbeing is affected by governmental policy choices in several ways. First, policies affect the individuals' income through its reduction or increment (i.e., economic impacts) and other non-economic components of wellbeing, such as health status and fatality risks. Second, policies have a heterogeneous effect on individuals by generating "losers" and "winners", so requiring to balance the gains and losses generated by policies. In the end, a trade-off between overall wellbeing and inequality may occur during the governmental policy choice.
Considering these aspects of policy choice (i.e., multidimensionality, individual heterogeneity, winners (and their gains) versus losers (and their losses), and inequality-overall wellbeing trade-off), a suitable methodology that can be implemented to assess governmental policy is the "Social welfare function" (SWF) that respects all the policy choice's requirements.
For policy evaluation concerning infrastructure, risk regulation, climate change, education, antitrust, healthcare, consumer protection, and so on, the SWF framework can be implemented as a substantial improvement of the cost-benefit analysis (CBA).
Intending to rank policies, the SWF framework, which is *welfarist-consequentialist*[17] as the CBA approach, is based on three components: a numerical indicator of individual wellbeing $w(.)$ that converts each individual's outcome into a list of wellbeing numbers; a rule E to rank the lists of wellbeing numbers to identify which vector is better (worse) than or equally good as the other[18]; and an uncertainty module through which policies

[16] This CBA model produces a complete quasiordering of the outcomes set and respects the principles of Strong Pareto and Pareto Indifference. For more detail about these principles, see Adler (2019) pp. 96-97.

[17] Consequentialist because the policies' ordering of SWF comes from the outcomes' ordering, and welfarist because the outcomes' ranking is derived by the wellbeing trend of individuals in some populations of interest in the different outcomes. The population of interest is fixed with N individuals that exist in all the possible outcomes under consideration.

[18] There are two main types of rule E. 1) *Utilitarian rule*: a simple sum of wellbeing numbers that is insensitive to the distribution of wellbeing itself. For instance, given two vectors (10, 26, 50, 2) and (5, 26, 17, 37), the first is ranked better than the second because 10+26+50+2=88 is higher than 5+26+17+37=85. 2) *Continuous-prioritarian rule*: the sum of transformed wellbeing numbers through

are ranked in terms of probability distributions across outcomes.
These three components are relevant from an ethical perspective, considering that the SWF methodology is a normative approach for the ethical evaluation of governmental policies to assess if a policy is better or worse than alternative policies.
Focusing on the first component, the SWF generates a "social" outcome comparison taking into account the *welfare* of each individual in the population of interest (Adler (2019) pp.10). The comparison can be made in terms of levels of wellbeing or differences in wellbeing, both of which can be intrapersonal or interpersonal. In Table 1, a summary of these comparisons is displayed.

Tab. 1. Types of wellbeing comparisons

	Intrapersonal	**Interpersonal**
Levels	One individual i and two outcomes x_1 and x_2	Two individuals i and m and two outcomes x_1 and x_2
Differences	One individual i and four outcomes x_1, x_2, x_3, x_4	A group of different people i, m, n, o

Explanation: *Intrapersonal level comparison*: i in x_1 is at least as well off as i in x_2. *Interpersonal level comparison*: i in x_1 is at least as well off as m in x_2. *Intrapersonal difference comparison*: the difference in i's wellbeing between x_1 and x_2 is at least as large as the difference in i's wellbeing between x_3 and x_4. *Interpersonal difference comparison*: the wellbeing difference between i in x_1 and m in x_2 is at least as large as the wellbeing difference between n in x_3 and o in x_4. The outcome's notation (i.e., x_1, x_2, x_3, x_4) may refer to the same or different outcome.

These four types of comparisons can be admissible or inadmissible depending upon the wellbeing theory followed (i.e., preference theory, experientialist theory, objective-good theory).[19] Economists traditionally consider the wellbeing measure as a preference-based measure, constructed with the vNM method.[20] Following this theory, an individual i is better off in one outcome x_1 than x_2 if she prefers the first one under conditions of good information and rational deliberation.[21]
Following the preference theory, the outcomes are converted through a wellbeing measure into vectors of individual wellbeing numbers. These vectors and the corresponding outcomes are ranked using the rule E of SWF that could be utilitarian or prioritarian.[22] The

a $g(.)$ function that is sensitive to the distribution of wellbeing (e.g., the sum-of-square-root function). For instance, considering the same vectors mentioned above, the first is ranked worse than the second because $\sqrt{10} + \sqrt{26} + \sqrt{50} + \sqrt{2} = 16.75$ is lower than $\sqrt{5} + \sqrt{26} + \sqrt{17} + \sqrt{37} = 17.54$. This approach also takes into account the "declining marginal wellbeing" effect of income (See Adler (2019) pp. 16 for more details).

[19] See Adler (2019)'s chapter 2 for a detailed discussion about the admission or not of these comparisons.

[20] See Adler (2019) app.D.1 for a detailed description.

[21] Alternatively, the hedonic (or experientialist) theory considers individual wellbeing taking into account pains and pleasures, perceptions, feelings of satisfaction, that a person experiences in outcomes. Finally, the objective theory focuses on objective goods that impact an individual's wellbeing, such as life, knowledge, play, and religion.

[22] As displayed in Appendix B, the utilitarian SWF ranked outcomes accordingly $x_1 \succeq x_2$ iff $(w_1(x_1), ..., w_N(x_1)) \succeq (w_1(x_2), ..., w_N(x_2))$, thus $\sum_{i=1}^{N} w_i(x_1) \geq \sum_{i=1}^{N} w_i(x_2)$., while the prioritarian SWF ranked outcomes accordingly $x_1 \succeq x_2$ iff $\sum_{i=1}^{N} g(w_i(x_1)) \geq \sum_{i=1}^{N} g(w_i(x_2))$.

axioms representing the basis for different SWFs are Pareto Indifference, Strong Pareto, Anonymity, Pigou-Dalton, Separability, and Continuity.[23]
A relevant matter is related to the SWF's selection among the different types of SWF.[24] This decision involves ethical concerns and requires consideration of the "reflective equilibrium" approach in ethical thinking.
If a decision-maker has to choose from a set of alternative policies $\{P_1, P_2, ..\}$, these policies are ranked by the Social Welfare Function (SWF) from best to worst. This ranking is done through an "uncertainty module" for the rule E.[25] The rule E is selected based on ethical arguments and associated axioms.
Following the SWF framework used by Adler (2019) in the domain of risk regulation, our study aims to apply the same methodology in the health sector. In the literature, this approach was used mainly in the domain of tax policy (Mirrlees (1971)). Following Adler's approach applied to risk regulation is helpful to understand better how the SWF framework differs from cost-benefit analysis (CBA), which is typically used for non-tax policies like health policy.
One way to evaluate people's opinions about the distribution of some goods, such as income, is by conducting a survey or laboratory experiment, as suggested by Amiel et al. (1999). In such studies, participants are asked to assess the distribution of the good as an external observer since they are not a part of the population being distributed to. This helps ensure impartiality in their evaluation. The SWF axioms of Anonymity, Strong Pareto, and Pigou-Dalton are tested using these rankings.
The second type of study suggested by (Amiel et al. (1999)) uses surveys or experiments that concentrate on the Social Welfare Function (SWF) priority parameter, such as the Atkinson parameter γ. The study uses a "leaky transfer" question in terms of income, asking respondents to consider and compare various income distributions. The study then estimates the priority parameter by adopting the rule E, which operates on vectors of income amounts rather than wellbeing numbers.
Another strand of literature (Spadaro et al. (2015)) does not use survey data but identifies SWF for a given society by looking at the policies in place in that society. The data used in this case are economic data "D" about society, such as the distribution of individual wage rates or pre-tax income, and the existing governmental policy "P".
Many academics use the SWF framework to analyse tax policies. However, this framework can also be used to rank any set of policies $\{P_1, P_2, ..\}$, even non-tax based ones such as policies related to health, safety, environmental protection, and regulation of fatality. Some experts (Kaplow (1996), 2004, 2010) argue that the SWF framework should

[23] See Adler (2019) app. F for more formal statements of the major axioms.

[24] See Adler (2019) app. E for the different possible forms that the SWF can assume.

[25] See Appendix B, equations from B.9 to B.11.

only be used to design tax policies (i.e., "Tax only view"), while non-tax policies should be guided by CBA.[26] In Appendix B, we report the SWF framework to determine the economic costs that are socially feasible to bear to reduce the number of fatalities and other negative effects of the COVID-19 pandemic, applying an aggregation formula for the entire population.
Table 2 summarises the three steps that occur interactively to apply the SWF framework to a policy choice: outcome description, prediction, and valuation (Adler (2019)).[27]

Tab. 2. Steps description to apply the SWF framework to a policy choice: a summary

Step	Description
Outcome description	A welfarist SWF leads to construct an inter-personally comparable measure *w(.)* of well-being by using the vNM utility functions. Considering the *"history"* as a combination of a partially described (i.e., "pared-down") bundle of welfare-relevant attributes (e.g., consumption, income, longevity, health, leisure) and preferences regarding these bundles, an outcome is a possible combination of histories, one for each *N* individual in the population of interest. Input: individual *lifetime well-being* as single period (no life span description, constant attributes over time) or multi-period (description of the person's life span and attributes change over time). The choice between a one- period or a multi-period structure depends upon the extra decision-making costs of using the more complicated model. Indeed if the incremental costs of this latter model are zero, then it should be used, otherwise is better to use the simpler one. This decision must be taken before to apply the SWF framework in order to avoid doing infinite regress. Further, the "one period" model assumes fixed individuals' preferences, on the contrary the multi-period model is a preference-based theory of well-being looking to the heterogeneous preferences of each individual.
Prediction	Considering a group of feasible "*state of nature*", is required to map policies onto probability distributions across outcomes, whose sum is equal to unity. Each state of nature is independent by what policy is chosen and is a combination of possible world's events at or before the period of choice and feasible causal laws.
Valuation	Each policy is transformed into a probability distribution over well-being vectors that are ranked through *a rule E*, and finally an uncertainty module is associated to the rule *E* for the purpose of ranking policies. The uncertainty modules are: - *Utilitarian* (UUU), that ranks policy considering the "expected sum of individual lifetime well-being"; - *Ex-ante prioritarian* (EAP), that ranks policy considering the "sum of a concave transformation of expected individual lifetime well-being"; - *-Ex-post prioritarian* (EPP), that ranks policy considering the "sum of a strictly increasing and strictly concave transformation of realized individual lifetime well-being". Finally, the expected score for each potentially affected individual is defined through an *additive formula* that sum the expected score of each individual, obtaining *the expected policy score*. This additivity characteristic makes UUU and EPP "*correlation-insensitive*", thus they will rank two different policies with the very same probability distribution as equally good, also when the two policies differ in the probabilities that they assign to the distribution for *N* individuals.

In Appendix C, following the approach adopted by Ferranna et al. (2021), the value of a policy to remove the pandemic risk is defined using both CBA and SWF frameworks, taking into account the heterogeneous effect by age-income groups.

3.3 CBA vs SWF: key differences

The CBA and SWF approaches differ in how the wellbeing effects are quantified using a scale.

[26] Considering two non- tax policies $\{P_1, P_2, ..\}$, several versions of the linkage between CBA and the Strong Pareto principle existed, see Adler (2019) pp. 227-229).

[27] See Appendix B for a detailed explanation of these steps.

Indeed, through the CBA approach, wellbeing effects are quantified on a monetary scale, where welfare changes are enclosed as monetary equivalents. On the other hand, the SWF approach requires an interpersonally comparable measure of wellbeing $w(.)$ that can be realised by adopting the monetary equivalent of an individual. This difference is related to the scepticism of CBA about interpersonal comparisons and intrapersonal comparisons of differences in wellbeing. CBA only requires comparisons of wellbeing levels within an individual. This means examining the ranked preferences of bundles of attributes (such as income and non-income attributes) for each person. Doing so is sufficient to determine the person's monetary value. [28]

Therefore, if the scepticism about interpersonal comparisons is wrong, the CBA has real shortcomings compared to the SWF model because money's declining marginal welfare effect misrepresents its valuations, and CBA is insensitive to distributional analysis. Indeed, on the one hand, the interpersonal and intrapersonal comparability of wellbeing differences are presupposed for the diminishing marginal wellbeing impact of income[29], on the other hand, a shift in the baseline income distribution does not generate changes in CBA value.[30]

Considering that an interpersonal comparison is admissible, the CBA can be considered a particular version of the SWF (i.e., the best one) if monetary equivalents of the CBA approach are interpreted as interpersonally comparable values, and a guide for non-tax-and-transfer governmental policies (e.g., healthcare system, environmental regulators).

A crucial connection exists between CBA and SWF. A less widespread version of BCA, with distributional weights, sums of individual WTP/WTA amounts that are adjusted by weighting factors. In this manner, monetary benefits to worse-off people are valued more than monetary benefits to better-off ones. Any SWFs can be implemented through distributional weights applied to BCA, but this is in part controversial because there is no precise method provided for calculating weights.[31] However, the prioritarian SWF gives the intellectual foundation for distributionally weighted CBA.

[28] For a detailed example between these two approaches is suggested to see Adler (2019) pp. 32-37.

[29] Comparing the welfare change generated by a given dollar to some person to the one generated by giving a dollar to someone at a higher or lower income. CBA in this situation is distorted compared to utilitarian values.

[30] If the individual benefits from a policy, as compared to the baseline scenario with inaction, the monetary measure of her benefit is the amount she is willing to pay (WTP) for the policy implementation; if she is damaged, the measure of her hitch is the amount she is willing to accept (WTA) as compensation. The overall indicator of the policy's attractiveness is obtained by summing the WTP amounts and subtracting the WTA values. In addition, better-off people tend to have greater WTP or WTA than worse-off individuals.

[31] Some approaches for the weights' definition developed outside the health sector are summarised by Cookson et al. (2022).

4 Application: Assessing the COVID-19 pandemic's impact on wellbeing in the USA

Intending to assess the COVID-19 pandemic impact under control policies in the United States and following the COVID-19 simulator created by Fleurbaey et al. (2020), Ferranna et al. (2021) define a model whose aim is initially to represent the distribution of fatalities and costs by income quintiles and age groups, and after to define the individual wellbeing function before proceeding to the evaluation of the policy.[32] The first aim is reached by defining the proportion of the total income loss due to control policy implementation and then by defining the proportion of individuals for each age group and income quintile that die due to COVID-19. In this regard, two scenarios are considered for the distribution of fatalities across income quintiles and three scenarios for the distribution of policy costs.
Before the pandemic, considering an annual GDP per capita equal to \$65,000, the income distribution per capita[33] is q_i =(\$16,250; \$32,500; \$74,750; \$152,750) from the lowest income quintile to the highest one. Firstly, Ferranna et al. (2021) surpass a limitation of the model developed by Adler et al. (2020) by analysing COVID-19 mortality taking into account the heterogeneous effect across ages and not only across income quintiles. Considering that older people have a higher risk of dying than young (that represent 84% of the population), Verity et al. (2020) define the overall average infection fatality rate (IFR hereafter) as equal to 0.95%, the IFR for young people equal to 0.28% and that for old people equal to 4.36%. Without policy intervention, assuming that 70% of the population is infected, the likelihood of infectious disease is equal to 0.67% (i.e., 70% × 0.95%), and its spread is the same in all age groups and income quintiles.
Assuming also that the different socioeconomic groups of an individual can impact the fatality rate due to different access to the healthcare system, in Table 3, the COVID-19 mortality rates by age and income groups are shown from the lowest socioeconomic groups (1^{st} quintile) to the highest one (5^{st} quintile). Each mortality rate is defined assuming that 70% of the population gets infected without intervention. The mortality rate increases in low socioeconomic groups with an elasticity of fatalities to income $f = -0.5$.

Tab. 3. COVID-19 mortality rates by age and income groups

	1^{st} **quintile**	2^{nd} **quintile**	3^{rd} **quintile**	4^{th} **quintile**	5^{th} **quintile**
Young	0.32%	0.23%	0.18%	0.15%	0.10%
Old	4.96%	3.51%	2.87%	2.31%	1.62%

Source:(Ferranna et al. (2021) p. 22).

[32] In Appendix C, the model is defined through a general theoretical framework constructed following the specific model developed by Ferranna et al. (2021).

[33] The income distribution is obtained by $\frac{q_i N}{0.2N}\$65,000$.

If $f = 0$, the distribution of deaths is independent of income, so the mortality risk of young people is 0.2%, while for older people is 3.05%.

Upon analysing the costs associated with implementing the control policy, it was found that although it had a heterogeneous effect on the population, it reduced economic activity and contracted the GDP. Indeed, the costs burden people in the low socioeconomic groups more. In this regard, three scenarios were depicted by Ferranna et al. (2021). First, the monetary costs are borne by individuals considering their income with the elasticity of policy costs to income $c = 1$. The percentages paid by each individual are equal to the income distribution q_i to which the individual belongs. In the second, the costs are borne disproportionately by lower-income individuals with $c < 1$, taking into account that young people may be more affected by the negative effects of the policy. In this case, the percentages of policy costs paid by each individual are, from the lowest income quintiles to the highest one, 11%, 15%, 19%, 23%, and 33%.

Finally, when the elasticity of costs to income is $c > 1$, the policy costs bear on high-income categories, and the percentages of costs paid by each individual who belongs to one income quintile are, from the lowest to the highest income category, 2%, 6%, 11%, 21%, and 60%.

In addition, the authors consider the Atkinson social welfare function that takes into account the γ parameter for relative risk aversion, consumption and longevity as attributes, and the lifetime wellbeing period-by-period. They also define the expected lifetime individual wellbeing (or utility) function for each period, both in the pre-pandemic scenario (without intervention) and the pandemic one (with control policy), and separately for young individuals (under 65 years old) and older individuals (equal and over 65 years old).[34] After that, the authors compute the portion of the individual's income that he/she is willing to sacrifice to eliminate the pandemic risk by income and age group, under the scenario of the absence of intervention and without income loss.[35] In this regard, the old age group experiences a higher fatality risk rate, so the maximum income loss that is socially acceptable for them for some intervention that eliminates the risk of COVID-19 is higher than the young age group. This result is not surprising because people at the bottom of the income distribution are less willing to pay than people in the upper part of the distribution. Table 4 shows the individual's willingness to pay for policy intervention, considering the disproportionate impact for socioeconomic groups (the first number in each column) and the impact independent of income (the second number in each column) by age and income groups.

[34] See Appendix C, equations C.4 and C.5.

[35] See Appendix C, equations C.7 and C.8.

Tab. 4. Willingness to pay by individuals for a control policy to remove COVID-19 by age-income groups

	1^{st} **quintile**	2^{nd} **quintile**	3^{rd} **quintile**	4^{th} **quintile**	5^{th} **quintile**
Young	9.1%, 5.8%	17.7%, 15.8%	23%, 24.2%	28.6%, 34.6%	38.3%, 54%
Old	38.2%, 27.5%	56.4%, 53%	63.7%, 65.2%	69.9%, 75.41%	77.9%, 86.9%

Source:Ferranna et al. (2021), pp. 25 and 74)

Finally, Table 5 displays for each scenario and SWF the maximum percentages of income loss socially acceptable to pay for an intervention to remove the COVID-19 mortality risk.[36]

Tab. 5. Maximum percentages of GDP loss that are socially acceptable to pay for an intervention to remove the mortality risk associated with the pandemic

Scenario	**BCA (%)**	**Utilitarianism (%)**	**Ex-ante prioritarianism (%)**		**Ex-post prioritarianism (%)**	
			$\gamma = 1$	$\gamma = 2$	$\gamma = 1$	$\gamma = 2$
Scenario 1: - Regressive distribution of deaths - Regressive distribution of costs - Only the young pay the costs	36,8	15,3	12,7	10,6	13,1	11,1
Scenario 2: - Regressive distribution of deaths - Distribution of costs proportional to income - Only the young pay the costs	36,8	26,4	23,2	20,3	24	21,3
Scenario 3: - Regressive distribution of deaths - Progressive distribution of costs - Only the young pay the costs	36,8	40,9	39,7	38,2	41	40
Scenario 4: - Regressive distribution of deaths - Regressive distribution of costs - All age groups pay the costs	36,8	16,2	13,5	11,2	14	11,9
Scenario 5: - Distribution of deaths independent of income - Regressive distribution of costs - Only the young pay the costs	44,7	16,1	12,7	9,9	13,2	10,5

Source: (Ferranna et al. (2021), pp. 28)

With the benefit-cost analysis (BCA), the maximum socially acceptable cost to avoid all COVID-19 deaths is equal to 36.8% of annual aggregate GDP, regardless of who bears the burden of the control policy costs. With control policy costs proportional to income, all individuals pay 36.8% of GDP to remove the COVID-19 deaths; if the policy costs are

[36] See Appendix C, equations from C.9 to C.12.

disproportionated bearing on low-income quintiles, those in these quintiles would sacrifice 79% of their income, whereas those in the fifth quintile would sacrifice 26% of their own income (Ferranna et al. (2021)). Considering that the BCA analysis does not care about the distribution of costs, it would suggest any control policy that removes the COVID-19 deaths if their costs are less than 36.8% of GDP.

Concerning SWF approaches, three alternative SWFs can be implemented (utilitarian, ex-ante prioritarian, and ex-post prioritarian) to evaluate the control policy impact with income loss compared to the uncontrolled policy without income loss.

Ferranna et al. (2021) assume an Atkinson prioritarian SWF as described in equation (A.4) considering $\gamma = 1, 2$.

The five scenarios defined by the authors are displayed in Table 5. For most scenarios, the CBA approach endorses more costly policies than the SWF approach to remove the pandemic risk, except for scenario 3, where for the SWF approach, the COVID-19 policy costs are higher than BCA. Summarising[37], the results found by Ferranna et al. (2021) are:

- More progressive distribution of costs, higher socially acceptable GDP loss and a lower reduction in welfare, with the control policy preferred over no policy intervention (i.e., assumption of decreasing value of money[38]);

- When the distribution of costs is more regressive, the socially acceptable GDP loss is lower for prioritarianism compared to utilitarianism, and the latter is larger than BCA. An ex-ante prioritarian policymaker, who seeks to protect vulnerable individuals who are unlikely to be affected by COVID-19 (e.g., the poor and young), is less likely to support a control policy that removes the pandemic if the γ parameter is higher.[39] This is because a higher γ parameter corresponds to a lower maximum GDP loss for the policymaker.

- The ex-post prioritarian socially acceptable GDP loss is larger than the ex-ante prioritarian one. Compared to the ex-ante approach, the young in the ex-post prioritarian approach are the worst-off only in expectation, so the situation might improve. The worst-off, in this case, is not only those who die prematurely due to the pandemic but also those who die due to other causes and who do not die but pay the policy costs. The latter category requires protection, leading the policymaker to not invest in the control policy. Therefore, to protect the interests of those who

[37] A detailed analysis for each scenario is done by Ferranna et al. (2021), pp. 29-33.

[38] Dollars paid by low socioeconomic groups reduce their wellbeing and total utilitarian welfare more than equal dollars paid by high socioeconomic groups.

[39] In the first scenario, for instance, the poor and the young people are in the lowest socioeconomic groups.

die due to the pandemic, larger policy income losses are accepted with an ex-post prioritarian approach than a utilitarian one;

- When comparing scenario 5 to scenario 1, based on BCA analysis, policies that decrease the fatality risk of people in the high socioeconomic group seem to bear more burden. On the other hand, utilitarianism values the policy that reduces fatality risk regardless of income, rather than one that is regressive in terms of the distribution of deaths. This is because the focus is on wealthy life and not on the worse-off life. However, both ex-ante and ex-post prioritarianism prioritize policies that reduce fatality risk in a regressive manner, meaning that they give more value to policies that benefit those who are worse off;

- When comparing scenario 4 with scenario 1, it is important to consider the distribution of policy costs among different age groups, rather than just focusing on the young. In such cases, the prioritarianism approach assigns more value to control policies when the distribution of costs is regressive. This is because the health burdens of COVID-19 are also more regressive in nature. However, in situations where both health and non-health burdens of the pandemic are combined with regressive policy costs, the value assigned to control policy by BCA and SWF approaches changes. In such cases, the more regressive the burdens are, the more value is assigned to control policy by BCA approach and less by SWF approach;

- The ex-post prioritarianism approach may be preferable to the ex-ante approach in evaluating pandemic policies. This is because, at the population level, some individuals will die, but we do not know their identities.

Some limitations of the analysis conducted by Ferranna et al. (2021) are:

- The morbidity effects (e.g., pain and suffering) of the pandemic are not taken into account, and these effects can increase the cost of the pandemic;

- Individual behaviour (e.g., fear of infection, social and political trust) plays a substantial role in reducing the value of control policies due to endogenous social distancing effects;

- Short-term evaluation of financial impacts generated by the control policy, without considering the impact of government debts across individuals and across time;

- The economic losses of the pandemic are underestimated without considering the behavioural changes with an uncontrolled policy (or without intervention).

For a general graphical representation of the implementation of the CBA and SWF methodologies, it is helpful to recall the graphs obtained by Adler et al. (2020). Furthermore, comparing fig.2 and fig.3 (Adler et al. (2020), pp.11-13) both the BCA and the SWF models display that the suppression policy is preferable with respect to the mitigation one.[40]

5 Extension: trust and its impact on social distancing measure

In the pandemic simulator developed by Fleurbaey et al. (2020), similar to the SIR epidemiological model realised by Kermack and McKendrick (1927), the infection is based on parameters of contact frequency (i.e., Soc as the basic number of contacts reduced by the contact-reduction policy), infection's probability CR during any contact for who have no immunity, and CRI for those who have recovered, also considering mortality as endogenous to hospital capacity. Additionally, the model takes into account voluntary precautions ($Caut$ parameter) adopted by the population due to an increase in the number of deaths, as well as other policy interventions.
The model assumes that an individual is infected during the week following the contamination, thus not immediately.
Therefore, defining a sequence of weeks over two years, an individual contaminated on week t is infected on week $t+1$ and is isolated at home or hospital on weeks $t+2$, $t+3$ after which the individual dies with a probability ω_n or recovers with a probability γ_n.
The equation (1) defined by Fleurbaey et al. (2020) to calculate the number of new infectious people in week t is the following:

$$\begin{aligned} New\ infected_t = (Pop - Current\ infected_{t-1} - Current\ cured_{t-1} - Dead_{t-1} \times \\ (1-(1-CR)^{\alpha}) + Current\ cured_{t-1} \times (1-(1-CRI)^{\alpha}) \end{aligned} \tag{1}$$

where α is the number of contagious people met in week $t-1$, namely[41]:

$$Soc \times \left(\frac{1 - \frac{Contact\ reduction_{t-1}}{100}}{1 + (Caut \times Mortality\ rate_{t-1})} \times \frac{New\ infected_{t-1} \times (1 - Testing_{t-1})}{Pop - Dead_{t-1}} \right) \tag{2}$$

To obtain the number of contagious individuals met in week t is required to replace $t-1$ with t into the equation (2).
However, political and social trust can interactively impact the individuals' social distancing behaviour.
To take into account how people's trust and risk perception can impact the social distancing measure, we define two subgroups of susceptible individuals in the state S based

[40] For a detailed graphical analysis of the control policies' impacts and their evolution over weeks is helpful to see Adler et al. (2020), pp.10-13.

[41] To understand better how the author defines testing, hospitalization rate, deaths rate and the calibration of the parameters for illustrative purposes is useful to see the model explanation in his pandemic simulator (Fleurbaey et al. (2020)).

on the probability of progression to infected, going from the state S (susceptible) to I (infectious) into the SIR model.[42] The first subgroup S_1 includes all individuals who ignore social distancing measures because they have high social trust, low political trust and low-risk perception. Instead, the second subgroup S_2 includes those who follow social distancing measures and take additional precautions because they have low social trust, high political trust and high-risk perception. In particular, equation (1) is modified considering that:

$$CR = \Theta \times c_n \tag{4}$$

where Θ denotes the transmission rate that remains the same for all S subgroups due to the similar behavior of the virus regardless of group heterogeneity. On the other hand, c_n is associated with the level of significance of the transmission probability linked to each subgroup and the adherence level towards social distancing policies, which, in turn, depends on the level of trust and risk perception. Assuming that ST_i is the social trust that can assume a value $ST_i \in [0, 1]$, and RP_i is the risk perception that assumes value $RP_i \in [0, 1]$, if:

$$ST_i(t) > RP_i(t) \tag{5}$$

this means that the social trust is higher than the risk perception. Hence, individuals in the S_1 subgroup have a higher probability c_1 of contracting the virus than S_2 due to less adherence to social distancing measures, leading to greater virus transmission. Otherwise, if:

$$ST_i(t) \leq RP_i(t) \tag{6}$$

the social trust is lower than the risk perception. Thus, individuals are in S_2 with a lower probability c_2 of contracting the virus than S_1, thanks to more adherence to social distancing measures.

The value of the reproduction rate R is determined by the product of two parameters:

[42] In the SIR (Susceptible-Infectious-Recovery) model, assuming: a fixed population with no birth and no non-COVID fatalities; once a susceptible individual becomes infected, she immediately moves into the infectious state; once infectious, a person dies with a constant rate Θ_n and probability ω_n or she recovers with a probability γ_n; the subgroups of S are not correlated but can overlap; then:

$$\begin{aligned}
\frac{dS}{dt} &= -\sum_{n=1}^{2} CR\ S_n I \\
\frac{dI}{dt} &= \sum_{n=1}^{2} CR\ S_n I - \omega_n I_n - \gamma_n I_n \\
\frac{dR}{dt} &= \gamma_n I_n
\end{aligned} \tag{3}$$

where $S + I + R = 1$. Considering that there is only one infectious at the beginning, the initial condition for the SIR model is $S = \frac{N-1}{N} \approx 1$, $I = \frac{1}{N} \approx 0$, and $R = 0$.

Soc (the basic number of contacts) and CR (the infection rate). However, we do not have data on Soc and CR separately. To determine the number of contacts with infectious people based on these two parameters, we set a threshold for each subgroup. This helps us implement a contact reduction policy. In the case of S_1, where social trust is higher than risk perception, implementing social distancing measures without any voluntary precautions (i.e., $Caut = 0$) leads to a maximum reduction of 10% in contacts. However, for S_2, where social trust is lower than risk perception, the combination of social distancing measures and voluntary precautions (i.e., $Caut > 0$) leads to a minimum reduction of 40% in contacts.
As we can see in the pandemic simulator (Fleurbaey et al. (2020)) based on the USA population, in the first stage of the pandemic (from week 10 to 24) the public risk perception related to the virus is high with higher adherence to the social distancing measure (from 40% to 60% contact reduction). In contrast, since week 25, the risk perceptions might reduce because people would become more familiar with the virus and have a high social trust, leading to less adherence to the social distancing measure (from 10% to 0% contact reduction).
From a policy point of view, Adler et al. (2020) show that contagion reduction is complementary to contact reduction. Indeed, without contagion reduction, the control policy is less costly but saves fewer lives; otherwise fixing a contagion reduction of 40% in a suppression policy saves more lives at a smaller cost in a shorter time.
After analysing the behavior of two subgroups (S1 and S2), and taking into account the varied preferences of individuals towards trust and risk perceptions, it has been concluded that the number of infections will follow a similar pattern to the benchmark scenario for those in S1 with null or low impact of NPI and high mortality rates. On the other hand, for those in S2, the number of infections will follow a similar pattern to what has been depicted in the simulator by Fleurbaey et al. (2020), which considers policy implementation with a contact reduction policy and the behavior of the entire population without taking into account the trust components.

6 Conclusions

During the COVID-19 pandemic, many studies (Adler et al. (2020), Ferranna et al. (2021)) have been conducted to assess the impact of both health and non-health factors related to the virus. To reduce the spread of the virus, non-pharmaceutical interventions such as suppression and mitigation policies were implemented. These interventions have been analyzed in several studies to determine their impact on the wellbeing of individuals. The studies consider the relative impact of COVID-19 burdens and the costs of control policies, but they do not provide a detailed explanation of the evaluation frameworks that can be used. Our work aims to contribute to the strand of literature for evaluating the impact of tax policy and non-tax policy. The first part of our paper describes two methodologies that can be used for this purpose: cost-benefit analysis and social welfare function analysis. In the second part, we apply these methodologies to a case study conducted by Ferranna et al. (2021), using the pandemic simulator developed by Fleurbaey et al. (2020).

Ferranna et al. (2021) define the policy's value to remove the pandemic's risk by age and income groups. In this regard, their model represents the fatalities' distribution and policy costs by income quintiles and age groups. After defining the individual wellbeing function, they proceed to the policy evaluation using the CBA and the SWF (i.e., utilitarianism and prioritarianism) approaches.

According to their research, control policies are more valuable for SWF (social welfare function) than for BCA (benefit-cost analysis) when the COVID-19 burdens are more regressive. As for the costs, if policy costs are more regressive, then the γ parameter is higher and ex-ante prioritarianism is less supportive of control policy than utilitarianism. The SWF is a rich and flexible methodology sensitive to the distributions of the control policy costs and benefits among the population compared to the CBA framework.

Independently from the evaluation method adopted, an uncontrolled policy is not the best policy compared to the control one because its societal costs are higher than the control policy.

For both methodologies, it is relevant how severe the trade-off between saving lives and saving livelihoods is; indeed, a more severe trade-off means that BCA supports more aggressive control policies. Otherwise, suppression policy is accepted by both methodologies. Relevant is also the horizon of the policy because considering short-run economic costs, a suppression policy is preferred to the control one.

COVID-19 policy interventions work if the public accepts them. In this regard, few studies analyse the relationship between trust perception (social and political) and social distancing measure acceptance by individuals. For this reason, our work also aims to amplify the pandemic simulator developed by Fleurbaey et al. (2020) considering that the infection's probability CR during any contact for those who have no immunity depends on the level of adherence of individuals to social distancing policies that in turn depends on the level of trust and risk perception.

The findings in the literature show that when there is low social trust, high political trust and high-risk perception, as in the first weeks of the pandemic, there is a high acceptance of the pandemic measures, especially of the social distancing one.

To sum up, this work focuses on the analysis of the CBA and SWF frameworks for COVID-19 policies, but they can be applied to evaluate other health interventions in another epidemic context, also considering our general framework developed in the appendix to analyse the heterogeneous effect by age and income groups.

As a further extension of this work, it is feasible to use the pandemic simulator to assess the COVID-19 pandemic's impact in other countries, like the United Kingdom, France or developing countries that were mainly affected by the coronavirus pandemic.

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Appendix

A.Cost-benefit analysis framework

To determine the economic costs that can be incurred to reduce the number of fatalities and negative effects of the pandemic, a benefit-cost analysis (BCA) is conducted, converting the impact of pandemic policies into monetary values, which are then added up.[43] Considering a bundle $\alpha = (\$y, j)$[44] of income y and non-income j attributes, assuming a set of outcomes $\mathbf{O}$=$\{x_b, x_1, x_2...\}$ where x_b is the outcome in the baseline scenario without new policy intervention and x_1, x_2 are the outcomes with new policy intervention. Each individual i has a fixed preference R_i for the attribute bundles, then $\alpha_i(x_1) = (\$y_i(x_1), j_i(x_1))$ is the bundle of individual i in a specific outcome x_1 with new policy implementation.

The monetary equivalent of individual i for a given outcome x_1 is defined as $ME_i(x_1) = \Delta\$y$ such that an individual with fixed preference R_i is indifferent between $(\$y_i(x_b) + \Delta\$y, j_i(x_b))$ and $(\$y_i(x_1), j_i(x_1))$.

In a certainty module, the $\Delta\$y$ can be defined in terms of $u^{R_i}(.)$ which is a Von Neumann–Morgenstern utility function (vNM hereinafter). In this latter case, $u^{R_i}(\$y_i(x_b) + \Delta\$y, j_i(x_b)) = u^{R_i}(\$y_i(x_1), j_i(x_1))$.

With the CBA approach, the outcomes are ranked as follows:

$$x_1 \succeq x_2 \text{ iff } \sum_{i=1}^{N} ME_i(x_1) \geq \sum_{i=1}^{N} ME_i(x_2) \tag{A.1}$$

In an uncertainty module (that is explained in the Appendix B), given a set of policies $\{B, P_1, P_2, ...\}$, where B is the baseline scenario with inaction, assuming a fine set $\mathbf{Z}$=$\{z, z^{\star}, ...\}$ of "state of nature" with a probability for each state z equal to $\pi(z) > 0$, than $(\$y_i(x_1^{P_1,z}), j_i(x_1^{P_1,z}))$ is the bundle of income and other non-income attributes that the individual i obtains in the outcome x_1 of new policy P_1 in the "state of nature" z, namely $x_1^{P_1,z}$.

In all "states of nature" z, $ME_i(P_1)$ is a constant payment to individual i for what he/she is indifferent between the inaction scenario B and policy implementation P_1. In relative

[43] In the pandemic simulator, the only economic cost computed is that related to the contact reduction due to lockdown policies and voluntary actions adopted by the population. A contact reduction of 1% reduces GDP by CCR% (set at 50% in the model for a pure illustration scope). This assumption is consistent with the reduction of activity observed during lockdown times and estimates the recession and its alternation caused by the pandemic and the policy interventions implemented.

[44] Individual income is denoted with $\$y$, where y is a typical symbol used for income identification and the dollar sign as a reminder.

term, $ME_i(P_1) = \Delta\$y$ such that:

$$\sum_{z\in\mathbf{Z}} \pi(z)u^{R_i}(\$y_i(x_b^z) + \Delta\$y, j_i(x_b^z)) = \sum_{z\in\mathbf{Z}} \pi(z)u^{R_i}(\$y_i(x_1^{P_1,z}), j_i(x_1^{P_1,z})) \tag{A.2}$$

To rank policies, the following rule is applied:

$$P_1 \succeq^P P_2 \text{ iff} \sum_{i=1}^{N} ME_i(P_1) \geq \sum_{i=1}^{N} ME_i(P_2) \tag{A.3}$$

Finally, CBA is "correlation-insensitive", indeed $ME_i(P_1)$ is fixed by the lottery over bundles of attributes that person i obtains with policy P_1 and is independent of the lotteries obtained from other individuals. Then, given policy P_1, the probability that individual i obtains bundle $\alpha^\star = (\$y, j)$ is equal to $\rho_i^{P_1}(\alpha^\star) = \sum_{z\in Z:\alpha_i^{P_1,z}=\alpha^\star} \pi(z)$. Then, $ME_i(P_1)$ is $\Delta\$y$ such that:

$$\sum_{\alpha^\star} \rho_i^B(\alpha^\star)u^{R_i}(\$y + \Delta\$y, j) = \sum_{\alpha^\star} \rho_i^{P_1}(\alpha^\star)u^{R_i}(\alpha^\star) \tag{A.4}$$

Instead of looking to the "equivalent variations" of the current income y, the CBA approach can also be applied to environmental, health and safety regulations, as well as to the bundle of welfare attributes such as longevity, health, income histories (LHI hereinafter) that leads to the definition of a lifetime wellbeing level for an individual. In this latter case, in the baseline scenario B an individual i can face one lottery over LHI histories and with a policy P_1 he/she has a different lottery. Given a $ME_iw(x_1)$ such that the current-year income in every history in the baseline lottery is increased by $\Delta\$y$, the individual i would be indifferent between the two lotteries and her monetary equivalents would be the same.

Adler (2017) explains how policy impacts are decomposed into three dimensions for the CBA analysis in governmental practice: cost, fatality risk, and health. Initially, an overall monetary amount is assigned to a given policy P_1 that is equal to the sum of the total "costs" of the policy in terms of individual income change and its total monetised risk-reduction and health-improvement benefits using population-average valuation methods (e.g., VSL, VSLY and QALY).

B.Social welfare function framework

This model measures health and non-health impact on an individual's wellbeing, whose gains and losses are aggregated to obtain an overall measure of the policy benefits. The starting point of the SWF analysis requires measuring the wellbeing level related to different possible people's lives represented by bundles of goods that matter to individuals, like income, health, and longevity.

Several types of measures of the wellbeing level were developed: the lifetime satisfaction scores (Clark et al. (2019), Layard et al. (2020)); the individual preferences between probability distributions (”lotteries”) over alternative possible lives (Adler (2019)); the income corrected for the value of non-market aspects of life (i.e., longevity) (Fleurbaey and Blanchet (2013)); and the capability approach looking at the opportunities in the various aspects of life (Sen et al. (1999)).
Adler (2019) highlights three steps, summarised in Table 2 in the main text, that occur interactively to apply the SWF framework to a policy choice: outcome description, prediction, and valuation.

Outcome description. By using the parameters of the pandemic simulator developed by Fleurbaey et al. (2020) and the SWF framework defined by Adler (2017),(2019), (2020), societal wellbeing is obtained considering the level of annual income per capita equally enjoyed by the population over a lifetime of 85 years.[45] Assuming that the population is portioned into five income quintiles q_i where $\sum_{i=1}^{5} q_i = 1$, then the wellbeing is measured in terms of equivalent income per capita:

$$\left(\frac{Y_i L_i}{85}\right)\left(\frac{L_i}{85}\right)^{\alpha} \tag{B.1}$$

where L_i is longevity in quintile i, Y_i is the annual income per capita in quintile i, and α is calibrated considering the willingness to pay for one additional year and it is equal to VSLY for the average citizen, and proportioned to income, namely $(1 + \frac{VSLY}{GDP})$.
By using the equivalent income to measure societal wellbeing, individual lottery preference information is not required. Thus, this approach is more tractable than the vNM ones. The approach needs a ”reference” package of non-income attributes (e.g., health state, longevity) that are set at a high level.[46]
A person’s income is transformed into an equivalent income by normalising it for the difference between her actual non-income attributes and the reference package. Considering a bundle $\alpha = (\$y, j)$ of income and non-income attributes, and j^{ref} as the reference package, then the equivalent income $\$y^{equiv}$ made the individual indifferent between $(\$y, j)$ and $(\$y^{equiv}, j^{ref})$.[47] The equivalent income approach satisfies the ”No Difference” axiom,

[45] In the simulator the data about the income shares per quintile derive from the World Bank and that about the life expectancy at birth per income quintile is defined using data from `https://opportunityinsights.org/data/?geographic_level=0&topic=0&paper_id=573#resource` for the USA and from Murtin et al. (2017) for OECD countries.

[46] For instance, the reference health status is set as excellent health rather than poor or fair health.

[47] For instance, in the pandemic simulator, in the USA, the reference level of longevity j^{ref} is considered equal to 85 years. The GDP/per capita is 65,456, the annual income per capita in the last quintile is 153,494.32, the longevity in the last quintile is equal to 82.3, and the VSLY for the average citizen is equal to three times the GDP (so 196,368). An individual in the last quintile is willing to give up

because people with the same preferences and the same welfare attributes bundles have the same wellbeing numbers, and the Sovereignty axiom because if someone prefers one bundle to another, the equivalent income for the former is higher than the latter. However, this approach fails to satisfy the Bernoulli principle, which is not applicable because the equivalent income needs to consider an individual's lottery preferences. Further, the equivalent income approach endorses the continuous-prioritarian SWF that is sensitive to the distribution of wellbeing itself, giving priority to the worse off.

In the model defined by Adler et al. (2020), both individual lifetime wellbeing and societal are expressed in terms of annual permanent income per capita (i.e., equally-distributed equivalent)[48] and the reference level of longevity (i.e., 85 years) has no impact on percentage changes.

Generally speaking, given a fixed population with N individuals, a bundle of attributes α, $A_t = (\alpha_{it}, ..., \alpha_{Nt})$ is the set of feasible bundles of welfare attributes (i.e., attribute matrix) in period t for each individual i whose vector is α_{it}. Social welfare is defined in two steps (Decancq and Schokkaert (2021)) and through a social welfare function $W(.)$ whose argument is the attribute matrix A_t. Initially, a wellbeing measure is defined for each individual i, namely $w_{it} = w_i(\alpha_{it})$, generating a vector $w_t = (w_{it}, ..., w_{Nt})$ of N wellbeing measures. Finally, the wellbeing measures are transformed by $g(.)$, a strictly increasing and concave function[49], and then averaged. The generalised utilitarian social welfare function is then defined as:

$$W(A_t) = \frac{1}{N} \sum_{i=1}^{N} g(w_i(\alpha_{it})) \tag{B.2}$$

This social welfare function satisfies the Anonymity principle for wellbeing in each period and cross-sectional data. Representing the social welfare function in terms of its equally-distributed equivalent [50], we obtain the following:

$$\tilde{W}(A_t) = \frac{1}{g} \left[\frac{1}{N} \sum_{i=1}^{N} g(w_i(\alpha_{it})) \right] \tag{B.3}$$

18,593.08 to be in the greater life expectancy, thus his equivalent income (defined following equation (B.1)) is 134,901.24 for his bundle ($153.494,32; 82.3) and he is indifferent between ($153.494,32; 82.3), and ($134,901.24; 85).

[48] Considering the example in the previous footnote, the equally-distributed equivalent in the USA is equal to 52,990 and is obtained by making an arithmetic mean of the equivalent income of each quintile.

[49] The feature of the strictly concave function $g(.)$ leads to a social improvement through redistribution from the better off to the worse off, highlighting the crucial difference between the utilitarian and the prioritarian approach as a measure of social welfare (Decancq and Schokkaert (2021)).

[50] Denotes the level of wellbeing that, when equally distributed, would yield the same societal wellbeing as the unequal situation.

One advantage of this approach is that the equally-distributed equivalent (EDE hereafter) is expressed in the same units as individual wellbeing. Hence, individuals with the same average wellbeing level $\bar{w}$ also have the same EDE in an equal situation. In contrast, the EDE will be strictly lower than the average wellbeing level in an unequal situation if the $g(.)$ is strictly increasing and strictly concave (i.e., prioritarian case).
Among the subfamilies of prioritarian social welfare functions, the most important are the Atkinson and Kolm-Pollak. The first is the most popular and depends on an inequality-aversion parameter γ that can assume any positive number, and it expresses the degree of priority for the worse off. As γ rises, the Atkinson $g(.)$ function gives a higher degree of priority to the worse off, becoming more concave. If $\gamma = 0$ the SWF becomes utilitarian; if $\gamma \sim \infty$, the SWF becomes leximin.
In order to obtain the Atkinson social welfare function, the function $g(.)$ is defined as follows:

$$\begin{cases} g^{ATK}(w_i(.)) = (1-\gamma)^{-1} w_i(.)^{1-\gamma} \text{ if } \gamma > 0, \gamma \neq 1 \\ g^{ATK}(w_i(.)) = ln w_i(.) \text{ if } \gamma = 1. \end{cases} \tag{B.4}$$

Then, the equally-distributed equivalent of the Atkinson social welfare function is:

$$\tilde{W}_{\gamma}^{ATK}(A_t) = \left[\frac{1}{N}\sum_{i=1}^{N} g(w_i(\alpha_{it}))^{1-\gamma}\right]^{(1-\gamma)^{-1}} \tag{B.5}$$

The prioritarian approach can be decomposed by defining the equally-distributed equivalent of social welfare as a function of the average and the inequality of individual wellbeing, namely:

$$\tilde{W}_{\gamma}^{ATK}(A_t) = \mu(A_t)[1 - AI_{\gamma}(A_t)] \tag{B.6}$$

where $\mu(A_t) = \frac{\sum_i (w_i(\alpha_{it}))}{N}$ is the mean wellbeing in period t and $AI_{\gamma}(.)$ is the relative Atkinson-index of inequality in wellbeing considering the parameter γ for the inequality aversion. Atkinson-index of inequality is required to consider the social welfare loss caused by wellbeing inequality.[51]
The SWF approach initially requires defining the social welfare function and then choosing the individual's wellbeing function.
A central point in the prioritarian approach is the lifetime perspective on individual's wellbeing to define which individuals are better off focusing on social welfare in one period, as usual in the literature, or in more periods, with several tricky issues.
Firstly, assuming a set of outcomes $\mathbf{O} = \{x_1, x_2, ...\}$, a fixed population of individuals $\{1, ..., N\}$, and a wellbeing measure $w(.)$ that maps a given outcome x_1 into wellbeing

[51] The larger the correction made by the inequality index, the larger the inequality in wellbeing. From the utilitarian point of view, $\gamma = 0$ because no priority is given to the worse-off. Thus, the inequality index is also equal to zero for any bundle of attributes, leading the social welfare to be equal to the average wellbeing (Decancq and Schokkaert (2021)).

numbers' vector $(w_1(x_1), ..., w_N(x_1))$. Then, wellbeing vectors are ranked following a rule E that could be utilitarian[52] (i.e., the SWF is obtained as the sum of wellbeing numbers) or prioritarian.[53] Intra-and interpersonal wellbeing levels and differences comparisons are admissible.

By using the wellbeing measure, it is possible to define the lifetime wellbeing of an individual that is the input into the SWF. To assign a lifetime wellbeing level to each individual, defining the outcomes with some features of ethical interest is required. In each outcome, an individual's wellbeing is defined by a bundle of attributes α_{it} that can be of two types: welfare attributes, if they directly define lifetime wellbeing, and further attributes that provide additional information about the outcome (e.g., demographic characteristics, educational attainment, occupation, environmental conditions, individual data[54] (i.e., name, date of birth)).

To define the wellbeing measure, A is the set of feasible bundles of *welfare attributes*, namely longevity, income and health. To evaluate the lifetime wellbeing of someone, one is required to know his lifespan L whose information is obtained considering the *longevity* attribute as the expression of the individual's length-of-life in the population of interest. Given the set of policies $\mathbf{P}$, L_{max} is the longest lifespan assigned a non-zero probability. For instance, the lifespan of an individual can be reduced due to an increase in the infection fatality rate (IFR)[55] due to COVID-19.

Another relevant attribute is the *income* during each individual's period alive, as a proxy for the individual's consumption. These two attributes are available on an annual basis. Considering that these risks impact individual health status across his lifetime, the last attribute that is required to be considered is *health*, which is defined using a QALY-type measure of someone's health quality each year. The health attribute, yearly income, and longevity define an individual's lifetime utility.

According to Adler (2017), the bundle of welfare attributes can be defined as the individual's longevity, health, and income (LHI). By gathering information about an individual's preferences, we can determine their welfare attributes, which in turn help us define their lifetime wellbeing level. In technical terms:

$$w_i(x_1) = u_i(y_i^l(x_1), ..., y_i^{L_i(x_1)}(x_1); h_i^1(x_1), ..., h_i^{L_i(x_1)}(x_1)) \tag{B.7}$$

where $L_i(x_1)$ is the lifespan of individual i in outcome x_1, $y_i^l(x_1)$ is the income of individual

[52] The utilitarian SWF ranked outcomes accordingly: $x_1 \succeq x_2$ iff $(w_1(x_1), ..., w_N(x_1)) \succeq (w_1(x_2), ..., w_N(x_2))$, thus $\sum_{i=1}^N w_i(x_1) \geq \sum_{i=1}^N w_i(x_2)$.

[53] The prioritarian SWF ranked outcomes accordingly: $x_1 \succeq x_2$ iff $\sum_{i=1}^N g(w_i(x_1)) \geq \sum_{i=1}^N g(w_i(x_2))$.

[54] The SWF framework does not require the use of these individual attributes, as well as CBA.

[55] For instance, the average IFR for age groups is equal to 0.6-0.94% in the USA, 0.72-1.08% in the UK, and 0.83-1.19% in France (Verity et al. (2020), Salje et al. (2020), Baguelin et al. (2020)).

i in outcome x_1 during her l-th year of life, $h_i^l(x_1)$ is the individual health quality in outcome x_1 during the l-th year of file, and $u_i(.)$ is the rescaled vNM utility function of individual i assuming homogeneous preferences.[56]
This equation can be simplified by considering the lifetime utility as the sum of the annual utility and the homogeneous individual's preference[57] dropping the individual-specific subscript from the utility function in the equation (B.7).
Assuming that individual i is now in year l of her life, so her age last birthday is $(l-1)$, and a baseline scenario B without policy intervention. The individual's realised baseline bundle of welfare attributes from years 1 to $(l-1)$ is $(y_i^{B,1}(x_1),...,y_i^{B,l-1}(x_1);h_i^{B,1}(x_1),...,h_i^{B,l-1}(x_1))$, while the baseline bundle of welfare attributes from years l to L_{max}[58] is $(y_i^{B,1}(x_1),...,y_i^{B,L_{max}}(x_1);h_i^{B,1}(x_1),...,h_i^{B,L_{max}}(x_1))$.
Considering that the individual's likelihood of surviving to the end of year l of her life, conditional on being alive at its beginning, is equal to s^l. Then, the mortality risk for year l is (1-s^l). In this scenario, the individual i's baseline likelihood of surviving from years l to L_{max} is defined as $(s_i^{B,l},...,s_i^{B,L_{max}})$.
Following these notations, a policy intervention to reduce the risk of COVID-19 infectious disease at some financial cost can be described as a list of lotteries, one for each individual in the population of interest, over bundles of welfare attributes. In this context, the policy-makers should choose between an uncontrolled policy (i.e., the baseline scenario B with the choice of doing nothing) and alternative policies (i.e., suppression or control policies). Each choice is a lottery (i.e., probability distribution) across LHI histories for each population member.
The individual i's welfare attributes and survival probabilities from years l to L_{max} change due to a policy P_1 by an amount equal to $\Delta y_i^{P_1,l}$, $\Delta h_i^{P_1,l}$, and $\Delta s_i^{P_1,l}$. In year l, the new i's income, health and survival probability as a result of the policy P_1 implementation become:

$$\begin{aligned} y_i^{P_1,l} &= y_i^{B,l} + \Delta y_i^{P_1,l} \\ h_i^{P_1,l} &= h_i^{B,l} + \Delta h_i^{P_1,l} \\ s_i^{P_1,l} &= s_i^{B,l} + \Delta s_i^{P_1,l} \end{aligned} \tag{B.8}$$

[56] Assuming that the vNM utility function is additive, then $u_i(y_i^l,...,y_i^{L_i};h_i^1,...,h_i^{L_i}) = \mu(y_i^l) + ... + \mu(y_i^{L_i}) + \mu(h_i^1) + ... + \mu(h_i^{L_i})$, where μ is the period utility function. Considering $\mu^\star(.) = r\mu(.) + c$, with $r > 0$ as a positive linear transformation of $\mu(.)$ and $u^\star(.)$ the equivalent vNM utility function. Both $u(.)$ and $u^\star$ are the same if each individual has the same lifespan; otherwise, they are not. See Adler (2019) pp.293-294 for more details.

[57] Adler (2017) in Appendix A.2 defines how to generalise the wellbeing measure in the case of heterogeneous preferences.

[58] By considering years from l to L_{max} means to define the income amount that an individual will earn and consume in each year if she survives to the end of that year Adler (2019) pp 292.

The vector of welfare attributes generated with the policy P_1 for each individual and that of baseline lead to a lottery over longevity/income/health bundles.

Prediction. Under the uncertainty module[59], Adler (2017) assumes a finite set $\mathbf{Z}$=$\{z, z^{\star}, ...\}$ of "state of nature" whose probability for each state z is $\pi(z) > 0$. Considering the baseline scenario B with inaction and the set of alternative policies $\mathbf{P} = \{P_1, P_2, ...\}$, the outcome of the baseline scenario choice is $x_1^{B,z}$ in state z, and $x_1^{P_1,z}$ is the outcome of policy P_1 in state z.
Given a policy P_1, each person faces a *prospect* (i.e., a probability distribution over the outcomes and wellbeing levels associated).

Valuation. To rank choices under the uncertainty module, three procedures can be adopted (Adler (2017)[60]:

- *utilitarianism-under-uncertainty* (W^{UUU}), where choices are ranked according to the expected sum of individual wellbeing, with the outcome that is multiplied by the probability of the outcome itself. In mathematical terms:

$$P_1 \succeq^P P_2 \text{ iff } \sum_{z \in Z} \pi(z) \sum_{i=1}^{N} w_i(x_1^{P_1,z}) \geq \sum_{z \in Z} \pi(z) \sum_{i=1}^{N} w_i(x_1^{P_2,z}) \tag{B.9}$$

- *ex-post prioritarianism* (W^{EPP}), where choices are ranked according to the expected sum of transformed individual wellbeing whose transformation is obtained considering the prioritarian $g(.)$ function that is strictly increasing and concave. The outcome is multiplied by the probability of the outcome itself. In mathematical terms:

$$P_1 \succeq^P P_2 \text{ iff } \sum_{z \in Z} \pi(z) \sum_{i=1}^{N} g(w_i(x_1^{P_1,z})) \geq \sum_{z \in Z} \pi(z) \sum_{i=1}^{N} g(w_i(x_1^{P_2,z})) \tag{B.10}$$

- *ex-ante prioritarianism*(W^{EAP}), where choices are ranked according to the sum of transformed expected individual wellbeing obtained by taking the expected wellbeing number, transformed using the $g(.)$ function and summing up. In mathematical

[59] For rule E, an uncertainty module defines a complete quasiordering of the $\mathbf{P}$ set under some axioms (Adler (2019)pp. 130-138,278-280).

[60] Several advantages are related to the use of these uncertainty modules. Following the Separability axiom, individuals who are not affected because their level of wellbeing does not change across the state of nature of different policies by the policy can be ignored by the policy analyst.
In addition, the two modules are score-based, so they satisfy the Continuity axiom. Further, the expected scores are used to compare policies; thus, the "Expected Value Ethical Decision-making" axiom is also satisfied.

terms:

$$P_1 \succeq^P P_2 \text{ iff } \sum_{i=1}^{N} g\Big(\sum_{z\in Z}\pi(z)w_i(x_1^{P_1,z})\Big) \geq \sum_{i=1}^{N} g\Big(\sum_{z\in Z}\pi(z)w_i(x_1^{P_2,z})\Big) \quad \text{(B.11)}$$

Considering that EAP violates the stochastic-dominance and the time-consistency axioms, the choice is between UUU and EPP. The latter satisfies the Equity Dominance axiom[61], whereas the former satisfies the Ex-Ante Pareto Principle.[62] The choice between UUU and EPP is not easy. For this reason, Adler (2017) considers both approaches in his analysis of the SWF framework.[63]

Let $\alpha_i^{P_1,z}$ be the bundle of welfare attributes of individual i in the the outcome $x_1^{P_1,z}$ that is obtained from policy P_1 given state z. Given policy P_1, the probability that the individual i obtains the bundle $\alpha^\star$ is equal to $\rho_i^{P_1}(\alpha^\star) = \sum_{z\in Z:\alpha_i^{P_1,z}=\alpha^\star}\pi(z)$.

The previous equations defined for UUU, EPP, and EAP can be modified taking into account the lottery theory over welfare-attributed bundles. Considering that R represents the homogeneous individual's preference, the three equations become (Adler (2017)):

$$W^{UUU}: \sum_{i=1}^{N}\sum_{\alpha\in\mathbf{A}}\rho_i^{P_1}(\alpha)u^{R_i}(\alpha) \quad \text{(B.12)}$$

$$W^{EPP}: \sum_{i=1}^{N}\sum_{\alpha\in\mathbf{A}}\rho_i^{P_1}(\alpha)g(u^{R_i}(\alpha)) \quad \text{(B.13)}$$

$$W^{EAP}: \sum_{i=1}^{N} g\Big(\sum_{\alpha\in\mathbf{A}}\rho_i^{P_1}(\alpha)(u^{R_i}(\alpha)\Big) \quad \text{(B.14)}$$

Modifying these three equations, Adler (2017) pp.29-30, also take into account the cohorts structure whose choice for purposes of environmental, health and safety regulation depends on the data available and causal models. In general, a cohort should include all individuals with the same year of birth, prior-year income, prior-year health quality, and the cluster of other attributes (e.g., physical, demographic, etc.).

A more recent adjustment was made by Ferranna et al. (2021) looking at the difference between "young" (<65 years old) and "old" (≥ 65 years old) individuals and more than

[61] Considering two choices P_1 and P_2, P_1 is better than P_2 such that every strictly, possible and with non-zero probability outcome of P_1 has the same total wellbeing as every possible outcome of P_2 but is more equally distributed.

[62] If choice P_1 has an individual's expected wellbeing at least as large as her expected wellbeing with choice P_2 and in the choice P_1 at least one person has greater expected wellbeing, thus P_1 is better than P_2.

[63] See Adler (2017) pp.24-25 to understand better the conflict existing between UUU and EPP approaches.

five income groups, considering a bundle of attributes that includes income and longevity. A limitation of the analysis conducted by Adler et al. (2020) is that they needed to assess the heterogeneous impact of the policy by age groups.

C. The impact of control policies in the USA by income quintiles and age groups: a theoretical framework

Distributions of costs and deaths. Following the methodological approach developed by Ferranna et al. (2021) and the parameters introduced by Fleurbaey et al. (2020) in his pandemic simulator, we define the theoretical framework to assess the impact of the control policy of COVID-19 across age categories and income groups, comparing the CBA and the SWF approaches.

Let us define the model by looking at heterogeneous effects by age categories e. In particular, the population is partitioned into two age categories: "young" (y) (<65 years old) and "old" (o) (≥65 years old), namely $e = (y, o)$.

Then, following the income distribution defined by income quintiles $q_i = (5\%, 10\%, 15\%, 23\%, 47\%)$ where $\sum_{i=1}^{5} q_i = 1$, individuals are divided into five income categories $i = (1, ..., 5)$ defined taking into account the 2019 U.S. structure of the population by age (U.S. Census Bureau 2020) where 84% of the population is young.

By introducing the control policy to remove the pandemic, a portion of the total income is lost by age and income categories. Table C1 displays the age-income combinations obtained.

Tab. C1. Age-income combinations

	young	old
q_1	q_1y	q_1o
q_2	q_2y	q_2o
q_3	q_3y	q_3o
q_4	q_4y	q_4o
q_5	q_5y	q_5o

For each combination, c is the elasticity of costs to income[64], θ_e is the share of costs paid by age categories e whose size is $0.2n_eN$ and n_e is the share of individuals in age categories e, and the portion of costs paid is $\frac{q_i^c\theta_e}{\sum_i q_i^c}$. Then, the proportion of the total income loss by age-income combinations is:

$$\theta_{ie} = \frac{q_i^c\theta_e}{\sum_i q_i^c}\frac{1}{0.2n_eN} = \frac{1}{0.2N}\frac{q_i^c}{\sum_i q_i^c}\frac{\theta_e}{n_e} = \frac{5}{N}\frac{q_i^c}{\sum_i q_i^c}\frac{\theta_e}{n_e} \tag{C.1}$$

[64] If $c = 1$ the income loss is proportional to income, if $c < 1$ there is a regressive distribution of costs that bear on people in the low-income categories., and if $c > 1$ there is a progressive distribution of costs that bear on high-income categories.

where N is the total population, $\frac{5}{N}$ is the income category size. If $\frac{\theta_e}{n_e} = 1$, the economic costs bear on all age categories, while when $\frac{\theta_e}{n_e} = \frac{1}{n_y}$, the burden of economic costs falls only on young with $\theta_o = 0$.
The COVID-19 pandemic reduces the aggregate income by a certain amount of GDP (i.e., ΔGDP). Thus, individuals in age-group categories combinations pay $\theta_{ie}\Delta GDP$.
The same approach can be applied to define the distribution of deaths. Defining f as the elasticity of fatalities to income[65], Ω_e as the proportion of deaths experienced by people in age categories e, (d_{ie}) as the deaths number of individuals in age-income combinations among the total number of pandemic deaths (d) equal to $d_{ie} = \frac{q_i^f \Omega_e}{\sum_i q_i^f} d$, and the mortality rates for each age-income combinations equal to $\Omega_{ie} = \frac{d_{ie}}{0.2 n_e N}$. Then, the share of people in each age-income combination that died due to the pandemic is:

$$\Omega_{ie} = \frac{5}{N} \frac{q_i^f}{\sum_i q_i^f} \frac{\Omega_e}{n_e} d \tag{C.2}$$

If $\frac{\Omega_e}{n_e} = 1$, the mortality rate is the same in all age categories. Following the U.S. structure of the population by age, the IFR is equal to 0.28% for young and 4.36% for older people and the likelihood of getting infected is $\Omega_y = 0.25$ and $\Omega_o = 0.75$, respectively.

Individual wellbeing function. To define the individual lifetime wellbeing function, a bundle of attributes that includes income and longevity $\alpha = \{Y^l, ..., Y^{L_{max}}\}$ is considered.[66]
Adopting the Atkinson social welfare function and its γ parameter as an indicator of relative risk aversion, the period utility of the individual is $w(Y_{ie}) = \frac{Y_{ie}^{1-\gamma}}{1-\gamma}$, where Y_{ie} is the income uses as a proxy of the consumption of individuals in the age-income combination.

- Pre-pandemic period. The income is equal to the income quintiles' value, so $Y_{ie} = Y_i = \frac{5}{N} q_i GDP$ with GDP designed as aggregate income.
Assuming a contraction of the aggregate income of GDP^{max} due to the introduction of the control policy to eliminate the pandemic, with economic costs that occur in one period, the income of the period is equal to $Y_{ie} = Y_i - \theta_{ie} GDP^{max}$.
The likelihood of premature deaths is negatively correlated with income categories. In the case study, assuming as reference income level the median of the income categories (i.e., the third quintile), the probability for young of premature deaths, before reaching an old age > 65, is defined as $\rho_{iy} = 13\%$ with an average age of young individuals equal to

[65] If $f = 0$, individuals who die due to the pandemic (i.e., the mortality risk) are independent of income, while if $f < 0$, there is a regressive distribution of deaths that bear on low socioeconomic groups.

[66] In the Appendix C the income is denoted by the letter Y instead of y as in the general SWF framework to distinguish it from y that indicates "young" people.

$\bar{e}_y = 51$, while the probability for old of premature deaths, before reaching the desirable longevity 85 and the life expectancy for over 85 of 88, is $\rho_{io} = 43\%$ with an average age of old individuals equal to $\bar{e}_o = 76$.
For each age-income combination, the death probabilities shown in Table C2 are defined through a re-scaling, starting from the likelihood of dying for the third quintile times the probability of dying for each income quintile (i.e., 1.5, 1.3, 0.9, 0.75).

Tab. C2. Probabilities of dying for each age-income combination

	young	old
q_1	19%	57%
q_2	16%	49%
q_3	13%	43%
q_4	12%	40%
q_5	10%	34%

- During the pandemic period. The COVID-19 pandemic rised the number of fatalities with a probability of dying prematurely defined as:

$$\rho^{\star}_{ie} = \rho_{ie} + \Omega_{ie} \tag{C.3}$$

In year l (current year) of the individual life, the average age of young and old age categories are equal to $\bar{e}^l_y = 51$ and $\bar{e}^l_o = 76$, the minimum age of old people is $e^{min}_o = 65$, the desirable longevity for old people is $e^{ref}_o = 85$, and the life expectancy for people over 85 is $e^{max}_o = 88$. Then, the age last birthday is defined as $(\bar{e}^l_y - 1)$ and $(\bar{e}^l_o - 1)$ for each age category.
The expected lifetime utility of people in each age-income combination is defined both for old and young people. For old people it is:

$$E_{io} = (\bar{e}^l_o - 1)w(Y_i) + w(Y_{ie}) + (1 - \rho^{\star}_{io})(e^{max}_o - \bar{e}^l_o)w(Y_i) \tag{C.4}$$

For young people it is:

$$E_{iy} = (\bar{e}^l_y - 1)w(Y_i) + w(Y_{ie}) + (1 - \rho^{\star}_{io})[\rho_{io}(\bar{e}^l_o - \bar{e}^l_y)w(Y_i) + (1 - \rho_{io})(e^{max}_o - \bar{e}^l_y)w(Y_i)] \tag{C.5}$$

where $Y_{ie} = Y_i - \theta_{io} GDP^{max}$ for old people and $Y_{ie} = Y_i - \theta_{iy} GDP^{max}$ for young.
Finally, the realised lifetime utility of a person in the age-income combination who dies exactly at $l = (51, 76, 88)$ is defined as:

$$W_{ie}(l) = (l - 1)w(Y_i) + w(Y_{ie}) = (l - 1)w(Y_i) + w(Y_i - \theta_{ie} GDP^{max}) \tag{C.6}$$

Willingness to pay to remove COVID-19. Without control policy intervention, the equation (C.4), considering the willingness to pay $WTP_{ie} = \theta_{ie} \Delta GDP$, becomes for the old people equal to:

$$E_{io}(\rho_{io}, WTP_{io}) \equiv (\bar{e}_o^l - 1)w(Y_i) + w(Y_{ie}) + (1-\rho_{io})(e_o^{max} - \bar{e}_o^l)w(Y_i) \equiv E_{io}(\rho_{io}^\star, \Delta GDP) \tag{C.7}$$

where $Y_{ie} = Y_i - WTP_{io} = Y_i - \theta_{io}\Delta GDP$.
For young people, equation (C.5) is modified like equation (C.7), but replacing $Y_{ie} = Y_i - WTP_{iy} = Y_i - \theta_{iy}\Delta GDP$, so the final equivalent equation is:

$$E_{iy}(\rho_{iy}, WTP_{iy}) \equiv E_{iy}(\rho_{iy}^\star, \Delta GDP) \tag{C.8}$$

In Table 4 in Section 4, the people's willingness to pay to remove COVID-19 is displayed, assuming that without intervention there is no income loss, so $\Delta GDP = 0$.

Policy evaluation: BCA vs SWFs. Considering $N = n_y + (1-n_y) = n_y + n_o$ the total population pre-pandemic, the control policy costs GDP_B^{max} for the cost-benefit analysis (BCA) is equal to the unweighted sum of the willingness to pay of people to remove the pandemic, namely:

$$GDP_B^{max} = \frac{N}{5}\sum_{i=1}^{5}(n_y WTP_{iy} + n_o WTP_{io}) \tag{C.9}$$

Considering the alternative SWFs approaches and adapting the general formulas used in the Appendix B (i.e., eq. B.12, B.13, B.14), taking into account the age-income combinations and the $g(.)$ transformation function strictly increasing and strictly concave, both with control policy (i.e., with CP) and not (i.e., no CP), then the three SWFs become:

$$\begin{aligned}
&\textbf{Utilitarianism (with CP)} \rightarrow W^{UUU} = \frac{N}{5}\sum_{i=1}^{5}(n_y E_{iy} + n_o E_{io}) \\
&\textbf{Utilitarianism (No CP)} \rightarrow W^{UUU}(\rho_{iy}, \rho_{io}, GDP_U^{max}) \equiv \frac{N}{5}\sum_{i=1}^{5}(n_y E_{iy}(\rho_{iy}, GDP_U^{max}) + \\
&\qquad n_o E_{io}(\rho_{io}, GDP_U^{max}) = W^{UUU}(\rho_{iy}^\star, \rho_{io}^\star, \Delta GDP)
\end{aligned} \tag{C.10}$$

$$\textbf{Ex-ante prioritarianism (with CP)} \rightarrow W^{EAP} = \frac{N}{5}\sum_{i=1}^{5}(n_y g(E_{iy}) + n_o g(E_{io}))$$

$$\textbf{Ex-ante prioritarianism (no CP)} \rightarrow W^{EAP}(\rho_{iy}, \rho_{io}, GDP_{AP}^{max}) \equiv$$

$$\frac{N}{5}\sum_{i=1}^{5}(n_y g(E_{iy}(\rho_{iy}, GDP_{AP}^{max})) + n_o g(E_{io}(\rho_{io}, GDP_{AP}^{max}) = W^{EAP}(\rho_{iy}^{\star}, \rho_{io}^{\star}, \Delta GDP) \tag{C.11}$$

$$\begin{gathered}
\textbf{Ex-post prioritarianism (with CP)} \rightarrow W^{EPP} = \frac{n_y N}{5}\sum_{i=1}^{5}[\rho_{iy}^{\star} g(W_{iy}(\bar{e}_{iy}^{l})) \\
+ (1-\rho_{iy}^{\star})\rho_{io} g(W_{iy}(\bar{e}_{io}^{l})) + (1-\rho_{iy}^{\star})(1-\rho_{io}) g(W_{iy}(e_o^{max}))] \\
+ \frac{n_o N}{5}\sum_{i=1}^{5}[\rho_{io}^{\star} g(W_{io}(\bar{e}_o^{l})) + (1-\rho_{io}^{\star}) g(W_{io}(e_o^{max})] \\
\textbf{Ex-post prioritarianism (no CP)} \rightarrow W^{EPP}(\rho_{iy}, \rho_{io}, GDP_{PP}^{max}) \equiv \\
\frac{n_y N}{5}\sum_{i=1}^{5}[\rho_{iy} g(W_{iy}(\bar{e}_y^{l}, GDP_{PP}^{max})) + (1-\rho_{iy})\rho_{io} g(W_{iy}(\bar{e}_o^{l}, GDP_{PP}^{max})) \\
+ (1-\rho_{iy})(1-\rho_{io}) g(W_{iy}(e_o^{max}, GDP_{PP}^{max})] + \frac{n_o N}{5}\sum_{i=1}^{5}[\rho_{io} g(W_{io}(\bar{e}_o^{l}, GDP_{PP}^{max})) \\
+ (1-\rho_{io}) g(W_{io}(e_o^{max}, GDP_{PP}^{max}))] = W^{EPP}(\rho_{iy}^{\star}, \rho_{io}^{\star}, \Delta GDP)
\end{gathered} \tag{C.12}$$

with $W_{ie}(l, GDP_{PP}^{max}) = (l-1)w(Y_i) + w(Y_i - \theta_{ie} GDP_{PP}^{max})$.
The GDP^{max} is the maximum income loss socially acceptable defined in terms of reduction in current aggregate income that individuals are willing to suffer to remove the COVID-19 infectious disease.
The equations with uncontrolled policy $E_{ie}(\rho_{ie}, GDP^{max})$ are obtained for each age category replacing in equations (C.4) and (C.5) the GDP^{max} as the maximum income loss socially acceptable for each SWF approach. Table 5, in Section 4, shows the results obtained computing the value of GDP^{max} in equations from (C.10) to (C.12).