

ARTICLE

# Mask Mandate Costs

Patrick Carlin<sup>1</sup>, Shyam Raman<sup>2</sup>, Kosali Simon<sup>3</sup>, Ryan Sullivan<sup>4</sup> and Coady Wing<sup>3</sup>

<sup>1</sup>Washington State University, Pullman, WA, USA

<sup>2</sup>Williams College, Williamstown, MA, USA

<sup>3</sup>Indiana University Bloomington, Bloomington, IN, USA

<sup>4</sup>Naval Postgraduate School, Monterey, CA, USA

**Corresponding author:** Ryan Sullivan; Email: [rsulliv@nps.edu](mailto:rsulliv@nps.edu)

**Keywords:** masking; mask mandate costs; VSL; benefit-cost analysis; COVID-19

**JEL Codes:** H0; I0

## Abstract

Mask mandates were controversial policies during the pandemic. Although there is considerable research on the benefits of masks, there has been no research on the distribution of perceived costs of compliance with mask mandates. This article presents the results from a hypothetical set of questions related to mask-wearing behavior and opinions that were asked of a nationally representative sample of over 4,000 participants in early 2022. We use survey valuation methods to assess how much participants would be willing to pay to be exempted from rules of mandatory community masking. The survey asks specifically about a 3-month exemption. We find that the majority of respondents (56%) are not willing to pay to be exempted from mandatory masking. However, the average person was willing to pay \$525, and a small segment of the population (0.9%) stated they were willing to pay over \$5,000 to be exempted from the mandate. Younger respondents stated higher willingness to pay to avoid the mandate than older respondents. Combining our results with standard measures of the value of a statistical life, we estimate that a 3-month masking order was perceived as cost-effective through willingness to pay questions only if at least 13,333 lives were saved by the policy.

## 1. Introduction

Government mandates requiring people to wear a mask in various settings, such as stores, schools, workplaces, and airplanes, have been one of the most controversial public health regulations of the COVID-19 pandemic (Scoville *et al.*, 2022). Mask mandates were widespread: at least 39 state governments imposed a mask mandate of some type at some time during the pandemic (Markowitz, 2023). Among health officials and researchers, most of the debate has centered around whether and how much masks and mask mandates generate public health benefits (Centers for Disease Control and Prevention, 2021; Jefferson *et al.*, 2023). In contrast, there is comparatively little discussion of the costs of complying with mask mandates to understand actual masking behavior, and no prior research that tries to estimate the overall social costs of mask mandates.

One explanation for the lack of research on the social costs of masking is that it may seem self-evident that the costs of a mask mandate are essentially zero or are at least much smaller than the benefits of masking. However, if mask wearing is perceived as completely cost free by mask wearers, a mandate would not be needed. The need for a mandate may hold under an assumption that the costs are due solely to misinformation. Common economic tools of survey valuation methods can help to clarify the situation by assessing net perceived benefits. Standard arguments about allocative efficiencies can also be applied; compliance costs may vary across people and situations, and a mandate is generally a blunt tool that does little to achieve the benefits from an action at the lowest societal costs possible.

The lack of research on the costs of such a large government policy is surprising and departs from standard practice. Longstanding federal guidelines recommend the use of formal benefit–cost techniques to evaluate the appropriateness of government health interventions and regulations (US Department of Health and Human Services, 2016; Circular A-4, 2023). Despite these requirements, no regulatory analysis has been completed for mandatory masking orders<sup>1</sup>.

In this article, we present the first research on the costs of mandatory masking orders in the United States. We collected survey data from more than 4,000 respondents using the survey platform Lucid. The survey was in the field from 16 to 24 February 2022, and it collected detailed demographic information as well as information about beliefs related to masks and mask mandates. We use stated preference methods (i.e., open-ended questions and discrete choice experiments) that are standard in the benefit–cost analysis (BCA) literature to shed light on the costs of mask mandates, including both direct questions about willingness to pay (WTP) to be exempt from a mandate for 3 months and the specific reasons for not wanting to wear a mask.

We find that 56% of respondents stated they would be willing to pay \$0 to be exempt from a 3-month masking mandate. In contrast, the weighted average WTP estimate for an exemption in the survey is \$525, indicating the cost of mask mandates is borne by a minority of the population. We find substantial differences across age groups with 18–29 year olds in our survey willing to pay on average over \$1,200 to be exempt from the masking mandate and the elderly (65+ year olds) willing to pay on average only about \$50. In addition, we find parents are willing to pay just over \$800 on average for each of their children to be exempt from mask mandates in school settings. The top reasons listed for not wanting to wear a mask were difficulties breathing (48%) and discomfort (45%), followed by difficulties in socializing, including not being verbally understood (36%) and missing facial expressions (28%).

We use these estimates of WTP for an exemption to calculate break-even values for the number of lives that would need to be saved for a 3-month mask mandate to be cost-effective. We use value per statistical life (VSL) estimates from the literature to monetize the value of mortality reductions due to masks. Our WTP for exemption estimates imply that a 3-month masking order in the United States has a total cost of roughly \$164 billion. Given this cost estimate and using the Health and Human Services (HHS) VSL of \$12.29 million (US \$2022), the mask mandate would need to save 13,333 lives over a 3-month period to be cost-effective.

<sup>1</sup> Executive Order 12866 requires agencies to submit a formal regulatory impact analysis for any regulations that are considered “economically significant” (i.e., any regulation that has an annual impact of \$100 million or more). Masking policies occurred mainly at the state level and thus were not subject to this formal requirement.

While the focus of this study is on mask mandate costs, we also provide a literature review on the benefits of masking to place our results on cost in the appropriate context. In general, the observational studies in the literature indicate masking reduces COVID-19 infection rates by roughly 70%–80% (Centers for Disease Control and Prevention, 2021). In contrast, the randomized controlled trial (RCT) studies show masking reduces infection rates by only 0%–10% (Jefferson *et al.*, 2023). For the purposes of a formal BCA on mask mandates, the cost-effectiveness of a mask mandate depends upon which studies are used to determine the benefits side of the equation. During the time period we study, using the benefit estimates from most of the observational studies would suggest a nationwide masking mandate would be considered cost-effective. Using the results from the RCT studies would suggest the opposite.

There are some limitations to our work worth noting. First, our results are from a stated preference framework based on hypothetical scenarios. These are not revealed preferences estimates, in other words. Second, our estimates reflect the behaviors of early 2022. The costs could vary over time, so extrapolating to other periods should be done cautiously. Third, although we ask respondents reasons for their WTP for a mask exemption, we cannot say how much each reason contributes to the cost. Nonetheless, this article presents the first estimates of the costs of mask mandates and highlights important demographic differences in WTP, making progress toward a complete BCA.

## 2. Data collection

### 2.1. Survey data collection

We recruited respondents with the assistance of Lucid, a survey recruitment firm that leverages quota-based sampling to provide demographically representative samples of people in the United States (Berinsky *et al.*, 2012). Prior work has shown randomized experimental effects are comparable to those in national probability surveys (Coppock & McClellan, 2019).

Our survey sample was restricted to respondents who were Americans aged 18 years and older. In total, 4,465 American adults were contacted, and 4,060 were successfully recruited to complete an internet-based survey. The survey took about 10 minutes to complete. It mainly focused on the topic of masks and mask mandates but also collected basic demographic and social information.

We developed survey weights to help ensure that our survey sample was representative of the US adult population along several dimensions. To construct the weights, we obtained the 2019 American Community Survey (ACS) and limited the sample to adults (18+). We formed a stacked data file by vertically concatenating the ACS file with our survey data. In the stacked data file, let  $A_i$  be a dummy variable indicating that person was drawn from the ACS data rather than the Lucid sample. And let  $X_i$  be a vector of harmonized demographic covariates that appear in both the ACS and Lucid samples. We fit logistic regression models of ACS membership ( $A_i$ ) on covariates ( $X_i$ ). We used the coefficients to compute the predicted probability that each person belonged to the ACS sample. The survey weight is  $w_i = \hat{p}_i / (1 - \hat{p}_i)$ , where  $\hat{p}_i$  is the predicted probability for person  $i$ . Weighting the Lucid data by  $w_i$  helps align the distribution of covariates  $X_i$  in the Lucid sample with the distribution of  $X_i$  in the US adult population<sup>2</sup>.

<sup>2</sup> This procedure is similar to the one used in Carlin *et al.* (2022).

**Table 1.** Descriptive statistics

Variable	Weighted means	Raw means	ACS
Age 18–29	0.20	0.20	0.19
Age 30–44	0.25	0.27	0.24
Age 45–64	0.30	0.31	0.31
Age 65+	0.21	0.17	0.21
Female	0.51	0.52	0.51
Asian	0.06	0.04	0.06
Black	0.11	0.11	0.12
White	0.65	0.68	0.63
Hispanic	0.16	0.13	0.16

*Note:* The first column shows the demographic variable, the second column shows the weighted mean in our survey sample with the weights calculated as shown in Section 2.1, the third column shows the raw means in our survey sample with no weighting; and the fourth column shows the means from the American Community Survey, which uses the weighting procedure described by the Census Bureau (2010).

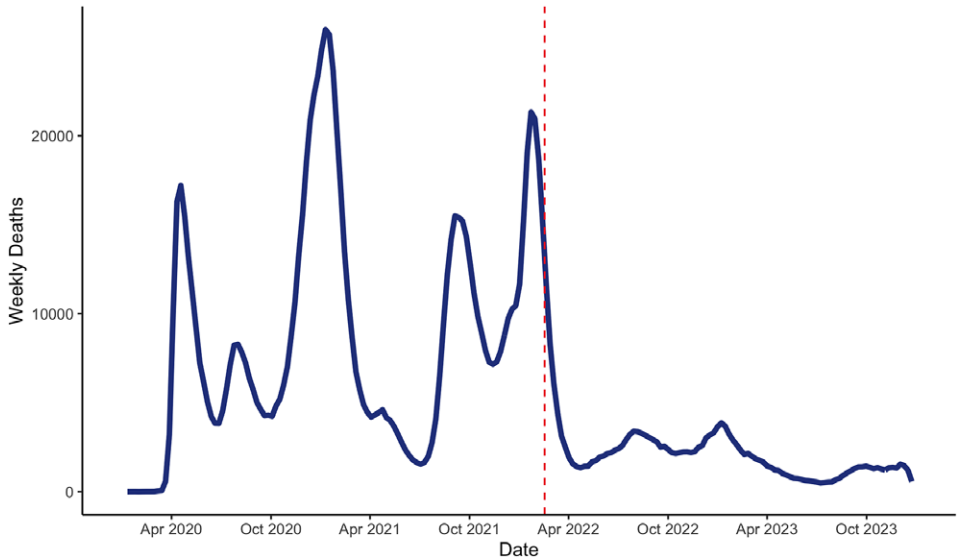
Table 1 shows the descriptive statistics for a collection of social, demographic, and political characteristics of the raw Lucid sample, weighted Lucid sample, and the ACS population benchmark. Even without the weights, the composition of the Lucid sample is very similar to the composition of the US adult population in terms of gender, race-ethnicity, and age distribution.

Our survey was in the field from February 16 to 24 2022, which corresponds to the end of the Omicron surge in early 2022. Figure 1 shows that COVID-19 deaths were declining at the time of the survey. COVID-19 deaths had a (local) peak of 21,322 weekly deaths in late January and continued to fall until April 2022. There were 11,563 COVID-19 deaths during the week of 19 February, which was the midpoint of our survey window. By early March, COVID-19 deaths were around 6,000 per week, and by early April 2022 were down to just under 2,000 per week.

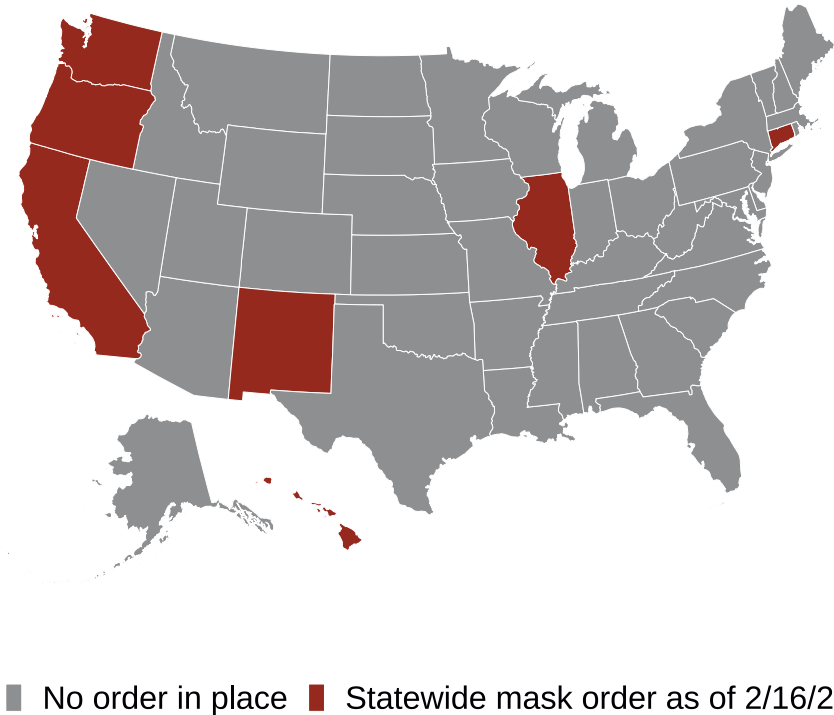
Given the decline in COVID-19 deaths, many states started to eliminate their statewide mask mandates in early 2022. Figure 2 shows the distribution of state mask mandates across the country as of 16 February 2022. Seven states (Hawaii, Oregon, Washington, California, Illinois, Connecticut, and New Mexico) had statewide mask mandates in place at the start of our survey. Four other states (Delaware, Rhode Island, Nevada, and New York) had only recently ended their statewide mask mandates in early February 2022. Therefore, mask mandates were fresh in the minds of participants, and a substantial minority of respondents were still under a mandate at the time of the survey (Ballotpedia, 2022). All 50 states had officially rescinded their statewide mask mandates by April 2022.

## 2.2. WTP to avoid a mask mandate

To understand the costs of mask mandates and how they are distributed across members of the population, we developed two stated preference strategies to measure how much people would be willing to pay to avoid or be exempt from a mask mandate. Although paying a fee to be excluded from a requirement that applies to other people was not a proposed policy option in any state that we know of, this hypothetical situation speaks to an individual net cost of compliance. Such opt-out fees are used in other contexts; for example, people



**Figure 1.** Weekly COVID-19 deaths as reported by the CDC. The data were downloaded from the CDC's COVID tracker. The dashed red line shows when respondents answered the survey.



**Figure 2.** Map of mask mandates. The *states* highlighted in red had a mask order in place during the time of our survey according to Ballotpedia (2022). The gray states had either repealed their mask mandates or never implemented a mandate.

routinely pay more to avoid time-consuming and inconvenient security procedures at airports using programs like TSA pre-check that conduct extra screening at the time of enrollment (Viscusi & Zeckhauser, 2003). In the environmental policy context, tradable emission permits essentially provide a way for some firms to emit additional pollutants through the purchase of a permit, and, in some settings, businesses can purchase permits that allow them to exceed noise level regulations. In its original form, the Affordable Care Act was designed to an insurance coverage requirement for all adults but allowed people to remain uninsured if they paid a particular fine/tax. During the Civil War, people were allowed to purchase a personal exemption from the military draft for \$300 (Earnhart, 1966).

Our first elicitation method is based around open-ended responses to direct questions about WTP. These measures are appealing because they provide concrete and person-specific answers to questions about how people seem to perceive the net benefits of complying with a mask mandate and how many people consider the net benefits to be negative. However, open-ended elicitation methods are sometimes criticized because respondents may give unrealistic answers to novel hypothetical questions (Hausman, 2012). In essence, one might worry that people are “inventing” a WTP number rather than accurately reporting their valuation of an available option. Thus, our second elicitation method is based on randomized price offerings in a discrete choice experiment. These measures are perhaps less subject to the “inventing a number” concern, although they too represent a hypothetical scenario and not an actual revealed preference action.

### 2.2.1. Open-ended responses

We started by asking open-ended questions about how much people would be willing to pay to be personally exempt from a mask mandate. We presented all respondents with the option to pay to be personally exempt from a mask mandate for a period of 3 months. In addition, we presented parents with another option to pay for their child to be exempt from a school mask mandate for a period of 3 months. The exact wording of the questions is as follows:

- What is the maximum amount you would pay to be personally exempt from a mask mandate over the next 3 months?
- What is the maximum amount you would pay per child for them to be personally exempt from a mask mandate in schools over the next 3 months?

The raw survey results included some implausible responses, including one respondent who claimed to be willing to pay over \$1 billion for an exemption. In our main analysis, we top-coded responses at \$10,000.

### 2.2.2. Discrete choice experiments

We also measured WTP to be exempt from a mask mandate using randomized price offerings in a discrete choice experiment. In the experiment, respondents were presented with a short vignette explaining a mask mandate policy and an opportunity to opt out in return for a fee.

Respondents were randomly assigned to a price offering and then were asked if they would pay to opt out of the mandate at the randomly assigned price.

The exact wording of the vignette is:

Current projections show that over the next 3 months, we can expect an additional 31,946 COVID-19 deaths in the United States. Given there are approximately 330 million Americans, this translates to a COVID-19 fatality rate of 9.68 per 100,000 people over the course of this time period. Suppose there was a mask mandate law that is expected to be in place for the next 3 months. Let us say, for a hypothetical fee, you could pay to be exempt from the mandate. Therefore, you would not be legally obligated to wear a mask during this 3-month time period (if you pay this fee). If the out-of-pocket fee was  $\$X_j$ , would you choose to pay the fee to not be legally required to wear a mask?

For each respondent, the value of  $\$X_j$  was randomly assigned to one of the following prices: \$10, \$50, \$150, \$500, \$1,000, and \$3,000.

For all respondents who indicated that they were parents of school-aged children, we followed up with another hypothetical scenario. In this case, the hypothetical fee would exempt their children from mask mandates in schools. The exact wording is:

Suppose there was a mask mandate law for all schools which is expected to be in place for the next 3 months. Let us say, for a hypothetical fee, you could pay for your child or children to be exempt from the mandate. Therefore, your children would not be legally obligated to wear a mask in school during this 3-month time period (if you pay this fee). If the out-of-pocket fee was  $\$X_j$  per child, would you choose to pay the fee for them to not be legally required to wear a mask in their school?

As before, each respondent was presented with a randomly assigned price offering drawn from: \$10, \$50, \$150, \$500, \$1,000, and \$3,000.

### 3. Empirical strategy and results

#### 3.1. Mask mandate costs by subpopulation and COVID-19 beliefs and experiences

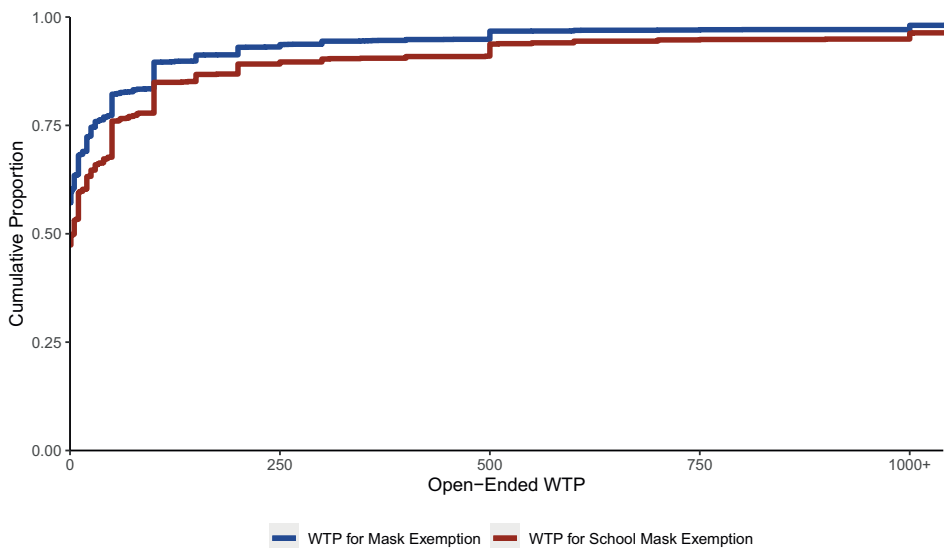
We measure WTP for an exemption to a mask mandate by comparing average and median response to the open-ended elicitation by age group. Table 2 reports the mean and median WTP for personal exemption as well as the mean and median for parental WTP to exempt children from school mask mandates. In both cases, the distribution of WTP is right skewed. The modal WTP was zero and the median is much lower than the mean. Average and median WTP decline with age, consistent with the idea that the perceived net benefits of compliance are lower for younger people. We also present the distribution of WTP using a CDF as in Figure 3. This shows the stated WTP for an exemption for both the general mask mandate and the school mask mandate<sup>3</sup>. There was a slightly higher WTP for the school mask mandate exemption, but both show that most of the cost are from a smaller, younger portion of the population. Further, both show approximately 50% of respondents reporting they were not willing to pay for the exemption and approximately 1% willing to pay  $\geq \$5000$  for the exemption.

<sup>3</sup> We also asked parents their WTP for an exemption for all school-aged children rather than just their own children. This number was even higher with an average value of \$1,165. As a comparison, this value is roughly 44% than the value shown in Table 2. However, for comparability to the personal mandate, we only include WTP for respondents' children exemptions in the analysis.

**Table 2.** Average and median WTP for exemption by age group

Age group	Average	Median
18–29	1258.58	4.00
30–44	595.63	0.55
45–64	120.59	0.00
65p	49.59	0.00
Children	809.70	4.00

Note: The first column shows the age group, which includes parents answering on behalf of school-aged children. The second column presents the weighted average of WTP with responses top-coded at \$10,000. The third column presents the median WTP.



**Figure 3.** Cumulative density plot of open-ended WTP. The blue line shows the CDF of open-ended WTP for an exemption to a general mask mandate. The red line shows the CDF of open-ended WTP for an exemption to a mask mandate in schools. Only those who responded that they had school-aged children were asked about WTP for an exemption to a mask mandate in schools.

It is also possible that the perceived net benefits of complying with a mask mandate may depend on a person’s subjective beliefs and experiences related to the pandemic. Indeed, recent work has argued that demand for the COVID-19 vaccine may exhibit “internalities” rooted in misperceptions, false beliefs, or other forms of behavioral hazard (Carlin *et al.*, 2022). It is possible that these factors may also help explain variation across people in the perceived benefits and costs of wearing a mask and complying with a mask mandate. Our survey instrument included questions related to a person’s experience with the COVID-19 pandemic:

- Do you personally know anyone who has tested positive for COVID-19 (including yourself)? Who has tested positive? Select all that apply. (1) You (2) Immediate family



(3) More distant family members (4) Close friends (5) More distant friend(s) or acquaintances

- Do you personally know anyone who has died due to complications from COVID-19? (1) Yes (2) No
- Please select from below what best describes your COVID-19 vaccination status. (1) I have not chosen to receive the COVID-19 vaccine (2) I have received a COVID-19 vaccine but not a booster (3) I have received a COVID-19 vaccine and booster

In addition to these questions about COVID-19 experiences, we also asked respondents to describe their beliefs about their own COVID-19 fatality risk and about how much wearing a mask would affect it. These items began with the following prompt providing aggregate information about overall COVID-19 mortality projections at the time of the survey:

Current projections show that over the next 3 months, we can expect an additional 31,946 COVID-19 deaths in the United States. Given there are approximately 330 million Americans, this translates to a COVID-19 fatality rate of 9.68 per 100,000 people over the course of this time period.

Following the prompt, respondents were asked:

- If you had to state specifically what your COVID-19 fatality risk is over the next 3 months, what would it be? (as a reminder, the average person's projected COVID-19 fatality risk over the next 3 months is 9.68 per 100,000):
- If you choose to consistently wear a mask over the next 3 months, by how much do you believe that would reduce your personal COVID-19 fatality risk? (as a reminder, the average person's projected COVID-19 fatality risk over the next 3 months is 9.68 per 100,000):

To study the way WTP for a 3-month exemption from a mask mandate depends on demographics, experiences, and beliefs, we fit the following regression model using ordinary least squares (OLSs):

$$WTP_i = D_i\alpha + E_i\delta + B_i\theta + u_i \quad (1)$$

The results from these models are presented in [Tables 3 and 4](#) for WTP for general mask mandates and school mask mandates, respectively. Self-reported fatality risks and vaccination status do not significantly impact the stated WTP. Likewise, there is no evidence that females or those with school-aged children have different WTPs. The results by race are mixed. There is some evidence that Black and Other race respondents have lower WTPs than White respondents. However, this result is only for the full model in the third column. Meanwhile, there is more consistent evidence that all other races have lower WTP for school mask mandate exemptions than White respondents. The most consistent result is that age is an important factor for determining WTP, although not all of the coefficients are significant in all the models. In the Model 3 in [Table 3](#), those aged 45–64 have \$192 higher WTP than those aged 65+; those aged 30–44 have \$987 higher WTP than those aged 65+; and those aged 18–29 have \$1163 higher WTP than those aged 65+. These regressions do not represent a causal analysis but can point to important determinants for WTP. In the following sections, we show that age does indeed appear to be an important factor in determining costs of mask mandates.

**Table 3.** Descriptive regressions for general mask mandate exemption

	Model 1	Model 2	Model 3
Self-fatality risk		0.001 (0.002)	0.000 (0.002)
Fatality risk w/ mask		0.948 (3.461)	0.806 (3.488)
Fully boosted		269.254 (237.160)	402.276 (246.004)
Asian	718.634* (388.133)		964.615** (431.526)
Black	142.141 (303.756)		−470.205 (406.970)
Hispanic	38.513 (259.769)		−94.430 (330.079)
Other race	−154.280 (580.168)		−449.417 (855.528)
Female	27.085 (178.795)		13.338 (217.117)
School-aged children	225.732 (223.190)		−291.747 (288.248)
Age 18–29	1118.446*** (293.288)		1176.477*** (375.104)
Age 30–44	379.410 (289.298)		992.184*** (356.606)
Age 45–64	20.555 (255.097)		205.356 (279.374)
Intercept	−1.638 (220.457)	252.021 (255.425)	−253.283 (358.768)
Observations	3967	2311	2311

\* $p < 0.1$ .

\*\* $p < 0.05$ .

\*\*\* $p < 0.001$ .

\*\*\*\* $p < 0.01$ .

*Note:* The dependent variable is the open-ended stated WTP for an exemption to a general mask mandate. Model 1 includes demographic variables. Model 2 includes self-assessed COVID risks. Model 3 includes both. White and 65+ are the reference race and age categories.

### 3.2. Break even analysis

US Department of Health and Human Services (2016) and Circular A-4 (2023) provide the standard guidelines for practitioners to use when completing BCAs for federal health regulations. As discussed in these documents, a typical BCA should discount the future stream of benefits and cost of a regulation by using an appropriate discount rate. The net present value (NPV) calculation should then be compared to any alternative courses of action. Policymakers can then decide the proper policy decision based on the estimates provided in the BCA.

Formally, the NPV of a mask mandate is given the following:

**Table 4.** Descriptive regressions for school mask mandate exemption

	Model 1	Model 2	Model 3
Self-fatality risk		0.001 (0.003)	0.000 (0.003)
Fatality risk w/ mask		−0.846 (6.423)	−3.397 (6.560)
Fully boosted		359.641 (401.440)	385.367 (410.135)
Asian	−932.300 (923.357)		−823.997 (749.561)
Black	−893.842 (699.292)		−558.398 (654.795)
Hispanic	164.923 (610.281)		−683.626 (531.157)
Other race	−764.434 (1350.433)		−553.770 (1526.339)
Female	−562.452 (455.937)		−473.612 (402.276)
Age 18–29	1494.118 (1438.065)		655.775 (1171.352)
Age 30–44	967.522 (1352.916)		962.945 (1035.137)
Age 45–64	254.143 (1381.813)		115.619 (1047.442)
Intercept	455.174 (1333.868)	147.053 (421.759)	−91.068 (1087.539)
Observations	1042	514	514

<sup>†</sup>p < 0.1.

\*p < 0.05.

\*\*p < 0.01.

\*\*\*p < 0.001.

*Note:* The dependent variable is the open-ended stated WTP for an exemption to their child's school mask mandate. This was only asked if the respondent indicated that they had a school-aged child in the house. Model 1 includes demographic variables. Model 2 includes self-assessed COVID risks. Model 3 includes both. White and 65+ are the reference race and age categories.

$$NPV = \sum_{t=0}^n \frac{Benefits_t - Cost_t}{(1+r)^t} \quad (2)$$

In the equation, *NPV* is the net present value of the mask mandate, *Benefits<sub>t</sub>* is the monetized value of the benefits of the mask mandate in time period *t*, *Cost<sub>t</sub>* is the monetized value of the costs of the mask mandate in time period *t*, *n* is the number of time periods, and *r* is the discount rate. The summation of the net benefits, discounted over all time periods calculates the *NPV* of the mask mandate.

In the case where calculating the benefits for a policy is difficult or uncertain, researchers may use break-even analysis as a substitute for a standard BCA (Sunstein, 2020). Given the uncertainty of the estimates in the benefits of masking literature (Centers for Disease Control

**Table 5.** Three-month mandatory masking break-even analysis

Panel A: Three-month mandatory masking order exemption cost

	5–17	18–29	30–44	45–64	65+	Total
Average willingness to pay to be exempt	\$809.70	\$1,258.58	\$595.63	\$120.59	\$49.59	\$524.73
Population (in millions)	54.40	54.08	65.35	83.92	54.53	312.28
Total exemption cost (in millions US\$2022)	\$44,047	\$68,064	\$38,924	\$10,120	\$2,704	\$163,863

Panel B: VSL estimates and break-even values

	COVID age-adjusted VSL \$5.16 million (US\$2022)	HHS VSL \$12.29 million (US\$2022)
Break-even lives needed to be saved <sup>a</sup>	31,756 lives	13,333 lives
Comparison number of lives lost due to COVID–19 <sup>b</sup>	30,497 COVID deaths	30,497 COVID deaths

<sup>a</sup>For a 3-month mandatory masking order to be cost-effective (total exemption cost of \$163,863 million/VSL).

<sup>b</sup>During the 3-month time period after the survey (March–May 2022).

and Prevention, 2021; Jefferson *et al.*, 2023), we use a break-even analysis format to provide cutoff values for the number of lives needed to be saved for a mask mandate to be considered cost-effective.

We make several assumptions in the break-even framework. First, we assume that the number of prevented deaths due to the mask mandate is the only category to consider for the benefits calculation.<sup>4</sup> Each of these prevented deaths is valued at \$12.29 million (US\$2022) as recommended in the US Department of Health and Human Services (2016) guidelines. Second, we assume the benefits and cost of the mandate do not go past the 3-month time period we study. Third, we assume a discount rate of zero in all of our calculations, which simplifies the calculation and is reasonable over a short horizon. Therefore, we are left with the following equation for our break-even analysis:

$$NPV = VSL \times PD - Cost \quad (3)$$

In this representation, *NPV* is the net present value of the mask mandate, *VSL* is a value of \$12.29 million per statistical life, *PD* is the number of prevented deaths due to implementing the mask mandate, and *Cost* is the overall cost of the mask mandate. If the value of the prevented deaths due to the mask mandate is greater than the cost, then the implementation of the masking order would be considered cost-effective since the *NPV* is greater than zero. If the opposite is true, then the masking order would not be considered cost-effective. We use average WTP estimates to be exempt from mask mandates to approximate the overall cost on society. Table 5 highlights these results.

<sup>4</sup> Other benefits may come into play in a more detailed model. For example, the prevention of non-fatal infections could be considered an additional benefit of masking orders. We discuss these considerations and how they may impact our results in Section 3.2.2.

Panel A in Table 5 displays cost estimates across different age groups for a 3-month mask mandate in the United States at the end of the Omicron surge in early 2022. The older adult (65+ year olds) age group has the lowest WTP estimate, with an average value of roughly \$50 willing to be paid to be exempt from the mandate. The next lowest is the 45–64 age group with an average WTP estimate of \$121, \$596 for the 30–44 age group, and \$1,259 for the youngest (18–29 year olds) adult age group. Parents answering on behalf of children (5–17 year olds) have an average WTP estimate of \$810. The weighted average WTP estimate across all age groups (children and adults) is \$525.

In order to provide an overall cost estimate, we multiply the average WTP estimates by age group with their respective Census population totals. Using this method, we find that the overall mask mandate cost for school-aged children (5–17 year olds) is around \$44 billion. For the adult population age groups, we find costs are \$68 billion for the 18–29 age group, \$39 billion for 30–44 year olds, \$10 billion for 45–64 year olds, and \$3 billion for the elderly. The aggregate cost total for all age groups is \$164 billion.<sup>5</sup>

Panel B in Table 5 provides break-even values to estimate the number lives that would need to be saved for a 3-month mask mandate to be considered cost-effective. To provide these break-even estimates, we divide the overall mandate cost of \$164 billion (as calculated in Panel A) by two separate VSL estimates. Our primary results use the HHS VSL of \$12.29 million (US\$2022) as the basis for its analysis. Using this value, we find at least 13,333 lives would need to be saved for a nationwide mask mandate to be considered cost-effective.

As a sensitivity analysis in Panel B in Table 5, we analyze how the results might change by using an age-adjusted VSL. The literature has shown COVID-19 deaths have been largely concentrated in the elderly population and adjusting for this factor can lower the VSL by roughly half (Robinson *et al.*, 2021; Viscusi, 2021).<sup>6</sup>

<sup>5</sup> Notably, our cost estimates do not include the cost of mandatory masking for the 2- to 4-year-old age group, even though mandatory masking was required for this age group in many areas of the country. The Census numbers state that this age group consists of 11.74 million children. Assuming the 2–4 year olds have the same cost as the 5–17 year olds (\$809.70 per child on average), then including the 2–4 year olds in the final cost estimate would increase the overall cost by \$9.506 billion. Therefore, the final cost estimate would increase to roughly \$173 billion (in contrast to the \$164 billion as shown in Table 5).

<sup>6</sup> There is a large literature on adjusting VSL estimates by age (Kniesner *et al.*, 2006, 2022; Murphy & Topel, 2006; Viscusi & Aldy, 2007; Aldy & Viscusi, 2008; Viscusi, 2018, 2020a, 2020b, 2021). The two primary methods for adjusting the VSL by age include: (1) a constant VSLY approach and (2) an inverse-U method. The constant VSLY approach is calculated by dividing the central VSL estimate by the discounted life expectancy at the average age of those being studied. Then, the analyst multiplies this constant value by the discounted life expectancy for each age group and weight by the number of deaths in each age group (Robinson *et al.*, 2021). The inverse-U method uses empirical data to determine the VSL as broken down by different age groups (Aldy & Viscusi, 2008). This method typically uses labor market data by age groupings to estimate the VSL via wages regressed on fatality risk while controlling for other factors in the analysis (e.g., job type, gender, race, etc.). As a comparison, Robinson *et al.* (2021) found using the constant VSLY approach for COVID-19 deaths lowers the VSL by 58% and the inverse-U results in a decrease in the VSL by 22%. Even though, there have been advocates for adjusting the COVID-19 VSL by age (Allen, 2022), others provide contrarian views on age adjustments. As Kniesner *et al.* (2022) note, “the estimated VSL in the United States for people aged 55–62 is not materially different than for those aged 18–25” using the inverse-U method. Furthermore, there have been public outcries by senior citizen groups in the past over utilizing a senior VSL discount (e.g., see the debate over the Clear Skies Initiative for details). These types of issues have resulted in most analyses not using an age-adjusted VSL in regulatory affairs.

For our sensitivity analysis, we use the COVID-19 age-adjusted VSL of \$5.16 million (US\$2022) per statistical life from Robinson *et al.* (2021) in the analysis.<sup>7</sup> Using this age-adjusted VSL estimate, we find at least 31,756 lives would need to be saved for a 3-month mask mandate to be considered cost-effective.

As a comparison, the CDC reports that 30,497 lives were lost due to COVID-19 during the 3-month follow-up time period for our survey. Therefore, the age-adjusted results suggest the number of lives saved from a nationwide mask mandate would need to be roughly 104% of the COVID-19 deaths during the same time period in order to pass a benefit–cost test. Using the HHS VSL of \$12.29 million suggests roughly 44% of the number of COVID-19 deaths would need to be saved for a 3-month mandate to be considered cost-effective.

### 3.2.1. BCA and the benefits of masking literature

The last section details the break-even values for determining the cost-effectiveness of a nationwide masking mandate. The primary results indicate at least 13,333 lives (or roughly 44% of the COVID-19 deaths during this 3-month time period) would need to be saved for a mandate to be considered cost-effective. This begs the question: Would a 3-month mandate pass a standard BCA test? The answer to that question is uncertain and largely depends on how one interprets the benefits of masking literature.

The literature on the benefits of masking literature has produced a wide range of estimates showing large benefits to no benefits and even negative effects. The precision of the estimates depends upon a large number of factors including the population studied, location, time period, data, and methodology.

On the pro-masking side, the Centers for Disease Control and Prevention (2021) lists 18 separate studies detailing the benefits of masking. Out of these 18 studies, one was a cluster-randomized trial, three were cohort studies, one was a case–control study, one was a population-based intervention, one used a serial cross-sectional survey design, nine were population-based intervention studies with trend analysis, and two used counterfactual modeling with national data.

The study showing the largest benefit of masking from the CDC list is Hendrix (2020). The Hendrix study analyzes universal masking in a hair salon setting in Springfield, MO, in the early stages of the COVID-19 pandemic. It shows no COVID-19 symptoms were identified among the 139 (masked) clients or their secondary contacts in follow-up testing even though they were serviced by two (masked) symptomatically infected stylists – essentially showing a 100% prevention rate when masking. Other studies discussed by the CDC also show large benefits to masking (often in the 70%–80% effectiveness range).

For example, Doung-Ngern *et al.* (2020) conducted a case–control study that included 211 cases of COVID-19 and 839 controls in Thailand in April–May 2020. They find always wearing a mask reduces infection by 77%. A cohort study by Payne *et al.* (2020) analyzed the impact of mask wearing (self-reported) on infections for 382 U.S. Navy service members aboard the USS Theodore Roosevelt in late March 2020. They find masking reduced the risk of infection by 70%. Another example listed by the CDC is the retrospective cohort study by

<sup>7</sup> We updated the original \$4.47 million (US\$2019) age-adjusted VSL using the constant value per statistical life-year approach from Robinson *et al.* (2021) for inflation and earnings using a 1.0 income elasticity.

Wang *et al.* (2020) that analyzed 335 people in 124 families and with at least one laboratory confirmed COVID-19 case. That study was conducted in February–March 2020 in China and showed masking reduced the risk of secondary infection by 79%. These are just some of the studies listed by the CDC that document the benefits of masking. In summary, the CDC generally promotes the use of masking due to these influential studies, except in the case of low-risk time periods or activities.

The current Centers for Disease Control and Prevention (2023) guidance uses hospitalization rates to determine when people should mask in society. While the Centers for Disease Control and Prevention (2023) states that people may choose to wear a mask at any time, they determine that it is most useful during periods of medium or high COVID-19 hospitalization levels. In areas with medium risk levels, the CDC recommends the following: (1) If you are at high risk of getting very sick, wear a high-quality mask or respirator (e.g., N95) when indoors in public. (2) If you have household or social contact with someone at high risk for getting sick, consider self-testing to detect infection before contact, and consider wearing a high-quality mask when indoors with them. In areas with high-risk levels, the CDC recommends the following (1) Wear a high-quality mask or respirator (2) If you are at high risk of getting very sick, consider avoiding non-essential indoor activities in public where you could be exposed. In contrast, arguably, the most influential critique of masking to date has been the Jefferson *et al.* (2023) study published by the Cochrane Library. Jefferson *et al.* (2023) analyzed the results from 78 RCTs and cluster-RCTs that focused on physical interventions to prevent respiratory virus transmission. Their main conclusions on masking are as follows:

Jefferson *et al.* (2023): “There is uncertainty about the effects of face masks. The low to moderate certainty of evidence means our confidence in the effect estimate is limited, and that the true effect may be different from the observed estimate of the effect. The pooled results of RCTs did not show a clear reduction in respiratory viral infection with the use of medical/surgical masks. There were no clear differences between the use of medical/surgical masks compared with N95/P2 respirators in healthcare workers when used in routine care to reduce respiratory viral infection.”

The results from Jefferson *et al.*’s (2023) study were highlighted in national newspapers, including the Wall Street Journal, New York Times, and Washington Post. The fact that Jefferson *et al.* (2023) focused on RCTs instead of observational studies was used by critics to justify the end of mask mandates. Two of the most influential RCTs, as discussed in the Jefferson *et al.*’s review, were Bundgaard *et al.* (2021) and Abaluck *et al.* (2022). This is mainly because they both were completed during the COVID-19 pandemic (unlike many of the other studies discussed in the Jefferson *et al.*’s review).

Abaluck *et al.* (2022) conducted an RCT of community-level mask promotion in rural Bangladesh from November 2020 to April 2021. A total of 600 villages and 342,183 adults were included in the analysis. Individuals in the treatment arms received free masks, information on the importance of masking, role modeling by community leaders, and in-person reminders for 8 weeks. These participants were compared to the control group with no interventions with follow-up testing. The authors find that in villages randomized to surgical masks, the results show an overall 11.1% relative reduction in symptomatic COVID-19 infections when compared to the control group.

Bundgaard *et al.* (2021) conducted an RCT of mask promotion in Denmark in April–May 2020. A total of 3,030 participants were assigned to the recommendation to wear masks



(together with a supply of 50 surgical masks and instructions on proper usage) and 2,994 were assigned to the control group. The authors find little to no difference between the treatment and control groups when follow-up infection rates were analyzed.

Studies such as these (Bundgaard *et al.*, 2021; Abaluck *et al.*, 2022) as well as other RCTs in the Jefferson *et al.*'s review mostly show a range of no impact to a relatively small impact from mask wearing on infection rates. However, the debate continues as to how cost-effective mask mandates may be considering the counter studies cited by the CDC.

For the purposes of a formal BCA on mask mandates, the cost-effectiveness depends upon which studies to use on the benefits side of the equation. Our cost estimates suggest at least 44% of the COVID-19 deaths would need to be prevented for a nationwide masking mandate to be considered cost-effective. Some of the high-end estimates documented by the CDC indicate that masking reduces infection rates by 70%–80%. Using these studies would suggest a nationwide masking mandate during the time period, we study would be considered cost-effective. In contrast, the results from some of the RCT studies as discussed in Jefferson *et al.* (2023) would suggest the opposite.

### 3.2.2. Other factors and sensitivity analysis

Other factors might be considered in a formal BCA or sensitivity analyses. In some cases, the assumptions used in the initial BCA may change the results completely depending upon which method researchers choose to implement. For example, including non-fatal infections in addition to the prevention of deaths in the benefits calculations or using alternative methods for valuing statistical lives could play a role in the results of a formal BCA.

The literature on valuing non-fatal COVID-19 infections has been relatively sparse. Kniesner and Sullivan (2020) was one of the first studies to estimate the cost of non-fatal infections. Notably, this study was completed in the early stages of the pandemic before vaccines and effective treatments were widely available. Kniesner and Sullivan (2020) utilize severity/injury estimates from the Department of Transportation as a means to calculate the value of non-fatal COVID-19 infections from January 2020 to November 2020. They estimate a weighted average cost of \$46,000 per non-fatal COVID-19 infection. The authors go on to state, “because of the larger numbers of cases involved our calculations imply that non-fatal infections are as economically serious in the aggregate as ultimately fatal infections.”

Viscusi (2020b) utilizes a variety of health outcome comparisons to estimate the cost of non-fatal COVID-19 infections. On the lower end, he discusses previous research that has found controlling cases of asthma has coalesced around a \$3,000 per unit cost. He uses this value to estimate minor COVID-19 non-fatal costs. On the higher end, Viscusi (2020b) uses chronic bronchitis as a comparison with cost estimates of \$3.4 million per case for severe non-fatal COVID-19 outcomes. His final estimates indicate, including non-fatal values in any cost calculation increases the expected health losses associated with COVID-19 illnesses by 10%–40%.

Robinson *et al.* (2022) provide the most up-to-date estimates in the literature for COVID-19 non-fatal infections. They provide estimates based on three different severity categories including mild, severe, and critical cases. For their cost estimates, Robinson *et al.* (2022) use the values for preventing proxy diseases (e.g., ranging from mild influenza for minor COVID-19 cases to sepsis for critical COVID-19 cases) and their duration as a basis for their analysis. They find the value of averting a case of COVID-19 for an individual of



average age is about \$5,300 for mild cases, \$18,000 for severe cases, and \$1.8 million for critical cases.

There are clearly a wide range of estimates available in the non-fatal COVID-19 valuation literature. These studies indicate including the prevention of non-fatal COVID-19 infections in a BCA may increase the benefit value by anywhere from 10% up to 100%. The exact amount is unclear, but the range suggests the impact could be substantial and should be considered in sensitivity analyses.

In our preferred break-even analysis estimates, we utilize a \$12.29 million VSL in the calculations. Due to the age distribution of COVID-19 deaths, some researchers have recommended using age-adjusted values instead of population average VSL estimates in the results (Allen, 2022). This is one reason why we include age-adjusted results as a sensitivity analysis. While age might play an important role in the calculations, it is not the only VSL adjustment that could impact the results (Robinson *et al.*, 2021; Kniesner *et al.*, 2022). Other factors, such as dread and uncertainty, size of the risk factor, income, or demographic composition (e.g., race) of the fatalities could impact which VSL estimates to use in any analysis.

Diseases that have a high amount of dread and uncertainty tend to have much higher VSL estimates in comparison to more typical death types.<sup>8</sup> For example, cancer deaths have been shown to have VSL estimates that are roughly 21% higher than those of normal deaths (Viscusi *et al.*, 2014). Other death types such as those from severe acute respiratory syndrome and influenza have shown higher VSL estimates as well (Liu *et al.*, 2005; Gyrð-Hansen *et al.*, 2008). Given the dread and uncertainty associated with COVID-19 for large portions of the population, it is possible that there could be a dread component in the VSL calculations that may increase their values, resulting in potentially higher benefits for mask mandates.

In contrast, other adjustments, such as the size of the risk factor, income, and demographic characteristics, could suggest a lower COVID-19 VSL. For example, most VSL estimates in the literature use small changes in the probability of death (e.g., one per 100,000) to make their calculations. For standard models, economists have generally found that individuals are willing to pay roughly \$120 for every one per 100,000 reduction in fatality risk. This equates to a \$12 million VSL. However, most people would not be willing to pay \$1.2 million for a one in 10 fatality risk reduction. This is because budget constraints for non-wealthy individuals often restrict the ability to pay for these types of large fatality risk reductions.

Therefore, high-risk death types could suggest the use of a lower VSL used in the analysis (Eeckhoudt & Hammitt, 2001, 2004; Kaplow, 2005; Alolayan *et al.*, 2017; Hammitt, 2020; Robinson *et al.*, 2022). However, the literature has shown that high-risk factors do not tend to play a role in the calculations until the fatality risk approaches one per 1,000 (Hammitt, 2020; Robinson *et al.*, 2022). For COVID-19 deaths, this threshold would not impact the younger population groups. On the other hand, some of the high-risk groups (such as the elderly in nursing homes) could have a lower COVID-19 VSL because of this factor.

It has been shown that COVID-19 fatalities have been concentrated in minoritized groups and those with lower income levels. The literature has shown that racially and ethnically minoritized groups and those with lower incomes tend to have lower VSL estimates in

<sup>8</sup> A dread and uncertainty premium has also been found for morbidity effects (see Gentry & Viscusi (2016) for a review of that literature).

comparison to the average population. For example, Viscusi (2003) found VSLs that vary substantially by race. However, the guidelines in Circular A-4 do not recommend adjusting the VSL by race. We support these guidelines and share the view of many economists who believe that the VSL should not be adjusted by racial dimensions due to ethical concerns (Kniesner *et al.*, 2024).

In terms of adjusting the VSL by income, the literature has generally found income elasticity estimates in the 0.6 to 1.4 range (Viscusi & Aldy, 2003; Kniesner *et al.*, 2010; Hammitt & Robinson, 2011; Lindhjem *et al.*, 2011; Doucouliagos *et al.*, 2014; US Department of Health and Human Services, 2016; US Department of Transportation, 2016; Viscusi & Masterman, 2017; Masterman & Viscusi, 2018; Viscusi, 2018). This range suggests a 10% decrease in income will result in a decrease of 6%–14% in the VSL. Given the lower income levels of COVID-19 deaths, it is possible that this could lead to a lower COVID-19 VSL, which then leads to a lower benefit calculation for mask mandates.

As detailed in this section, the assumptions used in any formal BCA could dramatically impact the results of any policy decision. For example, including the prevention of non-fatal infections in the analysis would increase the benefits of a mask mandate. The same would be true if analysts use a higher VSL due to dread and uncertainty adjustments. In contrast, using a lower VSL due to the characteristics, such as age or lower incomes would tend to lower the benefits of mask mandates. These types of adjustments lead to different results depending upon the preferences of the analyst. Practitioners and policymakers should take these types of adjustments into consideration in future sensitivity analyses.

### 3.3. Discrete choice experiments

In the discrete choice survey experiments, respondents were asked whether they would choose to pay a fee for an exemption to the general mask mandate as well as the school mask mandate (if they had school-aged children) if the fee was a particular (randomly assigned) price value. By comparing the fraction of people who report that they would pay the specified price to opt out at each level, these experiments trace out a cumulative distribution function of the survey populations stated that WTP for an exemption. We report these price-treatment group means for each price level overall and by age group, providing a non-parametric estimate of the demand for an exemption. To improve precision, we also fit regression models that adjust for covariates and impose additional structure on the shape of the demand curve across different price levels. Specifically, we consider two basic regression models. The first model models the effects of price using a sequence of price level indicator variables:

$$\begin{aligned} \text{Exemption}_i = & \beta_0 + \beta_1 1(P_i = \$50) + \beta_2 1(P_i = \$150) + \beta_3 1(P_i = \$500) \\ & + \beta_4 1(P_i = \$1000) + \beta_5 1(P_i = \$3000) + X_i\theta + \epsilon_i \end{aligned} \quad (4)$$

We also fit more parsimonious specifications in which the randomly assigned price enters the model linearly:

$$\text{Exemption}_i = \beta_0 + \beta_1 P_i + X_i\theta + \epsilon_i \quad (5)$$

In each of these models,  $X_i$  is a vector of demographic covariates.

The causal interpretation of the results from these models is dependent on a successful randomization procedure for price. Therefore, we show the balance along demographic variables for each randomly assigned price in the general mask mandate experiment and for

**Table 6.** Covariate means by randomized price offer for mask mandate exemption

Panel A: General mask mandates										
Randomized price	Asian	Black	Hispanic	White	Female	Age 18–29	Age 30–44	Age 45–64	Age 65+	Fully vaccinated
10	0.04	0.13	0.14	0.72	0.52	0.20	0.29	0.34	0.18	0.59
50	0.04	0.12	0.12	0.72	0.54	0.21	0.28	0.34	0.17	0.64
150	0.04	0.12	0.12	0.74	0.54	0.19	0.28	0.32	0.20	0.62
500	0.05	0.12	0.11	0.72	0.49	0.22	0.28	0.34	0.16	0.62
1000	0.05	0.13	0.15	0.70	0.52	0.22	0.28	0.34	0.16	0.63
3000	0.04	0.12	0.12	0.73	0.50	0.22	0.30	0.31	0.17	0.64
Panel B: School mask mandates										
Randomized price	Asian	Black	Hispanic	White	Female	Age 18–29	Age 30–44	Age 45–64	Age 65+	Fully vaccinated
10	0.05	0.16	0.14	0.66	0.54	0.10	0.62	0.26	0.02	0.59
50	0.08	0.13	0.14	0.69	0.59	0.15	0.52	0.30	0.03	0.58
150	0.04	0.18	0.12	0.65	0.56	0.20	0.52	0.26	0.02	0.52
500	0.04	0.14	0.16	0.64	0.58	0.17	0.58	0.23	0.02	0.42
1000	0.06	0.12	0.15	0.71	0.53	0.18	0.52	0.28	0.02	0.53
3000	0.03	0.17	0.17	0.68	0.57	0.18	0.54	0.24	0.03	0.55
Not asked	0.04	0.11	0.12	0.74	0.50	0.23	0.19	0.36	0.22	0.65

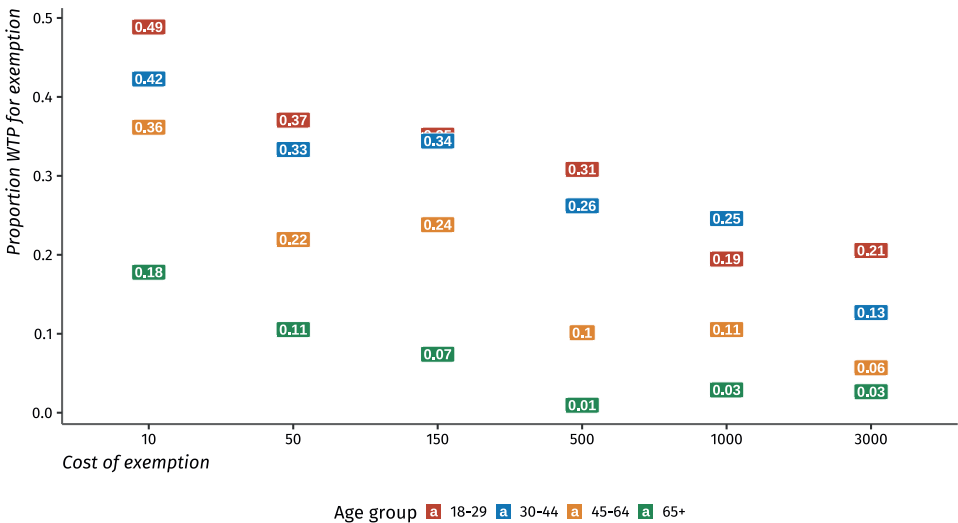
*Note:* The first column shows the randomized price given to respondents to be exempt from a general mask mandate. The remaining columns show the unweighted means for various demographics to show that the randomization procedure was effective.

the school mask mandate experiment in Table 6. All the variables seem well-balanced among the respondents. The bottom row in Table 6 shows that those who were not asked about the school mask mandate (those without school-aged children) were whiter and older than the rest of the sample, meaning that those who responded to the school mask mandate were less white and younger. Therefore, direct comparisons of those numbers should be interpreted carefully.

We first present the non-parametric results in Figure 4. As expected, the younger group responded that they were WTP more frequently than the older group for each price point. Furthermore, as price increased, the share of respondents WTP falls, consistent with economic theory. Even at a price of \$10, less than 50% of the younger age group was WTP. This provides further evidence that the costs are driven by a minority of the population with high WTP, whereas most of the population had a WTP of \$0.

We present the results in Table 7 where the price is modeled as a series of dummies for each randomly offered price. The reference category is \$10. As expected, each coefficient for costs are negative and rising as cost rises. There is evidence in this model that females have lower WTP and that those with school-aged children have higher WTP (for a general mask mandate). The age groups show higher WTP as age increases. Table 8 shows similar results when we model cost linearly in thousands of dollars. Taken together, these results show that the costs for mask mandates are higher for males and are concentrated in a younger population, possibly including those with school-aged children.

Indeed, Figure 5 shows the WTP for an exemption to a school mask mandate. The take-up of the exemption decreases as price increases, as predicted by economic theory. Furthermore, this figure shows that, at each randomly assigned price, take-up is higher than in the



**Figure 4.** Take-up of the mask mandate exemption by randomized price and age group. The figure shows the unweighted means of the number of respondents who indicated they were WTP for a mask mandate exemption by cost and age group. The red rectangle indicates 18–29 year olds, the blue rectangle indicates 30–44 year olds, the yellow rectangle indicates 45–64 year olds, and the green rectangle indicates 65+ year olds.

**Table 7.** Regression results for the general mask mandate exemption

	Model 1	Model 2
Cost = \$50	−0.107*** (0.022)	−0.103*** (0.021)
Cost = \$150	−0.117*** (0.022)	−0.112*** (0.021)
Cost = \$500	−0.190*** (0.022)	−0.196*** (0.021)
Cost = \$1000	−0.212*** (0.022)	−0.215*** (0.021)
Cost = \$3000	−0.258*** (0.022)	−0.264*** (0.021)
Asian		−0.037 (0.027)
Black		0.017 (0.021)
Hispanic		−0.014 (0.018)
Other race		0.002 (0.040)
Female		−0.069*** (0.012)
School-aged children		0.100*** (0.015)
Age 18–29		0.232*** (0.020)
Age 30–44		0.172*** (0.020)
Age 45–64		0.089*** (0.018)
Intercept	0.361*** (0.016)	0.253*** (0.020)
Observations	4001	4001

<sup>†</sup> $p < 0.1$ .

\* $p < 0.05$ .

\*\* $p < 0.01$ .

\*\*\* $p < 0.001$ .

*Note:* The dependent variable is a binary choice of whether the respondent would pay in the discrete choice experiment. Model 2 includes control variables. White and 65+ are the reference race and age categories. The independent variables are dummies for each randomized price offers.

general mask mandate experiment. For example, at a price of \$10, 60% of respondents indicated that they would be willing to pay for the school mask mandate exemption. At a price of \$3000, 22% of respondents indicated they were willing to pay for the school mandate exemption. This is in comparison to 49% and 20% for the same prices in the general mask mandate experiment.

**Table 8.** Regression results for linearized price for the general mask mandate exemption

	Model 1	Model 2
Cost (Thousands \$)	−0.062*** (0.006)	−0.065*** (0.006)
Asian		−0.042 (0.027)
Black		0.018 (0.021)
Hispanic		−0.012 (0.018)
Other race		0.000 (0.040)
Female		−0.069*** (0.012)
School-aged children		0.099*** (0.016)
Age 18–29		0.229*** (0.020)
Age 30–44		0.172*** (0.020)
Age 45–64		0.087*** (0.018)
Intercept	0.263*** (0.008)	0.157*** (0.016)
Observations	4001	4001

\* $p < 0.1$ .

\*\* $p < 0.05$ .

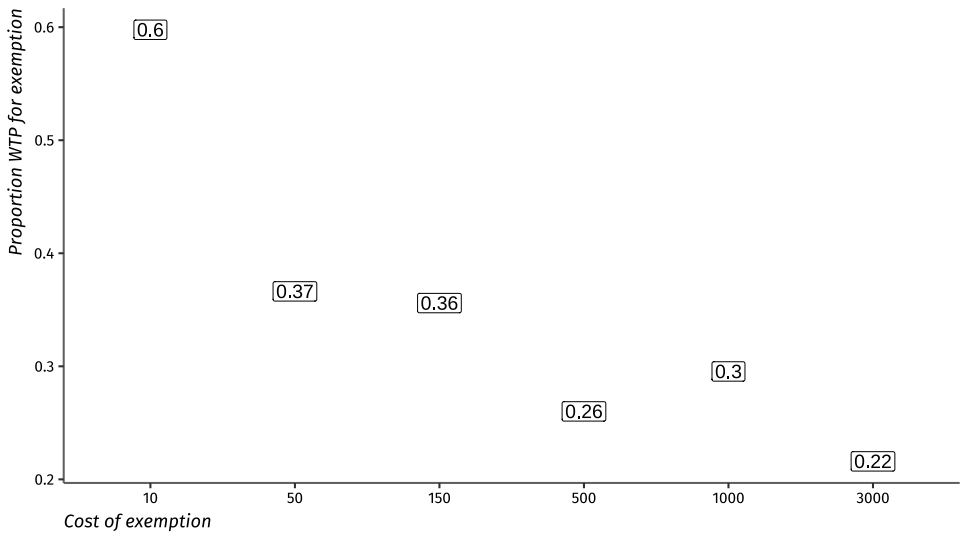
\*\*\* $p < 0.01$ .

\*\*\*\* $p < 0.001$ .

*Note:* The dependent variable is a binary choice of whether the respondent would pay in the discrete choice experiment. Model 2 includes control variables. White and 65+ are the reference race and age categories. The independent variable is linearized price offer.

The results in Tables 9 and 10 present a parametric version of Figure 5 using OLS to control for demographics. Again, the reference category is \$10 in the regressions with dummies for each price, and we use thousands of dollars to report results for linearized price. There appears to be higher WTP for school mask mandate exemptions, although the results are noisier due to the sample size restriction to 1048 respondents with school-aged children. The pattern with age groups is weaker, likely because the older group is far less likely to have school-aged children. These results show that females have lower WTP as well as each race group, although those coefficients are not always significant. The takeaway from these results is that there is a similar pattern for the school mask mandate costs as with the general mask mandate in terms of who is shouldering the cost. However, there is higher WTP for school mask mandate exemptions at every price than for general mask mandate exemptions.

Following the discrete choice experiment, respondents were given the following prompt to elicit the reasons they were willing to pay for a mask mandate exemption:



**Figure 5.** Take-up of the school mask mandate exemption by randomized price. The figure shows the unweighted means of the number of respondents who indicated they were WTP for a school mask mandate exemption by cost. Only respondents with school-aged children were asked this question.

What are the main downsides to wearing a mask, for you? (click all that apply)

1. none, I am not willing to pay a fee to be exempt from a mask mandate
2. discomfort
3. hard to breathe
4. people cannot understand what I am saying
5. lack of facial expressions or emotions
6. physical pain
7. personal freedom
8. limits my ability to work efficiently
9. limits social interaction
10. limits my ability to work out in a gym
11. other (please list here)

Figure 6 presents the results from this question. The respondents were able to select as many choices as applied. The top reasons were difficulties breathing (48%) and discomfort (45%) followed by difficulties in socializing, including not being verbally understood (36%) and missing facial expressions (28%). “None” was chosen 24% of the time, likely because those who were not willing to pay also answered this question. However, this response was selected far less frequently than those rejecting the exemption for the mask mandate, suggesting that even those with \$0 WTP experienced some downsides of wearing a mask. Freedom and limits to interactions were all stated as reasons less than 25% of the time, whereas physical pain was listed only 7% of the time. The open-ended “other” option was only selected 7% of the time, and often these responses reiterated one or more of the selections, suggesting the list was fairly exhaustive. Some form of discomfort or difficulty

**Table 9.** Regression results for the school mask mandate exemption

	Model 1	Model 2
Cost = \$50	−0.216*** (0.050)	−0.205*** (0.049)
Cost = \$150	−0.226*** (0.049)	−0.235*** (0.049)
Cost = \$500	−0.323*** (0.050)	−0.331*** (0.049)
Cost = \$1000	−0.299*** (0.049)	−0.307*** (0.048)
Cost = \$3000	−0.381*** (0.049)	−0.385*** (0.048)
Asian		−0.087 (0.057)
Black		−0.052 (0.043)
Hispanic		−0.037 (0.038)
Other race		−0.067 (0.084)
Female		−0.147*** (0.028)
Age 18–29		0.202* (0.089)
Age 30–44		0.084 (0.084)
Age 45–64		−0.022 (0.086)
Intercept	0.589*** (0.035)	0.622*** (0.089)
Observations	1048	1048

\* $p < 0.1$ .

\*\* $p < 0.05$ .

\*\*\* $p < 0.01$ .

\*\*\* $p < 0.001$ .

*Note:* The dependent variable is a binary choice of whether the respondent would pay in the discrete choice experiment. Model 2 includes control variables. White and 65+ are the reference race and age categories. The independent variables are dummies for each randomized price offers. Only the 1048 respondents with school-aged children were asked this question.

interacting socially were the top reasons for being willing to pay a fee to be exempt from the mask mandate.

### 3.4. Summary of results

We present the results for an open-ended WTP survey question, a break-even analysis based on the open-ended WTP, and a discrete choice experiment where prices for mask exemption are randomly assigned to respondents. Overall, we find a majority of respondents (56%)



**Table 10.** Regression results for linearized price for the school mask mandate exemption

	Model 1	Model 2
Cost (Thousands \$)	−0.078*** (0.014)	−0.080*** (0.014)
Asian		−0.085 (0.058)
Black		−0.045 (0.044)
Hispanic		−0.033 (0.038)
Other race		−0.063 (0.085)
Female		−0.150*** (0.029)
Age 18–29		0.188* (0.091)
Age 30–44		0.088 (0.085)
Age 45–64		−0.023 (0.087)
Intercept	0.409*** (0.018)	0.441*** (0.085)
Observations	1048	1048

\* $p < 0.1$ .

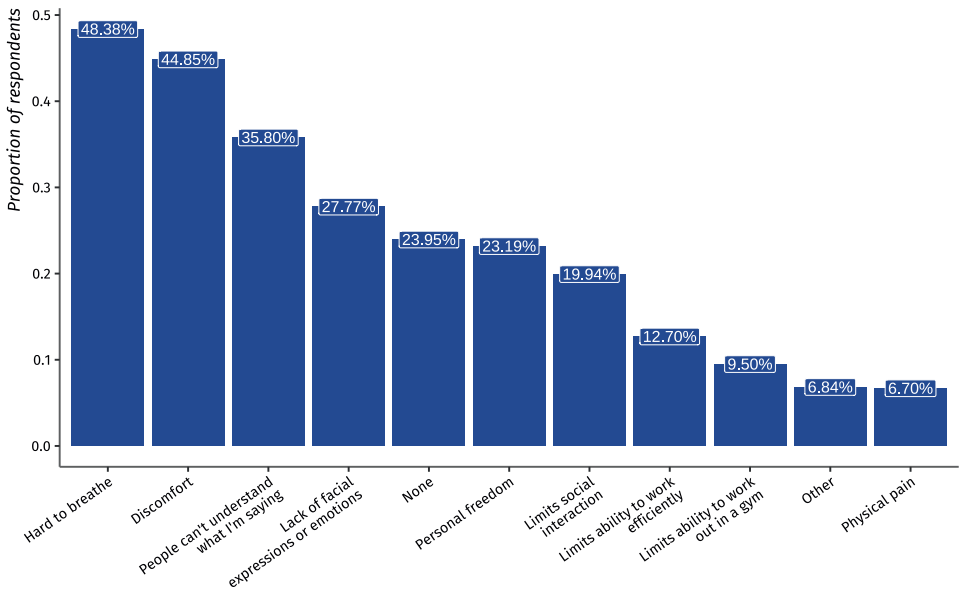
\* $p < 0.05$ .

\*\* $p < 0.01$ .

\*\*\* $p < 0.001$ .

*Note:* The dependent variable is a binary choice of whether the respondent would pay in the discrete choice experiment. Model 2 includes control variables. White and 65+ are the reference race and age categories. The independent variable is linearized price offer. Only the 1048 respondents with school-aged children were asked this question.

have a WTP of \$0—meaning the costs of a mask mandate are essentially \$0 for this group. Meanwhile, the costs of a mask mandate are concentrated in a smaller and younger portion of the population. Indeed, the median stated WTP is \$0, while the average is \$525. We supplement these findings with a discrete choice experiment. It shows similar results where no price offering had more than 50% of respondents indicating that they would be WTP. However, 20% of the younger group state they were WTP \$3000. We also use OLS to control for demographic variables. Age group was the most consistently important dependent variable. In fact, our analysis suggests that those aged 18–29 have \$655 higher WTP as compared to the 65+ group. In the discrete choice experiment, they were 23 percentage points more likely to indicate they would pay the price to be exempt from mandates. Discomfort and difficulty socializing were the top reasons given for those who were willing to pay for an exemption to the mask mandate. We add to the literature on mask mandates by providing estimates of the cost side of a BCA. Although there are many factors that affect what VSL value maybe best to use, using the HHS \$12.29 million VSL estimate, a mask mandate is cost-effective if it saves 13,333 lives in a 3-month period.



**Figure 6.** Respondents’ main downsides to wearing a mask. Respondents were asked to choose all reasons that applied for them being willing to pay for a mask mandate exemption. Open-ended responses often reiterated the responses already presented. All respondents answered the question, regardless of their stated willingness to pay.

4. Conclusion

The costs of non-pharmacological interventions in response to communicable public health threats, such as mandatory masking orders, which were prevalent during the COVID-19 Public Health Emergency continue to be hotly debated topics in economics. Given the widespread use of masking regulations throughout the COVID-19 pandemic, it is important that policymakers are guided by accurate regulatory assessments. This requires the use of precise estimates on both the benefits and costs of masking orders in a formal BCA framework.

Although this article does not make a direct determination on the benefits of masking orders, it does provide critical new information on cost, using methods of survey valuation. Our estimates indicate widespread differences across demographics with the younger adult population (18–29 year-olds) willing to pay on average over \$1,200 to be exempt from a 3-month mask mandate and older adults (65+ year-olds) willing to pay on average only about \$50. In addition, we find parents are willing to pay just over \$800 on average for each of their children to be exempt from mask mandates in school settings. Respondents indicated that discomfort and difficulty socializing were the top reasons given for those who were willing to pay for an exemption to the mask mandate. Our final cost estimates indicate a 3-month masking order in the United States has a total cost of roughly \$164 billion. Using a \$12.29 million VSL estimate from HHS, we estimate 13,333 as the number of lives to be saved for a 3-month masking mandate to be considered cost-effective.

**Acknowledgments.** The views expressed here are those of the authors and do not reflect the official policy or position of the Department of Defense, the US Government, or any other institution with which the authors are

affiliated. Special thanks to Glenn Blomquist, Elissa Gentry, Thomas J. Kniesner, Sarah Kreps, W. Kip Viscusi, and the seminar participants at the Southern Economic Association conference for helpful comments.

**Competing interest.** The authors declare none.

## References

- Abaluck, J., L. H. Kwong, A. Styczynski, A. Haque, M. A. Kabir, E. Bates-Jefferys, E. Crawford, *et al.* 2022. "Impact of Community Masking on Covid-19: A Cluster-Randomized Trial in Bangladesh." *Science*, 375 (6577): eabi9069.
- Aldy, J. E., and W. K. Viscusi. 2008. "Adjusting the Value of a Statistical Life for Age and Cohort Effects." *The Review of Economics and Statistics*, 90(3): 573–581.
- Allen, D. W. 2022. "Covid-19 Lockdown Cost/Benefits: A Critical Assessment of the Literature." *International Journal of the Economics of Business*, 29(1): 1–32.
- Alolayan, M. A., J. S. Evans, and J. K. Hammitt. 2017. "Valuing Mortality Risk in Kuwait: Stated-Preference with a New Consistency Test." *Environmental and Resource Economics*, 66(4): 629–646.
- Ballotpedia. 2022. State-Level Mask Requirements in Response to the Coronavirus (Covid-19) Pandemic, 2020–2022.
- Berinsky, A. J., G. A. Huber, and G. S. Lenz. 2012. "Evaluating Online Labor Markets for Experimental Research: Amazon.com's Mechanical Turk." *Political Analysis*, 20(3): 351–368.
- Bundgaard, H., J. S. Bundgaard, D. E. T. Raaschou-Pedersen, C. von Buchwald, T. Todsen, J. B. Norsk, M. M. Pries-Heje, *et al.* 2021. "Effectiveness of Adding a Mask Recommendation to Other Public Health Measures to Prevent Sars-Cov-2 Infection in Danish Mask Wearers: A Randomized Controlled Trial." *Annals of Internal Medicine*, 174(3): 335–343.
- Census Bureau 2010. ACS Design and Methodology. "Chapter 11. Weighting and Estimation". U.S. Census Bureau: Washington DC.
- Carlin, P., B. E. Dixon, K. I. Simon, R. Sullivan, and C. Wing (2022). How Undervalued is the Covid-19 Vaccine? Evidence from Discrete Choice Experiments and VSL Benchmarks. Technical Report, National Bureau of Economic Research.
- Centers for Disease Control and Prevention. 2021. Science Brief: Community Use of Masks to Control the Spread of Sars-Cov-2.
- Centers for Disease Control and Prevention. 2023. Use and Care of Masks.
- Circular A-4. 2023. Office of Management and Budget: Circular A-4 Regulatory Analysis.
- Coppock, A., and O. A. McClellan. 2019. "Validating the Demographic, Political, Psychological, and Experimental Results Obtained from a New Source of Online Survey Respondents." *Research & Politics*, 6(1): 2053168018822174.
- Doucouliagos, H., T. D. Stanley, and W. K. Viscusi. 2014. "Publication Selection and the Income Elasticity of the Value of a Statistical Life." *Journal of Health Economics*, 33: 67–75.
- Doung-Ngern, P., R. Suphanchaimat, A. Panjangampatthana, C. Janekrongtham, D. Ruampoom, N. Daochaeng, N. Eungkanit, *et al.* 2020. "Case-Control Study of Use of Personal Protective Measures and Risk for Sars-Cov 2 Infection, Thailand." *Emerging Infectious Diseases*, 26(11): 2607.
- Earnhart, H. G. 1966. Commutation: Democratic or Undemocratic? *Civil War History* 12 (2): 132–142.
- Eeckhoudt, L. R., and J. K. Hammitt. 2001. "Background Risks and the Value of a Statistical Life." *Journal of Risk and Uncertainty*, 23(3): 261–279.
- Eeckhoudt, L. R., and J. K. Hammitt. 2004. "Does Risk Aversion Increase the Value of Mortality Risk?" *Journal of Environmental Economics and Management*, 47(1): 13–29.
- Gentry, E. P., and W. K. Viscusi. 2016. "The Fatality and Morbidity Components of the Value of Statistical Life." *Journal of Health Economics*, 46: 90–99.
- Gyrd-Hansen, D., P. A. Halvorsen, and I. S. Kristiansen. 2008. "Willingness-To-Pay for a Statistical Life in the Times of a Pandemic." *Health Economics*, 17(1): 55–66.
- Hammitt, J. K. 2020. "Valuing Mortality Risk in the Time of Covid-19." *Journal of Risk and Uncertainty*, 61(2): 129–154.
- Hammitt, J. K., and L. A. Robinson. 2011. "The Income Elasticity of the Value Per Statistical Life: Transferring Estimates between High and Low Income Populations." *Journal of Benefit-Cost Analysis*, 2(1): 1–27.

- Hausman, J. 2012. "Contingent Valuation: From Dubious to Hopeless." *Journal of Economic Perspectives*, 26(4): 43–56.
- Hendrix, M. J. 2020. Absence of Apparent Transmission of Sars-Cov-2 from Two Stylists After Exposure at a Hair Salon with a Universal Face Covering Policy—Springfield, Missouri, May 2020. *MMWR. Morbidity and Mortality Weekly Report* 69, 930–932.
- Jefferson, T., L. Dooley, E. Ferroni, L. A. Al-Ansary, M. L. van Driel, G. A. Bawazeer, M. A. Jones, T. C. Hoffmann, J. Clark, E. M. Beller, et al. (2023). Physical Interventions to Interrupt or Reduce the Spread of Respiratory Viruses. *Cochrane Database of Systematic Reviews* 1(1): 1–437.
- Kaplow, L. 2005. "The Value of a Statistical Life and the Coefficient of Relative Risk Aversion." *Journal of Risk and Uncertainty*, 31(1): 23–34.
- Kniesner, T. J., and R. Sullivan. 2020. "The Forgotten Numbers: A Closer Look at Covid-19 Non-Fatal Valuations." *Journal of Risk and Uncertainty*, 61(2): 155–176.
- Kniesner, T. J., R. S. Sullivan, and W. K. Viscusi. 2022. "What are 750,000 Senior Covid Deaths Worth?" *Regulation*, 45: 8.
- Kniesner, T. J., Sullivan, R., and W. K. Viscusi. 2024. The military VSL. Vanderbilt Law Research Paper. [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=4971099](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4971099)
- Kniesner, T. J., W. K. Viscusi, and J. P. Ziliak. 2006. "Life-Cycle Consumption and the Age-Adjusted Value of Life." *Contributions in Economic Analysis & Policy*, 5(1): 1–34.
- Kniesner, T. J., W. K. Viscusi, and J. P. Ziliak. 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.
- Lindhjem, H., S. Navrud, N. A. Braathen, and V. Biaisque. 2011. "Valuing Mortality Risk Reductions from Environmental, Transport, and Health Policies: A Global Meta-Analysis of Stated Preference Studies." *Risk Analysis: An International Journal*, 31(9): 1381–1407.
- Liu, J.-T., J. K. Hammitt, J.-D. Wang, and M.-W. Tsou. 2005. "Valuation of the Risk of Sars in Taiwan." *Health Economics*, 14(1): 83–91.
- Markowitz, A. 2023. State-By-State Guide to Face Mask Requirements. American Association of Retired Persons (AARP).
- Masterman, C. J., and W. K. Viscusi. 2018. "The Income Elasticity of Global Values of a Statistical Life: Stated Preference Evidence." *Journal of Benefit-Cost Analysis*, 9(3): 407–434.
- Murphy, K. M., and R. H. Topel. 2006. "The Value of Health and Longevity." *Journal of Political Economy*, 114(5): 871–904.
- Payne, D. C., S. E. Smith-Jeffcoat, G. Nowak, U. Chukwuma, J. R. Geibe, R. J. Hawkins, J. A. Johnson, et al. 2020. "Sars-Cov-2 Infections and Serologic Responses from a Sample of US Navy Service Members—USS Theodore Roosevelt, April 2020." *Morbidity and Mortality Weekly Report*, 69(23): 714.
- Robinson, L. A., M. R. Eber, and J. K. Hammitt. 2022. "Valuing Covid-19 Morbidity Risk Reductions." *Journal of Benefit-Cost Analysis*, 13(2): 247–268.
- Robinson, L. A., R. Sullivan, and J. F. Shogren. 2021. "Do the Benefits of Covid-19 Policies Exceed the Costs? Exploring Uncertainties in the Age–VSL Relationship." *Risk Analysis*, 41(5): 761–770.
- Scoville, C., A. McCumber, R. Amironesei, and J. Jeon. 2022. "Mask Refusal Backlash: The Politicization of Face Masks in the American Public Sphere during the Early Stages of the Covid-19 Pandemic." *Socius*, 8: 23780231221093158.
- Sunstein, C. R. 2020. *Valuing Life: Humanizing the Regulatory State*. Chicago, IL: University of Chicago Press.
- US Department of Health and Human Services. 2016. Guidelines for Regulatory Impact Analysis.
- US Department of Transportation. 2016. Revised Departmental Guidance on Valuation of a Statistical Life in Economic Analysis.
- Viscusi, W. K. 2003. "Racial Differences in Labor Market Values of a Statistical Life." *Journal of Risk and Uncertainty*, 27: 239–256.
- Viscusi, W. K. 2018. *Pricing Lives: Guideposts for a Safer Society*. Princeton, NJ: Princeton University Press.
- Viscusi, W. K. 2020a. "Efficient Ethical Principles for Making Fatal Choices." *Notre Dame Law Review*, 96: 1461.
- Viscusi, W. K. 2020b. "Pricing the Global Health Risks of the Covid-19 Pandemic." *Journal of Risk and Uncertainty*, 61(2): 101–128.
- Viscusi, W. K. 2021. "Economic Lessons for Covid-19 Pandemic Policies." *Southern Economic Journal*, 87(4): 1064–1089.
- Viscusi, W. K., and J. E. Aldy. 2003. "The Value of a Statistical Life: A Critical Review of Market Estimates Throughout the World." *Journal of Risk and Uncertainty*, 27(1): 5–76.

- Viscusi, W. K., and J. E. Aldy. 2007. "Labor Market Estimates of the Senior Discount for the Value of Statistical Life." *Journal of Environmental Economics and Management*, 53(3): 377–392.
- Viscusi, W. K., J. Huber, and J. Bell. 2014. "Assessing Whether there is a Cancer Premium for the Value of a Statistical Life." *Health Economics*, 23(4): 384–396.
- Viscusi, W. K., and C. J. Masterman. 2017. "Income Elasticities and Global Values of a Statistical Life." *Journal of Benefit-Cost Analysis*, 8(2): 226–250.
- Viscusi, W. K., and R. J. Zeckhauser. 2003. "Sacrificing Civil Liberties to Reduce Terrorism Risks." *Journal of Risk and Uncertainty*, 26: 99–120.
- Wang, Y., H. Tian, L. Zhang, M. Zhang, D. Guo, W. Wu, X. Zhang, *et al.* 2020. "Reduction of Secondary Transmission of Sars-Cov-2 in Households by Face Mask Use, Disinfection and Social Distancing: A Cohort Study in Beijing, China." *BMJ Global Health*, 5(5): e002794.