# Stated Preference Estimates of the Average Social Cost of Carbon*

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April 1, 2023

## Abstract

This paper provides stated preference (SP) estimates of the *average* social cost of carbon (ASCC) for use in the evaluation of the benefits and costs of climate policy. We find a U.S. average willingness-to-pay (WTP) of $1,116 per year to keep global warming less than 2°C by 2100. Combining the WTP estimate with population projections and assessments of the required emission reductions, we find a *domestic* ASCC of $8 per tonne of carbon dioxide. Applying a benefits transfer approach to infer WTP in other countries, we obtain an estimate of the *global* ASCC of $39 per tonne, with a 95-percent confidence interval of $32-$48. The estimate is insensitive to the discount rate, but it does vary with assumptions about the income elasticity of WTP and the rate of change in marginal abatement costs. Reasonable scenarios create a range of estimates between $12-$118 per tonne. A breakeven analysis finds that global average benefits of $50, $100, $150, and $200 per tonne correspond with U.S. monthly WTP values of $119, $238, $356, and $475, respectively. We also examine the impact of distributional weighting based on the elasticity of the marginal utility of income, providing distributionally-weighted estimates of the global ASCC for use in all countries. We argue that a SP estimate of the ASCC is a useful complement to existing estimates of the *marginal* social cost of carbon (SCC) based on different valuation approaches, and that using our framework translating global benefit measures into corresponding WTP amounts provides a familiar benchmark for interpreting magnitudes.

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## 1. Introduction

Economic analysis of climate policy often requires an estimate of the benefits of avoided greenhouse gas (GHG) emissions. The social cost of carbon (SCC) is the standard metric for this purpose. The SCC measures the monetized damages of an additional tonne of carbon dioxide ($CO_2$) emissions, or the $CO_2$ equivalent of another GHG, into the atmosphere. The avoided damages represent the benefits of emissions reductions, and quantitative estimates of the SCC play a critical role in benefit-cost analysis (BCA). Use of the SCC is pervasive not only within the academic literature (Tol 2023), but also among governments around the world as an economic justification for climate policy (Aldy et al. 2021; IWG-SCC 2021; U.S. EPA 2023).

There are two primary methods for estimating the SCC. First is the use of integrated assessment models (IAMs) that estimate how a marginal change in emissions affects well-being measured in monetary units. The SCC is the present value of these impacts (Nordhaus 2017; Waldhoff et al. 2014; Kikstra et al. 2021; Rennert et al. 2022). While IAMs are not without controversy (Pindyck 2013, 2017; Stock and Metcalf 2017), they are the most common approach for estimating the SCC (Tol 2023). The second approach is based on bottom-up, econometric studies that examine how temperature changes affect specific sectors. The results of these studies are sector-specific, partial SCCs, with recent applications focusing on mortality (Carlton et al. 2022), labor productivity (Rode et al. 2022), agriculture (Hultgren et al. 2022), and energy (Rode et al. 2021).

This paper contributes another approach for estimating the benefits of GHG emissions reductions: a stated preference (SP) estimate of the average SCC (ASCC). SP methods estimate economic values based on direct survey questions, and the approach is commonly employed for nonmarket valuation and BCA (Johnston et al. 2017). We argue that a SP estimate of the ASCC adds a useful data point to the growing evidence on the economic benefits of reducing GHG emissions. Existing methods are highly technical in their use of modeling and econometric estimates, and they have a wide range of uncertainty. The ultimate question is nevertheless relatively straightforward: how much should society be willing to pay to reduce emissions? The novel approach of this paper is to simply ask people, employing a standard methodology for nonmarket valuation. Because the approach is based directly on public preferences, in contrast to expert analysis, it adds complementary estimates with the potential to bolster political support for efficient climate policy.

There are, however, several challenges for SP estimation and interpretation of an ASCC in ways comparable to the familiar SCC. One challenge inherent to the SP method is that survey respondents may over-state their willingness to pay (WTP) due to hypothetical bias. While good survey design can reduce hypothetical bias (Johnston et al. 2017), all nonmarket valuation techniques have shortcomings. When compared to IAM estimates, for example, concerns about hypothetical bias should be traded off against uncertain and less transparent modeling assumptions. Whether hypothetical bias is ultimately a concern is also likely to depend on how the estimates compare to those of other approaches. In what follows, we show that SP estimates of the ASCC are lower than the most recent evidence on the SCC.[1]

A second challenge arises because the SCC is a marginal rather than average measure. Because a one tonne change in emissions is infinitesimally small on a global scale, it is difficult to imagine its impacts for purposes of eliciting WTP in a survey question. We therefore focus on estimating the *average* benefit of a non-marginal reduction in emissions. In particular, we derive an estimate consistent with the change in emissions necessary to meet the internationally agreed upon target of limiting global warming to 2°C above pre-industrial levels. Previous research has advocated use of the ASCC over the marginal SCC because of comparative transparency, consistent long-term policy guidance, and insensitivity to modeling assumptions, especially the discount rate (Pindyck 2017, 2019). In this setting, the ASCC is also a lower bound for the SCC assuming marginal damages are increasing in the level of cumulative emissions.

A third challenge is due to the fact that reducing GHG emissions provides a global public good. This means that SP elicitation of the ASCC should reflect the aggregate WTP of the

[1] With respect to estimates of the value of a statistical life (VSL), SP estimates are often lower than revealed-preference estimates based on hedonic wage studies, and both are used as part of a meta-analysis justifying the official estimate of the VSL for federal regulatory impact analysis (U.S. EPA 2010).

world population. While conducting a globally representative survey is possible, it is difficult and costly. As an alternative, we survey a representative sample of the U.S. population and apply a benefits transfer approach to infer estimates of WTP in other countries based on differences in income (Rosenberger and Loomis 2002; Czajkowski et al. 2017; Johnston et al. 2021). Our analysis thus provides estimates of the domestic ASCC in the United States and for all other countries based on the benefits transfer approach. When combined, we estimate the global ASCC, which is comparable to the global SCC typically used for official BCAs (Kotchen 2018; Howard and Schwartz 2019; U.S. EPA 2023).

A fourth challenge is how to accommodate the growing concern about income inequality when deriving an estimate of the ASCC. While there is no consensus on how (or even whether) to account for distributional concerns in BCA, studies have begun to do so using distributional weights when deriving estimates of the SCC (Azar and Sterner 1996; Anthoff et al. 2009; Anthoff and Emmerling 2019; Adler et al. 2017; Tol 2019). Germany currently uses a weighted SCC, and the U.S. government recently proposed a particular approach to distributional weighting of benefits and costs for official regulatory analysis (OMB 2023). Consistent with these guidelines, we include a distributionally-weighted analysis that produces country-specific estimates of the ASCC, showing how the results change with different assumptions about the key parameter of the marginal utility of income.

There is clear demand for SP estimates of the benefits and costs of changes in GHG emissions. A recent update to the SCC for U.S. federal regulatory analysis (U.S. EPA 2023) includes a section on different sources of evidence in support of the estimates, with discussion of limited survey-based estimates. Two of the referenced studies are based on the WTP of individuals based on vehicle choice experiments (Achtnicht 2012; Hulshof and Mulder 2020). However, these results are notably distinct from a global SCC, as they quantify an individual's benefit of reducing one tonne of their own emissions, rather than global benefits.[2] Pindyck (2017, 2019) conducts a survey to elicit expert opinion on climate change

[2] A number of other studies in the literature us SP methods to estimate WTP per tonne to reduce GHG emissions, but these are typically estimates for individuals and for a particular policy or choice. Hence they do not aim to estimate the global benefits or costs for general policy analysis comparable to the SCC. Alberini et al. (2018) provides an example with many helpful references.

and its economic impacts, but the analysis differs from ours methodologically because his estimates are not a SP estimate of individual WTP to mitigate climate change.

To our knowledge, this paper is the first study that uses SP methods to generate broadly applicable estimates comparable to those of the SCC and based on a general population survey. Our central estimate is \$39 per tonne, with a 95-percent confidence interval of \$32-\$48. The estimate is insensitive to the discount rate, but it does vary with assumptions about the income elasticity of WTP, and the rate of change in marginal abatement costs. Reasonable scenarios create a range of estimates between \$12-\$118 per tonne.

Another contribution of this paper is a breakeven analysis, based on our conceptual framework, that maps any value of the global ASCC into a corresponding U.S. monthly mean WTP. This portion of our analysis does not rely on our survey based WTP and is therefore robust to potential skepticism about the reliability of SP estimates. The value of this analysis is to provide points of reference, based on readily interpretable monthly WTP, as a way to interpret the magnitude of the global benefits of changes in emissions. We find for our central scenario that global average benefits of \$50, \$100, \$150, and \$200 per tonne correspond with U.S. monthly WTP values of \$119, \$238, \$356, and \$475, respectively. One way to interpret these results is as a "reality check" on estimated global benefits of emissions reductions and observed carbon prices vis-à-vis what may or may not seem like plausible WTP amounts.

The remainder of the paper proceeds as follows. The next section develops the conceptual framework for how to aggregate estimates of WTP to achieve a 2ºC warming target into an estimate of the ASCC for use in policy analysis. Section 3 describes our survey methods and reports basic summary statistics. Section 4 focuses on the analysis of WTP for the U.S. population. Section 5 includes the main results on the global ASCC. Section 6 reports the results of our breakeven analysis. Section 7 examines sensitivity of the global ASCC to distributional weighting based on differences in income across countries. Finally, Section 7 concludes with a brief summary and comparison of our estimates to others in the literature.

## 2. Conceptual Framework

We develop a conceptual framework to show how aggregate WTP to achieve a 2ºC warming target in 2100 can be used to estimate the ASCC. To begin, assume for simplicity a representative individual that will live to the year 2100, with constant real income $w$ and $T$ years remaining. Assume further that the individual has complete information, and there is no uncertainty. Although there are many paths of emission reductions to achieve the 2ºC target in 2100, assume initially there is a single path (we will consider multiple paths later). For $t = 0, \dots, T$, let $m_t$ denote the business-as-usual (BAU) path of emissions, and $m'_t$ the path associated with 2ºC.

The object of interest is the economic value the individual places on moving from path $m_t$ to $m'_t$. To facilitate implementation in a survey setting, we assume the individual's valuation is expressed as a constant WTP (in real terms) in each year. The individual's $WTP$ will therefore satisfy

$$\sum_{t=0}^{T} \beta^t v(w, m_t) = \sum_{t=0}^{T} \beta^t v(w - WTP, m'_t), \tag{1}$$

where $v(w, m)$ is a time-invariant indirect utility function, $\beta = 1/(1 + r)$ is the discount factor, and $r$ is the discount rate. It follows that the present value compensating variation measure is

$$B = \sum_{t=0}^{T} \beta^t WTP. \tag{2}$$

This represents the present value of a constant stream of income the individual is willing to give up to avoid the BAU path of emissions in favor of one with a 2ºC temperature change in 2100, while maintaining the same level of utility. Assuming no income effects, $B$ also represents the cost to the individual of taking no action and experiencing the BAU temperature change.[3]

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[3] An alternative way to see the same result relies on the expenditure function approach (Freeman et al. 2014). The present value, compensating variation of moving from the BAU emissions path to the 2°C path can be written as

To interpret the benefit (cost) on a per tonne basis, it may be tempting to consider the ratio $B/\sum_{t=0}^{T}(m_t - m_t')$, but this neglects to take account of two features (Pindyck 2017, 2019). First is that abatement further into the future is less costly in present value. Second is that marginal abatement costs can change over time. Capturing both of these effects, we write the present value of emissions adjusted on a cost basis as

$$C = \sum_{t=0}^{T} \beta^t \alpha^t \Delta m_t, \tag{3}$$

where $\alpha = 1/(1-z)$, $z$ is the rate of change in abatement costs, and $\Delta m_t \equiv m_t - m_t'$ is the difference in abatement paths for each year $t$. If abatement costs are declining over time, then $z < 0$, and the decline in abatement costs operates like an additional discount factor. Previous studies (Pindyck 2017, 2019) assume the real cost of abatement is constant (i.e., $z = 0$) based on offsetting arguments: costs are likely to decline because of innovation, yet they are likely to increase because of fewer and fewer low-cost opportunities. With this assumption, emissions are discounted at the same rate as the individual's $WTP$. Here we allow for the possibility that abatement costs increase or decrease over time and examine the implications of different assumptions.

The representative individual's benefit (cost) per tonne is therefore the ratio $B/C$, which depends on the $WTP$, the discount rate, the rate of change in real abatement costs, and the path of emission reductions. We now turn from a representative individual to aggregating over populations that provide the basis for both a domestic and global ASCC.

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$$\begin{aligned} B &= e\left(m, \sum_{t=0}^{T} \beta^t v(w, m_t)\right) - e\left(m', \sum_{t=0}^{T} \beta^t v(w, m_t)\right) \\ &= \sum_{t=0}^{T} \beta^t w - e\left(m_t', \sum_{t=0}^{T} v(w, m_t)\right), \end{aligned}$$

where $e(\cdot)$ is the present value expenditure function, and $m$ and $m'$ denote the corresponding emissions paths over all $t$. The expression is the difference between the present value of income given the BAU emissions path and the expenditure needed to maintain the same level of indirect utility given the 2°C emission path. Then, assuming the measure of WTP is a constant annuity for $T$ years, it will satisfy $B = \sum_{t=0}^{T} \beta^t WTP$.

### 2.1. The Domestic and Global ASCC

Now assume the individual is from a particular country $h$, with population $Pop_{ht}$ in year $t$. Assume further that the individual's $WTP$ is the population average for country $h$, and therefore denoted $WTP_h$. The present value aggregate *domestic* ASCC for country $h$ is then

$$ASCC_h = \frac{B_h}{C} = \frac{\sum_{t=0}^{T} \beta^t \, Pop_{ht} WTP_h}{\sum_{t=0}^{T} \beta^t \alpha^t \Delta m_t}, \tag{4}$$

where the average, within country benefit is scaled by the country population in each year. The domestic ASCC reflects the aggregate, average benefits (costs) per tonne in country $h$ from meeting (foregoing) the 2°C target.

To estimate the *global* ASCC, we need an estimate $WTP_h$ for all $h$ countries that can be scaled up by population estimates $Pop_{ht}$ for all $t$. In effect, the necessary input is equation (4) for all $h$ counties. The global estimate (assuming no distributional weighting, which we consider later) is then simply a sum across countries:

$$ASCC_G = \sum_h ASCC_h. \tag{5}$$

The data and parameters underlying this estimate are country-specific WTPs and population trends, the discount rate, the rate of change in real abatement costs, and the global path of emission reductions. The distinction between the domestic and global ASCC parallel that between the domestic and global SCC. The former is useful for understanding domestic benefits and costs, while the latter apply globally and provide the basis for most benefit-cost analyses (Kotchen 2018; Howard and Schwartz 2019; US EPA 2023).

### 2.2. A Benefits Transfer Approach

We now describe how to estimate the global ASCC with more limited data. In our empirical application, data are only available on $WTP_h$ for a single country (i.e., the United States). We therefore use a benefits transfer approach to estimate $WTP_h$ in other countries based on differences in income (Rosenberger and Loomis 2002; Czajkowski et al. 2017; Johnston et al. 2021). Let $h = k$ denote the country for which we have an estimate of $WTP_k$. An estimate for other countries can then be obtained according to the following adjustment:

$$WTP_h = WTP_k \times \left(\frac{w_h}{w_k}\right)^{\eta}, \tag{6}$$

where $\eta$ is the income elasticity of WTP. Benchmarks for what to use for this parameter include proportional shifts (i.e., $\eta = 1$) and related estimates in the literature. We consider both approaches in our subsequent analysis, using assumptions informed by estimates of the income elasticity of the value of a statistical life (VSL) and climate-related WTP estimates. Then, with an estimate of $WTP_h$ for each country, along with population projections for all $h$ countries, we follow the preceding steps to arrive at estimates of the $ASCC_h$ for each country and of the $ASCC_G$ for all countries combined. As mentioned, though described later in the paper, we also consider distributionally-weighted estimates of the global ASCC to examine the implications of taking account of income inequality across countries.

## 3. Survey Questions and Responses

We collected data through a nationally representative survey of 1,015 U.S. adults over the age of 18 between January 20 and 26, 2023. The survey was administered online through the Ipsos KnowledgePanel using the Omnibus Methodology.

Our primary survey question was designed to elicit WTP to reduce global emissions from a BAU emissions trajectory consistent with the IPCC's expected 4°C temperature increase by 2100 to a trajectory with only a 2°C increase (Riahi et al. 2022). Respondents were informed that meeting the 2°C target would increase the cost of goods and services that people buy (Kotchen and Reiling 1994). To add an element of consequentiality (Johnston et al. 2017; Caron and Groves 2007; Vossler et al. 2012), the question noted that responses will help inform policymakers about climate policy. The valuation question was a referendum format, asking whether respondents would be willing to pay a randomized amount more in additional expenses per month to meet the 2°C target. The exact text of the WTP question was the following:

> Scientists estimate that global warming pollution is on track to increase global average temperatures 4 degrees Celsius (7.2 degrees Fahrenheit) by the year 2100. Global warming is already causing higher temperatures,

more extreme weather, and rising sea levels. These changes harm property, agriculture, human health, and national security.

Scientists also advise that limiting global warming to a maximum average temperature increase of 2 degrees Celsius (3.6 degrees Fahrenheit) is critical to avoid far more severe impacts. However, staying below 2-degrees warming will require changes to the economy that lower pollution, and these will increase the cost of goods and services that people buy.

If achieving the 2-degree goal were to cost you <u>$X per month more than you currently spend</u>, would you be willing to pay this additional amount? Your answer will help policymakers make important decisions about climate policy.

- Yes, I would pay $X more per month to meet the 2-degree target.
- No, I would not pay $X more per month and understand that global temperatures may increase 4 degrees by 2100.

The randomized dollar amounts, indicated with $X, were chosen to be roughly in line with estimates in the literature of previous WTP studies on related topics (e.g., Carlsson et al. 2012). Seven different levels were chosen and assigned with the probabilities indicated in parentheses: $6 (.1), $16 (.1), $26 (.2), $45 (.2), $85 (.2), $124 (.1), $165 (.1). Table 1 reports the distribution of yes/no responses for each specified amount.

We asked a follow-up question to identify potential protest responses. Protest responses are those for which a “no” response is due to rejection of the survey scenario, rather than reflecting a respondent’s WTP less than the randomized dollar amount. It is standard practice to exclude protest responses when deriving population estimates of WTP (Johnston et al. 2017). The exact text of the follow-up question was the following:

You answered “no” to the previous question about whether you would pay <u>$X per month</u> to meet the 2-degree target. Which of the following best describes the main reason for your “no” response? (Select one)

[1] It is more than I would pay.

[2] I do not think global warming is a problem.

[3] I do not believe the science that predicts 4 degrees of warming by 2100.

[4] I do not think it is possible to keep global warming below 2 degrees.

[5] Other reason, please explain: ______________________________

Response categories [3] and [4] are designated protest responses, along with others from the open-ended response category. The protest write-in responses were most commonly associated with statements about how it should be the responsibility of others (e.g., corporations) to address climate change or how the proposed scenario is unrealistic. Importantly, respondents that indicate they do not believe in climate change are coded as legitimate "no" responses. In total, we identify 285 protest responses: 89 for response [3], 133 for response [4], and the remainder for the write-in responses. Following convention in the literature, we exclude these observations from subsequent analysis, along with 37 respondents that refused to answer the WTP question, resulting in 693 observations for the complete statistical analysis.[4] Table 1 reports the breakdown of the different responses corresponding with the specific amount in the valuation question.

We included an additional question in the survey to ask whether respondents believe climate change is affecting them personally. The specific survey question was "To what extent do you think that global warming is already affecting you personally?" The response categories were "don't know," "not at all," "only a little," "a moderate amount," and "a great deal." We convert responses into a binary variable for whether respondents think global warming is affecting them personally using the latter three categories. Table 2 provides basic summary statistics for this question, along with those for sociodemographic variables

[4] A meta-analysis of protest responses across contingent valuation studies finds an overall mean of 18 percent protests responses (Meyerhoff and Liebe 2010). While the percentage is higher here, at 32 percent including the non-responses, this may not be surprising given how climate change is such a broad concern and often controversial. Nevertheless, the rate here is still well within the range found in other studies. For example, Meyerhoff and Liebe (2010) find rates higher than 40 percent across many categories of resources valued and question formats. To explore determinants of the protest responses, we include the results of logit models in supplementary appendix Table S1. We include a model with all demographic variables and one with only those in our the WTP models. We find that respondents are less likely to protest if they believe globally warming is already affecting them, their political party affiliation is Democratic, and if they are older.

for respondents, all of which are based on previously reported information for the Ipsos KnowledgePanel. These include household income, years of education, political party affiliation, gender, age, and household size.

## 4. Willingness to Pay

We begin with estimation of logit models to examine variables that affect yes/no responses to the WTP question. Table 3 reports the results of two models: one with only the specified dollar amount as an explanatory variable, and one with sociodemographic variables as well. Because we found no statistically significant effects of age, gender, and household size, these variables are excluded from the model. The logit results conform with expectation. Consistent with economic theory, we find that the probability of a "yes" response is decreasing in the specified dollar amount. The result holds when the specified amount is the only right-hand side variable and when adding additional covariates. Based on the marginal effects evaluated at the mean, we find that a $10 increase in the specified amount decreases the probability of a "yes" response by 2 percentage points.

Turning to the other explanatory variables, we find a large effect of respondent's thinking that global warming is already affecting them, increasing the probability of a "yes" response by 28 percentage points. Both household income and education increase the probably of responding "yes." Democrats are more likely to respond "yes" compared to independents and those with no political party affiliation (which together comprise the omitted category), whereas Republicans are less likely. The latter effect is larger, increasing the probability of a "no" responses by 15 percentage points.

Based on the logit model with covariates, we estimate mean WTP using two standard approaches (Hanemann 1984, 1989). The first is considered conservative because it admits the possibility for respondents to have a negative WTP. The second assumes only positive WTP, truncating the distribution at zero. These estimates of mean WTP are reported in

Figure 1, both as monthly and annual means.[5] We also estimate bias-corrected and accelerated (BCa) bootstrapped confidence intervals, and these too are reported in Figure 1. Allowing the possibility for negative values, we find a mean WTP of $92 per month, with a 95-percent confidence interval of $75-$115. This translates to an annual WTP of $1,116, with a 95-percent confidence interval of $900-$1,382. Truncating the distribution at zero increases the point estimates to $113 per month, or $1,360 per year, yet the confidence intervals overlap, indicating statistically insignificant differences.

To evaluate sensitivity of the results, we also calculate mean WTP using two additional methods, the results of which are also shown in Figure 1. One is the spike model (Kristrom 1997), which requires identifying a subset of respondents who are not in the market, meaning they are indifferent, with zero WTP. For this purpose, we use respondents answering "no" to the WTP question and "I do not think global warming is a problem" in the follow-up question, i.e., response category [2]. The other approach is the non-parametric, Turnbull lower-bound estimator (Haab and McConnell 1997). As with the logit model, we estimate both models using population weights and confidence intervals using the BCa bootstrap method. Although not reported, the spike model generates coefficient estimates similar to those for the logit model, whereas the Turnbull model does not estimate relationships with other variables.

Both the spike and Turnbull estimates are below the logit estimates, but all confidence intervals are overlapping. Our preferred estimate is the logit specification, where we admit the possibility for negative WTP. This is the most familiar approach in the literature, and it provides a central estimate.

The survey question intentionally did not specify an end date on the monthly WTP. The reason is to obtain an estimate of the annual mean WTP that can be applied to the population year after year until 2100. Then, for a given discount rate, we can derive a mean estimate of $B$ in equation (2), which is a key input for estimating both the domestic and global

[5] In a supplementary online appendix, we report tables that include the complete set of data underlying all figures reported in the main text. These tables include point estimates and confidence intervals.

ASCC. In particular, the estimate can then be scaled by population forecasts out to the year 2100. In what follows, we use the estimate of \$1,116 per year (95-percent confidence interval of \$900-\$1,382), although alternative estimates can be readily substituted into the same framework if preferred.

## 5. Average Social Costs of Carbon

Additional sources of data are necessary to obtain estimates of the ASCC. First is the annual change in emissions from a BAU 4ºC path to a 2ºC path by 2100. We obtain data on the necessary change in annual emissions from the wide range of emissions and warming scenarios in the IPCC Scenarios Database (IPCC 2022). The IPCC projects warming in 2100 for 1,202 emissions scenarios. Among these, we identify BAU 4º pathways as all those associated with a predicted temperature increase between 3.8º and 4.2º in 2100, and 2º pathways as all those with predicted temperature increases between 1.8º and 2.2º. We then take pairwise differences between the resulting 33 scenarios for 4ºC and 236 scenarios for 2ºC. This procedure yields 33 x 236 = 7,788 emission reduction pathways, and Figure 2a illustrates $\Delta m_t$ in each year for all pathways out to 2100.

The second source of additional data is population projections for each country. These we obtain from the Shared Socioeconomic Pathways (SSP) corresponding with the different emissions scenarios (SSP Database 2023). The country-level population projections are reported in five-year age bins that we use to 2100. We linearly interpolate the projections to obtain annual projections for each of the five corresponding SSP families associated with the emissions scenarios included in either the 4ºC or 2ºC cases.[6] We then link each of our 7,788 emission reduction pathways to these population projections by taking the average of the SSP population projections for the two trajectories differenced in each scenario. Figure 2b illustrates the different global population scenarios across pairings. It turns out that 88 percent of the averaged population pathways are simply the SSP2 scenario because it is the projection used most frequently for both the BAU and 2ºC emissions trajectories. Note

[6] To match our survey population, we count only individuals over 18 years old. To obtain 18- and 19-year-old population estimates, we use two-fifths of the bin reported in the range of 15- to 19-year-olds.

that, although Figure 2a illustrates global population projections, we use country-specific estimates in our analysis.[7]

We focus first on estimates of the U.S. domestic ASCC. Recall from equation (4) that further assumptions are necessary about the discount rate and the rate of change in marginal abatement costs. Figure 3 illustrates the results across a range of standard discount rates (1.5, 2, and 3 percent) and annual changes in marginal abatement costs from ±2 percent. The bars reported in the figure reflect the domestic ASCC corresponding with the mean emission reduction pathway and mean WTP estimate. We characterize uncertainty in three different ways. The first (shown on the right side of each bar in the figure) is based on only uncertainty in the estimate of mean WTP, that is, using the 95-percent confidence interval of the WTP estimate and the mean emission pathway. The others (shown on the left side of each bar in the figure) account for the range of different emissions pathways. The inner hash marks reflect the estimates using the extreme emissions pathways and mean WTP. The range outside the hashmarks reflects the extreme emissions pathways and the upper and lower bounds of the 95-percent confidence internal of the mean WTP.[8]

Consider, for example, the central scenario of $r = .02$ and $z = 0$. The estimate is \$8, with a 95-percent confidence interval of \$6-\$10, reflecting only uncertainty in the mean WTP. This estimate represents the benefit per tonne to present and future U.S. residents over the age of 18 assuming the average WTP remains constant to 2100 and population changes according to projections. If we also account for uncertainty in the emission reduction scenarios (which do not have probability weights), we find a range of \$6-\$12 assuming the mean WTP, and \$5-\$14 accounting for both scenario and WTP uncertainty.

The estimates in Figure 3 are insensitive to the discount rate, which is a result noted previously by Pindyck (2017, 2019) as a desirable feature of considering the average rather than marginal SCC. The results vary substantially, however, with different assumptions about

[7] This applies for estimates of the domestic ASCC for each country and for the aggregated global ASCC.

[8] Specifically, the lowest (highest) estimate of the range corresponds with the highest (lowest) reduction in emissions and the lower (higher) bound of the WTP estimate.

the annual rate of change in marginal abatement costs. With marginal abatement costs decreasing or increasing 2 percent per year, the central estimate of $8 per tonne increases to $17 or decreases to $3, respectively. Recall from equation (4) that decreasing marginal abatement costs, for example, decreases the present value of cost-adjusted, future tonnes. This has the consequence of increasing the present value of the average benefit (or cost) per tonne. As shown in the figure, the confidence intervals also widen in cases with higher estimates.

Next, to arrive at an estimate of the global ASCC, which is our primary focus, we need to carry out a benefits transfer to estimate average WTP for countries other than the United States. The key source of data is differences in income across counties, and this we measure using 2022 gross domestic product (GDP) per capita from the International Monetary Fund's World Economic Outlook Database (IMF 2023). Then according to equation (6), we assume an income elasticity of WTP. We consider a range of values ($\eta = .5, .75, 1$), informed by the literature on the income elasticity of the VSL (Viscusi and Aldy 2003; Viscusi and Masterman 2017; Masterman and Viscusi 2018) and limited evidence across countries on WTP to avoid climate change (Carlsson et al. 2012).[9]

The global ASCC, based on equation (5), generalizes the estimate to represent the benefits (or costs) to residents of all countries. Figure 4 illustrates the results assuming initially no change in marginal abatement costs (i.e., $z = 0$). We again report uncertainty ranges of the estimates corresponding with the same three approaches described for Figure 3. For the central case of $r = .02$ and $\eta = .75$, the estimate of the global ASCC is $39 per tonne, with a WTP 95-percent confidence interval of $32-48, and a wider range from $23-$65 reflecting uncertainty over both emissions scenarios and WTP. This reflects the estimated global benefit (cost) per tonne of moving from a 4ºC to a 2ºC temperature increase by 2100. For these global estimates, we find that a higher discount rate increases the estimate, though

[9] We also estimate an income elasticity of WTP based on our survey sample and the estimated logit model. This produces and estimate 0.4. The estimate is nevertheless limited for purposes of the benefits transfer because it is based on the relatively high income of the U.S. population, rather than reflecting the range of incomes across countries. Empirical evidence underscores that within-country estimates of income elasticity of WTP do not reflect cross-country income elasticity of WTP and assuming a reasonable income elasticity of WTP is a preferred approach (Czajkowski et al., 2017).

the effect is not large. The increase follows because, for some countries, discounting reduces the numerator in equation (4) by more than the denominator. More substantial differences arise with alternative assumptions about the income elasticity of WTP. Assuming an income elasticity of .5 increases the estimate of the global ASCC to $57, whereas assuming an income elasticity of one (i.e., WTP proportional to income) decreases the global ASCC to $29 per tonne.

Alternative assumptions about the rate of change in marginal abatement costs substantially affect the global ASCC. These results are shown in Figure 5. Continuing with the central case ($r = .02$ and $\eta = .75$), the estimate of the global ASCC increases to $81 with an annual 2-percent decline in abatement costs. Reflecting uncertainty, the range of this estimate is from $66-$100 for uncertainty in mean WTP and $45-$165 for uncertainty in both mean WTP and the emissions scenario. If abatement costs are increasing at 2 percent, the central estimate falls to $16 per tonne. These results highlight how the rate of change in marginal abatement costs matters far more than the discount rate. While debate about the most appropriate discount rate is ongoing, often drawing on philosophical concerns about intergenerational ethics (Stern 2007; Nordhaus 2007), assumptions about the rate of change in marginal abatement costs seem potentially less contentious, in part because there is a clear empirical basis.[10]

## 6. Breakeven Willingness to Pay

Our empirical analysis thus far has been structured around translating SP estimates of mean WTP in the United States for limiting global warming into estimates of the global ASCC. However, the conceptual framework we develop enables reversing the direction of analysis to begin with a global ASCC and asking what mean WTP is consistent with that value.

Framing analysis in this way helps to address potential skepticism about the validity of SP techniques for estimating WTP. SP estimates generate controversy in the literature, and one might expect concerns to be especially present when it comes to valuing the benefits of

[10] See Pindyck (2017, 2019) for further discussion about this as a potential advantage of using the average SCC compared to the marginal SCC.

avoiding climate change, and problem over a long period of time and global in scope. Additionally, as with any SP survey, some readers are likely to take issue with one aspect or another of our specific WTP question. A breakeven analysis addresses these concerns by not leaning entirely on the results of our particular survey, but rather focusing on how a seemingly plausible range of WTP estimates map into the global ASCC.

Another advantage of a breakeven analysis is that focal points have emerged in the literature about the benefits (costs) per tonne of changes in GHG emissions. Most common are estimates of the SCC at values of \$50 per tonne and more recent estimates of \$185 and \$190 (Rennert et al. 2022; U.S. EPA 2030). To be clear, the SCC (a marginal measure) differs from the ASCC (an average measure), but the potential applications for policy analysis are similar. Pindyck (2017, 2019) makes this case, and his expert elicitation produces preferred estimates of the ASCC that range between \$80 and \$200 per tonne.

The breakeven analysis that follows provides a framework for mapping views about the global benefits into a U.S. mean monthly WTP, so researchers and the public can have a familiar reference point to evaluate the potential plausibility of any given estimate of the global benefits. Importantly, this portion of our analysis does not rely on our survey based estimated WTP; it relies only on the conceptual framework and assumed parameter values, for which we show sensitivity analysis.

Substituting (6) into (5), we can solve for the relationship between the global ASCC and U.S. mean WTP:

$$ASCC_G = \frac{\sum_h \sum_{t=0}^{T} \beta^t \, Pop_{ht} \left(\frac{w_h}{w_k}\right)^{\eta}}{\sum_{t=0}^{T} \beta^t \alpha^t \Delta m_t} \times WTP_k \tag{7}$$

where $k$ denotes the United States. The relationship is linear, and we can see how it depends on each of the parameters and underlying data on GDP per capita, the change in emissions, and country-specific population projections.

Figure 6 illustrates the results, where the different panels show sensitivity to the change in emissions scenario, the income elasticity of WTP $\eta$, and the rate of change in marginal abatement costs $z$. We omit results based on different discount rates because we have already shown relative insensitivity to this parameter. Also shown in the figure are reference points corresponding to our estimates of the U.S. mean WTP and the 95 percent confidence intervals (see logit results in Figure 1). Each panel illustrates results for a U.S. average monthly WTP up to $200. For example, the lower line in the top panel shows that a monthly WTP of $200 corresponds with a global ASCC of approximately $60 assuming our central estimates of the parameters and the highest present value emission reduction scenario.

We also report in the supplementary appendix (Table S6) the estimated magnitude of the slope coefficients underlying all of the lines illustrated in Figure 6. This way readers can calculate any mapping between a global ASCC and mean WTP in the United States for a preferred scenario. For example, we find for our central scenario (i.e., the middle line in all three panels of Figure 6) that the values of the global ASCC of $50, $100, $150, and $200 correspond with U.S. monthly WTP values of $119, $238, $356, and $475, respectively. We believe these points of reference, based on readily interpretable monthly WTP, provide a novel way to interpret the magnitude of the global benefits of changes in emissions. The framework can also readily accommodate alternative assumptions, and importantly, it applies regardless of whether one is skeptical or not about the validity of specific SP estimates.

## 7. Distributionally-Weighted Estimates

There is growing interest in the use of distributionally weighted estimates of benefits and costs for BCA in general (OMB 2023; Acland and Greenberg 2023) and for estimates of the SCC in particular (Azar and Sterner 1996; Anthoff et al. 2009; Anthoff and Emmerling 2019; Adler et al. 2017; Tol 2019). The intention is to take account of diminishing marginal utility of income when aggregating benefits or costs among groups. The standard approach is to apply weights based on the assumption of isoelastic utility, in which case the marginal utility of income is equal to $w^{-\varepsilon}$, where $\varepsilon > 0$ is the elasticity of the marginal utility of income.[11]

Indeed, the U.S. Office of Budget and Management (OMB 2023) recommends this approach in recent revisions to Circular No. A-4, which provides official guidance to federal agencies about how to carryout regulatory impact analyses. There are, however, open questions about how the U.S. government proposes to treat equity weighting with international impacts, and the EPA (2023) estimates of the revised SCC are not equity weighted.[12] What follows should therefore be interpreted as one potential approach to addressing distributional concerns, while acknowledging that how best to accomplish this objective remains subject to debate in the academic literature and for official policy analysis. Nevertheless, the approach we employ is standard and currently in use for both BCA and estimates of the SCC.

The distributionally weighted estimate of the global ASCC requires normalizing the estimate to a particular level of income. Accordingly, an important feature to keep in mind is that the approach implies a different estimate of the global ASCC for use in each country, depending on the country's level of income. Assuming normalization to the income level of country $k$, the weight for aggregating estimates of other countries $h$ can be written as

$$\phi_h^k = \left(\frac{w_h}{w_k}\right)^{-\varepsilon}. \tag{7}$$

Note that the weight is unity for country $h = k$ (and any other countries that have the same level of income), and greater (less) than unity to the extent that $w_h < (>) w_k$. In effect,

[11] The isoelastic utility function takes the form $U(w) = (w^{1-\varepsilon} - 1)/(1 - \varepsilon)$ if $\varepsilon \neq 1$, and $U(w) = \ln(w)$ if $\varepsilon = 1$.

[12] When discussing distributional weighting, the OMB (2023) guidance focuses on domestic benefits and costs, and there is relatively little mention of international impacts. The guidance states that altering the approach "may be appropriate when analyzing regulations with international scope" (p. 67, footnote 126), but it does not discuss options for what alternations might be appropriate other than referencing an earlier section of the report on the Scope of Analysis. In that section, the OMB is clear about incorporating international climate damages, but it is silent on distributional weighting. Hence, at present, the OMB is clear about accounting for international impacts, yet whether distributional weighting should occur and how remains unclear, and as noted the EPA did not employ equity weights for it estimates of the SCC. The EPA (2023) does, however, discuss the issue and notes that it "will continue to assess the broader literature on BCA, social welfare, and equity as it seeks to apply the best available science in its analyses" (p. 167).

lower income countries are up-weighted while higher income countries are down-weighed. And greater values of $\varepsilon$, which reflect greater diminishing marginal utility of income, increase the effect of weighting.

The distributionally weighted, global ASCC for use in country $k$ is then

$$ASCC_G^k = \sum_h \phi_h^k ASCC_h. \tag{8}$$

This differs from equation (5) not only because of the weights, but also because the global estimate now depends on the reference country. Intuitively, the estimate is country-specific because the units are consumption-equivalent dollars for the average individual in the reference country. The country-specific distributionally weighted ASCC is then a measure of the per tonne costs (benefits) of changes in emissions in the reference country that can be used for BCAs. It is nevertheless important to keep in mind that the estimates represent the *global* benefits (or costs) for the reference country even though the estimate is country-specific.

Figure 7 illustrates the results for all countries over a range of values for $\varepsilon$ that are estimated and employed in the literature (Rennert et al. 2022; OMB 2023; Acland and Greenberg 2023; Gandelman and Hernandez-Murillo 2015; Havranek et al. 2015; Drupp et al. 2018; Groom and Maddison 2019). Assuming our central case ($r = .02$, $\eta = .75$, and $z = 0$), and the central estimate of $\varepsilon = 1.4$, the U.S. estimate of the distributionally-weighted, global ASCC is \$1,191 per tonne.[13] This is a substantial increase from the comparable unweighted estimate of \$39, and this echoes the results of previous studies that find estimates highly sensitive to the parameterized marginal utility of income. The implication, in this case, is that when taking distributional weighting into account internationally, \$1,191 is the benefit (cost) per tonne to consider (rather than \$39) for potential use in BCAs within the United States.[14]

[13] Based on a literature review, $\varepsilon = 1.4$ is the OMB's (2023) recommended value for the income elasticity of marginal utility.

[14] We report the distributionally weighted ASCCs for all countries in Table S7 of the supplementary online appendix.

The U.S. estimate changes to $613 and $2,414 for elasticity estimates of 1.2 and 1.6, respectively. These results are also shown in Figure 7 along with those for other countries and different these parameter values. While the same pattern applies to all high-income countries, distributional weighting causes a decrease in the estimate for relatively low-income countries, and it makes less of a difference for those that are middle-income. At $\varepsilon = 1.4$, for example, the estimate is $10 for India, $60 for Brazil, and $102 for China. As the elasticity converges to zero, the estimate for all countries converges back to the unweighted, global ASCC of $39 per tonne.

## 8. Conclusion

We believe this paper contributes the first SP estimates of the benefits or costs per tonne of GHG emissions for general use in policy analysis. Previous research advances the notation of using an average (rather than marginal) estimate of the SCC, and it uses expert elicitation with detailed questions about the effects of climate change on economic growth and the reduction in emissions required to avoid such effects (Pindyck 2017, 2019). This paper takes a more direct approach: we use survey methods to ask people much they would be willing to pay to reduce emissions in order to meet the internationally agreed upon target of limiting emissions to 2°C by 2100. We are then able to interpret these WTP measures on a per tonne basis using a range of IPCC estimates on the emission reductions necessary to achieve the 2°C target. While our survey focuses on the United States, we are able to derive estimates of the global ASCC using a benefits transfer approach. We also show the impact of distributional weighting on estimates of the global ASCC.

One reason researchers may have stayed away from survey-based, nonmarket valuation is concern about hypothetical bias. We nevertheless find results substantially lower than most SCC estimates in the literature. A recent meta-analysis (Tol 2023) finds that studies conducted within the last decade produce estimates that range between $40 and $525 per tonne for high and low discount rate scenarios. A similar range of estimates is found in the detailed analysis included in the EPA (2023) revisions to the SCC. By way of comparison, our central estimate here is $39, but we show the effect of alternative assumptions about the income elasticity of WTP and the rate of change in marginal abatement costs. Reasonable scenarios create a range of estimates between \$12-\$118 per tonne, and unlike the SCC, we find that the results are insensitive to the discount rate. When making comparisons to the SCC, however, it is worth emphasizing that we focus on the *average* SCC, and this estimate should be lower than the *marginal* SCC when the marginal costs of climate damages are increasing in the cumulative level of emissions and over time.

The conceptual framework that we develop here should also be of interest even to those skeptical of SP techniques for estimating WTP, especially for an issue at the scale of climate change. We show how the model enables a transparent mapping between any estimate of the average benefits per tonne and the corresponding mean WTP among U.S. residents. Based on our central scenario, for example, with find that the values of the global ASCC of \$50, \$100, \$150, and \$200 correspond with U.S. monthly WTP values of \$119, \$238, \$356, and \$475, respectively. We believe that the translation of global average benefits into a familiar WTP estimate can provide something akin to a "reality check" on estimated global benefits of emissions reductions and observed carbon prices in policy vis-à-vis whether they reflect plausible WTP amounts.

Finally, we argue that no single estimate of climate damages should emerge at the expense of others. The scale and complexity of the problem, along with the uncertainty and need for assumptions, is simply too great. It is the expanding body of evidence that has value in documenting the real and substantial economic damages of climate change—and therefore the benefits of mitigation. At present, the real challenge is not whether current policies are consistent with optimal climate policy that balances benefits and costs. Instead, substantial challenges remain to persuade significant portions of the population and political leaders that any meaningful climate policies are worthwhile. Accordingly, the estimates provided here will contribute because, alongside the existing literature, they add a new measure of economic value based directly on public preferences.

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## Tables and Figures

**Table 1:** Summary of responses to the WTP question for each specified dollar amount

| Specified amount | Total obs. | Yes | No | Protest responses | Refused responses |
|---|---|---|---|---|---|
| $6 | 101 | 56 | 12 | 26 | 7 |
| $16 | 102 | 39 | 20 | 39 | 4 |
| $26 | 202 | 95 | 47 | 56 | 4 |
| $45 | 203 | 88 | 62 | 47 | 6 |
| $85 | 204 | 75 | 70 | 49 | 10 |
| $124 | 103 | 30 | 32 | 38 | 3 |
| $165 | 100 | 22 | 45 | 30 | 3 |
| Total | 1015 | 405 | 288 | 285 | 37 |

**Table 2:** Summary statistics of sociodemographic variables

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Experience global warming (proportion) | 0.72 | 0.45 | 0.00 | 1.00 |
| Household income ($1,000s) | 95.81 | 68.16 | 5.00 | 250.00 |
| Education (years) | 14.20 | 2.88 | 0.00 | 20.00 |
| Democrat (proportion) | 0.38 | 0.48 | 0.00 | 1.00 |
| Republican (proportion) | 0.24 | 0.43 | 0.00 | 1.00 |
| Independent (proportion) | 0.27 | 0.44 | 0.00 | 1.00 |
| No party affiliation (proportion) | 0.11 | 0.31 | 0.00 | 1.00 |
| Female (proportion) | 0.51 | 0.50 | 0.00 | 1.00 |
| Age (years) | 47.26 | 18.33 | 18.00 | 94.00 |
| Household size (individuals) | 2.76 | 1.51 | 1.00 | 12.00 |

*Notes:* Summary statistics are based on 693 non-protest observations to the WTP question. Means and standard deviations are weighted using population weights. All variables are based on standard demographics for the Ipsos KnowledgePanel, with the exception of having experienced global warming personally.

**Table 3:** Logit models of WTP responses

| | (1) | | (2) | |
|---|---|---|---|---|
| Specified amount ($X) | −0.010*** | [−0.0023] | −0.013*** | [−.0021] |
| | (0.002) | | (0.002) | |
| Experience global warming | | | 1.744*** | [0.282] |
| | | | (0.221) | |
| Household Income (000's) | | | 0.005*** | [0.008] |
| | | | (0.002) | |
| Education (years) | | | 0.094*** | [0.016] |
| | | | (0.038) | |
| Democrat | | | 0.589*** | [0.097] |
| | | | (0.217) | |
| Republican | | | −0.897*** | [−0.148] |
| | | | (0.240) | |
| Constant | 0.968*** | | −1.849*** | |
| | (0.132) | | (0.516) | |
| Observations | 693 | | 693 | |
| Log Likelihood | -481.921 | | -366.557 | |
| Akaike Inf. Crit. | 967.842 | | 747.113 | |

*Notes:* Models are estimated using population weights. Standard errors are reported in parentheses, and marginal effects (reported in brackets) are evaluated at the variable means. All coefficient estimates are statistically significant at the 99-percent level, as indicated by three asterisks.

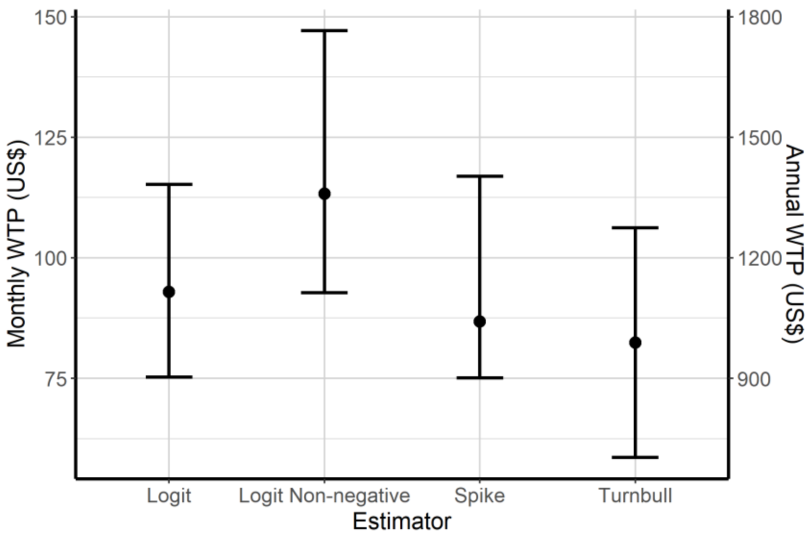


**Figure 1: Mean WTP and 95 percent confidence intervals for different estimators.** The different estimates are based on a logit model, a logit model with the cumulative distribution function truncated at zero, a spike model, and a lower-bound Turnbull estimate. The range shows 95 percent bootstrapped confidence intervals. The left and right vertical axes are scaled as monthly and annual WTP, respectively.

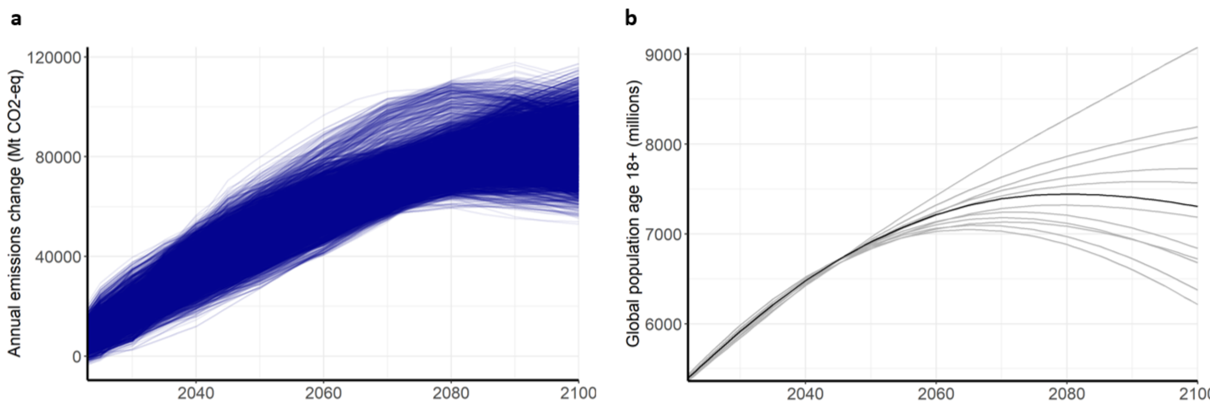


**Figure 2: Pathways for the change in emissions and global population for BAU 4°C to 2°C degrees by 2100.** Panel a shows the annual reduction in emissions for 7,788 scenarios based on the difference between IPCC pathways with temperature changes 3.8-4.2° and 1.8-2.2° by 2100. Panel b shows all global population trajectories corresponding with the emission reduction scenarios. Each is the average of two SSP population trajectories corresponding to the pairwise combination of emissions trajectories. The trajectory in bold (SSP 2) corresponds to 88 percent of the scenario combinations.

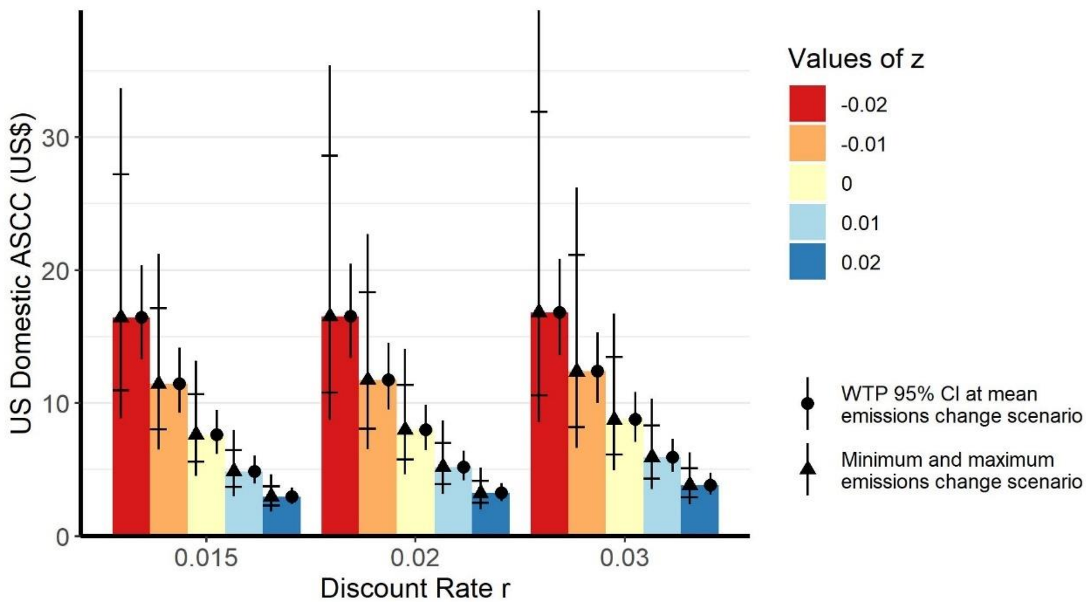


**Figure 3: Estimates of the U.S. domestic ASCC.** The U.S. domestic ASCC is the estimated benefit (cost) per tonne to U.S. residents of moving from a BAU 4ºC temperature increase by 2100 to a 2ºC increase. Values of *z* are different assumptions about the rate of change in marginal abatement costs. For each bar, the right-side confidence intervals reflect uncertainty in the estimate of mean WTP. The left side reflects the range of estimates across the emissions reduction scenarios, where the inner hash marks are evaluated at the mean WTP, and the outer extremes are bounds reflecting both emissions and WTP uncertainty.

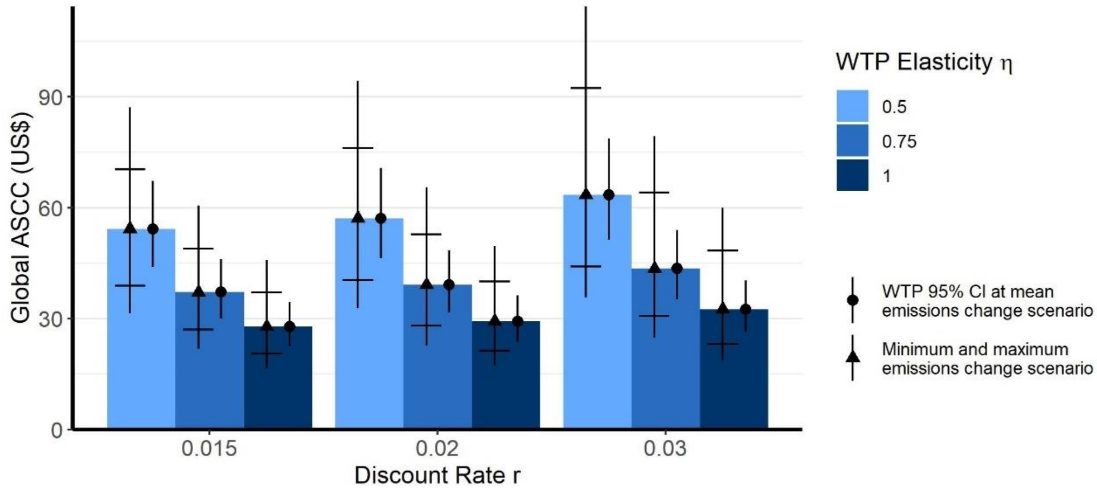


**Figure 4: Estimates of the global ASCC with different discount rates and WTP elasticities.** The estimates are relatively insensitive to the discount rate, $r$, but they vary with different assumptions about the elasticity of WTP, $\eta$. All estimates assume a zero rate of change in the marginal abatement costs, i.e., $z = 0$. For each bar, the right side confidence intervals reflect uncertainty in the estimate of mean WTP. The left side reflects the range of estimates across the emissions reduction scenarios, where the inner hash marks are evaluated at the mean WTP and the outer extremes are bounds reflecting both emissions and WTP uncertainty.

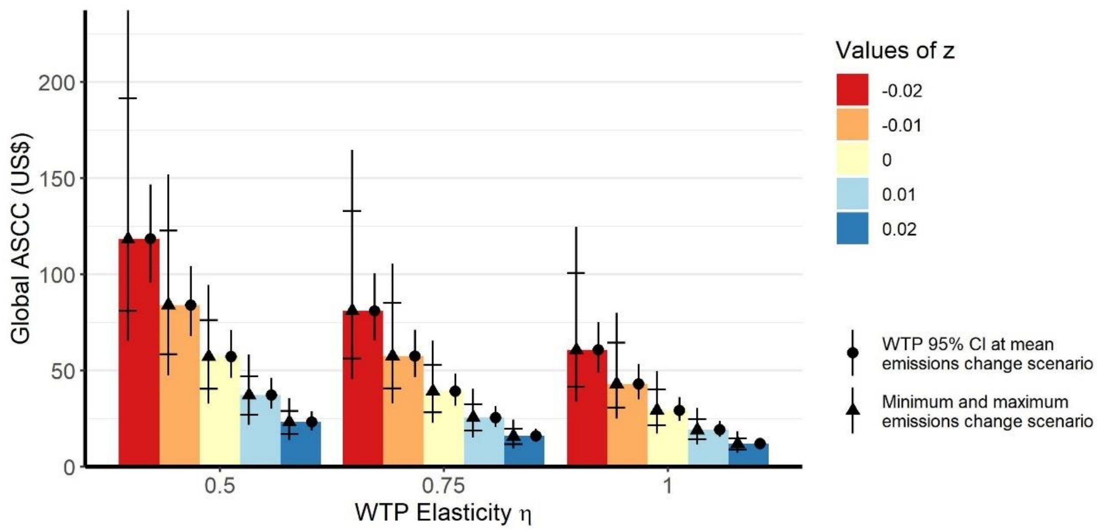


**Figure 5: Estimates of the global ASCC with different WTP elasticities and assumptions about the rate of change in marginal abatement costs.** The figure reports results for different assumptions about the WTP elasticity, $\eta$, and the rate of change in marginal abatement costs, $z$. All estimates are based on the central discount rate of $r = .02$. For each bar, the right side confidence intervals reflect uncertainty in the estimate of mean WTP. The left side reflects the range of estimates across the emissions reduction scenarios, where the inner hash marks are evaluated at the mean WTP and the outer extremes are bounds reflecting both emissions and WTP uncertainty.

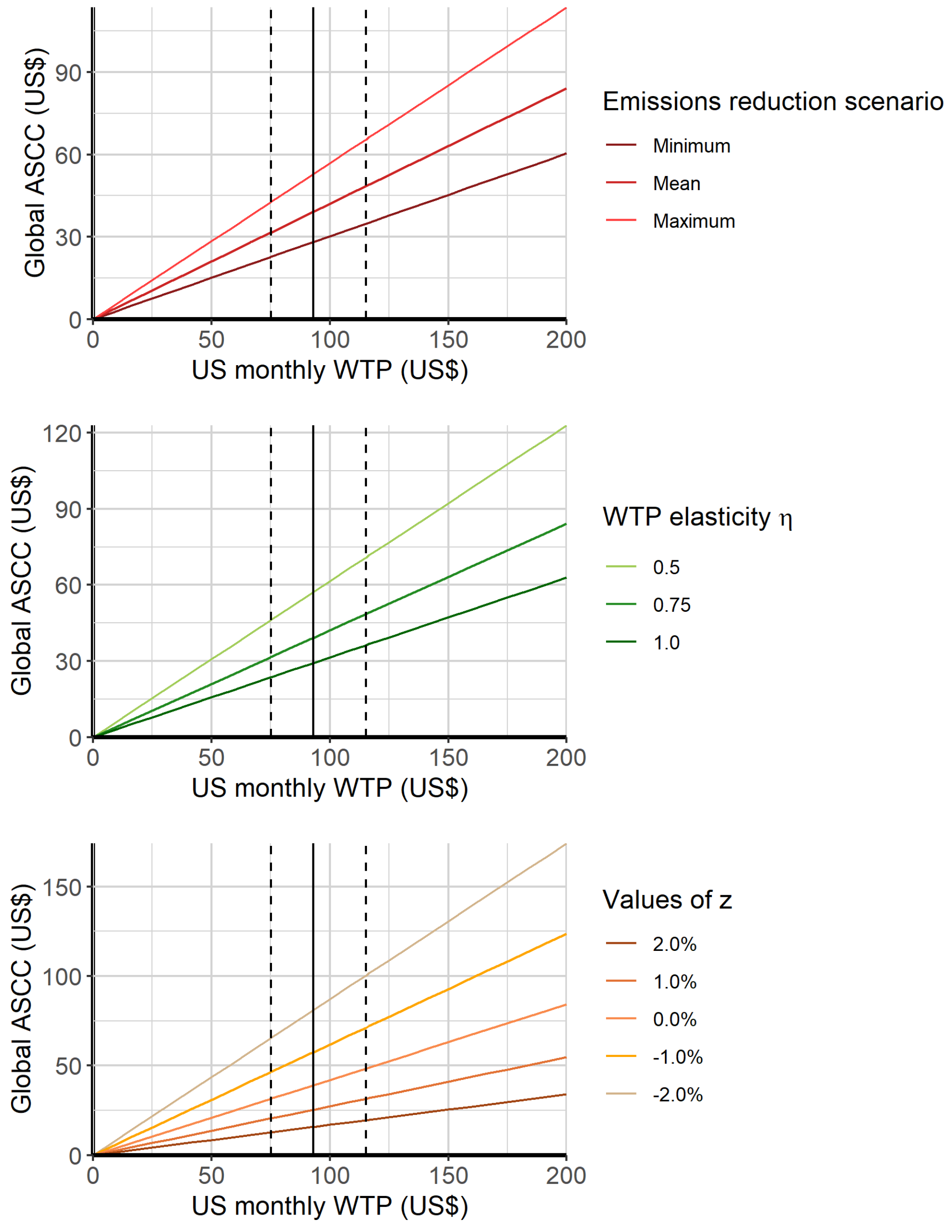


**Figure 6: Relationship between the global ASCC and U.S. monthly WTP with different assumptions about the emissions scenario and parameter values.** The top panel shows sensitivity to the emissions scenario, the middle panel to the income elasticity of WTP $\eta$, and the bottom to the rate of change in marginal abatement costs $z$. The vertical lines correspond with our SP estimate of mean WTP and the 95 percent confidence interval. All scenarios assume the central discount rate of $r = .02$.

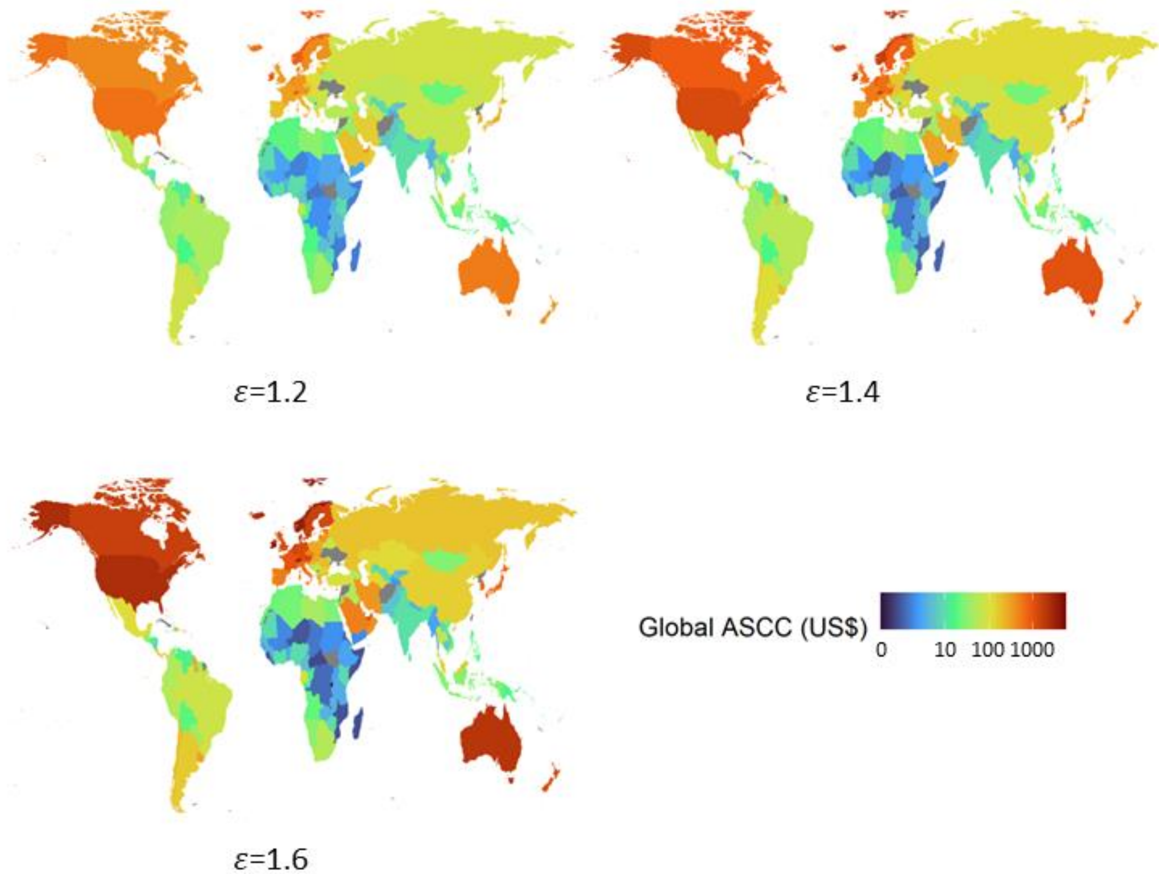


**Figure 7: Estimates of the distributionally-weighted global ASCC for each country.** The country-specific, distributionally-weighted, global ASCC is the benefit (cost) per tonne to consider when the change is emissions has costs (benefits) accruing to the specific country based on it level of income per capita. Panel a shows results with the elasticity of the marginal utility of income $\varepsilon = 1.2$. Panel b shows results for $\varepsilon = 1.4$, and Panel c for $\varepsilon = 1.6$.

*Supplementary Material for Online Publication*

# Stated Preference Estimates of the Average Social Cost of Carbon

Matthew Ashenfarb and Matthew J. Kotchen

**Table S1:** Logit models of protest response to the WTP question

| | (1) | | (2) | |
|---|---|---|---|---|
| Experience global warming | -0.703*** | [-0.142] | -0.721*** | [-0.147] |
| | (0.150) | | (0.149) | |
| Household Income (000's) | -0.001 | [-0.0002] | -0.001 | -[0.0002] |
| | (0.001) | | (0.001) | |
| Education (years) | -0.026 | [-0.005] | -0.025 | [-0.005] |
| | (0.029) | | (0.029) | |
| Democrat | -0.614*** | [-0.125] | -0.564*** | [-0.115] |
| | (0.179) | | (0.177) | |
| Republican | 0.019 | [0.004] | 0.053 | [0.011] |
| | (0.166) | | (0.165) | |
| Female | 0.108 | [0.022] | | |
| | (0.142) | | | |
| Age | 0.009** | [0.002] | | |
| | (0.004) | | | |
| Household size | 0.030 | [0.006] | | |
| | (0.052) | | | |
| Constant | -0.304 | | 0.271 | |
| | (0.498) | | (0.382) | |
| Observations | 1,014 | | 1,014 | |
| Log Likelihood | -601.5 | | -604.1 | |
| Akaike Inf. Crit. | 1,221 | | 1,220 | |

*Notes:* Models are estimated using population weights. Standard errors are reported in parentheses, and marginal effects (reported in brackets) are evaluated at the variable means. One, two, or three asterisks indicate statistical significance at the 90-, 95-, or 99-percent levels, respectively

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**Table S2:** Data underlying Figure 1, mean monthly and annual WTP for the United States

| Method | Monthly WTP | Annual WTP |
|---|---|---|
| Logit | 92.96 | 1115.52 |
| | (75.02, 115.16) | (900.24, 1381.92) |
| Logit, non-negative distribution | 113.31 | 1359.72 |
| | (93.38, 148.84) | (1120.56, 1786.08) |
| Turnbull | 82.39 | 988.68 |
| | (58.59, 106.20) | (703.08, 1274.4) |
| Spike | 86.76 | 1041.12 |
| | (75.21, 116.68) | (902.52, 1400.16) |

**Table S3:** Data underlying Figure 3, U.S. domestic ASC

| | | Mean emissions scenario | | | Range across emissions scenarios | | | |
|---|---|---|---|---|---|---|---|---|
| $r$ | $z$ | Mean WTP | 95% Low WTP | 95% High WTP | Mean WTP | Mean WTP | 95% Low WTP | 95% High WTP |
| 0.015 | -0.02 | 16.43 | 13.29 | 20.36 | 10.95 | 27.19 | 8.86 | 33.69 |
| 0.015 | -0.01 | 11.44 | 9.26 | 14.18 | 8.01 | 17.14 | 6.48 | 21.24 |
| 0.015 | 0 | 7.63 | 6.17 | 9.45 | 5.58 | 10.65 | 4.52 | 13.19 |
| 0.015 | 0.01 | 4.86 | 3.93 | 6.03 | 3.68 | 6.44 | 2.98 | 7.97 |
| 0.015 | 0.02 | 2.96 | 2.4 | 3.67 | 2.29 | 3.74 | 1.85 | 4.64 |
| 0.02 | -0.02 | 16.52 | 13.37 | 20.47 | 10.8 | 28.59 | 8.74 | 35.42 |
| 0.02 | -0.01 | 11.73 | 9.49 | 14.53 | 8.07 | 18.33 | 6.53 | 22.71 |
| 0.02 | 0 | 7.98 | 6.45 | 9.88 | 5.75 | 11.37 | 4.66 | 14.09 |
| 0.02 | 0.01 | 5.19 | 4.2 | 6.43 | 3.9 | 6.99 | 3.15 | 8.67 |
| 0.02 | 0.02 | 3.22 | 2.61 | 3.99 | 2.48 | 4.13 | 2.01 | 5.12 |
| 0.03 | -0.02 | 16.82 | 13.61 | 20.84 | 10.57 | 31.89 | 8.55 | 39.52 |
| 0.03 | -0.01 | 12.38 | 10.02 | 15.34 | 8.2 | 21.14 | 6.64 | 26.2 |
| 0.03 | 0 | 8.75 | 7.08 | 10.85 | 6.11 | 13.49 | 4.94 | 16.71 |
| 0.03 | 0.01 | 5.93 | 4.79 | 7.34 | 4.33 | 8.33 | 3.51 | 10.32 |
| 0.03 | 0.02 | 3.83 | 3.1 | 4.75 | 2.92 | 5.09 | 2.36 | 6.31 |

**Table S4:** Data underlying Figure 4, the global ASCC by discount rate and WTP elasticities

| | | Mean emissions scenario | | | Range across emissions scenarios | | | |
|---|---|---|---|---|---|---|---|---|
| $r$ | $\eta$ | Mean WTP | 95% Low WTP | 95% High WTP | Mean WTP | Mean WTP | 95% Low WTP | 95% High WTP |
| 0.015 | 0.5 | 54.29 | 43.93 | 67.28 | 38.81 | 70.37 | 31.4 | 87.2 |
| 0.015 | 0.75 | 37.13 | 30.05 | 46.02 | 26.96 | 48.89 | 21.81 | 60.58 |
| 0.015 | 1 | 27.78 | 22.48 | 34.43 | 20.45 | 37.08 | 16.55 | 45.95 |
| 0.02 | 0.5 | 57.15 | 46.24 | 70.82 | 40.47 | 76.13 | 32.75 | 94.33 |
| 0.02 | 0.75 | 39.12 | 31.65 | 48.47 | 28.1 | 52.85 | 22.74 | 65.49 |
| 0.02 | 1 | 29.26 | 23.68 | 36.26 | 21.29 | 40.04 | 17.22 | 49.61 |
| 0.03 | 0.5 | 63.47 | 51.36 | 78.65 | 44.12 | 92.37 | 35.7 | 114.46 |
| 0.03 | 0.75 | 43.5 | 35.2 | 53.91 | 30.6 | 64.06 | 24.76 | 79.38 |
| 0.03 | 1 | 32.54 | 26.33 | 40.32 | 23.13 | 48.42 | 18.71 | 60 |

**Table S5:** Data underlying Figure 5, the global ASCC with different WTP elasticities and assumptions about the rate of change in marginal abatement costs

| | | Mean emissions scenario | | | Range across emissions scenarios | | | |
|---|---|---|---|---|---|---|---|---|
| $\eta$ | $z$ | Mean WTP | 95% Low WTP | 95% High WTP | Mean WTP | Mean WTP | 95% Low WTP | 95% High WTP |
| 0.5 | -0.02 | 118.34 | 95.75 | 146.64 | 80.93 | 191.36 | 65.48 | 237.12 |
| 0.5 | -0.01 | 84.02 | 67.98 | 104.11 | 58.46 | 122.68 | 47.3 | 152.02 |
| 0.5 | 0 | 57.15 | 46.24 | 70.82 | 40.47 | 76.13 | 32.75 | 94.33 |
| 0.5 | 0.01 | 37.17 | 30.07 | 46.06 | 26.78 | 46.85 | 21.67 | 58.06 |
| 0.5 | 0.02 | 23.1 | 18.69 | 28.62 | 16.8 | 28.84 | 13.59 | 35.73 |
| 0.75 | -0.02 | 81 | 65.54 | 100.37 | 56.18 | 132.85 | 45.46 | 164.62 |
| 0.75 | -0.01 | 57.51 | 46.53 | 71.26 | 40.58 | 85.17 | 32.84 | 105.54 |
| 0.75 | 0 | 39.12 | 31.65 | 48.47 | 28.1 | 52.85 | 22.74 | 65.49 |
| 0.75 | 0.01 | 25.44 | 20.58 | 31.52 | 18.59 | 32.5 | 15.04 | 40.28 |
| 0.75 | 0.02 | 15.81 | 12.79 | 19.59 | 11.66 | 19.73 | 9.44 | 24.45 |
| 1 | -0.02 | 60.59 | 49.03 | 75.08 | 41.47 | 100.64 | 33.55 | 124.7 |
| 1 | -0.01 | 43.02 | 34.81 | 53.31 | 30.74 | 64.52 | 24.88 | 79.95 |
| 1 | 0 | 29.26 | 23.68 | 36.26 | 21.29 | 40.04 | 17.22 | 49.61 |
| 1 | 0.01 | 19.03 | 15.4 | 23.58 | 14.09 | 24.62 | 11.4 | 30.51 |
| 1 | 0.02 | 11.83 | 9.57 | 14.65 | 8.83 | 14.76 | 7.15 | 18.29 |

**Table S6:** Data underlying Figure 6, relationship between the average GCSS and U.S. monthly WTP with different and emissions scenarios and parameter assumptions

| | $r$ | Emissions | $\eta$ | $z$ | Coefficient |
|---|---|---|---|---|---|
| Top panel | 0.02 | Low | 0.75 | 0 | 0.569 |
| | 0.02 | Mean | 0.75 | 0 | 0.421 |
| | 0.02 | High | 0.75 | 0 | 0.302 |
| Middle panel | 0.02 | Mean | 0.5 | 0 | 0.615 |
| | 0.02 | Mean | 0.75 | 0 | 0.421 |
| | 0.02 | Mean | 1.0 | 0 | 0.315 |
| Bottom Panel | 0.02 | Mean | 0.75 | -0.02 | 0.871 |
| | 0.02 | Mean | 0.75 | -0.01 | 0.619 |
| | 0.02 | Mean | 0.75 | 0 | 0.421 |
| | 0.02 | Mean | 0.75 | 0.01 | 0.274 |
| | 0.02 | Mean | 0.75 | 0.02 | 0.170 |

**Table S7:** Data underlying Figure 7, estimates of the distributionally-weighted global ASCC for each country, along with 2022 GDP per capita

| Country | GDP/CAP | $\varepsilon = 1.2$ | $\varepsilon = 1.4$ | $\varepsilon = 1.6$ |
|---|---|---|---|---|
| Albania | 6369.009 | 32 | 38 | 47 |
| Algeria | 4151.437 | 19 | 21 | 23 |
| Angola | 3790.704 | 17 | 18 | 20 |
| Argentina | 13621.86 | 79 | 109 | 157 |
| Armenia | 5971.816 | 29 | 34 | 42 |
| Aruba | 31990.12 | 220 | 360 | 615 |
| Australia | 66407.6 | 528 | 1001 | 1980 |
| Austria | 52061.65 | 394 | 712 | 1341 |
| Azerbaijan | 6842.028 | 35 | 42 | 52 |
| Bahamas | 32246.24 | 222 | 364 | 623 |
| Bahrain | 28691.77 | 193 | 309 | 517 |
| Bangladesh | 2734.109 | 11 | 12 | 12 |
| Barbados | 20003.71 | 125 | 187 | 290 |
| Belarus | 8567.349 | 45 | 57 | 75 |
| Belgium | 50597.87 | 381 | 684 | 1281 |
| Belize | 6096.324 | 30 | 35 | 43 |

| | | | | |
|---|---|---|---|---|
| Benin | 1366.871 | 5 | 4 | 4 |
| Bhutan | 3562.306 | 16 | 17 | 18 |
| Bolivia | 3631.335 | 16 | 17 | 19 |
| Bos and Herzeg | 6818.396 | 34 | 41 | 52 |
| Botswana | 7347.738 | 38 | 46 | 58 |
| Brazil | 8857.47 | 47 | 60 | 79 |
| Brunei | 42939.4 | 313 | 544 | 985 |
| Bulgaria | 12505.01 | 71 | 97 | 137 |
| Burkina Faso | 824.884 | 3 | 2 | 2 |
| Burundi | 292.619 | 1 | 1 | 0 |
| Cambodia | 3600.223 | 7 | 6 | 6 |
| Cameroon | 1771.384 | 6 | 5 | 5 |
| Canada | 1584.003 | 438 | 804 | 1541 |
| Cape Verde | 56794.02 | 16 | 17 | 19 |
| Central African Rep | 495.936 | 1 | 1 | 1 |
| Chad | 743.373 | 2 | 2 | 2 |
| Chile | 15603.61 | 93 | 132 | 195 |
| China | 12970.33 | 74 | 102 | 145 |
| Colombia | 6644.492 | 33 | 40 | 50 |
| Comoros | 1299.682 | 5 | 4 | 4 |
| Costa Rica | 13089.86 | 75 | 103 | 147 |
| Croatia | 17318.05 | 105 | 152 | 230 |
| Cyprus | 29534.74 | 200 | 322 | 541 |
| Czech Republic | 28094.62 | 188 | 300 | 500 |
| Dem. Rep. of Congo | 660.21 | 2 | 2 | 1 |
| Denmark | 65713.41 | 521 | 986 | 1947 |
| Djibouti | 3665.827 | 16 | 17 | 19 |
| Dominican Republic | 10573.15 | 58 | 76 | 105 |
| Ecuador | 6412.728 | 32 | 38 | 47 |
| Egypt | 4504.369 | 21 | 23 | 27 |
| El Salvador | 4883.047 | 23 | 26 | 30 |
| Equatorial Guinea | 11264.42 | 63 | 83 | 116 |
| Eritrea | 646.957 | 2 | 2 | 1 |
| Estonia | 29343.93 | 198 | 319 | 536 |
| Ethiopia | 1097.584 | 4 | 3 | 3 |
| Fiji | 5341.288 | 26 | 29 | 35 |
| Finland | 50818.38 | 383 | 688 | 1290 |
| France | 42330.45 | 308 | 533 | 963 |
| Gabon | 10281.78 | 56 | 73 | 100 |
| Gambia | 846.171 | 3 | 2 | 2 |
| Georgia | 6769.73 | 34 | 41 | 51 |
| Germany | 48397.8 | 361 | 643 | 1193 |
| Ghana | 2368.814 | 10 | 9 | 10 |

| | | | | |
|---|---|---|---|---|
| Greece | 20875.78 | 132 | 198 | 311 |
| Grenada | 10476.52 | 58 | 75 | 103 |
| Guatemala | 4879.866 | 23 | 26 | 30 |
| Guinea | 1345.568 | 5 | 4 | 4 |
| Guinea-Bissau | 856.62 | 3 | 2 | 2 |
| Guyana | 18744.63 | 116 | 170 | 262 |
| Haiti | 1672.69 | 6 | 6 | 5 |
| Honduras | 2969.35 | 13 | 13 | 14 |
| Hong Kong SAR | 49699.59 | 373 | 667 | 1245 |
| Hungary | 18982.75 | 117 | 173 | 267 |
| Iceland | 73981.34 | 601 | 1164 | 2353 |
| India | 2465.865 | 10 | 10 | 10 |
| Indonesia | 4691.236 | 22 | 24 | 29 |
| Iran | 23033.52 | 148 | 227 | 364 |
| Iraq | 6695.851 | 34 | 40 | 50 |
| Ireland | 102217.4 | 886 | 1830 | 3947 |
| Israel | 55358.84 | 424 | 776 | 1480 |
| Italy | 33739.75 | 234 | 388 | 670 |
| Ivory Coast | 2418.436 | 10 | 10 | 10 |
| Jamaica | 5870.1 | 29 | 34 | 41 |
| Japan | 34357.86 | 239 | 398 | 690 |
| Jordan | 4666.199 | 22 | 24 | 28 |
| Kazakhstan | 11590.63 | 65 | 87 | 121 |
| Kenya | 2255.48 | 9 | 9 | 9 |
| Kuwait | 38123.22 | 271 | 460 | 815 |
| Kyrgyzstan | 1434.873 | 5 | 5 | 4 |
| Laos | 2172.151 | 9 | 8 | 8 |
| Latvia | 21481.52 | 136 | 206 | 325 |
| Lesotho | 1186.744 | 4 | 4 | 3 |
| Liberia | 735.185 | 2 | 2 | 1 |
| Libya | 6025.68 | 30 | 35 | 43 |
| Lithuania | 24031.62 | 156 | 241 | 389 |
| Luxembourg | 127672.5 | 1157 | 2499 | 5634 |
| Macao SAR | 33608.41 | 233 | 386 | 666 |
| Madagascar | 521.578 | 2 | 1 | 1 |
| Malawi | 522.963 | 2 | 1 | 1 |
| Malaysia | 13107.88 | 75 | 103 | 148 |
| Maldives | 15097.15 | 89 | 126 | 185 |
| Mali | 857.976 | 3 | 2 | 2 |
| Malta | 32912.47 | 227 | 375 | 644 |
| Mauritania | 2328.251 | 9 | 9 | 9 |
| Mauritius | 9111.606 | 49 | 62 | 82 |
| Mexico | 10947.98 | 61 | 80 | 111 |

| | | | | |
|---|---|---|---|---|
| Moldova | 5528.591 | 27 | 31 | 37 |
| Mongolia | 4541.572 | 21 | 23 | 27 |
| Montenegro | 9849.566 | 53 | 69 | 93 |
| Morocco | 3896.214 | 18 | 19 | 21 |
| Mozambique | 542.095 | 2 | 1 | 1 |
| Myanmar | 1104.747 | 4 | 3 | 3 |
| Namibia | 4808.922 | 23 | 25 | 30 |
| Nepal | 1292.959 | 5 | 4 | 4 |
| Netherlands | 56297.8 | 433 | 794 | 1520 |
| New Zealand | 47278.49 | 351 | 622 | 1149 |
| Nicaragua | 2375.331 | 10 | 9 | 10 |
| Niger | 561.222 | 2 | 1 | 1 |
| Nigeria | 2326.23 | 9 | 9 | 9 |
| North Macedonia | 6815.772 | 34 | 41 | 52 |
| Norway | 92645.97 | 787 | 1595 | 3373 |
| Oman | 23541.51 | 152 | 234 | 377 |
| Pakistan | 1658.363 | 6 | 6 | 5 |
| Panama | 16172.62 | 97 | 139 | 207 |
| Papua New Guinea | 3427.214 | 15 | 16 | 17 |
| Paraguay | 5615.392 | 27 | 32 | 38 |
| Peru | 7004.793 | 36 | 43 | 54 |
| Philippines | 3597.483 | 16 | 17 | 19 |
| Poland | 19023.23 | 118 | 174 | 268 |
| Portugal | 24910.41 | 163 | 254 | 412 |
| Puerto Rico | 38442.85 | 274 | 466 | 826 |
| Qatar | 82886.79 | 689 | 1365 | 2822 |
| Republic of Congo | 2945.102 | 13 | 13 | 14 |
| Romania | 15618.84 | 93 | 132 | 195 |
| Russia | 14665.25 | 86 | 121 | 177 |
| Rwanda | 912.744 | 3 | 2 | 2 |
| Saint Lucia | 10762.97 | 59 | 78 | 108 |
| St. Vin & Gren | 8546.1 | 45 | 57 | 74 |
| Samoa | 4128.365 | 19 | 20 | 23 |
| Saudi Arabia | 27941.49 | 187 | 298 | 495 |
| Senegal | 1558.144 | 6 | 5 | 5 |
| Serbia | 9164.266 | 49 | 63 | 83 |
| Sierra Leone | 493.572 | 1 | 1 | 1 |
| Singapore | 79426.14 | 654 | 1286 | 2636 |
| Slovakia | 20564.86 | 129 | 194 | 303 |
| Slovenia | 29469.39 | 199 | 321 | 540 |
| Solomon Islands | 2239.622 | 9 | 9 | 9 |
| Somalia | 539.001 | 2 | 1 | 1 |
| South Africa | 6738.926 | 34 | 41 | 51 |

| | | | | |
|---|---|---|---|---|
| South Korea | 327.898 | 233 | 385 | 665 |
| Spain | 29198.09 | 197 | 317 | 532 |
| Sri Lanka | 3292.571 | 14 | 15 | 16 |
| Sudan | 916.033 | 3 | 2 | 2 |
| Suriname | 4879.822 | 23 | 26 | 30 |
| Sweden | 56361.43 | 434 | 795 | 1523 |
| Switzerland | 92434.49 | 785 | 1590 | 3360 |
| Tajikistan | 1014.926 | 4 | 3 | 2 |
| Tanzania | 1245.04 | 4 | 4 | 3 |
| Thailand | 7630.871 | 39 | 48 | 62 |
| Timor-Leste | 1792.71 | 7 | 6 | 6 |
| Togo | 960.833 | 3 | 3 | 2 |
| Tonga | 5008.125 | 24 | 27 | 32 |
| Trinidad | 20746.3 | 131 | 196 | 308 |
| Tunisia | 3815.82 | 17 | 18 | 20 |
| Turkey | 9961.067 | 54 | 70 | 95 |
| Turkmenistan | 11928.8 | 67 | 90 | 127 |
| Uganda | 1105.59 | 4 | 3 | 3 |
| UK | 47317.57 | 351 | 623 | 1151 |
| United Arab Emirates | 47792.94 | 356 | 631 | 1170 |
| Uruguay | 20017.56 | 125 | 187 | 291 |
| USA | 75179.59 | 613 | 1191 | 2414 |
| Uzbekistan | 2243.096 | 9 | 9 | 9 |
| Vanuatu | 3049.75 | 13 | 13 | 14 |
| Venezuela | 3051.738 | 13 | 13 | 14 |
| Vietnam | 4162.938 | 19 | 21 | 24 |
| Yemen | 873.903 | 3 | 2 | 2 |
| Zambia | 1348.36 | 5 | 4 | 4 |
| Zimbabwe | 2420.22 | 10 | 10 | 10 |