Value of a Statistical Life under large mortality risk change: Theory and an application to COVID-19*

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Abstract

In the estimation of the benefits of mortality reduction, a simple approach is to multiply the value of a statistical life (VSL) by the expected reduction in fatalities, thus holding the VSL constant. This procedure approximates benefits for small changes in mortality, but inaccurately characterizes benefits for large risk changes because it does not account for variations in the VSL. Building on the theoretical framework of the VSL, we outline a practical approach to calculate the benefits of large mortality reductions. This approach is readily applicable, yielding closed-form expressions that only require statistics broadly available for VSL-based calculations. Using recent empirical estimates of the VSL, we apply this approach to estimate the benefits of social distancing to combat COVID-19 in the United States and Brazil, two of the countries most affected by the pandemic. Our findings show that social distancing generates a benefit of $4–4.4 trillion in the United States, and $0.6 trillion in Brazil. We extend this analysis to other 72 countries using VSL projections and find that benefits correspond to 17% of the gross national income on average. Our results indicate that the constant VSL approach overestimates the benefits of social distancing by 74% on average.

Keywords: Value of a Statistical Life, VSL, Cost-Benefit Analysis, COVID-19, Mortality Risk

JEL Codes: D12, D61, D78, D81, H12, I15

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1 Introduction

The value of a statistical life (VSL) is the cornerstone of analyzing the benefits of mortality risk reduction. Its foundation lies on the idea that, in equilibrium, a marginal change in the probability of dying can be compensated by a variation in wealth or income. For small changes in risk, benefits can be approximated by holding constant the estimated VSL—and thus the compensating marginal changes in income—and multiplying the VSL by the expected reduction in fatalities (U.S. Environmental Protection Agency, 1983; Viscusi and Aldy, 2003). This procedure, however, is inaccurate when risk changes are large and outside the sample intervals used to estimate the VSL because marginal compensations can vary substantially.

This paper outlines a practical approach to calculate the benefits of large mortality risk reductions. This approach is readily applicable, with closed-form expressions that only require population-level statistics frequently available for standard VSL-based calculations. We show that benefits calculated by linear extrapolation (i.e., constant marginal compensations) implicitly assume that individuals display increasing marginal utility, which contradicts a standard assumption of the VSL framework and leads to an imprecise representation of compensation for large changes in risk. Building on the VSL framework, we consider VSL estimates as locally valid at sample means, and derive expressions to characterize compensating variations for non-marginal changes at various baseline risk levels. We show that compensation—or willingness to pay for risk reduction—is concave in risk change when marginal utility is decreasing.

We apply the compensating variation approach to calculate the benefits of non-pharmaceutical interventions to combat the spread of the new coronavirus (SARS-CoV-2) and the ensuing COVID-19 pandemic. With countries worldwide facing recessions due to the pandemic, calculating the economic benefits of social distancing policies has become crucial. Epidemiologists have projected mortality risks that are orders of magnitude above work-related fatality risks (Walker et al., 2020). However, with the exception of recent work by Hall et al. (2020), estimates of the benefits of social distancing have assumed constant VSLs and overlooked the role of large risk changes (Thunström et al., 2020; Greenstone and Nigam, 2020).

Our application first considers two of the countries most affected by the COVID-19 pandemic: the United States and Brazil. For each country, we use recent estimates of the VSL and their sample statistics (Kniesner et al., 2012; Pereira et al., 2020) to calculate the benefits of mortality reduction due to social distancing (Walker et al., 2020). Our results show that the linear extrapolation approach may overestimate the benefits by 80 to 96%, for the US, and by 110 to 123% for Brazil. Next, we calculate the benefits of mitigation for other 72 countries using projected VSL estimates (Viscusi and Masterman, 2017). Based on calculations with age-specific mortality risks, we find that the benefits of social distancing correspond to 17% of the gross national income (GNI) on average (median 17%, 5–95th range [4%, 27%]). While we purposefully do not speculate about the costs of different mitigation policies, benefits in this range of magnitude likely exceed the costs of social distancing actions due to lower economic growth or increased public debt.

This paper makes two main contributions. First, it extends the theoretical framework of the

VSL first proposed by Drèze (1962) and extensively developed in later decades (e.g., Bergstrom, 1982; Viscusi, 1993; León and Miguel, 2017).[1] Among closely related studies on the relation between the VSL, risks, and properties of the utility function, Eeckhoudt and Hammitt (2001) examined the effect of background risks and find that large mortality and financial risks can significantly affect the VSL. They also demonstrated that the elasticity of the VSL with respect to income is expected to be larger than the relative risk aversion, a result further explored in Kaplow (2005). Eeckhoudt and Hammitt (2004) showed that risk aversion may increase or decrease the VSL, depending on the properties of the utility function and the levels of wealth and risk. We build on their findings to propose a method that links theory and empirical estimates to calculate compensations with non-marginal risk changes. Second, our paper contributes to the nascent literature estimating the benefits of mitigation policies related to the COVID-19 pandemic (Greenstone and Nigam, 2020; Thunström et al., 2020; Hall et al., 2020). Our method, here applied to pandemic policies, could also be used in other contexts with large mortality risk, such as disaster prevention and wars.

The rest of the paper is organized as follows. The next section develops the theoretical framework, derives the expressions for benefit calculation, and presents the implications of different approaches. We describe our data sources and outline our empirical method in Section 3, and report and discuss results in Section 4. Section 5 presents concluding remarks.

2 Theoretical framework

The canonical representation of the VSL (Viscusi, 1993; Viscusi and Aldy, 2003) establishes an expected utility of wealth w over a binary lottery with a one-period probability of survival s:

$$\mathcal{U}(w,s) = s\mathcal{U}_a(w) + (1-s)\mathcal{U}_d(w) \tag{1}$$

where $\mathcal{U}_a$ and $\mathcal{U}_d$ are, respectively, the utility of staying alive until next period and the bequest utility of dying during the current period. It is standard to assume $\mathcal{U}_a(w) > \mathcal{U}_d(w)$ and $\mathcal{U}_a'(w) > \mathcal{U}_d'(w) \geq 0$, so that individuals derive more utility of (additional) wealth when alive. Totally differentiating (1) holding utility constant, we obtain the standard expression for the VSL

$$\mathcal{V}(w,s) \equiv -\frac{dw}{ds} = \frac{\mathcal{U}_a(w) - \mathcal{U}_d(w)}{s\mathcal{U}_a'(w) + (1-s)\mathcal{U}_d'(w)} = \frac{\Delta\mathcal{U}}{E\mathcal{U}'} \tag{2}$$

where $\Delta\mathcal{U} \equiv \mathcal{U}_a - \mathcal{U}_d$ is the marginal change in expected utility due to a change in the survival probability, and $E\mathcal{U}' \equiv s\mathcal{U}_a'(w) + (1-s)\mathcal{U}_d'(w)$ is analogous to an expected marginal utility of wealth.[2]

[1] Viscusi and Aldy (2003) and Andersson and Treich (2011) present comprehensive reviews of the theoretical and empirical developments in this literature.

[2] We follow prior literature in not making a distinction between willingness-to-pay (WTP) and willingness-to-accept (WTA) in our theory.

The theory underlying VSL estimation often defines utility of consumption based on wealth (e.g., Bergstrom, 1982; Eeckhoudt and Hammitt, 2004; Kaplow, 2005). Empirical studies of the VSL, on the other hand, are frequently based on income metrics (e.g., Viscusi, 1993; Viscusi and Aldy, 2003; Kniesner et al., 2012). These are not necessarily at odds because the VSL is a statement about short-run marginal changes in wealth, which are reasonably approximated by variations in income. The distinction between wealth and income becomes necessary if one wants to examine large, non-marginal risk changes where the utility function specification is consequential.

2.1 Constant VSL approach

Simple benefit analyses of mortality reduction hold the VSL constant at an estimated $\bar{V}$, so that benefits are calculated as linear extrapolations. In particular, the benefit of a positive discrete change in survival probability from s to $s+h$, with $h \leq 1-s$, is given by

$$v_{linear} = h\bar{V} \tag{3}$$

This procedure, however, has strong implications for the shape of the utility function.

Proposition 1. *If the VSL does not vary with survival probability, then $\mathcal{U}(w,s)$ is convex in wealth (w).*

Proof. See Appendix A. □

Proposition 1 states that a linear extrapolation of benefits implies agents have increasing marginal utility and, consequently, a risk-seeking attitude. The intuition of this result is as follows. As the risk of dying increases (s becomes smaller), expected utility falls at a rate $\Delta\mathcal{U}$. Any wealth increment raises the alive utility ($\mathcal{U}_a$) more than bequest utility ($\mathcal{U}_d$). However, a smaller s also means that increments of utility when alive happen with lower probability, so the marginal expected utility of wealth $E\mathcal{U}'$ decreases. If an agent accepts linear compensation for an ever decreasing chance of survival, it must be the case that the expected utility of wealth increases more than linearly to compensate the loss of utility from the additional risk. Hence, while a linear benefit calculation may provide a good approximation for small changes in risk, this method may yield imprecise estimates for large changes.

2.2 Compensating variation approach

As an alternative to holding marginal changes constant, we examine how the compensation of a discrete risk change varies with the initial risk level and the size of change. Let the v be the maximum willingness to pay (or the opposite of the compensating variation) for a positive discrete change $h \leq 1-s$ in survival probability. Then, v is implicitly defined in the indifference condition $\mathcal{U}(w-v, s+h) = \mathcal{U}(w,s)$. By the Implicit Function Theorem, $\frac{\partial v}{\partial h} = \mathcal{V}(w-v, s+h) > 0$, which follows from the definition of the VSL. Moreover, it can be shown that

$$\frac{\partial^2 v}{\partial h^2} = \left(\frac{\partial v}{\partial h}\right)^2 \frac{(s+h)\mathcal{U''}_a(w-v) + (1-s-h)\mathcal{U''}_d(w-v)}{(s+h)\mathcal{U'}_a(w-v) + (1-s-h)\mathcal{U'}_d(w-v)} < 0 \tag{4}$$

which is negative due to the assumptions of $\mathcal{U''}_a$ and $\mathcal{U''}_d$ being negative. Hence, v is increasing and concave. The concavity of v indicates that the VSL, while positive, decreases as the survival probability increases (as in Eeckhoudt and Hammitt (2001)). This result follows from the assumption of decreasing marginal utility of wealth: the marginal willingness to pay for increments in survival probability decreases as wealth is reduced and marginal utility of wealth increases.

Going from an implicit definition of v to a form that is tractable for empirical use requires further assumptions. To do so, we modify the representation $\mathcal{U}$ to distinguish wealth (w) and income (y) so that existing empirical estimates of the VSL can be used to ground benefit analyses of large mortality risks. We depart from the canonical model by redefining $\mathcal{U}_a = u_a(c) + \phi(w)$. Function $u_a(c)$ is the utility of consumption of a homogeneous good with unitary price, with $u'_a > 0$ $u''_a < 0$. Function $\phi(w)$ is the continuation value, or the present value of future utility if alive in the next period with wealth w. Moreover, define $u_d(w) \equiv \mathcal{U}_d(w) - \phi(w)$ as the difference between the bequest utility and the continuation value. Then, we can represent expected utility as

$$U(y,s,w) = su_a(y) + (1-s)\,u_d(w) + \phi(w) \tag{5}$$

with the corresponding VSL given by

$$V(y,s,w) \equiv -\frac{dy}{ds} = \frac{u_a(y) - u_d(w)}{su'_a(y)} \tag{6}$$

In line with empirical work in the VSL literature (e.g., Viscusi and Aldy, 2003; Kniesner et al., 2012; Pereira et al., 2020), we abstract from savings, insurance, and other mechanisms of intertemporal transfer of wealth. This assumption of non-fungibility between wealth and income at the current period grants tractability but has two main implications. First, it imposes that current consumption and current income are equivalent ($c = y$), so that any risk compensation affects current consumption only. Second, it imposes that bequest utility and the continuation value are functions of wealth only and do not vary with current period income ($\partial u_d/\partial y = 0$).

We posit that any estimated VSL ($\bar{V}$) holds only locally for an agent at the mean variables $(\bar{y}, \bar{s}, \bar{w})$. This assumption makes it possible to characterize the compensating variation of a discrete survival probability change for an agent with mean income and wealth and any baseline survival probability s. The agent's maximum willingness to pay for a discrete survival probability increase from s to $s+h$ is implicitly defined in the indifference condition $U(\bar{y} - v(s,h), s+h, \bar{w}) = U(\bar{y}, s, \bar{w})$. Expanding this condition with identity (5) and applying (6) at the mean variables, we can solve for v as

$$v(s,h) = \bar{y} - u_a^{-1}\left(u_a(\bar{y}) - \frac{h}{s+h}\bar{V}\bar{s}u'_a(\bar{y})\right) \tag{7}$$

Function $v(s,h)$ is the base for calculating the benefits of discrete mortality risk reductions. In particular, we are interested in assessing the value of a risk change relative to the mean income, which we denote by $b(s,h) \equiv v(s,h)/\bar{y}$. To obtain a closed-form expression for the estimation of benefits, it is necessary to specify a utility function. In this paper, we consider the constant relative risk aversion (CRRA) utility, given by $u(y) = \frac{y^{1-\rho}-1}{1-\rho}$, where $\rho \equiv -y\frac{u''}{u'}$ is the Arrow-Pratt relative risk aversion coefficient. This particular function provides tractability while remaining flexible enough to accommodate different estimated levels of risk aversion for each country. For $\rho \neq 1$, the expression for the relative value of risk change is given by

$$b_{CRRA}(s,h) \equiv \frac{v_{CRRA}(s,h)}{\bar{y}} = 1 - \left[1 - (1-\rho)\left(\frac{h}{s+h}\right)\frac{\overline{V}}{\bar{y}}\bar{s}\right]^{1/(1-\rho)} \tag{8}$$

When $\rho = 1$, the CRRA becomes the log-utility function, for which the relative value of risk change is

$$b_{log}(s,h) \equiv \frac{v_{log}(s,h)}{\bar{y}} = 1 - \exp\left(-\frac{h}{s+h}\frac{\overline{V}}{\bar{y}}\bar{s}\right) \tag{9}$$

3 Empirical method and data

We estimate the benefits of reduced mortality risk promoted by social distancing during the COVID-19 pandemic, and compare the results using the constant VSL and the compensating variation approaches. Consistent with our theoretical framework, these estimates are based on representative agents with mean income and wealth.[3] In line with the US EPA (U.S. Environmental Protection Agency, 1983, 2010) and other institutions (Viscusi and Aldy, 2003; Viscusi and Masterman, 2017), we maintain a normative approach of no income or age-based discounting when calculating aggregate benefits.[4] The distribution of risks in a population, however, can be age-specific, as discussed in the next subsection. Subsection 3.2 outlines the data used to estimate benefits for a set of 74 countries.

3.1 Benefits and risk distribution

Motivated by the fact that COVID-19 mortality risk varies substantially by age group, we compare benefits using uniform and age-specific risks. The heterogeneity in risk does not affect estimates based on the constant VSL approach because of its linear form. However, the concavity of benefits based on the compensating variation approach indicates that estimates depend on the distribution of risks.

[3] Besides affecting mortality risks, the COVID-19 pandemic has also introduced shocks to income and output that can affect VSL. These macroeconomic shocks, however, have dynamically endogenous components because different mitigation strategies affect both short-term income and long-term economic recovery. Modeling these mechanisms is beyond the scope of our analysis, for which reason we rely on the latest available income data.

[4] Though we purposefully do not consider age or income-based discounting, our framework may be readily adapted to calculate the benefits for groups with different values for income and VSL, which are then combined to obtain the aggregate benefits.

Uniform risk All individuals face the same probability of survival if the pandemic is unmitigated, s_0, and same increase in probability due to social distancing, h_{SD}. In this case, the benefit of social distancing relative to mean the income is calculated by direct application of $b(s_0, h_{SD})$, which can be equation (8) or (9), depending on ρ.

Age-specific risks We subdivide the population into G age groups indexed by g. Each group has population weight w_g, unmitigated survival probability $s_{g,0}$, and probability increase $h_{g,SD}$. Then, the aggregate benefit relative to the mean income is

$$\sum_{g=1}^{G} w_g b\left(s_{g,0}, h_{g,SD}\right) \tag{10}$$

We report estimates based on uniform and age-specific risks to show they can be substantially different. Though benefits may vary for subgroups in a positive analysis, a policymaker may wish to disregard such differences and focus on the average case for normative reasons.

3.2 Data sources

The estimation of benefits requires data on the following statistics: mean baseline survival probability ($\bar{s}$), COVID-19 mortality risks (s_0 and h_{SD}), VSL ($\bar{V}$), mean income ($\bar{y}$), and risk aversion (ρ). Below, we describe each data source.

Mean baseline survival probability In the theoretical framework, this statistic refers to the mean individual in the sample used for VSL estimation. Since the VSL estimates in this paper come from compensating wage studies, we use average one-year survival probabilities for individuals between age 15 and age 60 to approximate the working-age population. This statistic is available at the country-level from the United Nations (UN) 2019 World Population Prospects.

COVID-19 mortality risks The age-specific unmitigated survival is determined by the baseline, pre-COVID-19 survival probability ($\bar{s}_g$) and the probability of surviving the COVID-19 pandemic[5] without social distancing ($s_{g,\text{unmit}}$). Thus, $s_{g,0} = \bar{s}_g s_{g,\text{unmit}}$. Similarly, survival probability with social distancing is $\bar{s}_g s_{g,\text{social dist.}}$, so that $h_{g,SD} = \bar{s}_g \left(s_{g,\text{social dist.}} - s_{g,\text{unmit}}\right)$

There are $G = 9$ age groups, arranged in decades for ages below 80 (0–9, 10–19, and so on) and for all ages at or above 80. We gather age group population and survival probabilities at the country level from the UN 2019 World Population Prospects. COVID-19 survival probabilities are obtained from Walker et al. (2020), which project the expected number of deaths over a year under different scenarios. These projections for over 200 countries take into account differences in demographics and healthcare system capacity. We consider two scenarios reported in Walker

[5]Mortality risk in COVID-19 projections are respective to the finite duration of the pandemic (one year in Walker et al. (2020)). As such, the our calculations are relative to a single period. For other types of persistent exposure to risk, however, our framework can be extended to a multi-period calculation with inter-temporal discounting.

et al. (2020) that use a reproduction number[6] of 3: (i) Unmitigated: no reduction in the frequency of social contact; and (ii) Social distancing: social contact in the general population decreases by 40 to 45%. As Walker et al. (2020) only provide data on aggregate deaths, we calculate age group-specific mortality based on the corresponding population weights and infection fatality rates (IFR) used in their simulations (Verity et al., 2020).[7]

VSL and income Here we make a distinction between estimated values obtained directly from the literature, for the US and Brazil, and projected values using a method proposed in the literature. Benefit calculations use the estimated VSL from two studies based on compensating wage differentials: Kniesner et al. (2012), for the US, and Pereira et al. (2020), for Brazil. Both studies estimate the VSL using a semilog form; we select the values resulting from the static first-difference estimator used in both papers. To maintain consistency, we follow these studies in their choice of income statistics. Mean wages for 2018, the latest year available, are obtained from the Bureau of Labor Statistics (BLS, for the US) and the Instituto Brasileiro de Geografia e Estatística (IBGE, for Brazil). Brazilian wages are converted to US dollars with purchase power parity (PPP) using the World Bank's GDP-based PPP conversion factor (2.02 BRL to USD for year 2018).

We extend the benefit analysis to another 72 countries using the method proposed by Viscusi and Masterman (2017) to project the US VSL to other countries. As in Viscusi and Masterman (2017), we use an income elasticity of the VSL equal to one, so that the VSL of country c is given by $V_c = V_{US} y_c / y_{US}$. We also follow their choice of income statistic by using the latest values of gross national income (GNI) per capita, in PPP US dollars, from the World Bank data.

Risk aversion We obtain the Arrow-Pratt relative risk aversion coefficients estimated from a cross-country survey in Gandelman and Hernández-Murillo (2015). They show that test statistics fail to reject the null hypothesis of $\rho = 1$ for almost all countries. Our results show that benefits estimated using CRRA and log utility are fairly similar; the only exceptions are cases with very low, and perhaps unreasonable, values of ρ. For these reasons, we choose to report our main estimates based on the more robust assumption of $\rho = 1$ for all countries. We report CRRA-based benefits in Appendix B, Tables B.3 and B.4.

The statistics used in the estimation for the US and Brazil are reported in Table 1. The scenarios and model parameters for other counties are reported in Tables B.1 and B.2.

[6] The reproduction number, or R_0, relates to how contagious a disease potentially is. It indicates the expected number of individuals to which an infected person transmits the disease when the entire population is susceptible.

[7] The infection fatality rate is the probability of dying conditional on being infected. With a uniform attack rate (probability of infection), the share of total deaths corresponding to age group g is given by $w_g IFR_g / \overline{IFR}$, where IFR_g and $\overline{IFR}$ are the group-specific and mean IFRs.

Table 1: Pandemic scenarios, VSL, and model parameters

	United States	Brazil
Population, million	331	213
COVID-19 deaths per 100,000:		
- *Unmitigated*	791	512
- *Social distancing*	410	271
Mean annual wage ($\bar{y}$)	\$57,266	\$14,204
VSL at mean wage ($\bar{V}$)	\$7.70 M	\$2.70 M
Baseline survival prob. ($\bar{s}$)	0.99731	0.99652
Relative risk aversion (ρ)	1.39	0.63

4 Results

4.1 Benefits based on the estimated VSL

We start by illustrating the difference in benefits estimated with different approaches. Figure 1 displays the benefit of mortality reduction as a percentage of the mean income for a US individual with a one-year fatality probability of 2% ($s_0 = 0.98$). The horizontal axis indicates the proportional reduction in fatality probability and each curve represents a different approach: linear (Eq. 3), log-utility (Eq. 9) and CRRA (Eq. 8).

Figure 1 summarizes two key takeaways. First, it shows that linear and nonlinear methods yield very similar benefits for small changes in mortality risk. However, as risk changes become large, the total and marginal benefits diverge. For example, the log-utility benefit is 55% lower than the linear extrapolation for a 50% reduction in probability of death. This difference is driven by the rising marginal utility of income when additional income is allocated to lowering the probability of dying. Second, the graph shows that benefits computed assuming a log-utility and CRRA yield similar results. This is explained by the estimated relative risk aversion coefficient being close to 1 for the US ($\rho = 1.39$).

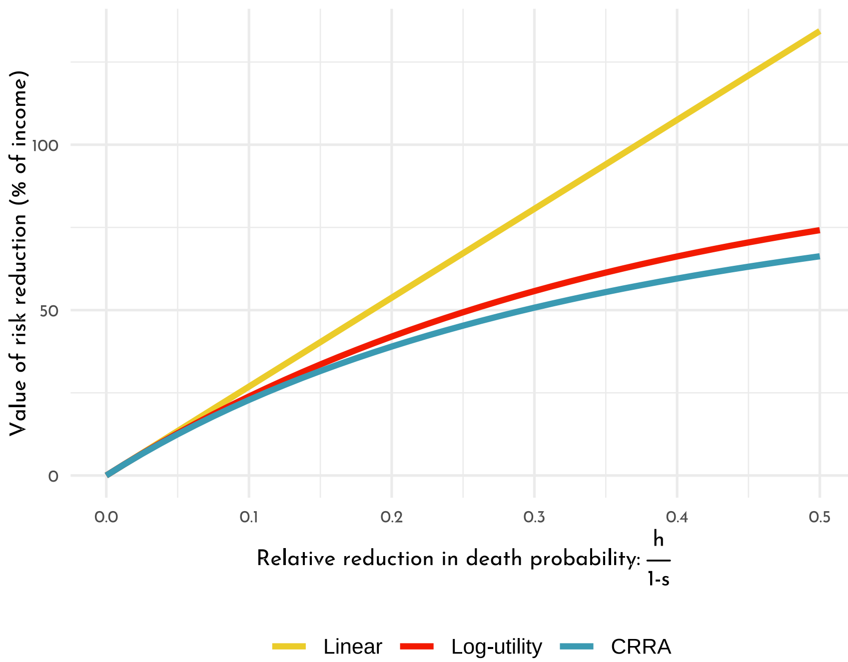

Figure 1: Illustration of benefit estimates for the United States

We present the estimates of aggregate benefits of mortality reduction from social distancing in Figure 2, with results for each method, risk distribution assumption, and country. Consistent with the theoretical framework, these graphs show that benefits based on nonlinear methods are lower than those based on the linear approach. For both countries, benefits based on age-specific risks correspond to 19 to 23% of income, whereas the linear approach estimates range from 44 to 48%. For the US, these benefits amount to $4–4.4 trillion ($9.1 trillion for the linear method), while for Brazil they amount to approximately $0.6 trillion ($1.3 trillion for the linear method). Therefore, the linear method overestimates the benefits of social distancing by 107–125% for the US, and by 109–124% for Brazil. Table B.3 reports all numerical estimates.

Our estimates based on the compensating variation are broadly lower than those based on the linear approach reported in the recent literature. For instance, Greenstone and Nigam (2020) estimate a value of $7.9 trillion, while Thunström et al. (2020) estimate a value of $12.4 trillion. These papers, however, use slightly different mortality reduction scenarios, different VSL estimates, or different assumptions on risk adjustment. Greenstone and Nigam (2020) use age-varying VSL (Murphy and Topel, 2006), and Thunström et al. (2020) use a VSL of $10 million (Viscusi, 2018). Our linear estimate, at $9.1 trillion, is close to the midpoint between these two estimates from the literature. However, once we account for changes in the VSL, the estimated benefit falls by more than a half. Our results are more similar to Hall et al. (2020), which also account for decreasing marginal utility using a calibrated CRRA model. They estimate benefits of 24–31% of income, but under a different risk scenario: they assume a higher average mortality change of 0.44% (Ferguson et al., 2020), while our estimates are based on a change of 0.38% (Walker et al., 2020).

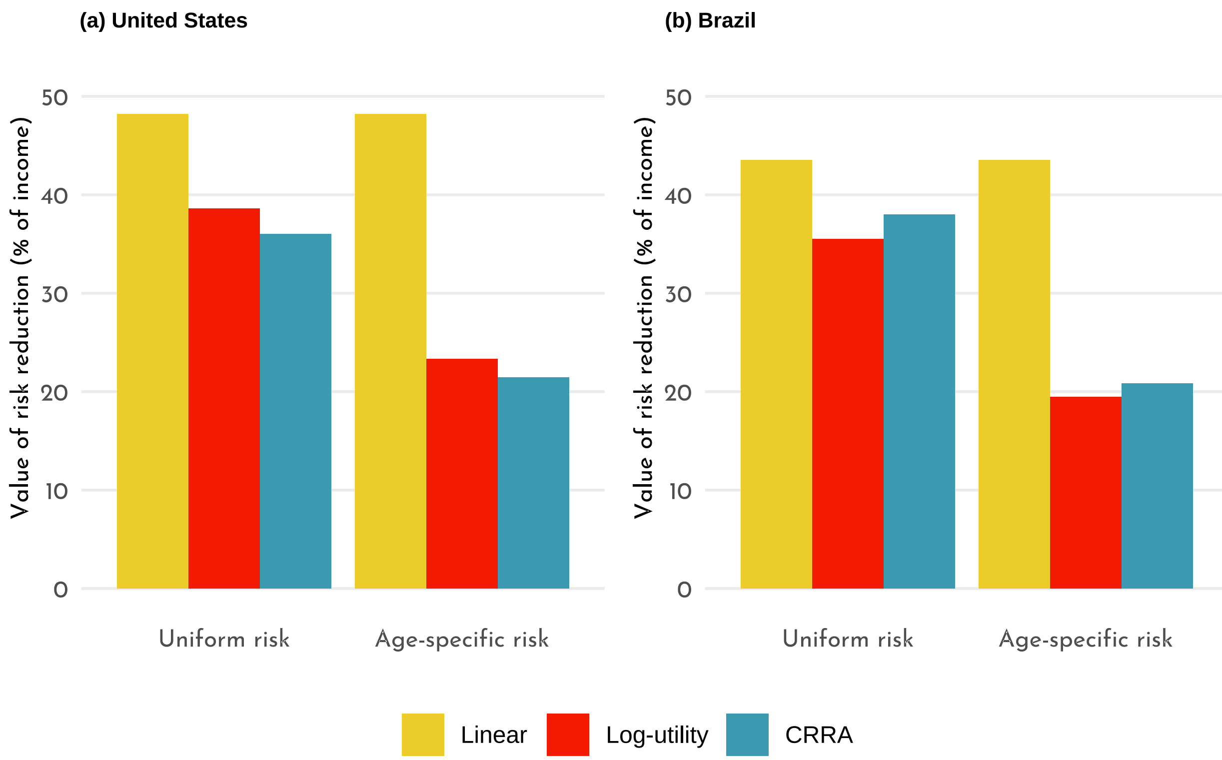

Figure 2: Aggregate benefits of social distancing

Figure 2 also demonstrates the role of ρ, which explains the differences between log-utility and CRRA estimates. Panel (a) shows that log-utility estimates are higher than CRRA estimates for the US. This result is due to the US utility function being relatively more concave than the log utility, with ρ greater than 1. The opposite is true for Brazil: as shown in panel (b) log-utility estimates are lower than CRRA because ρ for Brazil is 0.63.

Another key result in Figure 2 is the difference between estimates based on uniform and age-specific risks. This difference is driven by Jensen's inequality: with a concave benefit curve, the expected benefit with heterogeneous risks is lower than the benefit at the expected risk. To examine the components of this difference, we present benefit estimates for the United States by age group in Figure 3 (and for Brazil in Figure B.1), along with the respective distributions of risk, risk change, and population. Panel (a) shows the benefits relative to income for each age group, while panel (b) shows the share of total benefits experienced by each group. Panel (c) displays the baseline mortality rates in the unmitigated pandemic scenario (accounting for both the baseline and COVID-19 risks), and panel (d) the reduction, due to social distancing, in the probability of dying. Finally, panel (e) presents the population weights of each age group.

Panel (a) in Figure 3 reveals that individuals at age 50 or above experience the largest benefits from social distancing. As panels (c) and (d) show, these individuals have a higher baseline mortality and experience the largest reductions in the probability of death under social distancing. Due to the combination of these factors, individuals aged 50+ correspond to 92% of benefits across

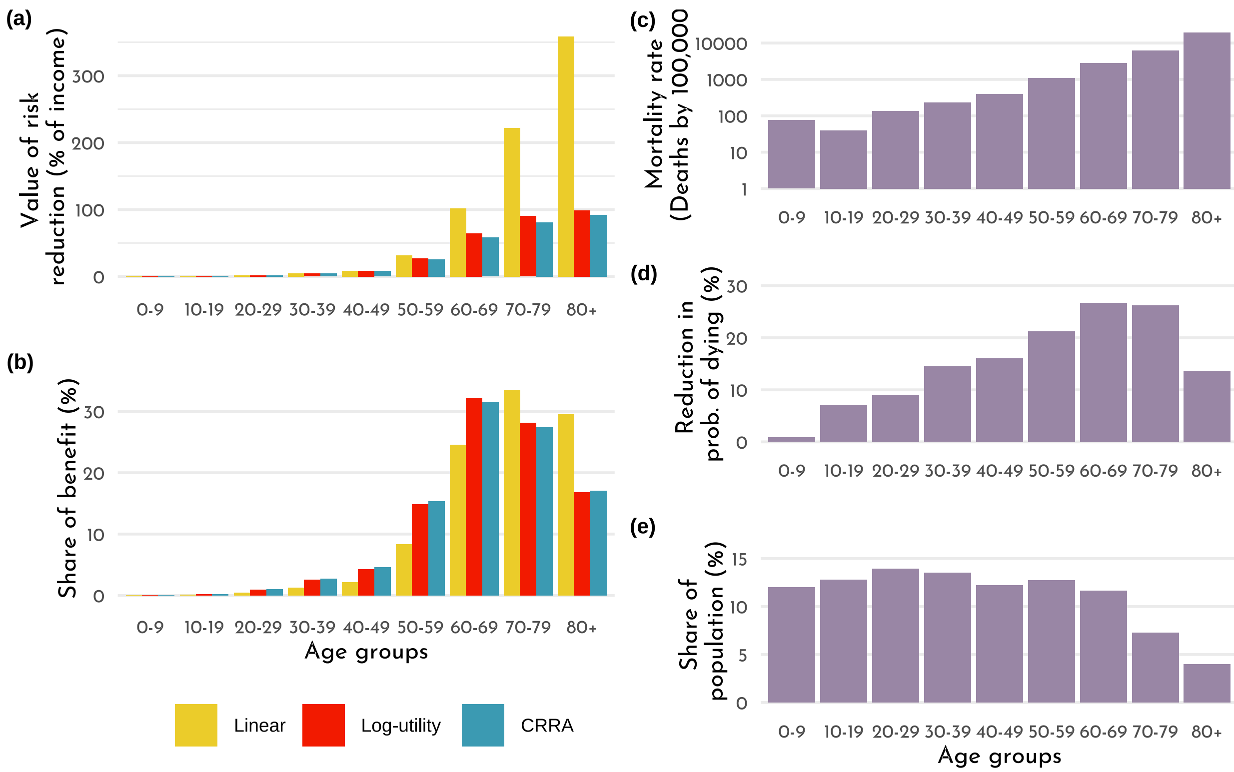

Figure 3: Benefits with age-specific risks for the United States and distributions of benefit shares, baseline mortality, mortality change, and population

all methods, despite representing only 35% of the population.

Figure 3 also indicates that the distribution of benefits are similar across methods. The exception is for the age group 80 or above, for which the linear method yields the largest difference to compensating variation methods. This difference highlights the fact that benefits calculated with the linear method grow substantially across age groups, while other methods report benefits levelling off below 100%. As discussed in Section 2.2, this difference is explained by the fact that the linear approach implicitly assumes an increasing marginal utility and imposes no limits to benefits. In contrast, the compensating variation to risk reductions in our framework is bounded by current income. Hence, for extreme risk changes where the context suggests benefits could exceed income, other approaches may be more appropriate, such as life cycle models (Murphy and Topel, 2006; Hall and Jones, 2007).

4.2 Benefits based on the projected VSL

We extend the estimation of the benefits of social distancing to other 72 countries. Calculations are based on the VSL projection method from Viscusi and Masterman (2017). We highlight that many of these countries are middle- and low-income economies for which the literature may not offer reliable VSL estimates. Figure 4 presents the estimated benefits for each country and scenario

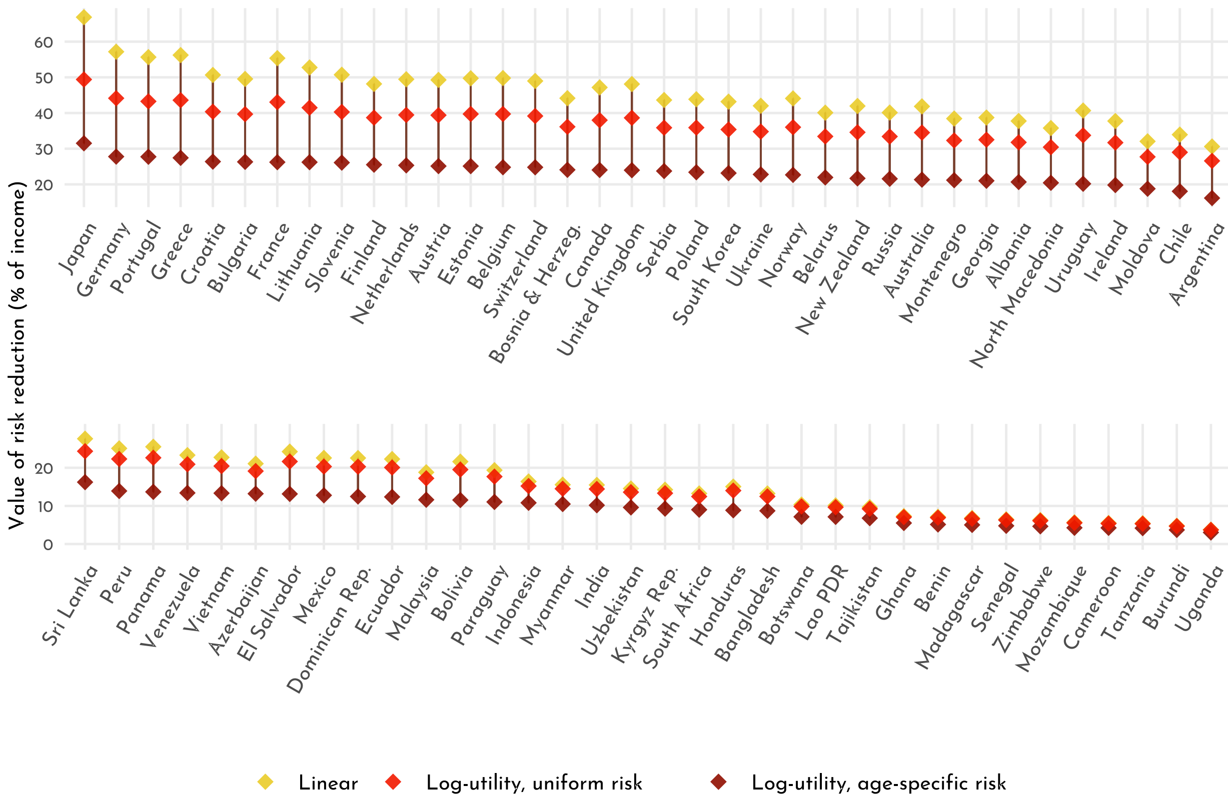

Figure 4: Benefit estimation for countries

comparing the linear and log-utility methods.[8] Based on age-specific risks, our results show that the average benefit of social distancing corresponds to 17% of GNI (median 17%, 5–95th range [4%, 29%]) for all 74 countries (including the US and Brazil). Moreover, the linear method overestimates benefits by 74% on average (median 83%, 5–95th range [31%, 103%]). Benefit estimates for each country and method are presented in Tables B.3 and B.4.

Figure 4 documents two other findings. First, the ordering of countries—based on the log-utility and age-specific risk—corresponds to the ordering of factors most relevant to benefit calculation. Countries with higher income and more vulnerable populations appear mostly on the left hand-side, with larger relative gains of social distancing. Countries with lower income or lower COVID-19 mortality changes, such as Tanzania, Zimbabwe and Uganda, stand to the right of the plot. These differences in mortality changes across countries reflect demographic considerations (e.g. younger vs. older population) and healthcare capacity (Walker et al., 2020). Second, this Figure shows that differences between linear and log-utility estimates increase with the magnitude of the risk reduction due to social distancing, thus in line with the mechanism discussed in Figure 1.

[8]We compare benefit estimates based on log-utility and CRRA in Figure B.2, which shows that these methods yield very similar results.

5 Conclusion

Empirical estimates of the VSL varying over large fatality risks are scarce, thus requiring benefit analyses to extrapolate from commonly narrow ranges of risk used in VSL estimation. A simplistic approach is to hold the VSL constant, which imposes limiting assumptions on the characterization of risk compensations. To address this limitation in a practical perspective, we propose an approach, grounded on the theory of VSL, that adjusts compensations for large risk changes. This method acknowledges that current VSL estimates are valid locally and characterizes compensating variations of non-marginal changes to calculate benefits. We apply the proposed method to calculate the benefits of mitigation policies to combat COVID-19, and compare the outcomes of different approaches. Results indicate that linear estimates may substantially overestimate the benefits of large risk reductions. This practical approach is applicable to computing economic benefits in other situations involving large variations in mortality risk, such as climate change, natural disasters and wars.

Although this paper makes progress in estimating the benefits of large reductions in mortality risk, we can identify limitations and open avenues for future research. The theoretical framework underlying our method considers the VSL values estimated from labor markets. As such, most limitations of this VSL estimation approach also apply to the present method (Viscusi and Aldy, 2003). For instance, the VSL estimates may be subject to biases related to mismeasurement and misperception of work-related fatality risks, and to selection on workers' risk preferences. Moreover, we assume that compensations does not vary with the type of fatality, so that the willingness to pay to avoid work-related fatality is the same as to any other cause. In practice, it is possible that avoiding specific fatal diseases, such as COVID-19, may be associated with a larger willingness to pay. Our method addresses the benefit of reducing one's own mortality; in doing so, we overlook the value individuals may place on (i) the lives of relatives, friends, and community members, and (ii) staying healthy and avoiding potential COVID-19 sequelae. Finally, while we contend that a theory-based approach is preferable to ignoring risk scale altogether, the accuracy of benefit calculations could further improve with empirical estimates of the VSL over large risk ranges.

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A Proof of Proposition 1

Proposition 1. *If the VSL does not vary with survival probability, then $\mathcal{U}(w,s)$ is convex in wealth (w).*

Proof. As defined in the theoretical framework, the canonical representation defines expected utility of wealth h over a binary lottery with probability of survival s

$$\mathcal{U}(w,s_t) = s\mathcal{U}_a(w) + (1-s)\mathcal{U}_d(w) \tag{11}$$

with $\mathcal{U}_a(w) > \mathcal{U}_a(w)$ and $\mathcal{U}_a'(w) > \mathcal{U}_d'(w) \geq 0$ for all w.

We start by deriving two identities that are useful in this proof: (12) and (16). First, we can express the change in utility from a change in s, from s_I to s_F, holding wealth level at some value $\bar{w}$. Applying (11), after some algebraic manipulation, yields

$$\begin{aligned}
\mathcal{U}(\bar{w},s_I) &= \mathcal{U}(\bar{w},s_I) - \mathcal{U}(\bar{w},s_F) + \mathcal{U}(\bar{w},s_F) \\
&= s_F\mathcal{U}_a(\bar{w}) + (1-s_F)\mathcal{U}_d(\bar{w}) - (s_F - s_I)(\mathcal{U}_a(\bar{w}) - \mathcal{U}_d(\bar{w})) \\
&= \mathcal{U}(\bar{w},s_F) - (s_F - s_I)\Delta\mathcal{U}(\bar{w}) \\
\mathcal{U}(\bar{w},s_I) &= \mathcal{U}(\bar{w},s_I) + (s_F - s_I)\Delta\mathcal{U}(\bar{w})
\end{aligned} \tag{12}$$

where $\Delta\mathcal{U}(w) \equiv \mathcal{U}_a(w) - \mathcal{U}_d(w)$.

Second, for a discrete risk reduction from s_0 to $s_1 > s_0$, note that holding the VSL fixed implies that

$$w_1 = w_0 - V(s_1 - s_0) \tag{13}$$

Consider a convex combination

$$\tilde{w} = \lambda w_0 + (1-\lambda)w_1 \tag{14}$$

with $\lambda \in [0,1]$. Applying the fixed VSL equation (13) into (14), we have

$$\begin{aligned}
\tilde{w} &= \lambda w_0 + (1-\lambda)(w_0 - V(s_1 - s_0)) \\
\tilde{w} &= w_0 - (1-\lambda)V(s_1 - s_0)
\end{aligned} \tag{15}$$

Then, evaluate (13) with a change from s_0 to some $\tilde{s}$ and apply (15) to obtain

$$
\begin{aligned}
\tilde{w} &= w_0 - V(\tilde{s} - s_0) \\
w_0 - (1-\lambda) V(s_1 - s_0) &= w_0 - V(\tilde{s} - s_0) \\
\tilde{s} - s_0 &= (1-\lambda)(s_1 - s_0)
\end{aligned} \tag{16}
$$

With identities (12) and (16), we can proceed with the proof. In equilibrium, changes in s are compensated by a variation in w, so that

$$
\mathcal{U}(w_0, s_0) = \mathcal{U}(\tilde{w}, \tilde{s}) \tag{17}
$$

and

$$
\mathcal{U}(\tilde{w}, \tilde{s}) = \mathcal{U}(w_1, s_1) \tag{18}
$$

We change the level risk level to s_0 on the the right-hand side of (17) using identity (12)

$$
\begin{aligned}
\mathcal{U}(w_0, s_0) &= \mathcal{U}(\tilde{w}, s_0) + (\tilde{s} - s_0)\,\Delta\mathcal{U}(\tilde{w}) \\
\mathcal{U}(w_0, s_0) &= \mathcal{U}(\tilde{w}, s_0) + (1-\lambda)(s_1 - s_0)\,\Delta\mathcal{U}(\tilde{w})
\end{aligned} \tag{19}
$$

where the last step used (16). Similarly, change the level risk level to s_0 by applying (12) to both sides of (18).

$$
\begin{aligned}
\mathcal{U}(w_1, s_0) + (s_1 - s_0)\,\Delta\mathcal{U}(w_1) &= \mathcal{U}(\tilde{w}, s_0) + (\tilde{s} - s_0)\,\Delta\mathcal{U}(\tilde{w}) \\
\mathcal{U}(w_1, s_0) &= \mathcal{U}(\tilde{w}, s_0) + (\tilde{s} - s_0)\,\Delta\mathcal{U}(\tilde{w}) - (s_1 - s_0)\,\Delta\mathcal{U}(w_1) \\
\mathcal{U}(w_1, s_0) &= \mathcal{U}(\tilde{w}, s_0) + (1-\lambda)(s_1 - s_0)\,\Delta\mathcal{U}(\tilde{w}) - (s_1 - s_0)\,\Delta\mathcal{U}(w_1) \\
\mathcal{U}(w_1, s_0) &= \mathcal{U}(\tilde{w}, s_0) + (s_1 - s_0)\left[(1-\lambda)\,\Delta\mathcal{U}(\tilde{w}) - \Delta\mathcal{U}(w_1)\right]
\end{aligned} \tag{20}
$$

in which we used (16) from the third to the fourth line. Multiplying both sides of (19) by λ, both sides of (20) by $(1-\lambda)$, and summing them, it follows that the left-hand side of the resulting equality is

$$
\lambda\mathcal{U}(w_0, s_0) + (1-\lambda)\mathcal{U}(w_1, s_0) \tag{21}
$$

while the right-hand side is

$$
\begin{aligned}
&\lambda \left\{\mathcal{U}\left(\tilde{w}, s_0\right)+(1-\lambda)\left(s_1-s_0\right) \Delta \mathcal{U}\left(\tilde{w}\right)\right\}+(1-\lambda)\left\{\mathcal{U}\left(\tilde{w}, s_0\right)+\left(s_1-s_0\right)\left[(1-\lambda) \Delta \mathcal{U}\left(\tilde{w}\right)-\Delta \mathcal{U}\left(w_1\right)\right]\right\} \\
=&\mathcal{U}\left(\tilde{w}, s_0\right)+(1-\lambda)\left(s_1-s_0\right) \Delta \mathcal{U}\left(\tilde{w}\right)-(1-\lambda)\left\{\left(s_1-s_0\right) \Delta \mathcal{U}\left(w_1\right)\right\} \\
=&\mathcal{U}\left(\tilde{w}, s_0\right)+(1-\lambda)\left(s_1-s_0\right)\left[\Delta \mathcal{U}\left(\tilde{w}\right)-\Delta \mathcal{U}\left(w_1\right)\right] \qquad (22)
\end{aligned}
$$

The last term within square brackets can be written as

$$
\Delta \mathcal{U}\left(\tilde{w}\right)-\Delta \mathcal{U}\left(w_1\right)=\left[\mathcal{U}_a\left(\tilde{w}\right)-\mathcal{U}_a\left(w_1\right)\right]-\left[\mathcal{U}_d\left(\tilde{w}\right)-\mathcal{U}_d\left(w_1\right)\right] \qquad (23)
$$

Both terms on the right-hand side of (23) are positive by monotonicity of $\mathcal{U}_a$ and $\mathcal{U}_d$. Since $\mathcal{U}_a'(w) > \mathcal{U}_d'(w)\,\forall w$, it follows that $\mathcal{U}_a(\tilde{w}) - \mathcal{U}_a(w_1) > \mathcal{U}_d(\tilde{w}) - \mathcal{U}_d(w_1)$. Hence, from the equality of expressions (21) and (22), plugging in the definition of $\tilde{w}$ (Eq. 14), we conclude that

$$
\lambda \mathcal{U}\left(w_0, s_0\right)+(1-\lambda) \mathcal{U}\left(w_1, s_0\right)>\mathcal{U}\left(\lambda w_0+(1-\lambda) w_1, s_0\right)
$$

thus proving that $\mathcal{U}$ is convex in w. In other words, extrapolating benefits linearly is equivalent to assuming that agents have increasing marginal utility of consumption and, thus, risk-loving preferences.

□

B Additional information

In this Appendix we present additional details on the statistics and results. Tables B.1 and B.2 display country statistics used for the estimation of the benefits of social distancing. Tables B.3 and B.4 show the estimated benefits under each method and for each country, including the United States and Brazil.

Figure B.1 is similar to Figure 3 and displays the age group-specific benefits and the respective distributions of mortality and population for Brazil. We note that the key aspects in the analysis for the United States still hold for Brazil: individuals aged 50 or above face high baseline mortality and experience the most benefits from social distancing. Despite having a younger population, the composition of benefits for Brazil is similar to the United States. One difference between these cases, however, is that the benefits are maxed out in Brazil for age group 80 or above; this occurs both because of the larger risks Brazilian seniors are exposed at the baseline and the higher value of VSL as a share of income estimated in the literature.

We compare the results between log-utility assuming $\rho = 1$ for all countries, and CRRA, using estimated values of ρ in Gandelman and Hernández-Murillo (2015). Figure B.2 shows the results based on age-specific risks under each method. As expected, the difference of estimates between log-utility and CRRA is larger when ρ is far from 1. However, we highlight that these differences are usually small, except perhaps when ρ is close to zero.

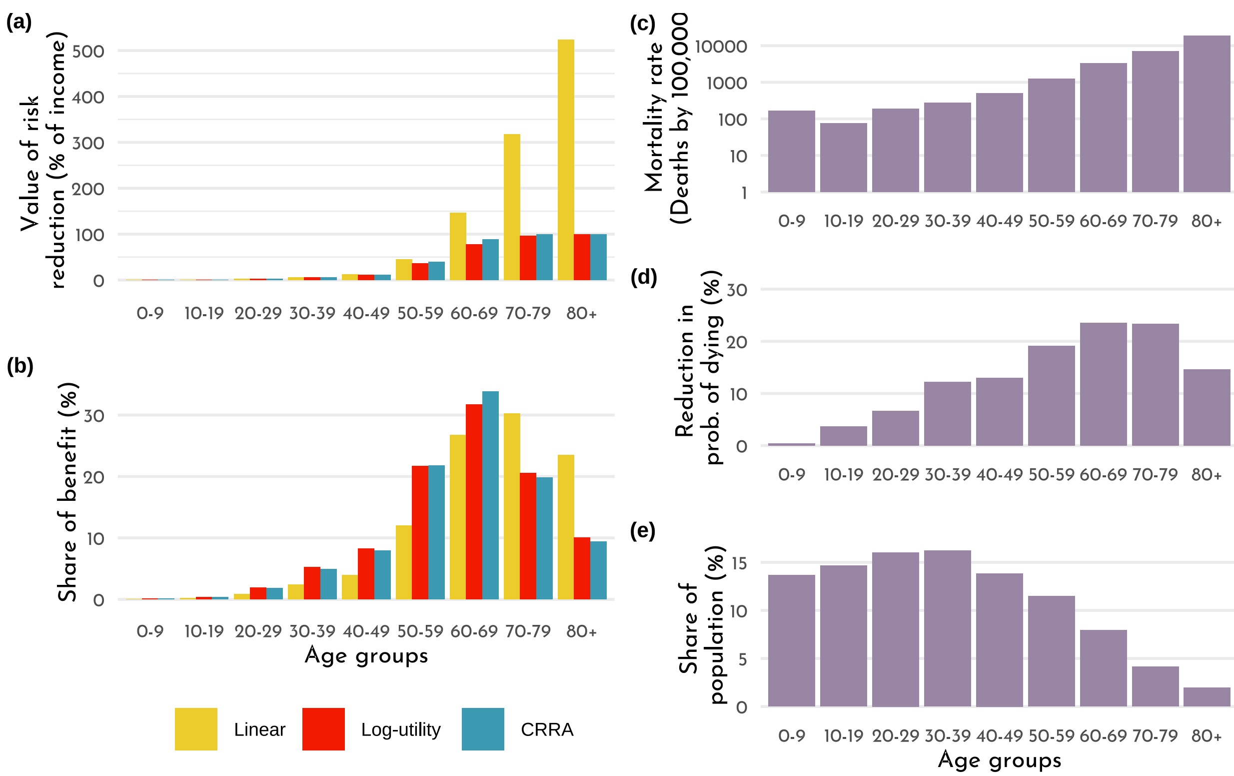

Figure B.1: Benefits with age-specific risks for Brazil

Table B.1: Statistics for other countries.

		COVID-19 deaths					
Country	Population	Unmitigated	Social dist.	GNI pc	VSL	$\bar{s}$	ρ
Albania	2.88	658	321	13.35	1.61	0.99830	0.1
Argentina	45.20	566	294	19.87	2.40	0.99725	1.2
Australia	25.50	712	343	50.05	6.05	0.99870	1.2
Austria	9.01	831	391	55.30	6.68	0.99851	1.1
Azerbaijan	10.14	425	237	17.10	2.07	0.99711	1.8
Bangladesh	164.69	387	271	4.57	0.55	0.99669	1.3
Belarus	9.45	706	343	19.24	2.32	0.99631	0.1
Belgium	11.59	940	495	51.74	6.25	0.99833	1.6
Benin	12.12	235	172	2.41	0.29	0.99385	0.2
Bolivia	11.67	417	229	7.67	0.93	0.99545	0.2
Bosnia & Herzeg.	3.28	756	361	14.58	1.76	0.99789	0.7
Botswana	2.35	303	212	18.00	2.17	0.99483	0.9
Bulgaria	6.95	843	392	22.30	2.69	0.99667	1.1
Burundi	11.89	180	138	0.75	0.09	0.99239	2.2
Cameroon	26.55	201	151	3.70	0.45	0.99182	0.8
Canada	37.74	852	437	47.59	5.75	0.99854	0.8
Chile	19.12	611	315	24.19	2.92	0.99799	1.1
Croatia	4.11	863	401	27.18	3.28	0.99798	0.3
Dominican Rep.	10.85	431	236	16.95	2.05	0.99610	0.3
Ecuador	17.64	427	234	11.42	1.38	0.99692	1.4
El Salvador	6.49	465	250	7.86	0.95	0.99541	0.5
Estonia	1.33	841	394	34.97	4.23	0.99748	0.5
Finland	5.54	815	387	48.58	5.87	0.99830	0.6
France	65.27	1106	616	46.36	5.60	0.99821	1.4
Georgia	3.99	687	334	11.50	1.39	0.99631	0.9
Germany	83.78	1039	530	54.56	6.59	0.99831	0.8
Ghana	31.07	239	174	4.65	0.56	0.99385	0.6
Greece	10.42	933	430	29.67	3.58	0.99836	1.1
Honduras	9.90	317	186	4.79	0.58	0.99652	0.9
India	1380.00	432	296	7.68	0.93	0.99553	0.9
Indonesia	273.52	423	279	12.67	1.53	0.99621	1.2
Ireland	4.94	653	321	67.05	8.10	0.99859	0.3

Notes: Population in millions. COVID-19 deaths per 100,000 individuals. GNI pc is the gross national income per capita in thousand US dollars. VSL, in million US dollars, projected following Viscusi and Masterman (2017) and updated using the latest GNI. Dollar values are adjusted by purchase power parity for 2018. $\bar{s}$ is the average baseline, one-year survival probability for individuals with age between 15 and 60. ρ is the relative risk aversion coefficient. See section 3.2 for data sources.

Table B.2: Statistics for other countries, part 2.

Country	Population	COVID-19 deaths Unmitigated	COVID-19 deaths Social dist.	GNI pc	VSL	$\bar{s}$	ρ
Japan	126.48	1070	480	44.38	5.36	0.99877	0.4
Kyrgyz Rep.	6.52	315	189	3.78	0.46	0.99623	1.8
Lao PDR	7.28	298	209	7.09	0.86	0.99536	0.4
Lithuania	2.72	872	405	34.32	4.15	0.99605	1.2
Madagascar	27.69	228	168	1.84	0.22	0.99463	0.7
Malaysia	32.37	455	291	30.65	3.70	0.99695	1.9
Mexico	128.93	435	237	19.34	2.34	0.99658	0.8
Moldova	4.03	586	298	7.62	0.92	0.99586	1.2
Montenegro	0.63	682	333	20.93	2.53	0.99768	2.1
Mozambique	31.26	204	153	1.43	0.17	0.99092	1.1
Myanmar	54.41	408	270	6.50	0.79	0.99496	1.0
Netherlands	17.13	822	384	56.89	6.87	0.99870	0.1
New Zealand	4.82	711	341	39.41	4.76	0.99854	1.1
North Macedonia	2.08	642	318	15.67	1.89	0.99778	1.3
Norway	5.42	746	356	68.31	8.25	0.99866	1.2
Panama	4.31	476	255	23.55	2.85	0.99724	0.2
Paraguay	7.13	384	214	13.22	1.60	0.99648	0.5
Peru	32.97	473	253	13.71	1.66	0.99716	1.4
Poland	37.85	775	387	30.01	3.63	0.99739	0.4
Portugal	10.20	922	424	32.68	3.95	0.99836	1.1
Russia	145.93	701	341	26.90	3.25	0.99494	0.6
Senegal	16.74	221	164	3.67	0.44	0.99550	1.9
Serbia	8.74	758	360	16.54	2.00	0.99736	0.3
Slovenia	2.08	850	397	37.45	4.52	0.99840	0.8
South Africa	59.31	364	245	13.25	1.60	0.99136	1.3
South Korea	51.27	730	353	40.09	4.84	0.99866	0.3
Sri Lanka	21.41	642	399	13.11	1.58	0.99750	0.7
Switzerland	8.65	821	386	68.82	8.32	0.99889	1.2
Tajikistan	9.54	240	155	4.05	0.49	0.99679	1.2
Tanzania	59.73	197	149	3.14	0.38	0.99423	1.3
Uganda	45.74	156	123	1.97	0.24	0.99283	0.7
Ukraine	43.73	739	356	9.03	1.09	0.99526	0.4
United Kingdom	67.89	872	444	45.35	5.48	0.99839	1.0
Uruguay	3.47	727	368	21.94	2.65	0.99739	0.9
Uzbekistan	33.47	322	193	8.81	1.06	0.99669	3.0
Venezuela	28.44	446	242	17.90	2.16	0.99626	2.1
Vietnam	97.34	528	330	6.93	0.84	0.99672	1.1
Zimbabwe	14.86	219	163	3.02	0.36	0.98998	0.0

Notes: Population in millions. COVID-19 deaths per 100,000 individuals. GNI pc is the gross national income per capita in thousand US dollars. VSL, in million US dollars, projected following Viscusi and Masterman (2017) and updated using the latest GNI. Dollar values are adjusted by purchase power parity for 2018. $\bar{s}$ is the average baseline, one-year survival probability for individuals with age between 15 and 60. ρ is the relative risk aversion coefficient. See section 3.2 for data sources.

Table B.3: Benefits of social distancing as percentage of the GNI per capita.

Country	Linear	Log-utility		CRRA	
		Age-specific	Uniform	Age-specific	Uniform
United States	42.2	23.3	38.6	21.5	36.0
Brazil	43.5	19.5	35.5	20.8	38.0
Albania	37.8	20.7	31.8	24.8	37.1
Argentina	30.6	16.2	26.6	15.5	25.9
Australia	41.9	21.3	34.5	20.5	33.6
Austria	49.3	25.1	39.4	24.7	38.8
Azerbaijan	21.1	13.2	19.1	11.4	17.7
Bangladesh	13.3	8.7	12.5	8.3	12.3
Belarus	40.1	21.9	33.4	26.7	39.9
Belgium	49.8	24.8	39.7	22.1	36.0
Benin	7.1	5.1	6.9	6.0	7.1
Bolivia	21.6	11.5	19.5	13.5	21.3
Bosnia & Herzeg.	44.1	24.1	36.1	25.7	38.1
Botswana	10.3	7.2	9.9	7.2	9.9
Bulgaria	49.5	26.3	39.7	25.9	39.2
Burundi	4.8	3.7	4.7	3.2	4.6
Cameroon	5.5	4.3	5.4	4.4	5.4
Canada	47.2	24.0	38.0	25.0	39.3
Chile	33.9	18.1	29.0	17.6	28.5
Croatia	50.7	26.4	40.4	30.3	47.2
Dominican Rep.	22.6	12.5	20.3	14.2	21.8
Ecuador	22.3	12.4	20.1	11.5	19.3
El Salvador	24.2	13.1	21.6	14.4	22.8
Estonia	49.7	25.1	39.7	27.9	44.1
Finland	48.2	25.5	38.7	28.3	42.3
France	55.4	26.2	43.1	23.9	39.6
Georgia	38.7	21.0	32.5	21.6	33.2
Germany	57.2	27.8	44.1	29.2	46.5
Ghana	7.3	5.5	7.1	5.9	7.2
Greece	56.2	27.4	43.6	26.9	42.9
Honduras	15.1	8.9	14.0	9.0	14.1
India	15.5	10.2	14.4	10.3	14.5
Indonesia	16.4	10.8	15.2	10.3	14.9
Ireland	37.7	19.8	31.7	22.5	35.5

Table B.4: Benefits of social distancing as percentage of the GNI per capita, part 2.

Country	Linear	Log-utility		CRRA	
		Age-specific	Uniform	Age-specific	Uniform
Japan	66.9	31.5	49.4	35.3	57.6
Kyrgyz Rep.	14.2	9.3	13.3	8.1	12.7
Lao PDR	10.1	7.1	9.7	8.1	10.0
Lithuania	52.8	26.2	41.5	24.9	39.7
Madagascar	6.8	5.0	6.6	5.3	6.7
Malaysia	18.8	11.6	17.2	9.9	16.0
Mexico	22.6	12.8	20.3	13.4	20.8
Moldova	32.1	18.8	27.7	18.0	27.0
Montenegro	38.4	21.2	32.3	17.1	27.7
Mozambique	5.7	4.3	5.5	4.2	5.5
Myanmar	15.6	10.5	14.5	10.5	14.5
Netherlands	49.5	25.3	39.5	30.3	48.7
New Zealand	42.0	21.7	34.6	21.0	33.7
North Macedonia	35.8	20.4	30.4	19.0	29.0
Norway	44.1	22.7	36.0	21.9	35.0
Panama	25.5	13.7	22.6	16.0	25.0
Paraguay	19.4	11.0	17.7	12.3	18.6
Peru	25.1	13.9	22.3	12.8	21.3
Poland	43.9	23.4	35.9	26.7	40.6
Portugal	55.7	27.7	43.3	27.3	42.6
Russia	40.1	21.6	33.4	23.3	35.5
Senegal	6.5	4.8	6.3	4.2	6.1
Serbia	43.6	23.7	35.9	27.6	41.6
Slovenia	50.7	26.1	40.3	27.1	41.7
South Africa	13.3	9.0	12.5	8.5	12.2
South Korea	43.2	23.2	35.4	26.9	40.9
Sri Lanka	27.6	16.2	24.3	17.5	25.3
Switzerland	49.0	24.8	39.2	23.7	37.7
Tajikistan	9.7	6.8	9.2	6.6	9.2
Tanzania	5.5	4.2	5.3	4.0	5.3
Uganda	3.8	3.0	3.7	3.2	3.7
Ukraine	42.0	22.8	34.8	25.6	38.7
United Kingdom	48.1	24.0	38.6	23.8	38.4
Uruguay	40.7	20.2	33.7	20.6	34.3
Uzbekistan	14.6	9.6	13.6	7.3	12.1
Venezuela	23.3	13.4	20.9	11.1	18.9
Vietnam	22.7	13.3	20.5	13.0	20.2
Zimbabwe	6.3	4.7	6.1	5.5	6.3

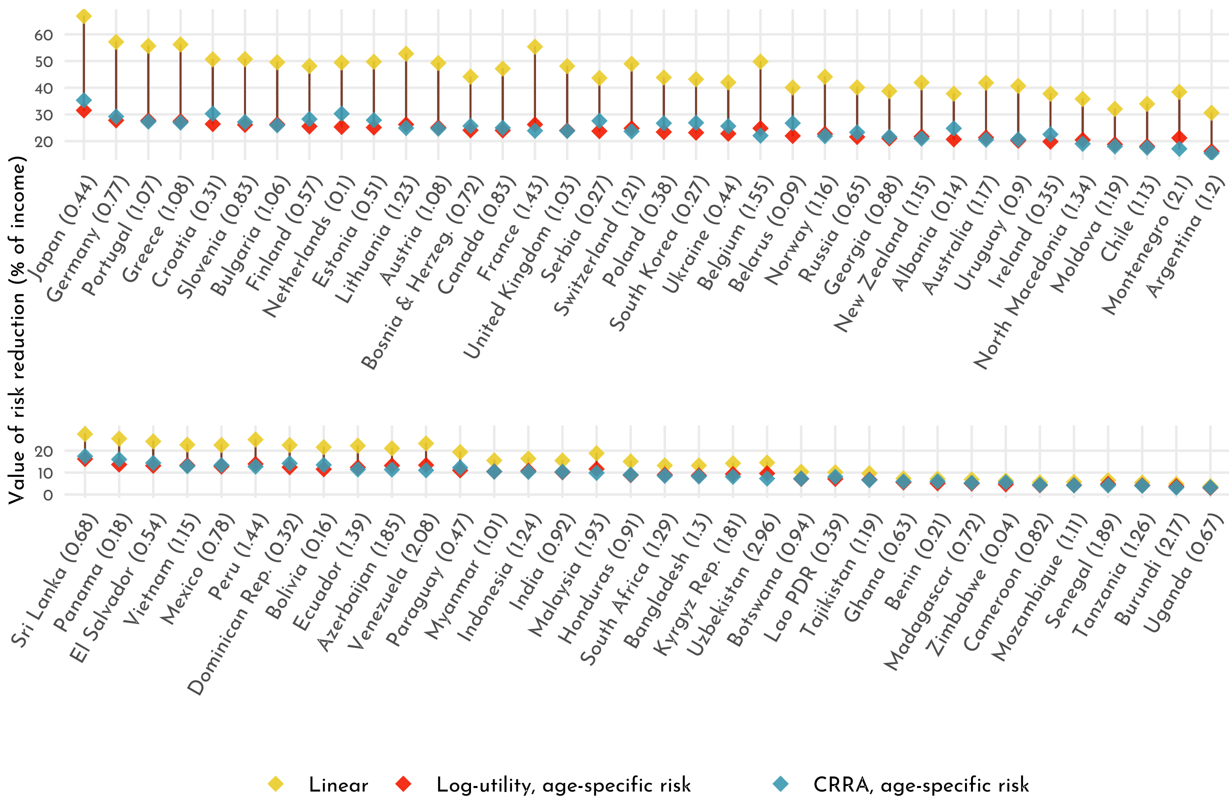

Figure B.2: Comparison of benefit estimation using different methods for each country. Relative risk aversion (ρ) in parentheses.