Valuing COVID-19 Mortality and Morbidity Risk Reductions in U.S. Department of Health and Human Services Regulatory Impact Analyses

July 2021

Prepared for:
Aaron Kearsley and Scott Douglas
Office of Science and Data Policy
Office of the Assistant Secretary for Planning and Evaluation
U.S. Department of Health and Human Services

Prepared by:
Lisa A. Robinson, Harvard T.H. Chan School of Public Health, Center for Health Decision Science and Center for Risk Analysis
Michael R. Eber, Harvard T.H. Chan School of Public Health, Center for Health Decision Science
James K. Hammitt, Harvard T.H. Chan School of Public Health, Center for Health Decision Science and Center for Risk Analysis; Toulouse School of Economics, Université de Toulouse Capitole

Under subcontract to:
Industrial Economics, Incorporated
Jennifer R. Baxter, Principal

ACKNOWLEDGEMENTS

This report develops an approach for valuing COVID-19 mortality and morbidity risk reductions based on the U.S. Department of Health and Human Services (HHS) *Guidelines for Regulatory Impact Analysis.* It illustrates the approach using data available at the time the report was drafted. Recognizing that new information on COVID-19 impacts continues to emerge and that the effects of individual regulations will vary, we expect this approach will be updated and tailored as needed.

The underlying research was conducted in two phases. Amber Jessup of the HHS Office of the Assistant Secretary for Planning and Evaluation (ASPE) commissioned and guided the initial work; the final report for the first phase was completed in September 2020. Aaron Kearsley and Scott Douglas of ASPE commissioned and guided the second phase, which involved updating that report to reflect research conducted through March 2021 as well as additional review by HHS staff. Lisa A. Robinson, Michael R. Eber, and James K. Hammitt (Harvard T.H. Chan School of Public Health) conducted the research and drafted the report under subcontract to Industrial Economics, Incorporated (IEc). Jennifer R. Baxter was the IEc project director and Mathematica Policy Research was the prime contractor.

For their helpful advice and comments on previous drafts, we thank Trinidad Beleche, Scott Douglas, Amber Jessup, and Aaron Kearsley (ASPE); Brian Maskery and Jamison Pike (U.S. Centers for Disease Control and Prevention), and Kathryn Dotzel, Ioana (Julia) Marasteanu, Cristina McLaughlin, Maria Kuecken, Janet Peckham, and Kevin Wood (U.S. Food and Drug Administration).

ED_006573_00001315-00002

CONTENTS

ACKNOWLEDGEMENTS 2

EXECUTIVE SUMMARY 4

CHAPTER 1: INTRODUCTION 11

1.1 HHS Valuation Approach 11

1.2 Overview of Following Chapters 14

CHAPTER 2: VALUING COVID-19 MORTALITY RISK REDUCTIONS 15

2.1 Characteristics of COVID-19 Mortality Risks 15

2.2 Valuing COVID-19 Mortality Risks 17

2.2.1 Individual Characteristics 18

2.2.2 Risk Characteristics 24

2.2.3 Other-Regarding Preferences 28

2.3 Summary and Conclusions 30

CHAPTER 3: VALUING COVID-19 MORBIDITY RISK REDUCTIONS 32

3.1 Characteristics of COVID-19 Morbidity Risks 32

3.1.1 Individual Characteristics 33

3.1.2 Risk Characteristics 34

3.1.3 Similar Diseases Used as Proxies 37

3.2 Willingness to Pay Estimates 39

3.3 Monetized QALY Estimates 42

3.3.1 HRQL Estimates from COVID-19 Studies 45

3.3.2 HRQL Estimates from Studies of Similar Conditions 47

3.3.3 Values per Nonfatal Statistical Case 55

3.4 Summary and Conclusions 59

REFERENCES 60

ED_006573_00001315-00003

EXECUTIVE SUMMARY

In 2016, the U.S. Department of Health and Human Services (HHS) finalized its *Guidelines for Regulatory Impact Analysis* (hereafter *Guidelines*) under the leadership of its Assistant Secretary for Planning and Evaluation (ASPE) and Analytics Team. In Chapter 3, "Assess Benefits," the *Guidelines* discuss the approach used to value mortality and morbidity risk reductions, commonly referred to as the value per statistical life (VSL) and the value per statistical case (VSC) respectively.

Valuing risk reductions associated with regulations or other policies that address the novel coronavirus disease 2019 (COVID-19) presents major challenges, however. This paper addresses these challenges. We summarize the impacts of COVID-19 on health and longevity, describe the conceptual framework for valuation, investigate the available valuation research, and discuss the implications. We recognize that the impact of the virus is rapidly evolving and that new data are continually emerging. Our focus is on developing and illustrating an approach for estimating the value per expected death or nonfatal case averted, that can be adapted to changing circumstances as needed.

Background

In benefit-cost analysis, the value of an improvement, such as a decrease in mortality or morbidity risk , is typically based on individual willingness to pay (WTP). In other words, the value is derived from how much money affected individuals would exchange for a risk reduction they expect to experience, given their budget constraints and preferences for spending on other goods and services. Generally, changes in mortality risks are valued separately from changes in morbidity risks, due in part to limitations in the available empirical work.

These WTP estimates are described as estimates of the value per statistical life (VSL) when valuing expected changes in mortality risk. The VSL terminology is frequently misinterpreted, however. VSL is not the value that the analyst, the researcher, or the government places on saving an individual from certain death. Rather it reflects research on the extent to which individuals are willing to exchange money for small changes in their own risks within a defined time period. The benefit of a reduction in mortality risk can be calculated by multiplying VSL by the expected number of deaths averted by a regulation or other policy.

The 2016 *Guidelines* recommend low, central, and high population-average VSL estimates for use in HHS regulatory impact analyses (hereafter referred to as HHS's VSL estimates). These estimates are derived from a criteria-driven review of the empirical literature (Robinson and Hammitt 2016). The *Guidelines* also suggest that analysts conduct sensitivity analysis when the regulation or other policy largely affects mortality risks among the very old or very young. This sensitivity analysis is based on constant value per quality-adjusted life year (QALY) estimates derived from HHS's VSL estimates. The value per QALY that results is then multiplied by the expected change in QALYs attributable to the regulation, leading to higher values per expected death averted for younger individuals and lower values for older individuals. The derivation of the value per QALY involves dividing the estimated VSL by the discounted expected QALYs for a person of average age, and therefore depends on the discount rate. Government-wide

ED_006573_00001315-00004

guidance indicates that regulatory analyses should be conducted using both 3 percent and 7 percent rates. The resulting estimates are provided in Table ES.1, updated to reflect 2020 dollars and income levels.

Table ES.1 HHS VSL and Value per QALY Estimates (2020 dollars and income levels)

	VSL Estimate	Value per QALY 3 percent discount rate	Value per QALY 7 percent discount rate
Low	$5.3 million	$270,000	$450,000
Central	$11.4 million	$580,000	$970,000
High	$17.4 million	$880,000	$1,470,000

Conceptually, the approach for valuing nonfatal risk reductions is similar; WTP estimates are converted into the value per statistical case (VSC). HHS policies affect a wide range of nonfatal health conditions that vary in severity, duration, and other characteristics. Given this diversity, the *Guidelines* provide a framework for estimating these values rather than recommending specific values. Analysts should first review the literature to determine whether suitable WTP estimates of reasonable quality are available for the nonfatal risk reductions of concern. If not, the *Guidelines* recommend that analysts use monetized QALYs as a proxy. The constant value per QALY (see Table ES.1 above) is multiplied by the expected change in QALYs to estimate the value per nonfatal case. Regardless of whether WTP or monetized QALY estimates are used for valuation, costs that are not included in these estimates can be added to reflect the total impact of the health condition on social welfare, as discussed in more detail in Chapter 3 of the *Guidelines*.

Valuing COVID-19 Mortality Risk Reductions

The VSL estimates recommended in the HHS *Guidelines* reflect population-average values. Those whose COVID-19 mortality risks are likely to be most affected by HHS regulations or other policies may differ from the general population in numerous respects, including their age, underlying health status, and other characteristics. Similar to deaths from all causes, COVID-19 deaths have been concentrated among the elderly. While the population aged 65 and over comprises a minority of the United States population (16.3 percent), this group accounted for most (81.0 percent) of the deaths for which COVID-19 was listed among the causes as of January 2021. COVID-19 deaths also appear to be largely among individuals whose health is otherwise impaired; the available data suggest that 96 percent of those who have died with COVID-19 have one or more underlying health conditions.

In addition, deaths associated with COVID-19 appear to have occurred disproportionately among individuals with certain demographic and socioeconomic characteristics. This variation likely results from differences in exposure as well as health status and other factors. Deaths have occurred disproportionately among males, and lower-income populations may be more vulnerable. Researchers have also identified disproportionately high rates of COVID-19 mortality in certain communities and disparities by race, ethnicity, and other factors.

ED_006573_00001315-00005

The characteristics of COVID-19 mortality risks also differ from the characteristics of the more common and familiar risks frequently considered in the valuation studies that underlie HHS's VSL estimates. These studies largely address accidental deaths, particularly those associated with job-related injuries. COVID-19 deaths may be preceded by severe symptoms, including fever, shortness of breath, high respiratory rate, and cough. Patients are often admitted to an intensive care unit (ICU) and put on mechanical ventilation, which requires that they be placed in a medically induced coma. The median duration of illness between symptom onset and death in the United States appears to have been between 13 and 17 days.

The novelty of COVID-19 also has implications for how these risks are perceived. COVID-19 risks may be more dreaded as well as more unfamiliar and uncertain than more common risks. Patients may need to be isolated from family members during treatment due to infectiousness. The values placed on risks of the same magnitude may vary depending on their causes and other characteristics due to these types of psychological or emotional responses. Thus individuals may value reducing their risk of dying from COVID-19 differently than they value reducing the risk of dying from another cause, even if the risk reduction is 1-in-10,000 in both cases.

Research on the value of reducing COVID-19 mortality risks is ongoing and there is no consensus on how to best estimate these values. Thus, we follow the benefit transfer framework discussed in Chapter 3 of the HHS *Guidelines* and explore the effects of differences between COVID-19 mortality risks and the more common and familiar risks that underlie HHS's VSL estimates.

The research that provides the basis for the recommended HHS VSL estimates includes six revealed preference studies and one meta-analysis that address the tradeoff between occupational risks and wages, and three stated preference studies that elicit WTP for risks from food-related illnesses, motor vehicle accidents, and other causes. All ten of these studies include the general adult U.S. population, although the wage-risk studies are limited to those who are employed.

In contrast, as indicated by the above discussion, COVID-19 affects individuals with characteristics that differ from those of the average member of the population, including age, health status, and income. The characteristics of COVID-19 risks also differ from the risks included in these studies, including morbidity prior to death, qualitative risk attributes, and the magnitude of the risk change.

Both theory and empirical research suggest that the extent to which the recommended HHS VSL estimates should be adjusted to reflect these differences is highly uncertain. In Table ES.2, we summarize the effects of differences between the COVID-19 context and the contexts considered in developing the HHS population-average VSL estimates. As indicated by the table, these effects may be counterbalancing to an unknown extent.

ED_006573_00001315-00006

Table ES.2 Potential Direction of Effect

Differences between COVID-19 and Risks Commonly Studied[a]	Effect on HHS VSL Estimates[b]
Individual characteristics	
1. Disproportionately affects the elderly	May *decrease* VSL
2. Disproportionately affects those in impaired health	May *increase or decrease* VSL
3. Reduces income below pre-pandemic levels	May *decrease* VSL
Risk characteristics	
1. Involves more substantial morbidity prior to death	May *increase* VSL
2. Viewed as more dreaded and uncertain	May *increase* VSL
3. May involve a larger risk change	May *decrease* VSL

a. Assumes COVID-19 mortality risk reductions attributable to the regulation or other policy will follow the same patterns as incurred cases to-date.
b. Compared to HHS population-average VSL estimates. Because the magnitude of these effects is uncertain, it is unclear whether in combination the net effect will be an increase or decrease.

Many of these differences may be best addressed through qualitative discussion, given gaps and inconsistencies in the available empirical VSL research. Where quantitative adjustment is possible, it should be included in sensitivity analysis rather than featured in the primary results to highlight associated uncertainties. In particular, as discussed earlier, if the mortality risks disproportionately affect the very old or the very young, analysts should include the standard sensitivity analysis recommended in Chapter 3 of the HHS *Guidelines*, applying a constant value per QALY to adjust for age.

Analysts will also need to consider the extent to which the attributes explored here are relevant to a specific analysis. Different policies may affect mortality among different population subgroups and may vary in the disease characteristics they affect. The availability of vaccines and the emergence of new variants may also affect the incidence and characteristics of COVID-19 deaths.

One question that arises in the COVID-19 and other contexts is whether and how to include preferences for mortality risk reductions that accrue to others, such as those related to the risk of infecting family members or members of the broader community. Presumably, all risk reductions would be included in the risk assessment and valued using the VSL estimates discussed above, including both the risk change accrued by those initially infected and those whom they subsequently infect. The question is whether the VSL estimates should be adjusted to reflect concerns about infecting other people.

The review that underlies the HHS VSL estimates (Robinson and Hammitt 2016) includes only studies that provide estimates of individual WTP for reductions in their own risks, excluding studies that address individual WTP for risk reductions that accrue to others. This approach is consistent with the overall benefit-cost analysis framework, which assumes that the individual is the best or most legitimate judge of his or her own welfare. The appropriate treatment of altruism and other types of other-regarding preferences raises difficult conceptual and empirical issues that have not been resolved. Hence concerns about the risks potentially imposed on others are generally addressed qualitatively.

In sum, for policies that address COVID-19 mortality, we suggest that analysts:

ED_006573_00001315-00007

- Apply the central, high, and VSL estimates recommended in the HHS *Guidelines*;
- Conduct sensitivity analysis when policies disproportionately affect the very young or very old, by applying the value per QALY estimates recommended in the HHS *Guidelines*.
- Discuss individual and risk attributes that may affect these values qualitatively or explore them in sensitivity analysis, based on the information provided in this report and elsewhere.

This approach is necessitated in part due to limitations in the existing VSL literature and in part due to the lack of valuation research that explicitly addresses COVID-19 mortality risk reductions. We are hopeful that such research will begin to emerge soon, in which case the review and recommendations in this report can be updated. Regardless, it is unlikely that a "one-size-fits-all" VSL for COVID-19 policies will result, given that different policies will have differing effects.

Valuing COVID-19 Morbidity Risk Reductions

The substantial variation in symptoms across nonfatal COVID-19 cases is increasingly apparent, and additional information on these symptoms is continuing to emerge. Because WTP studies have not yet been completed for nonfatal cases of COVID-19, we develop a categorization scheme that can be used to compare COVID-19 symptoms to those of other illnesses. We recognize that the approach to categorization will need to be refined as more data become available. In addition, the incidence and characteristics of COVID-19 morbidity may change as new variants emerge and as a larger proportion of the population is vaccinated. The approach may also require adjustment to reflect the impacts of a specific regulation or other policy.

The true number of U.S. COVID-19 cases is not known and is underreported for various reasons, including the lack of universal testing. Individuals with asymptomatic or mild infections are less likely to be tested or receive medical care and thus are less likely to be included in COVID-19 reporting systems. Conversely, individuals with more severe disease are much more likely to seek care and to be tested and identified as infected.

The distribution of reported nonfatal cases by age appears to differ from the distribution of reported fatalities, based on data available as of January 2021. While reported fatalities occurred disproportionately among the elderly, reported nonfatal cases occurred more frequently among adults age 18 to 64. However, this result may in part reflect patterns in exposure and in reporting, which are likely to change over time.

As is the case for COVID-19 deaths, those who experience more severe symptomatic nonfatal illness appear to often have underlying health impairments, such as diabetes, heart disease including hypertension, and chronic lung disease. Nonfatal cases also appear to be more common among individuals with certain socioeconomic characteristics, which again may reflect differences in exposure as well as other factors.

Some individuals infected with SARS-CoV-2 (the pathogen that causes COVID-19) may not experience any symptoms. Symptomatic COVID-19 cases can be categorized as mild, severe, and critical, with most

ED_006573_00001315-00008

identified cases fitting into the mild category. The symptoms within each category are generally similar across age groups. However, most cases documented among younger populations are less severe than those among older populations.

As a starting point for valuation, in Table ES.3 we provide a categorization scheme for symptomatic nonfatal cases based on the data available as of January 2021. We recognize that this approach reflects an oversimplification and that explicit assessment of associated uncertainties is essential. We describe each acute and post-acute phase of the disease for mild, severe, and critical cases, note similar diseases that we use as proxies for valuation, and provide estimates of typical duration, based on review of the available literature. While we do not include asymptomatic cases at this time, some evidence is now emerging that suggests that cases that are initially asymptomatic or mildly symptomatic may ultimately lead to impaired health over the longer run. Continued review of the emerging research is needed to determine whether and how to refine this approach.

Table ES.3 COVID-19 Phases, Similar Diseases, and Durations for Symptomatic Cases

Severity Category	COVID-19 Phase	Similar Proxy Disease	Typical Duration
Mild case	• Mild acute phase • Mild post-acute phase	• Influenza • Chronic obstructive pulmonary disease	• 10 days • 15 days
Severe case	• Mild acute phase • Severe acute phase • Severe post-acute phase	• Influenza • Influenza with respiratory complications • Chronic obstructive pulmonary disease	• 7 days • 6 days • 50 days
Critical case	• Mild acute phase • Critical acute phase • Critical post-acute phase	• Influenza • Sepsis, conditions requiring involving acute respiratory failure, prolonged mechanical ventilation. • Chronic health states associated with sepsis, conditions involving acute respiratory failure, conditions requiring prolonged mechanical ventilation.	• 7 days • 12 days • Remaining lifetime

Note: The information in this table is provided as a starting point for the valuation research discussed in this paper and is used to illustrate the results. It will require refinement as more data on COVID-19 morbidity become available.

The conceptual framework for valuing morbidity risk reductions is similar to the framework for valuing mortality risk reductions described above. In this case, however, we are interested in an individual's willingness to exchange income (or wealth) for changes in his or her own risk of nonfatal illnesses. We expect these values to vary depending on the characteristics of the individuals and of the risks, including the characteristics discussed in the VSL context previously.

A major challenge in this case, however, is that base values are not available for the nonfatal risks of concern. Hence, we conduct a criteria-driven review to develop estimates for nonfatal COVID-19 cases. We first review the WTP literature for nonfatal illnesses with symptoms similar to those of COVID-19, focusing on the proxy diseases listed above in Table ES-3: influenza, chronic obstructive pulmonary disease (COPD), sepsis, conditions involving acute respiratory failure, and conditions requiring prolonged

ED_006573_00001315-00009

mechanical ventilation. We find very few WTP studies that address these conditions, providing only limited insight into the value of reducing these risks.

We next review the QALY literature for the same conditions, focusing on health-related quality of life (HRQL) estimates for nonfatal cases. While this literature is also limited, it is substantially more extensive than the WTP literature and provides more insight into these values. We develop illustrative, population-average estimates for individuals at different ages based on HRQL and duration estimates from the literature and HHS's estimates of the value per QALY (reported above in Table ES.1). We find that the value of averting a nonfatal statistical case of COVID-19 for an individual age 40 may be about $8,000 for mild cases, $18,000 for severe cases, and $1.8 million for critical cases. These estimates provide indicators of the likely magnitude of the values, but rest on several simplifying assumptions.

Given these uncertainties, these estimates should be used only to illustrate the potential magnitude of the benefits associated with averting nonfatal cases. They should be accompanied by both qualitative discussion and quantitative analysis of uncertainty based on the information provided in this paper and in other sources, following the general approaches for assessing uncertainty described in Chapter 6 of the HHS *Guidelines*. The quantitative assessment should include investigation of uncertainty in both the HRQL and the duration estimates as well as in the monetary value per QALY. In addition, these values should be updated to reflect new information on the characteristics of nonfatal COVID-19 cases and tailored to the effects of the specific regulation or other policy under consideration.

ED_006573_00001315-00010

CHAPTER 1: INTRODUCTION

In 2016, the U.S. Department of Health and Human Services (HHS) finalized its *Guidelines for Regulatory Impact Analysis* (hereafter *Guidelines*) under the leadership of its Assistant Secretary for Planning and Evaluation (ASPE) and Analytics Team. The *Guidelines* discuss how to value mortality and morbidity risk reductions when assessing the impacts of HHS regulations and other policies, relying on estimates of the value per statistical life (VSL) for expected changes in fatalities and the value per statistical case (VSC) for expected changes in nonfatal illnesses.

Valuing risk reductions associated with regulations or other policies that address the novel coronavirus disease 2019 (COVID-19) presents major challenges, however. Some of these challenges reflect uncertainties related to the impacts of the disease, including the characteristics of the individuals most likely to be affected and its symptoms and duration. Other challenges relate to gaps and inconsistencies in the available valuation research.

In this paper, we explore these issues, building on the HHS *Guidelines*. We summarize the data currently available on the effects of COVID-19, describe the conceptual framework for valuation, investigate the available empirical research, and discuss the implications. We recognize that the impact of the virus is rapidly evolving and that new data are continually emerging, and focus on developing and illustrating an approach that can be adapted to changing circumstances as needed.

This chapter summarizes the approaches for valuing mortality and morbidity risk reductions discussed in the HHS *Guidelines* then provides an overview of the remainder of the paper. Throughout, we assume that readers are familiar with the *Guidelines* and focus on highlighting key issues that arise when addressing COVID-19 regulations and policies.

1.1 HHS Valuation Approach

The *Guidelines* address the analysis of major HHS regulations, as required by Executive Order 12866 (Clinton 1993) and Executive Order 13563 (Obama 2011), and by implementing guidance from the U.S. Office of Management and Budget (OMB 2003). In Chapter 3, "Assess Benefits," the *Guidelines* discuss the approach for valuing mortality and morbidity risk reductions. In addition to summarizing this approach below, we report updated values expressed in 2020 dollars (at 2020 income levels).[1]

In benefit-cost analysis, the value of an improvement, such as a decrease in the risk of dying or becoming ill, is typically based on individual willingness to pay (WTP). In other words, the value is derived from the maximum amount of money affected individuals would exchange for the risk reduction they would experience, given their budget constraints and preferences for spending on other goods and services.

[1] Appendix D to the HHS *Guidelines* (HHS 2021) describes the process for adjusting these values in detail and provides updated estimates.

ED_006573_00001315-00011

By convention, these WTP estimates are converted to VSL estimates when valuing expected changes in the number of deaths. The VSL terminology is frequently misinterpreted, however. VSL is not the value that the analyst, the researcher, or the government places on saving an individual from certain death. Rather it reflects estimates of the amount of money individuals are willing to exchange for small changes in their own risks within a defined time period. People make many such decisions in their day-to-day lives, for example when choosing how to balance job-related risks and wages or whether to pay more for a safer car.

If on average a member of the U.S. population is willing to pay $1,000 for a 1 in 10,000 reduction in their own mortality risk in a given year, the equivalent VSL can be calculated by dividing individual WTP by the risk change:

$1,000 WTP ÷ 1/10,000 risk change
= $10.0 million VSL

In other words, a population-average VSL of $10 million indicates that the typical individual is willing to pay $1,000 to decrease his or her chance of dying in a given year by 1 in 10,000.

The value to a population is calculated by summing individual WTP across those affected. If an intervention would reduce mortality risk by 1 in 10,000 to each of 10,000 individuals, and if each is willing to pay $1,000 for a 1 in 10,000 change in his or her own risk, the total value is $10 million (10,000 x $1,000) and one fewer person would be expected to die that year (10,000 x 1/10,000).

The *Guidelines* recommend low, central, and high VSL estimates for use in HHS regulatory impact analyses, based on a criteria-driven review reported in Robinson and Hammitt (2016). That review follows the benefit transfer framework (at times referred to as "value" transfer) discussed in Chapter 3 of the HHS *Guidelines*. The authors identify six revealed preference studies and one meta-analysis that meet the criteria, all of which consider the tradeoff between occupational risks and wages. They also identify three stated preference studies that meet the criteria, which elicit WTP for reducing mortality risks associated with food-related illnesses, motor vehicle accidents, and other causes.[2] In combination, these studies lead to VSL estimates ranging from $4.2 million to $13.7 million with a mid-point of $9.0 million, in 2013 dollars at 2013 income levels. HHS uses these values as the basis of its population-average low, high, and central VSL estimates respectively.

As discussed in more detail in the HHS *Guidelines*, these estimates must be updated annually to reflect the effects of inflation in previous years as well as historic and predicted future changes in real income. Table 1.1 reports the values in 2020 dollars at 2020 income levels.

[2] The revealed preference studies include Viscusi (2004); Kniesner and Viscusi (2005); Hersch and Viscusi (2010); Lee and Taylor (2013); Scotton (2013); and Viscusi (2013). The meta-analysis is Viscusi (2015). The stated preference studies include Corso, Hammitt, and Graham (2001); Hammitt and Haninger (2010); and Cameron and DeShazo (2013).

ED_006573_00001315-00012

Table 1.1 HHS Population-Average VSL Estimates

	2013 dollars and income levels	2020 dollars and income levels
Low	$4.2 million	$5.3 million
Central	$9.0 million	$11.4 million
High	$13.7 million	$17.4 million

Source: HHS *Guidelines* Appendix D (HHS 2021)

The HHS *Guidelines* also suggest that analysts conduct sensitivity analysis when the regulatory or other policy disproportionately affects mortality risks among those who are much older or younger than the average member of the population. This sensitivity analysis is based on values per quality-adjusted life year (QALY) derived from the VSL estimates. The derivation of these values assumes that the population-average VSL reflects the present value of expected future life years for the average individual included in the underlying studies (assumed to be age 40), adjusted for expected health-related quality of life (HQRL) at each age. The resulting constant value per QALY is then multiplied by the present value of the change in expected future QALYs for those individuals affected by the policy.

The HHS value per QALY estimates for 2020 are provided in Table 1.2, based on the 2020 VSL estimates in Table 1.1. These estimates vary depending on the discount rate used when calculating present values; the HHS *Guidelines* as well as OMB (2003) require that regulatory analyses be conducted using both 3 percent and 7 percent rates.

Table 1.2 HHS Value per QALY Estimates (2020 dollars and income levels)

	VSL Estimate	Value per QALY 3 percent discount rate	Value per QALY 7 percent discount rate
Low	$5.3 million	$270,000	$450,000
Central	$11.4 million	$580,000	$970,000
High	$17.4 million	$880,000	$1,470,000

Source: HHS *Guidelines* Appendix D (HHS 2021)

Due to inconsistencies and gaps in the underlying research, this approach relies on several simplifying assumptions related to the effects of age and life expectancy on VSL, as discussed in more detail later in this paper.

Conceptually, the approach is similar when valuing nonfatal cases of illness. Estimates of individual WTP are converted to value per statistical case (VSC) estimates. However, for nonfatal illnesses, the *Guidelines* do not recommend specific values. HHS policies potentially affect a wide range of nonfatal health conditions that vary in severity, duration, and other characteristics. The *Guidelines* instead provide a framework for estimating these values.

Analysts should first review the literature to determine whether suitable WTP estimates of reasonable quality are available for the nonfatal risk reductions of concern. If not, the *Guidelines* recommend that analysts use monetized QALYs as a proxy. In this case, a constant value per QALY is multiplied by the

ED_006573_00001315-00013

expected change in QALYs to estimate the value per statistical case averted. The expected change in QALYs in this context is derived by multiplying the change in HRQL associated with the change in risk by its duration.

Regardless of whether WTP or monetized QALY estimates are used for valuation, costs that are not included in these estimates can be added to reflect the total impact of the health condition on social welfare. These costs typically include those incurred by third parties rather than by the affected individual, such as medical costs covered by insurance and caregiving provided by friends and family. See *Guidelines* Chapter 3 for more discussion.

1.2 Overview of Following Chapters

The remainder of this paper discusses the application of these *Guidelines* to reductions in COVID-19 mortality risk (in Chapter 2) and morbidity risk (in Chapter 3), considering possible adjustments and approaches for addressing uncertainty. In each chapter, we first discuss the characteristics of COVID-19 risks based on the data available as of January 2021, including the characteristics of those most likely to be affected and of the disease itself. We then address valuation of these risks, including theoretical expectations and empirical research findings.

We are writing this paper at a time when the context for these analyses is evolving rapidly, due to emerging scientific research, changes in the virus itself, and the availability of vaccines. The COVID-19 data that we provide at the beginning of each chapter is historical and provided largely for context.

The impacts of a specific regulation or other policy will vary from what is seen in these data for several reasons. First, analysts will have access to updated data on COVID-19 incidence and impacts. Second, as discussed in Chapter 2 of the HHS *Guidelines*, regulatory analyses focus on realistic incremental changes. They predict conditions with and without implementation of a specific policy, rather than comparing hypothetical scenarios such as conditions with and without any COVID-19 incidence. Third, an individual regulation or alternative policy may focus on risks among certain population subgroups or on specific disease attributes rather than addressing all cases nationally. For example, some policies may address COVID-19 risks among young children or the elderly, focusing on practices in childcare centers or nursing homes. Others may affect a subset of disease characteristics, for example by encouraging treatments or other interventions that reduce disease severity or mortality rates without affecting overall incidence.

Most importantly, the availability of vaccines is profoundly altering the disease trajectory, including the baseline conditions to which a policy is compared and the likely impacts of a policy over time. For example, in the near-term (i.e., in the Spring of 2021) deaths will likely decrease more rapidly among the elderly and others for whom vaccination is a high priority; while over the longer run deaths among all age groups are expected to decrease.

ED_006573_00001315-00014

CHAPTER 2: VALUING COVID-19 MORTALITY RISK REDUCTIONS

In this chapter, we provide data on COVID-19 mortality risks, including the characteristics of the individuals affected and the risks themselves. We then discuss how these characteristics may influence the values placed on reductions in these risks.

2.1 Characteristics of COVID-19 Mortality Risks

According to the Centers for Disease Control and Prevention (CDC), as of January 21, 2021 there had been 404,689 U.S. deaths involving COVID-19 (CDC 2021a). COVID-19 was a leading cause of death in 2020, ranking behind only heart disease and cancer according to initial estimates (Woolf et al. 2021; Koh et al. 2021).

Similar to deaths from all causes, these deaths have been concentrated among the elderly, as summarized in Table 2.1.[3] While the population aged 65 and over comprises a minority of the United States population (16.3 percent), this group accounts for most (81.0 percent) of the deaths for which COVID-19 was listed among the causes. Similarly, most (73.2 percent) deaths not involving COVID-19 are among this age group. Researchers using alternative estimation methods also find that excess deaths due to COVID-19 are concentrated among the elderly (National Center for Health Statistics 2021).

Table 2.1 Distribution of U.S. Population and Deaths by Age Group

Age Group	U.S. Population[a]	Deaths by Cause Involving COVID-19[b]	Deaths by Cause Not involving COVID-19[b]
0–14	18.7%	<0.1%	0.9%
15–24	13.0%	0.2%	2.4%
25–34	13.9%	0.7%	3.3%
35–44	12.7%	1.7%	4.5%
45–54	12.6%	4.7%	10.3%
55–64	12.9%	11.7%	12.0%
65–74	9.7%	21.3%	11.3%
75–84	4.8%	27.6%	29.0%
85+	1.8%	32.1%	32.9%
Total	100.0%	100.0%[c]	100.0%[c]

Detail may not add to total due to rounding.
a. 2019 data from "Age and Sex Composition in the United States: 2019," U.S. Census Bureau, as viewed June 21, 2020. https://www.census.gov/data/tables/2019/demo/age-and-sex/2019-age-sex-composition.html. The total estimated population was 324,356,000.
b. January 1, 2020 through January 16, 2021 data from "Provisional COVID-19 Death Counts by Sex, Age, and State," National Center on Health Statistics, U.S. Centers for Disease Control and Prevention, as viewed January 21, 2021. https://data.cdc.gov/NCHS/Provisional-COVID-19-Death-Counts-by-Sex-Age-and-S/9bhg-hcku. Deaths involving COVID-19 totaled 347,131 and deaths not involving COVID-19 totaled 2,982,776 over this time period.

[3] The preceding paragraph provides a more recent and hence higher count than the table (as of January 21 rather than January 16); the lag results because detailed data reported in Table 2.1 take longer to process.

ED_006573_00001315-00015

COVID-19 deaths appear to have been largely among individuals with underlying health conditions. Only about half of all deaths involving COVID-19 reported to CDC included data on underlying health status. However, these data show that the vast majority of individuals (96 percent) who died with COVID-19 have one or more underlying health conditions (Stokes et al. 2020).[4] In the absence of COVID-19, the life expectancy of individuals who have characteristics similar to those who have died with COVID-19 may be lower than the life expectancy of others at the same age due to the presence of underlying health conditions (Briggs et al. 2020). European data suggest that their life expectancy may be approximately 20 percent lower on average(Hanlon et al. 2021).

Deaths associated with COVID-19 also appear to occur disproportionately among individuals with certain demographic and socioeconomic characteristics. This variation likely results from differences in exposure as well as health status and other factors. Deaths occur disproportionately among males (Stokes et al. 2020). Lower-income populations may be more vulnerable. For example, Raifman and Raifman (2020) find that individuals with household income less than $25,000 were more likely to be at higher risk of severe illness from COVID-19.

The impacts also vary across race and ethnic groups. For example, McLaren (2020) finds that county COVID-19 mortality rates are positively correlated with the share of the population identified as Black or African-American, Hispanic or Latino, Asian, and American Indian and Alaska Native in the U.S. Census. Similarly, Benitez et al. (2020) find that COVID-19 cases per capita are significantly correlated with the proportions of Black and Hispanic residents and that these differences explain much of the racial disparities in COVID-19 deaths. In a large retrospective cohort study of a Louisiana health system, Price-Haywood et al. (2020) report that about 77 percent of hospitalized cases and about 71 percent of fatal cases were Black patients, although Black people represent only 31 percent of the total population. Gold et al. (2020) find that non-Hispanic Black patients were overrepresented in eight Georgia hospitals. Azar et al. (2020) similarly find that non-Hispanic Black patients were significantly more likely to become hospitalized than non-Hispanic white patients, even when controlling for other important factors.

COVID-19 deaths may be preceded by extended periods of severe symptoms, including fever, shortness of breath, high respiratory rate, and cough (Bhatraju et al. 2020; Stokes et al. 2020). In the United States, as of January 2021, approximately 20 percent of hospitalized patients over the age of 50 with COVID-19 have been put on mechanical ventilation, which requires that individuals be placed in a medically induced coma (CDC 2021b). In addition to experiencing these symptoms, patients are generally isolated, dying without being surrounded by their loved ones.

CDC (2021b) estimates that the median duration of illness between symptom onset and death in the United States is between 13 and 17 days. Duration is highly dependent upon care received. Less time will elapse among patients with do-not-resuscitate orders (Bhatraju et al. 2020) and those who do not receive intensive treatments due to low perceived chance of survival (Vincent and Taccone 2020).

---

[4] Data on underlying conditions for all cases (both fatal and nonfatal) indicates that the most common are diabetes (30 percent of individuals with reported health status), heart disease including hypertension (32 percent), and chronic lung disease (18 percent).

ED_006573_00001315-00016

Estimates of deaths by cause are always uncertain due to difficulties in determining the cause and inconsistencies in reporting. Estimates of COVID-19 deaths are no exception. For example, most states and jurisdictions report confirmed and probable cases and deaths, while others report cases and deaths based on confirmatory laboratory evidence (CDC 2021c). At times, this discrepancy in reporting was magnified by limited testing capacity and accuracy (CDC 2021c).

Even in the absence of widespread vaccination or changes in the virus itself, the distribution and characteristics of COVID-19 deaths would likely shift over time due to changes in exposure, treatment, and other factors as well as changes in reporting practices and in the models used for estimation. As noted earlier, the above data are provided as context for the discussion that follows. For any particular regulatory analysis, analysts will need to explore the data and other evidence available at the time of the analysis to estimate the expected incidence of deaths under baseline conditions and with the policy.

2.2 Valuing COVID-19 Mortality Risks

In this section, we explore differences between the COVID-19 mortality risks described above and the risks addressed by the studies that underlie HHS's population-average VSL estimates, discussing the implications for valuation. We first address key differences between the individuals included in the VSL studies and the individuals most likely to be affected by COVID-19 regulations and policies. These include age, health status, and income. We next consider key differences between the risks addressed in the VSL studies and COVID-19 risks. These include morbidity prior to death, qualitative risk attributes, and the magnitude of the risk change. We conclude by exploring concerns related to incorporating other-regarding preferences (such as altruism) in the infectious disease context. As noted earlier, whether these differences are relevant to a specific analysis will depend on the characteristics of the regulation or policy under consideration, as well as on the extent to which baseline conditions change as a result of vaccinations and other developments.

For each individual and risk attribute, we first discuss conceptual issues and theoretical expectations then summarize related empirical work, focusing on peer-reviewed research that addresses the U.S. population. While this discussion provides insight into the possible direction of the effects, the available data are insufficient to support quantitative adjustment in most cases for several reasons. First, empirical research on the implications of many factors is limited and often inconsistent, and the quality of the studies and their applicability to HHS regulations and policies varies. Second, this research does not directly address COVID-19. While research on other conditions provides useful information, it suggests that the factors we explore are likely to have counterbalancing effects in the COVID-19 context. Third, the available research focuses on diverse scenarios and populations and uses varying methods. It is unclear whether similar findings would emerge if the studies were more consistent with the approaches used in the studies that underlie the HHS estimates. Finally, as noted earlier, the extent to which each of these factors is relevant to a particular analysis will vary, depending on the population and risks addressed.

ED_006573_00001315-00017

We expect new valuation research that specifically addresses COVID-19 mortality risks will be published in the future that will aid in addressing these issues.[5] This section provides information that can be used in HHS regulatory analyses in the interim, without the benefit of this research. Because any individual study will have advantages and limitations, as new research becomes available it should be considered in combination with the studies discussed below and other research when assessing the implications for HHS regulatory analysis. More information on the factors to consider in reviewing this literature is provided in Chapter 3 of the HHS *Guidelines*.

At minimum, the review that follows can be used to support qualitative discussion of associated uncertainties, using the approaches described in Chapter 6 of the HHS *Guidelines*. This review also may be useful to those conducting new valuation studies, identifying issues in need of further exploration.

2.2.1 Individual Characteristics

As introduced in Chapter 1, VSL estimates are generally derived from estimates of individual WTP for small risk changes within a defined time period. Conceptually, VSL measures the rate at which an individual would pay to increase his or her chance of surviving the current period, forgoing other consumption to reduce the chance of death (see Hammitt 2020). This means that VSL depends on both the benefits of survival and the opportunity cost of spending, which in turn depend on the individual's characteristics and circumstances as well as his or her preferences. Larger benefits of survival increase VSL while a higher opportunity cost of spending decreases VSL.

The benefit of surviving the current year depends on what the future promises. For example, conditional on surviving, the individual may expect a long or short life, good or poor health, or high or low income. By increasing the chance of surviving the year, the individual increases his or her chance of experiencing this uncertain future. The chances of experiencing specific future conditions differ between individuals and depend on factors such as age, gender, chronic health conditions, employment, and education.

The opportunity cost of spending to reduce exposure to risk also depends on individual characteristics and circumstances over time. This opportunity cost is the utility forgone by reducing consumption of other goods and services, where utility is defined as the level of well-being. This opportunity cost is reasonably assumed to be smaller when wealth or income are larger.

Below, we discuss three key differences between the individuals addressed by the studies that underlie the HHS VSL estimates and those who may be affected by COVID-19 regulations and policies given pre-vaccine trends. These include age and the associated life expectancy, baseline health status, and income or wealth. As noted earlier, COVID-19 risks may also vary across genders and across race and ethnic

[5] A search of EconLit on February 12, 2021, did not identify any peer reviewed, published journal articles that report the results of primary research conducted in the U.S. that explicitly addresses COVID-19. The search focused on research published between March 1, 2020 and the search date, using the keywords "VSL" or "mortality risk" and "COVID."

ED_006573_00001315-00018

groups. We reference the HHS *Guidelines* on adjusting for age and life expectancy as well as changes in income, while noting that the effect of baseline health status is uncertain.

2.2.1.1 Age and Life Expectancy

The studies that underlie the HHS VSL estimates address the values held by working age adults. Some studies include older teens and many exclude those over age 62 or 65 (see Robinson and Hammitt 2016). The VSL estimates highlighted by the study authors and used to develop the estimates featured in the HHS *Guidelines* are generally averages based on the full sample. Not all studies report the average age of those studied, but it appears to be around age 40. As discussed in section 2.1, those dying from COVID-19 have been substantially older, generally over 65.

Conceptually, we expect VSL to vary with age over the lifecycle (see Hammitt 2020). One reason is that remaining life expectancy typically decreases with age. Because a younger person typically has more expected life years remaining if he or she survives the current year than does an older person, the benefit of surviving the current year can be smaller for the older person. This effect tends to cause VSL to fall with age.

But life expectancy can also affect the opportunity cost of spending. A longer life expectancy can increase the risk of outliving one's resources. If an individual will have no future income and must support herself or himself from existing wealth, the opportunity cost of spending increases with life expectancy. Any money that such an individual spends on reducing their mortality risk decreases the amount they have to spend on other goods and services, potentially affecting their quality of life adversely. If the effect of a short life expectancy on decreasing the opportunity cost of spending exceeds its effect on decreasing the benefit of surviving the current period, a shorter life expectancy can increase VSL. Alternatively, if the individual expects to have future income from employment, a pension, an annuity, or other sources, then the effect of life expectancy on the opportunity cost of spending is smaller or even reversed. In this case, the opportunity cost of spending can decrease with life expectancy. In combination with the effect of life expectancy on the benefit of surviving the current year, VSL should increase with life expectancy and hence decrease with age.

Theoretical models tend to show that VSL rises in early adulthood, peaks in middle age, and then declines (e.g., Shepard and Zeckhauser 1984; Murphy and Topel 2006). Much of the empirical work that considers the trade-off between wages and risks across all workers also yields such an inverted-U pattern, although the rate of increase and decrease and the age at which VSL peaks varies (see Kniesner, Viscusi, and Ziliak 2006; Aldy and Viscusi 2007; Viscusi and Aldy 2007; Aldy and Viscusi 2008; Aldy 2019). A study of the types of automobiles that individuals own, which includes older individuals, finds a similar pattern (O'Brien 2018). In contrast, a series of wage-risk studies focused on older workers (age 51 and above and their spouses) finds that the VSL remains constant or increases with age (summarized in Evans and Smith 2006).

Stated-preference research can address the relationships between age and VSL among individuals older or younger than working age or outside of the workforce for other reasons. A recent review (Robinson

et al. 2019) found that values for children generally exceed values for adults by a factor of 1.5 or more.[6] While some studies suggest that the divergence between child and adult values decreases as the child ages, this finding is not universal. For older adults, the stated-preference evidence is inconsistent. Some studies do not find statistically significant relationships with age, while others find that the VSL decreases among older individuals in varying patterns and amounts (Krupnick 2007). One study (Cameron, DeShazo, and Stiffler 2010) finds an inverted-U relationship, similar to many of the wage-risk studies.

Robinson, Sullivan, and Shogren (2021) explore the effects of uncertainties in the age-VSL relationship in the COVID-19 context, comparing the effects of three approaches: (1) a population-average VSL; (2) a constant value per statistical life-year (VSLY); and (3) a VSL that follows an inverted-U pattern, peaking in middle age. Their first approach applies the 2019 HHS central population-average estimate ($10.6 million) to all age groups. In the second approach, they divide that VSL by the expected present value of future life years at age 40 to derive a constant VSLY, using a 3 percent discount rate, then multiply that constant by the expected present value of future life years for each age group.[7] In the third approach, they apply the inverted-U from the Aldy and Viscusi (2008) cohort-adjusted model, assuming that VSL at age 40 is the same as the HHS central population-average estimate. The Aldy and Viscusi study includes only working adults ages 18 to 62. Robinson, Sullivan, and Shogren assume the value is constant for ages 18 and younger and 62 and older, reflecting uncertainty about the values outside the ages included in that study. Applied to the U.S. age distribution of COVID-19 deaths as of May 2020, Robinson, Sullivan, and Shogren find that these approaches result in average VSL estimates of $10.6 million, $4.5 million, and $8.3 million respectively.

This illustrative comparison highlights the implications of uncertainties in the relationship between VSL and age, indicating that the findings of any analysis will depend on both the age distribution of those affected and the details of the approach used to adjust VSL for age. The use of a constant VSLY or value per QALY may better approximate the findings of the research on values for children, because it yields higher values at younger ages than does the application of a constant VSL or an inverted-U function. For older individuals, the use of either a constant VSLY or value per QALY, or an inverted-U, leads to lower values in comparison to the values for those in middle-age. While lower values among the elderly are consistent with some but not all of the empirical literature, the extent to which the values decrease is highly uncertain.

Thus both theory and empirical research suggest the relationship between the population-average VSL and the VSL for older individuals affected by changes in COVID-19 mortality risks is uncertain. The sensitivity analysis recommended in the HHS *Guidelines* provides a useful illustration of the potential

---

[6] Because children are generally not treated as autonomous economic agents and have little or no wealth, the VSL for children is estimated as their parent's WTP to decrease the child's mortality risk. This is consistent with the fact that parents are authorized to make many decisions that shape the child's wellbeing.

[7] This approach is similar to the constant value per QALY approach recommended in the HHS *Guidelines*. However, because quality of life generally declines with age, expected QALYs at each year of age are smaller than expected life years. As a result, dividing VSL by expected life years rather than expected QALYs leads to a smaller constant.

ED_006573_00001315-00020

impacts, yielding values that decrease with age.[8] That sensitivity analysis follows the intuition that lower VSL estimates may be applicable to older individuals because they have fewer expected life years remaining in comparison to the average member of the population. It provides only a rough approximation of the effects of age on VSL, however. More empirical research is needed to better understand the relationship between VSL and age or life-expectancy.

2.2.1.2 Baseline Health Status

As described earlier, the research that provides the basis for the HHS VSL estimates generally addresses the adult U.S. population, regardless of health status, although the wage-risk studies are limited to those healthy enough to work. In contrast, deaths from COVID-19 appear to occur disproportionately among those with underlying health conditions. However, the extent to which those dying are less healthy than others of the same age is uncertain.

The impact of underlying health conditions on VSL depends on the relationship between the benefits of survival and the opportunity costs of decreasing spending on other goods or services. While the benefit of surviving is larger if future health is likely to be better, the opportunity cost of spending may vary with expected future health. If the utility gained by consuming goods and services increases with health, then better future health increases the opportunity cost of spending. If this effect is large enough, it may more than offset the higher benefit of survival, causing VSL to decrease with expected future health.

For most goods and services, it seems reasonable to assume that the contribution of consumption to utility is larger, or at least not smaller, when health is better. Consistent with this assumption, Viscusi and Evans (1990), Sloan et al. (1998), and Finkelstein et al. (2013) find that the marginal utility of income is larger when health is better. The effect may be small or negligible over a wide range of health levels, but extremely poor health (e.g., being bed-ridden) precludes one's ability to benefit from consuming many goods and services without increasing the benefit of consuming others. One important exception is that bad health increases the utility gain from consuming appropriate medical goods and services. If these expenses are not fully covered by insurance, poor health can increase the opportunity cost of spending, leading to a decrease in VSL.

Current health has little or no effect on VSL, except through its implications for future health. In the extreme case of a current health state that is worse than dead, perhaps because of excruciating pain, increasing the chance of survival is still beneficial if future health is expected to be better than being dead and to persist long enough to make enduring the current condition worthwhile.

As illustrated by the examples in this discussion, the effect of baseline health on VSL depends on the nature of any impairment. The data on the relationship between specific impairments and the likelihood of death from COVID-19 is evolving and involves a potentially large number of conditions with varying

[8] This sensitivity analysis should also be applied if the policy disproportionately reduces risks among children. Such sensitivity analysis is not needed if impacts follow the same age distribution as the overall population (with an average age around 40), because the results of applying a constant value per QALY will be the same as using the population-average VSL.

ED_006573_00001315-00021

effects. This leads to difficulties in estimating the effects on the VSL, given that these effects will differ across health conditions.

Regardless, the empirical research on the effect of health impairments on the VSL is limited and inconclusive, with mixed results. As noted above, the results depend on factors such as the nature and severity of the health condition (e.g., Alberini et al. 2004; DeShazo and Cameron 2005; Evans and Smith 2008). Another complication is that health status is correlated with age, declining as one ages (e.g., Hanmer et al. 2006; Fryback et al. 2007). This correlation has made it difficult to separate the effects of age and health status in empirical work. Thus whether and how to adjust a population-average VSL to reflect differences in the health status of those affected by COVID-19 risk reductions is highly uncertain.

2.2.1.3 Income

As introduced in Chapter 1, the HHS *Guidelines* recommend updating VSL to reflect changes in population-average real income, reflecting the change in resources individuals have available to spend on risk reductions and other things. A key input into this adjustment is an estimate of the VSL income elasticity, which measures the extent to which WTP per unit of risk reduction is expected to change in response to an income change. It is typically expressed as the percentage change in the VSL associated with a one percent change in real income.[9] The *Guidelines* recommend applying an elasticity of 1.0, using the change in real earnings to estimate income.[10]

Income is important in the COVID-19 context because the COVID-19 epidemic and responses to it are reducing population-average earnings, taking into account the effects of unemployment and reduced labor force participation as well as shifts between fulltime and parttime work. Whether employment and earnings will continue to decrease, and whether and when they will return to pre-epidemic levels, is uncertain at this time. In addition, as noted previously, lower-income individuals may be disproportionately affected by COVID-19 risks, widening the gap between low- and high-income individuals. Those with limited incomes may be more vulnerable due to their underlying health status and access to health care services, and may find it more difficult to undertake protective measures. For example, they may live in more crowded conditions and may have a stronger need to continue working regardless of the safety of their commute and work environment.

In the discussion that follows, we focus on the effects of COVID-19 on population-average earnings. HHS generally does not adjust the VSL to reflect income differences within the population, applying the same VSL to all groups. However, concern about the impacts on population subgroups emphasizes the need to consider the distribution of the impacts across those who are advantaged and disadvantaged as well as

---

[9] As discussed in more detail in *Guidelines* Chapter 3, the formula is $VSL_{(year\ y)} = VSL_{(year\ x)} * (1+\text{real income growth rate})^{elasticity*(y-x)}$.

[10] The *Guidelines* also note that analysts may wish to experiment with different values if the estimates of net benefits are significantly affected by the elasticity estimate. Under normal conditions (in the absence of COVID-19), it seems unlikely that changes in the elasticity would substantially affect the analytic conclusions, however. In recent years, U.S. real earnings typically grew around 1 or 2 percent per year, leading to relatively small year-to-year changes in VSL. See HHS *Guidelines* Appendix D for more information on this adjustment (HHS 2021).

ED_006573_00001315-00022

the total net benefits, as required by OMB guidance (OMB 2003) and discussed in Chapter 7 of the HHS *Guidelines*.

Ideally, the VSL income adjustment would be based on lifetime wealth rather than earnings and would consider all income sources. Conceptually, in the simplest case, imagine an individual who has no current or future income but must support herself or himself from existing wealth. The benefit of survival is larger if wealth is higher, because she or he can consume more and higher-quality goods and services. The opportunity cost of spending is smaller if wealth is higher. Combining these effects implies that VSL is larger when wealth is higher.

VSL studies generally focus on earnings rather than wealth or total income, however, because earnings are more easily measured. VSL increases with expected future income as well as with wealth. When future income is higher, it increases the benefit of survival, because the individual can consume more. It also decreases the opportunity cost of spending because the individual need not save as much to spend in future periods (or can borrow more to spend in the current period). As for wealth, future income increases the benefit of survival and reduces the opportunity cost of spending, and so increases VSL.

The sensitivity of VSL to a reduction in current income depends on the individual's wealth and ability to borrow against future income. If she or he is cash-constrained (has little liquid wealth or ability to borrow), the opportunity cost of spending is higher, which decreases VSL. If the individual is not cash constrained, VSL should not be very sensitive to a temporary drop in current income. However, if current income falls because of unemployment, economic recession, onset of disability, or another factor that decreases expected future income, then VSL will decrease. This effect is largely due to the effect of expected future income on VSL.

As summarized in Chapter 3 of the *Guidelines* and elsewhere, some research suggests that a one percent change in U.S. income leads to less than a one percent change in the VSL and other research suggests it leads to more than a one percent change, although the U.S. estimates appear to be coalescing around an elasticity of about 1.0. Some studies completed after the *Guidelines* were finalized find smaller elasticities. In a meta-analysis of global wage-risk studies, Viscusi and Masterman (2017) estimate U.S. VSL income elasticity as between 0.5 and 0.7. In a meta-analysis of global stated preference studies, Masterman and Viscusi (2018) estimate income elasticity as 0.55 to 0.85 for VSLs above $2 million. Other research that uses different methods suggests higher elasticities. For example, in a wage-risk study that relies on U.S. panel data, Kniesner, Viscusi and Ziliak (2010) find VSL income elasticities ranging from 1.23 to 2.24 across income quantiles, with a midpoint value of 1.76. Given the range of values found in the literature, it appears that the 1.0 elasticity recommended in the HHS *Guidelines* is a reasonable default.

When adjusting for income, key questions include how to best estimate the effect of the pandemic on population income and whether the effect is likely to be short-lived or persistent. Predictions of economic impacts are highly uncertain at present, although the outlook is improving with the introduction of vaccines. VSL is also likely to be more sensitive to long-run changes than to transient

effects. Thus although COVID-19 appears to have decreased population-average earnings and employment in the near-term, the extent to which VSL in turn decreased is uncertain and may be proportionately less than would be associated with a longer-term income change.

2.2.2 Risk Characteristics

U.S. regulatory agencies rely primarily on VSL studies that examine the trade-off between deaths from on-the-job injuries and wages, regardless of whether the agency's policies primarily affect deaths from injuries or from illnesses. This approach results largely from limitations in the available research. The review that underlies the HHS VSL estimates (Robinson and Hammitt 2016) explicitly addresses this issue. The authors find that few U.S. studies of illness-related risks meet criteria for quality and applicability, and those that do yield similar values to studies of injury-related risks. More precisely, as noted earlier, the HHS values are based on six revealed preference studies and one meta-analysis that address the tradeoff between occupational risks and wages, and three stated preference studies that elicit WTP for risks from food-related illnesses, motor vehicle accidents, and other causes. Thus these estimates do not reflect the characteristics of diseases similar to COVID-19.

In the discussion that follows, we consider three differences between the risks considered in these studies and the risks associated with COVID-19. These include morbidity prior to death, qualitative risk attributes, and the magnitude of the risk change. While the available research provides insights into whether these attributes may increase or decrease individual WTP for changes in mortality risk and hence the VSL, it generally does not support specific quantitative adjustments. Thus we suggest that analysts describe these effects qualitatively or explore them in sensitivity analysis, based on the discussion that follows.

2.2.2.1 Morbidity Prior to Death

The studies that underlie the HHS VSL estimates focus largely on occupational risks that lead to relatively immediate death from injury. For example, Gentry and Viscusi (2016) estimate that 82 percent of all occupational deaths occur within a day of injury; the average number of days between injury and death is 4.2. In contrast, as noted in section 2.1, COVID-19 deaths are generally preceded by about two weeks of symptoms, including fever, shortness of breath, high respiratory rate, and cough. They may also involve being placed on mechanical ventilation in a medically induced coma.

Conceptually, VSL is expected to vary depending on the cause of death. A death that includes significant pain and suffering is worse than a painless death, holding all else constant. Much of the literature on variation in VSL related to the cause of death focuses on fatal cancers, which include morbidity prior to death and may also be dreaded for other reasons (see next section for more discussion of the effects of dread). In a white paper prepared for consideration by its Science Advisory Board, U.S. Environmental Protection Agency (EPA) staff reviewed the related literature (EPA 2016). They identified three studies that meet their selection criteria and address fatal cancers (Hammitt and Haninger 2010; Chestnut, Rowe, and Breffle 2012; and Viscusi, Huber, and Bell 2014). Only the first two compare WTP for fatal cancer risks with those due to other causes; neither finds evidence of a cancer differential. In its review

ED_006573_00001315-00024

of that 2016 white paper, EPA's Science Advisory Board (2017) concluded that there is not sufficient evidence to justify an adjustment, recommending that EPA continue its current practice of using the same VSL to value mortality risks from cancer and from other causes.

This finding may have little relevance for the valuation of COVID-19 risk reductions, however, given the many differences between COVID-19 morbidity and the morbidity associated with cancers. The severity and duration of cancer-related morbidity varies significantly across types of cancers and depends in part on the treatments pursued. Some cancers may lead to more significant morbidity than COVID-19; others may not. In addition, many of the studies of fatal cancers consider incremental differences between cancers and other causes that differ from the causes that underlie the HHS VSL estimates. The magnitude of this increment is likely to also vary depending on the population surveyed and other characteristics of the approach.

An alternative to relying on the VSL literature is to add the morbidity values for nonfatal cases discussed in the next chapter to the VSL for fatal cases in sensitivity analysis. This approach may lead to some double counting because the HHS VSL estimates likely reflect some morbidity prior to death, as illustrated by Gentry and Viscusi (2016). However, adding the values for nonfatal cases to VSL allows analysts to explore the sensitivity of the results to COVID-19 morbidity prior to death and to determine whether the incremental difference is significant enough to affect the analytic conclusions; e.g., whether it noticeably affects the extent to which the benefits of the policy exceed the costs.

2.2.2.2 Qualitative Risk Attributes

Conceptually, VSL for a particular risk depends on the individual's perceptions of that risk and his or her preferences. The VSL studies that underlie the HHS estimates address relatively common and familiar risks associated with occupation, food, and traffic safety. In contrast, COVID-19 is relatively new and unknown, and the magnitude of the risks is uncertain especially as new variants emerge.

Two seminal papers are relevant in this context. First, Slovic (1987) categorizes risks according to the extent to which they are dreaded and unknown. Dread risks include those involving "perceived lack of control, dread, catastrophic potential, fatal consequences, and the inequitable distribution of risks and benefits;" unknown risks include those "judged to be unobservable, unknown, new, and delayed in their manifestation of harm." Many of these characteristics apply to COVID-19 risks and are likely to affect valuation. Second, individuals are often averse to ambiguity, disliking risks more when the probabilities are more uncertain. Ellsberg (1961) notes that ambiguity depends on the amount, type, reliability, and unanimity of information on probabilities and the resulting degree of confidence one has in the data.

Unlike morbidity prior to death, which has a physical manifestation, these perceptions are primarily psychological and subjective. Such perceptions may lead individuals to rank risks of the same expected magnitude (e.g., 1 in 10,000) and same outcome (e.g., immediate death) differently when they stem from different causes. A risk that is more dreaded and unknown, and more ambiguous, is likely to be associated with a larger WTP for the risk reduction.

ED_006573_00001315-00025

Standard theory provides no guidance about how large such an effect can be compared with the difference in utility between surviving the current period and dying. In a 2010 review, Robinson, Hammitt, Aldy, Krupnick, and Baxter explored these issues in the context of terrorism risks. Although concerns about terrorism differ from concerns about COVID-19 in many respects, they also share some similarities. In both cases, the risks may be viewed as less controllable, voluntary, and familiar, and more feared, than the risks typically addressed in VSL studies. Just as terrorism studies disagree on the likelihood of attack, the data on the likelihood of COVID-19 infection and death are evolving and uncertain.

Robinson et al. (2010) identified 15 relevant studies, all of which use stated preference methods and were conducted in the U.S. or other high-income countries.[11,12] Eight consider trade-offs between risks of different types without eliciting WTP; the remaining seven provide monetary values. The causes of death considered were diverse, including several types of cancer; exposures to pesticides, air, or water pollution, or hazardous or nuclear wastes; transportation accidents, including air, motor vehicle, rail, and pedestrian crashes; and homicides, terrorist attacks, drownings, or fires.

In the studies that address differences across risks, the estimates featured by the authors suggest no difference in the values in many cases, with most studies suggesting that values differ by a factor less than two. The quality of the studies varies however, and the extent to which the results are applicable to COVID-19 risk reductions in the U.S. is uncertain. In addition to addressing different populations and scenarios, these studies use methods that differ from the methods used in studies that underlie the HHS VSL estimates. A study that valued reductions in risks with different attributes but using similar methods and populations as those underlying the HHS VSL estimates could lead to differentials that vary from those found in these diverse studies.

The 2010 review includes three studies that address how aversion to ambiguity affects the values individuals place on mortality risk reductions (Viscusi et al. 1991; Shogren 2005; Riddel and Shaw 2006). These studies suggest that ambiguity may increase values by a factor of two or less, implying that the VSL could be somewhat higher for more ambiguous risks. More recently, Treich (2010) explored the effects of ambiguity on VSL in a theoretical model and found the impact was relatively modest. However, this result applies to cases where the baseline risk is ambiguous but the risk reduction is not; ambiguity aversion need not increase WTP for a protective action when its efficacy is ambiguous (Treich 2010; Bleichrodt et al. 2019). At least in the near term, while information on the effectiveness of different protective measures is evolving, it appears that both baseline risks and the size of the risk

[11] The 15 studies include: Viscusi et al. (1991); Jones-Lee and Loomes (1995); Magat et al. (1996); Subramanian and Cropper (2000); Chilton et al. (2002); Hammitt and Liu (2004); Carlsson et al. (2004); Shogren (2005); Chilton et al. (2006); Itaoka et al. (2006); Riddel and Shaw (2006); Van Houtven et al. (2008); Adamowicz et al. (2009); Viscusi (2009); Hammitt and Haninger (2010).

[12] In a more recent paper, Pike et al. (2020) explore perceptions of pandemic risks in the Ebola context and find that individuals are relatively unconcerned, placing a higher value on avoiding environmental disasters and terrorist attacks.

ED_006573_00001315-00026

reduction are likely to be ambiguous in the case of COVID-19. The advent of extensively tested vaccines may change this perception.

One study worth highlighting is Liu et al. (2005). While this study does not address the U.S. population, it does address an illness more similar to COVID-19: the severe acute respiratory syndrome (SARS) outbreak in Taiwan. The authors found values that were substantially greater than values previously estimated for Taiwan, by factors ranging from roughly 1.5 to 6 times larger than those for fatal lung disease or cancer from air pollution.

Note that the risk perception literature suggests that catastrophic risks are more feared than less catastrophic risks (Hammitt and Treich 2007, Rheinberger and Treich 2017, Hammitt 2020). Holding constant the expected number of deaths, there are two ways in which a risk can be more catastrophic, as discussed in these articles. One is when individuals' risks are positively correlated, for example, when the number of deaths from COVID-19 depends on how effectively the spread of infection is controlled. Another way is when the risks are more equal: if individual risks are concentrated on a small share of the population (such as, in the case of COVID-19, the elderly), the number of deaths is unlikely to be large relative to the population because most people face a very small risk. The effect of these concerns on WTP is uncertain, however, and they may increase or decrease the VSL.

In sum, although the effects of qualitative risk perceptions on the VSL for COVID-19 risk reductions are complex, varying, and perhaps somewhat counterbalancing, it appears that the VSL for such risks may be larger than for the risks more commonly studied. One question in need of further investigation is the extent to which these perceptions reflect thoughtful and well-informed judgments or exaggerated reactions and perhaps momentary panic. It is possible that individuals' perceptions about COVID-19 risk and the appropriate VSL have evolved as experience and knowledge about the risk have increased.

As discussed in the HHS *Guidelines*, the goal of benefit-cost analysis is to identify policies that increase net social welfare, reflecting individual preferences. However, as Robinson and Hammitt (2011) note, if emotional reactions lead individuals to make choices that do not correspond with their own definition of their welfare, benefit-cost analysis that relies on these choices for valuation may fail to meet this goal. Ideally, benefit-cost analysis should be based on well-informed, thoughtful preferences.

Increased fear and anxiety may be important societal consequences of the COVID-19 pandemic. However, since interventions that reduce mortality and morbidity risks are unlikely to yield a proportional reduction in fear and anxiety, we do not recommend adjusting the VSL to account for these concerns, or for discrepancies between individual perceptions and observed mortality risks for COVID-19. Instead, we recommend that a discussion of fear and anxiety be addressed separately in the analysis, allowing the analyst and policymakers to understand these important outcomes outside the context of reductions in mortality and morbidity.

ED_006573_00001315-00027

2.2.2.3 Magnitude of Risk Change

Most of the studies that underlie the HHS VSL estimates address WTP for an annual risk reduction and consider relatively small risk changes, generally with magnitudes around 1 in 10,000. The duration of the change in risk associated with COVID-19 regulations or other policies may be similar. Assuming that COVID-19 is eventually controlled through vaccination, the need for protective policies may be relatively short-lived.

However, the size of the risk change will likely vary depending on the policy. Some early COVID-19 benefit-cost analyses addressed relatively large risk changes; for example comparing stringent and fully effective social distancing policies to a baseline of no intervention. Regulatory analyses typically address smaller, more incremental, changes. For example, analysts might be interested in comparing COVID-19 risks under current policies to COVID-19 risks with a change in the required protective measures.

The amount an individual would pay for a small reduction in the chance of dying in the current period is approximately equal to his or her VSL times the risk reduction. For example, if an individual's VSL is $10 million, that individual would be willing to pay approximately $100 to decrease his or her current mortality risk by 1 in 100,000. Clearly, however, most individuals would not be willing to pay $100,000 to decrease current mortality risk by 1 in 100; such a large payment would be infeasible. This implies that the average rate at which an individual is willing to pay for risk reduction (WTP divided by the risk reduction) decreases as the risk reduction increases.

Under the standard theoretical model underlying VSL, the rate does not fall very sharply until the individual's willingness to pay rises to 10 percent or more of his or her ability to pay (Hammitt 2020). (As noted earlier, ability to pay is often assumed to be equivalent to income.) While the relationship between WTP and the size of the risk reduction depends on the assumptions used in the calculations (especially the income elasticity of VSL), the rate is not likely to decrease substantially until the risk change exceeds about 1 in 1,000; for larger risk reductions, the ratio of WTP to risk reduction will be much smaller than VSL. Since most analyses conducted by HHS are likely to yield mortality risk changes smaller than 1 in 1,000, no adjustment in the VSL for the size of the risk reduction will be needed. In the rare case that a policy leads to a larger risk change, analysts may wish to follow the approach in Hammitt (2020) to adjust VSL in sensitivity analysis.

2.2.3 Other-Regarding Preferences

One issue that arises in the COVID-19 and other contexts is whether and how to include preferences for risk reductions that accrue to others. Presumably, the risk assessment will count all cases associated with the regulation or other policy, including those prevented directly and those prevented indirectly by decreasing the number of infected people in the population. For example, in estimating the risk reductions associated with a policy that increases protective measures at daycare centers or nursing homes, analysts would consider both the change in infections that accrue to those who work at, live in, or visit these locations, and to those whom they may subsequently infect. Each expected case prevented would be valued using the per case estimates discussed in this paper.

ED_006573_00001315-00028

The question is whether these per case estimates should be adjusted to address effects on others' well-being. An individual's WTP to reduce his or her own risk may be affected by the desire to also reduce the risk of infecting family, friends, and members of the larger community. The Robinson and Hammitt (2016) review that underlies the HHS VSL estimates explicitly includes only those studies that provide estimates of individual WTP for reductions in the individual's own risks, excluding studies that address individual WTP for risk reductions that accrue to others. This approach is consistent with the overall benefit-cost analysis framework, which assumes that the individual is the best or most legitimate judge of his or her own welfare.

In the COVID-19 context, concern about risk reductions that accrue to others may take many forms and may change as vaccines and more effective treatments become available. For example, individuals may have a stronger than usual desire to limit risks to their loved ones, if those who die are likely to be isolated rather than surrounded by friends and family. In addition, the infection rate among the community affects both one's own risk of infection and the likelihood of restrictions that will affect one's ability to shop, socialize, and earn income.

Conceptually, a pure altruist would care about how those affected weigh both the benefits and costs they accrue, which is likely to lead to the same conclusions about whether the net benefits of a policy are positive as would an analysis that considers only self-regarding preferences (Jones-Lee 1991; Bergstrom 2006). A paternalistic altruist may instead weight some impacts, such as improved health or increased longevity, differently than do the individuals affected, which could affect the conclusion about net benefits. Separating these types of altruism in empirical research is challenging, however.

In addition, other regarding preferences are not always altruistic. As discussed in Robinson and Hammitt (2011), such preferences may take many forms, including a social welfare perspective that aims to increase overall welfare by helping others, particularly those less-well off; difference aversion, which focuses on reducing differences between oneself and others; reciprocity, which aims to reward or penalize others depending on the perceived fairness of their actions; and relative position, where preferences are defined relative to others.

Estimating WTP for risk reductions that accrue to others also raises practical challenges. While some studies address risk reductions to the community at-large rather than only to oneself, they at times find counterintuitive results. For example, some find that WTP for a private risk reduction is higher than WTP for a public program that also benefits others (e.g., Svensson and Johansson 2010; Lindhjem et al. 2011). This result suggests that respondents may not fully accept the scenario presented in the survey; for instance, they may not believe that a public program will be effective. Thus for both conceptual and practical reasons, other-regarding preferences may be best handled in qualitative discussion rather than through quantitative adjustment.

ED_006573_00001315-00029

2.3 Summary and Conclusions

The discussion above suggests that the extent to which the recommended HHS VSL estimates should be adjusted for application to COVID-19 risks is highly uncertain. Most differences between the contexts considered in these studies and the COVID-19 context may be best addressed through qualitative discussion at this time, given gaps and inconsistencies in the available empirical research. The one exception is adjustments for age if a regulation would disproportionately affect the very young or very old. In such cases analysts should follow the recommendations for sensitivity analysis in the HHS *Guidelines*. If analysts wish to explore other quantitative adjustments, the results should be included in sensitivity analysis rather than featured in the primary results to highlight associated uncertainties. More generally, analysts will need to explore the extent to which the attributes explored in this chapter are relevant to a specific analysis. Different policies may affect different population subgroups and may vary in the disease characteristics they effect.

In Table 2.2, we summarize the effects of the characteristics we consider; i.e., potential adjustments to the HHS population-average VSL estimates to address the specific population and risks affected by a COVID-19 regulation or other policy. These include three key differences in the individuals affected: age, health status, and income. They also include three key differences in the risks addressed: morbidity prior to death, qualitative risk attributes, and the magnitude of the risk change. We also explore concerns related to incorporating other-regarding preferences (such as altruism) in the infectious disease context, but do not include them in Table 2.2 because of concerns about how to best incorporate these concerns within the benefit-cost analysis framework.

Table 2.2 Potential Direction of Effect

Differences between COVID-19 and Risks Commonly Studied[a]	Effect on HHS VSL Estimates[b]
Individual characteristics	
1. Disproportionately affects the elderly	May *decrease* VSL
2. Disproportionately affects those in impaired health	May *increase or decrease* VSL
3. Reduces income below pre-pandemic levels	May *decrease* VSL
Risk characteristics	
1. Involves more substantial morbidity prior to death	May *increase* VSL
2. Viewed as more dreaded and uncertain	May *increase* VSL
3. May involve a larger risk change	May *decrease* VSL

a. Assumes COVID-19 risk reductions attributable to the regulation or other policy will follow the same patterns as incurred cases to-date.

b. Compared to HHS population-average estimates. Because the magnitude of these effects is uncertain, it is unclear whether the net effect will be an increase or decrease.

The attribute-by-attribute approach we undertake in this chapter is necessitated by the lack of valuation research that explicitly addresses COVID-19 mortality risk reductions and has several limitations as noted earlier. In addition, in recent years there has been relatively little new research estimating VSL in the U.S. Most recent work has involved reviews or meta-analyses of previously completed studies or additional analysis of data sets that have been previously explored, including extensive use of the Census of Fatal Occupational Injuries to estimate the value of changes in job-related risks. However, the

ED_006573_00001315-00030

VSL plays an important role in informing COVID-19 policy decisions and has received substantial attention in the media and in scholarly work. We expect this interest will motivate new VSL research and ultimately provide improved information on these values. As such new research emerges, analysts should review that literature to determine the implications, if any, for the approach discussed in this chapter, following the benefit transfer framework described in Chapter 3 of the HHS *Guidelines*. Regardless, it is unlikely that a "one-size-fits-all" VSL for COVID-19 policies will result, given that different policies will have differing effects.

ED_006573_00001315-00031

CHAPTER 3: VALUING COVID-19 MORBIDITY RISK REDUCTIONS

As discussed in Chapter 1, the HHS *Guidelines* do not recommend specific values for changes in nonfatal illness risks. The *Guidelines* instead provide a framework for estimating these values, recommending that analysts first review the literature to determine whether suitable WTP estimates of reasonable quality are available for the risk reductions of concern. If not, the *Guidelines* recommend that analysts use monetized QALYs as a proxy, estimating the value per QALY using a constant derived from HHS's VSL estimates. As discussed in more detail in the HHS *Guidelines*, averted costs that would otherwise be incurred by third parties, such as medical costs covered by insurance or caregiving provided by family or friends, should be added to these values, taking care to avoid double-counting.

The conceptual framework for valuing morbidity risk reductions is the same as the framework for valuing mortality risk reductions. Thus, per case values are derived from individual's willingness to exchange income (or wealth) for changes in his or her own risk of nonfatal illnesses. These values will reflect the trade-off between the utility associated with improved health and the opportunity cost of spending on the risk reduction. We expect these values to vary depending on the characteristics of the individuals and of the risks, including the characteristics discussed in the VSL context previously.

A major difference between this chapter and the preceding one is that here we focus on developing new estimates rather than on adjusting existing estimates. For mortality risk reductions, HHS's base VSL estimates are derived from a recent criteria-driven review of the literature. Thus, in Chapter 2 our goal was to determine the extent to which other studies provide insight into adjusting the resulting values to better match the COVID-19 context. For morbidity risk reductions, no similar literature review is available. After summarizing the characteristics of COVID-related morbidity, we review the limited relevant WTP literature available then turn to developing estimates of monetized QALYs as a proxy.

As was true for mortality risk reductions, analysts will need to review more recent data to determine whether the characteristics of COVID-19 risks have changed significantly from what is described here, and also explore the impacts of the specific regulation or policy on these risks. As always, analysts should also assess the implications of related uncertainties, as discussed in Chapter 6 of the HHS *Guidelines*.

3.1 Characteristics of COVID-19 Morbidity Risks

Information on nonfatal cases of COVID-19 is evolving rapidly, as the substantial variation in symptoms across those infected becomes increasingly apparent. Our goal in this section is to provide a starting point for valuation by identifying the major features of the individuals affected and the symptoms they experience. We categorize cases by severity, focusing on common, widespread symptoms found in the available data to provide approximations that serve as representative cases. Our goal is not to exhaustively catalog potential impacts; we recognize symptoms vary across individuals and may not always conform to this categorization. Because little valuation research has been completed that explicitly addresses nonfatal COVID-19 cases, we also discuss the similarities between these categories

ED_006573_00001315-00032

and more familiar and prevalent illnesses. We then use these comparisons to develop the valuation approach in the sections that follow.

3.1.1 Individual Characteristics

According to the CDC, as of January 21, 2021 there had been 24,323,846 reported COVID-19 cases (CDC 2021a) in the United States. The true number of infections is not known and exceeds reported cases for several reasons, and the degree of underreporting varies over time. Asymptomatic infections and mild cases, which are less likely to involve testing or medical care, are more likely to be underreported than more severe cases.

With these caveats in mind, Table 3.1 shows the distribution of reported COVID-19 cases by age. In contrast to the distribution of deaths involving COVID-19 reported in Table 2.1 in the previous chapter, only a minority of reported cases occurred among the population aged 65 or older. Underreporting may be greater among younger age groups if children are less frequently tested and if cases among younger age groups are more likely to be asymptomatic or mild.

Table 3.1 Distribution of U.S. Population and Reported COVID-19 Cases by Age Group

Age Group	U.S. Population[a]	Reported COVID-19 Cases[b]
0–17	22.8%	11.0%
18–49	41.8%	54.0%
50–64	19.1%	20.6%
65–74	9.7%	7.7%
75–84	4.8%	4.1%
85+	1.8%	2.5%
Total	100.0%	100.0%

a. 2019 data from "Age and Sex Composition in the United States: 2019," U.S. Census Bureau, as viewed June 21, 2020. https://www.census.gov/data/tables/2019/demo/age-and-sex/2019-age-sex-composition.html. The total estimated population was 324,356,000.
b. January 22, 2020 – January 21, 2021 data from "Demographic Trends of COVID-19 cases and deaths in the US reported to CDC," U.S. Centers for Disease Control and Prevention, as viewed January 21, 2021. https://www.cdc.gov/covid-data-tracker/#demographics. The total number of reported COVID-19 cases as of January 21, 2021 was 24,323,846.

Individuals with diagnosed cases of COVID-19 appear more likely to have underlying health impairments than the general population. Only about one-fifth of all cases (fatal and nonfatal) reported to the CDC include data on baseline health status. Among those for whom data are available, about 70 percent have one or more underlying health conditions (Stokes et al. 2020). Those with such conditions are more likely than those without an identified condition to be hospitalized (45.4 percent vs. 7.6 percent) or admitted to the ICU (8.5 percent vs. 1.5 percent) (Stokes et al. 2020). The most common underlying conditions are diabetes, heart disease including hypertension, and chronic lung disease.

Nonfatal cases appear to be more common among individuals with certain socioeconomic characteristics, which may reflect differences in exposure as well as other factors. In particular, racial and ethnic minority populations have seen disproportionately high rates of infection and severe disease, as discussed in section 2.1. While a greater number of deaths have occurred among males, the majority of cases have been reported among females (Stokes et al. 2020). However, it is unclear whether this

ED_006573_00001315-00033

finding reflects differences in the extent to which men and women seek testing and medical care or other factors.

3.1.2 Risk Characteristics

As noted earlier, we focus on the most documented and well-established symptoms, recognizing that new data are continually emerging. Long-term effects are particularly uncertain, which is not surprising given that infections only became widespread within the past year. Some individuals infected with SARS-CoV-2, the pathogen that causes COVID-19, may not experience any symptoms, at least in the near-term. Evidence from contained environments with complete or near-complete testing suggests that many cases remain asymptomatic throughout the course of infection (Sakurai et al. 2020; CDC 2021a). Some have argued, however, that true asymptomatic infection is relatively rare; it may often be conflated with very mild infection or pre-symptomatic infection (Wiersinga et al. 2020). In addition, even initially asymptomatic infections and very mild infections may have important long-term effects, which are only beginning to be better understood.

CDC categorizes symptomatic COVID-19 cases as mild-to-moderate (henceforth shortened to "mild"), severe, and critical (CDC 2020a). Most cases identified to-date fit into the mild category (Wu and McGoogan 2020); symptoms may vary substantially across cases within this category. Within each category, the symptoms are generally similar across age groups (CDC 2020a). However, most cases documented among younger populations are less severe than those among older populations (Lu et al. 2020; Dong et al. 2020).[13]

We adapt descriptions of three severity levels of acute symptomatic disease from the published medical literature (Dong et al. 2020; Gandhi et al. 2020; Berlin et al. 2020; Wu and McGoogan 2020; CDC 2020a) in Table 3.2.[14] We focus on common, widespread symptoms; the list is not intended to be exhaustive and symptoms vary substantially across individuals. As noted earlier, our goal is to build towards categories that can be used to estimate values for nonfatal cases, not to provide definitive descriptions to be used for other purposes.

---

[13] There have been numerous reports of multisystem inflammatory syndrome in children (MIS-C) associated with the COVID-19 pandemic (Whittaker et al. 2020; Viner and Whittaker 2020; Dufort et al. 2020; Feldstein et al. 2020). Cases of MIS-C appear to lag behind cases of acute COVID-19 in the surrounding population. Not all cases of MIS-C have tested positive for SARS-CoV-2; the condition may be a delayed response to infection. At this time, MIS-C and its relationship with COVID-19 remain poorly understood; accordingly, we do not include the associated health risks in our valuation discussion, although we recognize that they may be severe.

[14] We start with descriptions from Dong et al. (2020), combining mild and moderate categories. We adapt thresholds for blood oxygen saturation based upon Gandhi et al. (2020) and Berlin et al. (2020). We then add to descriptions of categories based upon Wu and McGoogan (2020) and CDC (2020b).

ED_006573_00001315-00034

Table 3.2 Common Symptoms of Nonfatal COVID-19 Cases by Severity Level[a,b]

Disease Phase	Description
Mild Case	
Acute phase	Individuals will have symptoms of acute upper respiratory tract infection, which may include fever, fatigue, myalgia (muscle aches), cough, and sore throat. Some cases may have digestive symptoms, such as nausea, abdominal pain, and diarrhea. Loss of taste and smell are common symptoms. Individuals may have mild pneumonia (infection of the lungs), and some may have wheezing or dyspnea (shortness of breath) but blood oxygen saturation remains above 93 percent.
Post-acute phase	Individuals may have post-acute symptoms, such as cough, shortness of breath, fatigue, and pain.
Severe Case	
Acute phase	Individuals will have early symptoms similar to those of mild disease, such as fever and cough, which may be accompanied by gastrointestinal symptoms, such as diarrhea. The disease continues to progress for over a week. Dyspnea (shortness of breath), high respiratory rate, and/or blood oxygen saturation of ≤93 percent occur. Individuals typically have pneumonia and require supplementary oxygen. Individuals with severe disease should be hospitalized.
Post-acute phase	Individuals may have post-acute symptoms, such as cough, shortness of breath, fatigue, and pain.
Critical Case	
Acute phase	Individuals will have early symptoms similar to those of mild and severe disease. Individuals may quickly progress to respiratory failure and may also have septic shock, encephalopathy (brain disease), heart disease or failure, coagulation dysfunction (inability of blood to clot normally), and acute kidney injury. Organ dysfunction can be life-threatening. Individuals with critical disease often receive prolonged mechanical ventilation.
Post-acute phase	Individuals are likely to have long-term physical and cognitive impairment similar to other critical illnesses.

a. As discussed in the text, these descriptions are intended to aid in understanding major symptoms for valuation purposes, based on the data now available. They are not intended to be definitive or to be used for other purposes.
b. Adapted from: Dong et al. (2020); Gandhi et al. (2020); Berlin et al. (2020); Wu and McGoogan (2020); CDC (2020b).

To provide a starting point for estimating per case values, we assume that all symptomatic individuals begin by experiencing symptoms characteristic of mild disease. This assumption is consistent with the typical trajectory of COVID-19 for more severe cases (Berlin et al. 2020). We furthermore assume that individuals who experience only mild symptoms are not likely to be hospitalized, although some may be hospitalized for monitoring (Gandhi et al. 2020).

While many individuals will begin to recover after experiencing mild symptoms, others will progress to more severe stages. Those with severe disease are typically hospitalized and may be treated aggressively to avoid the need to implement emergency procedures if sudden respiratory arrest occurs (Berlin et al. 2020). Individuals with critical disease are likely to be treated in the ICU and require mechanical ventilation.

Across all severity levels, individuals often experience persistent symptoms rather than returning quickly to their pre-disease health status. While the long-term effects of COVID-19 are not yet fully known, survey evidence indicates that many individuals experience persistent fatigue, cough, shortness of breath, and pain months after symptom onset (Carfì et al. 2020; Tenforde et al. 2020; Patient-Led

ED_006573_00001315-00035

Research for COVID-19 2020; Longfonds 2020). A number of studies have also noted that severe post-acute symptoms are not restricted to individuals with severe and critical disease; some non-hospitalized individuals with initially mild disease may experience severe, persistent post-acute symptoms (Meys et al. 2020; Praschan et al. 2021; Moreno-Perez et al. 2021). Individuals with critical disease are likely to experience the most severe long-term effects on average, which may resemble physical and cognitive impairment seen among survivors of similar illnesses such as sepsis (Wiersinga et al. 2020).

In addition to information on severity, including symptoms and the effects of treatment, we require estimates of duration for valuation. In Table 3.3 we provide working assumptions based on the data available to-date, which we use to illustrate the valuation approach later in this chapter. As is the case for the information presented previously, these estimates are uncertain, and analysts should revisit them to determine whether updates are needed as well as explore the effects of varying these assumptions.

Table 3.3 Potential Duration of Nonfatal COVID-19 Cases by Severity Level[a]

Severity Category	Duration of Symptoms (working assumptions)
Mild case	10 days with mild symptoms plus 15 days with post-acute mild disease symptoms
Severe case	7 days with mild symptoms plus 6 days with severe symptoms plus 50 days post-acute severe disease symptoms
Critical case	7 days with mild symptoms plus 12 days with critical symptoms plus Remainder of lifetime post-acute critical disease symptoms

a. Estimates are used for illustrative purposes only. See text for data sources and discussion.

As indicated by Table 3.3, we use 10 days as our working assumption for the typical duration of acute symptoms among mild cases. This assumption is based upon evidence indicating that the typical duration may range between one and two weeks (CDC 2020b; World Health Organization 2020; Gandhi et al. 2020; Lee et al. 2020). We use seven days as our working assumption for the length of mild symptoms among severe and critical cases based upon evidence indicating that severe and critical symptoms develop after approximately seven days from initial symptom onset (Berlin et al. 2020; Wiersinga et al. 2020; Dong et al. 2020). We use six days as the length of severe symptoms; the typical length of hospital stay among nonfatal COVID-19 cases that do not involve admission to the ICU ranges from three days to over nine days (CDC 2021a; Lewnard et al. 2020; CDC 2020a). We use 12 days as our working assumption for the length of critical symptoms; among individuals admitted to the ICU, length of hospitalization typically ranges from 11 to 14 days (CDC 2021b).

As noted earlier, health impairments may continue after the acute phase of the illness. Our working assumptions for the duration of post-acute illness are based upon weaker evidence than those for the duration of acute illness. Limited long-term data are currently available, making it difficult to calculate the durations of post-acute symptoms. As indicated in Table 3.3 above, for mild cases we use 15 days as the illustrative length of post-acute symptoms, for a total of 25 days of symptoms. The available

ED_006573_00001315-00036

evidence suggests that symptoms may persist longer or shorter than this assumed duration.[15] Notably, approximately one in 10 COVID-19 patients experiences symptoms lasting longer than four weeks, which has been termed "long COVID" (Sivan and Taylor 2020). Data on these longer-term symptoms and their duration is evolving. For severe cases, we use 50 days as the illustrative length of chronic symptoms, for a total of 63 days with symptoms. Evidence from hospitalized individuals with COVID-19 indicates that post-acute symptoms may persist for shorter or longer time periods.[16] For critical cases, we draw on evidence suggesting that disability may be long-term among survivors of similar critical diseases, such as sepsis (Wiersinga et al. 2020). We follow others in assuming that a degree of disability for critical cases will be permanent (Khazeni et al. 2009).[17]

3.1.3 Similar Diseases Used as Proxies

As discussed previously, we are writing this paper at a time when valuation research that explicitly addresses nonfatal cases of COVID-19 is not available. Hence, we use the benefit transfer framework discussed in Chapter 3 of the HHS *Guidelines* to develop values based on similar conditions. Table 3.4 summarizes the categorization of symptoms of nonfatal cases by severity level and compares each set of symptoms with a disease involving similar symptoms.

---

[15] In one study, approximately 35 percent of symptomatic U.S. COVID-19 patients with a positive test result in an outpatient setting experienced continued symptoms when surveyed at a median of 16 days from the date of testing, which may have occurred after symptom onset (Tenforde et al. 2020). In a prospective cohort study, outpatients with COVID-19 returned to their normal health a median of 20 days after symptom onset (Blair et al. 2021). Data from the United Kingdom indicate that the median length of symptoms following infection is approximately 39.5 days (Office for National Statistics, 2020).

[16] At a mean of 60 days after the onset of initial COVID-19 symptoms, approximately 13 percent of individuals who were hospitalized reported no persistent symptoms, 32 percent reported one or two symptoms, and 55 percent reported three or more symptoms (Carfì et al. 2020).

[17] COVID-19 affects multiple organ systems, which may lead to long-term effects beyond those we have described. For example, COVID-19 has been reported to result in new-onset diabetes and severe complications of existing diabetes (Rubino et al. 2020). COVID-19 may result in persistent cardiovascular impacts (Puntmann et al. 2020). Neurological effects of COVID-19 may also be significant; among hospitalized COVID-19 patients, a variety of neurological syndromes have been observed (Helms et al. 2020; Paterson et al. 2020). Given the current lack of evidence on the frequency and duration of associated symptoms, we do not explicitly account for these health effects in developing the basis for valuation.

ED_006573_00001315-00037

Table 3.4 Examples of Diseases Similar to Nonfatal COVID-19 Cases by Severity Level[a]

Severity Category	Examples of Similar (Proxy) Diseases
Mild case	• Symptoms of initial acute, mild disease are similar to those of ***influenza***. • Post-acute symptoms are similar to those of ***chronic obstructive pulmonary disease (COPD)***.
Severe case	• Symptoms of initial acute, mild disease are similar to those of ***influenza***. • Subsequent acute, severe symptoms are similar to those of serious respiratory complications of ***influenza***. • Post-acute symptoms are similar to those of ***COPD.***
Critical case	• Symptoms of initial acute, mild disease are similar to those of ***influenza***. • Subsequent acute, critical disease may resemble ***sepsis***, a life-threatening complication of influenza and other infections, as well as ***conditions involving acute respiratory failure and conditions requiring prolonged mechanical ventilation***. • Post-acute symptoms may resemble chronic health states associated with ***sepsis***, ***conditions involving acute respiratory failure***, and ***conditions requiring prolonged mechanical ventilation***.

a. The effects of these diseases are not identical to the effects of COVID-19; rather they are similar diseases that have been well-studied and provide a starting point for the valuation discussion that follows.

The comparisons in Table 3.4 are based upon descriptions of acute disease symptoms by severity level provided previously in Table 3.3 and descriptions of post-acute disease symptoms provided in the text. Mild symptoms, which correspond to the first stage of symptoms for individuals with all disease severity levels based on our illustrative framework, are similar to symptoms of influenza (CDC 2020e).[18] Severe symptoms, experienced only by patients with severe disease, are similar to symptoms of influenza with severe respiratory complications (CDC 2020b). Critical symptoms may be similar to symptoms of sepsis (Wiersinga et al. 2020) and conditions involving acute respiratory failure, including conditions frequently requiring prolonged mechanical ventilation.

As for post-acute symptoms, research suggests that individuals with mild and severe disease often experience persistent cough, shortness of breath, and fatigue (Carfì et al. 2020; Tenforde et al. 2020). These symptoms, though they may not fully characterize the post-acute experience of individuals with COVID-19, are similar to those of chronic obstructive pulmonary disease (COPD).[19] Among individuals with critical disease, post-acute COVID-19 symptoms may resemble the post-acute experience of individuals with sepsis (Wiersinga et al. 2020). Survivors of respiratory failure and acute respiratory distress syndrome (ARDS) may experience similar long-lasting physical and psychological disability (Herridge et al. 2003; Herridge et al. 2011; Davidson et al. 1999).

[18] According to CDC, influenza symptoms may include "fever or feeling feverish/chills; cough; sore throat; runny or stuffy nose; muscle or body aches; headaches; fatigue (tiredness); some people may have vomiting and diarrhea, though this is more common in children than adults." https://www.cdc.gov/flu/symptoms/symptoms.htm, as viewed August 20, 2020.

[19] COPD includes emphysema and chronic bronchitis and involves breathing difficulties. According to CDC, symptoms include "frequent coughing or wheezing; excess phlegm or sputum; shortness of breath; trouble taking a deep breath." https://www.cdc.gov/copd/features/copd-symptoms-diagnosis-treatment.html, as viewed August 20, 2020.

ED_006573_00001315-00038

3.2 Willingness to Pay Estimates

In this section, we review the WTP literature for nonfatal illnesses with symptoms similar to those of COVID-19. We focus on influenza, chronic obstructive pulmonary disease (COPD), sepsis, conditions involving acute respiratory failure, and conditions requiring prolonged mechanical ventilation. The following section then reviews the QALY literature for the same conditions. In both sections, we select studies that address symptoms rather than the impacts of treatments. The availability and effectiveness of COVID-19 treatments are continuing to evolve, and are likely to have differing effects from the treatments available for these other conditions.

When reviewing both the WTP and QALY literature, we focus on the following.

1. Publicly available primary research, written in English, to ensure that those who apply these estimates and review the resulting analyses can access the underlying studies.
2. Research based on U.S. data collected within the past 20 years, assuming that the scope of most HHS regulatory analysis will cover the national population and that more recent studies are more likely to reflect current conditions and preferences.[20] More recent studies can also take advantage of advances in the available data, analytic methods, and best practices.
3. Research published in peer-reviewed articles or reports, as an indicator of quality.

As discussed in more detail later, we make some exceptions to these criteria to address limitations in the available research. In addition, because relatively few studies address the health conditions of concern, we do not apply more stringent criteria such as those used in developing HHS's VSL estimates (see Robinson and Hammitt 2016). Instead, we use the research available to inform our estimates and suggest that analysts carefully assess the effects of uncertainty.

To identify potentially applicable WTP research, we began by searching recent reviews that include U.S. studies of respiratory and other illnesses. These reviews vary in purpose and scope and are not necessarily comprehensive, but provide a useful starting point. They include Van Houtven et al. (2006), Gerking and Dickie (2013), Cameron (2014), Hunt et al. (2016), and Robinson et al. (2019).[21] We then searched EconLit for additional studies.[22] We identified five studies that meet the three criteria listed above, and summarize them in Table 3.5. All of these studies address individual WTP for averting the

[20] For the WTP studies, the search was conducted in August 2020 and covered studies that rely on data collected from 2000 to the search date. There is typically a significant lag between when data are collected and publication, as indicated by the data collection dates in Table 3.5.

[21] We thank Alistair Hunt (University of Bath) and Neal Fann (U.S. Environmental Protection Agency, Office of Air and Radiation) for useful advice.

[22] EconLit search terms included "WTP" or "willingness to pay," and "respiratory," "influenza," "flu," "COPD," "sepsis," or "ventilation." We limited the searches to peer-reviewed research published in English between 2000 and the search date. We then reviewed the abstracts to confirm that the study included primary valuation research and to identify the date of data collection and the location. We dropped those studies that did not report the results of primary research, did not include data collected in 2000 or later, or were not conducted in the United States. The search was conducted in August 2020.

ED_006573_00001315-00039

risks of influenza, COPD, or similar conditions; we did not find any WTP studies that address sepsis, acute respiratory failure, or mechanical ventilation explicitly.[23,24]

Table 3.5 Willingness to Pay Studies

Study	Data Collection Date	Risk Characteristics	Location	Respondent Characteristics
Dickie and Messman (2004)	2000	16 profiles of varying duration, including acute episodes of cough with phlegm, shortness of breath with wheezing, chest pain on deep inspiration, and/or fever with muscle pain and fatigue	Hattiesburg, Mississippi	284 respondents, parents or guardians of children age 3–17
Chestnut et al. (2006)	2002	Cardiovascular, acute respiratory, and chronic respiratory conditions requiring future hospitalization	California	397 respondents, previously hospitalized adult Kaiser Permanente patients
Johnston et al. (2010)	2008	Influenza, including fever, cough, sore throat, runny nose, and chills, lasting about 7 days	3 large U.S. employers[a]	2,006 respondents with at least one child age 17 or younger
Prosser et al. (2013)	2007	Influenza of varying durations and severity, without and with hospitalization	National	1,012 adult respondents
Hammitt and Haninger (2017)	2008	Conditions including influenza, respiratory infection, skin cancer, bronchitis, lung cancer, migraines, hepatitis, heart disease, liver disease, and Parkinson's disease with duration of 1 month, 1 year, or lifetime	National	2,184 adult respondents

a. Employers included "a national retail chain, a transportation company, and a durable goods manufacturing company" (Johnston et al. 2010).

Three of these studies (Dickie and Messman 2004; Chestnut et al. 2006; and Johnston et al. 2010), do not include nationally representative samples, both in terms of the locations from which the samples were drawn and the individual characteristics of the respondents. The remaining two studies are

[23] We exclude studies of asthma, given the significant differences between its symptoms and treatment and those associated with COVID-19. We also exclude studies of restricted activity days or school loss days associated with occasional exceedances of air pollution standards. While COVID-19 also restricts activities, the cause of the restrictions, their duration and pervasiveness, and nature of the restrictions, differ substantially from those that occur in the air pollution context.

[24] As discussed in the previous chapter, valuation of risks to others raises difficult, unresolved questions in the context of benefit-cost analysis. Thus, we only include studies that address risks to oneself, excluding studies (and estimates) that consider risk reductions that accrue to the community-at-large. The one exception is that we include studies of adult WTP to avoid risk to a child; typically parents or guardians as indicated under "Respondent Characteristics" in Table 3.5. As discussed in more detail in Robinson et al. (2019), in these cases we assume the adult is essentially acting as a proxy for the child, given the challenges of directly eliciting WTP from children.

ED_006573_00001315-00040

national samples of adults; one addresses influenza (Prosser et al. 2013), the other includes influenza and other respiratory conditions along with a several other illnesses (Hammitt and Haninger 2017).

In Table 3.6, we provide per case estimates from each study, focusing on the results featured by the authors in most cases. To the extent possible, we select the estimates that come closest to addressing the symptoms discussed in section 3.1. We update the values to 2020 dollars and income levels using the approach recommended in the HHS *Guidelines*. This approach involves using the Consumer Price Index to adjust for inflation, Current Population Survey earnings data to estimate the change in real income, and an income elasticity of 1.0 to reflect the extent to which the values change as real income changes.

Table 3.6 Willingness to Pay Per Case

Study	Health Outcome	WTP per Case:[a] As reported	WTP per Case: 2020 dollars and income level[b]
Dickie and Messman (2004)	Median WTP, 6-days, all symptoms	Child: $318 Parent: $167 (2000 dollars)	Child: $545 Parent: $287
Chestnut et al. (2006)	Mean WTP, 5-day hospitalization due to cardiac or respiratory illness	$2,400 (2002 dollars)	$3,900
Johnston, et al. (2010)	Mean (median) WTP to prevent influenza lasting about 7 days	Child: $142 ($50) Parent: $72 ($25) (2008 dollars)	Child: $191 ($68) Parent: $97 ($33)
Prosser, et al. (2013)	Incremental WTP to avert 1 day of uncomplicated influenza (self)	$62.54, $66.27[c] (2007 dollars)	$88.54, $93.81[c]
Prosser, et al. (2013)	Incremental WTP to avert 1 day of influenza with hospitalization (self)	$168.26, $513.06[c] (2007 dollars)	$238.18, $726.26[c]
Hammitt and Haninger (2017)	Value per statistical case of respiratory infection, 1 month	$639,000, $716,000[d] (2008 dollars)	$861,000, $965,000

a. Estimates highlighted by authors unless otherwise noted. See text for more discussion.
b. Updated to 2020 values based on the following:
- Inflation: Bureau of Labor Statistics, Consumer Price Index – All Urban Consumers, not seasonally adjusted (series CUUR0000SA0), downloaded from https://www.bls.gov/data/#prices, on April 15, 2021.
- Real income growth: Bureau of Labor Statistics, Current Population Survey, Median usual weekly earnings (series LEU0252881600), downloaded from https://www.bls.gov/webapps/legacy/cpswktab2.htm on April 15, 2021.
- Income elasticity: 1.0 based on HHS *Guidelines*.

c. The value listed first is based on traditional elicitation questions; the second is based on discrete choice experiment questions.
d. Value per statistical case for respiratory infection, 1 month duration, calculated using regression in Table 4 (pooled) with alternative values of health-related quality of life (HRQL) loss with respiratory infection (0.043, 0.070) and other parameters fixed as in Table 6. Note that dividing these estimates by 30 to obtain values per 1 day case would require extrapolating outside the sample and would be inconsistent with the authors' results, which find that values vary only weakly with duration.

The Hammitt and Haninger (2017) study is different in significant respects from the other studies identified, including the severity and duration of the effects and the elicitation strategy. The authors elicit WTP for small reductions in the risk of suffering a nonfatal illness described by its HRQL impacts using the EuroQoL-5D (EQ-5D) index and its duration (1 month, 1 year, or lifetime), with disease names

provided to half the respondents.[25] They estimate that WTP is larger for more severe and longer illness but is much less than proportionate to severity and duration. Compared to an approach that multiplies the expected QALY gain by a constant monetary value per QALY, this lack of proportionality yields values per statistical case that are much larger for short and mild illnesses, yet similar for lifetime chronic disease.

Of these studies, Prosser et al. (2013) and Hammitt and Haninger (2017) come closest to meeting our criteria; both are based on nationally representative samples and provide estimates for respiratory conditions. Only the Prosser et al. study explicitly addresses one of the illnesses identified in section 3.1 as a proxy for nonfatal cases of COVID-19. The Prosser et al. values for non-hospitalized influenza cases could be considered a reasonable proxy for COVID-19 acute mild disease, and their values for hospitalized cases could be considered a reasonable proxy for subsequent, more severe acute symptoms. When multiplied by the duration estimates in Table 3.3 in section 3.1 above, these estimates suggest values less than $1,000 per case of mild illness and less than $5,000 per case of severe illness for adults, excluding the post-acute symptoms. These estimates are much lower than the values that result from our alternative approach below. They also do not include treatment and other costs paid by third parties. The Hammitt and Haninger estimates are an imprecise match for our proxy conditions in terms of symptoms and duration. They are much larger than the values for all but critical cases using our alternative approach below, but provide some indication of the possible magnitude.

Without more research, the extent to which these differences result from the methods used for valuation, the populations and health outcomes studied, or other factors is unclear. Given that every study has advantages and limitations, ideally we would like to be able to combine the results across several studies for each endpoint. At present, it appears that the WTP literature provides relatively little information for quantifying the value of reducing the morbidity risks associated with COVID-19.

3.3 Monetized QALY Estimates

Given the limitations of the WTP literature, in this section we explore the implications of the QALY literature for valuation. QALYs are nonmonetary measures that combine the amount of time that an individual spends in a health state with a measure of the severity of the health state, as discussed in Chapter 3 and Appendix C of the HHS *Guidelines*. HHS converts QALY estimates into monetary values by multiplying them by a constant value per QALY derived from its VSL estimates; estimates for 2020 are provided in Chapter 1 of this paper.

QALYs are frequently used to integrate the effects of an intervention on both health and longevity. In the discussion that follows, we focus solely on their use to estimate changes in health while alive, given that our goal is to estimate the value of averting nonfatal effects. In developing QALY estimates, HRQL is commonly estimated using a scale anchored to zero (for states judged as bad as dead) and one (corresponding to full health), although HRQL may fall below zero when a state is deemed to be worse

[25] The EQ-5D is a generic instrument often used to describe HRQL; more information is available at https://euroqol.org/.

ED_006573_00001315-00042

than dead. This HRQL estimate is then multiplied by the duration of the health state to estimate the associated QALYs.

Our goal in this section is to identify HRQL estimates both for COVID-19 and for similar health outcomes (as discussed previously in section 3.1). We then compare these estimates of HRQL with the condition to HRQL without the condition, using estimates of population-average HRQL by age to represent likely health in the absence of COVID-19. We multiply these HRQL increments by duration for COVID-19 cases of differing severities to estimate the QALY gain associated with averting each type of case, and multiply the results by the central estimates of the constant value per QALY reported in Chapter 1.

In reviewing the QALY literature, we begin with the same three criteria as noted in the preceding discussion of the WTP literature, focusing on publicly available primary research, written in English, based on data collected from 2000 to the search date, and published in peer-reviewed articles or reports. While we prioritize U.S. research, we expand our scope to include HRQL data collected in other high-income countries to provide additional insight.[26]

In selecting studies, we apply additional selection criteria applicable to QALYs as recommended Figure 3.4 in the HHS *Guidelines* and replicated below.

1. QALY estimates should be based on research that addresses the risks and populations affected by the regulation.
2. The description of the effects of the health state on quality of life should be based on information from those who have experienced the condition (such as patients).
3. The preference weights placed on the health states should be based on a survey representative of the general U.S. population.
4. The "without new regulation" baseline (with the condition) should be compared to a realistic estimate of "with-regulation" health status, which takes into account factors (such as age and co-morbidities unrelated to the regulated hazard) that may lead those affected to be in less than perfect health once the regulation is implemented.
5. The implications of related uncertainties should be discussed and addressed quantitatively if significant.

We apply criteria 1, 2, and 3 directly as discussed below. To address criterion 4, in our illustrative calculations we assume that the analysis compares individuals with nonfatal cases of COVID-19 (in the absence of the regulation) to similar individuals of the same age without the condition (with the regulation), as discussed in more detail later in this section. Consistent with criterion 5, we also describe the uncertainties associated with this approach.

[26] Unlike WTP estimates, QALYs are not monetary values that reflect the opportunity cost of spending and hence may be less sensitive to cross-country economic differences. However, they may be sensitive to other differences such as cultural attitudes, lifestyle factors, and characteristics of the health care system.

ED_006573_00001315-00043

In addressing the first criterion, similarity of the risks and populations, we review both studies that characterize COVID-19 morbidity risks directly and studies that characterize the risks of the proxy conditions described in section 3.1, given that studies that explicitly address COVID-19 are limited. We assume that HHS analysts will primarily apply the values to regulations or other policies that affect the U.S. population nationally. Thus, ideally we would restrict attention to studies that collect data from representative samples of the U.S. population as a whole. Given the small number of studies that meet this criterion, we also consider studies that address a subset of the U.S. population; e.g., those in a particular location or health care system. We prioritize studies with data from at least 100 patients as an indicator of the likely representativeness of the sample. However, given the narrow patient inclusion criteria applied in some studies, we report data from smaller samples as supplementary estimates. We also include data from other high-income countries to provide insight when sufficient U.S. data are not available.[27]

To address the second criterion, descriptions of impacts from patients, we prioritize studies in which patients describe the effects of a disease on their quality of life. Commonly, these patients complete structured surveys associated with generic HRQL indices — such as the EQ-5D, Health Utilities Index (HUI), SF-6D, or Quality of Well-Being (QWB) Scale — that capture the impacts of a disease on dimensions of health, such as functional status and pain. When few such studies are available, we also consider studies that instead rely on expert assessment of impacts using a structured survey instrument.[28]

For the third criterion, preference weights, we focus on data from the general population. Structured survey instruments, such as those described above, are typically used to assess preferences for health states using weights derived from the responses of samples of the general public. We prioritize research using the EQ-5D index because weights specific to the U.S. population have been developed.[29] When few studies using this index and weights are available, we consider results using other HRQL indices as supporting evidence.[30]

---

[27] We define high-income as 50 percent or more of U.S. GNI per capita in 2018 using the purchasing power parity (PPP) method as documented by the World Bank (https://data.worldbank.org/indicator/NY.GNP.PCAP.PP.CD, as viewed August 22, 2020). At that time, GNI per capita for the U.S. was $63,780; hence, we include countries with a GNI per capita using the PPP method of $31,890 or higher. As noted in the text, for some outcomes we expanded the search to include all countries regardless of income level, due to the lack of research from higher income countries.

[28] We exclude estimates that are not based on primary research involving original data collection from patients or expert assessment using a structured survey instrument.

[29] When a study uses a single population to report results corresponding to the EQ-5D index as well as other HRQL estimates, we report only the EQ-5D estimates. When HRQL is weighted using estimates from multiple countries, we use weights corresponding to the U.S. or to the country closest to the U.S. in GNI per capita.

[30] We exclude HRQL estimates that use scales not indexed to values of zero and one.

ED_006573_00001315-00044

3.3.1 HRQL Estimates from COVID-19 Studies

To identify HRQL estimates from the literature for COVID-19, we conducted targeted Google Scholar searches using the criteria listed above.[31] The estimates that we present all use the EQ-5D index but come from high-income countries outside of the U.S., given that no evidence from the U.S. meeting our criteria was available. Table 3.7 presents the "with condition" HRQL estimates obtained from the review.

Table 3.7 HRQL Studies, COVID-19

Study	Location	HRQL Scale	Population	Average Age	Health State	HRQL Score
Garrigues et al. 2020	France, one hospital	EQ-5D, French weights	96 patients	64.1	COVID-19, hospitalized in ward, post-discharge, mean of 110.9 days after hospital admission[a]	0.86
Garrigues et al. 2020	France, one hospital	EQ-5D, French weights	24 patients	59.6	COVID-19, hospitalized in ICU, post-discharge, mean of 110.9 days after hospital admission[a]	0.82
Meys et al. 2020	Belgium, members of online support group	EQ-5D, German weights	622 patients	45	COVID-19, non-hospitalized, mean of 79 days after symptom onset	0.62
Garratt et al. 2021	Norway, population-based cohort	EQ-5D, U.K. weights	458 patients	49.5	COVID-19, non-hospitalized, mean of 4 months after symptom onset	0.82
Halpin et al. 2021	U.K., one hospital	EQ-5D, U.K. weights[b]	68 patients	70.5[c]	COVID-19, hospitalized in ward, mean of 48 days after hospital discharge[d]	0.724
Halpin et al. 2021	U.K., one hospital	EQ-5D, U.K. weights[b]	32 patients	58.5[c]	COVID-19, hospitalized in ICU, mean of 48 days after hospital discharge[d]	0.693
					Range of estimates, primary selection criteria	**0.62 to 0.86**
Supplementary estimates based on small samples and/or expert assessments						
Taboada et al. 2020	Spain, one hospital	EQ-5D, weights not specified	91 patients	65.5	COVID-19, critically ill, ARDS, admitted to ICU, 6 months after ICU discharge	0.7054
					Range of estimates, primary and supplemental studies	**0.62 to 0.86**

a. Mean time from hospital admission corresponds to the overall sample of 120 patients.
b. The authors do not explicitly report the country weights used but describe a U.K. population.
c. Age estimates correspond to sample medians.
d. Mean time after hospital discharge corresponds to the overall sample of 100 patients. Halpin et al. (2021) report that the median length of stay was 6.5 days for ward patients and 12 days for ICU patients.

[31] Search terms included "quality of life," "HRQL," "QOL," "EQ-5D" or "EuroQoL" and "COVID" or "COVID-19." The search was conducted in January 2021.

ED_006573_00001315-00045

All of the identified estimates correspond to HRQL of post-acute COVID-19. In these studies, HRQL was measured, at the earliest, an average of 48 days after hospital discharge, and at the latest, six months after ICU discharge. HRQL estimates range from 0.62 to 0.86, with higher values generally but not always corresponding to younger and less severely ill patient populations.

Given the different patient populations and small sample sizes, an important consideration is whether these estimates reflect the causal impact of COVID-19 – as opposed to idiosyncratic characteristics of the populations – and allow for extrapolation to the general U.S. population. Some studies have attempted to measure the change between recalled HRQL before COVID-19 and HRQL after COVID-19 diagnosis as an indicator of the likely causal effect of COVID-19, but these studies may be subject to recall bias. Halpin et al. (2021) asked patients to recall their HRQL prior to the COVID-19 episode and found that most patients reported a decline in HRQL after admission for COVID-19. Similarly, Taboada et al. (2020) found a significant decline in HRQL among ICU patients after the COVID-19 episode compared with their recalled HRQL prior to the episode. Other studies have noticed diminished HRQL among COVID-19 patients relative to general populations (Chen et al. 2020; Arnold et al. 2020; Garratt et al. 2021). However, these studies have not attempted to control for baseline patient characteristics and not all of these studies met the inclusion criteria for our review. Some, but not all, of these studies found a significant decline in HRQL among COVID-19 patients studied relative to the general population.

While post-acute outcomes for patients with mild COVID-19 generally appear good (Garratt et al. 2021), measured HRQL is low for certain populations of patients with initially mild disease. Meys et al (2020) report on a Belgian population consisting of members of an online support group, who reported a mean HRQL score of 0.62. This study is unlikely to be representative of the broader population of patients with initially mild COVID-19 symptoms, but it draws attention to the potential for persistent and poor outcomes that may not align with the severity of the acute episode. One Dutch study noted that a population of COVID-19 patients with initially mild disease who had symptoms persisting for greater than six weeks exhibited lower HRQL in most domains than a population of discharged hospitalized patients (van den Borst et al. 2020). While this population of non-hospitalized patients is unlikely to be representative of the broader population of patients with initially mild disease, these results highlight the heterogeneity in COVID-19 symptoms and suggest the need for careful measurement of the population-level effects of COVID-19.

Researchers have initiated follow-up studies to measure the effects of COVID-19 over a period of one year or longer (Marshall 2020). However, the results of these studies were not available at the time this review was conducted.

Given the limited body of evidence on COVID-19 HRQL – particularly the shortage of evidence on HRQL corresponding to acute disease, the uncertain representativeness of the samples used, and the lack of evidence on long-term HRQL – we rely primarily on HRQL estimates for related conditions to develop values. The following section describes results from review of these studies.

ED_006573_00001315-00046

3.3.2 HRQL Estimates from Studies of Similar Conditions

To identify HRQL estimates from the literature for conditions related to COVID-19 as described in section 3.1, we start with studies listed in the comprehensive Tufts Medical Center Cost-Effectiveness Analysis (CEA) Registry and compare them to the three criteria listed above.[32] Because that database focuses on cost-effectiveness analyses and excludes studies that provide QALY estimates without comparing them to costs, we reviewed the reference lists from relevant studies and also conducted targeted Google Scholar searches for each condition to identify additional studies.[33] We discuss our findings for each health condition below.

3.3.2.1 Influenza

As noted earlier, we begin with selection criteria that focus attention on those high-quality studies most applicable to the risks and populations likely to be addressed in HHS regulatory analyses. These include data collected from a sample at least 100 U.S. individuals, patient-reported HRQL estimates, and U.S. EQ-5D preference weights. However, we did not identify any studies of influenza that met these criteria. We then expanded our search to include data from other high-income countries and other HRQL indices, and identified three studies that provide nine estimates of HRQL across various influenza severity categories. When we further relaxed our criteria to include smaller sample sizes and expert assessments, we identified an additional four studies and five estimates of HRQL. We include both confirmed cases of influenza as well as influenza-like illnesses. Because descriptions of severity are not standardized across studies, these estimates may not be fully comparable.

Table 3.8 presents the "with condition" HRQL estimates from these studies, which vary from less than zero to 0.7. Excluding estimates based on small patient samples (less than 100 participants in total) or expert assessment narrows the range to between 0.23 and 0.7. Estimates tend to be higher for influenza cases noted as not involving hospital care (0.50 to 0.70) compared with cases noted as involving hospital care (0.23 to 0.62). Estimates were also higher for influenza-like illness compared with confirmed influenza disease. None of the studies reports using U.S. preference weights, which may lead to different results (Johnson et al. 2005; Galante et al. 2011).

---

[32] We thank Dan Ollendorf and Lauren Do, of Tufts Medical Center's Center for the Evaluation of Value and Risk in Health, for providing an extract from their CEA Registry that includes data from studies addressing respiratory conditions on April 16, 2020. More information on the CEA Registry is available here: https://cevr.tuftsmedicalcenter.org/databases/cea-registry.

[33] Search terms included "quality of life," "QOL," "EQ-5D" or "EuroQoL" and "influenza," "flu," "COPD," "sepsis," "mechanical ventilation," "acute respiratory distress syndrome," "ARDS," "acute respiratory failure," or "ARF." The search was conducted in August 2020.

ED_006573_00001315-00047

Table 3.8 HRQL Studies, Influenza

Study	Location	HRQL Scale	Population	Average Age	Health State	HRQL Score
Van Hoek et al. 2011	U.K. (England)	EQ-5D, U.K. weights	46 patients	Not provided	Influenza-like illness, worst day of illness	0.34
Van Hoek et al. 2011	U.K. (England)	EQ-5D, U.K. weights	114 patients	Not provided	Laboratory-confirmed H1N1 influenza, worst day of illness	0.29
Hollmann et al. 2013	Spain, 36 hospitals	EQ-5D, Spanish weights	563 patients	39.15	Laboratory-confirmed H1N1 influenza, outpatient care	0.50
Hollmann et al. 2013	Spain, 36 hospitals	EQ-5D, Spanish weights	432 patients	43.44	Laboratory-confirmed H1N1 influenza, inpatient care	0.23
Bilcke et al. 2014	Belgium, national sample	SF-6D, U.K. weights	1,107 patients	Not provided	Influenza-like illness, not seeking ambulatory or hospital care	0.70
Bilcke et al. 2014	Belgium, national sample	SF-6D, U.K. weights	1,116 patients	Not provided	Influenza-like illness, seeking ambulatory care	0.68
Bilcke et al. 2014	Belgium, national sample	SF-6D, U.K. weights	429 patients	Not provided	Physician-diagnosed influenza, seeking ambulatory care	0.68
Bilcke et al. 2014	Belgium, national sample	SF-6D, U.K. weights	24 patients	Not provided	Influenza-like illness, hospitalized	0.61
Bilcke et al. 2014	Belgium, national sample	SF-6D, U.K. weights	6 patients	Not provided	Physician-diagnosed influenza, hospitalized	0.62
					Range of estimates, primary selection criteria	**0.23 to 0.70**
Supplementary estimates based on small samples and/or expert assessments						
Griffin et al. 2001	U.K.	EQ-5D, U.K. weights	21 patients	Not provided	Laboratory-confirmed influenza infection	-0.066[c]
Griffin et al. 2001	U.K.	EQ-5D, U.K. weights	Expert assessment	N/A	Influenza among hypothetical high-risk patient	-0.263[c]
Brady et al. 2001	Canada	HUI Mark 3, weights not reported[a]	11 adults[b]	Not provided	Influenza	0.636
Mauskopf et al. 2000	N/A	QWB, weights not reported[a]	Expert assessment	N/A	Influenza	0.5579
Muennig and Khan 2001	N/A	QWB, weights not reported[a]	Expert assessment	N/A	Influenza-like illness	0.61
					Range of estimates, primary and supplemental studies	**-0.263 to 0.70**

a. Given the weights available, the HUI most likely reflects Canadian weights and the QWB most likely reflects U.S. weights.
b. Authors do not indicate whether adults were former patients.
c. Authors do not discuss the reasons for these very low HRQL scores.

ED_006573_00001315-00048

As noted in section 3.1, we use influenza as a proxy condition for the effects of the mild acute phase of COVID-19, and influenza with respiratory complications as a proxy for the severe acute phase. Thus for the mild acute phase, we rely on influenza HRQL estimates for cases not described as receiving hospital care, which range from 0.50 to 0.70. In our illustrative calculations later in this chapter, we use a working assumption of 0.60, the midpoint of this range, for the HRQL of acute, mild COVID-19. Similar estimates have been used in cost-effectiveness analyses to value HRQL of influenza without hospitalization (Lee et al. 2015).

In the severe acute phase, COVID-19 cases are typically hospitalized. We exclude the HRQL scores less than zero (worse than dead), because they come from a small study that does not explain the reason for these exceedingly low values. Accordingly, we focus on HRQL estimates for influenza cases identified as receiving hospital care which range from 0.23 to 0.62. In our illustrative examples, we use a working assumption of 0.43, the approximate midpoint of this range, for the HRQL of acute, severe COVID-19.

3.3.2.2 Chronic obstructive pulmonary disease (COPD)

Next, we review estimates of COPD as a proxy for post-acute severe COVID-19. Given the relatively large number of studies that address COPD, we are able to focus on those that meet our preferred selection criteria. These include data collected from a sample of at least 100 U.S. individuals, patient-reported quality of life estimates, and U.S. EQ-5D preference weights.

As indicated in Table 3.9, "with condition" estimates range from 0.62 to 0.83 for baseline COPD disease. Estimates for individuals with more severe disease are typically lower than estimates for individuals with milder disease. The symptoms of COPD vary over time and are more pronounced during disease exacerbations. When the HRQL of COPD exacerbations was explicitly assessed, HRQL estimates were also lower, ranging between 0.49 and 0.59.

ED_006573_00001315-00049

Table 3.9 HRQL Studies, COPD

Study	Location	HRQL Scale	Population	Average Age	Health State	HRQL Score
Solem et al. 2013	U.S., national	EQ-5D, U.S. weights	190 patients	67.4	COPD, severe	0.707
Solem et al. 2013	U.S., national	EQ-5D, U.S. weights	124 patients	68.8	COPD, very severe	0.623
Solem et al. 2013	U.S., national	EQ-5D, U.S. weights	190 patients	67.4	COPD, severe, most recent exacerbation	0.590
Solem et al. 2013	U.S., national	EQ-5D, U.S. weights	124 patients	68.8	COPD, very severe, most recent exacerbation	0.494
Lin et al. 2014	U.S., clinical centers	EQ-5D, U.S. weights[a]	102 patients	72.1	COPD, GOLD stage I[b]	0.81
Lin et al. 2014	U.S., clinical centers	EQ-5D, U.S. weights[a]	353 patients	68.3	COPD, GOLD stage II	0.81
Lin et al. 2014	U.S., clinical centers	EQ-5D, U.S. weights[a]	165 patients	67.7	COPD, GOLD stage III	0.76
Lin et al. 2014	U.S., clinical centers	EQ-5D, U.S. weights[a]	50 patients	65.1	COPD, GOLD stage IV	0.74
Rutten-van Mölken et al. 2006	14 countries[c]	EQ-5D, U.S. weights	622 patients	64.0	COPD, GOLD stage II	0.832
Rutten-van Mölken et al. 2006	14 countries[c]	EQ-5D, U.S. weights	513 patients	65.6	COPD, GOLD stage III	0.803
Rutten-van Mölken et al. 2006	14 countries[c]	EQ-5D, U.S. weights	91 patients	61.6	COPD, GOLD stage IV	0.731
Pickard et al. 2011	U.S., one Veterans Affairs hospital	EQ-5D, U.S. weights	23 patients	72.3	COPD, GOLD stage I	0.80
Pickard et al. 2011	U.S., one Veterans Affairs hospital	EQ-5D, U.S. weights	53 patients	71.7	COPD, GOLD stage II	0.70
Pickard et al. 2011	U.S., one Veterans Affairs hospital	EQ-5D, U.S. weights	27 patients	70.4	COPD, GOLD stage III	0.72
Pickard et al. 2011	U.S., one Veterans Affairs hospital	EQ-5D, U.S. weights	17 patients	73.3	COPD, GOLD stage IV	0.72
					Range of estimates, primary selection criteria[d]	**0.494 to 0.832**

a. The authors do not explicitly report the country weights used but refer to HRQL scores for the U.S. population.
b. "GOLD" refers to the Global Initiative for Chronic Obstructive Lung Disease grading system. More information is available at https://goldcopd.org/.
c. Countries include U.S., Czech Republic, Spain, Denmark, Germany, Poland, the Netherlands, Italy, France, Hungary, Russia, Belgium, and Australia. Of the total sample, 34.5% were U.S. patients. While the U.S. results are not reported separately, the authors estimate that U.S. patients had HRQL scores that were between 0.04 and 0.15 higher than the scores of Italian, Czech, Polish, and French patients but 0.06 lower than Danish patients.
d. Due to the large number of studies that meet our primary selection criteria, we do not report the results of supplemental COPD studies.

ED_006573_00001315-00050

Given that individuals with mild COVID-19 appear unlikely to experience very severe post-acute symptoms, we assume that moderate COPD (Global Initiative for Chronic Obstructive Lung Disease (GOLD) stage II) is the best proxy. We are not able to more precisely match post-acute COVID-19 symptoms to specific COPD severity levels given the limited COVID-19 data available. Estimates corresponding to moderate COPD ranged from 0.70 to 0.832. We use a working assumption of 0.77, the approximate midpoint of this range, in our illustrative calculations to correspond to HRQL of post-acute mild COVID-19 disease.

Information on post-acute severe COVID-19 symptoms is also limited, and we are again not able to precisely match the symptoms to a particular COPD category. We assume that severe COPD (GOLD stage III) corresponds most closely to post-acute severe COVID-19. Estimates for severe COPD HRQL ranged from 0.707 to 0.81. We use a working assumption of 0.76, the approximate midpoint of this range, for the HRQL associated with post-acute severe COVID-19.

3.3.2.3 Acute sepsis, respiratory failure, and prolonged mechanical ventilation

We next review the literature on acute sepsis, conditions involving acute respiratory failure, and conditions involving prolonged mechanical ventilation, which we use as proxies for acute critical COVID-19. Obtaining primary evidence on health status among critically ill patients is difficult and infrequently attempted (Heyland et al. 1998).

Consistent with these concerns, we did not find any studies that met our preferred criteria for inclusion. Expanding our criteria to include all countries regardless of income level, small sample sizes, and primary data collection from experts and the general public, we identified the two studies reported in Table 3.10. These studies report "with condition" HRQL estimates of -0.295 and 0.23.[34]

Table 3.10 HRQL Studies, Acute Sepsis and Mechanical Ventilation

Study	Location	HRQL Scale	Population[a]	Average Age	Health State	HRQL Score
Galante et al. 2011	Argentina, convenience sample	EQ-5D, U.K. weights	73 members of the general public	31	Sepsis from pneumococcal disease	-0.295
Hung et al. 2010	Taiwan, five medical institutions	EQ-5D, Taiwanese weights	55 patients	70.9	Conditions requiring prolonged mechanical ventilation	0.23
					Range of estimates, supplemental studies[a]	**-0.295 to 0.23**

a. No studies were identified that meet our primary selection criteria.

Given the limited data available, it is difficult to estimate HRQL for these conditions. Several studies have recommended using a HRQL estimates of 0.1 for sepsis and other conditions treated in the ICU (Wu et

[34] In addition to the limitations noted in the text, another concern in this case is the extent to which patients in particularly critical condition can be surveyed, which may bias available HRQL estimates upwards.

ED_006573_00001315-00051

al. 2018; Macario et al. 2006). Thus we use an estimate of 0.1 as a proxy to value acute critical cases of COVID-19.

3.3.2.4 Post-acute sepsis, respiratory failure, and prolonged mechanical ventilation

Finally, we review the literature on long-term outcomes of sepsis, conditions involving acute respiratory failure, and conditions involving prolonged mechanical ventilation as proxies for post-acute critical COVID-19. We again did not find any studies that met our preferred selection criteria. We then relaxed our criteria to consider evidence from other high-income countries and indices other than the EQ-5D. We identified four studies and seven estimates that met these criteria. When we further relaxed our criteria to allow for studies that collected data from fewer than 100 patients and evidence based upon expert assessment, we identified one additional study providing four HRQL estimates.

Table 3.11 reports the results, which include "with condition" HRQL scores ranging from 0.5 to 0.75 over a period of up to one year. These studies suggest that quality of life may improve somewhat for survivors of these conditions over the first three months following acute disease, but then plateaus. Estimates corresponding to six months or one year after the acute episode range between 0.64 and 0.75.

ED_006573_00001315-00052

Table 3.11 HRQL Studies, Post-Acute Sepsis, ARDS, and Acute Respiratory Failure

Study	Health State	HRQL Scale	Population[a]	Average Age	Health State	HRQL Score
Higgins et al. 2019	Australia, New Zealand, Finland, Hong Kong, Ireland, 51 hospitals	EQ-5D, U.K. weights	496 patients	63.1[a]	Septic shock, usual care, survivors at 6 months	0.64
Higgins et al. 2019	Australia, New Zealand, Finland, Hong Kong, Ireland, 51 hospitals	EQ-5D, U.K. weights	458 patients	63.1[a]	Septic shock, usual care, survivors at 12 months	0.64
Linko et al. 2010	Finland, 25 ICUs	EQ-5D, Finnish weights	288 patients	64	Acute respiratory failure, ICU survivors at 1 year	0.70
Hofhuis et al. 2008; Kip et al. 2018	Netherlands, one surgical-medical ICU	SF-36 converted to EQ-5D, U.K. weights[b]	121 patients	66[c]	Severe sepsis, at ICU discharge	0.50
Hofhuis et al. 2008; Kip et al. 2018	Netherlands, one surgical-medical ICU	SF-36 converted to EQ-5D, U.K. weights[b]	101 patients	66[c]	Severe sepsis, at hospital discharge	0.64
Hofhuis et al. 2008; Kip et al. 2018	Netherlands, one surgical-medical ICU	SF-36 converted to EQ-5D, U.K. weights[b]	96 patients	66[c]	Severe sepsis, 3 months after ICU discharge	0.73
Hofhuis et al. 2008; Kip et al. 2018	Netherlands, one surgical-medical ICU	SF-36 converted to EQ-5D, U.K. weights[b]	95 patients	66	Severe sepsis, 6 months after ICU discharge	0.75
					Range of estimates, primary selection criteria	**0.50 to 0.75**
Supplementary estimates based on small samples and/or expert assessments						
Drabinski et al. 2001	U.S., 53 hospitals	EQ-5D, weights not described (assumed U.S.)	93 patients	60	Severe sepsis, 30 days after initial hospitalization (some still hospitalized)	0.56
Drabinski et al. 2001	U.S., 53 hospitals	EQ-5D, weights not described (assumed U.S.)	93 patients	60	Severe sepsis, 60 days after initial hospitalization	0.62
Drabinski et al. 2001	U.S., 53 hospitals	EQ-5D, weights not described (assumed U.S.)	93 patients	60	Severe sepsis, 90 days after initial hospitalization	0.68
Drabinski et al. 2001	U.S., 53 hospitals	EQ-5D, weights not described (assumed U.S.)	93 patients	60	Severe sepsis, 180 days after initial hospitalization	0.69
					Range of estimates, primary and supplementary studies	**0.50 to 0.75**

a. Corresponds to average age of usual care population in the overall study (n=798), not all of whom had HRQL measured.
b. Authors do not report the source of the weights but refer to an algorithm based on U.K. weights.
c. Corresponds to survivors at 6 months. The larger population of patients mentioned in the trial includes 170 severe sepsis patients, not all of whom had HRQL measured, and this population had a mean age of 70.

ED_006573_00001315-00053

Our working assumption for our illustrative calculations is that individuals with critical COVID-19 disease will experience chronic symptoms for the remainder of their lives, consistent with prior research that has modeled the long-term effects of critical disease on patients (Khazeni et al. 2009). While longer-term HRQL scores were not available, some research suggests that HRQL remains depressed at five years among ICU survivors of acute respiratory distress syndrome (Herridge et al. 2011), as well as for other conditions treated in ICUs (Cuthbertson et al. 2010).[35] Based on the HRQL estimates we reviewed, we use a working assumption of 0.70, the midpoint of the range of estimates at 6 months or longer from the acute episode of critical disease, to correspond to the HRQL of post-acute critical COVID-19 disease. This estimate is particularly uncertain given the current limited knowledge of COVID-19 long-term effects and the limited data on long-term HRQL estimates for other critical diseases.

3.3.2.5 Summary of HRQL estimates

In Table 3.12, we summarize the results of our HRQL literature review, focusing on the studies that best meet our selection criteria. As is evident from the table, these estimates cover relatively wide ranges that come close to overlapping in most cases despite differences in the severity of the conditions. These ranges reflect variation in the populations, indices, weights, conditions, and other characteristics of the methodology across studies, not simply differences in the diseases themselves.

Table 3.12 Summary of "With Condition" HRQL Estimates

COVID-19 Phase	Similar Proxy Disease	"With Condition" HRQL Estimates for Proxy Disease[a]	Typical Age Group for Estimates[b]
Mild case			
Mild acute phase	Influenza	0.60 (0.50 – 0.70)	40 – 49
Mild post-acute phase	Chronic obstructive pulmonary disease	0.77 (0.70 – 0.83)	60 – 69
Severe case			
Mild acute phase	Influenza	0.60 (0.50 – 0.70)	40 – 49
Severe acute phase	Influenza with respiratory complications	0.43 (0.23 – 0.62)	40 – 49
Severe post-acute phase	Chronic obstructive pulmonary disease	0.76 (0.71 – 0.81)	60 – 69
Critical case			
Mild acute phase	Influenza	0.60 (0.50 – 0.70)	40 – 49
Critical acute phase	Sepsis, conditions requiring prolonged mechanical ventilation	0.10 (-0.30 – 0.23)	40 – 49
Critical post-acute phase	Chronic health states associated with sepsis, conditions involving acute respiratory failure, conditions requiring prolonged mechanical ventilation	0.70 (0.64 – 0.75)	60 – 69

a. Reported numbers include the midpoint of HRQL estimates from the literature reviewed above as well as the range of estimates.

b. Typical 10-year age bands that correspond most closely to the average ages of individuals considered in the studies.

[35] The risk of mortality is elevated for years after treatment for critical disease but is not captured by these HRQL estimates (Wiersinga et al. 2020; Cuthbertson et al. 2010). We discuss the valuation of COVID-19 mortality risks in Chapter 2.

ED_006573_00001315-00054

To estimate the effect of reducing the risk of COVID-19 infections, we need to calculate HRQL both with and without the condition. As discussed in more detail below, population-average HRQL generally decreases as age increases. Most of the studies we reviewed on average address middle-aged or elderly adults, as summarized in Table 3.12. It is unclear whether these "with condition" HRQL estimates would vary significantly if a younger or older population was considered. Uncertainties in the COVID-19 disease descriptions, in the identification of these proxy conditions, and in the methods, populations, and risks addressed in the literature summarized above, mean that the application of these estimates will lead to highly uncertain values. We illustrate the use of these estimates and discuss the implications in the following section.

3.3.3 Values per Nonfatal Statistical Case

In the regulatory analysis context, the estimates in the prior section reflect HRQL in the absence of the policy; i.e., with COVID-19. Estimating and valuing the gain attributable to a regulation or other policy that averts the condition requires three additional steps: (1) comparison to HRQL without the condition, (2) multiplication of the HRQL increment by duration to estimate the QALY gain, and (3) multiplication of the QALY gain by the values per QALY reported in Chapter 1.

In this section, we provide illustrative estimates. As noted earlier, analysts will need to review more recent data and consider the effects of the specific regulation or other policy to determine the age groups most likely affected and the characteristics of the cases averted.

To estimate HRQL in the absence of COVID-19, we rely on Hanmer et al. (2006) estimates of population-average HRQL, focusing on EQ-5D estimates with U.S. weights, consistent with the approach HHS uses to estimate the value per QALY. That study addresses individuals age 20 through 89 in 10-year age groups. We report the results in Table 3.13.

Table 3.13 Population-Average U.S. HRQL by Age Group[a]

Age Group	Population-Average HRQL Score[b]
20 – 29	0.921
30 – 39	0.906
40 – 49	0.875
50 – 59	0.849
60 – 69	0.826
70 – 79	0.787
80 – 89	0.753

a. Hanmer et al. (2006), Table 3.
b. Estimates are midpoint values for males and females. In some cases, the population- average HRQL scores are higher than the "with condition" HRQL scores summarized in Table 3.12. We describe an adjustment that may used in this case as part of our recommendations below.

Applying the estimates in Table 3.13 raises several challenges. First, given the prevalence of health impairments in those affected by severe COVID-19, in the absence of the disease their HRQL may be lower than the population-average for their age group. Second, the estimates of HRQL with the

ED_006573_00001315-00055

conditions in the previous sections reflect different age groups as well as different populations (with possibly different comorbidities than the population averages represented in Table 3.13), indices, and preference weights. Third, for the long-term post-acute effects of critical cases, we have little information on the extent to which HRQL changes over time. Finally, it is unclear how to generalize the estimates provided in Table 3.12 to alternative ages. Thus, the resulting estimates should be considered illustrative of possible magnitude rather than definitive.

To calculate the effect of illness on individuals with different baseline health, we assume that the illness decreases baseline health by a constant fraction, and that this proportional decrease is constant across age groups. To operationalize this calculation, we divide the "with condition" HRQL from Table 3.12 by the population-average HRQL from Table 3.13 for an individual in the corresponding typical age group. For example, we divide the HRQL for mild acute phase (influenza) by the HRQL for ages 40-49 and the HRQL for mild post-acute phase (COPD) by the HRQL for ages 60-69. We then multiply this intermediate estimate by the population-average HRQL corresponding to each age category to yield estimates of the "with condition" HRQL for each age range.

Individuals under age 20 were not included in the Hanmer et al. (2006) study we use to estimate "without condition" HRQL. Individuals under age 20 also were not well represented in the "with condition" estimates of HRQL obtained from literature review. Given the limited evidence, we suggest that analysts use HRQL estimates corresponding to the 20 to 29 age group to approximate HRQL among individuals under age 20. Similarly, given that estimates for individuals age 90 and older are not included in the Hanmer et al. (2006) study, we recommend that analysts use HRQL estimates corresponding to the 80 to 89 age group to approximate "without condition" HRQL among individuals 90 and older.

We use the resulting proportional changes in HRQL to estimate "with condition" HRQL for each severity category, phase, and for three illustrative ages (20, 40, and 70). These results are reported in Table 3.14. These estimates are generally in the range of estimates provided in Table 3.7, which summarizes the available evidence for patients with COVID-19. Thus, our estimates appear consistent with the limited COVID-19 HRQL data available.

Table 3.14 Estimated "With-Condition" HRQL for Proxy Conditions, Illustrative Estimates by Age

COVID-19 Phase	HRQL, Age 20	HRQL, Age 40	HRQL, Age 70
Mild Case			
• Mild acute phase	0.632	0.600	0.540
• Mild post-acute phase	0.858	0.816	0.373
Severe Case			
• Mild acute phase	0.632	0.600	0.540
• Severe acute phase	0.245	0.430	0.639
• Severe post-acute phase	0.847	0.805	0.724
Critical Case			
• Mild acute phase	0.632	0.600	0.540
• Critical acute phase	0.105	0.100	0.090
• Critical post-acute phase	0.078	0.174	0.667

ED_006573_00001315-00056

Next, we use the HRQL estimates reported in Table 3.13 and Table 3.14 to calculate the change in QALYs per symptomatic case. First, we calculate the absolute change in HRQL score for each category, phase, and age group, by comparing the values from the two tables. For example, the change in HRQL for the mild acute phase for a 40-year-old would be (0.875) − (0.600) = 0.275. We then multiply by the duration of each condition from section 3.1 to estimate the change in QALYs. As part of this calculation, we convert from days to years assuming 365 days per year. For example, the change in QALYs for the mild acute phase for a 40-year-old would be (0.275) * (10 / 365) = 0.008. The results for all disease phases and age groups are reported in Table 3.15.

Table 3.15 Estimated Change in QALYs per Nonfatal Symptomatic Case, based on Proxy Conditions

COVID-19 Phase	QALY change, age 20	QALY change, age 40	QALY change, age 70
Mild Case			
• Mild acute phase	0.008	0.008	0.007
• Mild post-acute phase	0.003	0.002	0.002
Severe Case			
• Mild acute phase	0.006	0.005	0.005
• Severe acute phase	0.008	0.007	0.007
• Severe post-acute phase	0.010	0.010	0.009
Critical Case			
• Mild acute phase	0.006	0.005	0.005
• Critical acute phase	0.027	0.025	0.023
• Critical post-acute phase, 3% discount rate [a,b]	3.907	3.120	1.502
• Critical post-acute phase, 7% discount rate [a,b]	2.067	1.841	1.132

a. In these calculations, we assume the post-acute effects are a constant decrement throughout the individual's lifetime for critical cases, given uncertainty about the duration of these impacts and the extent to which they change over time. Remaining life expectancy is calculated from conditional survival rates by year of age reported in Arias and Xu (2020). Because we focus here on nonfatal cases, these calculations do not include any change in life expectancy for those with the condition. See Chapter 2 for discussion of mortality risk reductions.
b. Discounting to reflect time preferences is necessary in this case because duration is greater than one year (see *Guidelines* Chapter 5).

Because analysts may wish to conduct sensitivity analyses regarding the QALY losses associated with nonfatal critical cases over time, Table 3.16 provides a detailed accounting of the present value of QALY changes for this highest severity group, adding the QALY changes experienced in each phase of critical disease together. The table provides estimates over a period of one year from the start of the individual's symptoms, over 10 years from the start of symptoms, and over the individual's remaining expected lifetime.

ED_006573_00001315-00057

Table 3.16 Estimated Change in QALYs per Nonfatal Critical Case Over Different Time Horizons[a]

Discount Rate	QALY change, age 20	QALY change, age 40	QALY change, age 70
One year time horizon			
3%	0.166	0.158	0.142
7%	0.166	0.158	0.142
Ten year time horizon			
3%	1.258	1.189	0.980
7%	1.080	1.021	0.848
Lifetime time horizon			
3%	3.940	3.151	1.530
7%	2.100	1.872	1.160

a. See text and preceding tables for discussion of assumptions underlying these estimates.

We then multiply the change in QALYs by the central estimates of the value per QALY from Chapter 1; $580,000 at a 3 percent discount rate and $970,000 at a 7 percent discount rate. We report the results in Table 3.17.

Table 3.17 Value per Nonfatal Statistical Case, Illustrative Estimates by Age[a]

Discount Rate	Value per case, age 20	Value per case, age 40	Value per case, age 70
Mild Case			
3%	$6,100	$5,800	$5,200
7%	$10,000	$9,700	$8,700
Severe Case			
3%	$14,000	$13,000	$12,000
7%	$23,000	$22,000	$19,000
Critical Case			
3%	$2,300,000	$1,800,000	$890,000
7%	$2,000,000	$1,800,000	$1,100,000

a. See text and preceding tables for discussion of assumptions underlying these estimates. Estimates are presented to two significant figures.

While reflecting several simplifying assumptions, these illustrative calculations show that the value per averted nonfatal case may vary substantially depending on the severity of the disease, ranging over orders of magnitude. Focusing on the mid-point between the two discount rates, these estimates suggest that the value of averting a case of COVID-19 for an individual at age 40 may be about $8,000 for mild cases, $18,000 for severe cases, and $1.8 million for critical cases. These estimates are substantially larger than the Prosser et al. WTP estimates for influenza discussed in Section 3.2, and the Hammitt and Haninger WTP estimates for one month of respiratory illness are between the values for severe and critical cases. The values in Table 3.17 are derived from a larger evidence base than the WTP estimates discussed in the previous section, providing more insight into the extent to which the values vary by the severity and duration of the conditions.

This approach involves many layers of uncertainty. First, the symptoms of COVID-19 may differ from the effects of the diseases we use as proxies in ways that affect HRQL. Second, for several of the proxy conditions, the HRQL literature is sparse. Third, HRQL with and without the condition may vary by age or underlying health impairments, influencing these estimates. Fourth, the duration of the symptoms may

ED_006573_00001315-00058

differ from our illustrative estimates. Finally, the long-term effects of COVID-19 are particularly uncertain at this time. These concerns suggest that these estimates should be used only in illustrative calculations with sensitivity analysis, accompanied by qualitative discussion and quantitative analysis of other uncertainties.

3.4 Summary and Conclusions

This chapter suggests that the value of reducing nonfatal COVID-19 risks is uncertain, but indicates the possible magnitude for cases of differing severity. We first review the WTP literature for nonfatal illnesses with symptoms similar to those of COVID-19, focusing on influenza, COPD, sepsis, conditions involving acute respiratory failure, and conditions requiring prolonged mechanical ventilation. We find that very few WTP studies address these conditions, providing only limited insight into the value of reducing these risks. We next review the QALY literature for the same conditions, focusing on HRQL estimates for nonfatal cases. While the HRQL literature is also limited, it is substantially more extensive than the WTP literature and provides more insight into these values.

We develop illustrative population-average per case estimates by age group, based on HRQL and duration estimates from the literature and HHS's estimates of the value per QALY. We find that the value of averting a case of COVID-19 for an individual of average age may be about $8,000 for mild cases, $18,000 for severe cases, and $1.8 million for critical cases. These estimates indicate the likely magnitude of the values, but rest on several simplifying assumptions. They also exclude medical and other costs borne by third parties and the productivity losses associated with caregiving by family and friends.

Given these uncertainties, these estimates should be used only to illustrate the potential magnitude of the benefits associated with averting nonfatal cases. They should be accompanied by both qualitative discussion and quantitative analysis of uncertainty based on the information provided in this chapter and other sources, following the general approaches for assessing uncertainty discussed in Chapter 6 of the HHS *Guidelines*. The quantitative assessment should include investigation of uncertainty in both the HRQL and the duration estimates. In addition, these values should be updated as needed to reflect additional information on the characteristics of nonfatal COVID-19 cases and tailored to the effects of the specific regulation or other policy under consideration.

ED_006573_00001315-00059

REFERENCES

Adamowicz, W., Dupont, D., Krupnick, A., & Zhang, J. 2009. Valuation of cancer and microbial disease risk reductions in municipal drinking water: An analysis of risk context using multiple valuation methods. Unpublished manuscript.

Alberini, A., Cropper, M., Krupnick, A., & Simon, N. 2004. Does the value of a statistical life vary with age and health status? Evidence from the U.S. and Canada. *Journal of Environmental Economics and Management* 48(1): 769–792

Aldy, J. E. 2019. Birds of a feather: Estimating the value of statistical life from dual-earner families. *Journal of Risk and Uncertainty* 58(2–3): 187–205.

Aldy, J. E., & Viscusi, W. K. 2007. Age differences in the value of statistical life: Revealed preference evidence. *Review of Environmental Economics and Policy* 1(2): 241–260.

Aldy, J. E., & Viscusi, W. K. 2008. Adjusting the value of a statistical life for age and cohort effects. *Review of Economics and Statistics* 90(3): 573–581.

Arias, E. & Xu, J. 2020. United States Life Tables, 2018. *National Vital Statistics Reports* 69(12): 1–44.

Arnold, D. T., Hamilton, F. W., Milne, A., Morley, A. J., Viner, J., Attwood, M., et al. 2020. Patient outcomes after hospitalisation with COVID-19 and implications for follow-up: results from a prospective UK cohort. *Thorax*. doi: 10.1136/thoraxjnl-2020-216086.

Azar, K. M., Shen, Z., Romanelli, R. J., Lockhart, S. H., Smits, K., Robinson, S., et al. 2020. Disparities In outcomes among COVID-19 patients in a large health care system in California. *Health Affairs* 39(7): 1253–1262.

Benitez, J. A., Courtemanche, C. J., & Yelowitz, A. 2020. Racial and ethnic disparities in COVID-19: evidence from six large cities. NBER Working Paper 27592.

Bergstrom, T.C. 2006. Benefit–cost in a benevolent society. *American Economic Review* 96(1): 339–351.

Berlin, D. A., Gulick, R. M., & Martinez, F. J. 2020. Severe Covid-19. *New England Journal of Medicine.* 383(25): 2451–2460.

Bhatraju, P. K., Ghassemieh, B. J., Nichols, M., Kim, R., Jerome, K. R., Nalla, A. K., et al. 2020. Covid-19 in critically ill patients in the Seattle region—case series. *New England Journal of Medicine* 382(21): 2012–2022.

Bilcke, J., Coenen, S., & Beutels, P. 2014. Influenza-like-illness and clinically diagnosed flu: Disease burden, costs and quality of life for patients seeking ambulatory care or no professional care at all. *PLOS ONE* 9(7): e102634.

Blair, P. W., Brown, D. M., Jang, M., Antar, A. A., Keruly, J. C., Bachu, V. S., et al. 2021. The clinical course of COVID-19 in the outpatient setting: a prospective cohort study. *Open Forum Infectious Diseases* 8(2): ofab007.

Bleichrodt, H., Courbage, C. & Rey, B. 2019. The value of a statistical life under changes in ambiguity. *Journal of Risk and Uncertainty* 58: 1–15.

ED_006573_00001315-00060

Brady, B., McAuley, L., & Shukla, V. 2001. Economic evaluation of zanamivir for the treatment of influenza. Ottawa: Canadian Coordinating Office for Health Technology Assessment.

Briggs, A. H., Goldstein, D. A., Kirwin, E., Meacock, R., Pandya, A., Vanness, D. J., & Wisløff, T. 2021. Estimating (quality-adjusted) life-year losses associated with deaths: With application to COVID-19. *Health Economics* 30(3): 699–707.

Cameron, T. A. 2014. Valuing morbidity in environmental benefit-cost analysis. *Annual Review of Resource Economics.* 6(1): 249–272.

Cameron, T.A., Deshazo, J.R., & Stiffler, P. 2010. Demand for health risk reductions: a cross-national comparison between the U.S. and Canada. *Journal of Risk and Uncertainty* 41: 245–273.

Carfì, A., Bernabei, R., Landi, F., for the Gemelli Against COVID-19 Post-Acute Care Study Group. 2020. Persistent symptoms in patients after acute COVID-19. *JAMA* 324(6):603–605.

Carlsson, F., O. Johansson-Stenman, & P. Martinsson. 2004. Is transport safety more valuable in the air? *Journal of Risk and Uncertainty* 28(2): 147–163.

Centers for Disease Control and Prevention. 2020a. Interim clinical guidance for management of patients with confirmed Coronavirus Disease (COVID-19). https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical-guidance-management-patients.html. Accessed July 9 2020.

Centers for Disease Control and Prevention. 2020b. Similarities and differences between flu and COVID-19. https://www.cdc.gov/flu/symptoms/flu-vs-covid19.htm. Accessed July 9 2020.

Centers for Disease Control and Prevention. 2021a. United States COVID-19 cases and deaths by state. https://www.cdc.gov/covid-data-tracker/#cases. Accessed January 21 2021.

Centers for Disease Control and Prevention. 2021b. COVID-19 pandemic planning scenarios. https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html. Accessed March 15 2021.

Centers for Disease Control and Prevention. 2021c. United States COVID-19 cases and deaths by state over time. https://data.cdc.gov/Case-Surveillance/United-States-COVID-19-Cases-and-Deaths-by-State-o/9mfq-cb36. Accessed April 7 2021.

Chen, K. Y., Li, T., Gong, F., Zhang, J. S., & Li, X. K. 2020. Predictors of health-related quality of life and influencing factors for COVID-19 patients, a follow-up at one month. *Frontiers in Psychiatry 11*(668).

Chestnut, L.G., Rowe, R.D. & Breffle, W.S. 2012. Economic valuation of mortality-risk reduction: Stated preference estimates from the United States and Canada. *Contemporary Economic Policy* 30(3): 399–416.

Chestnut, L.G., Thayer, M.A., Lazo, J.K. & Van Den Eeden, S.K., 2006. The economic value of preventing respiratory and cardiovascular hospitalizations. *Contemporary Economic Policy* 24(1): 127–143.

ED_006573_00001315-00061

Chilton, S., J. Covey, L. Hopkins, M. Jones-Lee, G. Loomes, N. Pidgeon, & A. Spencer. 2002. Public perceptions of risk and preference-based values of safety. *Journal of Risk and Uncertainty* 25(3): 211–232.

Chilton, S., M. Jones-Lee, F. Kiraly, H. Metcalf, & W. Pang. 2006. Dread risks. *Journal of Risk and Uncertainty* 33(3): 165–182.

Clinton, W.J. 1993. Executive Order 12866: Regulatory Planning and Review. Federal Register. 58(190): 51735- 51744. http://www.whitehouse.gov/omb/inforeg_regmatters

Corso, P.S., Hammitt, J.K., & Graham, J.D. 2001. Valuing mortality-risk reduction: using visual aids to improve the validity of contingent valuation. *Journal of Risk and Uncertainty* 23(2): 165–184.

Cuthbertson, B. H., Roughton, S., Jenkinson, D., MacLennan, G., & Vale, L. 2010. Quality of life in the five years after intensive care: a cohort study. *Critical Care* 14(1): R6.

Davidson, T. A., Caldwell, E. S., Curtis, J. R., Hudson, L. D., & Steinberg, K. P. 1999. Reduced quality of life in survivors of acute respiratory distress syndrome compared with critically ill control patients. *JAMA* 281(4): 354–360.

DeShazo J. R., & Cameron T. A. 2005. The effect of health status on willingness to pay for morbidity and mortality risk reductions. California Center for Population Research, On-Line Working Paper Series. CCPR-050-05.

Dickie M., & Messman V. L. 2004. Parental altruism and the value of avoiding acute illness: Are kids worth more than parents? *Journal of Environmental Economics and Management.* 48(3): 1146–74

Dong, Y., Mo, X., Hu, Y., Qi, X., Jiang, F., Jiang, Z., et al. 2020. Epidemiological characteristics of 2143 pediatric patients with 2019 coronavirus disease in China. *Pediatrics*. doi:10.1542/peds.2020-0702

Drabinski, A., Williams, G., & Formica, C. 2001. Observational evaluation of health state utilities among a cohort of sepsis patients. *Value in Health* 4(2): 128–129.

Dufort, E. M., Koumans, E. H., Chow, E. J., Rosenthal, E. M., Muse, A., Rowlands, J., et al. 2020. Multisystem inflammatory syndrome in children in New York State. *New England Journal of Medicine* 383: 347–358.

Ellsberg, D. 1961. Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics* 75(4): 643–669.

Evans, M. F., & Smith, V. K. 2006. Do we really understand the age–VSL relationship? *Resource and Energy Economics* 28(3): 242–261.

Evans, M. F., & Smith, V. K. 2008. Complementarity and the measurement of individual risk tradeoffs: accounting for quantity and quality of life effects. *Environmental and Resource Economics* 41(3): 381-400.

ED_006573_00001315-00062

Fryback, D.G., Dunham, N.C., Palta, M., Hanmer, J., Buechner, J., Cherepanov, D., Herrington, S., Hays, R.D., Kaplan, R.M., Ganiats, T.G. & Feeny, D. 2007. US norms for six generic health-related quality-of-life indexes from the National Health Measurement study. *Medical Care* 45(12): 1162–1170.

Feldstein, L. R., Rose, E. B., Horwitz, S. M., Collins, J. P., Newhams, M. M., Son, M. B. F., et al. 2020. Multisystem inflammatory syndrome in US children and adolescents. *New England Journal of Medicine* 383: 334–346.

Finkelstein A., Luttmer E.F.P., & Notowidigdo M.J. 2013. What good is wealth without health? The effect of health on the marginal utility of consumption. *Journal of the European Economic Association* 11(S1): 221–258.

Galante, J., Augustovski, F., Colantonio, L., Bardach, A., Caporale, J., Marti, S. G., et al. 2011. Estimation and comparison of EQ-5D health states' utility weights for pneumoccocal and human papillomavirus diseases in Argentina, Chile, and the United Kingdom. *Value in Health* 14(5): S60–S64.

Gandhi, R. T., Lynch, J. B., & del Rio, C. 2020. Mild or moderate COVID-19. *New England Journal of Medicine*. doi: 10.1056/NEJMcp2009249

Garratt, A. M., Ghanima, W., Einvik, G., & Stavem, K. 2021. Quality of life after COVID-19 without hospitalisation: good overall, but reduced in some dimensions. *The Journal of Infection*: S0163–4453.

Garrigues, E., Janvier, P., Kherabi, Y., Le Bot, A., Hamon, A., Gouze, H., et al. 2020. Post-discharge persistent symptoms and health-related quality of life after hospitalization for COVID-19. *Journal of Infection*, 81(6): e4–e6.

Gentry, E. P. & Viscusi, W. K., 2016. The fatality and morbidity components of the value of statistical life. *Journal of Health Economics* 46: 90–99.

Gerking, S., & Dickie, M. 2013. Valuing reductions in environmental risks to children's health. *Annual Review of Resource Economics* 5(1): 245–260.

Gold, J. A., Wong, K.K., Szablewski, C.M., Patel, P.R., Rossow, J., da Silva, J., et al. 2020. Characteristics and clinical outcomes of adult patients hospitalized with COVID-19—Georgia, March 2020. *Morbidity and Mortality Weekly Report* 69(18): 545–550.

Griffin, A. D., Perry, A. S., & Fleming, D. M. 2001. Cost-effectiveness analysis of inhaled zanamivir in the treatment of influenza A and B in high-risk patients. *Pharmacoeconomics* 19(3): 293–301.

Halpin, S. J., McIvor, C., Whyatt, G., Adams, A., Harvey, O., McLean, L., et al. 2021. Postdischarge symptoms and rehabilitation needs in survivors of COVID-19 infection: A cross-sectional evaluation. *Journal of Medical Virology*, *93*(2): 1013–1022.

Hammitt, J. K., 2020. Valuing mortality risk in the time of COVID-19. *Journal of Risk and Uncertainty* 61(2): 129–154.

ED_006573_00001315-00063

Hammitt, J. K. & Haninger, K. 2010. Valuing fatal risks to children and adults: effects of disease, latency, and risk aversion. *Journal of Risk and Uncertainty* 40: 57–83.

Hammitt, J. K. & Haninger, K. 2017. Valuing nonfatal health risk as a function of illness severity and duration: benefit transfer using QALYs. *Journal of Environmental Economics and Management* 82: 17–38.

Hammitt, J. K. & Liu, J.-T. 2004. Effects of disease type and latency on the value of mortality risk. *Journal of Risk and Uncertainty* 28(1): 73–95.

Hammitt, J. K. & Treich, N. 2007. Statistical vs. identified lives in benefit-cost analysis. *Journal of Risk and Uncertainty* 35(1): 45–66.

Hanlon, P., Chadwick, F., Shah, A., Wood, R., Minton, J., McCartney, G., et al. 2021. COVID-19–exploring the implications of long-term condition type and extent of multimorbidity on years of life lost: a modelling study [version 3; peer review: 3 approved]. *Wellcome Open Res* 5:75. https://doi.org/10.12688/wellcomeopenres.15849.1.

Hanmer, J., Lawrence, W. F., Anderson, J. P., Kaplan, R. M. & Fryback, D. G., 2006. Report of nationally representative values for the noninstitutionalized US adult population for 7 health-related quality-of-life scores. *Medical Decision Making* 26(4): 391–400.

Helms, J., Kremer, S., Merdji, H., Clere-Jehl, R., Schenck, M., Kummerlen, C., et al. 2020. Neurologic features in severe SARS-CoV-2 infection. *New England Journal of Medicine* 382: 2268–2270.

Herridge, M. S., Cheung, A. M., Tansey, C. M., Matte-Martyn, A., Diaz-Granados, N., Al-Saidi, F., et al. 2003. One-year outcomes in survivors of the acute respiratory distress syndrome. *New England Journal of Medicine* 348(8): 683–693.

Herridge, M. S., Tansey, C. M., Matté, A., Tomlinson, G., Diaz-Granados, N., Cooper, A., et al. 2011. Functional disability 5 years after acute respiratory distress syndrome. *New England Journal of Medicine* 364(14): 1293–1304.

Hersch, J., Viscusi, W. K. 2010. Immigrant status and the value of statistical life. *Journal of Human Resources* 45: 749–771.

Heyland, D. K., Guyatt, G., Cook, D. J., Meade, M., Juniper, E., Cronin, L., et al. 1998. Frequency and methodologic rigor of quality-of-life assessments in the critical care literature. *Critical Care Medicine* 26(3): 591–598.

Higgins, A. M., Peake, S. L., Bellomo, R., Cooper, D. J., Delaney, A., Harris, A. H., et al. 2019. Quality of life and 1-year survival in patients with early septic shock: long-term follow-up of the Australasian resuscitation in sepsis evaluation trial. *Critical Care Medicine* 47(6): 765–773.

Hofhuis, J. G., Spronk, P. E., van Stel, H. F., Schrijvers, A. J., Rommes, J. H., & Bakker, J. 2008. The impact of severe sepsis on health-related quality of life: a long-term follow-up study. *Anesthesia & Analgesia* 107(6): 1957–1964.

Hollmann, M., Garin, O., Galante, M., Ferrer, M., Dominguez, A., & Alonso, J. 2013. Impact of influenza on health-related quality of life among confirmed (H1N1) 2009 patients. *PLOS ONE* 8(3): e60477.

ED_006573_00001315-00064

Hung, M.-C., Yan, Y.-H., Fan, P.-S., Lin, M.-S., Chen, C.-R., Kuo, L.-C., et al. 2010. Measurement of quality of life using EQ-5D in patients on prolonged mechanical ventilation: comparison of patients, family caregivers, and nurses. *Quality of Life Research* 19(5): 721–727.

Hunt, A., Ferguson, J., Hurley, F., & Searl, A. 2016. Social costs of morbidity impacts of air pollution. OECD Environment Working Papers, No. 99. OECD Publishing, Paris. http://dx.doi.org/10.1787/5jm55j7cq0lv-en

Itaoka, K., A. Saito, A. Krupnick, W. Adamowicz, & T. Taniguchi. 2006. The effect of risk characteristics on the willingness to pay for mortality risk reductions from electric power generation. *Environmental and Resource Economics* 33, 371–398.

Johnson, J. A., Luo, N., Shaw, J. W., Kind, P., & Coons, S. J. 2005. Valuations of EQ-5D health states: are the United States and United Kingdom different? *Medical Care* 43(3): 221–228.

Johnston, S. S., Rousculp, M. D., Palmer, L. A., Chu, B. C., Mahadevia, P. J., & Nichol, K. L. 2010. Employees' willingness to pay to prevent influenza. *American Journal of Managed Care* 16: E205–E214.

Jones-Lee, M. W. 1991. Altruism and the value of other people's safety. *Journal of Risk and Uncertainty* 4(2): 213–219.

Jones-Lee, M. W. & G. Loomes. 1995. Scale and context effects in the valuation of transport safety. *Journal of Risk and Uncertainty* 11(3): 183–203.

Khazeni, N., Hutton, D. W., Garber, A. M., Hupert, N., & Owens, D. K. 2009. Effectiveness and cost-effectiveness of vaccination against pandemic influenza (H1N1) 2009. *Annals of Internal Medicine* 151(12): 829–839.

Kip, M. M., van Oers, J. A., Shajiei, A., Beishuizen, A., Berghuis, A. S., Girbes, A. R., et al. 2018. Cost-effectiveness of procalcitonin testing to guide antibiotic treatment duration in critically ill patients: results from a randomised controlled multicentre trial in the Netherlands. *Critical Care* 22(1): 1–10.

Kniesner, T. J., Viscusi, W. K. 2005. Value of a statistical life: relative position vs. relative age. *American Economic Review* 95 (2): 142–146.

Kniesner, T. J., Viscusi, W. K., & Ziliak, J. P. 2006. Life-cycle consumption and the age-adjusted value of life. *BE Journal of Economic Analysis and Policy* 5(1): 1–34.

Kniesner, T. J., Viscusi, W. K., & Ziliak, J. P. 2010. Policy relevant heterogeneity in the value of statistical life: New evidence from panel data quantile regressions. *Journal of Risk and Uncertainty* 40(1): 15–31.

Koh, H. K., Geller, A. C. and VanderWeele, T. J. 2021. Deaths from COVID-19. *JAMA*, *325*(2): 133–134.

Krupnick, A. 2007. Mortality-risk valuation and age: Stated preference evidence. *Review of Environmental Economics and Policy* 1(2): 261–282.

ED_006573_00001315-00065

Lee, B. Y., Bartsch, S. M., Brown, S. T., Cooley, P., Wheaton, W. D., & Zimmerman, R. K. 2015. Quantifying the economic value and quality of life impact of earlier influenza vaccination. *Medical Care* 53(3): 218.

Lee, J. M., Taylor, L. O. 2013. Randomized safety inspections and risk exposure on the job: quasi-experimental estimates of the value of a statistical life. Center for Economic Studies, U.S. Census Bureau. Discussion Paper CES 14-05.

Lee, Y.-H., Hong, C. M., Kim, D. H., Lee, T. H., & Lee, J. 2020. Clinical course of asymptomatic and mildly symptomatic patients with coronavirus disease admitted to community treatment centers, South Korea. *Emerging Infectious Diseases* 26(10).

Lewnard, J. A., Liu, V. X., Jackson, M. L., Schmidt, M. A., Jewell, B. L., Flores, J. P., et al. 2020. Incidence, clinical outcomes, and transmission dynamics of severe coronavirus disease 2019 in California and Washington: prospective cohort study. *BMJ* 369: m1923.

Lin, F.-J., Pickard, A. S., Krishnan, J. A., Joo, M. J., Au, D. H., Carson, S. S., et al. 2014. Measuring health-related quality of life in chronic obstructive pulmonary disease: properties of the EQ-5D-5L and PROMIS-43 short form. *BMC Medical Research Methodology* 14(1): 78.

Lindhjem H., Navrud S., Braathen N.A. & Biausque, V. 2011. Valuing mortality risk reductions from environmental, transport, and health policies: a global meta-analysis of stated-preference studies. *Risk Analysis* 31(9): 1381–1407.

Linko, R., Suojaranta-Ylinen, R., Karlsson, S., Ruokonen, E., Varpula, T., Pettilä, V., et al. 2010. One-year mortality, quality of life and predicted life-time cost-utility in critically ill patients with acute respiratory failure. *Critical Care* 14(2): R60.

Liu, J. T., Hammitt, J. K., Wang, J. D. & Tsou, M. W. 2005. Valuation of the risk of SARS in Taiwan. Health Economics, 14(1): 83–91.

Longfonds. 2020. Peiling schetst schokkend beeld gezondheid thuiszittende coronapatiënten [Dutch]. https://www.longfonds.nl/Peiling-schokkend-beeld-gezondheid-thuiszittende-coronapatienten. Accessed July 12 2020.

Lu, X., Zhang, L., Du, H., Zhang, J., Li, Y. Y., Qu, J., et al. 2020. SARS-CoV-2 infection in children. *New England Journal of Medicine* 382(17): 1663–1665.

Macario, A., Chow, J. L., & Dexter, F. 2006. A Markov computer simulation model of the economics of neuromuscular blockade in patients with acute respiratory distress syndrome. *BMC Medical Informatics and Decision Making* 6(1), 15.

Magat, W. A., W. K. Viscusi, & J. Huber. 1996. A reference lottery metric for valuing health. *Management Science* 42(8): 1118–1130.

Marshall, M. 2020. The lasting misery of coronavirus long-haulers. *Nature* 585(7825): 339-341. doi: 10.1038/d41586-020-02598-6.

Masterman, C. J. & Viscusi, W. K. 2018. The income elasticity of global values of a statistical life: stated preference evidence. *Journal of Benefit-Cost Analysis* 9(3): 407–434.

ED_006573_00001315-00066

Mauskopf, J. A., Cates, S. C., Griffin, A. D., Neighbors, D. M., Lamb, S. C., & Rutherford, C. 2000. Cost effectiveness of zanamivir for the treatment of influenza in a high risk population in Australia. *Pharmacoeconomics* 17(6): 611–620.

McLaren, J. 2020. Racial disparity in COVID-19 deaths: seeking economic roots with Census data. NBER Working Paper 27407.

Meys, R., Delbressine, J. M., Goërtz, Y. M., Vaes, A. W., Machado, F. V., Van Herck, M., et al. 2020. Generic and respiratory-specific quality of life in non-hospitalized patients with COVID-19. *Journal of Clinical Medicine 9*(12): 3993.

Moreno-Pérez, O., Merino, E., Leon-Ramirez, J. M., Andres, M., Ramos, J. M., Arenas-Jiménez, J., et al. 2021. Post-acute COVID-19 Syndrome. Incidence and risk factors: a Mediterranean cohort study. *Journal of Infection*. doi: 10.1016/j.jinf.2021.01.004

Muennig, P. A., & Khan, K. 2001. Cost-effectiveness of vaccination versus treatment of influenza in healthy adolescents and adults. *Clinical Infectious Diseases* 33(11): 1879–1885.

Murphy, K.M. & Topel, R.H. 2006. The value of health and longevity. *Journal of Political Economy*, 114(5): 871–904.

National Center for Health Statistics. 2021b. Excess deaths associated with COVID-19. https://www.cdc.gov/nchs/nvss/vsrr/covid19/excess_deaths.htm. Accessed January 21 2021.

Obama, B. 2011. Executive Order 13563: Improving Regulation and Regulatory Review. Federal Register. 76(14): 3821-3823. http://www.whitehouse.gov/omb/inforeg_regmatters

Office for National Statistics. 2020. Prevalence of long COVID symptoms and COVID-19 complications. https://www.ons.gov.uk/news/statementsandletters/theprevalenceoflongcovidsymptomsandcovid19complications. Accessed March 15 2021.

O'Brien, J. 2018. Age, autos, and the value of a statistical life. *Journal of Risk and Uncertainty* 57: 51–79.

Paterson, R. W., Brown, R. L., Benjamin, L., Nortley, R., Wiethoff, S., Bharucha, T., et al. 2020. The emerging spectrum of COVID-19 neurology: clinical, radiological and laboratory findings. *Brain* 143(10): 3104–3120.

Patient-Led Research for COVID-19. 2020. What does COVID-19 recovery actually look like? An analysis of the Prolonged COVID-19 Symptoms Survey by Patient-Led Research Team. https://patientresearchcovid19.com/research/report-1/. Accessed July 12 2020.

Pickard, A. S., Yang, Y., & Lee, T. A. 2011. Comparison of health-related quality of life measures in chronic obstructive pulmonary disease. *Health and Quality of Life Outcomes* 9(1): 26.

Pike, J., Shogren, J.F., Aadland, D., Viscusi, W.K., Finnoff, D., Skiba, A. and Daszak, P. 2020. Catastrophic Risk: Waking Up to the Reality of a Pandemic? *EcoHealth* 17(2): 217-221.

ED_006573_00001315-00067

Praschan, N., Josephy-Hernandez, S., Kim, D. D., Kritzer, M. D., Mukerji, S., Newhouse, A., et al. 2021. Implications of COVID-19 sequelae for health-care personnel. *The Lancet Respiratory Medicine.* doi: 10.1016/S2213-2600(20)30575-0.

Price-Haywood, E. G., Burton, J., Fort, D., & Seoane, L. 2020. Hospitalization and mortality among black patients and white patients with Covid-19. *New England Journal of Medicine* 382:2534–2543.

Prosser, L.A., Payne, K., Rusinak, D., Shi, P., & Messonnier, M. 2013. Using a discrete choice experiment to elicit time trade-off and willingness-to-pay amounts for influenza health-related quality of life at different ages. *Pharmacoeconomics* 31: 305–315.

Puntmann, V. O., Carerj, M. L., Wieters, I., Fahim, M., Arendt, C., Hoffmann, J., et al. 2020. Outcomes of cardiovascular magnetic resonance imaging in patients recently recovered from coronavirus disease 2019 (COVID-19). *JAMA Cardiology*. doi:10.1001/jamacardio.2020.3557.

Raifman, M. A., & Raifman, J. R. 2020. Disparities in the population at risk of severe illness from COVID-19 by race/ethnicity and income. *American Journal of Preventive Medicine* 59(1): 137–139.

Rheinberger, C.M. & Treich, N. 2017. Attitudes toward catastrophe. *Environmental and Resource Economics* 67(3): 609–636.

Riddel, M. & W.D. Shaw. 2006. A theoretically-consistent empirical model of non-expected utility: An application to nuclear-waste transport. *Journal of Risk and Uncertainty* 32(2): 131–150.

Robinson, L. A. & Hammitt, J. K., 2011. Behavioral economics and the conduct of benefit-cost analysis: towards principles and standards. *Journal of Benefit-Cost Analysis* 2(2): 1–51.

Robinson, L. A., & Hammitt, J. K. 2016. Valuing reductions in fatal illness risks: Implications of recent research. *Health Economics 25*(8): 1039–1052.

Robinson, L. A., Hammitt, J. K., Aldy, J. E., Krupnick, A. & Baxter, J. 2010. Valuing the risk of death from terrorist attacks. *Journal of Homeland Security and Emergency Management* 7(1).

Robinson, L. A., Raich, W., Hammitt, J. K., & O'Keeffe, L. 2019. Valuing children's fatality risk reductions. *Journal of Benefit-Cost Analysis* 10(2): 156–177.

Robinson, L.A., Sullivan, R. & Shogren, J.F., 2021. Do the benefits of COVID-19 policies exceed the costs? Exploring uncertainties in the age–VSL relationship. *Risk Analysis*. 41(5): 761-770. doi:10.1111/risa.13561

Rubino, F., Amiel, S. A., Zimmet, P., Alberti, G., Bornstein, S., Eckel, R. H., et al. 2020. New-onset diabetes in Covid-19. *New England Journal of Medicine* 383: 789–790.

Rutten-van Mölken, M. P., Oostenbrink, J. B., Tashkin, D. P., Burkhart, D., & Monz, B. U. 2006. Does quality of life of COPD patients as measured by the generic EuroQol five-dimension questionnaire differentiate between COPD severity stages? *Chest* 130(4): 1117–1128.

Sakurai, A., Sasaki, T., Kato, S., Hayashi, M., Tsuzuki, S.-i., Ishihara, T., et al. 2020. Natural history of asymptomatic SARS-CoV-2 infection. *New England Journal of Medicine*. doi:10.1056/NEJMc2013020

ED_006573_00001315-00068

Scotton, C.R. 2013. New risk rates, inter-industry differentials and the magnitude of VSL estimates. *Journal of Benefit-Cost Analysis*. 4(1): 39–80.

Shepard, D.S., & R.J. Zeckhauser. 1984. Survival versus consumption. *Management Science* 30(4): 423–439.

Shogren, J.F. 2005. Economics of diet and health: Research challenges. *Acta Agriculturae Scand Section C* 2(3-4): 117–127.

Sivan, M. & Taylor, S. 2020. NICE guideline on long covid. *BMJ* 371: m4938

Sloan, F. A., Viscusi, W. K., Chesson, H. W., Conover C. J., & Whetten-Goldstein, K. 1998. Alternative approaches to valuing intangible health losses: the evidence for multiple sclerosis. *Journal of Health Economics* 17: 475–497.

Slovic, P. 1987. Perception of risk. *Science* 236(4799): 280-285.

Solem, C. T., Sun, S. X., Sudharshan, L., Macahilig, C., Katyal, M., & Gao, X. 2013. Exacerbation-related impairment of quality of life and work productivity in severe and very severe chronic obstructive pulmonary disease. *International Journal of Chronic Obstructive Pulmonary Disease* 8: 641.

Stokes, E.K., Zambrano, L.D., Anderson, K.N., Marder, E.P., Raz, K.M., Felix, S.E.B., et al. 2020. Coronavirus Disease 2019 Case Surveillance—United States, January 22–May 30, 2020. *Morbidity and Mortality Weekly Report*, 69(24): 759.

Subramanian, U. & Cropper, M. 2000. Public choices between life saving programs: The tradeoff between qualitative factors and lives saved. *Journal of Risk and Uncertainty* 21(1): 117–149.

Svensson, M. & Johansson, M.V. 2010. Willingness to pay for private and public road safety in stated-preference studies: Why the difference? *Accident Analysis & Prevention* 42(4): 1205–1212.

Taboada, M., Moreno, E., Cariñena, A., Rey, T., Pita-Romero, R., Leal, S., et al. (2020). Quality of life, functional status, and persistent symptoms after intensive care of COVID-19 patients. *British Journal of Anaesthesia* 126(3): E110–E113.

Tenforde, M. W., Kim, S., Lindsell, C., Billig Rose, E., Shapiro, N., Files, C., et al. 2020. Symptom duration and risk factors for delayed return to usual health among outpatients with COVID-19 in a multistate health care systems network — United States, March–June 2020. *Morbidity and Mortality Weekly Report* 69(30): 993 –998.

Treich, N. 2010. The value of a statistical life under ambiguity aversion. *Journal of Environmental Economics and Management* 59(1): 15–26.

U.S. Department of Health and Human Services. 2016. Guidelines for Regulatrory Impact Analysis. https://aspe.hhs.gov/pdf-report/guidelines-regulatory-impact-analysis

U.S. Department of Health and Human Services. 2021. Guidelines for Regulatrory Impact Analysis, Appendix D: Updating Value per Statistical Life (VSL) Estimates for Inflation and Changes in Real Income. https://aspe.hhs.gov/pdf-report/updating-vsl-estimates

ED_006573_00001315-00069

U.S. Environmental Protection Agency. 2016. Valuing mortality risk reductions for policy: A meta-analytic approach. Prepared by the U.S. Environmental Protection Agency's Office of Policy, National Center for Environmental Economics, for review by the EPA's Science Advisory Board, Environmental Economics Advisory Committee. https://yosemite.epa.gov/sab/sabproduct.nsf/0/0CA9E925C9A702F285257F380050C842/$File/VSL%20white%20paper_final_020516.pdf

U.S. Environmental Protection Agency. 2017. SAB review of EPA's proposed methodology for updating mortality risk valuation estimates for policy analysis. EPA-SAB-2017-005. https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=P100ROQR.TXT

U.S. Office of Management and Budget. 2003. Circular A-4: Regulatory Analysis. http://www.whitehouse.gov/omb/inforeg_regpol_agency_review/

van den Borst B., Peters J.B., Brink M., Schoon Y., Bleeker-Rovers C.P., Schers H., et al. Comprehensive health assessment three months after recovery from acute COVID-19. 2020. *Clinical Infectious Diseases.* doi: 10.1093/cid/ciaa1750.

van Hoek, A. J., Underwood, A., Jit, M., Miller, E., & Edmunds, W. J. 2011. The impact of pandemic influenza H1N1 on health-related quality of life: a prospective population-based study. *PLOS ONE* 6(3): e17030.

Van Houtven, G., Sullivan, M.B., & Dockins, C. 2008. Cancer premiums and latency effects: A risk tradeoff approach for valuing reductions in fatal cancer risks. *Journal of Risk and Uncertainty* 36: 179–199.

Van Houtven, G., Powers, J., Jessup, A., & Yang, J. C. 2006. Valuing avoided morbidity using meta-regression analysis: what can health status measures and QALYs tell us about WTP? *Health Economics* 15(8): 775–795.

Vincent, J.-L., & Taccone, F. S. 2020. Understanding pathways to death in patients with COVID-19. *The Lancet Respiratory Medicine* 8(5): 430–432.

Viner, R. M., & Whittaker, E. 2020. Kawasaki-like disease: emerging complication during the COVID-19 pandemic. *The Lancet* 395(10239):1741–1743.

Viscusi, W. K. 2004. The value of life: estimates with risks by occupation and industry. *Economic Inquiry* 42(1): 29–48.

Viscusi, W. K. 2009. Valuing risks of death from terrorism and natural disasters. *Journal of Risk and Uncertainty* 38(3): 191–213.

Viscusi, W. K. 2013. Using data from the census of fatal occupational injuries (CFOI) to estimate the 'value of a statistical life'. *Monthly Labor Review*. Bureau of Labor Statistics.

Viscusi, W. K. 2015. The role of publication selection bias in estimates of the value of a statistical life. *American Journal of Health Economics* 1(1): 27–52.

Viscusi, W. K., & Aldy, J. E. 2007. Labor market estimates of the senior discount for the value of statistical life. *Journal of Environmental Economics and Management* 53(3): 377–392.

ED_006573_00001315-00070

Viscusi, W. K. & Evans, W. N. 1990. Utility functions that depend on health status: estimates and economic implications. *The American Economic Review* 80(3): 353–374.

Viscusi, W. K., Huber, J. & Bell, J. 2014. Assessing whether there is a cancer premium for the value of a statistical life. *Health Economics* 23(4): 384–396.

Viscusi, W. K., W. A. Magat, & J. Huber. 1991. Communication of ambiguous risk information. *Theory and Decision* 31(2-3): 159–173.

Viscusi, W. K. & Masterman, C. J., 2017. Income elasticities and global values of a statistical life. *Journal of Benefit-Cost Analysis* 8(2): 226–250.

Whittaker, E., Bamford, A., Kenny, J., Kaforou, M., Jones, C. E., Shah, P., et al. 2020. Clinical characteristics of 58 children with a pediatric inflammatory multisystem syndrome temporally associated with SARS-CoV-2. *JAMA* 324(3): 259–269.

Wiersinga, W. J., Rhodes, A., Cheng, A. C., Peacock, S. J., & Prescott, H. C. 2020. Pathophysiology, transmission, diagnosis, and treatment of Coronavirus Disease 2019 (COVID-19): a review. *JAMA*. doi:10.1001/jama.2020.12839.

Woolf, S. H., Chapman, D. A. & Lee, J. H. 2021. COVID-19 as the Leading Cause of Death in the United States. *JAMA 325*(2): 123–124.

World Health Organization. 2020. Report of the WHO-China joint mission on coronavirus disease 2019 (COVID-19). Geneva, Switzerland. https://www.who.int/docs/default-source/coronaviruse/who-china-joint-mission-on-covid-19-final-report.pdf

Wu, D., Chaiyakunapruk, N., Pratoomsoot, C., Lee, K., Chong, H., Nelson, R., et al. 2018. Cost-utility analysis of antiviral use under pandemic influenza using a novel approach–linking pharmacology, epidemiology and heath economics. *Epidemiology & Infection* 146(4): 496–507.

Wu, Z., & McGoogan, J. M. 2020. Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China: summary of a report of 72 314 cases from the Chinese Center for Disease Control and Prevention. *JAMA* 323(13): 1239–1242.

ED_006573_00001315-00071