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THE SOCIAL COST OF CARBON REVISITED

Robert S. Pindyck

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ABSTRACT

An estimate of the social cost of carbon (SCC) is key to climate policy. But how should we estimate the SCC? A common approach is to use an integrated assessment model (IAM) to simulate time paths for the atmospheric CO2 concentration, its impact on global mean temperature, and the resulting reductions in GDP and consumption. I have argued that IAMs have serious deficiencies that make them poorly suited for this job, but what is the alternative? I present a more transparent approach to estimating an average SCC, which I argue is a more useful guide for policy than the marginal SCC derived from IAMs. I rely on a survey through which I elicit expert opinions regarding (1) the probabilities of alternative economic outcomes of climate change, including extreme outcomes such as a 20% or greater reduction in GDP, but not the particular causes of those outcomes; and (2) the reduction in emissions required to avert an extreme outcome. My estimate of the average SCC is the ratio of the present value of damages from an extreme outcome to the total emission reduction needed to avert such an outcome. I discuss the survey instrument, explain how experts were identified, and present results. I obtain SCC estimates of $200/mt or higher, but the variation across experts is large. Trimming outliers and focusing on experts who expressed a high degree of confidence in their answers yields lower SCCs, $80 to $100/mt.

Robert S. Pindyck
MIT Sloan School of Management
100 Main Street, E62-522
Cambridge, MA 02142
and NBER
RPINDYCK@MIT.EDU

1 Introduction.

An estimate of the social cost of carbon (SCC) is a key input to the development of climate policy. The SCC measures the external cost of burning carbon, so pricing carbon at its full social cost (e.g., by imposing a carbon tax) requires an estimate of the SCC.[1]

But how should we estimate the SCC? The most common approach uses an integrated assessment model (IAM) to simulate time paths for the atmospheric CO_2 concentration (based on an assumed path of CO_2 emissions), the impact of a rising CO_2 concentration on global mean temperature (and perhaps other measures of climate change), and the reductions in GDP and consumption projected to result from rising temperatures. The idea is to start with some base case scenario, i.e., a path for current and future CO_2 emissions (which implies a path for temperature, GDP, etc.). Next, the path is perturbed by increasing current emissions by one ton, and then calculating a new (and slightly lower) path for consumption. The SCC is then the present value of the reductions in future consumption resulting from the additional ton of current emissions (based on some discount rate). This is how the U.S. government's Interagency Working Group (IWG) estimated the SCC.[2]

I have argued elsewhere that IAMs are poorly suited for this job. An important limitation of IAMs is that some of the equations that go into them — especially the damage functions that translate higher temperatures into reductions in GDP — are ad hoc, with little or no theoretical or empirical grounding.[3] As a result, these models can tell us nothing about the likelihood or possible impact of a catastrophic climate outcome, e.g., a temperature increase

[1] Some textbooks define the social cost of an activity as the total private plus external cost. In the climate change literature, however, the term social cost usually refers to only the external cost, so I will use that definition here. Also, the SCC is usually expressed in dollars per ton of CO_2. A ton of CO_2 contains 0.2727 tons of carbon, so an SCC of $10 per ton of CO_2 is equivalent to $36.67 per ton of carbon. The SCC numbers I present here are in terms of dollars per ton of CO_2.

[2] The IWG used three IAMs to arrive at estimates of the SCC. See Interagency Working Group on Social Cost of Carbon (2010, 2013). Also, see Greenstone, Kopits and Wolverton (2013) for an illuminating explanation of the process used by the IWG to estimate the SCC.

[3] In Pindyck (2013*a*,*b*, 2017*b*), I explain why some inputs to an IAM are arbitrary but can have a substantial effect on the results the model produces. This is one reason why IAMs differ so widely in their "predictions." Also, IAM-based analyses of climate policy create a perception of knowledge and precision that is illusory, and can thereby mislead policy-makers. For a discussion of some of the advantages and disadvantages of using IAMs to estimate the SCC, see Metcalf and Stock (2017). Burke et al. (2015) note that even coupled general circulation models (GCMs), which focus only on climate and do not have a damage function, vary widely in their predictions of changes in temperature and precipitation. Millner and McDermott (2016) and Dietz and Stern (2015) offer contrasting views of what we might learn from the damage functions and descriptions of economic growth that are part of most IAMs. An alternative approach to estimating the SCC, studied by Bansal, Kiku and Ochoa (2016), uses financial market data to determine how temperature changes affect equity prices, which are forward-looking and therefore account for expected long-run impacts.

above 4°C that has a very large impact on GDP. The reason is that we know very little about the probabilities of very large temperature increases, and we know even less about the likely economic impact of large (or even moderate) temperature increases that occur gradually, over many years. But as I will show, it is the possibility of a catastrophic climate outcome that is the main driver of the SCC. If we were certain that temperature increases and their economic impact will be small or moderate, we could conclude that the SCC is small. Unfortunately we are *not* certain that such a scenario is what we will experience.[4]

But if we don't use one or more IAMs to estimate the SCC, what can we do instead? This paper provides an alternative approach to estimating the SCC that relies on the elicitation of expert opinions regarding (1) the probabilities of alternative economic outcomes of climate change, and in particular extreme outcomes, but *not* the particular causes of those outcomes; and (2) the reduction in emissions that would be required to avoid those extreme outcomes. For example, an extreme outcome might be a 20% or greater reduction in GDP. Whether that outcome is the result of a large increase in temperature but moderate impact of temperature on GDP, or the opposite, is not of concern. What matters is the likelihood of such an outcome, and the abatement needed to avert it. Compared to the use of one or more IAMs, the result is a more straightforward and transparent approach to estimating the SCC.[5]

Focusing on catastrophic outcomes both simplifies and complicates the problem of estimating the SCC. It simplifies the problem by allowing us to focus on only a subset of possible economic outcomes, namely the more extreme ones, and not on the causes of the outcomes. This is consistent with the very notion of an SCC — the economic harm caused by emitting an additional ton of CO_2, irrespective of the economic and climate mechanisms that generate the harm. (Of course climate change could also cause non-economic damages, such as greater morbidity and mortality, the extinction of species, and social disruptions. I am assuming, as is typically done in the estimation of the SCC, that these non-economic damages could be monetized and included as part of the drop in GDP.)

Focusing on catastrophic outcomes also complicates matters because we know so little about the likelihood that they will occur. But that in turn supports the approach I take here.

[4]IAM-based estimates of the SCC range from around \$10 per metric ton to well over \$200/mt, and there has been little or no movement toward a consensus number. As a result, the focus of international climate negotiations has shifted from an SCC-based carbon tax to a set of targets that would put limits on temperature increases or atmospheric CO_2 concentrations, and which in turn imply targets for emission reductions. However, we do not know whether such targets are socially optimal. See Aldy et al. (2010) for a discussion of this issue, and an overview of climate policy design. I discuss the trade-off between taxes versus targets as the focus of policy, and introduce the methodology used in this paper in Pindyck (2017*a*).

[5]My objective is to estimate a *global* SCC, so the relevant climate impact is a reduction in world GDP. Kotchen (2016) shows that a set of domestic SCCs might be more appropriate as inputs to policy.

The use of a complex IAM or related model throws a curtain over our lack of knowledge, and creates a veneer of scientific legitimacy that suggests we know more than we do. The use of expert elicitation, on the other hand, is simple and transparent, and summarizes the views (however obtained) of researchers who have studied climate change and its impact. This approach acknowledges that currently the best we can do — especially with regard to extreme outcomes — is rely on the opinions of broad group of experts.

How do we know that the possibility of a catastrophic outcome is what matters for the SCC? Because unless we are ready to accept a discount rate on consumption that is extremely small (e.g., around 1%), the "most likely" scenarios for climate change cannot generate enough damages — in present value terms — to matter.[6] That is why the Interagency Working Group, which used a 3% discount rate, obtained the rather low estimate of $33 per ton for the SCC (recently updated to $39). Using some simple examples, I will show that low-probability but severe outcomes can dominate an estimate of the SCC.

One might argue that the approach suggested here involves a model of sorts, but it is a model that has very few moving parts, and is thus much more transparent than an IAM-based analysis. It works as follows:

1. The primary object of analysis is the economic impact of (anthropomorphic) climate change, where economic impact is measured by the reduction in GDP (broadly defined so as to include indirect impacts such as greater morbidity and mortality).[7]

2. The complex mechanisms by which ongoing CO_2 emissions can cause climate change, and by which climate change can reduce GDP, are ignored. The concern is only with the *outcomes* that can result from CO_2 emissions. Also, I focus on catastrophic outcomes, i.e., climate-caused percentage reductions in GDP that are large in magnitude.

3. What are the probabilities of these outcomes. For example, what is the probability that under "business as usual" (BAU), i.e., no significant global emissions abatement beyond that mandated by current policy, we will experience a climate-induced reduction in

[6] I have shown this in Pindyck (2011*b*, 2012), and will further demonstrate it in the next section. For a clear and thorough discussion of the choice of discount rate, see Gollier (2013).

[7] One could argue, based on theory and empirical evidence, that climate change will affect the *growth rate* of GDP rather than its level. For the theoretical arguments, see Pindyck (2011*b*, 2012) and the references therein. For empirical evidence see Dell, Jones and Olken (2012) and Bansal and Ochoa (2011). Working with growth rates would considerably complicate this analysis, so I work directly with levels (as is done in all of the IAM-based analyses I am aware of). Most economic studies of catastrophes and their impact are likewise based on level effects; see, e.g., Barro (2013), Martin (2008) and Martin and Pindyck (2015).

GDP 50 years from now of at least 10 percent? At least 20 percent? At least 50 percent? I rely on expert opinion for answers to these questions.

4. Next, what are the emission reductions needed to avert the more extreme outcomes? Starting with an expected growth rate of CO_2 emissions under BAU, by how much would that rate have to be reduced to avoid a climate-induced reduction in GDP 50 years from now of 20 percent or more? I again rely on expert opinion for answers.

5. With this information on outcome probabilities and emission reductions, I compute an *average* SCC, as opposed to the more conventional *marginal* SCC obtained from simulating IAMs. An average SCC has the advantage of providing long-run policy guidance, as explained below.

For an economist, relying on expert opinion might not seem very satisfying. Economists often build models to avoid relying on subjective (expert or otherwise) opinions. But remember that the inputs to IAMs (equations and parameter values) are already the result of expert opinion; in this case the modeler is the "expert." This is especially true when it comes to climate change impacts, where theory and data provide little guidance. Also, we would expect that that different experts will arrive at their opinions in different ways. Some might base their opinions on one or more IAMs, others on their studies of climate change and its impact, and others might combine information from models with other insights. The methods experts use to arrive at their opinions is not a variable of interest; what matters is that the experts are selected based on their established expertise.[8]

Experts, of course, are likely to disagree, particularly about climate change, where our knowledge is so limited. Focusing on catastrophic outcomes and the emission reductions needed to eliminate them may reduce the extent of disagreement, but the nature of that disagreement is also of interest. For example, do the opinions of climate scientists differ from those of economists, and if so, how? Are there systematic differences of opinion across experts in the U.S. versus Europe, or developing countries? And how extensive is the range of disagreement? The survey I conduct addresses these questions.

The main findings from the survey can be summarized as follows:

[8]As discussed later, experts will be selected based on their publications in relevant refereed journals. I am certainly not the first to utilize expert opinion as an input to climate policy; see, e.g., Nordhaus (1994), Kriegler et al. (2009), Zickfeld et al. (2010), Morgan (2014), and, for the use of expert opinion to quantify uncertainty, Oppenheimer, Little and Cooke (2016). For related expert elicitations of the long-run discount rate, see Drupp et al. (2015), Weitzman (2001), and Freeman and Groom (2015).

1. Although there is considerable heterogeneity across experts, many view the likelihood of an extreme outcome — a climate-induced reduction of GDP 50 years from now of 20% or more — as quite high (e.g., could occur with a probability of 20% or greater). As a result, the estimates of the average SCC are large, above $200 per metric ton. SCCs based on the responses of economists are lower (around $170), but those based on responses of climate scientists and residents of Europe were $300 or more.

2. However, the SCC estimates are much smaller ($100 or less) when based on a trimmed sample that excludes outliers, and is limited to respondents who expressed a high degree of confidence in their answers regarding the probabilities of alternative impacts. But even this trimmed sample yields an SCC that is well in excess of the roughly $40 numbers that have come from recent IAM-based analyses.

The next two sections present the methodology used to estimate the SCC. Section 2 begins with an example of a set of climate outcomes and their probabilities, of the sort that might be elicited from experts, and shows how those numbers can be translated into an outcome probability distribution. Section 3 explains the calculation of an average SCC, and illustrates with some numerical examples. In Sections 4 and 5, I discuss some of the details of the SCC calculations, the selection of experts, and the questionnaire used to elicit their opinions. The survey results are presented in Section 6. I estimate the SCC for each individual respondent, and also for the full set of respondents, and for subsets based on area of expertise (e.g., economics vs. climate science) and geographical location. The SCC estimates are quite high — in the range of $150 to $300 per metric ton, much higher than prevailing estimates derived from IAM-based analyses — but the variation across experts is large. I show how the SCC estimates vary across individuals and the extent to which the variation is due to area of expertise and/or location. I also show that the SCC estimates are smaller ($100 or less) when derived from a trimmed sample that excludes outliers and includes only respondents who expressed a high degree of confidence in their answers. Section 7 concludes with caveats and a discussion of how this analysis might be modified.

2 Methodology: Climate Impact Outcomes.

I begin with a distribution for the climate-induced percentage reduction in GDP 50 years from now. For simplicity, assume for now that the only possible impacts are reductions of $z = 0, .02, .05, .10, .20$, or $.50$ (and no other values), and that according to a hypothetical expert, the probabilities of these impacts are those given in the top part of Table 1, where

Table 1: PROBABILITIES OF CLIMATE IMPACTS FROM A HYPOTHETICAL EXPERT.

HORIZON: $T = 50$ YEARS						
% GDP Reduction, z	0	0.020	0.050	0.100	0.200	0.500
$\phi = -\ln(1-z)$	0	0.020	0.051	0.105	0.223	0.693
Prob	.25	.50	.10	.06	.05	.04
$1 - F(\phi)$	1	.75	.25	.15	.09	.04

F is the cumulative distribution corresponding to the probabilities in the third row.

Let Y_0 denote what GDP will be if there is no climate change (or if there is climate change but it has no impact), and define $\phi = -\ln(1-z)$. Then a climate change outcome z implies that GDP will be $e^{-\phi}Y_0$. Why introduce ϕ? Because I want to fit probability distributions for ϕ to expert opinion damage numbers of the sort shown in Table 1. While z is constrained to $0 \leq z \leq 1$, ϕ is unconstrained at the upper end. (For example, $\phi = 4.6$ corresponds to $z = .99$.) Thus I can compare the fits of both fat-tailed (e.g., Generalized Pareto) and thin-tailed (e.g., Gamma) distributions to the outcome probabilities from experts, and compare the implications of these different distributions for SCC estimates. This is useful because some have argued that the distribution is fat-tailed and that this implies a high SCC.[9] I denote the distribution for ϕ by $f(\phi)$.

For example, a possible distribution for ϕ is the (fat-tailed) Generalized Pareto:

$$f(\phi) = k\alpha(\phi - \theta)^{-\alpha-1}\ , \quad \phi \geq \theta + k^{1/\alpha} \tag{1}$$

The value of α determines the "fatness" of the tail; the smaller is α the fatter is the tail. If $\alpha > n$, the first n moments exist. Fitting the cumulative distribution to the numbers in Table 1 yields $\alpha = 0.774, \theta = -0.00976$, and $k = 0.0305$. In this case, $\alpha < 1$, so none of the moments exist, and we can say that the fitted distribution is extremely fat. (However, the fitted distribution begins at $\theta + k^{1/\alpha} = .00125$, so I will use a two-parameter version of the distribution with the constraint $\theta = -k^{1/\alpha}$.)

2.1 Impact Over Time.

Table 1 shows probabilities of climate-induced reductions in GDP at a specific horizon $T =$ 50 years. However, the impact of climate change is likely to begin before T and increase in magnitude after T. Thus we want to allow for percentage reductions in GDP that increase

[9] See Weitzman (2009, 2011). For an opposing point of view, see Pindyck (2011*a*).

over time but eventually level out at some maximum value. To make the dynamics as simple as possible, I assume that the percentage reduction in GDP, z_t, varies over time as follows:

$$z_t = z_m[1 - e^{-\beta t}] \tag{2}$$

Thus z_t starts at 0 and approaches a maximum z_m at a rate given by β. We want to calibrate the maximum percentage reduction z_m and the parameter β.

Suppose our hypothetical expert provides average numbers for z_t at two different points in time, $T_1 = 50$ years and $T_2 = 150$ years, which we denote by $\bar{z}_1$ and $\bar{z}_2$. From Table 1, $\bar{z}_1 = \mathbb{E}(z_1) = .05$ and suppose $\bar{z}_2 = \mathbb{E}(z_2) = .10$. Then we can use eqn. (2) to determine β:

$$[1 - e^{-\beta T_2}]/[1 - e^{-\beta T_1}] = \bar{z}_2/\bar{z}_1 = 2.0 \tag{3}$$

The solution to eqn. (3) is roughly $\beta = .01$. I take this parameter as fixed (non-stochastic).

This leaves the maximum impact z_m, which I treat as stochastic. Given β, the distribution for z_m follows directly from a distribution for z_1, which in turn would be derived from a range of expert opinions (for $T_1 = 50$). As a simple example, a distribution for z_1 could be derived from the probabilities in Table 1. Given that distribution, from eqn. (2):

$$\tilde{z}_m = \tilde{z}_1/[1 - e^{-\beta T_1}] \tag{4}$$

Eqn. (3) will not have a positive solution for β if $\bar{z}_2/\bar{z}_1$ is too large. With $T_1 = 50$ and $T_2 = 150$, $\bar{z}_2/\bar{z}_1 = 2.0$ implies that $\beta \approx .01$, but if $\bar{z}_2/\bar{z}_1$ were 3 or greater, the solution to eqn. (3) would be negative. If expert opinion yields a ratio $\bar{z}_2/\bar{z}_1$ such that the resulting value of β is negative, I set $\beta = .002$, which makes $\tilde{z}_m$ roughly ten times as large as $\tilde{z}_1$.

2.2 Reductions in GDP.

I assume that absent any impact of climate change, real GDP and consumption grow at the constant rate g. Benefits of abatement are measured in terms of avoided reductions in GDP, and thus include avoided reductions in investment and government spending as well as consumption. GDP begins at its initial value Y_0, and evolves as $(1 - z_t)Y_0e^{gt} = Y_0e^{gt-\phi_t}$.

What is the loss from climate-induced reductions in GDP? At any point in time, that loss is just $z_tY_0e^{gt} = (1 - e^{-\phi_t})Y_0e^{gt}$. Thus the distribution for z_1 (which follows from the distribution for ϕ_1) yields the distribution for climate damages in each period. As discussed below, that distribution is the basis for the benefit portion of our SCC calculation.

3 Estimating the SCC.

To calculate an SCC consistent with an outcome distribution, we also need expert opinion as to the reductions in GHG emissions required to avoid some range of outcomes. For example, we could ask how much emissions would have to be reduced to avoid the two worst scenarios in Table 1. We then measure benefits as the present value of the *expected avoided reductions* in the flow of GDP. This requires a discount rate, which I denote by R.

This estimate of the SCC begins with a scenario for the objective of GHG abatement. That scenario would be the truncation of the tail of the impact distribution (such as, in the context of Table 1, eliminating outcomes of $z \geq .20$). Let B_0 denote the present value of the resulting expected avoided reduction in the flow of GDP. The "cost" of this abatement scenario is the total amount of required emission reductions over some horizon, which I denote by ΔE (and is measured in tons of CO_2). Given B_0 and ΔE, the SCC is simply $B_0/\Delta E$. As discussed below, this an *average*, not a marginal, measure of the SCC.

Why focus on truncating the impact distribution? First, eliminating *any* future impact of climate change is probably impossible, and thus not interesting or informative. Second and more importantly, the tail of the distribution accounts for most of the expected damages from climate change (as I illustrate below with some examples). Thus avoiding catastrophic damages, as opposed to *any* damages, is likely to be the main objective of climate policy.

3.1 Average vs. Marginal SCC.

How does the average SCC that I estimate differ from the marginal SCC that is more commonly estimated? The usual approach is to begin with a "base case" time path of emissions and then increase only *this year's* emissions by one ton. The resulting flow of marginal damages, found by simulating an IAM with and without the one-ton change in emissions, is discounted back to compute the SCC.[10] The average SCC, on the other hand, is the present value of the flow of benefits from a much larger reduction in emissions now and throughout the future, divided by the total amount of the reduction over the same horizon. The marginal calculation is consistent with the way environmental economists usually measure the social cost of a pollutant, so why work with an average number?

First, the marginal SCC is of limited use as a guide for policy. It can tell us what *today's* carbon tax should be, but under the strong assumption that current and future emissions are on an optimal trajectory. Second, the marginal SCC (along the optimal trajectory) will

[10]This is how a marginal SCC was estimated by the Interagency Working Group. See, e.g., Interagency Working Group on Social Cost of Carbon (2010, 2013) and Greenstone, Kopits and Wolverton (2013).

change over time, but it is hard to imagine a climate policy based on a carbon tax or quota that changes each year.[11] The average SCC provides a guideline for policy over an extended period of time, which can be more useful, especially given the difficult and protracted process for actually agreeing on a climate policy.

In addition, this average SCC is much less sensitive to the choice of discount rate R than is the marginal SCC. The marginal SCC is the present value of the flow of benefits from a one-ton change in current emissions; an increase in R reduces that present value, but does nothing to the one-ton change in emissions. The average SCC is the present value of a flow of benefits, B_0, relative to the present value of a flow of emission reductions, ΔE. A higher discount rate reduces B_0 but also reduces ΔE. The numerical examples shown below illustrate this reduced sensitivity to the discount rate.

Finally, the marginal calculation requires the use of an IAM or related model with its many assumptions (especially regarding the damage function), and lack of transparency. Calculating a marginal SCC does not lend itself to expert elicitation, because no expert can tell us what will happen if we reduce emissions today by one ton. And even if we had confidence in the particular IAM that is used, the calculated SCC will be sensitive to the assumptions regarding the base-case time path for CO_2 emissions used in the simulations.

3.2 Benefits from Abatement.

The calculation of an average SCC uses a probability distribution for the impact of climate change under BAU and a scenario for the truncation of that distribution. Eqns. (2) and (4) are then used to calculate the benefit from truncating the distribution. For simplicity, I express damages below in terms of z rather than $\phi = -\ln(1-z)$.

The benefit from eliminating *any* climate change impact (an unlikely scenario) is

$$\begin{aligned} B_0 &= \int_0^\infty \mathbb{E}_0(z_t) Y_0 e^{(g-R)t} dt \\ &= \frac{\beta Y_0}{(R-g)(R+\beta-g)(1-e^{-\beta T_1})} \mathbb{E}_0(z_1) \end{aligned} \tag{5}$$

[11] Generally the marginal SCC will rise over time, even if the damage function is linear over some range of the atmospheric GHG concentration, for the same reason that the competitive (and socially optimal) price of a depletable resource will rise over time. Think of the unpolluted atmosphere as a resource that gets depleted as GHG emissions accumulate, with no damages from an increased GHG concentration until a threshold is reached, at which point damages become extremely large. More generally, if damages are a convex function of the GHG concentration, the SCC will still rise over time. This latter case is analogous to the price evolution of a depletable resource when the cost of extraction (or the cost of discovering new reserves) rises as depletion ensues, as in models such as Pindyck (1978) and Swierzbinski and Mendelsohn (1989). This point has been developed in some detail in Becker, Murphy and Topel (2011).

Here, $\mathbb{E}_0(z_1)$ denotes the expectation of z_1 based on the full distribution of possible impacts. It is more realistic and informative, however, to calculate the benefit from truncating the distribution, i.e., eliminating part of the right-hand tail. Letting $\mathbb{E}_1(z_1)$ denote the expectation of z_1 over the truncated distribution of impacts, the resulting benefit is

$$\begin{aligned} B_0 &= \int_0^\infty [\mathbb{E}_0(z_t) - \mathbb{E}_1(z_t)] Y_0 e^{(g-R)t} dt \\ &= Y_0 \left[\frac{\mathbb{E}_0(z_1) - \mathbb{E}_1(z_1)}{1 - e{-}\beta T_1} \right] \int_0^\infty [1 - e^{-\beta t}] e^{(g-R)t} dt \\ &= \frac{\beta Y_0 [\mathbb{E}_0(z_1) - \mathbb{E}_1(z_1)]}{(R-g)(R+\beta-g)(1-e^{-\beta T_1})} . \end{aligned} \tag{6}$$

Note that the truncated distribution for z_1 (the impact at T_1) also implies the distribution for z_t at every time t; these distributions are linked through eqn. (4).

In eqn. (6), $\beta Y_0[\mathbb{E}_0(z_1) - \mathbb{E}_1(z_1)]/(1 - e^{-\beta T_1})$ is the instantaneous flow of benefits from truncating the impact distribution, and dividing by $(R - g)(R + \beta - g)$ yields the present value of this flow. For example, in the top panel of Table 1, $\mathbb{E}_0(z_1) = .05$. Suppose by reducing emissions we can eliminate outcomes of $z \geq .20$. Increasing the other probabilities so they sum to one yields $\mathbb{E}_1(z_1) = .022$. Setting $\beta = .01$, $g = .02$ and $R = .04$, this implies $B_0 = .00071 Y_0/.0006 = 1.19 Y_0$. Note that in the *first year*, the benefit from this abatement policy would be less than 0.1% of GDP, but the annual benefit rises over time (as z_t rises), so B_0, the present value of the flow of annual benefits, is greater than current GDP.

3.3 Required Emission Reductions.

To estimate the SCC, we also need to know the emission reductions needed to truncate the distribution of possible climate impacts. Consider the example of eliminating the two worst outcomes in Table 1, i.e., $z \geq .20$. Suppose that (i) emissions this year are at a level E_0; (ii) under BAU emissions are expected to grow at the rate m_0; and (iii) according to expert opinion, to eliminate these worst outcomes the growth rate of emissions would have to be reduced to $m_1 < m_0$. (Note that m_1 could and probably would be negative.) We want the sum of all future emission reductions, ΔE, which we will compare to B_0.

If the cost of reducing emissions were very small, any positive SCC would justify a large reduction. But the cost of reducing emissions, at least substantially, is not small. One advantage of calculating a *marginal* SCC is that we do not need to know the cost of reducing emissions or the amount by which emissions should be reduced: If a carbon tax equal to the SCC is imposed, along the optimal trajectory today's emissions will be reduced to the point that the marginal cost of the last ton abated will equal the SCC. Of course this marginal SCC will vary over time, so that the size of the tax would likewise have to vary.

How should we calculate the sum of current and future emission reductions, ΔE? One possibility is to add up the total reduction in emissions from $t = 0$ to some horizon T. One problem with this approach is that the horizon T is arbitrary. A second problem is that even if abatement costs are constant, in present value terms it is cheaper to abate more in the future than today. Because I calculate an average SCC over an extended period of time, future costs of abatement (like future benefits) must be discounted.

Rather than simply adding up total required emission reductions, I will assume that the real cost per ton abated is constant over time. The real cost will be affected over time by two factors that work in opposite directions. Technological progress, e.g., the development of cheaper and better alternatives to fossil fuels, will reduce the cost over time. On the other hand, abatement becomes increasingly difficult (and costly) as emissions are reduced. It unclear which of these effects will dominate, so it is reasonable for purposes of estimating the SCC to assume that the cost is constant.

With the real cost of abatement constant, then irrespective of the value of that cost, future emission reductions can be discounted at the same rate R used to discount future benefits (as long as $m_0 < R$). Thus we can calculate ΔE as the present value of the flow of emissions at the BAU growth rate m_0 less the present value at the reduced growth rate m_1:

$$\begin{aligned} \Delta E &= E_0 \int_0^\infty \left[e^{(m_0 - R)t} - e^{(m_1 - R)t} \right] dt \\ &= \frac{(m_0 - m_1)E_0}{(R - m_0)(R - m_1)} \end{aligned} \tag{7}$$

In eqn. (7), the term $(m_0 - m_1)E_0$ is the instantaneous (current) reduction in emissions, and dividing by $(R - m_0)(R - m_1)$ yields the present value of the flow of emission reductions. For example, if the abatement policy is to reduce the growth rate of emissions from $m_0 = .02$ to $m_1 = -.02$, and if $R = .04$, $\Delta E = .04E_0/.0012 = 33.3E_0$, i.e., this year's abatement is 4% of current annual emissions, but the present value of all current and future emission reductions is about 30 times this year's emissions.

3.4 Average Social Cost of Carbon.

The average social cost of carbon is the ratio $B_0/\Delta E$. Using eqns. (6) and (7):

$$S = \frac{\beta Y_0 [\mathbb{E}_0(z_1) - \mathbb{E}_1(z_1)]/(1 - e^{-\beta T_1})}{(m_0 - m_1)E_0} \times \frac{(R - m_0)(R - m_1)}{(R - g)(R + \beta - g)} \tag{8}$$

The first fraction on the RHS of eqn. (8) can be thought of as an instantaneous SCC, i.e., the current benefit (in dollars) from truncating the impact distribution divided by the current reduction in emissions (in metric tons) needed to achieve that truncation. This instantaneous SCC is a flow variable, and the second fraction puts this flow in present value terms. Thus S is the present value of the flows of benefits and emission reductions that extend throughout the indefinite future.

3.5 Numerical Examples.

Here are some simple numerical examples based on the (hypothetical) numbers in Table 1 and data for world GDP and GHG emissions. World GHG emissions (CO_2e) in 2013 were about 33 billion metric tons. The average annual growth rate of world GHG emissions from 1990 through 2013 was about 3%. The U.S. and Europe had roughly zero emission growth over that period; almost all of the 3% growth was due to increased emissions from Asia, which are likely to slow over the coming decades, even without new international agreements and/or national climate policies. Thus I will assume that under BAU emissions would grow at an annual rate of 2% (so $m_0 = .02$). World GDP in 2013 was about $Y_0 = \$75$ trillion. I set $g = .02$ as the real per capita growth rate of GDP, and use a discount rate of $R = .04$. The numbers in Table 1 imply that β in eqn. (2) is about 0.01.

Suppose that by reducing the growth rate of emissions from $m_0 = .02$ to $m_1 = -.02$ we could avoid the two "catastrophic" outcomes in Table 1, i.e., $z = .20$ and $z = .50$. In the top part of Table 1, $\mathbb{E}_0(z_1) = .05$, and $\mathbb{E}_1(z_1) = .022$. (The latter is the expected value of z_1 for the truncated distribution.) From eqn. (6), the benefit of avoiding these outcomes is $B_0 = 42.36 \times Y_0(.05 - .022) = 1.186 \times Y_0 = \$89 \times 10^{12}$. Given 2013 emissions and the assumptions that $m_0 = .02$, $m_1 = -.02$, and $R = .04$, eqn. (7) gives $\Delta E = 1.10 \times 10^{12}$ metric tons. With these numbers, the implied SCC $= B_0/\Delta E = \$81$ per metric ton.

Recall from eqn. (8) that we can express the SCC as the product of two fractions. The first is the ratio of the current (annual) benefit flow to the current (annual) reduction in emissions. The second fraction puts these flows in present value terms, accounting for the growth of both benefits and abatement. In this example the first fraction, i.e, the current instantaneous SCC, is $.00071Y_0/.04E_0 = 5.33 \times 10^{10}/1.32 \times 10^9 = \$40.4$ per metric ton. The second fraction is $.0012/.0006 = 2$, yielding the present value SCC of \$81 per metric ton.

How does this result depend on the discount rate R? Table 2 shows the SCC and its components for discount rates ranging from .025 to .060. (We need $R > g$ and $R > m_0$, which means $R > .02$.) As one would expect, the benefit from truncating the outcome distribution,

Table 2: Sensitivity of SCC to Discount Rate.

R	B_0	ΔE	SCC
.025	712×10^{12}	5.87×10^{12}	\$121
.030	267×10^{12}	2.64×10^{12}	\$101
.040	89×10^{12}	1.10×10^{12}	\$81
.060	26.7×10^{12}	0.41×10^{12}	\$65

Note: B_0 is the benefit from truncating the distribution for z in Table 1, eliminating outcomes of $z \geq .20$, and is given by eqn. (6). ΔE is the required total reduction in emissions, given by eqn. (7), with the emission growth rate reduced from $m_0 = .02$ to $m_1 = -.02$. SCC $= B_0/\Delta E$. Also, $\beta = .01$, $g = .02$, and $T_1 = 50$ years.

B_0, declines sharply as R is increased; this is why estimates of the marginal SCC obtained from IAMs are so sensitive to the discount rate. But note that the total emission reduction, ΔE, also declines as R is increased, because the value of future emissions is discounted. The net result is that the (average) SCC declines as R is increased, but far less sharply.

3.6 Importance of Catastrophic Outcomes.

From the calculations of B_0 in the simple examples above, one can see that much of the SCC is attributable to the possibility of a catastrophic outcome. Recall from eqn. (5) the benefit from avoiding *any* climate change impact is proportional to $\mathbb{E}_0(z_1)$. The benefit from avoiding only the two "catastrophic" outcomes in Table 1, i.e., $z \geq .20$ and $z \geq .50$, is the same, but with $\mathbb{E}_0(z_1)$ replaced by $[\mathbb{E}_0(z_1) - \mathbb{E}_1(z_1)]$. Thus the fraction of the total benefit from eliminating any impact that is attributable to just the catastrophic outcomes is $1 - \mathbb{E}_1(z_1)/\,\mathbb{E}_0(z_1)$. For the numbers in the top part of Table 1, this fraction is roughly 60%.

The most extreme outcome in Table 1, $z = .50$, has an estimated probability of occurring of only .04 (and the probability of $z = .2$ *or* .5 is .09). But such an outcome amounts to a much greater loss of GDP than the expected value $\mathbb{E}_0(z_1) = .05$.

Of course the SCC also depends on the reduction in emissions required to truncate the impact distribution. Eliminating *any* climate outcome will require a far greater reduction in emissions than would eliminating only extreme outcomes. In the example, I assumed a reduction in the growth rate to $m_1 = -.02$ would suffice to eliminate a catastrophic outcome. Suppose (probably unrealistically) a reduction to $m_1 = -.05$ would eliminate any climate outcome. Setting $R = .04$ as before, the SCC is then \$124 metric ton. But now suppose the probability of $z_1 = .2$ or $z_1 = .5$ is zero. Scaling up the other probabilities in the top part of Table 1 so they sum to 1, the expected impact is now $\mathbb{E}_0(z_1) = .022$. Suppose once again that we can avoid *any* impact by reducing the growth rate to $m_1 = -.05$, so that $\Delta E = 1.28 \times 10^{12}$. Now $B_0 = 69 \times 10^{12}$, which implies an SCC of $B_0/\Delta E = \$55$. Compare this to the SCC of \$124 when there was a .09 probability of $z_1 \geq .20$; eliminating the possibility of these catastrophic outcomes reduces the SCC by more than half.

4 Estimating an SCC from Expert Opinions.

I estimate an average SCC that corresponds to the scenario in which CO_2 emissions growth is reduced sufficiently to truncate the outcome distribution so as to eliminate the possibility of a GDP reduction that is 20% or greater.[12] The required inputs are obtained from a survey of economists and climate scientists with established expertise in climate change impacts and policy. These inputs are used to calculate the benefit (B_0) from truncating the impact distribution, and the reduction in CO_2 emissions growth (from m_0 to m_1, yielding a total reduction ΔE) needed to achieve this truncation. Calculating the benefit in turn requires a distribution for the climate impact 50 years from now, as well as an expected impact at a longer horizon (the year 2150), $\bar{z}_2$, from which the parameter β is calculated using eqn. (3). Calculating the total emissions reduction requires the BAU emissions growth rate m_0 and reduced growth rate m_1, and both calculations require a discount rate R.

The impact distribution is derived from experts' responses regarding impact probabilities. Each expert is asked for the probability that the impact, i.e., reduction in GDP, will be 2% (5%, 10%, 20%, and 50%) or greater (and I impose a probability of 1 that the impact will be 0% or greater). As explained below, I fit four different probability distributions to these six probabilities for each expert, and to sets of probabilities across groups of experts.

4.1 Individual versus Group Estimates of the SCC.

The example in the previous section was based on a set of outcome probabilities and emission growth rates for one hypothetical expert. The survey I conducted yielded sets of such numbers from many experts, and of course the numbers differ across experts. At issue is how to use these sets of numbers to estimate the SCC. I do this in two different ways. First, I estimate SCCs for each individual respondent, which I use to explore heterogeneity across experts, and the extent to which that heterogeneity can be explained by region (e.g., U.S. vs.

[12] I could have chosen a different scenario, e.g., eliminate the possibility of a GDP reduction that is 10% or greater, or 50% or greater. However, initial tests with potential respondents showed some felt that 10% was too likely and might be impossible to avoid, and some felt that 50% was too speculative or otherwise difficult to related to emission reductions.

Europe) or area of expertise (economics vs. climate science).[13] I estimate these individual SCCs by fitting an outcome distribution to each expert's set of outcome probabilities, which I combine with the expert's response for m_0, m_1 and R. Second, I calculate average SCCs for the full set and several subsets of experts, as a way of aggregating opinions and obtaining SCC estimates that are closer to consensus. To obtain these group estimates of the SCC, I fit outcome distributions to the responses of sets of experts, and then use the average responses across each set for m_0, m_1 and R to calculate an SCC.

I examine differences across six subsets of respondents: (1) those with primary expertise in economics; (2) those with primary expertise in climate science; (3) those residing in North America; (4) those residing in Europe; (5) those residing in developing countries; and, for the group estimates, (6) those whose state a high level of confidence in both their reported outcome probabilities and emissions growth rate.

Individual Estimates. I first estimate an SCC for each individual respondent. To do this, I fit two-parameter probability distributions to the six "observations" for each respondent's set of impact probabilities (the five stated probabilities and the imposed probability of 1 that the impact will be non-negative). I fit four such distributions (Gamma, Lognormal, Pareto and Frechet), which, when combined with other inputs, will yield a set of four SCCs for each respondent. I examine the characteristics of these individual SCCs for each impact distribution, and for the entire set of SCCs based on the distribution for each respondent that has the best fit to the respondent's reported probabilities.

The other inputs needed to obtain the individual estimates are the respondent's beliefs about the most likely climate impacts in 2066 (50 years after the response) and in 2150, the BAU emissions growth rate (m_0), the emissions growth rate needed to avoid a climate-induced GDP reduction in 2066 of 20% or more (m_1), and a discount rate (R). The most likely impacts in 2066 and 2150 are used to calculate β for the respondent. This parameter, together with each fitted probability distribution for the climate impact in 2066 and the discount rate yields the benefit component (B_0) of the SCC (using eqn. (6)) for the respondent. The emission reduction component (ΔE) comes from the respondent's estimates of m_0 and m_1, along with R, using eqn. (7). The individual's SCC is $B_0/\Delta E$.

Group Estimates. Second, I estimate the SCC for the full set of respondents, and for several subsets. In this case I fit an outcome distribution to the full set (or subset) of respondents' outcome probabilities. As with the individual estimates, I fit the same four two-parameter probability distributions, and explore how the resulting SCCs differ across

[13]The individual survey responses are all confidential, including names and institutional affiliations. However, I do have each respondent's GPS location, from which I can determine the region of residence.

the distributions, and across the different subsets of respondents.

As with the individual estimates, I also use respondents' beliefs about the most likely climate impacts in 2066 and in 2150, the BAU emissions growth rate (m_0) and growth rate needed to avoid the 20% or greater GDP impact in 2066 (m_1), and the discount rate (R). For all of these inputs, I use average values over the set or subset of respondents. I then calculate corresponding values of β, and together with each fitted probability distribution for the climate impact in 2066, I calculate the benefit component (B_0) of the SCC for the set or subset of respondents. With the average values of m_0 and m_1 I likewise calculate the emission reduction component (ΔE) of the SCC for each set or subset of respondents.

4.2 Outcome Distributions.

Given respondents' outcome probabilities, I want to fit distributions to $\phi = -\ln(1-z)$ that begin at $\phi = 0$, peak at a value of ϕ that could be considered "most likely," and then gradually decline. Also, I want both thin- and fat-tailed distributions so I can examine whether a fat tail is any more consistent with a large value of the SCC. I therefore use the following four two-parameter distributions for ϕ, all of which hold for $\phi \geq 0$.[14]

The first is a Gamma distribution:[15]

$$f(\phi; \lambda, r) = \frac{\lambda^r}{\Gamma(r)} \phi^{r-1} e^{-\lambda\phi} \ , \tag{9}$$

where $\Gamma(r)$ is the gamma function. This distribution is thin-tailed for all $r \geq 0$ and $\lambda \geq 0$.

Second, the lognormal distribution, given by:

$$f(\phi; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma\phi} \exp\left[\frac{-(\ln\phi - \mu)^2}{2\sigma^2}\right] \ . \tag{10}$$

The lognormal distribution approaches zero exponentially, and is thus intermediate between a fat- and thin-tailed distribution.

Third, I use the two-parameter version of the generalized Pareto distribution:[16]

$$f(\phi; k, \alpha) = k\alpha(\phi + k^{1/\alpha})^{-\alpha-1} \ . \tag{11}$$

[14]There are three-parameter versions of the Gamma, Pareto, and Frechet distributions that allow for $\phi < 0$, and there is some evidence (see Pindyck (2012) and the references therein) that there is a small but non-zero probability that climate damages will be negative. But it is not feasible to fit a three-parameter distribution to the six "observations" for each individual respondent's set of outcome probabilities.

[15]The three-parameter displaced Gamma distribution is $f(\phi; \lambda, r, \theta) = \frac{\lambda^r}{\Gamma(r)}(\phi - \theta)^{r-1} e^{-\lambda(\phi-\theta)}$, $\phi \geq \theta$.

[16]The three-parameter version of this distribution is $f(\phi; k, \alpha, \theta) = k\alpha(\phi - \theta)^{-\alpha-1}$, $\phi \geq \theta + k^{1/\alpha}$.

This distribution is fat-tailed (approaches zero more slowly than exponentially), and the value of α determines the "fatness" of the tail; if $\alpha > n$, the first n moments exist.

Finally, I fit the two-parameter version of the Frechet (Generalized Extreme Value, Type II) distribution:[17]

$$f(\phi; k, \sigma) = \frac{1}{\sigma}(k\phi/\sigma)^{-1-1/k} \exp\left[-(k\phi/\sigma)^{-1/k}\right] \ , \tag{12}$$

with $k > 0$. This distribution is also fat-tailed, and the value of k determines the "fatness" of the tail; if $0 < k < 1/n$, the first n moments exist.

Because the Pareto and Frechet distributions are fat-tailed, depending on the parameter estimates (α for the Pareto and k for the Frechet), expectations and other moments of ϕ may not exist. For all four distributions I approximate such expectations by integrating to some maximum (but finite) value of ϕ, denoted by $\phi_{\max}$. I set $\phi_{\max} = 4.6$, which corresponds to $z_{\max} = .99$. Thus $\mathbb{E}_0(z_1) = 1 - \mathbb{E}_0(e^{-\phi_1})$ in eqns. (5) and (6) is calculated as

$$\mathbb{E}_0(z_1) = 1 - \int_0^{\phi_{\max}} e^{-\phi} f(\phi) d\phi \tag{13}$$

Also, $\mathbb{E}_1(z_1) = 1 - \mathbb{E}_1(e^{-\phi_1})$, the expectation of z_1 when the distribution has been truncated to eliminate outcomes for ϕ greater than some critical limit $\phi_c > 0$, is calculated as

$$\mathbb{E}_1(z_1) = 1 - \frac{1}{F(\phi_c)} \int_0^{\phi_c} e^{-\phi} f(\phi) d\phi \ , \tag{14}$$

where $F(\phi_c)$ is the cumulative distribution function corresponding to $f(\phi)$.

I estimate the parameters of each distribution from a least-squares fit of each corresponding cumulative distribution to the set of expert opinions regarding outcomes and probabilities. To get individual SCC estimates, I fit the cumulative distributions to the six "observations" for each individual respondent's set of probabilities. For the group SCC estimates, I fit the distributions to the full set (or subset) of respondents' outcome probabilities.

Which of the four distributions is "best?" Barring some theoretical argument for ranking them, I compare how they fit the "data" using the corrected R^2. For the individual responses, however, there is often little difference in the R^2s, which are almost always above .90 and usually above .95. Given the variability of the individual responses, fitting the distributions to sets of respondents' probabilities yields R^2s that are much lower. While they differ across distributions, the differences are not large, so I report results for all four distributions.

[17] The three-parameter version of this distribution is

$$f(\phi; k, \sigma, \mu) = (1/\sigma)[1 + k(\phi - \mu)/\sigma]^{-1-1/k} \exp - \left[1 + (-k(\phi - \mu)/\sigma)^{-1/k}\right] \ , \ \phi \geq \mu - \sigma/k.$$

5 The Survey.

In summary, estimating an average SCC requires: (i) the expected growth rate of emissions under BAU, m_0; (ii) probabilities of alternative climate-induced reductions in future GDP under BAU; (iii) the reduced growth rate of emissions needed to avoid an extreme outcome, m_1; (iv) the most likely climate impacts under BAU in 2066 (50 years from the time of the survey), z_1, and in 2150, z_2, from which I determine β in eqn. (3); and (v) the discount rate, R. To obtain this information, I survey economists and climate scientists with highly cited publications related to climate change and its impact. This section explains how experts are identified, presents the survey instrument, and explains how responses are processed.

5.1 Identification of Experts.

I want the opinions of people with significant research experience and expertise in climate change and its impact. This can include climate scientists, economists who have worked on climate change impacts and climate policy, as well as individuals whose main focus has been on policy design. What matters is that they have established expertise, the selection is as broad and inclusive as possible, and the selection is done as objectively as possible.

To identify experts, I use Web of Science (WoS) to find journal articles, book chapters, and other publications on climate change and its impacts published during the last 10 years. The WoS search capabilities are used to search publication titles, abstracts, and assigned keywords for particular climate change-related search terms. The search was conducted in November 2015 and returned approximately 50,000 publications. A list of the search terms used is shown in Table 3; all results included at least one search term from column A, or at least one search term from *each of* columns B and C.

This search yields publications on climate change written by climate scientists and economists. However, an initial search also yielded publications written by medical researchers, architects and planners, and others, and on review these publications had little or nothing to do with climate change. Thus, to isolate environmental and climate scientists and economists, the results were filtered to include only publications in five research areas as defined by Web of Science: agriculture, business and economics, environmental sciences and ecology, geology, and meteorology and atmospheric sciences. (These research areas are based on individual records in WoS, rather than authors or journals more generally.)

These results were further narrowed to include only the more highly cited publications in each field. After sorting records by research area, the top 10 percent of publication citation counts was identified for each area and each publication year. (This mitigates the

Table 3: Web of Science Climate Change Search Terms.

Single Search Terms	Joint Search Terms	
(A)	(B)	(C)
“climate change policy”	“ocean temperature”	“climate change”
“social cost of carbon”	“precipitation	“climate-change”
“climate policy”	“sea level rise”	“greenhouse gas”
“climate-change policy”	“sea level change”	“greenhouse gases”
“climate forcing”	“ocean acidity”	GHG
“radiative forcing”	catastrophe	($CO2$ AND emissions)
“climate feedbacks”	catastrophic	(“carbon dioxide” AND emissions)
“ climate sensitivity”	economy	
“equilibrium climate response”	economics	
“global mean surface temperature”	damages	
“carbon price”	mortality	
“carbon-price”	productivity	
“price of carbon”	risk	
“carbon tax”	“discount rate”	
“tax on carbon”	“atmospheric concentration”	
(“cap-and-trade” AND carbon)	GDP	
(carbon AND quota)	“gross domestic product”	
(carbon AND trade AND cap)		

Note: Quotation marks mean the phrase must appear exactly as written. Search results must include at least one search term in column A *or* at least one term from *each of* columns B and C.

effects of different citation practices by different research areas, and the higher numbers of citations expected for earlier publication years.) Table 4 shows (in column A) the number of publications in the top ten percent of citations returned by area. These highly cited publications were used to identify authors in each research area. For example, the business and economics search returned 632 distinct authors, while the meteorology and atmospheric sciences search returned 4,271 distinct authors, as shown in column B of the table.

Next, the lists of authors were pared down so that the percentage of authors in each research area matches the percentage of highly cited publications in that area. This is done because in some fields (e.g., geology) the authors listed on a paper might include everyone connected with the research, while in other fields (e.g., economics) only primary contributors are included. Thus I identify the research area with the smallest number of authors per publication, and pare down the list of authors in the other areas to match this number, retaining those authors with the most citations.[18] The adjusted number of authors in each

[18]For each author, a total citation count over the ten years is calculated from this universe of highly cited publications. For example, Author A might have had a publication in 2009 with 10 citations and another in 2011 with 5 citations, for a total of 15 cites.

Table 4: PUBLICATIONS AND AUTHORS BY WEB OF SCIENCE RESEARCH AREA.

Research Area	(A) No. Pubs, Top 10% of Cites	(B) No. Distinct Authors	(C) Adjusted No. Authors	(D) Avg. No. Authors per Publication	(E) No. Authors with Email Address
Agriculture	282	1474	686	2.43	660
Business & Economics	257	632	632	2.46	614
Environmental Sciences and Ecology	1873	8549	4630	2.47	4355
Geology	629	3507	1541	2.45	1465
Meteorology and Atmospheric Sciences	815	4271	2012	2.47	1883
Sub-Total:					8977
Duplicate Authors Across Fields:					2144
Total Authors with an Email Address:					**6833**

Note: Column A gives number of 10% most highly cited publications in each research area from WoS search, and Column B gives number of distinct authors from those publications. Column C adjusts number of authors in Column B to obtain the same average number of authors per publication across all research areas (about 2.45).

area is shown in column C of Table 4. Email addresses were found for most but not all of these authors; the number of authors with known email addresses is shown in column E.

After eliminating duplicates across research areas, this process led to a total of 6,833 authors. Using Qualtrics to run the survey, all of these authors were contacted via email during March and April 2016 and asked to respond to the (online) questionnaire, which is shown below. Respondents were told that their identities will be confidential, and only the overall results of the survey will be published. Those that agreed to respond were given the questionnaire. Of those contacted, approximately 1,000 responded and answered the survey questions, and the analysis of those responses is discussed below.

5.2 The Questionnaire.

Respondents are asked to read background information regarding the meaning of emission growth rates, GDP, and probabilities of alternative reductions in GDP.[19] Then they are asked to answer the questions below, skipping those they cannot or prefer not to answer.

[19] When listing possible outcomes, I begin with "mild" outcomes (e.g., a GDP reduction of 2%) and then move to more extreme outcomes. Morgan (2014) has argued that it is preferable to move from probabilities of extreme outcomes to less extreme ones, but when testing the questionnaire, I found that people then had more trouble thinking about probabilities.

They are also asked (not shown below) to report the confidence they have in their answers (on a scale of 1 to 5, where 5 is most confident).

- **Introduction**: The purpose of this survey is to estimate the social cost of carbon, an important input to climate policy. Experts, identified from their publications over the past decade, include climate scientists, economists, and others who work on climate policy. Respondents' identities will be kept confidential; only overall results of the survey will be published. Before proceeding, read the background information below. This questionnaire should take about 10 minutes to complete. You can skip any questions that you cannot or prefer not to answer. For Questions 1 to 6, we also ask how confident you are in your response.

- **Background Information**: The questions deal with the impact of climate change and the reductions in GHG emissions needed to limit that impact. "Impact" and "emission reductions" should be understood as follows:

  - **Impact**: This is measured as a climate-induced percentage reduction in GDP, broadly defined. Assume that *without* climate change, world real GDP will grow at 2% per year. Climate change, however, could cause floods and other natural disasters, reduce agricultural output, reduce labor productivity, and have other direct effects that would reduce GDP. Climate change might also have indirect effects, such as ecosystem destruction, social unrest, and increased morbidity and mortality that could further reduce GDP. At issue is *how much lower* future GDP might be as a result of climate change, relative to what it would be without climate change. Is the reduction in GDP likely to be only a few percent, or more than 20 percent (an outcome some economists would consider "catastrophic")?
  - **Emission Reductions**: While it may be impossible to avoid *any* future impact of climate change, by reducing the growth of GHG emissions we might avoid a very large impact. The average annual growth rate of world GHG emissions over the past 25 years was about 3%, but most of that growth was from Asia. (For the U.S. and Europe, emissions growth was close to zero.) Some countries have already taken steps to reduce emissions, so under "business as usual" (BAU), i.e., if *no additional steps* are taken to reduce emissions, that growth rate might fall to about 2%. However, many experts believe that the growth rate of emissions must drop below this BAU rate to avoid a large impact of climate change. What growth rate of emissions (negative or positive) is needed to avoid a large impact?

- **Question 1**: Under BAU (i.e., no additional steps are taken to reduce emissions), what is your best estimate of the average annual growth rate of world GHG emissions over the next 50 years? (You might believe that the growth rate will change over time; we want your estimate of the *average* growth rate over the next 50 years under BAU.)

  Average emissions growth rate under BAU:

- **Question 2**: If no additional steps are taken to reduce the growth rate of GHG emissions, what is the *most likely* climate-caused reduction in world GDP that we will witness in 50 years? In other words, how much lower (in percentage terms) will world GDP be in 2066 compared to what it would be if there were *no* climate change?

Most likely percentage reduction in GDP in 2066:

- **Question 3**: Again, suppose no additional steps are taken to reduce the growth rate of GHG emissions. What is the probability that 50 years from now, climate change will cause a reduction in world GDP of *at least 2 percent*? (In other words, because of climate change, GDP will be at least 2 percent lower than it would have been with no climate change.) What is the probability that climate change will cause a reduction in world GDP of at least 5 percent? At least 10 percent? At least 20 percent? At least 50 percent? (To put these numbers in context, during the Great Depression U.S. GDP fell 25 percent, and at the end of World War II Japan's GDP fell more than 50 percent.) Please express each answer as a probability between 0 and 1.

  Probability of 2% or greater reduction in GDP:

  Probability of 5% or greater reduction in GDP:

  Probability of 10% or greater reduction in GDP:

  Probability of 20% or greater reduction in GDP:

  Probability of 50% or greater reduction in GDP:

- **Question 4**: Now think about the far-distant future — the middle of the next century. If no additional steps are taken to reduce the growth rate of GHG emissions, what is the most likely climate-caused reduction in world GDP that we will witness in the year 2150? In other words, how much lower (in percentage terms) will world GDP be in 2150 compared to what it would be if there were no climate change?

  Most likely percentage reduction in GDP in 2150:

- **Question 5**: Return to the 50-year horizon, and the possibility that under BAU climate change will cause a reduction in GDP of at least 20 percent. In Question 1, we asked for your best estimate of the average annual growth rate of GHG emissions over the next 50 years under BAU. What is the average annual growth rate of GHG emissions needed to prevent a climate-induced reduction of world GDP of 20 percent or more? (By "prevent," we mean reduce the probability to near zero.) This value might be a positive number, corresponding to slowed growth of emissions, or a negative number corresponding to annual reductions in emissions.

  Average emissions growth rate to prevent 20% or greater reduction in GDP:

- **Question 6**: What discount rate should be used to evaluate future costs and benefits from GHG abatement? (Please provide a *single* discount rate.)

  Discount rate:

- **Question 7**: Is your expertise primarily in climate science (e.g., how GHG emissions affect climate), primarily in economics (e.g., how climate change can directly or indirectly affect the economy, costs of abatement, policy design, etc.), or in both?

  Expertise primarily in climate science, economics, or both:

5.3 Survey Responses.

About 1000 people responded, but some did not answer all of the questions, and some gave answers that seemed nonsensical and were therefore discarded. Examples of answers that were discarded include discount rates that are negative or above 50%, a most likely GDP loss greater than 100%, and impact probabilities greater than one. Despite efforts to clearly state the desired form of responses in the survey instructions, in some cases answers were ambiguous (e.g., a range instead of a single number for the most likely GDP impact, or "over 50%"). Where it was possible to meaningfully interpret such answers, they were recoded accordingly, but otherwise they were dropped. About 400 responses were dropped for these reasons. The details of this process are given in the Appendix.

In addition, I eliminated outliers by dropping responses where values for most likely GDP impact in 2150 and/or the reported probability of a 5% or greater GDP loss in 2066 fell outside the 5th percentile or 95th percentile. This left a total of 534 responses. (Results for the full sample, i.e., without eliminating responses outside the 5 to 95% range, are available from the author, and are qualitatively the same as the results reported in the next section.)

We would expect variation in the answers to the questionnaire, but as the results discussed below make clear, the extent of that variation turned out to be considerable. To see whether some of that variation is explained by observable characteristics of the respondents, I compare SCC estimates across the following groups of experts:

Economists vs. Climate Scientists. Question 7 asks respondents whether their expertise is primarily in economics or climate science. Do the results differ across these two groups? We might expect economists to assess GDP-based impacts, as well as the appropriate discount rate, differently than climate scientists.

Regional Differences. The survey is implemented in Qualtrics, which gives GPS coordinates for each respondent (although names and email addresses are not recorded). I use this data to compare SCC estimates for experts in the U.S. and in other parts of the world.

Degree of Confidence. Experts are asked to state how confident they are in their answers on a scale of 1 (not at all confident) to 5 (very confident). Most of the variation across experts comes from their assessments of impact probabilities, and there was wide variation in the stated degree of confidence in those assessments. I show below how the SCC estimates change if I drop answers for which the stated degree of confidence is below 3.

In the next section I report calculated SCC numbers based on the entire set of respondents, based on the different groups discussed above, and based on the choice of probability distribution for potential impacts. As I will show, although the variability across experts is considerable, the results are consistent with a general view that the SCC is much larger than the $40 or so estimates that have come from recent IAM-based analyses.

6 Results.

In this section I present selected results for individual and group-wise SCC estimates. I say "selected" because I calculated SCCs in a variety of ways — e.g., excluding impact responses outside the 5% to 95% range (reported here), excluding impact responses outside a 10% to 90% range, and not excluding any responses. Although I note the differences, for space reasons some details are omitted, but are available from the author on request.

Across the respondents, there was general agreement over the growth rate of emissions under BAU (m_0), as well as the emissions growth rate needed to avert an extreme impact (20% or greater) on GDP 50 years from now; reported values of m_1 were generally in the range of $-.01$ to $-.03$, and most were close to $-.02$. But opinions regarding the probabilities of alternative outcomes, and the most likely impact in 2150, varied widely. Reported discount rates also varied widely, but even using an exogenously imposed discount rate of .03, there is considerable variation in the individually calculated SCCs. That variation is due largely to variation in the reported impact probabilities.

I begin with the individually calculated SCCs. Here I fit a distribution to the probabilities reported by each respondent, which I use along with the respondent's reported values of m_1 and most likely impacts to calculate an SCC for the respondent. I calculate average SCCs for different groups of respondents, and use histograms to illustrate the extent to which the SCCs vary. Then I turn to the group-wise estimates, in which the distribution is fit to the reported impact probabilities of all members of the group. At the end of this section I assess what we can (and cannot) conclude about the SCC, and the implications for policy.

6.1 Individual SCC Estimates.

To calculate an SCC for each respondent, I use the most likely impacts in 2066 and 2150 for that respondent to obtain a value for β, and fit each of four probability distributions to the respondent's reported impact probabilities. Using this information along with the respondent's reported value of m_1, I calculate four SCC values (one for each distribution). This calculation also requires values for the discount rate R and the BAU emission growth rate m_0. For the results reported below, I used an average value of m_0 across all respondents (.023) and a discount rate fixed at .03. Reported discount rates varied widely across respondents (especially those with primary expertise in climate science rather than economics),

Table 5: Average SCC Estimates from Individual Responses.

Group	N	z_1	z_2	$\bar{m}_1$	SCC: Gamma	SCC: Lognormal	SCC: Pareto	SCC: Frechet	SCC: Highest R^2
All	386	.108	.284	$-.0168$	272.3	295.5	285.1	303.3	291.0
Economics	113	.086	.290	$-.0185$	153.1	178.5	159.4	202.7	173.7
Climate Science	220	.121	.315	$-.0174$	290.8	312.2	315.5	326.0	316.3
North America	170	.115	.298	$-.0197$	272.5	277.8	291.9	298.2	284.5
Europe	158	.115	.310	$-.0174$	262.7	279.3	278.3	301.0	284.2
Developing	30	.117	.247	$-.0140$	344.3	371.7	373.2	371.2	373.9

Note: For each group, z_1 and z_2 are average values of most likely GDP impacts in 2066 and 2150, N is number of respondents after dropping responses for which z_1 or z_2 fell outside the 5th or 95th percentiles, and $\bar{m}_1$ is the average value of the emission growth rate needed to truncate the impact distribution. The Ns across areas of expertise and regions do not sum to N for "All" because some respondents claimed expertise in both or neither field, and some reside in Asia or Latin America. SCCs were calculated by fitting a distribution (Gamma, etc.) to each respondent's stated outcome probabilities, using a BAU emissions growth rate (m_0) of .023 and a discount rate $R = .03$, and then averaged across the members of each group. The last column shows the average SCC for each group using the distribution for each respondent that gives the highest R^2.

and the .03 rate is close to the average rate for all respondents (.029) and equal to the rate used by the U.S. Interagency Working Group in their IAM-based estimate of the SCC.[20]

Table 5 shows the average SCC estimates for the individuals in each of several groups, and for each of the four probability distributions fit to each respondent's reported impact probabilities. Here N is number of respondents after dropping responses outside the 5th or 95th percentiles, and $\bar{m}_1$ is the average value of the emission growth rate needed to truncate the impact distribution. The Ns across areas of expertise and across regions need not sum to N for "All" because some respondents claimed expertise in both or neither field, and some reside in Asia or Latin America.[21] The last column shows the average SCC for each group using the distribution for each respondent that gives the highest R^2 for that respondent. (The average value of the highest R^2 ranged across groups from .9404 to .9603.)

[20] I also calculated individual SCCs using the values for m_0 and R supplied by each respondent. The results are qualitatively similar, and available from the author.

[21] The N for "All" is less than the 534 responses used in the group-wide estimates of the SCC because I dropped individual responses that were incomplete, whereas the group estimates used average values of these numbers, and thus included all respondents who at least provided impact probabilities.

As Table 5 shows, the variation of the mean SCCs across groups is greater than the variation across impact probability distributions. (I discuss the variation across the *individual* SCCs below.) As a group, economists have the lowest mean SCC, and correspondingly the lowest mean value for the most likely impact in 2066 under BAU (z_1). But note that even for economists, the mean SCC is large ($153 to $202, depending on the distribution), at least relative to the roughly $40 value reported by the Interagency Working Group. The mean SCCs are much higher for climate scientists (from $291 to $326). Also, with the exception of developing countries (from which there were only 30 complete responses), there is little geographical variation in these SCCs.

Within each group, however, there is considerable variation across respondents. This can be seen from the histograms in Figure 1, which shows the distribution of SCCs across respondents in each of four groups: economists, climate scientists, respondents residing in North American, and those residing in Europe. In each case the SCC for each individual respondent is calculated using the best-fit (highest R^2) impact distribution for that respondent.[22] The variation is much greater for climate scientists than for economists, and there is little difference between respondents in North America versus Europe.

To get a better sense of the variation across individual SCCs, Figure 2 shows the distribution of SCCs for all respondents, where each SCC is calculated using the best-fit probability distribution for that respondent, i.e., the distribution with the highest R^2. (The best-fit distribution varies across respondents.) About a third (121) of the SCCs are between 0 and $100, but many are spread out between $100 and $700 (so that the mean SCC is $291). This dispersion is not due to different opinions about the discount rate (which in this case was held fixed at .03), but rather very different opinions about the impact probabilities. For example, reported values of the most likely impact under BAU in 2066 ranged from .02 to .30 (with corresponding variation in reported impact probabilities). Put simply, there is considerable variation in respondents' views about the likelihood of alternative climate outcomes.

Histograms in Appendix B show the distribution of individually calculated SCCs across all respondents, grouped by the impact distribution from which they are calculated. The mean SCC varies very little across distributions, but the dispersion varies much more. SCCs generated from the fitted Lognormal and Frechet distributions are more dispersed than those generated from the Gamma and Pareto distributions.

[22] Figures 1 and 2 show SCCs from 0 to 1000. For each group there were 2 or 3 respondents with SCCs above 1000 (as high as 1800); they are not shown but were included in the calculation of the mean SCC.

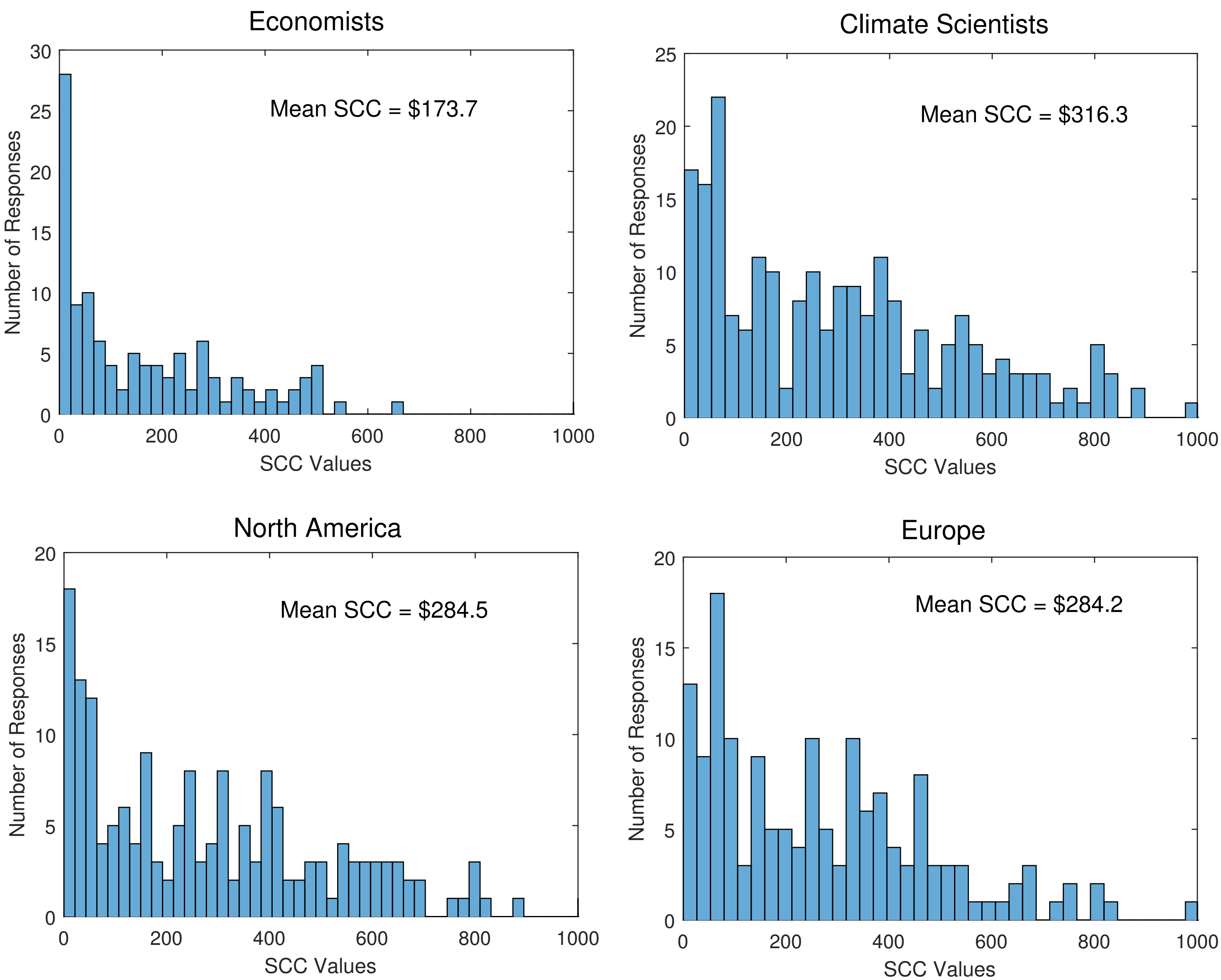

Figure 1: SCCs from Individual Responses, by Group, Using Distribution with Highest R^2

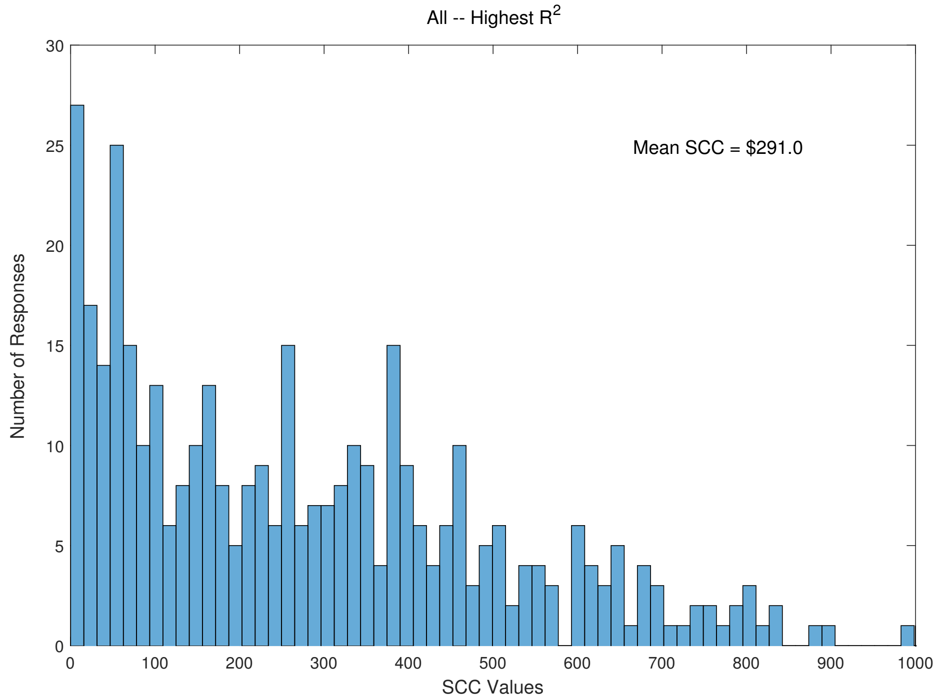

Figure 2: SCCs for All Individual Responses, Using Distribution with Highest R^2

6.2 Group Estimates of SCC.

I turn now to the group-wise SCC estimates, in which each probability distribution is fit to the reported impact probabilities of all members of the group (dropping responses outside the 5th or 95th percentiles). The results are summarized in Table 6, which shows SCC estimates for all respondents, respondents who stated a confidence level of 3 or greater in their reported impact probabilities, economists, climate scientists, residents of North America, of Europe, and of developing countries. For each group, SCC estimates are shown for each of the four distributions to which the reported impact probabilities were fit.

To calculate these SCCs, I used average values of the reported most likely GDP impacts in 2066 and 2150 ($\bar{z}_1$ and $\bar{z}_2$) for the group to calculate a value of β, using eqn. (3). I likewise used average values, shown in Table 6, of the BAU emission growth rate ($\bar{m}_0$), the emission growth rate needed to truncate the distribution ($\bar{m}_1$), and the discount rate $\bar{R}$.

Two results in Table 6 stand out. First, the SCCs for the group of respondents who claimed a high level of confidence in their reported impact probabilities are considerably lower (only about half as large) than the SCCs for "All" respondents and for other groups, including economists. There are two reasons for this. First, although the most likely outcomes (z_1 and z_2) they report are on average about the same as for the other groups, the "high confidence"

Table 6: SCC Estimates from Group Responses.

Parameter/ Distribution	All Respond.	All – High Confidence	Economists	Climate Scientists	North America	Europe	Developing Countries
N	534	230	157	307	269	229	53
$\bar{z}_1$	.1203	.1309	.1003	.1182	.1204	.1229	.1061
$\bar{z}_2$	.2923	.3062	.2648	.2977	.2904	.3024	.2368
β	.0024	.0034	.0022	.0020	.0026	.0021	.0047
$\bar{m}_0$	.0234	.0246	.0203	.0239	.0231	.0214	.0242
$\bar{m}_1$	−.0178	−.0200	−.0172	−.0175	−.0179	−.0183	−.0123
$\bar{R}$	.0293	.0261	.0273	.0313	.0294	.0260	.0414
Gamma:							
SCC	208.5	107.6	148.6	199.9	207.3	341.4	107.3
R^2	.3692	.1954	.4201	.2319	.1013	.2270	.2769
Lognormal:							
SCC	278.1	135.2	261.8	260.2	271.7	456.7	163.1
R^2	.3843	.2079	.4315	.2463	.1123	.2385	.2964
Pareto:							
SCC	15.0	4.0	22.2	11.4	8.6	21.5	5.0
R^2	.1899	.1648	.3586	.1848	.2054	.1888	.1399
Frechet:							
SCC	295.0	137.9	348.1	270.2	278.4	481.9	181.7
R^2	.3765	.1986	.4271	.2390	.1053	.2286	.2962

Note: For each group, N is number of respondents after dropping responses outside the 5th or 95th percentiles, $\bar{z}_1$ and $\bar{z}_2$ are average values of the most likely GDP impacts in 2066 and 2150, β is the corresponding dynamic adjustment parameter, $\bar{m}_0$ is the average BAU emission growth rate, $\bar{m}_1$ is the average emission growth rate needed to truncate the distribution, and $\bar{R}$ is the average discount rate. The SCCs were calculated by fitting a distribution to the stated outcome probabilities for the entire group. The Pareto distribution is potentially fat-tailed, but the estimated values of α were between 38 and 42, making the fitted distribution extremely thin-tailed.

Table 7: Group Estimates of SCC — All Respondents, 5th to 95th Percentiles

Distribution	SCC	R^2	$\mathbb{E}_0(z)$	$\mathbb{E}_1(z)$	Parameter Estimates
Gamma:	208.5	.3692	.139	.069	$\hat{r} = .6799$, $\hat{\lambda} = 4.078$
Lognormal:	278.1	.3843	.159	.066	$\hat{\mu} = -2.446$, $\hat{\sigma} = 1.476$
Pareto:	15.0	.1898	.056	.051	$\hat{\alpha} = 37.95$, $\hat{k} = 9.163 \times 10^{12}$
Frechet:	295.0	.3765	.160	.061	$\hat{k} = 1.2746$, $\hat{\sigma} = .0633$

Note: SCCs were calculated by fitting a distribution to the stated outcome probabilities for the entire group, after dropping responses outside the 5th to 95th percentiles. Values for $\bar{m}_0$, $\bar{m}_1$, etc. are shown in the second column of Table 6. The PDFs for the four distributions are given by eqns. (9), (10), (11) and (12). For each fitted distribution, $\mathbb{E}_0(z)$ is the expected value of the 2066 impact z under BAU, given by eqn. (13), and $\mathbb{E}_1(z)$ is the expected value of z under the truncated distribution, given by eqn. (14). The fitted CDFs and PDFs are shown in Figures 3 and 4.

group usually reported lower probabilities of extreme outcomes. Second, the average values of z_1 and z_2 they report results in a value of β somewhat larger than for other groups, which, as can be seen from eqn. (4), implies a lower long-run maximum impact.

Recall that for the individual SCC estimates, economists have the lowest average SCC compared to other groups, and correspondingly reported the lowest average value for the most likely impact in 2066 under BAU (z_1). That is not the case for the group-wise SCC estimates. Comparing economists to climate scientists — and ignoring for now the results for the Pareto distribution — the SCC for economists is lower than for climate scientists for the Gamma distribution, about the same for the Lognormal distribution, and higher for the Frechet distribution. The SCC estimates for Europe, on the other hand, are consistently much higher than for North America and for "All," irrespective of the distribution.

The second result that stands out is that the Pareto distribution yields extremely low SCC values for every group. The SCC value for "All Respondents" ranges from about \$200 to \$300 for the Gamma, Lognormal, and Frechet distributions, but is only \$15 for the Pareto. Table 7 summarizes the results for "All," including the parameter estimates for each distribution. Note that the fit of the Pareto distribution is worse than the other three (the R^2 is .19, compared to .37 to .38 for the other three). Also the fitted parameters for the Pareto distribution ($\hat{\alpha}$ is about 38) imply an extremely thin tail.

These differences in the fitted distributions can also be seen in the cumulative distribution functions and corresponding density functions, shown for All Respondents in Figures 3 and

4. The Pareto distribution is often used to characterize catastrophic events because it allows for a fat tail. But in this case the estimated distribution has an extremely thin tail, much thinner than even the Gamma distribution, for the relevant range of ϕ.[23]

In Figure 3, horizontal dashed lines indicate where the cumulative distribution reaches the point where $\phi = .223$ (which corresponds to $z = .20$). For the Gamma, Lognormal, and Frechet (GEV) distributions, this occurs where the cumulative probability is roughly .74. (It is slightly different for each of these three distribution, but in all cases close to .74.) This implies that the estimated probability of a "catastrophic" outcome, i.e., one in which GDP is reduced by 20% or more, is about .26. This is a large number, and explains why the SCCs are on the order of $200 or more. For the Pareto distribution, on the other hand, the cumulative probability is about .97, so that the probability of a "catastrophic" outcome is only about .03. As Figure 3 shows, the fit of the Pareto CDF seems to be driven largely by the reported probabilities of GDP impacts of 10% or less. The Pareto CDF provides a very poor fit to the reported probabilities of $\phi \geq .223$ (which partly explains the lower R^2).

In Sections 2 and 3, I used a simple example to show how the SCC is driven largely by the possibility of a catastrophic outcome. That basic result applies here as well. As Figure 3 illustrates, there is considerable dispersion for all of the reported probabilities (as shown by the vertical spread of the small circles at each value of ϕ). There are enough respondents who attached a high probability (above .30) to a GDP impact of 20% or greater to drive the SCC up. If we weigh all of these reported probabilities equally, the tails of the fitted distributions will be sufficiently thick to yield a high SCC. But perhaps the reported probabilities should not all be weighted equally. I address that question below.

6.3 What is the SCC?

The full sample of respondents yielded mean SCC estimates well above $200 per metric ton. This was true for individually estimated SCCs, i.e., obtained by fitting distributions to the probabilities reported by each respondent, which were used along with the respondent's reported values of m_1 and most likely impacts to calculate an SCC for the respondent. As shown in Table 5 and Figures 1 and 2, although SCCs based on the responses of economists were lower (an average of $174 using the distribution for each respondent that had the highest R^2), SCCs for other groups were close to $300. However, as is clear from Figures 1 and 2, there is a great deal of dispersion across experts.

Similar results came from the group-wise estimates of the SCC. The numbers in Tables 6

[23]See, e.g., Barro and Jin (2011) and Martin and Pindyck (2015). The smaller is α the fatter is the tail.

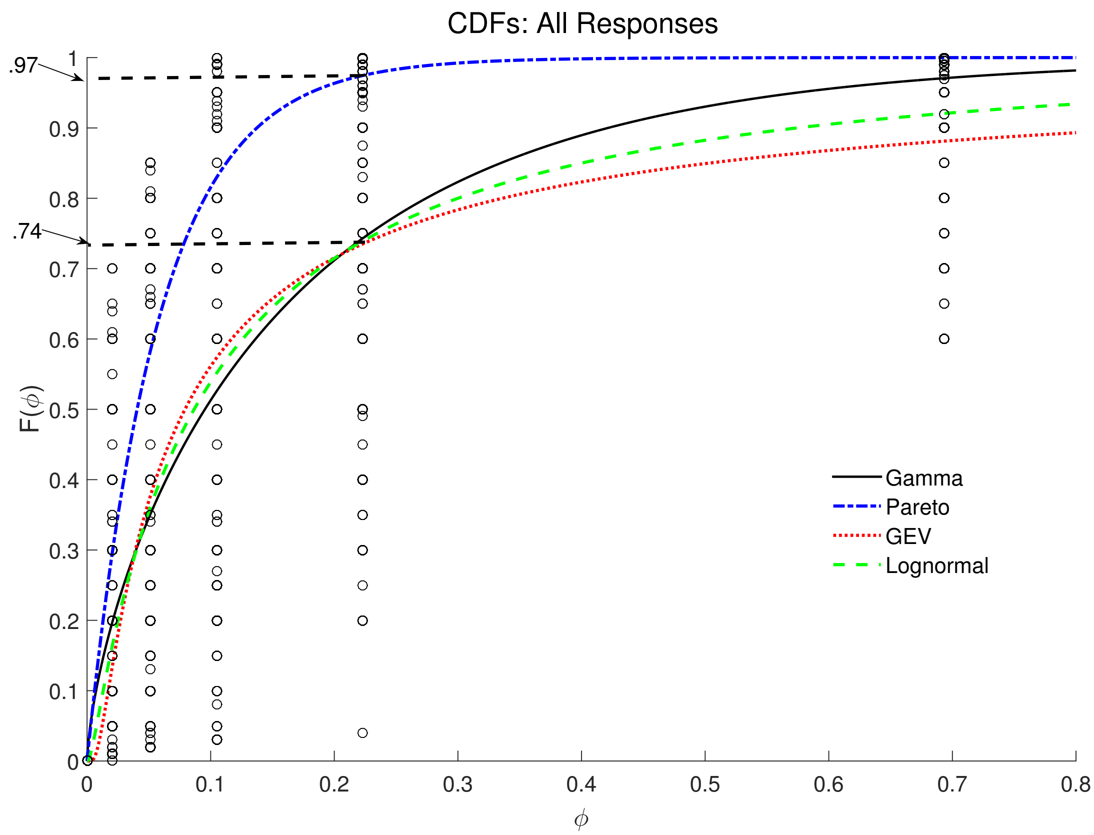

Figure 3: Fitted CDFs for All Respondents

and 7 are also consistent with an SCC above $200. (The fitted Pareto distribution is an exception, but I argued that because the fit of that distribution is poor, and because the estimated tail lies outside the reported probabilities for high impacts, it should be discounted.) But here, too, as Figure 3 illustrates, there is a great deal of dispersion across experts' beliefs about impact probabilities. This dispersion is particularly important when it comes to probabilities of extreme impacts, which are the main driver of the SCC.

In designing this survey, I sought the opinions of people with research experience in climate change and its impact, where experience was measured in terms of highly cited publications over the past 10 years. I also wanted the set of experts to be as broad as possible, and include climate scientists, economists who have worked on climate change impacts and policy, and individuals who have worked on policy design. The resulting set of experts who responded to the survey is indeed broad, which is both a plus and a minus. On the plus side, I have captured the opinions of a wide range of experts who have worked on climate change. But on the minus side, some of these experts have indicated (in their responses to the questions about their confidence in their answers) that they are very unsure

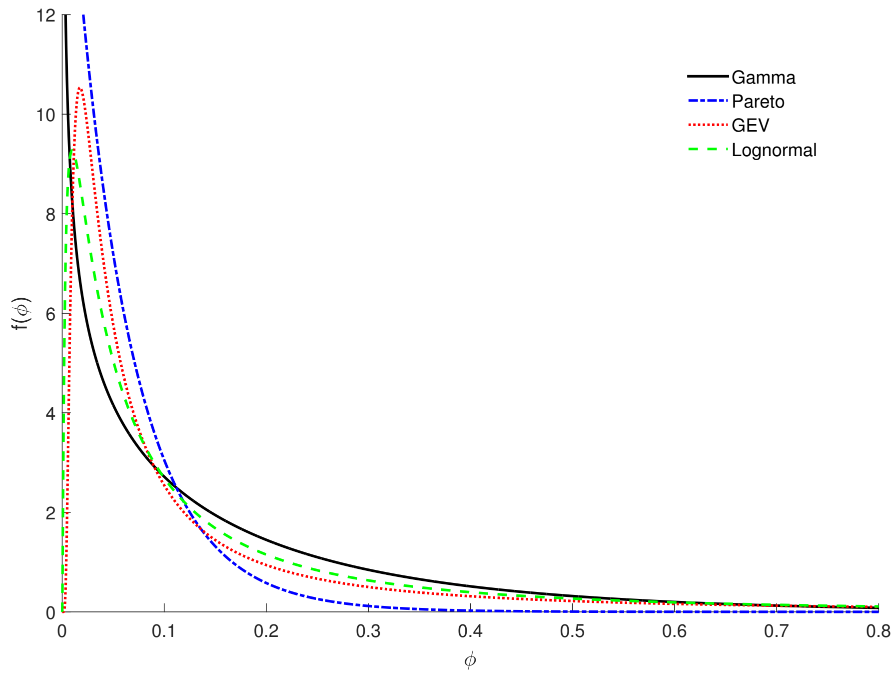

Figure 4: PDFs for All Respondents

about the probabilities of alternative climate impacts.

This suggests trimming the sample of responses and focusing on those experts who expressed a high degree of confidence (3 or higher on a scale of 1 to 5) in their views about the impact probabilities. The second column of Table 6 does just that, and the SCCs are indeed much lower — in the range of \$108 to \$138 — than they are for the other groups of respondents. Another way to trim the sample is to exclude "outliers." That has already been done to some extent, because I dropped responses where values for the most likely GDP impact in 2150 and/or probability of 5% or greater GDP loss in 2066 fell outside the 5th percentile or 95th percentile. To examine the impact of such outliers, I also calculated SCCs after dropping responses where these values fell outside the 10th or 90th percentile.

The results are shown in Table 8. To make a comparison easier, the first two columns of numbers replicate the first two columns of Table 6, i.e., all respondents within the 5th to 95th percentiles, and respondents expressing a high level of confidence, but also within the 5th to 95th percentiles. The next two columns exclude respondents in each group who are outside the 10th to 90th percentiles. The result of this further trimming is a substantial drop in the SCCs. Taking all respondents regardless of their expressed degree of confidence (and ignoring the Pareto distribution), the range of SCCs drops from \$209 – \$295 to \$147 – \$243. (In the Appendix, this change is also shown graphically by the fitted CDFs.) The last

Table 8: SCC Estimates from Group Responses — Trimmed.

Parameter/ Distribution	All, 5th to 95th Percent	High Conf., 5th to 95th Percent	All, 10th to 90th Percent	High Conf., 10th to 90th Percent
N	534	230	409	212
$\bar{z}_1$	.1203	.1309	.1072	.1300
$\bar{z}_2$	.2923	.3062	.2689	.2866
β	.0024	.0034	.0020	.0050
$\bar{m}_0$	.0234	.0246	.0238	.0248
$\bar{m}_1$	$-.0178$	$-.0200$	$-.0167$	$-.0201$
$\bar{R}$	.0293	.0261	.0291	.0258
Gamma:				
SCC	208.5	107.6	146.9	66.5
R^2	.3692	.1954	.4787	.3069
Lognormal:				
SCC	278.1	135.2	217.2	83.6
R^2	.3843	.2079	.4952	.3206
Pareto:				
SCC	15.0	4.0	14.8	2.6
R^2	.1899	.1648	.2333	.1502
Frechet:				
SCC	295.0	137.9	243.4	86.1
R^2	.3765	.1986	.4909	.3107

Note: For each group, N is number of respondents, $\bar{z}_1$ and $\bar{z}_2$ are average values of most likely GDP impacts in 2066 and 2150 and β is the corresponding dynamic adjustment parameter, $\bar{m}_0$ is average BAU emission growth rate, $\bar{m}_1$ is average emission growth rate needed to truncate the distribution in 2066, and $\bar{R}$ is the average discount rate.

column of Table 8 shows results for the trimmed set of respondents who expressed a high degree of confidence in their answers. For that "high confidence" group, trimming reduces the range of SCCs from \$108 – \$138 to \$67 – \$86.

So is the SCC number that should be used in policy applications closer to \$80 or \$200? The answer depends in part on how we evaluate the "expertise," and in particular the ability to assess probabilities of future climate outcomes, of the respondents. If one is willing to give more weight to the views of economists (who perhaps have a better understanding of GDP impacts) than climate scientists, give more weight to those respondents who express a higher level of confidence in the probabilities they report, and also trim outliers, then the right number is around \$80. But if one takes a more democratic view of "expertise" and treats all respondents equally, the right number is closer to \$200.[24]

Either way, the estimates of the SCC that have come out of this study are well in excess of the roughly \$40 estimates that have come from recent IAM-based analyses.

7 Concluding Remarks.

My estimates of the SCC are much higher than the numbers that have been used in recent policy analyses in the U.S. This is true for individually estimated SCCs, i.e., obtained by fitting distributions to the probabilities reported by each respondent, and also for the group-wise estimates of the SCC. Although there is variation across groups, the numbers I obtain are consistent with a value for the SCC in excess of \$200. However, there is a great deal of dispersion across experts' beliefs about impact probabilities, which creates dispersion across the individually estimated SCCs. This dispersion is particularly important when it comes to probabilities of extreme impacts, which are the main driver of the SCC.

One might interpret the dispersion to mean that there is so much disagreement about possible impacts of climate change that we simply can't rely on the opinions of experts to determine the "true" SCC. This does not mean, however, that we should rely instead on an IAM or related model, because to do so simply replaces the opinions of a large (but perhaps diverse) set of experts with the opinion of a single expert, namely the modeler.

Or, one could argue that the set of experts who responded to the survey is too broad, especially given that some of the respondents indicated that they are not very confident about their answers, especially with regard to the probabilities of alternative climate impacts. This suggest trimming the sample of responses and focusing on those experts who expressed a high degree of confidence in their views about the impact probabilities. Doing so results in much lower SCC numbers, around \$80 or so. Is the "correct" number closer to \$80 or to \$200? That depends on one's view of "expertise," which I leave to the reader. My own conclusion from these results is that the SCC is well above the \$39 IAM-based estimate of the Interagency Working Group that is being used in a variety of policy applications.

My approach to estimating the SCC has several advantages. Its focus on more extreme outcomes addresses what really matters for the SCC, and because of their reliance on IAMs and "most likely" scenarios, is missing from the calculations performed by the Interagency Working Group. Avoiding the use of one or more IAMs (which hide the extent of our lack

[24]While \$200 might seem very high, it is close to the implicit SCC that is consistent with the work of Stern (2008). The \$80 number, however, is close to the \$101 result of a preliminary test, in which the questionnaire was given to 20 economists, 11 of whom responded. See Pindyck (2017*a*) for details.

of knowledge) is another advantage. The use of expert elicitation is simple and transparent, and summarizes the views of researchers who have studied climate change and its impact.

I calculate an average SCC, not the marginal SCC that environmental economists usually use to measure the social cost of a pollutant. (Expert opinion cannot be used to determine the impact over the next century of emitting one extra ton of CO_2 today.) As a guide for policy, however, the marginal SCC is of limited use. It can tell us what *today's* carbon tax should be, assuming that total emissions are on an optimal trajectory, but it will change from year to year. The average SCC provides a guideline for policy over an extended period of time, which can be more useful, especially given the difficult and protracted process for actually agreeing on a climate policy. Finally, the average SCC is much less sensitive to the choice of discount rate than is the marginal SCC.

My objective has not been to obtain a "final" estimate of the average SCC, but rather to demonstrate how an approach based on expert elicitation can work and show the kinds of answers it can provide. There are still a variety of problems that remain unresolved. For example: (i) What set of possible climate impacts should be presented to survey respondents? Should more choices, including GDP losses greater than 50%, be presented? (ii) Should we fit probability distributions different from the ones I used to the survey responses on impacts? (iii) I used $T_1 = 50$ years and $T_2 = 134$ years (2016 and 2150) as time horizons, but one could argue for alternative horizons. And can experts have meaningful opinions about potential damages as far away as the year 2150? (iv) Are there ways to explicitly include ecosystem destruction, health effects, etc. as part of potential damages? These and other unresolved questions are one reason that I view this work as suggestive of an approach, rather than an attempt to arrive at a number that can be used in the next set of climate negotiations.

Appendix

A. Cleaning and Coding the Survey Data.

Some survey respondents failed to answer all of the questions, and some gave answers that were ambiguous. Where it was possible to meaningfully interpret ambiguous answers, they were recoded accordingly, but otherwise they were dropped. Details of this process are described below.

Recoding GDP 2066 Values: (1) Some responses were given in percentage form, and others in decimal form. If the mostly likely GDP impact in 2066 was greater than 1, this was interpreted as a percentage and divided by 100 to convert to decimal form. (2) If the mostly likely GDP impact was equal to 1 and the probability of a 2% or greater GDP reduction in 2066 was less than 0.9, this was interpreted as a percentage and divided by 100 to convert to decimal form. (3) One respondent wrote: "about 3.0%, depending also on Earth." This was recoded as 3%. (4) One respondent wrote: "> 5%. This was recoded as 5%. (5) One respondent wrote: "1-3%." This was recoded as 2%.

Recoding GDP 2150 Values: (1) If the most likely GDP impact in 2150 was greater than 1, this was interpreted as a percentage and divided by 100 to convert to decimal form. (2) One respondent wrote: "10-20%." This was recoded as 15%. (3) One wrote: "Over 50 percent." This was recoded as 50%. (4) One wrote: "> 20%". This was recoded as 20%.

Recoding Probabilities: (1) If probability of 2% or greater GDP loss was above 1, all probability values were interpreted as percentages and divided by 100 to convert to decimal form. (2) All probability observations were dropped if one value was missing (e.g., we dropped probabilities for 2% or greater GDP loss, 5% or greater, 10% or greater, and 20% or greater if respondent did not provide probability of 50% or greater GDP loss. (3) We flagged observations where probabilities increased rather than decreased for greater GDP losses, as these were not cumulative probabilities. But if these individual probabilities summed to less than 1, we summed successive probabilities to obtain the cumulative probability of 2% or greater GDP loss, 5% or greater, etc. (A sum less than 1 was allowed due to the potential for GDP loss less than 2%.) The remaining tagged responses were dropped, as it was not possible to extract meaningful probabilities. (4) We recoded probabilities of 1 for GDP loss greater than 2%, 5%, 10%, 20%, or 50% as 0.99, 0.98, 0.97, 0.96, and 0.95, respectively, reflecting the inherent difficulty of predicting levels of GDP loss. Similarly, we recoded probabilities of 0 for these successive levels of GDP loss as 0.01, 0.001, 0.0001, 0.00001, and 0.000001, respectively. (5) Observations where all probabilities were listed as 0 or 1 were dropped.

Recoding Discount Rates: (1) Responses with negative discount rates were dropped. (2) If the reported discount rate was above 0.1 we assumed this represented a percentage rather than a decimal rate and divided by 100 to express as a decimal. (3) A discount rate of exactly 0.1 was interpreted as a percentage only when the respondent included a percent sign. (4) Discount rates greater than 10% were dropped. (5) One respondent wrote: "I dont think this is a fixed number, but I will say 3." This was recoded as 3%. (6) One respondent wrote: "<3%." This was recoded as 3%.

Removing Extreme Responses: (1) Observations where most likely GDP loss in 2066 was above 50% or most likely GDP loss in 2150 was above 100% were dropped. (2) Additionally, for some of the SCC estimates, additional criteria were applied to drop extreme values. For example, for some of the results reported in this paper, we dropped responses where values for most likely GDP impact in 2150 and/or probability of 5% or greater GDP loss in 2066 fell outside the 5th percentile or 95th percentile. In another iteration, we dropped responses where these values fell outside the 10th percentile or 90th percentile.

Matching Latitude and Longitude to Continents: Latitude and longitude information for cities with populations greater than 1000 were downloaded from an open source database of geographic data, available at http://www.geonames.org. After rounding latitude and longitude values to the closest degree, the survey data were merged with this database. Where the rounded latitude and longitude values could match to more than one continent, the full (unrounded) latitude and longitude survey data were manually matched to continent names using Google Maps.

Generating Spreadsheets with Individual Results: Following the data cleaning described above, we only retained responses with non-missing, non-eliminated values for most likely GDP impacts in 2066 and 2150, probabilities of various levels of GDP loss in 2066, and required emissions reduction for avoiding a GDP loss greater than 20%. Responses with missing or eliminated values for the BAU emission growth rate or discount rate were retained because we used an average across all respondents for these values.

B. Some Additional Results.

Individual SCCs by Impact Distribution. The histograms in Figure 5 show the distribution of individually calculated SCCs across all respondents, grouped by the impact distribution from which they are calculated. The mean SCC varies very little across distributions, but the dispersion varies much more. The Gamma and Pareto distributions yield SCCs with a sharp peak at 0 to \$50, and then SCCs spread out between \$50 and \$800. The SCCs generated from the fitted lognormal and Frechet distributions decline gradually towards zero. The mean SCCs are between roughly \$270 and \$300 for all four distributions because of the large number of SCC values between \$200 and \$300.

Fitted CDFs for Different Groups of Respondents. Figure 3 showed the fitted CDFs for all respondents, after dropping responses where values for most likely GDP impact in 2150 and/or probability of a 5% or greater GDP loss in 2066 fell outside the 5th percentile or 95th percentile. In addition, I trimmed the sample further by dropping responses where these values fell outside the 10th percentile or 90th percentile. Figure 6 shows the fitted CDFs that result after this further trimming of the sample. Once again, the horizontal dashed lines indicate where the cumulative distribution reaches the point where $\phi = .223$ (which

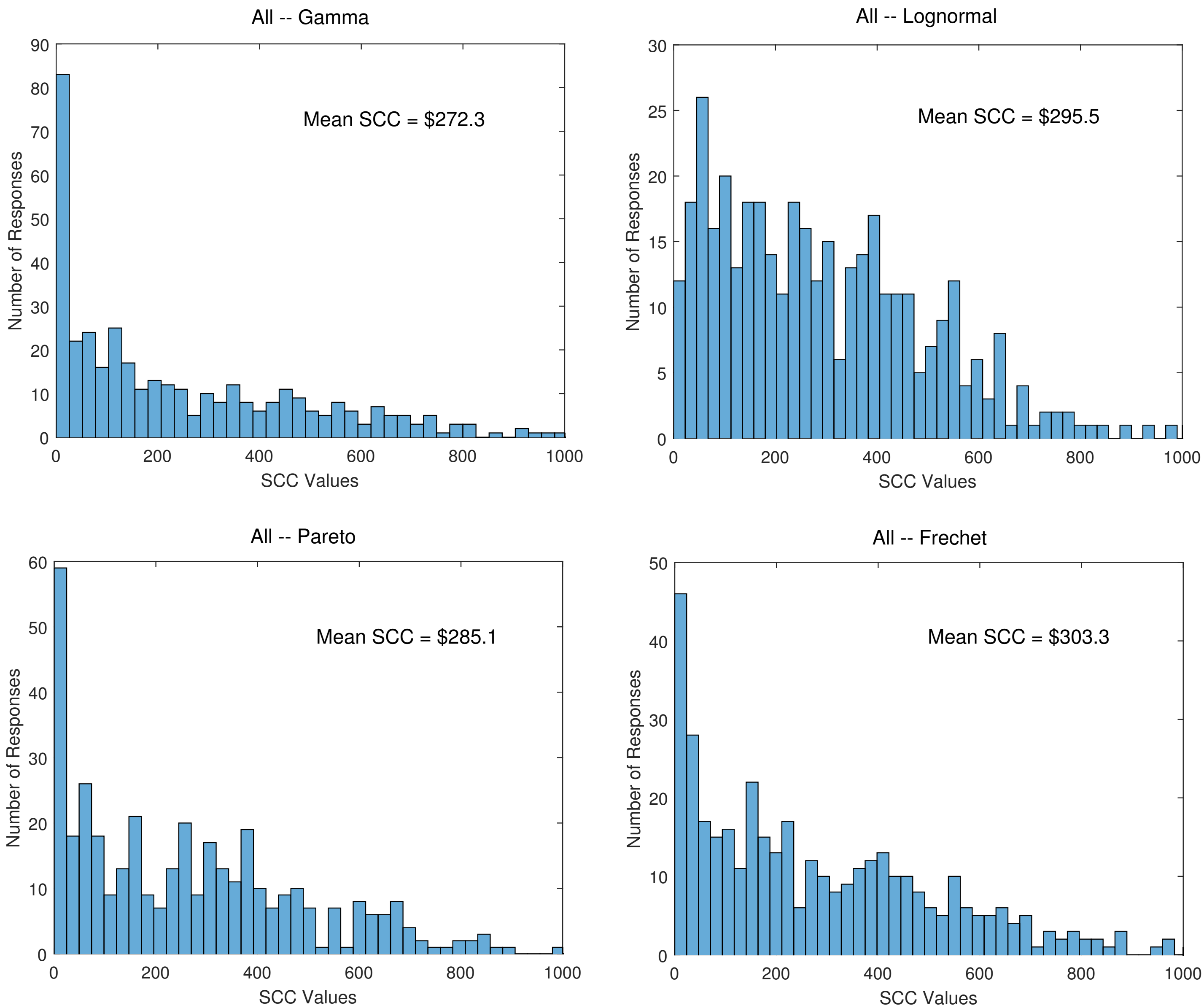

Figure 5: All Individual Responses, by Distribution

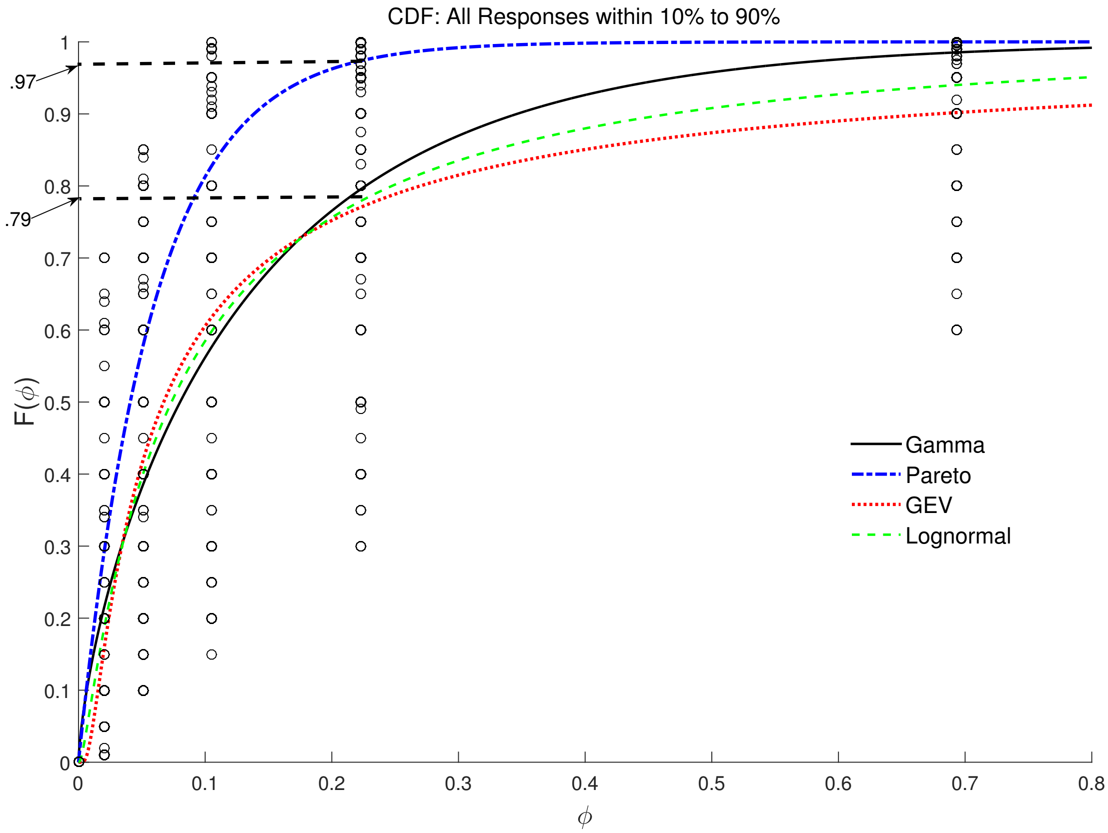

Figure 6: Fitted CDFs for All Respondents within 10% to 90% Range

corresponds to $z = .20$). For the Gamma, Lognormal, and Frechet (GEV) distributions, this occurs where the cumulative probability is roughly .79. This implies that the estimated probability of a "catastrophic" outcome, i.e., one in which GDP is reduced by 20% or more, is about .21. Recall from Figure 3 that this probability was about .26 when responses within the 5th/95th percentiles were included.

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