Journal of Environmental Economics and Management 94 (2019) 140–160

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

The social cost of carbon revisited☆

Robert S. Pindyck

Massachusetts Institute of Technology, Cambridge, MA 02142, USA

ARTICLE INFO

Article history:
Received 11 October 2017
Revised 9 February 2019
Accepted 17 February 2019
Available online 25 February 2019

JEL classification numbers:
Q5
Q54
D81

Keywords:
Climate policy
GHG emissions
Climate change impacts
Climate catastrophe
Damages
Uncertainty
Willingness to pay
Social cost of carbon
Expert survey

ABSTRACT

An estimate of the social cost of carbon (SCC) is crucial to climate policy. But how should we estimate the SCC? A common approach uses an integrated assessment model (IAM) to simulate time paths for the atmospheric CO_2 concentration, its impact on temperature, and resulting reductions in GDP. I have argued that IAMs have deficiencies that make them poorly suited for this job, but what is the alternative? I present an approach to estimating an *average* SCC, which I argue can be a useful guide for policy. I rely on a survey of experts to elicit opinions regarding (1) probabilities of alternative economic outcomes of climate change, but not the causes of those outcomes; and (2) the reduction in emissions required to avert an extreme outcome, i.e., a large climate-induced reduction in GDP. The average SCC is the ratio of the present value of lost GDP from an extreme outcome to the total emission reduction needed to avert that 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, but still well above the IAM-based estimates used by the U.S. government.

1. Introduction

An estimate of the social cost of carbon (SCC) is a crucial 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]

How should we estimate the SCC? A 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), its impact on temperature (and perhaps other measures of climate change), and the resulting reductions in GDP and consumption. One starts with a base case scenario,

☆ My special thanks to Sarah Armitage and Michael Carter for their outstanding research assistance. My thanks as well to Thomas Black, Roger Cooke, Tatiana Deryugina, Simon Dietz, Sergio Franklin, Peter Howard, Chris Knittel, Bob Litterman, Elena Manresa, Granger Morgan, Richard Newell, Talia Pindyck, Gerard Roe, Richard Schmalensee, Nick Stern, Martin Weitzman, and two anonymous referees for helpful comments and suggestions, and especially Alberto Cavallo and Tavneet Suri for their help in implementing the survey.

E-mail address: rpindyck@mit.edu.

[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. 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 metric ton of CO_2.

https://doi.org/10.1016/j.jeem.2019.02.003
0095-0696/

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 (slightly lower) path for consumption. The SCC is then the present value of the reductions in future consumption resulting from the additional ton of emissions (using some discount rate). This is how the U.S. government's Interagency Working Group (IWG) estimated the SCC.[2]

Some of the equations that go into IAMs — especially the damage functions that translate higher temperatures into reductions in GDP — lack a clear theoretical or empirical grounding.[3] As a result, these models tell us little about the likelihood of a catastrophic climate outcome, e.g., a temperature increase above 4 °C that greatly impacts GDP.[4] But as I will show, it is the possibility of a catastrophic outcome that is the main driver of the SCC. If we knew that temperature increases and their economic impact will be small or moderate, we could conclude that the SCC is not large. But we do *not* know that this will be the case.[5]

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 a survey of experts, in which they are asked their opinions regarding certain inputs to an SCC calculation: (1) the probabilities of alternative economic outcomes of climate change, especially extreme outcomes, but *not* the causes of those outcomes; and (2) the reduction in emissions required to avoid an extreme or catastrophic outcome. For example, a catastrophic 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 for this study. What matters is the likelihood of such an outcome, and the abatement needed to avert it.[6]

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 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 they will occur. But that in turn supports the approach I take here. The use of a complex model throws a curtain over our lack of knowledge, and suggests we know more than we do. The use of a survey is more 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 experts.

How do we know that a possible 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.[7] The information obtained from a survey of experts can shed light on this point. A low SCC estimate could result if experts think the discount rate should be the roughly 3% used in IAMs, or if experts think the likelihood of catastrophic damages is very low, or both. A high SCC estimate could result if experts think the discount rate should be very low (which we will see is not the case for the vast majority of those surveyed), or if they think the likelihood of catastrophic damages is substantial (which we will see is indeed the case for many of the experts surveyed).

One might argue that the approach used here involves a model, but it is one with very few moving parts. 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).[8]

[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 et al. (2013) for an illuminating explanation of the process used by the IWG to estimate the SCC.

[3] In Pindyck (2013, 2017b), 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." For a discussion of 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 climate change. Millner and McDermott (2016) and Dietz and Stern (2015) offer contrasting views of what we might learn from the damage functions that are part of most IAMs. Another approach to estimating the SCC, studied by Bansal et al. (2016), uses financial market data to determine how temperature changes affect equity prices, which are forward-looking and therefore should account for expected long-run impacts.

[4] Some IAMs purport to at least implicitly embody information about the likelihood of a very large temperature change, but there is criticism that the probabilities are poorly specified and the SCC estimates are derived using expected changes rather than the distribution of possible changes. See, e.g., Stern (2013).

[5] 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 (2017a).

[6] My objective is to estimate a *global* SCC, so the relevant climate impact is a reduction in world GDP. Kotchen (2018) shows that a set of domestic SCCs might be more appropriate as inputs to policy.

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

[8] 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, 2012) and the references therein. For empirical evidence see Dell et al. (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 (2014), Martin (2008) and Martin and Pindyck (2015).

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 GDP 50 years from now of at least 10 percent? At least 20 percent? At least 50 percent? I rely on a survey of experts 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 I compute an *average* SCC, as opposed to the more conventional *marginal* SCC obtained from simulating IAMs. An average SCC can provide 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 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 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. In this paper, the methods experts use to arrive at their opinions is not a variable of interest (although it might well be of interest for those who pursue variants of my survey approach). What matters here is that the experts are selected based on their established expertise.[9]

Experts, of course, are likely to disagree, but that is actually an advantage of this type of survey. Given the weak state of the underlying science and economics, it is important to get a better understanding of the range of opinion and the nature and extent of disagreement. 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? And what is the range of disagreement? The survey addresses these questions.

It turns out that there is considerable heterogeneity across experts, leading to a wide variation in the implied SCC numbers. This may simply reflect our very limited knowledge of the underlying science and economics. It therefore casts additional doubt on the use of an IAM — which implicitly presumes substantial knowledge of the underlying science and economics — to estimate the SCC. But the wide variation also means that there is no single SCC estimate that can be inferred from my survey results. Put simply, I cannot provide a specific SCC estimate, or even a narrow range, as a "conclusion" to this study.

So what can we conclude from this study? Several interesting things, which can be summarized as follows:

1. The quasi-official SCC estimates that have been produced and used by the U.S. government (roughly $40 per metric ton) are much lower than the values that conform with the beliefs of most experts ($80 to $300).
2. On average, the beliefs of climate scientists imply a much higher SCC (around $300 or more) than do the beliefs of economists (which imply an SCC of around $170).
3. The SCC numbers are largely driven by potential right-tail damage outcomes. Many respondents view the likelihood of an extreme outcome — in this case a climate-induced reduction of GDP 50 years from now of 20% or more — as quite high (e.g., could occur with probability 20% or greater).
4. The SCCs are smaller (around $80 to $100) 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 outcome probabilities. But even this trimmed sample yields an SCC well above the numbers that have come from recent IAM-based analyses.

The estimation framework and survey approach developed in this paper has been described in an earlier paper (Pindyck, 2017a). Thus the discussion here will focus on the key equations and on the intuition behind the estimation framework, with some of the details relegated to the Appendix. The earlier paper also presented results of a small pilot survey given to 20 environmental economists, 11 of whom completed the survey questions, but using different probability distributions for climate outcomes than in this paper. The results of that pilot survey implied an SCC estimate of $101 per metric ton, which is well above the numbers commonly used in analyses of climate policy. As we will see, the results presented here imply an even higher number for the SCC.

This paper differs from and adds to Pindyck (2017a) in other ways as well, largely because here I have survey results for several hundred heterogeneous respondents. This allows me test alternative probability distributions for climate change outcomes

[9] I am certainly not the first to utilize a survey 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 et al. (2016). For related survey work addressing the long-run discount rate, see Drupp et al. (2015), Weitzman (2001), and Freeman and Groom (2015).

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	0.25	0.50	0.10	0.06	0.05	0.04
$1 - F(\phi)$	1	0.75	0.25	0.15	0.09	0.04

(the fit of the Pareto distribution, for example, is strongly rejected). It allows me to evaluate the extent to which the SCC is driven by the possibility of an extreme outcome. And it allows me to compare the beliefs of different groups of experts — e.g., climate scientists versus economists, Europeans versus North Americans, and perhaps most importantly, respondents who have a high degree of confidence in their views versus those who do not.

The next section presents the methodology used to estimate the SCC. I begin with an example of a set of climate outcomes and their probabilities, and show how those numbers can be translated into an outcome probability distribution. I then explain the calculation of an average SCC. In Sections 3 and 4, I discuss details of the SCC calculations, the selection of experts, and the questionnaire used to elicit their opinions. The survey results are presented in Section 5. I estimate the SCC for each individual respondent, for the full set of respondents, and for subsets based expertise (economics vs. climate science) and geographical location. 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 when derived from a trimmed sample that excludes outliers and includes only respondents who expressed high confidence in their answers. I also discuss some of the problems with my survey, and how they might bias the results. Section 6 concludes with a discussion of how this analysis might be modified, and suggestions for further work.

2. Methodology

I begin with a distribution for *outcomes*: the climate-induced percentage reduction in GDP 50 years from now. Suppose the possible reductions are $z = 0$, 0.02, 0.05, 0.10, 0.20, or 0.50, with probabilities in Table 1, and F the corresponding cumulative distribution. Let Y_0 denote GDP with no climate impact, and define $\phi = -\ln(1 - z)$, so an outcome z implies GDP will be $e^{-\phi}Y_0$. I will fit probability distributions for ϕ to expert opinions of the sort in Table 1.[10]

Table 1 applies to a specific horizon $T = 50$ years, but the impact of climate change is likely to begin earlier and continue to increase after T. To account for this, I assume that the percentage reduction in GDP, z_t, varies over time as follows:

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

Thus z_t starts at 0 and approaches a maximum z_m at a rate given by β. To find β, I use average values for z_t at two points in time, $T_1 = 50$ years and $T_2 = 150$ years, denoted by $\bar{z}_1$ and $\bar{z}_2$. From Table 1, $\bar{z}_1 = \mathbb{E}(z_1) = .05$ and suppose $\bar{z}_2 = .10$. Then from eqn. (1):

$$[1 - e^{-\beta T_2}]/[1 - e^{-\beta T_1}] = \bar{z}_2/\bar{z}_1 = 2.06 \tag{2}$$

The solution to eqn. (2) is roughly $\beta = 0.01$. 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. From eqn. (1):

$$\tilde{z}_m = \tilde{z}_1/[1 - e^{-\beta T_1}] \tag{3}$$

Eqn. (2) will not have a positive solution for β if $\bar{z}_2/\bar{z}_1$ is too large. If $T_1 = 50$ and $T_2 = 150$, $\bar{z}_2/\bar{z}_1 = 2.06$ implies $\beta \approx 0.01$, but if $\bar{z}_2/\bar{z}_1$ were 3 or more, the solution for β is negative. If expert opinion yields a ratio $\bar{z}_2/\bar{z}_1$ that makes β negative, I set $\beta = 0.002$, so $\tilde{z}_m \approx 10 \times \tilde{z}_1$.

I assume that absent climate change, real GDP grows at rate g. The benefits of abatement are the avoided reductions in GDP, which begins at Y_0 and evolves as $(1 - z_t)Y_0e^{gt} = Y_0e^{gt-\phi_t}$. At time t, the climate-induced loss of GDP is $z_tY_0e^{gt} = (1 - e^{-\phi_t})Y_0e^{gt}$. Thus the distribution for z_1 (which follows from the distribution for ϕ_1) yields the distribution for climate damages in each period. Given some abatement program, benefits are the present value of expected avoided reductions in GDP, using a discount rate R.

2.1. Estimating the average SCC

We begin with a scenario for the objective of GHG abatement: the truncation of the tail of the outcome distribution. (Eliminating *any* impact of climate change is probably impossible, and thus uninteresting.) Let B_0 denote the present value of the

[10] While z is constrained to $0 \le z \le 1$, ϕ is unconstrained at the upper end (e.g., $\phi = 4.6$ corresponds to $z = 0.99$). Thus I can compare the fits and implied SCC estimates of fat-tailed (e.g., Frechet) and thin-tailed (e.g., Gamma) distributions to the outcome probabilities from experts. This is useful because some (e.g., Weitzman (2009, 2011)) have argued that the distribution is fat-tailed and this implies a high SCC.

resulting expected avoided reductions in GDP. The "cost" of this scenario is the total amount of required emission reductions over some horizon, denoted by ΔE (measured in tons of CO_2). Given B_0 and ΔE, the SCC is $B_0/\Delta E$. As discussed below, this an *average* measure of the SCC.

The usual way to estimate a marginal SCC is to begin with a "base case" time path of emissions and then increase *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, is discounted back to compute the SCC. The average SCC, on the other hand, is the present value of the flow of benefits from a large reduction in emissions now and throughout the future, divided by the total amount of the reduction. This average number has several advantages.

First, the marginal SCC 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 change over time, but it is hard to envision a time-varying climate policy.[11] The average SCC provides a guideline over an extended period of time, which is useful given the difficulty of agreeing on a policy.

In addition, the average SCC is much less sensitive to the choice of discount rate R. 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. 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. Increasing R reduces both B_0 and ΔE.

Finally, the marginal calculation requires the use of an IAM or related model. It does not lend itself to the use of a survey, 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 model, the calculated SCC will be sensitive to the base-case time path for CO_2 emissions chosen for the simulations.

2.2. Benefits from abatement and required emission reductions

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. (1) and (3) are then used to calculate the benefit from truncating the distribution. For simplicity, I express damages below in terms of z rather than $\phi = -\ln(1 - z)$. Letting $\mathbb{E}_0(z_1)$ denote the expectation of z_1 over the full distribution of possible impacts, and $\mathbb{E}_1(z_1)$ denote the expectation over the truncated distribution, the resulting benefit is:[12]

$$B_0 = \int_0^\infty [\mathbb{E}_0(z_t) - \mathbb{E}_1(z_t)] Y_0 e^{(g-R)t} dt = \frac{\beta Y_0[\mathbb{E}_0(z_1) - \mathbb{E}_1(z_1)]}{(R-g)(R+\beta-g)(1-e^{-\beta T_1})} . \tag{4}$$

Note that the truncated distribution for z_1 (the impact at T_1) gives us the distribution for z_t at every time t; these distributions are linked through eqn. (3). In eqn. (4), $\beta Y_0[\mathbb{E}_0(z_1) - \mathbb{E}_1(z_1)]/(1-e^{-\beta T_1})$ 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.[13]

Next, we want the emission reductions needed to truncate the distribution. Suppose (i) emissions this year are E_0 and under BAU are expected to grow at rate m_0; and (ii) to eliminate the worst outcomes the emissions growth rate must be reduced to $m_1 < m_0$. We want the sum of future emission reductions, ΔE. To calculate ΔE, I will assume that the real cost per ton abated is constant over time. That cost will be affected by two factors that work in opposite directions. Technological progress will reduce the cost over time. On the other hand, abatement becomes increasingly difficult (and costly) as emissions are reduced. It is unclear which effect will dominate, so I assume 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:

$$\Delta E = E_0 \int_0^\infty \left[e^{(m_0-R)t} - e^{(m_1-R)t}\right] dt = \frac{(m_0-m_1)E_0}{(R-m_0)(R-m_1)} \tag{5}$$

[11] The marginal SCC will rise over time, like the competitive (and socially optimal) price of a depletable resource. Think of the unpolluted atmosphere as a resource that gets depleted as the GHG concentration rises, with no damages 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 rise over time. This latter case is analogous to the price evolution of a depletable resource when the cost of extraction (or cost of discovering new reserves) rises as depletion ensues, as in models such as Pindyck (1978) and Swierzbinski and Mendelsohn (1989). This point is developed in some detail in Becker et al. (2011). An advantage of calculating a *marginal* SCC is that we do not need to know how much 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.

[12] The benefit from eliminating *any* climate change impact (an unlikely scenario) is $B_0 = \int_0^\infty \mathbb{E}_0(z_t) Y_0 e^{(g-R)t} dt = \beta Y_0 \mathbb{E}_0(z_1)/[(R-g)(R+\beta-g)(1-e^{-\beta T_1})]$.

[13] For example, in Table 1, $\mathbb{E}_0(z_1) = .05$. Suppose by reducing emissions we can eliminate outcomes of $z \geq 0.20$. Increasing the other probabilities so they sum to 1, $\mathbb{E}_1(z_1) = .023$. Setting $\beta = 0.01$, $g = 0.02$ and $R = 0.04$, $B_0 = 0.00071Y_0/0.0006 = 1.18Y_0$. In the *first year*, the benefit is only 0.035% of GDP, but the annual benefit rises over time (as z_t rises), so B_0, the present value of the flow of benefits, exceeds current GDP.

In eqn. (5), 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.[14]

The average social cost of carbon is the ratio $B_0/\Delta E$. Using eqns. (4) and (5):

$$S = \frac{\beta Y_0[\mathbb{E}_0(z_1) - \mathbb{E}_1(z_1)]/(1 - e^{-\beta T_1})}{(m_0 - m_1)E_0} \times \frac{(R - m_0)(R - m_1)}{(R - g)(R + \beta - g)} \tag{6}$$

The first fraction on the RHS of eqn. (6) 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.[15]

To illustrate the methodology, Appendix A presents numerical examples using the probabilities in Table 1. They show how an average SCC is less sensitive to the discount rate than a marginal SCC, and the importance of a catastrophic outcome for the SCC.

3. A survey approach to estimating the SCC

I estimate an average SCC based on a 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 of 20% or more. The required inputs are obtained from a survey of economists and climate scientists with established expertise in climate change impacts and policy.

Ideally, these inputs would come from a process of expert elicitation along the lines discussed by Morgan (2014), which is usually interactive, possibly involving multiple interviews with individual experts. The interviews can help ensure that the expert fully understands the nature and meaning of the questions (e.g., does a non-economist understand the meaning and measurement of GDP), and possibly to pose further questions based on the expert's responses. In this way, the meaning of qualitative words (e.g., "likely," "unlikely," and "most likely") can be clarified, and biases that arise when an expert is given an estimation task (e.g., "what is the probability of X happening") can be revealed and perhaps dealt with.

These biases can be particularly relevant for this study, in which experts are asked to estimate probabilities (of alternative climate impacts), growth rates of CO_2 emissions (under BAU and a rate that would eliminate the risk of a very large GDP impact), and a discount rate. For example, Manski and Molinari (2010) and Giustinelli et al. (2018) show that survey respondents tend to round off their answers to questions about probabilities (so that an estimated probability of 12% might be reported as 10%), and Hurd (2009) shows that in household surveys, respondents report subjective probabilities of stock market gains that are systematically lower than historical averages.

More generally, Morgan (2014) discusses a variety of pitfalls that can arise in expert elicitations, and how those pitfalls can (sometimes) be surmounted. The survey I conducted is not an expert elicitation of the sort Morgan advocates. It might best be thought of as a tailored survey approach to expert elicitation, with a specially targeted population (described in detail below). Interviews and follow-up questions were not feasible, in part due to resource limitations and in part due to a strict confidentiality requirement. (I could not collect or retain any identifying information about respondents.) Thus it is subject to misunderstandings about the meaning of questions, and to some of the biases that can arise when experts are given an estimation task. I have tried to design the survey questions to minimize these misunderstandings and biases, but they have certainly not been eliminated (and are discussed in detail in Section 5.4). Nonetheless, we will see that despite these limitations, the survey results provide useful information regarding what we know and don't know about the SCC and its components.

The inputs from the survey are used to calculate the benefit (B_0) from truncating the impact distribution and the necessary reduction in emissions growth. Calculating the benefit in turn requires a distribution for the climate impact 50 years from now, and an expected impact at a longer horizon (the year 2150), $\bar{z}_2$, from which the parameter β is found using eqn. (2). Calculating the total emissions reduction (ΔE) requires the BAU emissions growth rate m_0 and reduced growth rate m_1. 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 reduction in GDP 50 years from now, will be 2% (5%, 10%, 20%, and 50%) or more (and I impose a probability of 1 that the impact will be 0 or more). As explained below, I fit different probability distributions to these six probabilities for each expert, and then to sets of probabilities across groups of experts.

[14] For example, if the objective is to reduce the emissions growth rate from $m_0 = 0.02$ to $m_1 = -0.02$, and if $R = 0.04$, $\Delta E = 0.04E_0/0.0012 = 33.3E_0$, 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.

[15] How would relaxing the assumption that the real cost of abatement is constant affect ΔE and the SCC? Suppose we expect abatement costs to *rise* in real terms. That would change the optimal trajectory for abatement so that there is more now and less in the future. This would reduce both m_0 and m_1 (assuming they are chosen optimally), which is equivalent to increasing the discount rate used in eqn. (5) to calculate ΔE (but not the discount rate used to calculate B_0). This would reduce ΔE and thereby increase the SCC. The opposite would occur if we expect abatement costs to fall.

3.1. Individual versus group estimates of the SCC

The survey yields sets of outcome probabilities and emission growth rates from several hundred experts. I use these numbers to estimate the SCC in two ways. First, I estimate SCCs for every respondent individually, which I use to explore heterogeneity across experts. To do this, I fit an outcome distribution to each expert's set of outcome probabilities, which I combine with the expert's responses for m_0, m_1 and R. Second, I calculate 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. In this case, 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.

I examine differences among six subsets of respondents: (1) primary expertise in economics; (2) 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 who state a high level of confidence in their reported outcome probabilities.

Individual Estimates. To estimate an SCC for each respondent, I fit two-parameter probability distributions to the six "observations" for the respondent's set of impact probabilities (the five stated ones and the imposed probability of 1 that the impact is non-negative). Each distribution, along with other inputs, yields an SCC for the respondent. The other inputs are the respondent's beliefs about the most likely impacts in 2066 and 2150, which are used to calculate β, the BAU emissions growth rate (m_0), the emissions growth rate needed to avoid a GDP reduction in 2066 of 20% or more (m_1), and a discount rate (R).

Each fitted probability distribution is used to calculate the benefit component (B_0) of the SCC from eqn. (4). The emission reduction component (ΔE) comes from the respondent's estimates of m_0, m_1, and R, using eqn. (5). The individual's SCC is $B_0/\Delta E$. I examine the characteristics of these individual SCCs for each impact distribution, and the entire set of SCCs based on the distribution that best fits the respondent's reported probabilities.

Group Estimates. To estimate the SCC for the full set of respondents (and several subsets), I fit the same probability distributions to the full set (or subset) of respondents' outcome probabilities. For the most likely impacts in 2066 and in 2150 (used to calculate β), m_0, m_1, and R, I use average values over the set or subset of respondents. Using 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, and using the average values of m_0 and m_1, I calculate the emission reduction component (ΔE). I then explore how the resulting SCCs differ across the distributions, and across the different subsets of respondents.

3.2. Outcome distributions

I fit both thin- and fat-tailed two-parameter distributions for $\phi = -\ln(1-z)$ to respondents' outcome probabilities. The following right-skewed distributions hold for $\phi \geq 0$:[16]

$$\textit{Gamma}: \quad f(\phi;\lambda,r) = \frac{\lambda^r}{\Gamma(r)}\phi^{r-1}e^{-\lambda\phi} , \tag{7}$$

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

$$\textit{Lognormal}: \quad f(\phi;\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma\phi}\exp\left[\frac{-(\ln\phi-\mu)^2}{2\sigma^2}\right] . \tag{8}$$

This approaches zero exponentially, and is thus intermediate between fat- and thin-tailed.

$$\textit{Frechet(GEV, TypeII)}: \quad f(\phi;k,\sigma) = \frac{1}{\sigma}(k\phi/\sigma)^{-1-1/k}\exp\left[-(k\phi/\sigma)^{-1/k}\right] \tag{9}$$

with $k > 0$. This distribution is fat-tailed (approaches zero more slowly than exponentially) and k determines the "fatness" of the tail; if $0 < k < 1/n$, the first n moments exist.

$$\textit{GeneralizedPareto}: \quad f(\phi;k,\alpha) = k\alpha(\phi+k^{1/\alpha})^{-\alpha-1} \tag{10}$$

This is also fat-tailed; if $\alpha > n$, the first n moments exist.

I compute expectations by integrating to a maximum value $\phi_{\max} = 4.6$, which corresponds to $z_{\max} = 0.99$. Thus $\mathbb{E}_0(z_1) = 1 - \mathbb{E}_0(e^{-\phi_1})$ in eqn. (4) is calculated as

$$\mathbb{E}_0(z_1) = 1 - \int_0^{\phi_{\max}} e^{-\phi}f(\phi)d\phi \tag{11}$$

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 ϕ_c, is calculated as

$$\mathbb{E}_1(z_1) = 1 - \frac{1}{F(\phi_c)}\int_0^{\phi_c} e^{-\phi}f(\phi)d\phi , \tag{12}$$

[16] 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.

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

I estimate the two 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. In both cases, the parameters are estimated using nonlinear least squares.

Barring some theoretical argument for ranking the distributions, I compare how they fit the "data" using a simple R^2. For the individual responses, with only 4 degrees of freedom, almost all the R^2s are above 0.90. But the individual responses vary considerably, so fitting the distributions to sets of respondents' probabilities yields much lower R^2s. For the gamma, lognormal and Frechet distributions the differences are small. The generalized Pareto distribution, however, fits poorly, so I dropped it from the results presented below.[17]

4. The survey

In summary, the inputs to the average SCC are: (i) the expected growth rate of emissions under BAU, m_0; (ii) probabilities of alternative reductions in future GDP under BAU; (iii) the reduced growth rate of emissions, $m_1 < m_0$, needed to avoid a drop in GDP of 20% or more[18]; (iv) the most likely climate impacts under BAU in 2066 (50 years from the time of the survey) and 2150, to find β from eqn. (2); and (v) the discount rate, R. I obtain these inputs from a survey of economists and climate scientists. This section explains how experts are identified, presents the survey instrument, and explains how responses are processed.

4.1. Identification of experts

I want opinions of people with research experience and expertise in climate change and its impact. This includes climate scientists as well as economists and other social scientists who have worked on climate change and climate policy. What matters is established expertise, and a selection that is done as objectively as possible.

There are alternative ways to establish "expertise." One possibility is government experience working on the design or evaluation of climate policies, or involvement in recent international climate policy negotiations. While this kind of practical experience is valuable, it need not correlate with the scientific expertise needed to address the questions raised above. Instead, I evaluate expertise based on research that has had an impact on our understanding of climate change and climate policy, which I measure in terms of highly cited publications and reports related to climate change and its impact.

To identify experts, I used 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 searches publication titles, abstracts, and keywords for particular climate change-related search terms. The search, conducted in November 2015, returned about 50,000 publications. A list of the search terms used is shown in Table 2; 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 yielded publications on climate change by climate scientists and economists. However, it also yielded publications by medical researchers, architects and planners, and others, which 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 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 effects of different citation practices by different research areas, and the higher numbers of citations expected for earlier publication years.) Table 3 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.

The lists of authors were then 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. Email addresses were found for most of these authors; the number of authors with known email addresses is shown in column E.

Eliminating duplicates across fields left a total of 6833 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, shown below. Those who

[17] Fitting the distributions to the entire set of respondents, but dropping responses outside the 5th and 95th percentiles, the R^2s are in the range of 0.369–0.384 for gamma, lognormal and Frechet, but only 0.190 for the Pareto. (The Pareto is potentially fat-tailed, but the estimated value of α was 38, making the fitted distribution very thin-tailed.) For results that include the Pareto, see Pindyck (2016).

[18] I could have defined an extreme outcome differently, e.g., a drop in GDP of 10% or more, or 50% more. Initial tests showed some respondents felt 10% was too likely and impossible to avoid, and some felt 50% was too speculative or otherwise difficult to relate to emission reductions.

Table 2
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.

Table 3
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).

did not respond received a follow-up "reminder" a month later. Respondents were told that their identities will be confidential, and only overall results will be published. (Names and affiliations are confidential, but I used each respondent's GPS location to determine the region of residence.) Of those contacted, about 1000 responded, for a response rate of about 14.6%. However, as discussed below, only about 9% of those contacted provided usable responses.

4.2. The questionnaire

Respondents were given information about the meaning of emission growth rates, GDP, and outcome probabilities. Then they were asked to answer the questions below, skipping those they could not or preferred not to answer. They were also asked (not shown below) to report the confidence they had in their answers (on a scale of 1–5, 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 min 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**: Under BAU, what is the *most likely* climate-caused reduction in world GDP we will witness in 50 years? In other words, how much lower (in percentage terms) will GDP be in 2066 compared to what it would be with *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:

4.3. Survey responses

About 1000 people responded, but some did not answer all of the questions, and/or gave answers that were nonsensical and therefore discarded. Some 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 Appendix B.) Of the roughly 600 remaining respondents, 183 stated that their expertise was primarily in economics, 329 in climate science, and 80 in both. I then 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 5–95% range, are qualitatively the same as the results reported in the next section.)

There was considerable variation in the answers, which might be partly explained by characteristics of the respondents, so I compare SCC estimates across the following groups:

Economists vs. Climate Scientists. Question 7 asks whether respondent's expertise is primarily in economics or climate science. 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 SCC numbers based on (1) the full set of respondents; (2) the different groups discussed above; and (3) the probability distributions for potential impacts. Although the variability across experts is considerable, the results support the view that the SCC is much larger than the recent $40 or so estimates from the U.S. Government's Interagency Working Group.

5. Results

Respondents largely agreed about the growth rate of emissions under BAU (m_0) and the growth rate needed to avert a GDP impact of 20% or greater; reported values of m_1 were generally in the range of −0.01 to −0.03, and most were close to −0.02. But opinions regarding the probabilities of alternative outcomes, and the most likely impact in 2150, varied widely. Reported discount rates also varied, but even using an exogenously imposed discount rate of 0.03, 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.

5.1. Individual SCC estimates

I used the most likely impacts in 2066 and 2150 reported by each respondent to obtain a value for β, and fit probability distributions to the respondent's reported impact probabilities. Together with the respondent's reported value of m_1, I calculated SCC values 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 (0.023) and a discount rate of 0.03. Reported discount rates varied widely across respondents (especially those with primary expertise outside of economics), and the 0.03 rate is close to the average for all respondents (0.029) and equal to the rate used by the U.S. Interagency Working Group in their IAM-based estimate of the SCC.[19]

Table 4 shows the average SCC estimates for the individuals in each of several groups, and for each of three 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 $\overline{m}_1$ 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.[20] 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 0.9404 to 0.9603.)

As Table 4 shows, the fat-tailed Frechet distribution yields higher SCCs than the thin-tailed Gamma, but the difference is small compared to the variation of the mean SCCs across groups. Economists have the lowest mean SCC, and correspondingly the lowest mean value for the most likely impact in 2066 under BAU (z_1). But even for economists, the mean SCC is large ($153 to $203, depending on the distribution). The mean SCCs are much higher for climate scientists (from $291 to $326). Also, except for 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 Fig. 1, which shows the distribution of SCCs across respondents in each of four groups: economists, climate scientists, respon-

[19] 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.

[20] 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.

Table 4
Average SCC estimates from individual responses.

Group	N	z_1	z_2	$\overline{m}_1$	SCC: Gamma	SCC: Lognormal	SCC: Frechet	SCC: Highest R^2
All	386	0.108	0.284	−0.0168	272.3	295.5	303.3	291.0
Economics	113	0.086	0.290	−0.0185	153.1	178.5	202.7	173.7
Climate Science	220	0.121	0.315	−0.0174	290.8	312.2	326.0	316.3
North America	170	0.115	0.298	−0.0197	272.5	277.8	298.2	284.5
Europe	158	0.115	0.310	−0.0174	262.7	279.3	301.0	284.2
Developing	30	0.117	0.247	−0.0140	344.3	371.7	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 $\overline{m}_1$ 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 0.023 and discount rate $R = 0.03$, 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.

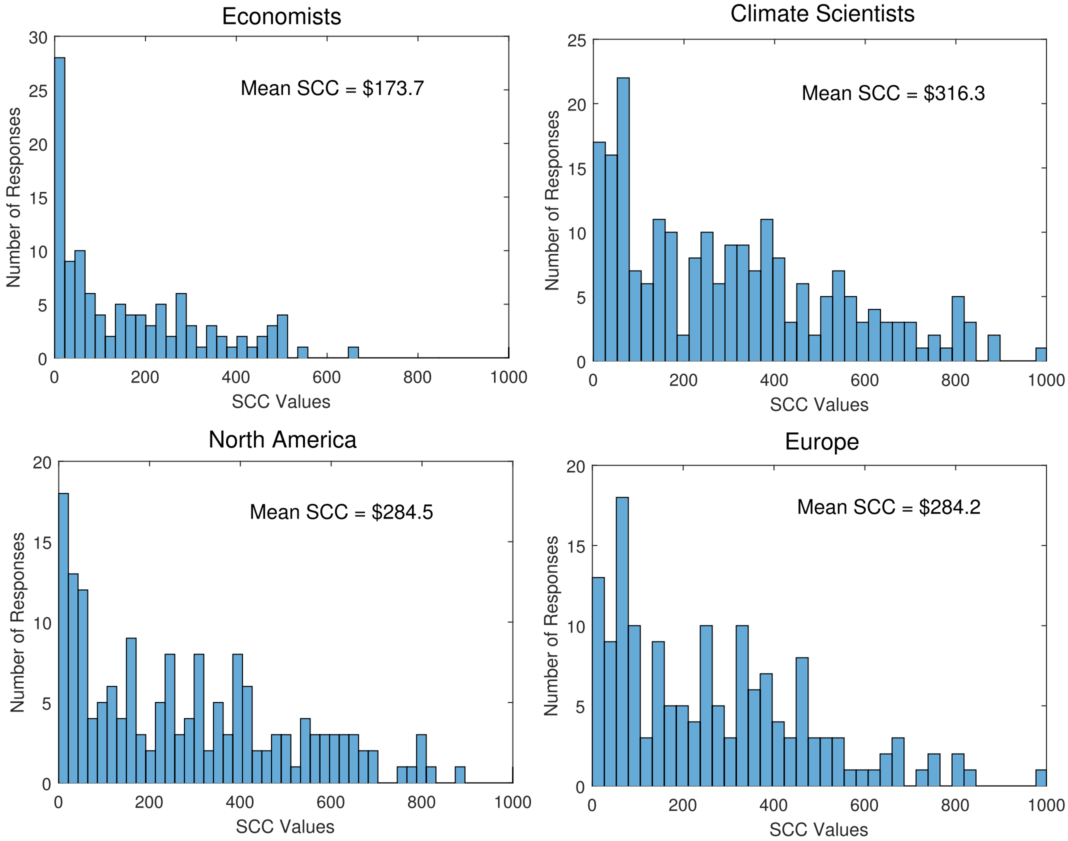

Fig. 1. SCCs from individual responses, by group, using distribution with highest R^2.

dents 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.[21] 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, Fig. 2 shows SCCs for all respondents, where each SCC uses the best-fit (highest R^2) probability distribution for that respondent. (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 the mean is $291. This dispersion is not due to different opinions about the discount rate (held fixed at 0.03), but rather very different opinions about the impact probabilities. For example, reported values of the most likely impact under BAU in 2066 ranged from 0.02 to 0.30 (with corresponding variation in reported impact probabilities). Put simply, there is considerable variation in respondents' views

[21] Figs. 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.

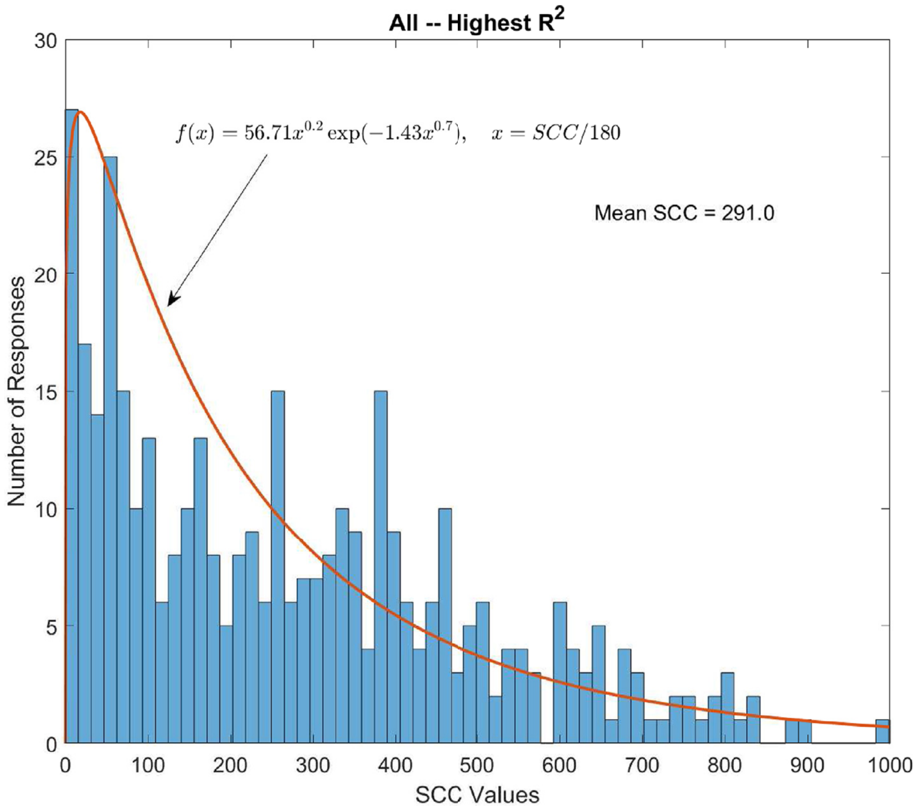

Fig. 2. SCCs for all individual responses, using distribution with highest R^2.

about the likelihood of alternative climate outcomes.

Another way to view the variation in the SCCs is by fitting a general probability distribution to the values in Fig. 2.[22] I used a three-parameter generalized gamma distribution:

$$g(x) = \frac{c/a^b}{\Gamma(b/c)} x^{a-1} \exp(-(x/a)^c)\,; \quad x \geq 0 \tag{13}$$

If $b = c$ this becomes a Weibull distribution; alternatively if $c = 1$ it is a regular gamma distribution, and if $a = c = 1$ it is an exponential distribution. The least squares estimates of these parameters are $\hat{a} = 0.6$, $\hat{b} = 1.2$, and $\hat{c} = 0.7$. Superimposed on the histogram in Fig. 2 is the scaled fitted distribution $f(x) = 40g(x)$, with $x = \text{SCC}/180$. The fitted distribution is close to the displaced gamma distribution which, as I showed in Pindyck (2012), provides a good fit to the distribution of climate sensitivity estimates provided by experts and research groups, as summarized by the Intergovernmental Panel on Climate Change (2007). Of course climate sensitivity (the equilibrium temperature increase resulting from a doubling of the atmospheric CO_2 concentration) is only one factor that goes into the SCC, but it is a key source of uncertainty, and the nature of that uncertainty has been extensively studied and documented.

5.2. Group estimates of the SCC

For the group-wise estimates, I used nonlinear least squares to fit each two-parameter probability distribution to the reported impact probabilities of all members of the group. (To do this, I dropped responses outside the 5th or 95th percentiles.) The results, summarized in Table 5, show SCC estimates for all respondents, those 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 three distributions to which the reported probabilities were fit. 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 obtain a value of β, using eqn. (2). I also used average values, shown in Table 5, of the BAU emission growth rate ($\overline{m}_0$), the growth rate needed to truncate the distribution ($\overline{m}_1$), and discount rate $\overline{R}$.

[22] My thanks to an anonymous referee for this suggestion.

Table 5
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
$\bar{z}_1$	0.1203	0.1309	0.1003	0.1182	0.1204	0.1229	0.1061
$\bar{z}_2$	0.2923	0.3062	0.2648	0.2977	0.2904	0.3024	0.2368
β	0.0024	0.0034	0.0022	0.0020	0.0026	0.0021	0.0047
$\overline{m}_0$	0.0234	0.0246	0.0203	0.0239	0.0231	0.0214	0.0242
$\overline{m}_1$	−0.0178	−0.0200	−0.0172	−0.0175	−0.0179	−0.0183	−0.0123
$\overline{R}$	0.0293	0.0261	0.0273	0.0313	0.0294	0.0260	0.0414
Gamma:							
SCC	208.5	107.6	148.6	199.9	207.3	341.4	107.3
R^2	0.3692	0.1954	0.4201	0.2319	0.1013	0.2270	0.2769
Lognormal:							
SCC	278.1	135.2	261.8	260.2	271.7	456.7	163.1
R^2	0.3843	0.2079	0.4315	0.2463	0.1123	0.2385	0.2964
Frechet:							
SCC	295.0	137.9	348.1	270.2	278.4	481.9	181.7
R^2	0.3765	0.1986	0.4271	0.2390	0.1053	0.2286	0.2962

Note: 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, $\overline{m}_0$ the average BAU emission growth rate, $\overline{m}_1$ the average emission growth rate needed to truncate the distribution, and $\overline{R}$ is the average discount rate. SCCs are calculated by fitting a distribution to the stated outcome probabilities for the entire group.

Table 6
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	0.3692	0.139	0.069	$\hat{r} = .6799$, $\hat{\lambda} = 4.078$
Lognormal:	278.1	0.3843	0.159	0.066	$\hat{\mu} = -2.446$, $\hat{\sigma} = 1.476$
Frechet:	295.0	0.3765	0.160	0.061	$\hat{k} = 1.2746$, $\hat{\sigma} = .0633$

Note: SCCs are calculated by fitting a distribution to the stated outcome probabilities for the entire group, after dropping responses outside the 5th and 95th percentiles. Values for $\overline{m}_0, \overline{m}_1$, etc. are shown in the second column of Table 5. The PDFs for the three distributions are given by eqns. (7)–(9). For each fitted distribution, $\mathbb{E}_0(z)$ is the expected value of the 2066 impact z under BAU, given by eqn. (11), and $\mathbb{E}_1(z)$ is the expected value of z under the truncated distribution, given by eqn. (12). The fitted CDFs are shown in Fig. 3.

Two results stand out. First, the SCCs for respondents with a high level of confidence in their reported impact probabilities are much lower (about half as large) than the SCCs for "All" respondents and for other groups. The reason is that 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" respondents usually reported lower probabilities of extreme outcomes. (Also, their average values of z_1 and z_2 yield a somewhat larger value of β, which, as can be seen from eqn. (3), implies a lower long-run maximum impact.)

Second, recall that for the individual SCC estimates, economists had the lowest average SCC compared to other groups (and 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. 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.

Table 6 summarizes the results for "All." Differences in the fitted distributions can also be seen in the cumulative distribution functions shown for All Respondents in Fig. 3.

In Fig. 3, a horizontal dashed line indicates where the cumulative distribution reaches the point where $\phi = 0.223$ (which corresponds to $z = 0.20$). For all three distributions, this occurs where the cumulative probability is roughly 0.74. This implies that the estimated probability of an outcome in which GDP is reduced by 20% or more is about 0.26. This is a large number, and explains why the SCCs are on the order of \$200 or more.

In Appendix A, 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 Fig. 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 were enough respondents who attached a high probability (above 0.30) to a GDP impact of 20% or greater to drive the SCC up. Weighing all of these reported probabilities equally, the tails of the fitted distributions are sufficiently thick to yield a high SCC. But perhaps the reported probabilities should not all be weighted equally. I address that question below.

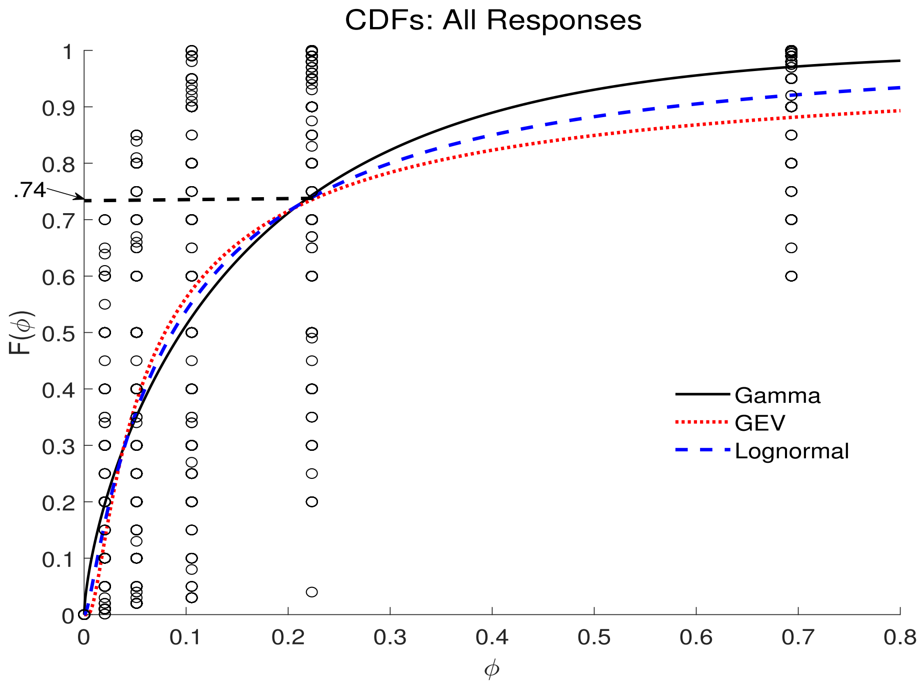

Fig. 3. Fitted CDFs for all respondents.

5.3. *What is the SCC?*

The full sample of respondents yielded mean SCC estimates above $200 per metric ton. This was true for individually estimated SCCs and for the group-wise estimates. As shown in Table 4 and Fig. 1, although the individually-estimated SCCs for economists were lower (on average $174 using the distribution for each respondent with the highest R^2), SCCs for other groups were close to $300. Similar results came from the group-wise estimates; the numbers in Tables 5 and 6 are also consistent with an SCC above $200. However, as Fig. 3 illustrates, there is considerable 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 a broad set of people with research experience in climate change and its impact. The resulting set of respondents 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. But on the minus side, some of these experts have indicated that they are very unsure about the probabilities of alternative climate impacts.

This suggests trimming the sample of responses and focusing on experts who expressed a high degree of confidence (3 or higher on a scale of 1–5) in their views about the impact probabilities. The second column of Table 5 does just that, and the SCCs are indeed much lower — in the range of $108 to $138. Another way to trim the sample is to exclude "outliers." I already 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 or 95th percentiles. Now I tried dropping responses where these values fell outside the 10th or 90th percentiles.

The results are shown in Table 7. To make a comparison easier, the first two columns of numbers replicate the first two columns of Table 5, 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. This further trimming leads to a substantial drop in the SCCs. Taking all respondents regardless of their degree of confidence, the range of SCCs drops from $209 – $295 to $147 – $243. The last column 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 for use in policy applications closer to $80 or $200? The answer depends in part on how we evaluate "expertise," and respondents' ability to assess probabilities of climate outcomes. If one gives more weight to the views of economists (who perhaps better understand GDP impacts), give more weight to respondents who express greater 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"

Table 7
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
$\bar{z}_1$	0.1203	0.1309	0.1072	0.1300
$\bar{z}_2$	0.2923	0.3062	0.2689	0.2866
β	0.0024	0.0034	0.0020	0.0050
$\overline{m}_0$	0.0234	0.0246	0.0238	0.0248
$\overline{m}_1$	−0.0178	−0.0200	−0.0167	−0.0201
$\overline{R}$	0.0293	0.0261	0.0291	0.0258
Gamma:				
SCC	208.5	107.6	146.9	66.5
R^2	0.3692	0.1954	0.4787	0.3069
Lognormal:				
SCC	278.1	135.2	217.2	83.6
R^2	0.3843	0.2079	0.4952	0.3206
Frechet:				
SCC	295.0	137.9	243.4	86.1
R^2	0.3765	0.1986	0.4909	0.3107

and treats all respondents equally, the right number is closer to \$200.[23] Either way, the SCC estimates from this study are well in excess of the roughly \$40 numbers from recent IAM-based analyses.

5.4. Some issues

When interpreting these results, keep in mind that this survey falls short of a full expert elicitation that is interactive in nature and allows for follow-up questions and responses. As explained earlier, it is subject to misunderstandings and biases on the part of respondents. Indeed, the results described above suggest the presence of some potential problems.

Wide Dispersion of Reported Probabilities. One interpretation of the wide dispersion in Figs. 2 and 3 is that it simply reflects our lack of knowledge about climate outcomes and their impact on the economy. In that case different experts could arrive at very different conclusions regarding the likelihood of alternative outcomes — even if they express a high degree of confidence in those conclusions — and it need not imply a bias in the results.[24] But the dispersion might also reflect an inherent difficulty in thinking about (and estimating) subjective probabilities.[25] Suppose, for example, that the reported probability of a 20% or greater reduction in GDP is $\widetilde{p}_{20} = p_{20} + \epsilon_{20}$, where p_{20} is the true probability and ϵ_{20} is a random variable with a skewed distribution (because $\widetilde{p}_{20} \geq 0$). This would imply an upward bias in the estimated probabilities.

Meaning and Measurement of GDP. Assessing future damages from climate change would be easier if all such damages represented reductions in GDP as typically measured. But even then, non-economists (and perhaps some economists) might not fully understand what is or is not included in GDP, and how it is measured. This might lead some to decline participating in the survey, or — more problematic — lead to probability estimates that are simply guesses. Making matters worse, some of the damages from climate change are likely to be indirect, e.g., ecosystem destruction, social unrest, and increases in morbidity and mortality, that are difficult to monetize. This has been a problem for the construction of IAMs, where the solution is typically for the modeler to include indirect damages by adding an *ad hoc* multiplier to direct damages. In principle, a survey approach could be advantageous in this regard, because it allows for many different opinions regarding the magnitude of these indirect effects, as opposed to the opinion of only one modeler. But it could also lead to an upward bias similar to that described above, in that estimated probabilities may include an error term with a skewed distribution. Furthermore, although the "Background Information" section of the Questionnaire states that these indirect effects should be included in the GDP reduction, some respondents may not have followed or even understood this direction, which could lead to a *downward* bias in their probability estimates.

The Scenario. My formulation of the SCC is based on a particular scenario which is somewhat arbitrary: reduce the growth rate of emissions enough to prevent a climate-induced reduction of world GDP of 20 percent or more. We could have instead considered a GDP reduction of 10 percent or more, or some other number. But even for this 20-percent number, some respondents might have had problems with the interpretation of the scenario. First, it is unclear that *any* emissions reduction would be sufficient to accomplish this objective, contrary to the implicit assumption in the survey question. Second, although the survey

[23] While \$200 might seem high, it is consistent with Stern (2008). The \$80 SCC is close to the \$101 result when the survey was given to 20 economists, 11 of whom responded. See Pindyck (2017a) for details.

[24] Some have argued that critical inputs to the SCC, e.g., climate sensitivity, are not just unknown but unknowable, and seeking consensus on these inputs is counterproductive. See, e.g., Allen and Frame (2007) and Oppenheimer et al. (2007).

[25] Morgan (2014) notes that experts in different fields can view probabilistic judgments in different ways, and states that "scientists and engineers …think naturally in terms of subjective probabilities, others …have been far less comfortable with such formulations." My own experience with economists is that they are equally comfortable with subjective probabilities, so this is unlikely to explain differences between the responses of economists versus climate scientists.

questions state that "By 'prevent,' we mean reduce the probability to near zero," there remains some ambiguity. Respondents might interpret "near zero" to mean a probability indistinguishable from zero, a probability of several percent, or something in between, and the interpretation could affect the estimate of the required emissions reduction. These problems need not imply a bias in the responses, but they are likely to add noise to the SCC estimates.

Low Response Rate. Only 14.6% of those contacted responded and answered the survey questions, and only about 9% provided coherent and thus usable answers. That raises the question of who responded, who did not, and why. Ideally, those who responded did so because they had more informed views about the likely impact of climate change, which would add to the credibility of the survey results. But this might not be the case. For example, it might be that those with very strong views (as opposed to more informed views) about climate change were more likely to respond, and even worse, might have responded strategically, reporting probabilities higher than what they actually believed (and thereby biasing the results upwards). If I had detailed information (e.g., citation counts, journal rankings for the citations, university affiliation, etc.) for all of the people who were contacted, it would be possible to analyze (e.g., by estimating a probit or related choice model) the extent to which various characteristics led people to respond or not respond to the request that they answer the survey questions. However, as explained earlier, the survey was conducted subject to strict confidentiality requirements, so that no information that might identify experts was requested or retained.

Survey Questions. There are other parts of the questionnaire that might have caused difficulty: (i) Climate policy is often framed in terms of reducing emissions by some percentage amount (e.g., a 25% reduction relative to the 2015 emissions level), as opposed to reducing the *growth rate* of emissions. Some respondents might have found it confusing to think about abatement in terms of growth rates. (ii) Respondents were asked about climate-induced reductions in GDP under BAU (business as usual), which is defined as "no additional steps are taken to reduce emissions." But respondents might have different views or be confused about the steps that have already been taken, i.e., policies already in place to reduce emissions. Respondents who (mistakenly) think that no steps have already been taken are likely to provide upwardly-biased estimates of future climate damages.

The Discount Rate. Respondents were asked to state what they thought was the appropriate discount rate, but the concept might be alien to some non-economists who have never thought about the present value of future costs and benefits. And even those economists who have thought a good deal about discount rates for climate policy disagree sharply about what the "correct" rate should be. The extent of the disagreement about the discount rate is evident in the survey-based studies of Drupp et al. (2015), Weitzman (2001), and Freeman and Groom (2015). Furthermore, there are significant theoretical issues regarding long-run discounting, as discussed in Gollier (2013). Because the discount rate is non-negative, an estimate that includes a random term will be upward-biased, downward-biasing the SCC.

Summary. Some of the problems discussed above (difficulty estimating probabilities; decisions to respond skewed towards people with strong views, some of whom answer strategically; and a mistaken belief that no steps have already been taken to reduce emissions) would be expected to bias the results upwards. Some (ignoring indirect, i.e., non-market damages; and noisy estimates of the discount rate) may have biased the results downwards. And some (ambiguity over "preventing" an extreme outcome; and confusion over reducing the growth rate rather than level of emissions) may have just added noise to the results. The direction and extent of any net bias is unclear. These possible sources of confusion might have been at least partly eliminated had an interactive expert elicitation been used, rather than the simple survey of experts that I conducted, and should be a focus of future work.

6. Concluding remarks

As I have stressed throughout, my survey approach to estimating an SCC has a number of shortcomings. This, together with the wide variation in experts' responses implies that I cannot offer a specific SCC estimate (or even a narrow range) as a "conclusion." On the other hand, several interesting and robust results emerge from this study.

First and perhaps most important, the SCC estimates that have been produced and used by the U.S. government (roughly $40 per metric ton) are much lower than the values that conform with the beliefs of most experts ($80 to $300). Second, on average the beliefs of climate scientists imply a much higher SCC than do the beliefs of economists. Third, the SCC estimates are largely driven by a potential extreme damage outcome (a GDP reduction of 20% or more), which many respondents view as quite likely. However, fat-tailed and thin-tailed distributions fit respondents' probability estimates equally well (see the R^2s in Tables 5–7), although a fat-tailed distribution (Frechet) yields higher SCCs. And finally, the SCC estimates are much smaller (around $80) when based on a trimmed sample that excludes outliers and is limited to respondents with a high degree of confidence in their answers regarding outcome probabilities. Whether the "correct" number is closer to $80 or to $200 depends on one's view of expertise, which I leave to the reader. But even the smaller SCC estimates are much larger than the IAM-based numbers used by the U.S. government.

My survey approach to estimating the SCC has several advantages. Its focus on more extreme outcomes addresses what matters most 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 need for one or more IAMs is another advantage. However, the survey I conducted is not a true expert elicitation, should not be viewed as a substitute for one. An expert elicitation is usually interactive and could include multiple interviews with experts to ensure that they fully understand the nature and meaning of the questions, so that biases that arise (e.g., when experts are faced with an estimation task such as assessing probabilities of alternative outcomes) can be revealed and perhaps dealt with. I have tried to design the survey questions to minimize these misunderstandings and biases, but they have not been eliminated (and are discussed in detail in Section 5.4). An expert elicitation would be highly valuable in this regard, and should be viewed as an important goal of future research.

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.) The average SCC provides a guide for policy over an extended period of time, which is useful given the difficulty of agreeing on any climate policy. Also, it is less sensitive to the choice of discount rate than the marginal SCC. On the other hand, the average SCC requires assumptions about outcome probability distributions (I tested several), the dynamic adjustment process (in this case the logistic growth function of eqn. (1)), real abatement costs (which I took as constant), and most importantly, a specific scenario (truncating the distribution to eliminate a GDP loss of 20% or more). However, these assumptions can be altered, as discussed below.

I have tried to show how a survey approach to estimating an SCC can work and the kinds of answers it can provide. There are a variety of issues that can be explored as part of further work. 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? (iii) I used $T_1 = 50$ years and $T_2 = 134$ years (2066 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 indirect effects such as ecosystem destruction, health effects, etc., as part of potential damages, perhaps by asking respondents to provide the "multiplier" that should be applied to lost GDP to account for those effects (or giving them such a multiplier)? (v) I have asked experts to provide estimates of the components of the SCC (emissions growth, GDP damage probabilities, and discount rates), but this requires a model to link these components, and one could argue that the model presented in this paper is somewhat arbitrary.

One obvious alternative to the approach I have used is to simply ask experts to provide their own estimates of the SCC, without imposing any structure on where those estimates come from. Experts might then base their estimates on some model (explicit or implicit), on the estimates of others that they have read about, or simply some opinion about climate change and its possible impact. But another alternative is to maintain the kind of structure I have used, but ask about possible climate impacts on different sectors of the economy, different regions, and/or different periods of time. In other words, one could envision survey approaches that involve more detailed — or less detailed — requests of experts.

Finally, it is important to keep in mind that my analysis pertains to world GDP, but there is likely to be considerable spatial variation in the effects of climate change (which is one reason that reaching an international agreement on climate policy is so difficult). One can imagine that policy be designed to provide a kind of global insurance in that areas with climate changes that reduce productivity are partially compensated for by areas that were previously unproductive and now become more productive.[26] This could be explored in the context of my average SCC calculation (especially given that some respondents are from developing countries). 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 to use in the next set of climate negotiations.

Appendix A. Numerical examples

These examples help illustrate the methodology, show how an average SCC is much less sensitive to the discount rate than a marginal SCC, and show the importance of a possible catastrophic outcome for the SCC. They use the outcome probabilities in Table 1, and 2013 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 even without new climate policies. Thus I will assume that under BAU emissions would grow at an annual rate of 2% (so $m_0 = 0.02$). World GDP in 2013 was about $Y_0 = \$75$ trillion. I set $g = 0.02$ as the real per capita growth rate of GDP, and use a discount rate of $R = 0.04$. The numbers in Table 1 imply that β in eqn. (1) is about 0.01.

Suppose that by reducing the growth rate of emissions from $m_0 = 0.02$ to $m_1 = -0.02$ we could avoid the two worst outcomes in Table 1, i.e., $z = 0.20$ and $z = 0.50$. Thus $\mathbb{E}_0(z_1) = .05$, and $\mathbb{E}_1(z_1) = .023$. (The latter is the expected value of z_1 for the truncated distribution.) From eqn. (4), the benefit of avoiding these outcomes is $B_0 = 42.36 \times Y_0(0.05 - 0.022) = 1.186 \times Y_0 = \$89 \times 10^{12}$. Given 2013 emissions and $m_0 = 0.02$, $m_1 = -0.02$, and $R = 0.04$, eqn. (5) gives $\Delta E = 1.10 \times 10^{12}$ metric tons. The implied SCC $= B_0/\Delta E = \$81$/mt.

Eqn. (6) expresses the SCC as the product of two fractions. The first is the ratio of the current benefit flow to the current reduction in emissions. The second fraction puts these flows in present value terms. In this example the first fraction, i.e, the current instantaneous SCC, is $0.00071Y_0/0.04E_0 = 5.33 \times 10^{10}/1.32 \times 10^9 = \$40.4$/mt. The second fraction is $0.0012/0.0006 = 2$, yielding the present value SCC of \$81/mt.

How does this result depend on the discount rate R? Table 8 shows the SCC and its components for discount rates ranging from 0.025 to 0.060. (We need $R > g$ and $R > m_0$, which means $R > 0.02$.) As one would expect, the benefit from truncating the outcome distribution, B_0, declines sharply as R is increased; this is why estimates of the marginal SCC are so sensitive to

[26] My thanks to an anonymous referee for making this point. This was explored by Nordhaus and Yang (1996), who divided the world up into rich and poor countries and used an IAM to calculate cooperative (Nash bargaining) and non-cooperative Nash equilibria for emission reductions.

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.

Table 8
Sensitivity of SCC to Discount Rate.

R	B_0	ΔE	SCC
0.025	712×10^{12}	5.87×10^{12}	\$121
0.030	267×10^{12}	2.64×10^{12}	\$101
0.040	89×10^{12}	1.10×10^{12}	\$81
0.060	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 $z \geq 0.20$, and is given by eqn. (4). ΔE is the required total reduction in emissions, given by eqn. (5), with the emission growth rate reduced from $m_0 = 0.02$ to $m_1 = -0.02$. SCC = $B_0/\Delta E$. Also, $\beta = 0.01$, $g = 0.02$, and $T_1 = 50$ years.

The calculations of B_0 in the examples above show that much of the SCC is attributable to the possibility of a catastrophic outcome. Note that the benefit of avoiding *any* climate change impact is proportional to $\mathbb{E}_0(z_1)$. The benefit from avoiding only the two worst outcomes in Table 1 is proportional to $[\mathbb{E}_0(z_1) - \mathbb{E}_1(z_1)]$. Thus the fraction of the benefit from eliminating any impact attributable to the catastrophic outcomes is $1 - \mathbb{E}_1(z_1)/\mathbb{E}_0(z_1)$. For the numbers in Table 1, this fraction is roughly 60%.

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, a reduction in the growth rate to $m_1 = -0.02$ would eliminate a catastrophic outcome. Suppose a reduction to $m_1 = -0.05$ would eliminate any outcome. With $R = 0.04$, the SCC is then \$124 metric ton. But now suppose the probability of $z_1 = 0.2$ or $z_1 = 0.5$ is zero. Scaling up the other probabilities in Table 1 so they sum to 1, the expected impact is now $\mathbb{E}_0(z_1) = .022$. With $m_1 = -0.05$, $\Delta E = 1.28 \times 10^{12}$. 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 0.09 probability of $z_1 \geq 0.20$; eliminating the possibility of these catastrophic outcomes reduces the SCC by more than half.

Appendix B. Cleaning and coding the survey data

Some survey respondents failed to answer all of the questions, and some gave ambiguous answers. When possible to meaningfully interpret ambiguous answers, they were recoded accordingly, but otherwise dropped. Details 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 most 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 values matched to more than one continent, the unrounded latitude and longitude 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.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2019.02.003.

References

Aldy, Joseph E., Krupnick, Alan J., Newell, Richard G., Parry, Ian W.H., Pizer, William A., 2010. Designing climate mitigation policy. J. Econ. Lit. 48 (4), 903–934.
Allen, Myles R., Frame, David J., 2007. Call off the quest. Science 318, 582–583.
Bansal, Ravi, Ochoa, Marcelo, 2011. Welfare Costs of Long-Run Temperature Shifts. National Bureau of Economic Research Working Paper 17574.
Bansal, Ravi, Kiku, Dana, Ochoa, Marcelo, 2016. Price of Long-Run Temperature Shifts in Capital Markets. National Bureau of Economic Research Working Paper 22529.
Barro, Robert J., 2014. Environmental protection, rare disasters, and discount rates. Economica 82 (325), 1–23.
Becker, Gary S., Murphy, Kevin M., Topel, Robert H., 2011. On the economics of climate policy. B. E. J. Econ. Anal. Policy 10, 1–25.
Burke, Marshall, Dykema, John, Lobell, David B., Miguel, Edward, Satyanath, Shanker, 2015. Incorporating climate uncertainty into estimates of climate change impacts. Rev. Econ. Stat. 97 (2), 461–471.
Dell, Melissa, Jones, Benjamin F., Olken, Benjamin A., 2012. Temperature shocks and economic growth: evidence from the last half century. Am. Econ. J. Macroecon. 4, 66–95.
Dietz, Simon, Stern, Nicholas, 2015. Endogenous growth, convexity of damage, and climate risk: how Nordhaus' framework supports deep cuts in carbon emissions. Econ. J. 125, 574–620.
Drupp, Moritz A., Freeman, Mark C., Groom, Ben, Nesje, Frikk, 2015. Discounting Disentangled: an Expert Survey on the Determinants of the Long-Term Social Discount Rate. Grantham Research Institute on Climate Change and the Environment Working Paper 172.
Freeman, Mark C., Groom, Ben, 2015. Positively gamma discounting: combining the opinions of experts on the social discount rate. Econ. J. 125, 1015–1024.
Giustinelli, Pamela, Manski, Charles F., Molinari, Francesca, 2018. Tail and Center Rounding of Probabilistic Expectations in the Health and Retirement Study. National Bureau of Economic Research Working Paper 24559.
Gollier, Christian, 2013. Pricing the Planet's Future. Princeton University Press.
Greenstone, Michael, Kopits, Elizabeth, Wolverton, Ann, 2013. Developing a social cost of carbon for use in U.S. Regulatory analysis: a methodology and interpretation. Rev. Environ. Econ. Pol. 7 (1), 23–46.
Hurd, Michael D., 2009. Subjective probabilities in household surveys. Ann. Rev. Econ. 1, 543–562.
Interagency Working Group on Social Cost of Carbon, 2010. Technical Support Document: Social Cost of Carbon for Regulatory Impact Analysis. U.S. Government.
Interagency Working Group on Social Cost of Carbon, 2013. Technical Support Document: Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis. U.S. Government.
Intergovernmental Panel on Climate Change, 2007. Climate Change 2007. Cambridge University Press.
Kotchen, Matthew J., 2018. Which social cost of carbon? A theoretical perspective. J. Assoc. Environ. Resour. Econ. 5 (3), 673–694.
Kriegler, Elmar, Hall, Jim W., Held, Hermann, Dawson, Richard, Schellnhuber, Hans Joachim, 2009. Imprecise probability assessment of tipping points in the climate system. Proc. Natl. Acad. Sci. Unit. States Am. 106 (13), 5041–5046.
Manski, Charles F., Molinari, Francesca, 2010. Rounding probabilistic expectations in surveys. J. Bus. Econ. Stat. 28 (2), 219–231.
Martin, Ian W.R., 2008. Disasters and the welfare cost of uncertainty. Am. Econ. Rev. 98 (2), 74–78.
Martin, Ian W.R., Pindyck, Robert S., 2015. Averting catastrophes: the strange economics of Scylla and Charybdis. Am. Econ. Rev. 105 (10), 2947–2985.
Metcalf, Gilbert E., Stock, James, 2017. The role of integrated assessment models in climate policy: a user's guide and assessment. Rev. Environ. Econ. Pol. 11 (1).
Millner, Antony, McDermott, Thomas K.J., 2016. Model confirmation in climate economics. Proc. Natl. Acad. Sci. Unit. States Am. 113 (31), 8675–8680.
Morgan, M. Granger, 2014. Use (and abuse) of expert elicitation in support of decision making for public policy. Proc. Natl. Acad. Sci. Unit. States Am. 111 (20), 7176–7184.
Nordhaus, William D., 1994. Expert opinion on climate change. Am. Sci. 82, 45–51.
Nordhaus, William D., Yang, Zili, 1996. A regional dynamic general-equilibrium model of alternative climate-change strategies. Am. Econ. Rev. 86 (4), 741–765.
Oppenheimer, Michael, O'Neill, Brian C., Webster, Mort, Agrawala, Shardul, 2007. The limits of consensus. Science 317 (5844), 1505–1506.
Oppenheimer, Michael, Little, Christopher M., Cooke, Roger M., 2016. Expert judgement and uncertainty quantification for climate change. Nat. Clim. Change 6, 445–451.
Pindyck, Robert S., 1978. The optimal exploration and production of nonrenewable resources. J. Polit. Econ. 86 (5), 841–861.
Pindyck, Robert S., 2011. Modeling the impact of warming in climate change economics. In: Libecap, G., Steckel, R. (Eds.), The Economics of Climate Change: Adaptations Past and Present. University of Chicago Press.
Pindyck, Robert S., 2012. Uncertain outcomes and climate change policy. J. Environ. Econ. Manag. 63, 289–303.
Pindyck, Robert S., 2013. Climate change policy: what do the models tell us? J. Econ. Lit. 51 (3), 860–872.
Pindyck, Robert S., 2016. The Social Cost of Carbon Revisited. National Bureau of Economic Research Working Paper 22807.
Pindyck, Robert S., 2017a. Taxes, targets, and the social cost of carbon. Economica 84 (335), 345–364.
Pindyck, Robert S., 2017b. The use and misuse of models for climate policy. Rev. Environ. Econ. Pol. 11 (1), 100–114.
Stern, Nicholas, 2008. The economics of climate change. Am. Econ. Rev. 98, 1–37.
Stern, Nicholas, 2013. The structure of economic modeling of the potential impacts of climate change has grafted gross underestimation onto already narrow science models. J. Econ. Lit. 51 (3), 838–859.

Swierzbinski, Joseph E., Mendelsohn, Robert, 1989. Exploration and exhaustible resources: the microfoundations of aggregate models. Int. Econ. Rev. 30 (1), 175–186.
Weitzman, Martin L., 2001. Gamma discounting. Am. Econ. Rev. 91, 260–271.
Weitzman, Martin L., 2009. On modeling and interpreting the economics of catastrophic climate change. Rev. Econ. Stat. 91, 1–19.
Weitzman, Martin L., 2011. Fat-tailed uncertainty and the economics of climate change. Rev. Environ. Econ. Pol. 5 (2), 275–292.
Zickfeld, Kirsten, Morgan, M. Granger, Frame, David J., Keith, David W., 2010. Expert judgments about transient climate response to alternative future trajectories of radiative forcing. Proc. Natl. Acad. Sci. Unit. States Am. 107 (28), 12451–12456.