The Wisdom of the Economic Crowd: Calibrating Integrated Assessment Models Using Consensus

Peter H Howard
Economics Director
Institute for Policy Integrity at New York University School of Law
HowardP@mercury.law.nyu.edu

and

Derek Sylvan
Strategy Director
Institute for Policy Integrity at New York University School of Law
sylvand@mercury.law.nyu.edu

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Abstract

The social cost of carbon (SCC) is one of the primary tools used to shape greenhouse gas (GHG) emissions reduction policies in the United States. The U.S. government's SCC estimates are derived from three integrated assessment models (IAMs), developed by four climate economists. However, some economists – most prominently Robert Pindyck (2015) – argue that IAMs are over-reliant on the opinions of their modelers and fail to capture the wider consensus of experts. Pindyck (2015) recommends abandoning IAMs altogether, and calculating a simple "average SCC" to reflect the general opinion of experts on climate change. We propose and test an alternate approach: instead of replacing IAMs, we use expert elicitation as a method for calibrating key uncertain parameters in IAMs (Nordhaus (1994), Schauer (1995) and Roughgarden and Schneider (1999) used similar efforts in the 1990s). This approach ensures that official U.S. SCC estimates reflect the wider consensus of the economic community. To test this methodology, we conduct a 15-question online survey of all those who have published an article related to climate change in a highly ranked, peer-reviewed economics or environmental economics journal since 1994. This survey included questions on the appropriate inter-generational discount rate and expected climate damages – two important, highly uncertain parameters in IAMs. We sent the survey to 1,103 experts who met our selection criteria, and received 365 completed surveys. We find strong evidence that expert consensus has shifted since the last expert elicitation studies on the economics of climate change were conducted, more than 20 years ago. In particular, the consensus discount rate has declined and expected damages have increased, such that IAMs – which have been relatively stagnant in their discount rate and damage assumptions – do not reflect the current economic consensus. Our data can help establish a baseline for IAMs, in addition to providing other useful information for policymakers. To illustrate this point, we use the results from this survey to re-calibrate an IAM (DICE-2013R) to reflect the current state of expert opinion on expected climate damages and discount rates, and re-calculate the SCC. In general, we find a significant increase in the SCC – more than 10-fold under most scenarios – supporting the hypothesis that current IAMs do not reflect the current scientific consensus.

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I. INTRODUCTION

The social cost of carbon (SCC) is one of the primary tools used to shape greenhouse gas (GHG) emissions reduction policies in the United States and other countries. The SCC – the marginal cost to the economy imposed by a unit of CO_2 emissions – is an essential number in U.S. government cost-benefit analyses of all regulations that affect GHG emissions. The SCC is estimated using Integrated Assessment Models (IAMs), which capture the various steps in the climate and economic processes that translate a marginal unit of CO_2 emissions into an economic damage. Given the significant uncertainties surrounding climate change impacts, each of these steps entails considerable parametric and structural uncertainties. As such, there is a wide range of SCC estimates in the economic literature. Several key economic relationships – most importantly the inter-generational discount rate and climate damage function(s) – are still actively debated in the literature, such that multiple divergent opinions are held within the economic community. As a consequence, IAMs and their results, including the SCC, are sensitive to many of the assumptions made by modelers with respect to these relationships.

Using the prevailing views of economists as a baseline for climate-economic models would help minimize the influence of modelers' assumptions over the SCC value. Expert elicitation could be used to capture the level of consensus (and uncertainty) within the economic community over key IAM inputs. This approach would better align IAMs with current professional opinion. However, this methodology is currently under-utilized in the climate-economic literature.

The U.S. government's SCC estimates rely primarily on the assumptions of a handful of climate economists. In 2007, the U.S. Court of Appeals for the Ninth Circuit ruled that executive-branch agencies are required to utilize the SCC in cost-benefit analyses of major regulations (and that the SCC value is certainly not zero). In the wake of this ruling, the Obama Administration launched the Interagency Working Group on the Social Cost of Carbon (IWG) to rigorously develop SCC estimates for consistent use across agencies. The IWG's 2010 estimates – and their updated values in 2013 – utilized the DICE (William Nordhaus), FUND (David Anthoff and Richard Tol), and PAGE (Chris Hope) models. The IWG maintained the assumptions of the individual modelers, except for some changes to the discount rate, climate sensitivity parameter, and socio-economic scenarios (Shogren. 2016; IWG, 2010; IWG, 2013). To calculate their official SCC estimates, the IWG ran a Monte Carlo simulation calculating 10,000 model-scenario-rate specific SCC estimates and then averaged the resulting 150,000 estimates - equally weighting each model and scenario – corresponding to discount rates of 2.5%, 3%, and 5%. Only under very limited conditions is such a methodology likely to reflect the consensus in the literature, and this potential is even more limited if the assumptions behind the three models fail to reflect the overall consensus in the literature.

The damage functions of the IAMs currently used by the IWG reflect the consensus views from the 1990s rather than the current consensus. As is well known in the literature, the climate damage functions used in these IAMs were calibrated using studies from the 1990s (Dietz et al., 2007; Revesz et al., 2014). This is true for all three of the models used by the IWG in 2013: FUND 3.5 (see Table 1), DICE-2010 (see Table 2 for calibration sources of DICE-99 upon which DICE-2010 is based), and PAGE09.[1] Given that many of the economic studies from the 1990s cited by these model developers in turn cite scientific literature that predates them, portions of these damage functions may rely on research that is more than two decades old (Revesz et al., 2014). Three IPCC assessment reports (2001, 2007, and 2014) have been released since the 1990s and there has been a recent explosion in statistical-based impact estimates (Revesz et al., 2014). As such, the current IAM damage functions clearly omit key information.

More generally, Pindyck (2015) argues in a working paper that IAMs are over-reliant on the opinions of their modelers.[2] He argues that IAMs essentially represent the modeler's informed opinion rather than the scientific consensus. Accordingly, he goes on to state that by presenting these opinions in the form of a "sophisticated" model, modelers dishonestly represent IAMs as current scientific consensus, instead of as a black box that transforms the modeler's assumptions into policy recommendations and SCC estimates.

Holladay et al. (2009) conducted a survey of economists who had published articles on climate change in leading economic journals, and found some evidence of this potential disparity between IAMs and general scientific consensus. Specifically, when asked to estimate the appropriate value for the global SCC, respondents provided a median estimate of $50; the 2010 IWG used a central estimate of $21. This reveals an incongruity between the views of the overall economic community and the opinions of IAM modelers. This disparity may result from disagreements over the climate-damage function or discount rate assumptions made by the IAM modelers and the IWG (2010), or potentially even over structural assumptions like the impact of climate change on economic growth.

To avoid the current situation in which IAM modelers are free to choose ambiguous parameter values (such as the probability of catastrophic outcomes, the discount rate, etc.) based on their own opinions, Pindyck (2015) proposes using a simple model with inputs determined by expert opinion from "a range of economists and climate scientists." Given a specific GHG scenario, experts would be asked about their assumptions for key values in determining the social cost of carbon: (1) the discount rate, (2) the probability of catastrophic outcomes (e.g., 10%, 30%, and 50% losses in GDP from climate change occurring in the next 50 years), and (3) the CO_2 emission reduction necessary to avoid these catastrophic outcomes. The initial two questions are essential in calculating the bulk of the net present value of benefits from avoiding emissions, which when divided by the emission reduction roughly approximates the SCC.[3]

As an alternative to the Pindyck (2015) methodology, this paper re-introduces expert elicitation as a method for calibrating key uncertain parameters in IAMs (Nordhaus, 1994; Schauer, 1995; Roughgarden and Schneider, 1999), so as to ensure that official U.S. estimates reflect the wider consensus of the economic community. While Pindyck (2015) argues for abandoning current IAMs entirely, we believe that this approach throws the baby out with the bath water. We agree with Pindyck (2015) that current IAMs are over-reliant on the opinions of four economists, who are unlikely to reflect the overall consensus of the literature. However, we believe that expert elicitation can be used to calibrate key parameters such as the discount rate and the damage function. This approach maintains IAMs and their structures to model the complex relationship between emissions and warming, calibrated using scientific data. This modeling is essential for capturing difficult-to-visualize marginal concepts. Without IAMs, economists would need to think through the full translation of emissions into warming into damages into social welfare loss (including complex feedback effects) in order to calculate the SCC. Our approach makes use of IAMs but ensures that highly uncertain economic parameters are calibrated to the current consensus views of experts on climate economics. With regular updates, we should expect this consensus to converge with the estimates in the literature that withstand peer review.

Specifically, in this paper, we attempt to establish expert consensus on the economics of climate change by conducting a survey of all those who have published an article related to climate change in a highly ranked, peer-reviewed economics or environmental economics journal since 1994. We designed a 15-question online survey focused on climate change risks, estimated economic impacts, and policy responses. This survey included questions on the appropriate inter-generational discount rate and the magnitude of climate damages, partially drawn from the wording used in a commonly cited Nordhaus (1994) survey. We invited the 1,103 experts who met our selection criteria to participate, and we received 365 completed surveys.

Our data can help establish a baseline for IAMs, in addition to providing other useful information for policymakers. To illustrate this point, we utilize the results from this survey to re-calibrate DICE-2013R to reflect the current state of expert opinion on expected climate damages and discount rates, and re-calculate the SCC. In general, we find a significant increase in the SCC, supporting the hypothesis that current IAMs do not reflect the current scientific consensus.

The paper is structured as follows: Section II reviews the key literature, focusing on previous surveys of economists on climate change and discount rates. Section III reviews the methodology for selecting our sample and conducting the survey. Section IV presents our key survey results. Section V uses survey results to calibrate new climate damage curves and discount rates, and uses them to calculate new SCC estimates. Section VI discusses our results, focusing on what steps are necessary to improve this modeling approach (including the key issue of who should be defined as a relevant expert group). Finally, Section VII concludes with a recap of our key results.

II. LITERATURE REVIEW

Our study builds on several past expert elicitations related to climate damages and discount rates. These past studies were only partially successful in affecting IAM assumptions. Eventually, IAMs adopted alternative calibration methodologies.

Climate Damage Functions

There are two general approaches to calibrating climate damage functions: the bottom-up approach (estimating sector and region damage estimates) and the top-down approach (analyzing the total economy using coarser methods) (Mendelsohn et al., 2000). Each of these approaches employs a variety of identification strategies, including enumerative, expert elicitation, meta-analysis, and statistical approaches (Tol, 2009; Howard and Sterner, 2016). IAMs most commonly use the bottom-up approach with an enumerative strategy, though in the latest version of DICE-2013, Nordhaus replaced this methodology with a top-down approach employing a meta-analysis of global climate damage estimates. In general, these bottom-up estimation techniques currently ignore the latest impact estimates using statistical techniques – such as panel methods – to identify climate damages at the global, regional, and sector scales (e.g., Dell et al. (2012), Burke et al. (2015), Houser et al., 2014, and Schlenker and Roberts, 2009).

Two top-down approaches that are easily reproducible and less time-intensive are expert elicitation (Nordhaus, 1994; Howard and Sylvan, 2015) and meta-analysis at the global scale (Tol, 2009; Tol, 2014; Newbold and Marten, 2014; Howard and Sterner, 2016). While both methods are clearly advantageous from the reproducibility perspective, only surveys allow for the estimation of omitted climate impacts – though only to the extent that they are considered by experts. There is also the potential to derive regional-sector estimates, though this has only been done in a general sense up to now for developed versus developing regions and market versus non-market impacts (Nordhaus, 1994). However, in addition to benefiting and suffering from many of the advantages and shortcomings of stated preference studies, surveys of experts also depend on how they define expertise and select respondents; the results differ by academic field, area of expertise, and level of expertise (Nordhaus, 1994; Howard and Sylvan, 2015). To fully capture the level of uncertainty perceived across the discipline, one should ask a broad section of experts. If instead, an analyst is interested in knowing only the view of experts on IAMs, a more objective methodology may be to conduct a meta-analysis of global damage estimates (many of which are authored by these experts).[4]

Just over twenty years ago, William Nordhaus published the results of what is likely the most influential economic survey about the effects of climate change to date (Nordhaus, 1994). In the oft-cited survey, Nordhaus interviewed 19 experts on climate change (10 economists, four other social scientists, and five natural scientists), each of whom had a working knowledge of economic statistics. He asked respondents to answer a series of questions under three scenarios: a 3°C increase by 2090 (Scenario A), a 6°C increase by 2175 (Scenario B), and a 6°C increase by 2090 (Scenario C). He then asked respondents to estimate the 10th, 50th, and 90th percentiles of climate damages to GDP (market impacts only) under each scenario. At the 50th percentile, the mean and median losses were 3.6% and 1.9% under Scenarios A. For each of these scenarios, he also asked respondents to estimate the probability of catastrophic damages equivalent to a 25% decline in GDP; for Scenario A, he found mean and median probabilities of 4.8% and 0.5%, respectively. The overall results varied greatly between academic disciplines with the eight mainstream economists and the three natural scientists providing conservative and high estimates, respectively.

The Nordhaus (1994) survey is still often cited, despite being two decades old and using a small sample size, though its use in calculating the social cost of carbon has waned. After its development, Nordhaus (1994) used its results for sensitivity analysis with respect to catastrophic climate change, the rate of temperature change, and uncertainty over the non-catastrophic damage function in DICE-1994.[5] As one of the few estimates of the impacts of extreme climate change, DICE-1999 though DICE-2010 still relied on the survey to calibrate a risk premium associated with the catastrophic portion of the climate impacts.

Other analysts have also used the Nordhaus (1994) survey results to calibrate DICE damage functions, including Roughgarden and Schneider (1999), who utilize the Nordhaus (1994) results to calibrate damage functions using methods similar to ours. Using the central estimates for scenarios A and C from Nordhaus (1994), Roughgarden and Schneider (1999) calibrate (1) a deterministic (non-catastrophic) damage function to the median responses (for all respondents and for each discipline), and (2) a stochastic (non-catastrophic and catastrophic) damage function – which they call a subjective damage function - by fitting a Weibull distribution (a potentially positive-skewed distribution) to all six responses (10^{th} percentile, 50^{th} percentile, and 90^{th} percentiles for Scenarios A and C) for each respondent and then averaging the distributions by assigning equal weight to each to construct an aggregate quadratic damage function. Running a Monte Carlo simulation with the resulting damage functions, the authors find a four- to eight-fold increase in the optimal carbon tax (i.e., the SCC on the optimal emissions path). In another study, Peck and Teisberg (1995) calibrated a catastrophic damage function using the estimates of the probability of a catastrophic loss for Scenarios A and C. More recently, in meta-analyses of global climate change impact estimates (Tol, 2009; Tol, 2014; Nordhaus and Sztorc, 2013), Nordhaus' 1994 survey stands as the sole climate damage estimate derived by expert elicitation.

In a less commonly cited survey, Schauer (1995) surveyed 14 experts on climate change of which 10 report climate impacts. Schauer (1995) estimates mean and median declines in global GDP of 5.2% and 2.6%, respectively, with a variance of 71.3% for a doubling of CO_2 (equivalent to a 2.5 °C increase relative to pre-industrial temperature using the IPCC consensus of the time). These results are roughly the same as Nordhaus' (1994) scenario A. Using these and other survey results with respect to uncertain scientific and economic parameters (including the long-run average discount and growth rate of the global economy), Schauer (1995) calibrated a shadow price model for the SCC.

These previous expert surveys focused on handpicked experts – including scientists – rather than a large sample of economists (as in our study). Information about the science and economics of climate change has greatly improved over the past 20 years, and our survey attempts to provide a current understanding of experts' views on some of the same economic damage estimates Nordhaus explored. Furthermore, like Roughgarden and Schneider (1999), our study appropriately calibrates a continuous distribution of climate damages that captures non-catastrophic and catastrophic impacts, though we use slightly different techniques and questions. Unlike Roughgarden and Schneider (1999) we also calibrate the discount rate utilizing survey responses, following Schauer (1995).

Expert Surveys on Discount Rates

The most prominent survey about discount rates is Weitzman (2001), which conducted an e-mail survey of 2,800 Ph.D. economists on the social discount rate. Using "unscreened sampling" of economists of varying backgrounds and fields to ensure balance, Weitzman asked respondents to provide the appropriate discount rate to use in climate change cost-benefit analyses.[6] He obtained approximately 2,160 responses (a 77% response rate), of which 12% were given with objections to the question.[7] His mean and median responses were approximately 4% and 3%, respectively; he had a standard deviation of approximately 3%. Similarly, in a sub-sample of 50 "blue ribbon" economists, Weitzman again found a mean response of approximately 4% and a standard deviation of 3%. Essentially, results from Weitzman

(2001) support the argument that the choice of expert group does not matter in terms of their discount rate selection.

These results are similar to the Schauer (1995) survey discussed above, which asked 14 experts to also estimate "the long-term average real discount rate for greenhouse damages (%/year)." From ten responses to this question, the study found a mean and median of 4.9% and 2.5% with a standard deviation of 5.5%.

In a more recent survey, Drupp et al. (2015) surveyed 627 "experts" – as determined by publication in leading economic journals – on social discount rates. The authors asked respondents to provide their opinion on a variety of discount rate parameters, including a constant discount rate. In total, 197 economists responded (a 31% response rate), of which 185 provided quantitative responses. Unlike Weitzman (2001) and Schauer (1995), the authors found that the mean and median of the constant discount rate are 2.25% and 2%, respectively and a general consensus that the social discount rate was between 1% and 3%.

Together, these studies provide evidence that the scientific consensus on the appropriate discount rate for calculating the social cost of carbon has declined over the last 20 years. Consequently, current IAMs and the IWG (2010; 2013) are out of date. In the former case, the authors of the IAMs utilize the Ramsey discount rate equation – which implies non-constant rates that decline over time with GDP per capita. For current versions of IAM, the constant discount rate equivalent – i.e., a constant rate that results in the same SCC value as their base model using the Ramsey equation – tends to be closer to the results of Weitzman (2001) than Drupp et al. (2015): 2.92% in FUND and 4.25% in DICE. In the latter case, by utilizing discount rates of 2.5%, 3%, and 5%, the IWG (2010; 2013) captures discount centered on the Wietzman (2001) estimates instead of the Drupp et al. (2015) estimates. Thus, current versions of IAMs and the IWG fail to capture discount rates below 2.5%.

III. SURVEY METHODOLOGY

In an attempt to gauge expert consensus on key economic issues related to climate change, we surveyed more than 1,000 of the world's leading experts on climate economics. We sent each respondent a link to a 15-question online survey, with questions focused on climate change risks, economic damage estimates, and policy responses. In total, 1,187 experts met our selection criteria, and we could successfully locate 1,103 (the intended recipients of the survey). We received 365 completed surveys – a response rate of 31.1%.[8]

Survey Design

Our survey was designed to accomplish multiple objectives, including soliciting specific estimates of the appropriate inter-generational discount rate, economic impacts of climate change, and the likelihood of catastrophic outcomes. We surveyed respondents on a variety of topics, including:

- An estimate of when the economic impacts will first have a negative impact on the global economy (Question 5)

- The appropriateness of the United States government's "social cost of carbon" valuation, and the discount rate that should be used in related calculations (Questions 10-12);
- Estimates for the economic impact of a 3°C increase in global mean temperature, including "catastrophic" impacts (Questions 13-15).

Because we sought to compare our respondents' views to the opinions expressed in other surveys, some of our questions used wording from a 2009 Institute for Policy Integrity survey, and some of our climate damage questions maintained the wording and scenarios of Nordhaus (1994) (Questions 13 and 15). The full text of our survey is included as Appendix B.

Selection of Respondents

We sought to identify a pool of respondents with demonstrated expertise in the economics of climate change. Building on the approach used in a prior survey by the Institute for Policy Integrity (Holladay et al., 2009), we compiled a list of all authors who had published an article related to climate change in a leading economics or environmental economics journal since 1994.[9] We included all papers that referenced climate change and had implications for the climate change debate, even if that was not their main focus.[10] We defined leading journals as those ranked in the top 25 economics journals or top five environmental economics journals, according to two rankings published in peer-reviewed publications. Given that the rankings of various journals have changed during this time frame, we used rankings from two time periods[11] and included any journal listed as a top-25 economics journal in either ranking. In total, our final list included 32 economic journals.[12] See Appendix A.

Specifically, we conducted a thorough search of each journal for articles that mentioned "climate change" or "global warming" and significantly discussed the benefits, costs, or uncertainties of climate policies; applied or criticized a climate model; or explored the costs of climate change.

After removing experts who had died or individuals we could not locate, our review revealed 1,187 authors who fit our selection criteria.[13] We then excluded respondents who stated that they no longer worked in this field and those for whom we could not find a working email address. With these authors removed, the total pool of experts was 1,103.

Our methodology for choosing respondents could potentially suffer from selection bias, given that highly ranked academic journals might not publish articles encompassing the entire spectrum of thought on climate change economics. However, we believe our approach adequately identified a large sample with demonstrated expertise in the economics of climate change. Furthermore, our respondents were representative of a wide range of opinions, based on the diverse and often conflicting arguments made in their published articles.[14]

We disaggregated our respondent pool into various subsets based on the type of journal publications (economics versus environmental economics); the number of relevant articles a respondent had published; and the specific areas of expertise a respondent identified in one of the survey questions. This allowed us to analyze any differences in the views of various subsets. Information about the response patterns of various respondent subsets is discussed in Howard and Sylvan (2015).

Survey Administration and Response Rate

We sent each respondent an email message that described the nature of this project, informed them of the reason for their selection, and requested their participation through an embedded hyperlink to the survey.[15] We administered the survey online through SurveyMonkey.com, creating separate but identical surveys for each respondent subset so that data could be segregated. The first page of the online survey had nine multiple-choice questions, and the second page had two multiple-choice questions and four open-ended questions that asked for a numerical response in a text box. Respondents were told that the survey would take less than 15 minutes to complete, and that individual responses would be anonymous (the survey did not ask for any identifying information or track individual responses). The survey remained open for 18 days, and respondents were sent two reminder emails that included deadline details. These emails were sent to the entire pool since we could not determine who had already completed the survey.

Excluding those who did not receive our e-mail, our overall response rate was 33.1%. Not all respondents answered every question, and there was some variation by subgroup; see Table 1. This rate is roughly consistent with the average response rate for online surveys of this type.[16]

IV. SURVEY RESULTS

Our results reveal several areas where expert consensus exists on the economics of climate change, and others where more research is necessary. Our key findings with respect to calibrating IAM parameters – specifically the appropriate discount rates (question 12) and damage function (questions 5, 13 and 15) – are discussed below. For a review of all survey results, see Howard and Sylvan (2015).

Respondent Expertise by Issue Area

Our first survey question sought to clarify respondents' specific areas of expertise, based on the topics of their climate-related publications. Respondents were asked to check all topic areas on which they had published, from the following list: climate change risks; estimated damages from climate change; global climate strategies; international agreements/game theory; greenhouse gas control mechanisms; integrated assessment models/social cost of carbon; climate change adaptation; other climate-related topics; and none. This list of topics closely resembles the sections of our survey.[17] Of those who responded to our survey, only one respondent did not answer this question, and only nine respondents stated that they had not published on any of the listed topics.[18]

Each topic was relatively well represented; see Figure 1. The topic with the fewest published respondents was Climate Change Adaptation (22%), while Greenhouse Gas Control Mechanisms had the most with 38%. Of the 153 respondents that had published on "Other Climate-Related Topics" outside of our list, 72.5% had also published a paper on at least one topic covered in our survey. As such, 85.5% of our total respondents published on at least one of the topics covered in our survey.

For this paper, we are potentially interested in experts who published on damages, adaptation, and integrated assessment models. We refer to these as respondents with relevant publications.

Estimating Climate Impacts

We asked respondents to provide their best estimate of how a specific future climate scenario might affect the global economy. Specifically, we asked respondents to focus on a business-as-usual path of emissions with no major new climate policies implemented.

We also surveyed respondents on two specified temperature changes. In the first impact question (question 5), we asked respondents the time frame during which they believed the net global economic impacts of climate change would become negative. Given the business-as-usual pathway assumptions, we can use this question to approximate the temperature change at which respondents believe impacts will become negative. In the second set of impact questions (questions 13 and 15), respondents were asked to consider the following scenario: "global mean temperature increases by 3°C relative to the pre-industrial era (i.e., a 2.1°C increase from the current period) by approximately 2090. This scenario roughly approximates a 'business-as-usual' path for greenhouse gas emissions." While some business-as-usual projections estimate higher temperature increases,[19] our scenario is identical to that in Nordhaus (1994) in order to allow for apples-to-apples comparison. For this scenario, we asked for an estimate of the how this temperature increase might impact global GDP (in percentage terms) – including both market and non-market goods. Specifically, under this scenario, we asked respondents to provide the most likely impact as well as the probability that GDP loss will be 25% or higher.

Unlike previous studies, we did not ask respondents to specify the 10th, 50th, and 90th percentiles of impacts (Nordhaus, 1994; Schauer, 1995) or conduct a performance assessment (i.e., a section of the survey that includes questions with answers that are unknown to the experts but which can be analyzed to verify the accuracy of their responses) (Cooke, 2013). Instead, we focused on three different types of impact questions under business-as-usual: year of negative impacts, most likely impact (% of GDP) at 3 °C in 2090, and probability of catastrophic loss (25% or more loss of GDP). This allowed us to check for the consistency of an expert's responses. Incompatible results (e.g., stating that the most likely impact is a 30% loss of GDP while also estimating only a 10% probability of GDP loss greater than 25%) demonstrate poor predictive power; these inconsistent results are somewhat akin to "incentive incompatible" responses in the stated preference literature (e.g., contingent valuation, choice experiments, etc.). While this approach does not directly test performance, we are able to drop (i.e., apply zero weight to) respondents whose contradictory answers might undermine our model predictions. We chose this approach over the inclusion of a performance-based question given the difficulty of assessing expert performance in the context of climate change, where seed variables – "variables from the experts' area of expertise for which the true values are available post hoc" – are difficult to determine (Cooke and Goossens, 2008).

Question 5: When Will Climate Change Begin to Have a Net Negative Affect on the Global Economy?

One of our most noteworthy findings emerged from a question about when the net effects of climate change will first have a negative impact on the global economy; see Table 2 and Figure 2. Policymakers and journalists often discuss damages from climate change as a problem for the distant future,[20] but 40.6% of our respondents believed that "climate change is already having a negative effect on the global economy." Many others believed the net impact would be negative by 2025 or 2050; approximately 90%

of total respondents believed that climate change will damage the global economy by mid-century. There was almost universal agreement that there will be a negative effect by the end of the century (97%).

The median estimate for when the net effects of climate change will become negative was “by 2025”. This is true regardless of how we group the experts: all respondents, only those publishing in economics journals or only in environmental economics journals, those with one or multiple publications, or those who published on IAMs, climate damages, or climate adaptation. Taking 2020 as the year that climate impacts become net negative (i.e., the value between 2015 and 2025), we find that the median expert expects a net negative impact from climate change globally for approximately a 1 °C temperature increase (as predicted in DICE and FUND) compared to an approximately 3 °C increase (around 2080) in FUND (Tol, 2013b) – the sole IAM with significant initial climate benefits.

For this question, the mean results are almost identical.[21] The mean impact year and mean impact temperature increase are approximately 2020 and a 1 °C increase, respectively. Again, this result holds regardless of how we group respondents.

Question 13: What is your best guess (median/50th percentile estimate) of the impact on global output, as a percentage of GDP? Please include non-market and market impacts, and factor in adaptation to climate change.

This question is almost identical to one used in Nordhaus (1994), and we find that economic experts are now estimating larger impacts from climate change. In response to this question, the mean and median estimates were GDP losses of 10.2% and 5.5%, respectively, with a variance of 133%. See Table 3 and Figure 3. These average impact estimates are higher than most previous predictions, including Nordhaus (1994), which found mean and median GDP loss estimates of 3.6% and 1.9%. Schauer (1995) estimated mean and median losses of 5.2% and 2.6% for a very similar scenario.[22] These previous estimates relied on the results of a small number of handpicked experts – including scientists – instead of a large sample of economists. Based on the 95% confidence interval, our mean estimates are significantly different than both studies’ estimates.

These estimates are also higher than those from the three IAMs used by the U.S. government to calculate the official SCC. DICE-2010 estimates a GDP loss of roughly 2.4% for a 3°C increase relative to the pre-industrial temperature (based on RICE-2010); FUND projects a GDP *increase* of 1.42% for 1°C of warming and roughly a 0% impact for approximately 3 °C of warming (Tol, 2013b); and PAGE09 projects a GDP loss of 1.12% for a 3°C increase.[23] The implications of this finding could be significant: the damage estimates that the U.S. government is currently using to help evaluate policies may be far more conservative than those predicted by a large sample of expert economists.

Similar results were found for all subsets of experts, with some minor exceptions: the mean impact for those publishing in economics journals was slightly more conservative at a 7.1% loss, while the mean impact for those who published in environmental journals was higher: an 11.5% loss. Experts with multiple publications had a mean of a 9.1% loss, while those with one publication had a mean of a 10.7% loss. Those who had published on IAMs had a mean loss of 8.5% compared to those who published on climate damages (11.7% loss) and on climate change adaptation (11.2% loss). For each sub-group, our mean results exceed those of previous estimates: Nordhaus (1994), Schauer (1995), and all three IAMs.

If we trim the data to eliminate outliers, we get slightly lower damage estimates. If we restrict our attention to estimates between the 1st and 99th percentiles, we find that the mean and median losses are 10.2% and 6%, respectively, for the overall sample. If we further restrict our attention to estimates between the 5th and 95th percentile, we find mean and median estimates of 8.7% and 5% losses, respectively. Again, these trimmed estimates are still higher than previous estimates and IAMs.

Question 15: What is your median/50th percentile estimate of the probability of a high-consequence outcome (a 25% loss or more in global income indefinitely) if global average temperature were to increase 3°C by 2090?

Our final survey question asked respondents to estimate the probability of catastrophic impacts from a 3°C global temperature increase by 2090. Our question read: "Some people are concerned about a low-probability, high-consequence outcome from climate change, potentially caused by environmental tipping points. Assume by 'high-consequence' we mean a 25% loss or more in global income indefinitely. (Global output dropped by approximately 25% during the Great Depression.) What is your median/50th percentile estimate of the probability of such a high-consequence outcome if global average temperature were to increase 3°C by 2090?"

On average, respondents' best estimate of the probability of a "high-consequence" outcome was between 10% and 20%, though the variance in the response was quite high.[24] The mean and median probabilities were 22% and 10%, respectively; see Table 4 and Figure 4. These results are unaffected by trimming at the 95th and 99th percentiles. Furthermore, the results were fairly consistent across the various sub-groups, though respondents who have published in an economics journal differed from the general sample with mean and median probabilities of 11.3% and 5%, respectively.

Our respondents estimated a higher probability of catastrophic outcomes than the Nordhaus survey revealed for an identical warming scenario.[25] Specifically, we find that our results are significantly (statistically) different than the Nordhaus (1994) survey result, even for each sub-group.

Choosing an Appropriate (Constant) Discount Rate

Our first open-ended survey question (question 12) asked respondents to provide the appropriate constant discount rate for calculating the SCC. Our pool of experts believed that the appropriate constant discount rate should be equal to or less than 3% (which is the central discount rate used by the government). See Table 5 and Figure 5. For reference, DICE-2013R and FUND specify a Ramsey discount rate equivalent to a constant rate of 4.25% and 2.92%, respectively. IWG's (2010; 2013) chosen rates are 2.5%, 3%, and 5%.

For those who responded to this question, the mean and median estimates were approximately 3% and 2%, respectively. This median response is lower than the lowest discount rate (2.5%) used by the U.S. government in the calculation of the official SCC. Again, this finding suggests that the IAMs and the federal government are undervaluing strong climate protections by discounting their benefits at a higher rate than experts recommend.

For most relevant subgroups, the median and mean rates are 2% and 3%, respectively. There are several exceptions: 1.5% was the median discount rate for experts with multiple publications; approximately 2% was the mean discount rate for experts identified based on a publication in an economics journal or who published in on climate damages; and approximately 2.5% was the mean discount rate for experts who identified as publishing on climate adaptation. While we again find a disparity between the current expert consensus and discount rate assumptions made by IAM modelers and the IWG, we also find – like Weitzman (2001) – little variation in in the preferred discount rate between sub-groups of experts.

In general, if we trim the full dataset to eliminate outliers, the consensus discount rate declines. If we trim the upper and lower 1% and 5% outliers, the mean shifts downwards to 2.3% and 1.9%, respectively, and the median stays constant at 2%. If instead we follow Weitzman (2001) – such that we trim estimates below 0.5% and above 12% - we find a mean and median of 2.6% and 2%. Trimming further highlights the disparity between the economic community at large and IAM modelers and the IWG.

Additionally, we find that responses in the 90^{th} percentile vary from 3% to 5%. This strongly suggests that experts believe that the 5% discount rate – the maximum rate used by the U.S. government – is on the high end of what economists recommend. A 7% discount rate – which some have advocated using in official calculations – is clearly inappropriate.

Our results are similar to Drupp et al. (2015) who find that the mean and median of the constant discount rate are 2.25% and 2%, respectively. (Our findings match these results especially closely when we exclude outliers.) Like Drupp et al. (2015), our results are slightly below the mean and median found by Weitzman (2001) of 4% and 3%, respectively.

Appropriate SCC Value

Just as we found disparity between the current expert consensus and discount rate and damage assumptions made by IAM modelers and the IWG, we also find a discrepancy on the official U.S. SCC value. We asked respondents if they believed that the official U.S. central estimate of the SCC ($37 in 2007 USD) was appropriate (see question 10 in Appendix B). 51% of respondents believed that this SCC value was too low, while 18% responded that it was an appropriate value. Only 8% of respondents believed that it was too high. Consistent with their differing responses on damages and discount rates than those chosen by the IWG, the general consensus was that the official central U.S. SCC estimate was too low.

V. Results

Using our survey results on climate damages (Questions 5, 13, and 15), we are able to construct climate damage curves. We construct deterministic damage curves following DICE-2013R to capture non-catastrophic climate impacts, while we also construct stochastic climate damage functions to capture total climate impacts (non-catastrophic and catastrophic impacts). Using these damage curves in DICE (while maintaining DICE's deterministic structure), we estimate the SCC such that it reflects the current state of expert opinion on expected economic damages from climate change.

We also explore the effects of alternative the discount rate assumptions. Following the IWG (2010; 2013), we replace the Ramsey discount rate specification used by Nordhaus with a constant discount rate. Because unlike the IWG we maintain the optimal structure of DICE-2013R, we instead specify an elasticity of marginal utility of consumption of zero (i.e., a risk-neutral central planner) and specify a constant discount rate to replace the pure rate of time preference. We implement this change with the original and re-calibrated DICE damage functions.

Non-catastrophic Damages

Using these survey results, we can calibrate non-catastrophic climate damage functions to replace the DICE-2013 damage function.[26] Much in the way that Nordhaus and Boyer (1999) and Nordhaus (2008) used the responses in the Nordhaus (1994) survey to calibrate catastrophic damages in the DICE-99 and DICE-2007 models, we utilize responses to our survey to calibrate the DICE damage function – $D = \alpha_1 T + \alpha_2 T^2$ where D is the % decline in GDP from a T °C increase in global average surface temperature above the pre-industrial level – to reflect the current consensus of economic experts on climate change. Following the DICE-2013R assumption, we calibrate α_2 using responses to questions 13 assuming no initial climate benefits from climate change (i.e., $\alpha_1 = 0$). Making the traditional assumption that damages are equal to zero when the temperature increase equals zero, this parameter equals the mean (or median) damage estimate drawn from responses to question 13 divided by the corresponding temperature increase – a 3°C increase relative to pre-industrial temperatures – squared (i.e., $\alpha_2 = \frac{D}{T^2} = \frac{D}{9}$). We calibrate the parameter α_2 using responses to our survey by the various sub-groups and responses to Nordhaus (1994). See Table 6a and Figure 6a.

As expected given the responses to questions 13, our mean and median damage functions are above Nordhaus' (1994) mean and median damage functions for non-catastrophic impacts. Specifically, the damage coefficient calibrated using all responses to question 13 is slightly below a three-fold increase from Nordhaus (1994). Even when α_2 is calibrated using response to question 13 from relatively conservative subgroups – those who published in economic journals or who have expertise in integrated assessment models – the coefficient is two-fold or higher than Nordhaus' (1994).

Interestingly – even with the rather arbitrary quadratic functional form - our resulting damage functions correspond to recent scientific literature cited by Weitzman (2010) in arguing that 99% of GDP will be lost for a 12°C increase. We find that climate change will result in a 100% loss in GDP for 9°C (mean) to 13 °C (median) increases when considering only non-catastrophic impacts. Alternatively, the quadratic damage function calibrated to the mean and median responses of the Nordhaus (1994) study implies threshold temperatures of 16°C and 22°C, respectively, while the recent DICE-2013 damage function implies a 100% decline in GDP for a 19°C increase in temperature above pre-industrial levels.

Given that the consensus-based damage functions drawn from our survey imply higher impacts than those generated from IAMs, it is unsurprising that they suggest that the SCC is higher than the estimates from DICE and other models. The base scenario run of DICE-2013R estimates a 2015 SCC[27] of $23/metric ton in current (i.e., 2016) USD. If we maintain Nordhaus' assumption of no initial benefits from climate change and replace the DICE-2013R damage function with the damage functions estimated above, we find a three- to 16-fold increase in the 2015 SCC, depending on the expert group of interest. If we use the damage function corresponding to the consensus of all responses to question 13, the 2015 SCC increases to $113/metric ton in current USD – almost a five-fold increase with respect to DICE-2013R and a three-fold increase with respect to Nordhaus (1994); see Table 7 and Figures 7 and 8a.

Allowing for initial benefits from climate change. A concern may be that while these damage curves are more accurate for high temperatures, they are too high for low-temperature increases. To test the sensitivity of our results, we calibrate α_1 and α_2 allowing for initial benefits from climate change (i.e., $\alpha_1 > 0$). To calibrate the two parameters, we utilize responses to question 5 – in addition to question 13 – as an additional data point for calibrating the damage function. In question 5, we asked respondents when they believed that the net effect of climate change will be become negative. The median response to this question was "by 2025", regardless of group, and the mean response was 2020. Given that the predicted temperature increase for FUND and DICE is approximately 1°C in 2020, respectively, we assumed that the mean and median respondents believe impacts will become negative (i.e., equal zero) when global average surface temperature rises by one degree Celsius relative to the pre-industrial period. We assume that respondents did not consider catastrophic damages[28] when answering question 5. See Table 6b and Figure 6b.

The damage functions calculated using this second method imply lower impacts for low temperatures increases, relative to the damage function calculated above assuming no initial benefits from climate change. Specifically, the damage functions are lower for temperature increases up to 3 °C and higher thereafter. A 100% decline in GDP results from a 8°C (mean) or 11°C (median) increase, depending on whether the mean or median responses were used to calibrate the damage function, respectively.

Again, our SCC estimates greatly exceed the DICE-2013R SCC estimates. The 2015 SCC increases by four-fold to eight-fold from the $23-per-metric-ton estimate, depending on the expert group of interest. For example, if we calibrate the damage function using the consensus drawn from all response to questions 5 and 13, the 2015 SCC increases to $144/metric ton. The SCC increases when we relax the assumption of no initial benefits from climate change (with respect to our earlier results when we assumed no initial benefits), implying that the short-run benefits of climate change are far outweighed by the resulting steeper damage function with respect to temperature.[29] This result is consistent across all expert groups considered. See Table 7 and Figures 7 and 8b.

Limiting damages to 100% of GDP. There may be a concern that these results are due to the quadratic functional form of the DICE-2013R damage function, which technically allows impacts that exceed 100% GDP. While no temperature is observed during the above runs that would produce such an impact, we replace the DICE-2013 damage function with the earlier DICE function form $D = \frac{\alpha_1 T + \alpha_2 T^2}{1 + \alpha_1 T + \alpha_2 T^2}$ where $\alpha_1 > 0$ in DICE-1999 and $\alpha_1 = 0$ in DICE-2007 (Nordhaus and Sztorc, 2013); see Tables 6c and 6d and Figure 6a and 6b.

With these capped damage functions, the SCC still significantly increases from the base version of DICE. In general, the 2015 SCC increases by three- to nine-fold relative to DICE-2013R, though not to the same extent as the non-limited damage functions (with some exceptions). See Table 7 and Figures 8c and 8d.

Overall results. Our results imply that calibrating the DICE damage function to reflect consensus view on non-catastrophic damages from climate change significantly increase the SCC with respect to DICE-2013R and Nordhaus (1994). While we find that the various consensus views on climate damages (according to all definitions of experts that we considered) imply a significant increase in the SCC, we find significant variation by group of experts. For example, the 2015 SCC increases to \$66 to \$204 per metric ton depending on the expert group and damage functional form considered. Given that all of the expert groups – on average – also selected lower constant discount rates than implied by the DICE-2013R model, the consensus view calls for even higher SCC estimates that obtained above.

Catastrophic Damages

Like the default version of DICE-2013R, the above damage curves and their corresponding SCC estimates capture only non-catastrophic impacts. However, earlier versions of DICE (DICE-99, DICE-2007, and DICE-2010) included an expected value of catastrophic climate change impacts in the DICE damage function. Given that tipping points and catastrophic damages are of major concern for policymakers, capturing the potential for catastrophic impacts in the SCC is critical to making efficient policy decisions.

In earlier versions of DICE, Nordhaus estimated the certainty-equivalent value of catastrophic damages using survey results from Nordhaus (1994) to a question almost identical to our question 15. In order to match earlier versions of DICE, we calibrate a catastrophic damage coefficient in addition to the non-catastrophic damage coefficient calibrated above. Following Nordhaus and Boyer (1999), the catastrophic damage coefficient equals the catastrophic impact (a 25% decline in GDP) multiplied by the probability of such an impact occurring (drawn from responses to question 15) divided by the corresponding temperature increase squared (i.e., $\alpha_{cat} = \frac{-0.25*p}{T^2} = \frac{-0.25}{9}p$).[30] If we add the resulting catastrophic damage function to the non-catastrophic damages estimated earlier, the resulting damage functions are much higher than the non-catastrophic impacts alone – see Tables 6a and 6b and Figure 9 – and imply even higher SCC estimates.

This methodology is no longer practical given our results. Given the deterministic structure of DICE, this methodology was sensible when non-catastrophic impacts were relatively low compared to the catastrophic impacts of a 25% or more loss of GDP. While we expected the most likely climate impact for a 3 °C in global average temperature by 2090 would exceed the impact found by Nordhaus (1994), we were surprised to find that a substantial portion of economists thought that the most likely economic impact given 3 °C of warming was a double-digit-percentage GDP decrease, and some even expected impacts above 25% (our catastrophic scenario). Thus, we could no longer capture catastrophic impacts using the Nordhaus methodology

Instead, we followed Roughgarden and Schneider (1999) and Schauer (1995) in calibrating the probability distribution functions for the damage function parameters – i.e., α_1 and α_2 – and then running a Monte Carlo simulation using DICE. Assuming that there is no probability of initial benefits from climate change for a 3 °C increase in temperature, we utilize two methods to calibrate five parametric distributions (Weibull, Pareto, Beta, Log-normal, and Triangular)[31] of the economic damage (in terms of % of GDP loss) of a 3 °C increase using responses to questions 13 and 15.

In the first method (which we call the "untrimmed-group" method), we utilize the mean response to each question to develop two data points for calibration, assuming that these values represent the wisdom of the crowd.[32] For each expert group and Nordhaus (1994), we calibrate each of these distributions using their mean responses. See Figures 10a to 10e.

In the second method (which we call the "trimmed-individual" method) – used by Roughgarden and Schneider (1999) and Schauer (1995) – we use the responses of each individual (who responded to both questions 13 and 15) to calibrate individual-specific damage distributions (i.e., the probability of a X% decline in GDP for a 3 °C increase in global average surface temperature for all Xs between 0 and 100), and then take the average probability across all individuals for each impact level (from 0% to 100% of GDP) using each of these distributions. Consistent with assuming no initial benefits from climate change, we assume that the handful of individuals who predict climate benefits according to question 13 or question 15 would predict no impact from climate change if provided this restriction (the exception being the triangle distribution).[33] Additionally, we drop individuals who provided inconsistent responses to questions 13 and 15 (see Table 8);[34] this results in a drop of approximately 25% of all responses with some variation by group.[35] For each expert group and Nordhaus (1994), we calibrate four distributions using their mean responses to questions 13 and 15.[36] See Figures 11a to 11d.

From these results, it is clear that over the last two decades the economic consensus on climate impacts has become more pessimistic. Regardless of the distribution chosen and the calibration method, the cumulative distribution for net climate damages (specifically, for a 3 °C in global average surface temperature by 2090) has shifted to the right over time (with respect to Nordhaus (1994)). In other words, there is a higher probability for any impact level between 0% and 100% of GDP than was estimated two decades ago. Even so, there is considerable variation between groups, with experts publishing in economic journals and on IAMs being less pessimistic and authors publishing in environmental journals and on climate damages and adaptation being more pessimistic. For most impact levels, the general consensus appears to be less pessimistic when we utilize the "trimmed-individual" methodology as compared to the "untrimmed-group" approach. However, this does not hold for high-impact levels (see Figures 12a to 12e); the "trimmed-individual" methodology assigns significantly higher probabilities to high impact losses.[37] Similarly, various distributions overlap each other for most impact levels, with the exception being high-impact levels. The triangular and beta distributions appear to be the most optimistic distributions, while the Pareto and log-normal distributions are the most pessimistic; see Figures 13a and 13b.

Using these distributions calibrated to all responses to questions 13 and 15, we run Monte Carlo simulations using the DICE model. Specifically, using the four functional forms for the damage functions discussed in the previous sub-section, we randomly draw 1,000 impact estimates for a 3°C increase from each of the five distributions, calibrated using the trimmed-group and untrimmed-individual methods. For damage functions with initial benefits (i.e., $\alpha_1 > 0$) from climate change, we assume that impacts equal zero for a 1 °C regardless of the draw.[38] In general, we find that the DICE-2013R model preforms poorly for higher-impact draws – i.e., unrealistic savings rates and interest rates for all damage functional forms and unrealistic climate damage estimates when we limit impacts to 100% of GDP – particularly for impact draws implying GDP losses greater than 80% to 90% for a 3 °C increase.[39] Ideally, we would have asked respondents what the maximum impact was for a 3 °C by 2090. Instead, we choose to limit our attention to distributions that are thin-tailed for higher temperatures - the beta, Weibull, and triangle distributions calibrated using the untrimmed-group methodology – to avoid high-impact draws that result in unrealistic model solutions.[40,41] Using these distributions, we calculate the mean SCC estimate for each year; see Table 9 and Figure 14a to 14d.

As expected, the mean SCC estimates that capture catastrophic impacts are higher than the corresponding non-catastrophic SCC estimates estimated in the previous sub-section, regardless of the damage function utilized; see Table 10. For the 2015 SCC, we see an average increase across all distributions and damage functions of 63% with a range of 28% to 109%, when including catastrophic impacts. For example, the 2015 SCC corresponding to the damage function with only a quadratic coefficient and with no limit on impacts increased by 75% from $113/metric ton (when considering only non-catastrophic impacts) to $197/metric ton (when modeling total impacts using a Weibull distribution). This implies, on average, an $85 SCC increase for catastrophic damages if our modeling assumptions hold. The percentage increases were higher for damage functions that did not limit GDP losses to 100% of GDP or allowed for initial benefits from climate change (i.e., had a steeper damage function). In general, the triangular distribution – regardless of whether we limited impacts to negative for a 3 °C increase – also implied a greater increase. Overall, the responses to our survey of economic experts potentially imply significant catastrophic impacts, though the results differ widely based on the form of the damage function (i.e., $26 to $157).

The distributions that we dropped due to fat tails imply even larger catastrophic impacts. In fact, catastrophic impacts become so probable at a 3 °C increase that the DICE model no longer becomes reliable or even capable of being solved without applying additional constraints (e.g., a minimum consumption requirement). On the one hand, it is possible that these cataclysmic results would be avoided if we had asked respondents to provide a maximum impact estimate. On the other hand, these results potentially support Weitzman's dismal theorem. Like his results, the significant probability of cataclysmic GDP losses potentially implies a strategy of minimizing the costs of avoiding these risks (e.g., meeting a 2 °C increase limit) over cost-benefit analysis.

Discount rate

As discussed earlier, we re-run the original model using a constant discount rate. For the base case, we utilize approximately the average DICE discount rate – i.e., the average of DICE's Ramsey discount rate that Nordhaus calibrated to match observed savings behavior and that declines over time with GDP per capita[42] – over the first 100 years; climate damages in the first century are responsible for the bulk of the SCC. We find a constant rate equivalent of approximately 4.25%. This rate also so happens to produce an SCC value that is approximately equivalent to what would be found with the Ramsey equation.

We compare this to the SCC calculated using discount rates of 2% and 3% – approximately the median and mean responses for all respondents and sub-groups. Using the Base DICE-2013R damage function, switching the discount rate to 3% and 2% increases the SCC by 126% and 440%, respectively. The SCC for the trimmed mean of 2.5% – which we find when we trim at the lower and upper first and fifth percentiles regardless of the sub-group – represents a 333% increase. See Table 11.

If we combine this with the calibrated damage functions specified earlier, we will further increase the SCC. See Table 11 and 12 for the SCC corresponding to these different discount rates using quadratic damage function without initial benefits and with initial climate benefits, respectively (without limit on damages). The range of the 2015 SCC in current dollars (i.e., 2016 USD) is approximately \$100 to \$500 per metric ton of CO2e (five to twenty-one fold increase relative to the DICE-2013R base estimate) when excluding initial benefits and \$171 to \$590 when including them (six-and a half to a twenty-five fold increase); the most likely impact (i.e., using the mean responses) according to all respondents is a ten-fold increase with and without initial benefits. Thus, the expert consensus on the value of the SCC appears to be substantially higher than the base DICE-2013R estimate, regardless of whether you analyze the complete set of respondents or the various sub-groups (though there is significant variation between sub-groups).

Specifying a distribution to fit the discount rate is particularly challenging given that a large portion of respondents reported values equal or below 0% (30 respondents) and a small portion of respondents reported discount rates above 7% (11 respondents). If we choose to model the distribution of discount rates, we can approximate a triangular distribution that overlaps with the IWG (2010; 201) discount range by choosing 0% and 5% to represent the lower and upper bounds, respectively; these values represent the 10th and 90th percentiles. I select as the mode, the median of our current responses (i.e., 2%). Compared to the other possible distributions that we fit to capture the positive-skewed nature of our responses using a maximum likelihood estimator – beta, log-normal, Weibull, and generalize Pareto distributions – the triangular distributions that we specify exaggerate the mean and median discount rate values. For these other distributions, the median discount rate is between 0.6% and 1.3%, except for the generalized Pareto distribution when the data is trimmed at the 95th and 99th percentiles. See Tables 15a to 15c.

Using the 10th, 50th, and 90th percentiles to calibrate a triangle distribution, we find almost identical distributions across all groups. There are some small differences for some subgroups: those publishing in economics journals have a 10th percentile of 0.5% and a 90th percentile of 4%, those who have multiple publications have a 50th percentile of 1.5% and a 90% percentile of 3%, and those who identified as experts on damages and IAMs had a 90th percentile of 4%. We do not calibrate the other cumulative distributions across the differing groups, though we expect the distributions to be relatively stable.

To shorten our analysis, we do not run the full Monte Carlo simulation using the stochastic damage function (which include non-catastrophic and catastrophic) impacts. Given that a constant discount rate of 4.25% is necessary to achieve an SCC value equivalent to the SCC using the Ramsey discount rate, specifying such an uncertain distribution will certainly increase the SCC further. This will occur to a greater extent if we rely on the maximum likelihood estimated cumulative distribution functions, instead of the triangular distribution.

VI. Discussion

Our general finding above is that the current IAM models – as represented by DICE-2013R – do not align with the current consensus of experts, with respect to climate damages and discount rates.[43] The current DICE-2013R damage function underestimates climate damages relative to the consensus of experts – regardless of sub-group of experts considered – on the economics of climate change; it appears that experts' estimates have increased over time while IAM damage functions have remained relatively stagnant – such that they still reflect the 1990 values to which they were originally calibrated. Similarly, the current DICE-2013R discount rate assumes a higher discount rate than the current expert consensus – regardless of the sub-group of experts considered. Most likely, this disparity results from IAM modelers calibrating the simplest version of the Ramsey discount rate to ensure that savings behavior is consistent with consumer behavior. However, it is necessary for IAMs and the IWG to consider a more complex Ramsey equation consistent with uncertainty[44] and/or more complex preferences, including relative prices and Epstein-Zin preferences (Drupp et al., 2015; Hoel and Sterner, 2007; Traeger, 2014a).[45] Regardless of which subgroups of experts we consider, these disparities result in a significant underestimation of the SCC relative to the expert consensus – though the exact magnitude of the discrepancy depends on who is considered an expert.

Given the large potential magnitude of these disparities, it is critical that the IWG and other agencies calibrate highly uncertain parameters in IAMs using the consensus of the wider field instead of relying on IAM modelers to distill the rapidly expanding climate change literature. It is impossible for four academics to be responsible for such a Herculean task. We provide one potential solution: to estimate highly uncertain parameters using expert consensus, updating this consensus every two to three years as the IWG updates its SCC estimates. Over time, survey responses will likely converge as data and estimation strategies improve, such that a consensus can be reached.[46]

Before the IWG or other agencies adopt a survey-calibration approach, it will be necessary to define a representative range of experts. Given the heterogeneity of differing potential groups of experts, we recommend that the IWG and agencies consider a broad section of experts to fully capture the level of perceived uncertainty in the community of scholars studying climate change, including scientists, social scientists, and others in relevant interdisciplinary fields (following the lead of Nordhaus (1994)). If the IWG or other agencies use the survey approach to elicit the opinion of a large and heterogeneous group of experts who differ greatly in their opinions, the agency should report the central Monte Carlo results, accounting for all expert responses and for each subgroup for purposes of sensitivity-analysis (Roughgarden and Schneider, 1999). If instead, the IWG is interested in knowing only the view of experts on IAMs, a more objective methodology may be to conduct a meta-analysis of global damage estimates (many of which are authored by these experts).

There are several additional improvements necessary before operationalizing this methodology for calibrating IAMs to estimate the SCC. First, future expert elicitations on the economics of climate change should aim to develop seed variables – i.e., questions with answers that are not known to the experts but which can be analyzed to verify the accuracy of the response – in order to weight the expertise of the respondents. While we do collect data on expertise (i.e., number of publications and areas of publication), research indicates that highly informed respondents – as indicated by themselves or their peers – will not necessarily provide more accurate responses (Cooke, 2016). While we attempted to address this issue by checking for consistency in responses, a seed question may provide us greater confidence in our ability to predict climate impacts.[47]

Second, following Nordhaus (1994), it would be useful to ask respondents for the minimum (or 10th percentile) and maximum (or 90th) percentile impacts for a 3 °C increase. Because a consensus of our survey respondents estimated a higher-than-expected probability of a catastrophic impact from climate change, we are unable to calibrate fat-tailed distributions without a significant possibility of a complete societal collapse. While this may actually reflect individuals' opinions, it could instead reflect the properties of the probability distribution function that we chose to calibrate to capture non-catastrophic and catastrophic impacts. One potential way to determine what is driving these results would be to include questions seeking information about the tails of the distribution.

Third, it would be helpful to collect more information about how respondents think climate impacts will occur and assign proportions of the most likely impact estimates to these pathways. For example, we currently ask respondents what percentage of GDP will be lost for a 3 °C increase by 2090, implicitly assuming that none of this loss is due to the impact of climate change on economic growth.[48] Instead, it would be useful to collect information on both the growth pathway (i.e., the % of the GDP loss due to a decline in the growth rate) and the breakdown of growth impacts between various economic sectors. Doing so would allow us to update the structure of IAMs and re-calibrate IAM damage functions. Similarly, we currently ask respondents what the probability of a 25% or more loss of GDP will be for a 3 °C increase by 2090. It would be useful to collect information on the most likely pathways for catastrophic climate impacts, such as environmental tipping points, societal tipping points (i.e., migration, violence, and conflict), or variance in the potential impacts.[49] Doing so would allow us to better understand how to treat catastrophic impacts in the IAM structure.

Last, we need to consider which IAM parameters qualify for calibration using expert elicitation. In general, these should be highly uncertain variables with potentially irreducible differences – i.e., these should be parameters that experts can hold contradictory opinions over such that collecting additional data will not sufficiently decrease standard errors (Freeman and Groom, 2014). In addition to the discount rate and damage functions, some other potential candidates include: the long-run growth rate of the economy (after 2100), the limits and costs of adaptation, and the limits and price of a backstop technology (i.e., a complete conversion to carbon free energy sources and/or carbon capture technologies including ambient air capture).

VII. Conclusions

Some economists have recently criticized IAMs for failing to reflect scientific consensus, particularly in their treatment of highly uncertain variables. In particular, Pindyck (2015) has argued that IAMs simply reflect the views of a handful of modelers, and that they should be abandoned altogether and supplanted by an "average cost of carbon," calculated using expert elicitation. While we agree that current IAMs are overly reliant on the opinions of their developers, we instead advocate for calibrating highly uncertain parameters using expert elicitation, while maintaining the IAM methodology. This approach is advantageous in that it avoids requiring economists or other climate experts to think through all of the complicated steps in a climate-economic process that translates an additional unit of carbon emissions into a social welfare loss. Using expert consensus to calibrate key uncertain parameters – like climate damages and discount rates – allows researchers to leverage the model structure of IAMs while making their underlying modeling assumptions more transparent.

To demonstrate this methodology, we surveyed 1,103 experts on the economics of climate change – all those who have authored an article related to climate change in a highly ranked economics or environmental economics journal since 1994. (We received 365 responses.) In casting a wider net than many previous surveys of economists on climate change, we avoid many of the pitfalls of previous studies, including small sample size. Using these survey results, we calibrate several potential damage functions and select appropriate discount rates to reflect the current economic consensus. Finally, we replace DICE-2013R's damage and discount rate parameters to reflect the overall consensus of respondents, and calculate the SCC.

There are several key takeaways from our study:

- Economic experts believe that climate change will begin to have a net negative impact on the global economy very soon – the median estimate was "by 2025," with many saying that climate change is already negatively affecting the economy. This differs greatly from the assumptions behind the FUND model.
- On average, economic experts predict far higher economic impacts from climate change (specifically from a 3 °C global mean temperature increase) than the estimates found in landmark surveys from the 1990s (Nordhaus, 1994; Schauer, 1995) and the current IAMs (DICE, FUND, and PAGE). While the variance in responses is high, our results are statistically different than these previous estimates.
- When asked to specify the appropriate constant discount rate for the calculation of the SCC, economic experts recommended rates lower than or roughly equal to the lower ranges of those used by the U.S. government.
- We find significant variation between the various subgroups in our survey with respect to damages at 3 °C, but these subgroups give fairly consistent estimates for when net global impacts will become negative, and what discount rate should be used. All subgroups predict significantly higher impacts than current IAM models assume, and support the use of discount rates equal to or lower than the current rates chosen by the IWG.
- When incorporating all relevant assumptions from our survey, our SCC estimates are more than 10-fold higher than the DICE estimates, indicating a disparity between current IAM models and economic consensus. Accounting for non-catastrophic impacts alone (and using the DICE discount rate), the SCC increased by three- to six-fold relative to the DICE-2013R estimate, using all responses to our survey. Accounting for both non-catastrophic and catastrophic impacts, the SCC increased by four- to 10-fold, using all responses to our survey. Finally, accounting for

differences in the discount rate as well as non-catastrophic damages, we find increases in the SCC by over a factor of 10.

This last finding is consistent with our survey finding that 2 out of 3 economic experts on the economics of climate change (who provided an opinion) believed the current U.S. central estimate of the SCC ($37 in 2007 USD) was too low as compared to too high or the appropriate value.

Given the significant differences between current IAMs and the current expert consensus on the economics of climate change, the IWG should consider two changes to its current methodology for calculating the SCC. First, it should develop a damage module to capture this difference in damages. Recently, the National Academy of Sciences (NAS, 2016) suggested that the IWG develop a common climate module – an independent model of the global climate system to translate emissions into temperature change that can be plugged into each IAM – to model the relationship between CO2 emissions and global mean surface temperature over time, along with the underlying uncertainty in this relationship. Similarly, the IWG would benefit from an expansion of this module system to other aspects of IAMs – particularly damages. As suggested by the NAS, these modules should be simple, transparent, and easily updatable, such that the module reflects the best available science with respect to central tendency and uncertainty, in an easily understandable way. Our expert consensus methodology meets these requirements, and has the ability to be disaggregated to fit the FUND and PAGE damage functions, with the addition of sector-based damage questions.

Second, the IWG should consider a wider range of constant discount rates than it currently considers. While the IWG currently considers a range of 2.5% to 5%, our survey findings support a range of 0% to 5%. This range is consistent with Drupp et al (2015). Given political constraints, the IWG might limit the range from 1% to 5% such that the current 2.5% discount rate is replaced by 1%.

Before adopting the expert elicitation methodology, the IWG should consider making several improvements (outlined in the previous section). Most importantly, the IWG should determine which parameters meet the requirement for “highly uncertain,” such that expert opinion should be used for calibration. Then, the IWG should determine the group(s) of experts best suited to identify the values of these parameters. We support the widest possible definition of expertise within the appropriate field, such that a broad set of scientists and social scientists can provide input on scientific and economic parameters, respectively. Inter-disciplinary fields should also be considered. Researchers should also use sensitivity analysis with respect to the various types of experts considered, to demonstrate the true range of potential values. Our study represents a potential starting point for this methodology.

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Table 1. Response and Completion Rates of Survey, as defined by AAORP (2011)

Respondent Subset	Responses: Number of Complete and Partial responses	Response Rate (RR1 and RR2) Based on All Experts Who Met Our Selection Criteria (i.e., relative to 1,187)	Response Rate (RR5 and RR6) Excluding Those Who We Were Unable to Contact (i.e., relative to 1,103)	Completion Rate: % of Respondents Who Completed the Question
Total	365	30.7%	33.1%	-
Economics Journals	98	31.9%	33.2%	-
Environmental Journals	267	30.3%	33.0%	-
One publication	266	28.3%	30.7%	-
Multiple Publications	99	40.1%	41.8%	-
Multiple Choice Questions on 1st Page of Survey - All Respondents	349 to 364	29.4% to 30.7%	31.6% to 33%	95.6% to 99.7%
Multiple Choice Questions on 2nd Page of Survey - All Respondents	338 to 339	28.5% to 28.6%	30.6% to 30.7%	92.6% to 92.9%
Open Ended Questions on 2nd Page of Survey - All Respondents	213 to 238	17.9% to 20.1%	20.1% to 21.6%	58.4% to 65.2%

Table 2a. % of All Respondent to Question 5 by Responses and Group, including response rate

Groups	Climate change is already having a negative effect on the global economy	By 2025	By 2050	By 2075	By 2100	After 2100	Climate change will not have a negative effect on the global economy	Response rate
All	40.6%	22.5%	25.8%	5.0%	3.1%	1.1%	1.9%	98.6%
Economics	28.9%	24.7%	30.9%	5.2%	7.2%	-	3.1%	99.0%
Environmental	44.9%	21.7%	24.0%	4.9%	1.5%	1.5%	1.5%	98.5%
Multiple	42.4%	25.3%	24.2%	5.1%	2.0%	-	1.0%	100.0%
One	39.8%	21.5%	26.4%	5.0%	3.4%	1.5%	2.3%	98.1%
Estimated Damages from Climate	36.0%	29.2%	23.6%	4.5%	2.2%	1.1%	3.4%	98.9%
Integrated Assessment Models	35.8%	27.5%	22.9%	7.3%	4.6%	1.8%	-	99.1%

Table 2b. 95% Confidence Interval of the Cumulative % of All Respondent to Question 5 by Responses and Group, including response rate

95% Confidence Interval														
Groups	By 2015		By 2025		By 2050		By 2075		By 2100		Negative effect at some point in time		No negative effect at any time	
All	36.3%	44.8%	58.9%	67.2%	86.2%	91.6%	91.8%	96.0%	95.5%	98.4%	96.9%	99.2%	0.8%	3.1%
Economics	21.4%	36.3%	45.4%	61.8%	78.6%	90.5%	84.7%	94.7%	94.1%	99.8%	94.1%	99.8%	0.2%	5.9%
Environmental	39.8%	49.9%	61.8%	71.3%	87.5%	93.5%	93.3%	97.6%	95.2%	98.7%	97.2%	99.7%	0.3%	2.8%
Multiple	34.9%	50.0%	60.5%	74.8%	87.8%	96.1%	94.4%	99.6%	97.5%	100.5%	97.5%	100.5%	-0.5%	2.5%
One	34.8%	44.9%	56.3%	66.3%	84.4%	91.1%	90.0%	95.4%	94.2%	98.1%	96.2%	99.2%	0.8%	3.8%
Estimated Damages from Climate*	26.0%	45.9%	55.3%	75.1%	82.2%	95.3%	88.0%	98.5%	91.2%	99.8%	92.9%	100.4%	-0.4%	7.1%
Integrated Assessment Models*	30.4%	41.2%	57.9%	68.7%	81.6%	90.9%	89.6%	97.5%	95.2%	101.1%	100.0%	100.0%	-	-

**Calculates confidence interval without finite population correction*

Table 3. Summary of Responses to Question 13 by Group, including response rate

Groups	Mean	Std. Dev.	Min	Max	10%	50% (median)	90%	95% Confidence Interval		Response	Response Rate
All	-10.2	11.5	-60	28.968	-20	-5.5	-1	-11.5	-8.9	234	64.1%
Economics	-7.1	9.9	-50	3	-15	-5	-1	-9.2	-5.0	69	70.4%
Environmental	-11.5	11.9	-60	28.968	-25	-10	-1.8	-13.1	-9.9	165	61.8%
Multiple	-9.1	11.3	-60	1	-20	-5	-1.5	-11.4	-6.9	70	70.7%
One	-10.7	11.6	-50	28.968	-25	-8	-1	-12.3	-9.0	164	61.7%
Estimated Damages from Climate*	-11.7	15.3	-60	3	-40	-5	0	-15.4	-7.9	63	70.0%
Integrated Assessment Models*	-8.5	9.9	-50	3	-20	-5	-1	-10.6	-6.3	82	74.5%
Climate-Change Adaptation*	-11.2	14.6	-60	5	-40	-5	-1	-14.9	-7.4	59	72.8%

**Calculates confidence interval without finite population correction*

Table 4. Summary of Responses to Question 15 by Group, including response rate

Groups	Mean	Std. Dev.	Min	Max	10%	50% (median)	90%	95% Confidence Interval		Response	Response Rate
All	22.0	25.8	0	100	0.08	10	70	19.0	24.9	238	65.2%
Economics	11.3	18.5	0	90	0.01	5	30	7.4	15.1	68	69.4%
Environmental	26.2	27.0	0	100	0.15	20	72.5	22.6	29.9	170	63.7%
Multiple	20.0	25.8	0	99	0.01	5	70	14.8	25.1	69	69.7%
One	22.8	25.8	0	100	0.1	10	70	19.3	26.3	169	63.5%
Estimated Damages from Climate*	23.0	27.1	0	90	0.05	10	70	16.2	29.8	61	67.8%
Integrated Assessment Models*	15.9	21.6	0	90	0.01	5	50	11.2	20.5	83	75.5%
Climate-Change Adaptation*	20.6	24.3	0	90	0.05	10	60	14.5	26.7	61	75.3%

**Calculates confidence interval without finite population correction*

Table 5. Summary of Responses to Question 12 by Group, including response rate

Groups	Mean	Std. Dev.	Min	Max	10%	50% (median)	90%	95% Confidence Interval		Respons e	Respons e Rate
All	3.1	9.4	-1.5	100	0	2	5	2.0	4.3	220	60.3%
Economics	2.2	1.7	-0.1	10	0.5	2	4	1.8	2.6	63	64.3%
Environmental	3.5	11.1	-1.5	100	0	2	5	1.9	5.1	157	58.8%
Multiple	3.0	11.6	0	95	0	1.5	3	0.6	5.4	66	66.7%
One	3.2	8.4	-1.5	100	0	2	5	2.0	4.4	154	57.9%
Integrated Assessment Models*	3.1	11.0	-0.1	95	0	2	4	0.6	5.6	74	67.3%

**Calculates confidence interval without finite population correction*

Table 6a. Coefficients of Quadratic Damages Estimating Using Our Survey (i.e., questions 13 and 15) and Nordhaus' Survey, assuming no initial benefits from climate change

Study	Groups	Non-catastrophic				Catastrophic				Total			
		Mean	Median	95% - Low	95% - High	Mean	Median	95% - Low	95% - High	Mean	Median	95% - Low	95% - High
Our Study	All	-1.13	-0.61	-0.99	-1.28	-0.61	-0.28	-0.53	-0.69	-1.74	-0.89	-1.52	-1.97
	Economics	-0.79	-0.56	-0.56	-1.02	-0.31	-0.14	-0.21	-0.42	-1.10	-0.69	-0.77	-1.44
	Environmental	-1.28	-1.11	-1.09	-1.46	-0.73	-0.56	-0.63	-0.83	-2.01	-1.67	-1.72	-2.29
	Multiple	-1.02	-0.56	-0.77	-1.27	-0.55	-0.14	-0.41	-0.70	-1.57	-0.69	-1.18	-1.96
	One	-1.18	-0.89	-1.00	-1.36	-0.63	-0.28	-0.53	-0.73	-1.82	-1.17	-1.54	-2.09
	Estimated Damages from Climate*	-1.30	-0.56	-0.88	-1.72	-0.64	-0.28	-0.45	-0.83	-1.94	-0.83	-1.33	-2.54
	Integrated Assessment Models*	-0.94	-0.56	-0.70	-1.18	-0.44	-0.14	-0.31	-0.57	-1.38	-0.69	-1.02	-1.75
Nordhaus (1994)	All	-0.40	-0.21	-	-	-0.13	-0.01	-	-	-0.53	-0.23	-	-

Table 6b. Coefficients of Quadratic Damages Estimating Using Our Survey (i.e., questions 5, 13 and 15), allowing for initial benefits from climate change

Groups	Mean			Median (50th Percentile)		
	Non-catastrophic		catastrophic	Non-catastrophic		catastrophic
	Linear	Quadratic	Quadratic	Linear	Quadratic	Quadratic
All	1.70	-1.70	-0.61	0.92	-0.92	-0.28
Economic	1.19	-1.19	-0.31	0.83	-0.83	-0.14
Environm	1.92	-1.92	-0.73	1.67	-1.67	-0.56
Multiple	1.52	-1.52	-0.55	0.83	-0.83	-0.14
One	1.78	-1.78	-0.63	1.33	-1.33	-0.28
Damage*	1.94	-1.94	-0.64	0.83	-0.83	-0.28
IAM*	1.41	-1.41	-0.44	0.83	-0.83	-0.14

Table 6c. Coefficients of Non-Catastrophic, Quadratic Damages Estimating Using Our Survey (i.e., question 13) and Nordhaus' Survey, assuming no initial benefits from climate change and a limit to climate impacts of GDP of 100%

Study	Groups	Non-Catastrophic			
		Mean	**Median**	**95% - Low**	**95% - High**
Our Study	**All**	-1.26	-0.65	-1.08	-1.45
	Economics	-0.85	-0.58	-0.59	-1.12
	Environmental	-1.44	-1.23	-1.21	-1.68
	Multiple	-1.12	-0.58	-0.82	-1.43
	One	-1.33	-0.97	-1.10	-1.56
	Damage*	-1.47	-0.58	-0.95	-2.03
	IAM*	-1.03	-0.58	-0.75	-1.32
Nordhaus (1994)	**All**	-0.41	-0.22	-	-

Table 6d. Coefficients of Non-Catastrophic, Quadratic Damages Estimating Using Our Survey (i.e., questions 5 and 13) and Nordhaus' Survey, allowing for initial benefits from climate change and assuming limit to climate impacts of GDP of 100%

Study	Groups	Mean		Median		95% - Low		95% - High	
		Linear	Quadratic	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic
Our Study	All	1.8941	-1.8941	0.9700	-0.9700	1.6242	-1.6242	2.1720	-2.1720
	Economics	1.2771	-1.2771	0.8772	-0.8772	0.8864	-0.8864	1.6856	-1.6856
	Environmental	2.1649	-2.1649	1.8519	-1.8519	1.8218	-1.8218	2.5209	-2.5209
	Multiple	1.6766	-1.6766	0.8772	-0.8772	1.2341	-1.2341	2.1414	-2.1414
	One	1.9885	-1.9885	1.4493	-1.4493	1.6564	-1.6564	2.3328	-2.3328
	Damage*	2.2006	-2.2006	0.8772	-0.8772	1.4276	-1.4276	3.0425	-3.0425
	IAM*	1.5434	-1.5434	0.8772	-0.8772	1.1277	-1.1277	1.9790	-1.9790

Table 7. 2015 SCC (2015 USD per metric ton of CO2) Damage Functions Calibrated to Our Survey (Questions 5 and 13)

Study	Groups	No Limit on Damages		Limit of 100% of GDP on Damages	
		Quadratic only	Linear and Quadratic	Quadratic only	Linear and Quadratic
Our Study	All	$113	$144	$96	$115
	Economics	$74	$92	$66	$79
	Environmental	$132	$169	$108	$130
	Multiple	$99	$124	$85	$103
	One	$119	$153	$100	$121
	Damage*	$134	$171	$110	$204
	IAM*	$90	$113	$79	$126
	Adapt*	$126	$162	$105	$191
Nordhaus (1994)	All	$35	-	$33	-
DICE-2013R	All	$23	-	-	-

Table 8. The Number and Percentage of Inconsistent Responses, by Group

Group	All Responses	Consistent Responses	% of Inconstent Responses
All	238	174	-27%
Economics	68	58	-15%
Environmental	170	116	-32%
Multiple	69	49	-29%
One	169	125	-26%
Damages	61	45	-26%
IAMs	83	66	-20%
Adaptation	61	44	-28%

Table 9. 2015 SCC for stochastic (non-catastrophic and catastrophic) damages, by damage function and distribution (2016 USD)

	No Limit on Damages								No Initial benfits							
	Quadratic Only				Linear and Quadratic				Quadratic Only				Linear and Quadratic			
Year/Distribution	Beta	Weibull	Triangular	Triangular (Zeroed)	Beta	Weibull	Triangula *r	Triangular (Zeroed)	Beta	Weibull	Triangular	Triangular (zeroed)	Beta	Weibull	Triangular	Triangular ((zeroed)
2010	$165	$178	$191	$205	$213	$226	$250	$266	$109	$114	$109	$125	$133	$149	$147	$154
2015	$188	$197	$215	$232	$243	$252	$281	$300	$124	$127	$122	$141	$155	$163	$169	$178
2020	$219	$225	$249	$268	$285	$291	$327	$350	$141	$143	$137	$160	$180	$186	$195	$206
2025	$256	$261	$290	$313	$337	$340	$384	$411	$161	$162	$152	$181	$207	$212	$222	$236
2030	$298	$302	$337	$364	$396	$397	$448	$481	$181	$181	$169	$202	$236	$240	$250	$267
2035	$345	$348	$389	$421	$461	$460	$520	$557	$202	$202	$185	$225	$267	$268	$278	$299
2040	$396	$397	$445	$481	$531	$528	$595	$638	$224	$223	$200	$247	$297	$298	$305	$330
2045	$450	$449	$504	$545	$606	$600	$673	$722	$246	$244	$214	$269	$327	$326	$330	$360
2050	$507	$504	$565	$611	$683	$674	$752	$807	$268	$265	$226	$290	$356	$354	$352	$388

Table 10. % of 2015 SCC for damages due to catastrophic impacts, by damage function and distribution

	No Limit on Damages								No Initial benfits							
	Quadratic Only				Linear and Quadratic				Quadratic Only				Linear and Quadratic			
Year/Distribution	Beta	Weibull	Triangular	Triangular (Zeroed)	Beta	Weibull	Triangular	Triangular (Zeroed)	Beta	Weibull	Triangular	Triangular (zeroed)	Beta	Weibull	Triangular	Triangular (zeroed)
2015	67%	75%	91%	106%	69%	75%	96%	109%	30%	33%	28%	48%	35%	42%	47%	55%

Table 11. 2015 SCC (2016 USD per metric ton of CO2) with Damage Functions and Discount Rates Calibrated to Our Survey (Questions 12 and 13) by Discount Rate and Sub-group, with no initial benefits from climate change

Discount Rate	Sub-groups									
	Base	Nordhaus	All	Economics	Environmental	Multiple	One	Damages	IAMs	Adaptation
Ramsey	$23	$35	$113	$74	$132	$99	$119	$134	$90	$126
4.25%	$23	$34	$103	$65	$102	$82	$94	$103	$76	$99
3%	$51	$75	$222	$143	$219	$180	$205	$222	$167	$214
2%	$122	$179	$499	$331	$493	$411	$463	$499	$384	$481

Table 12. 2015 SCC (2016 USD per metric ton of CO2) with Damage Functions and Discount Rates Calibrated to Our Survey (Questions 5, 12, and 13) by Discount Rate and Sub-group, with initial benefits from climate change

Discount Rate	Sub-groups								
	Nordhaus	All	Economics	Environmental	Multiple	One	Damages	IAMs	Adaptation
Ramsey	-	$143	$91	$168	$123	$151	$170	$112	$161
4.25%	-	$104	$75	$116	$94	$109	$117	$88	$113
3%	-	$233	$171	$258	$212	$242	$260	$199	$251
2%	-	$536	$406	$585	$493	$555	$590	$465	$572

Figure 1. Topics of respondents' publications on climate change

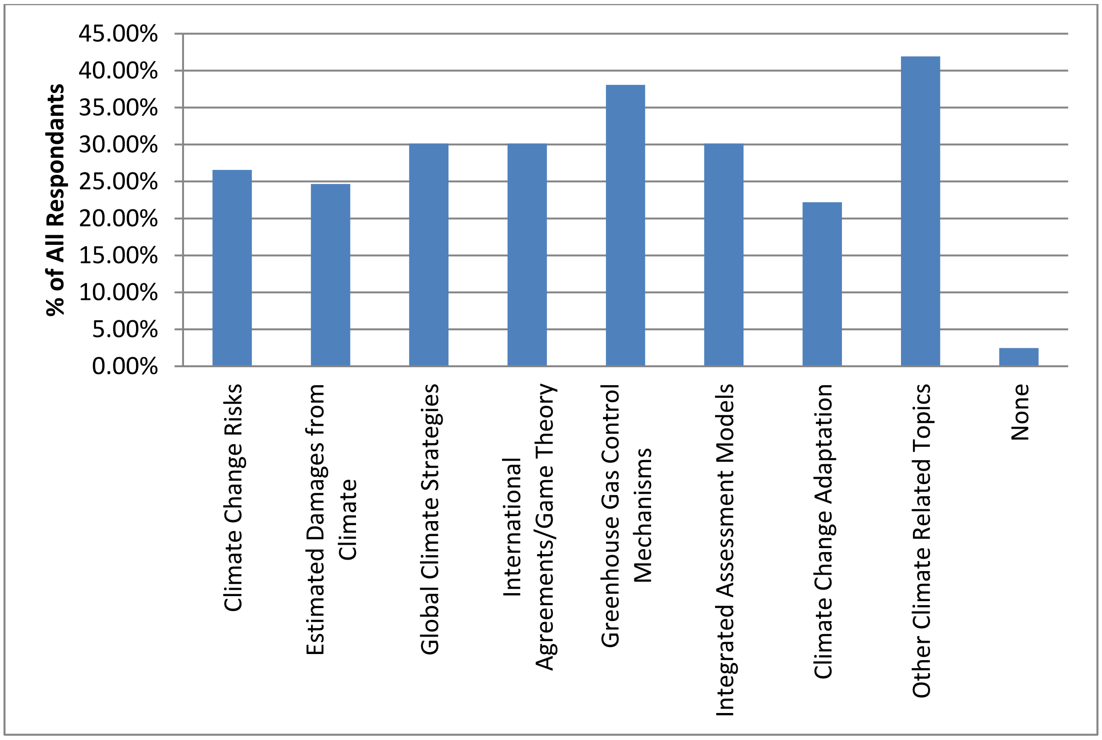


Figure 2. During what time period do you believe the net effects of climate change will first have a negative impact on the global economy?

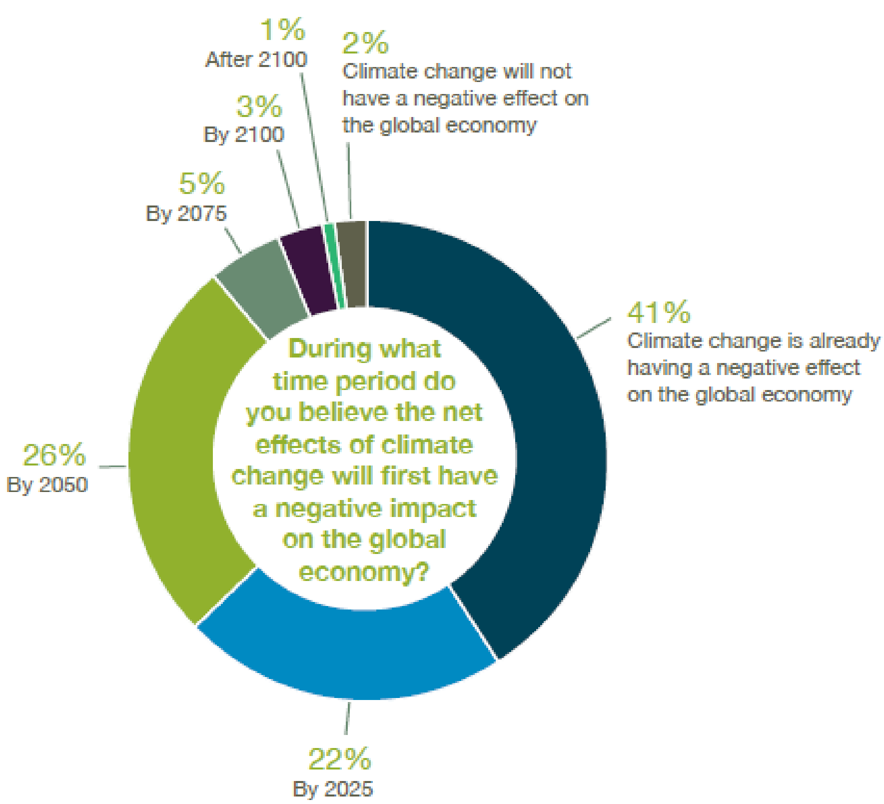


Figure 3. Histogram, Kernel Density Plot, and Normal-Density Plot of Constant Discount Rate (to Question 12)

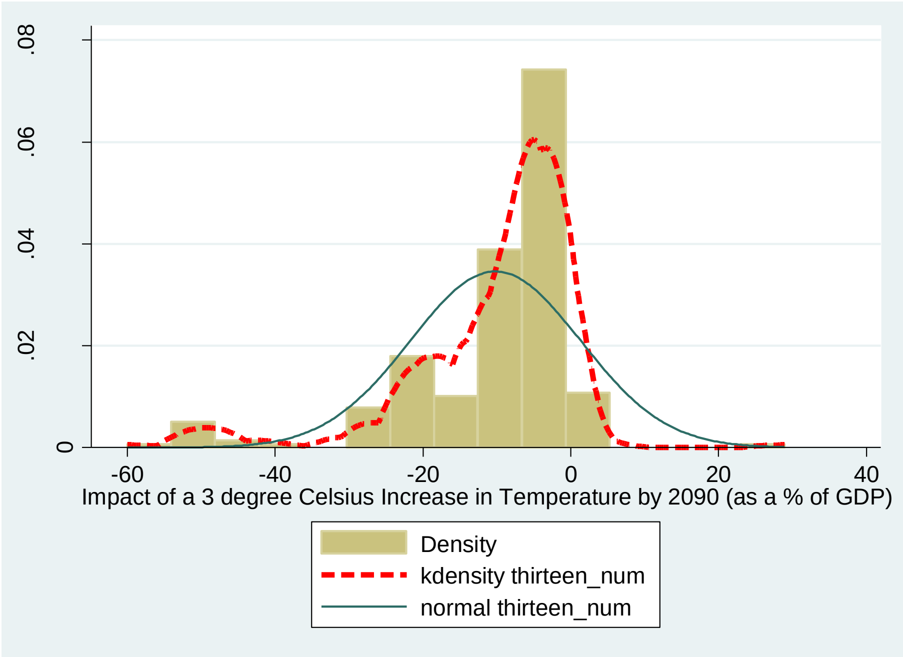


Figure 4. Histogram, Kernel Density Plot, and Normal-Density Plot of Most Likely Climate Damages (to Question 13)

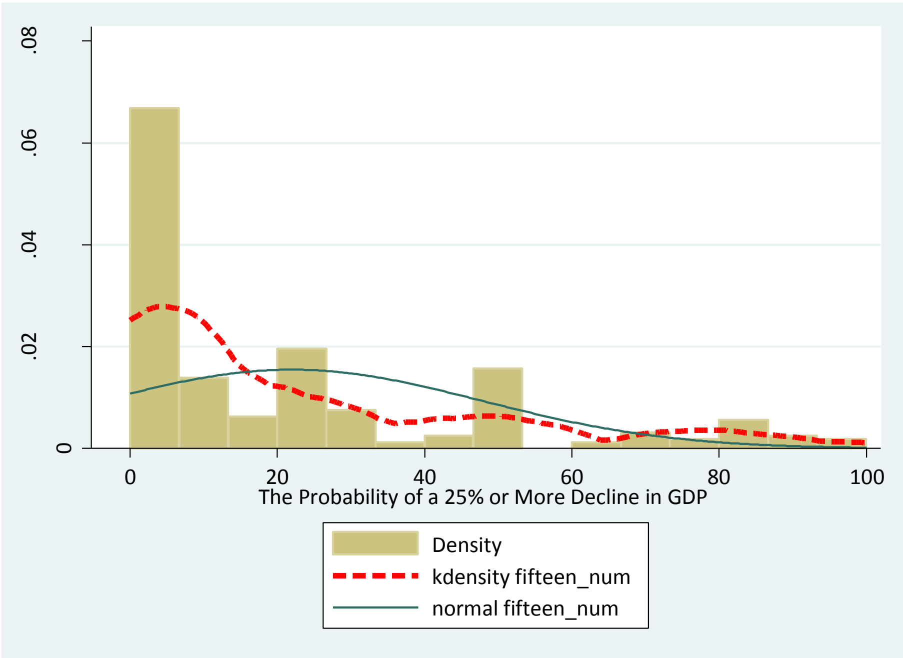
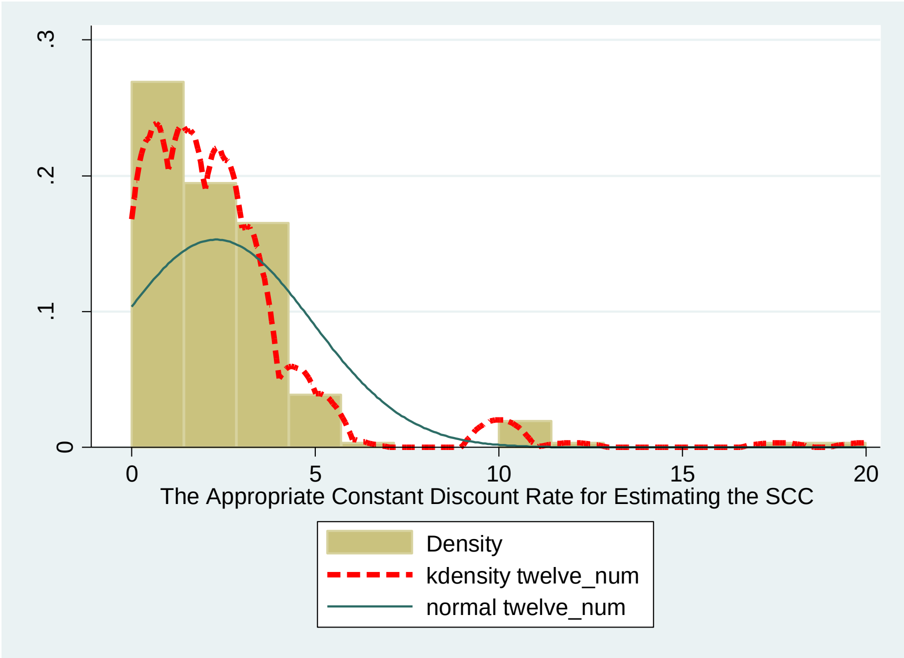
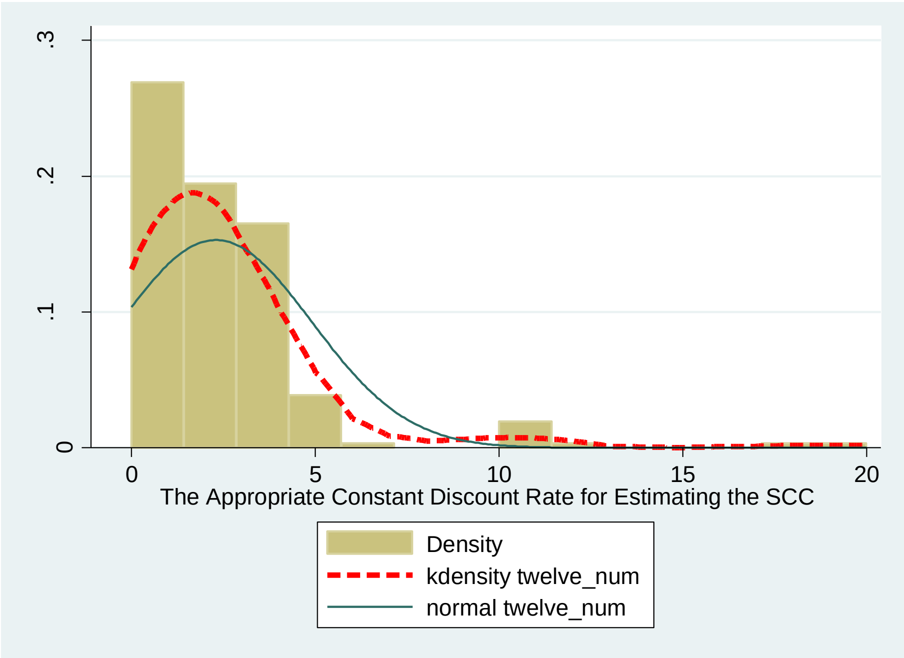


Figure 5a. Histogram, Kernel Density Plot, and Normal-Density Plot of Catastrophic Climate Damages (to Question 15)



***Histogram with bottom 1% and top 99% trimmed**

Figure 5b. Histogram, Kernel Density Plot (width of 1.35), and Normal-Density Plot of Catastrophic Climate Damages (to Question 15)



***Histogram with bottom 1% and top 99% trimmed**

Figure 6a. Non-Catastrophic Damage Functions Calibrated using Responses to our Survey (i.e., questions 13) and Nordhaus' (1994) Survey, assuming no initial benefits from climate change

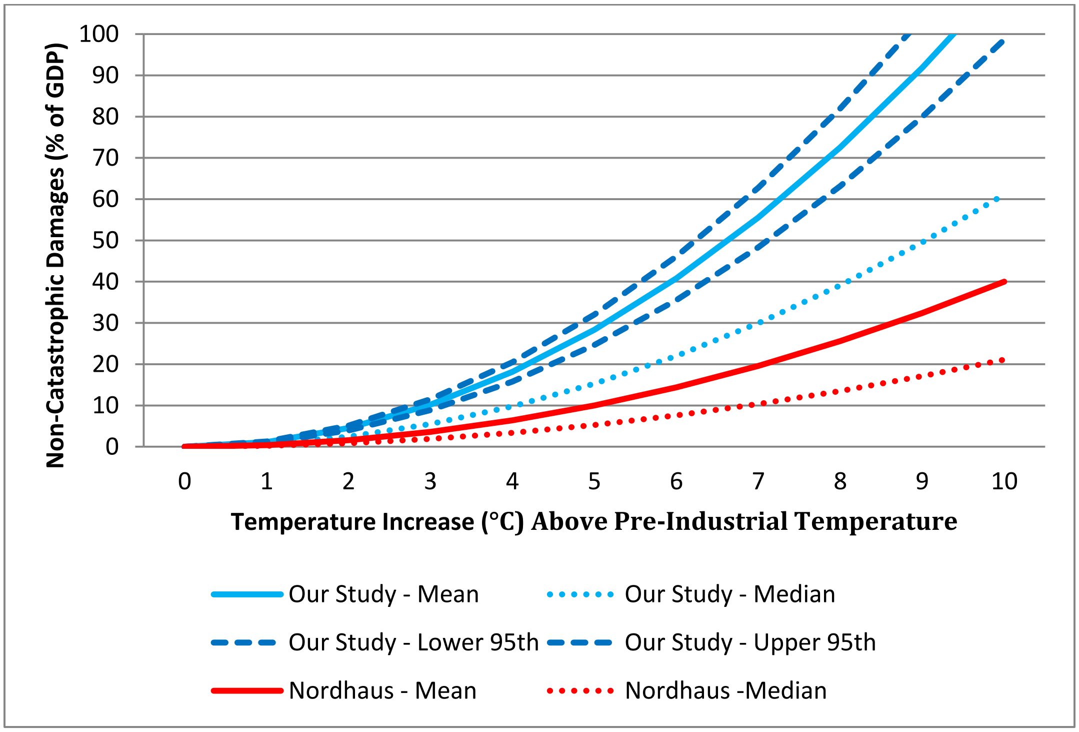


Figure 6b. Damage Functions Calibrated using Responses to Our Survey (i.e., questions 5 and 13) assuming initial benefits and/or a limit on GDP impacts of 100% of GDP

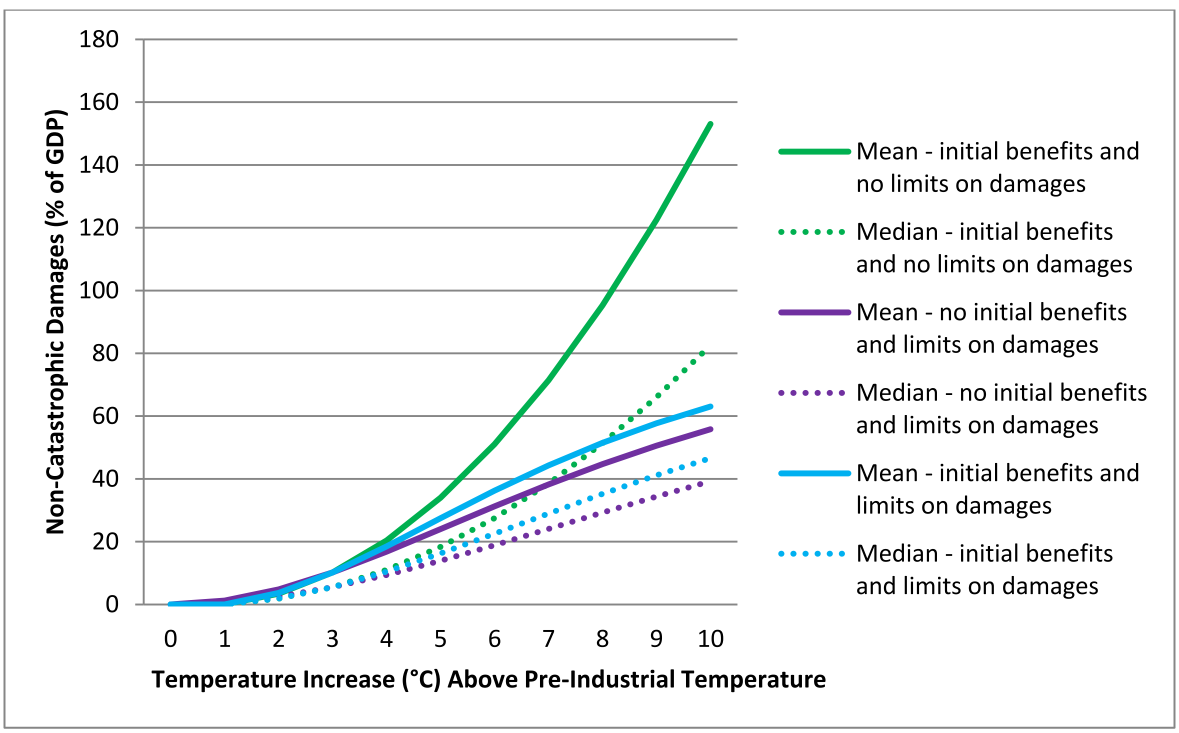
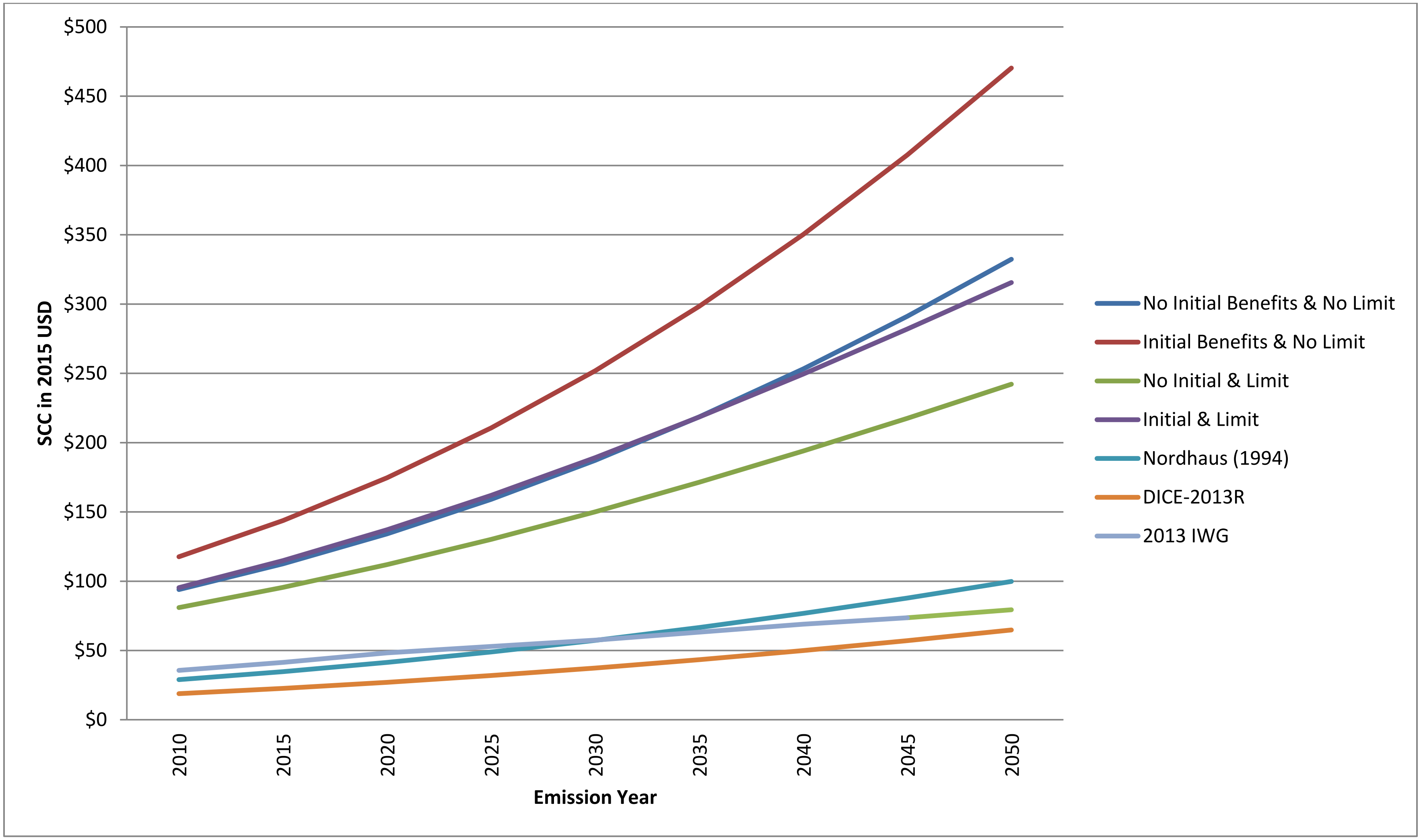
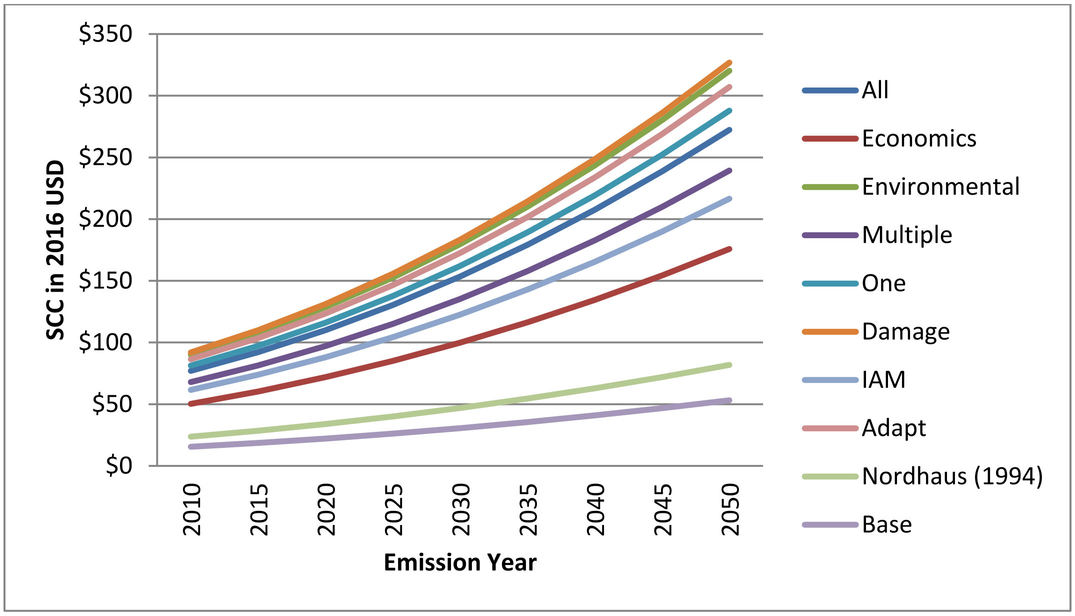


Figure 7. The SCC for Emissions from 2010 to 2050 in 2015 USD using Damage Functions Calibrated using All Responses to Our Survey (i.e., questions 5 and 13)



Figures 8a. The SCC for Emissions from 2010 to 2050 in 2016 USD using a Quadratic Damage Functions Assuming No Initial Climate Benefits (i.e., question 13), by group



Figures 8b. The SCC for Emissions from 2010 to 2050 in 2015 USD using a Quadratic Damage Functions Allowing for Initial Climate Benefits (i.e., questions 5 and 13), by group

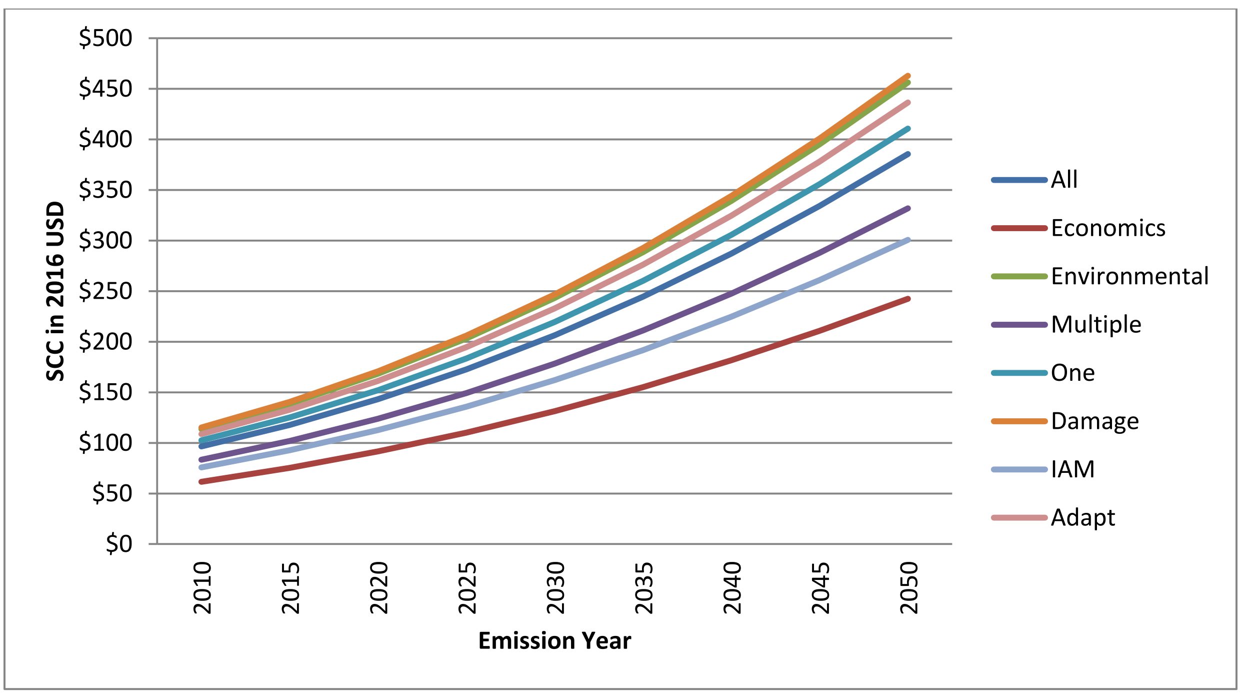


Figure 8c. The SCC for Emissions from 2010 to 2050 in 2015 USD using the DICE-2007 Damage Function (i.e., question 13), by group

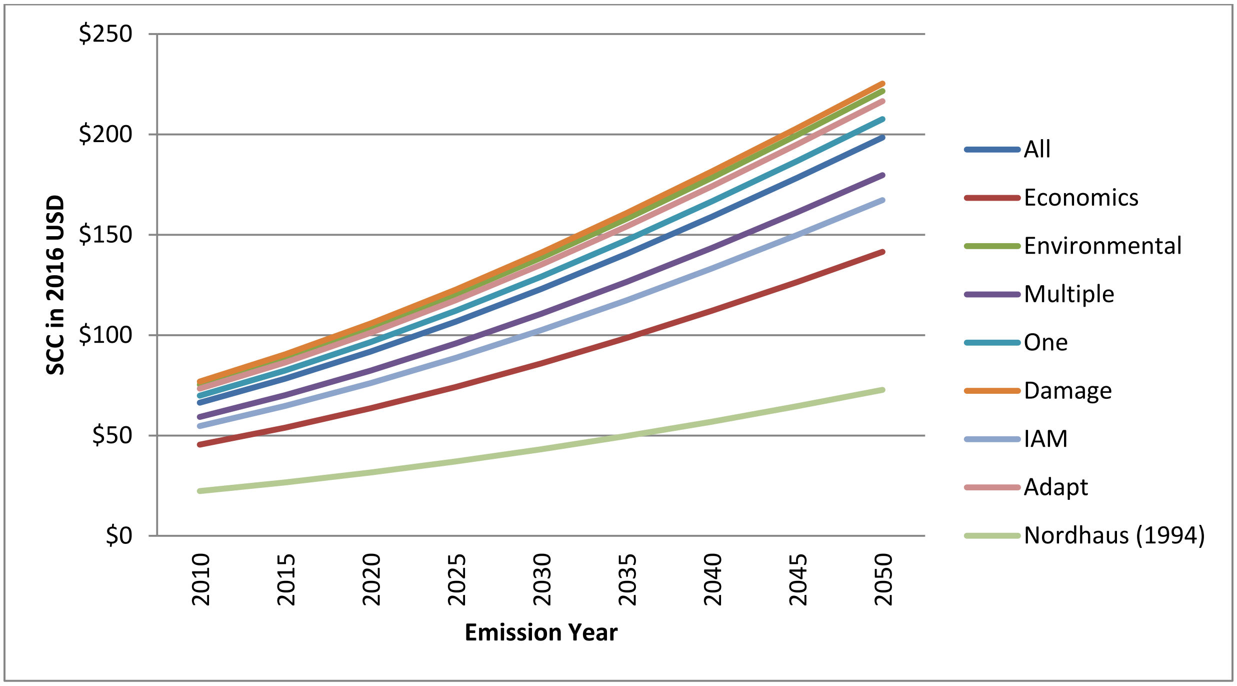


Figure 8d. The SCC for Emissions from 2010 to 2050 in 2015 USD using the DICE-1999 Damage Function (i.e., questions 5 and 13), by group

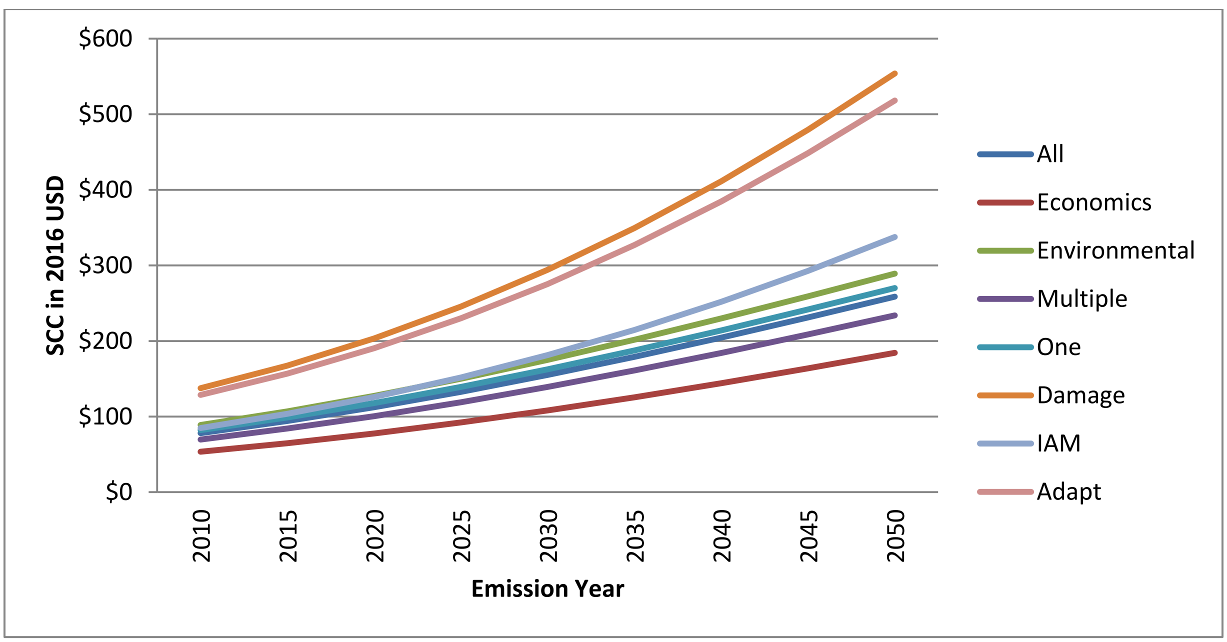


Figure 9. Deterministic Damage Functions Including Expected Catastrophic Impact (i.e., Risk Premium Calibration Method) using Responses to Our Survey (i.e., questions 13 and 15) and Nordhaus' Survey, assuming no initial benefits from climate change

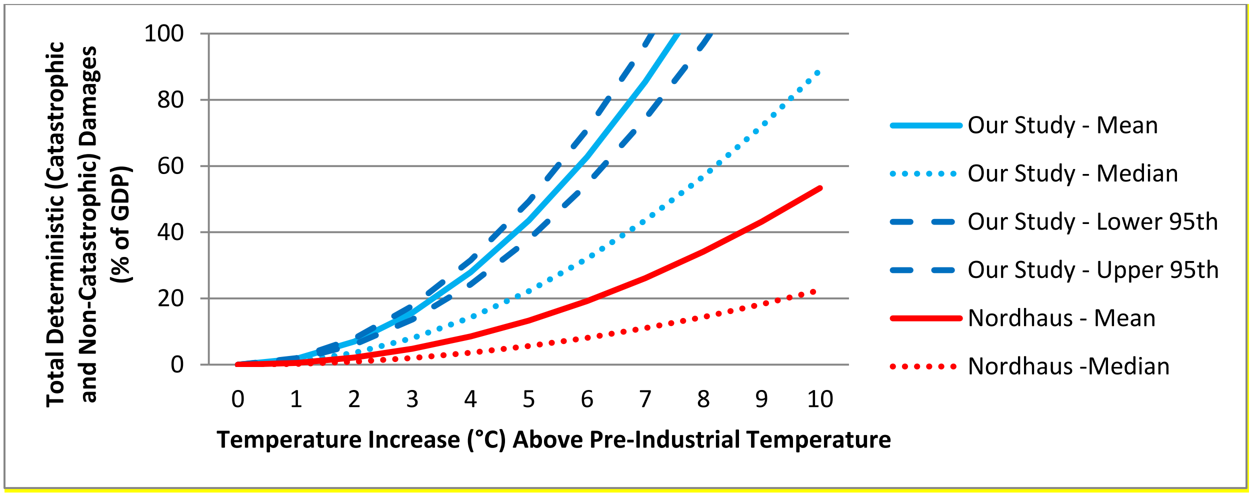


Figure 10a. Cumulative Weibull Distribution Calibrated Using the "Untrimmed-Group" Methodology, by Group

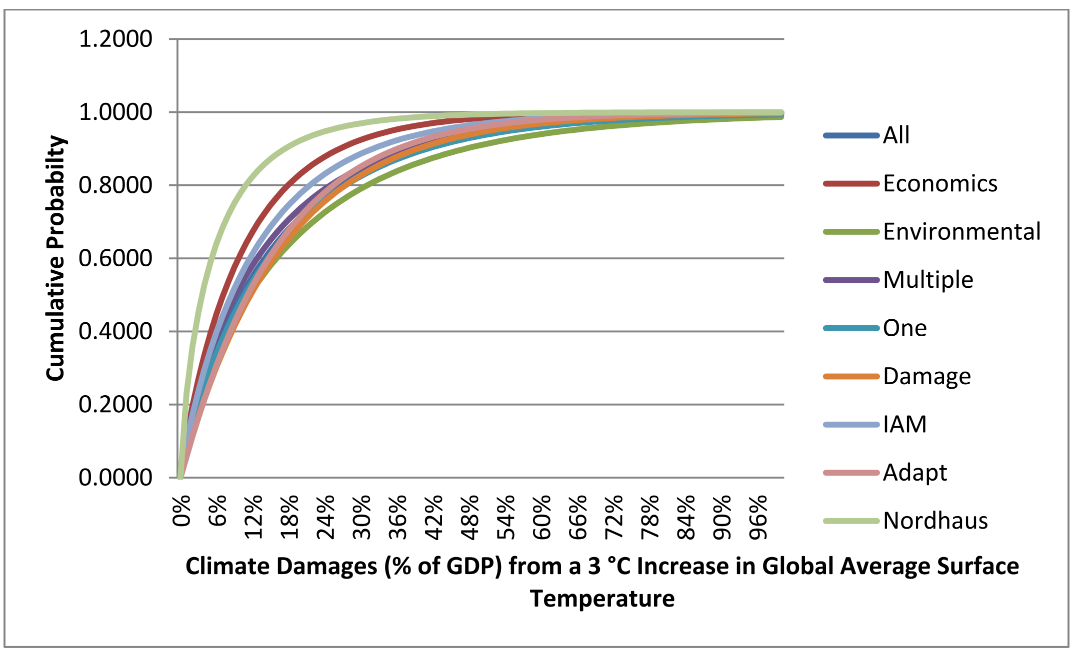


Figure 10b. The Cumulative Pareto Distribution Calibrated Using the "Untrimmed-Group" Methodology, by Group

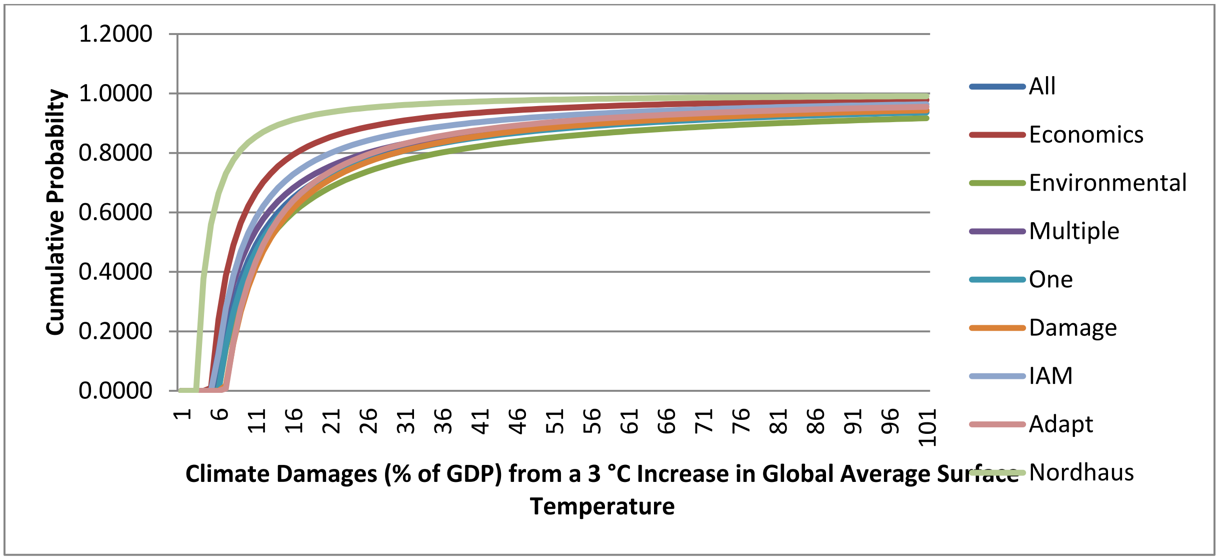


Figure 10c. The Cumulative Log-Normal Distribution Calibrated Using the "Untrimmed-Group" Methodology, by Group

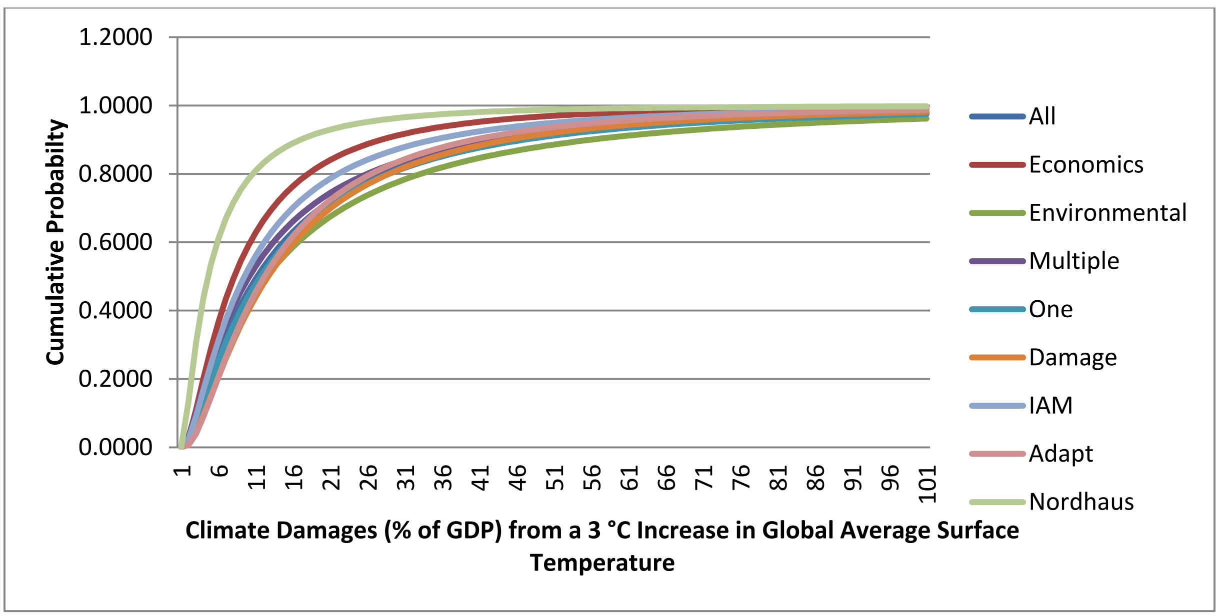


Figure 10d. The Cumulative Beta Distribution Calibrated Using the "Untrimmed-Group" Methodology, by Group

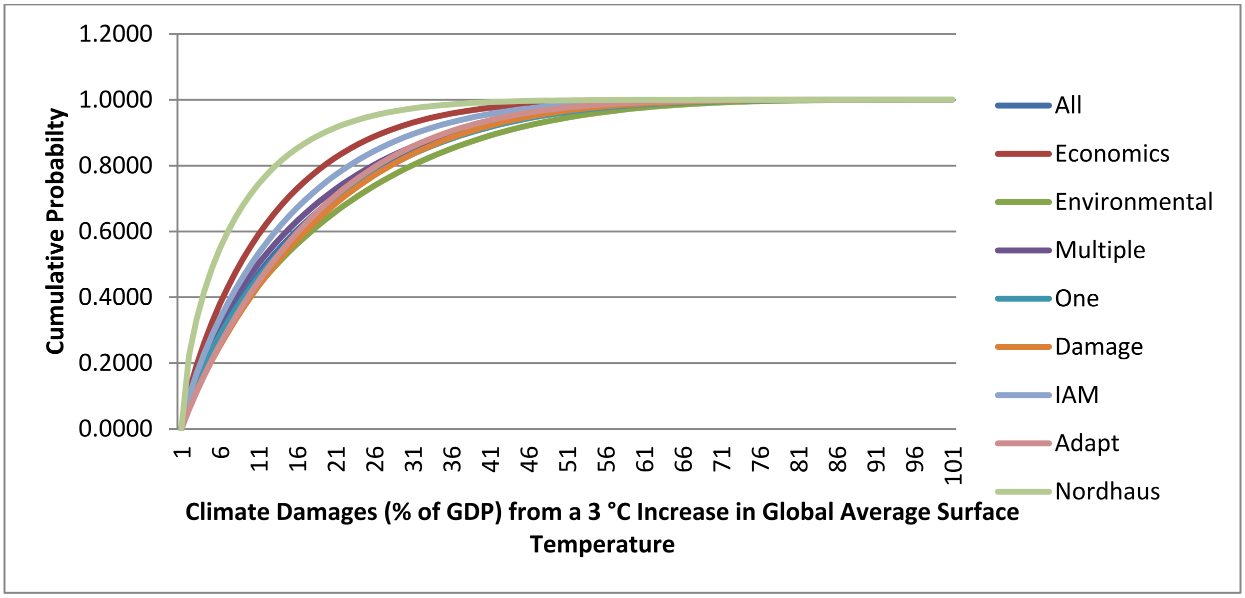


Figure 10e. The Cumulative Triangular Distribution Calibrated Using the "Untrimmed-Group" Methodology, by Group

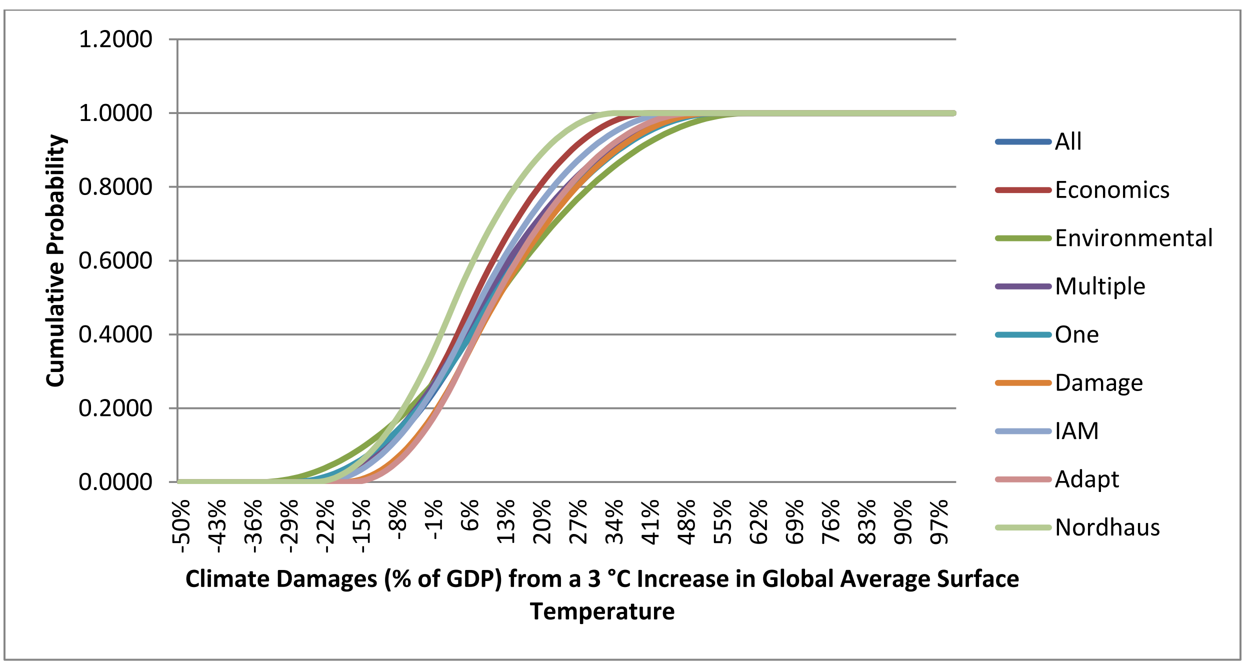


Figure 11a. Cumulative Weibull Distribution Calibrated Using the "Trimmed-individual" Methodology, by Group

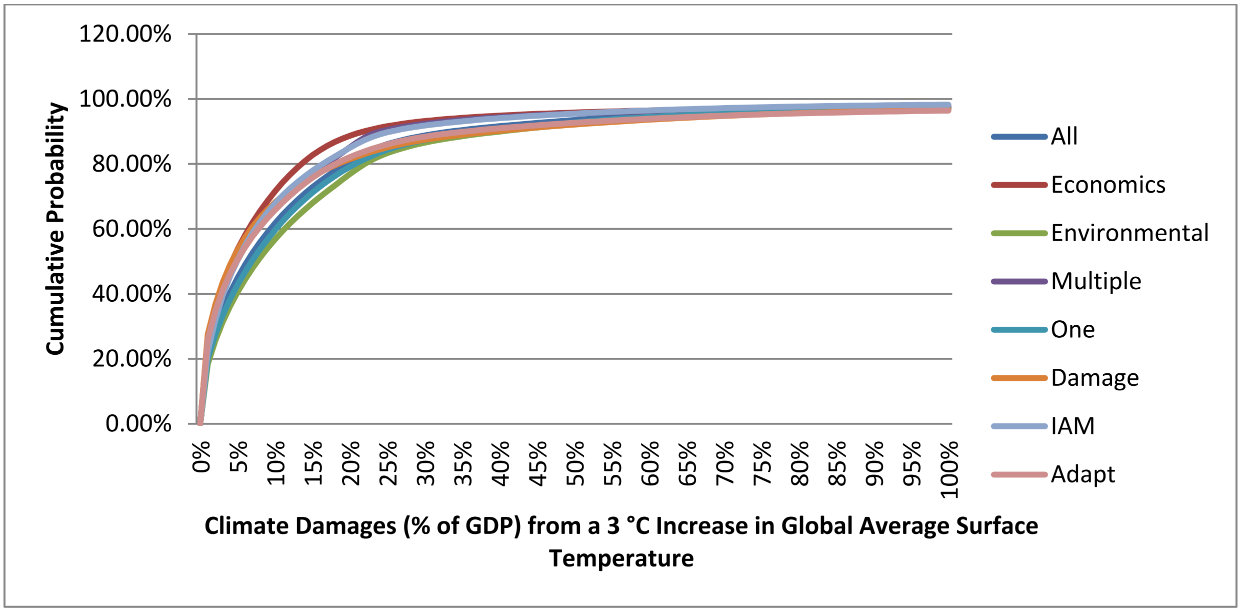


Figure 11b. The Cumulative Pareto Distribution Calibrated Using the "Trimmed-individual" Methodology, by Group

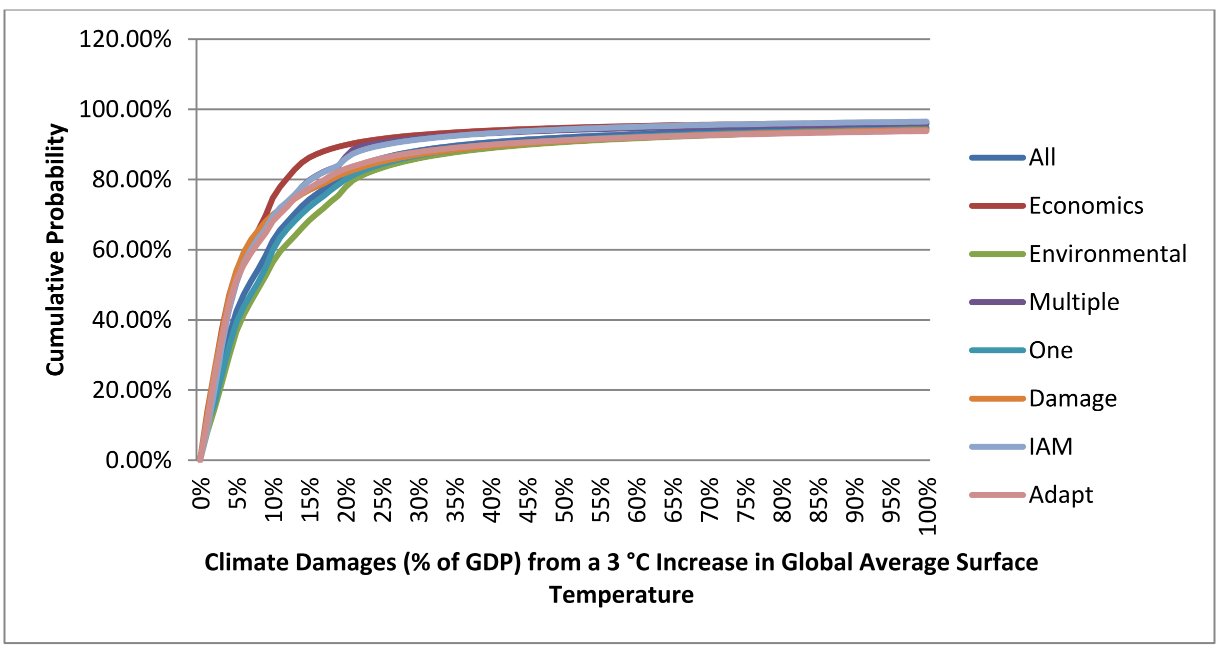


Figure 11c. The Cumulative Log-Normal Distribution Calibrated Using the "Trimmed-individual" Methodology, by Group

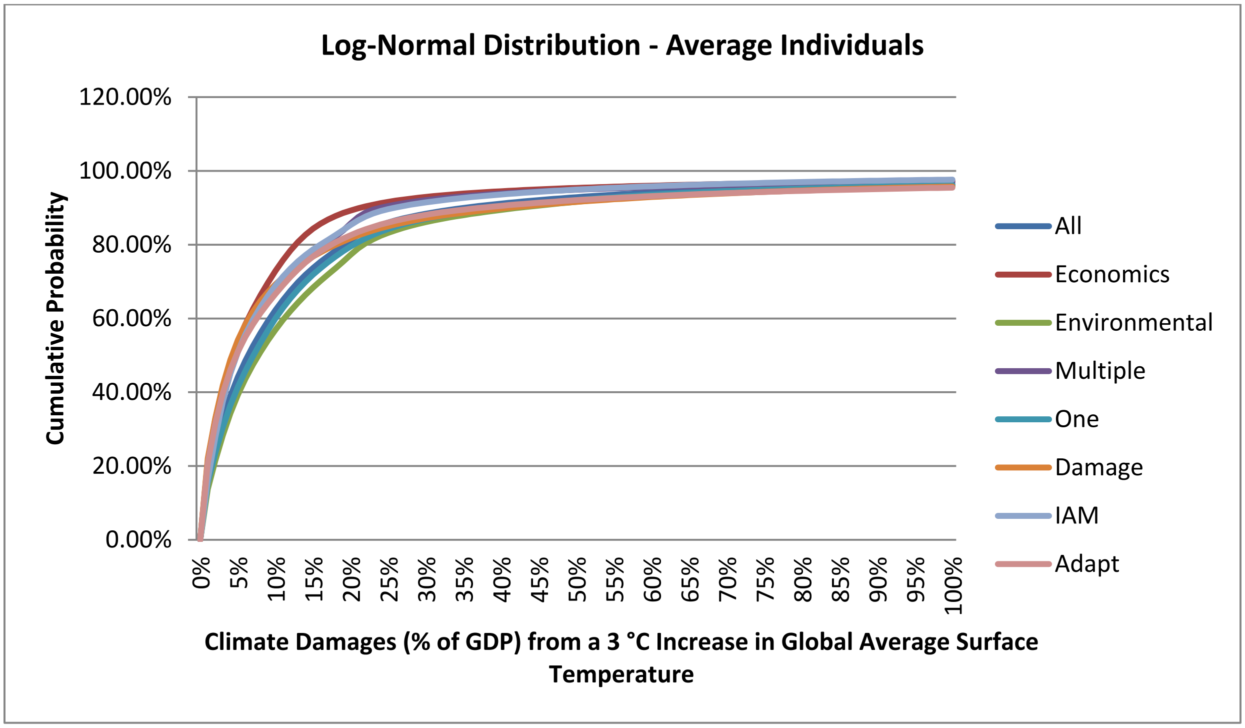


Figure 11d. The Cumulative Beta Distribution Calibrated Using the "Trimmed-individual" Methodology, by Group

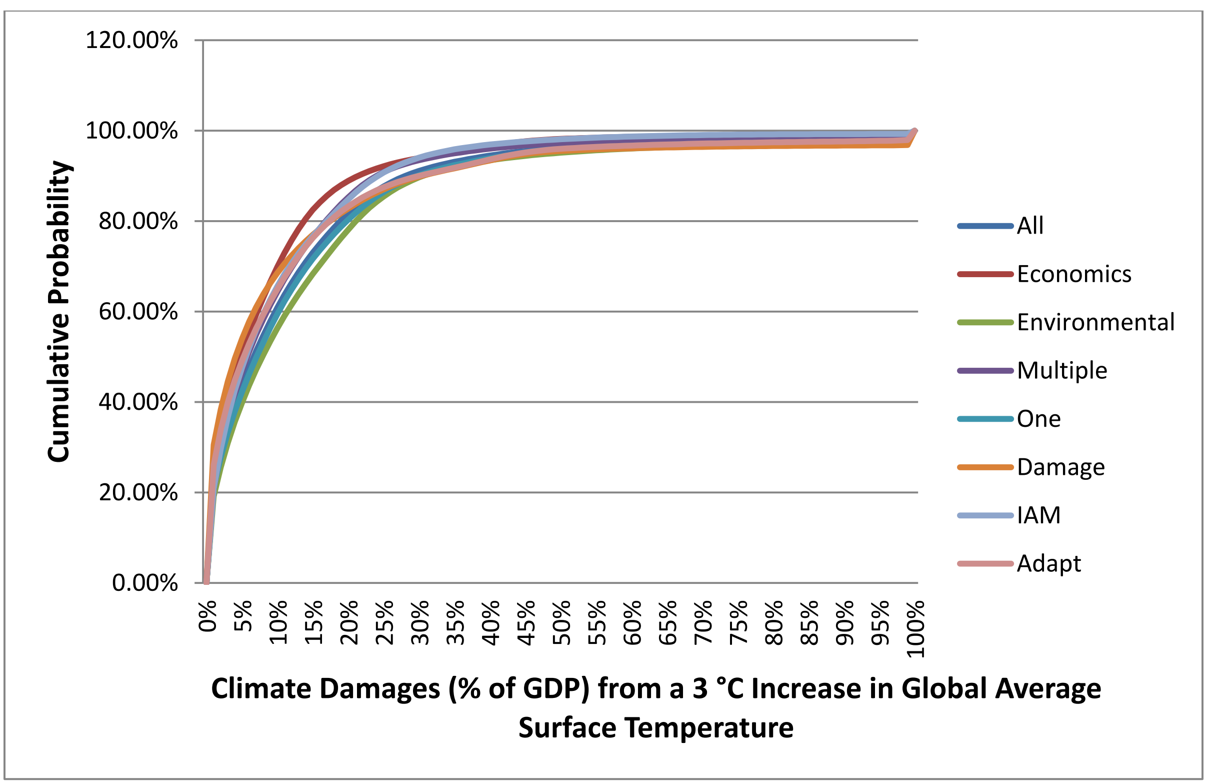


Figure 12a. Cumulative Weibull Distribution Calibrated Using All Observations, by Calibration Method

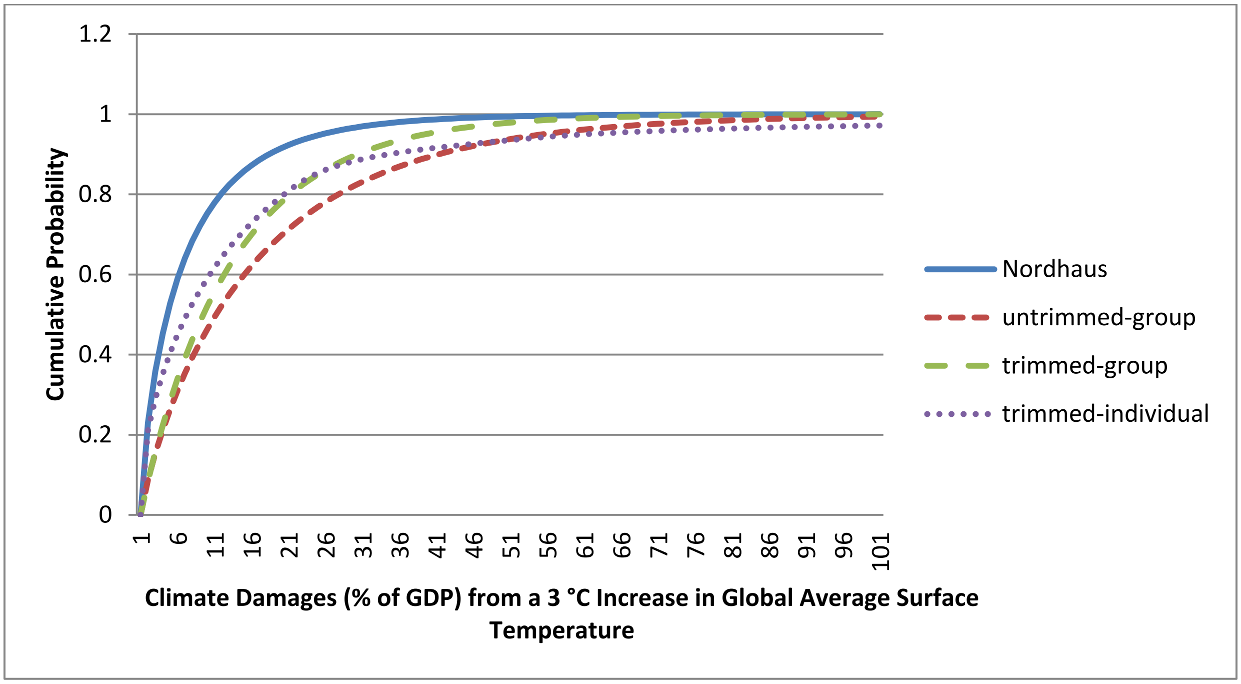


Figure 12b. The Cumulative Pareto Distribution Calibrated Using All Observations, by Calibration Method

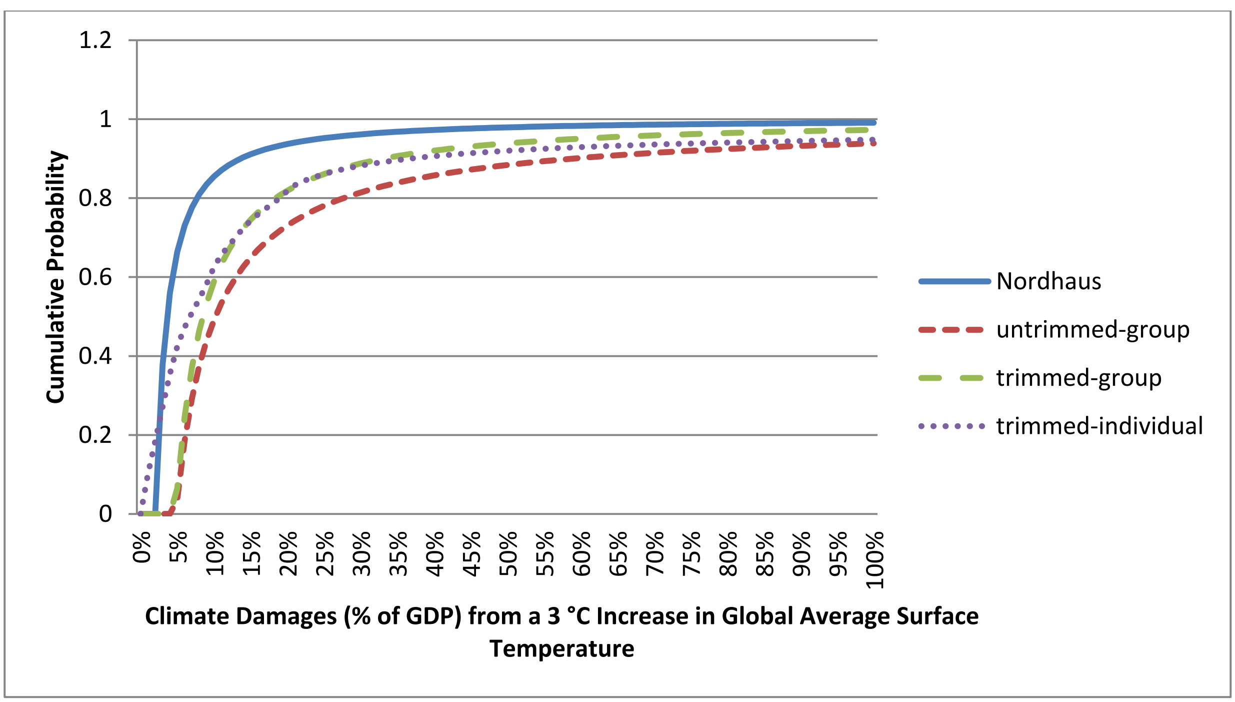


Figure 12c. The Cumulative Log-Normal Distribution Calibrated Using All Observations, by Calibration Method

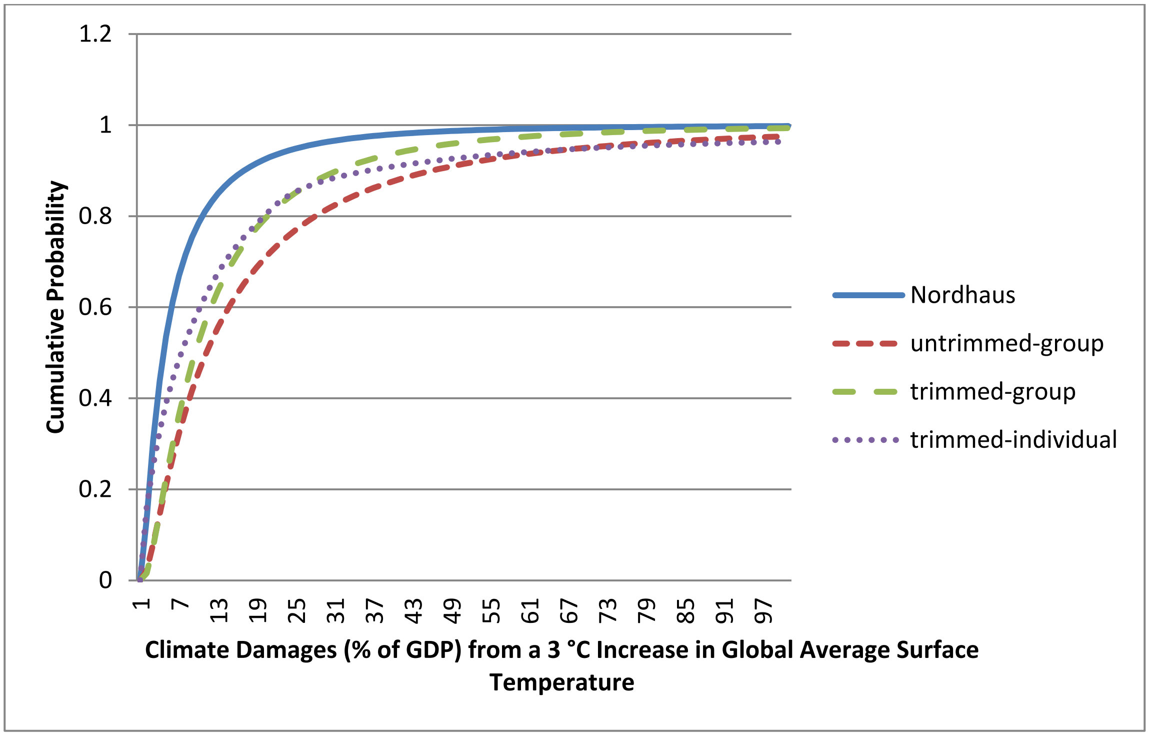


Figure 12d. The Cumulative Beta Distribution Calibrated Using All Observations, by Calibration Method

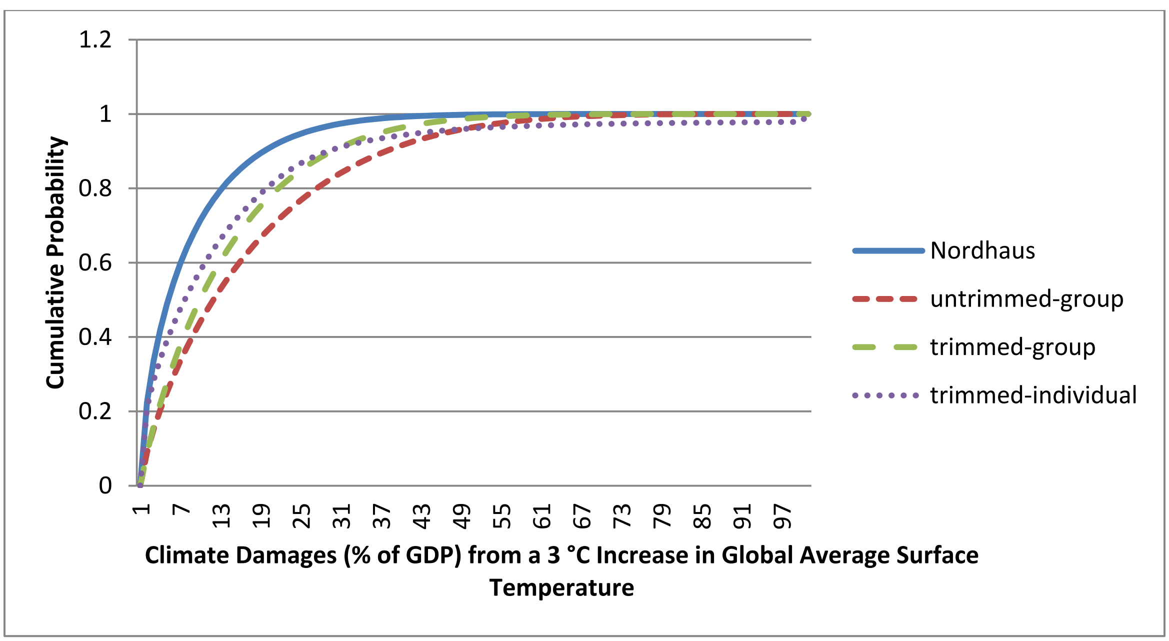


Figure 12e. The Cumulative Triangular Distribution Calibrated Using All Observations, by Calibration Method

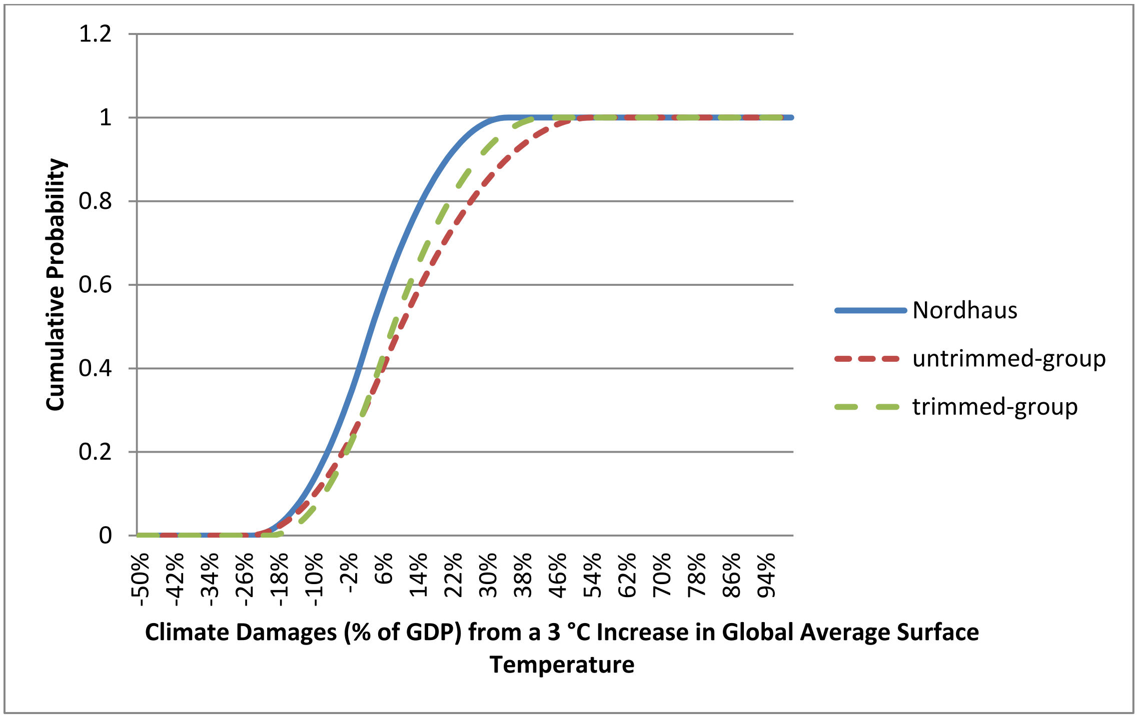


Figure 13a. Cumulative Distribution Calibrated Using the "Untrimmed-Group" Methodology and All Responses, by Distribution

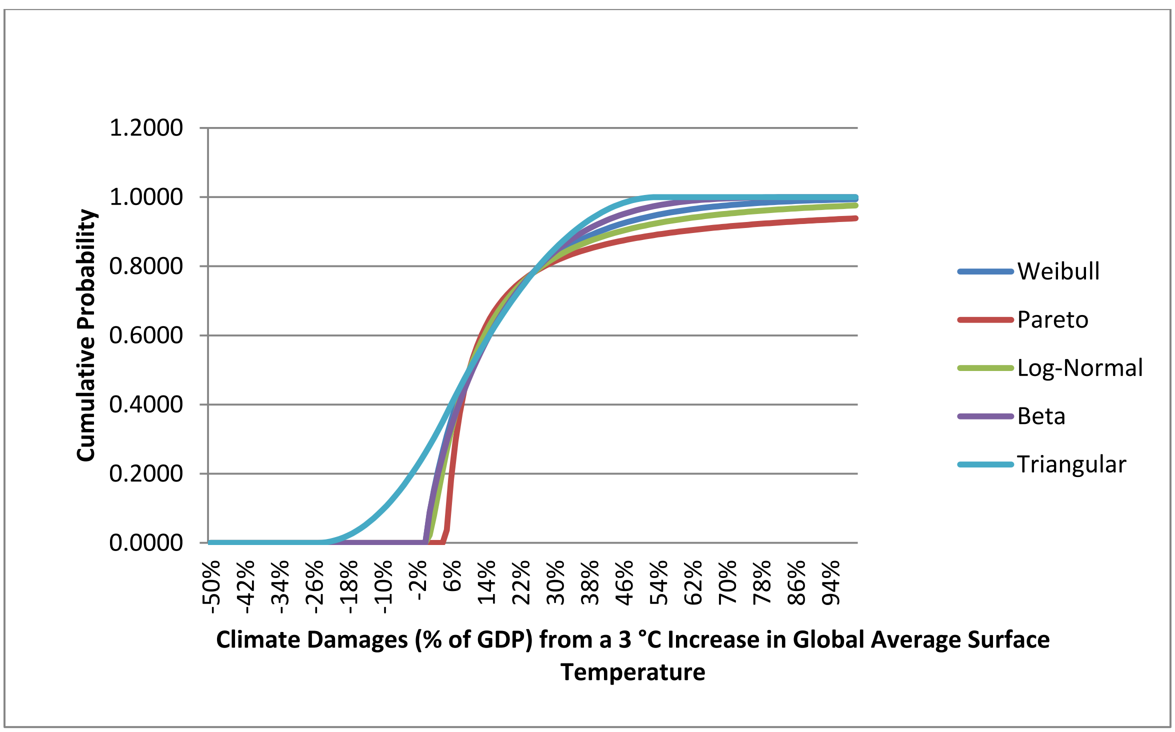


Figure 13b. Cumulative Distribution Calibrated Using the "Trimmed-Individual" Methodology and All Consistent Responses, by Distribution

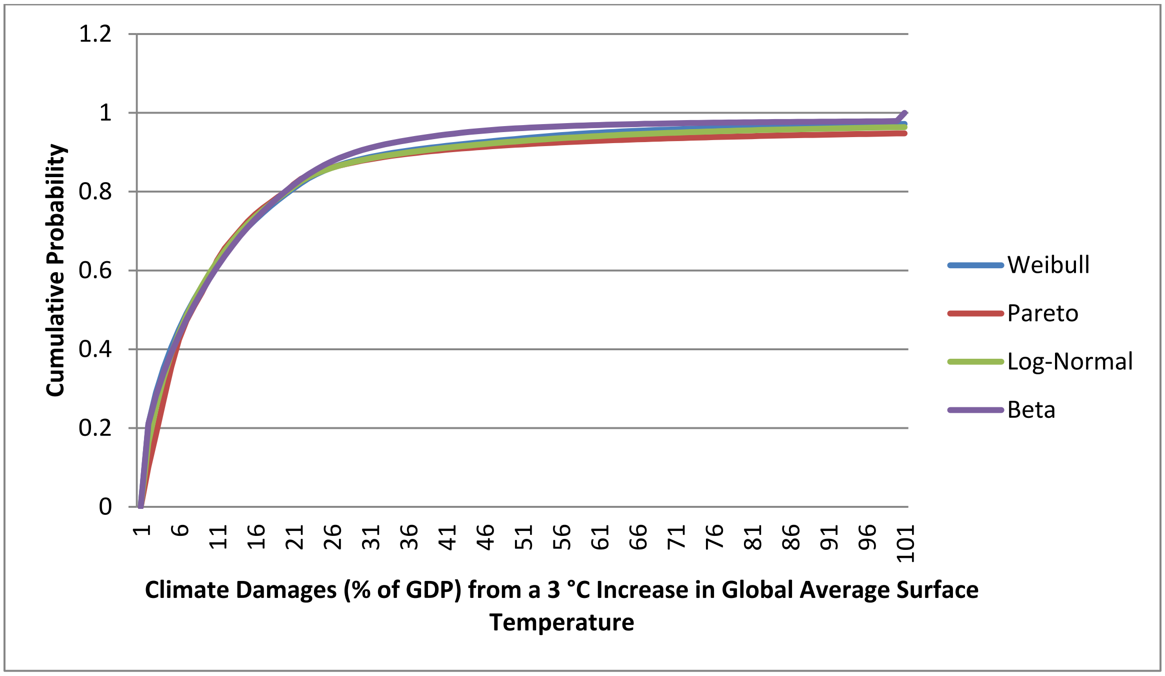


Figure 14a. The Social Cost of Carbon from 2010 to 2050 Using the Quadratic Damage Function Assuming No Initial Benefits from Climate Change, by Distribution

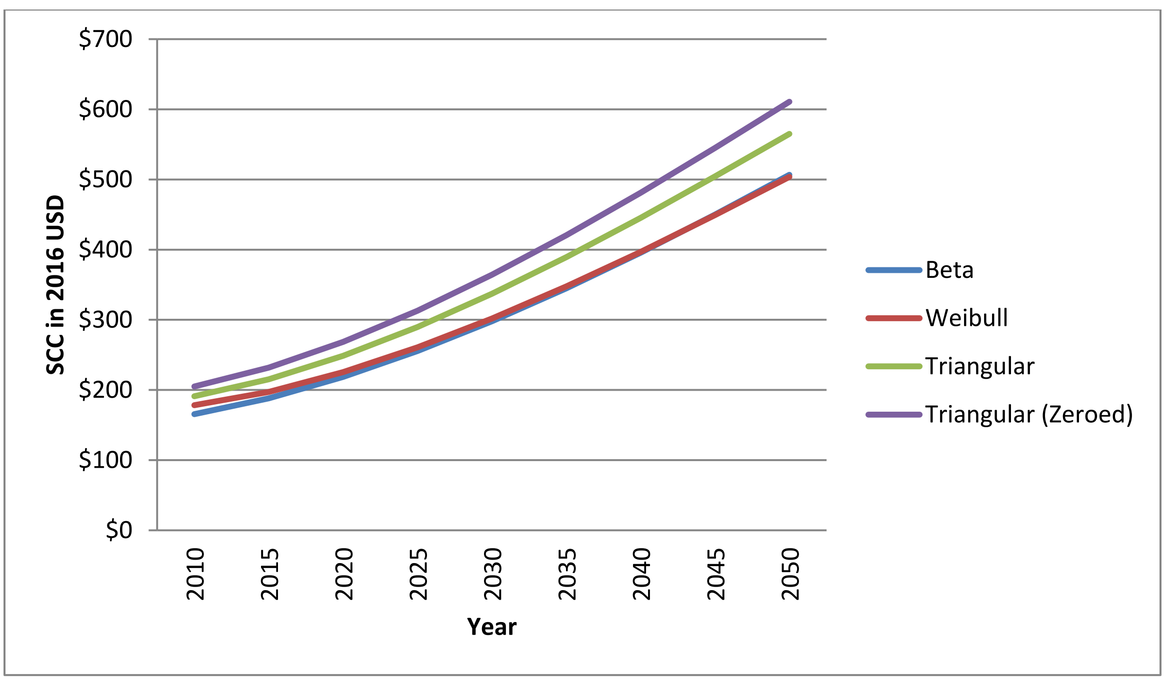


Figure 14b. The Social Cost of Carbon from 2010 to 2050 Using the Quadratic Damage Function Allowing for an Initial Benefits from Climate Change, by Distribution

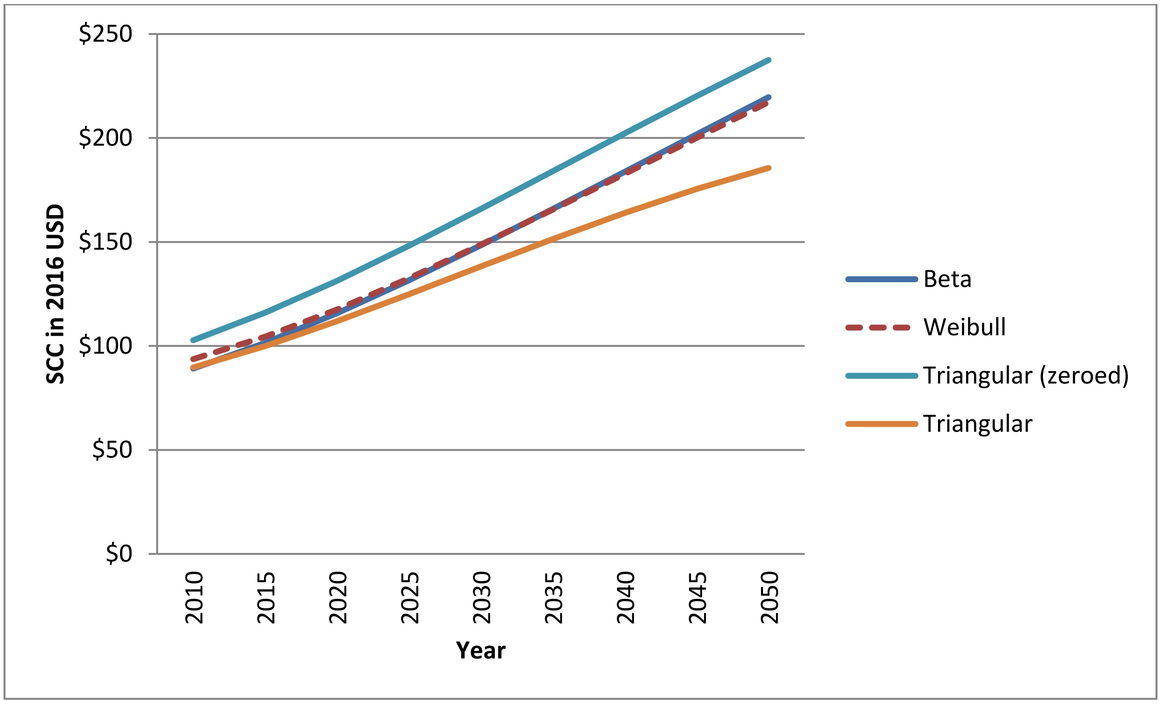


Figure 14c. The Social Cost of Carbon from 2010 to 2050 Using the DICE-2007 Damage Functional Form, by Distribution

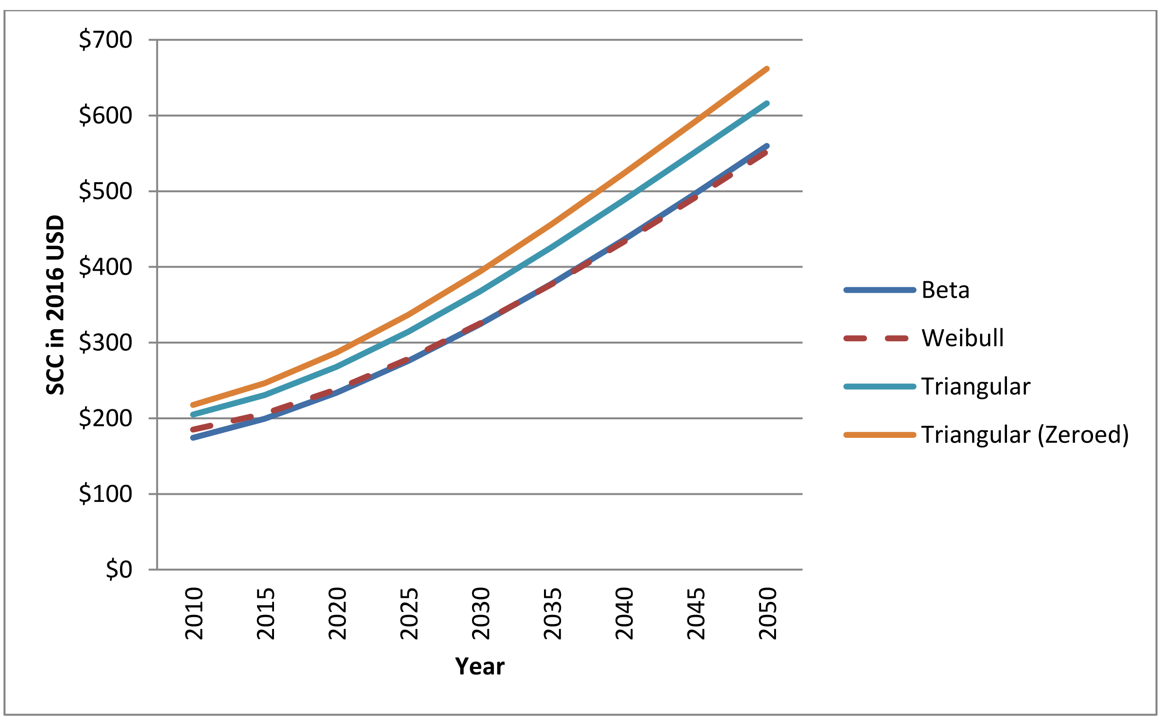


Figure 14d. The Social Cost of Carbon from 2010 to 2050 Using the DICE-1999 Damage Functional Form, by Distribution

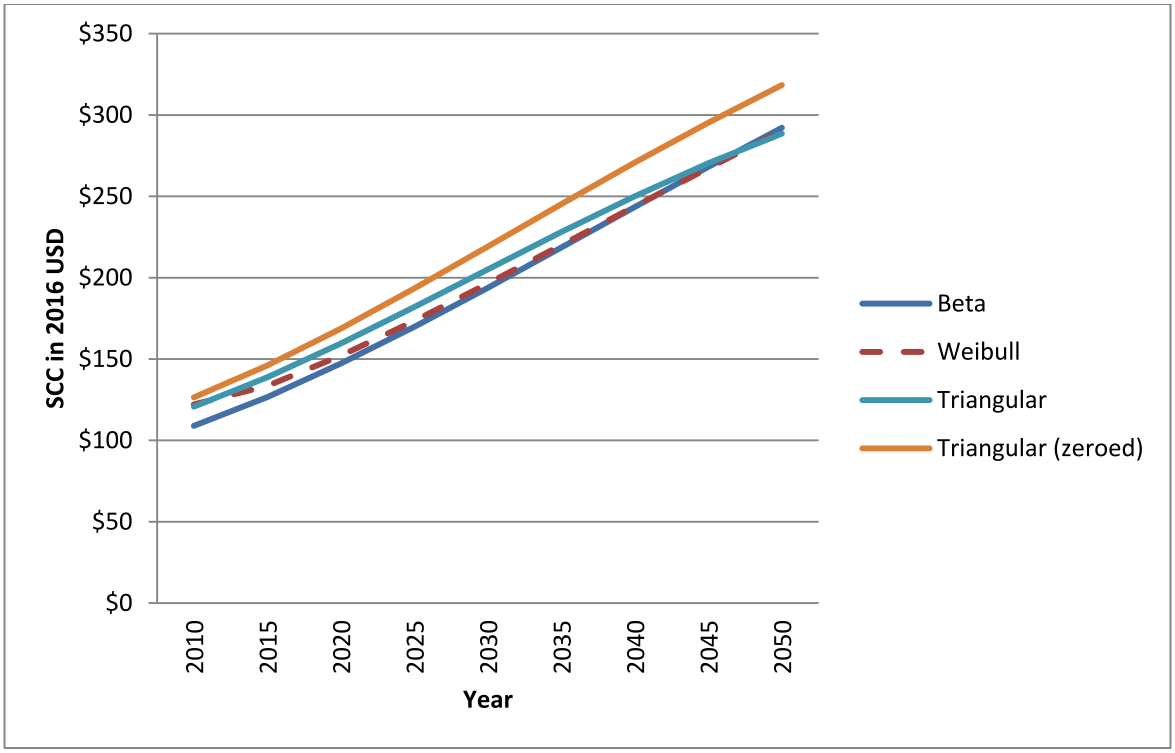


Figure 15a: Cumulative Distribution Functions of Discount Rates without Trimming

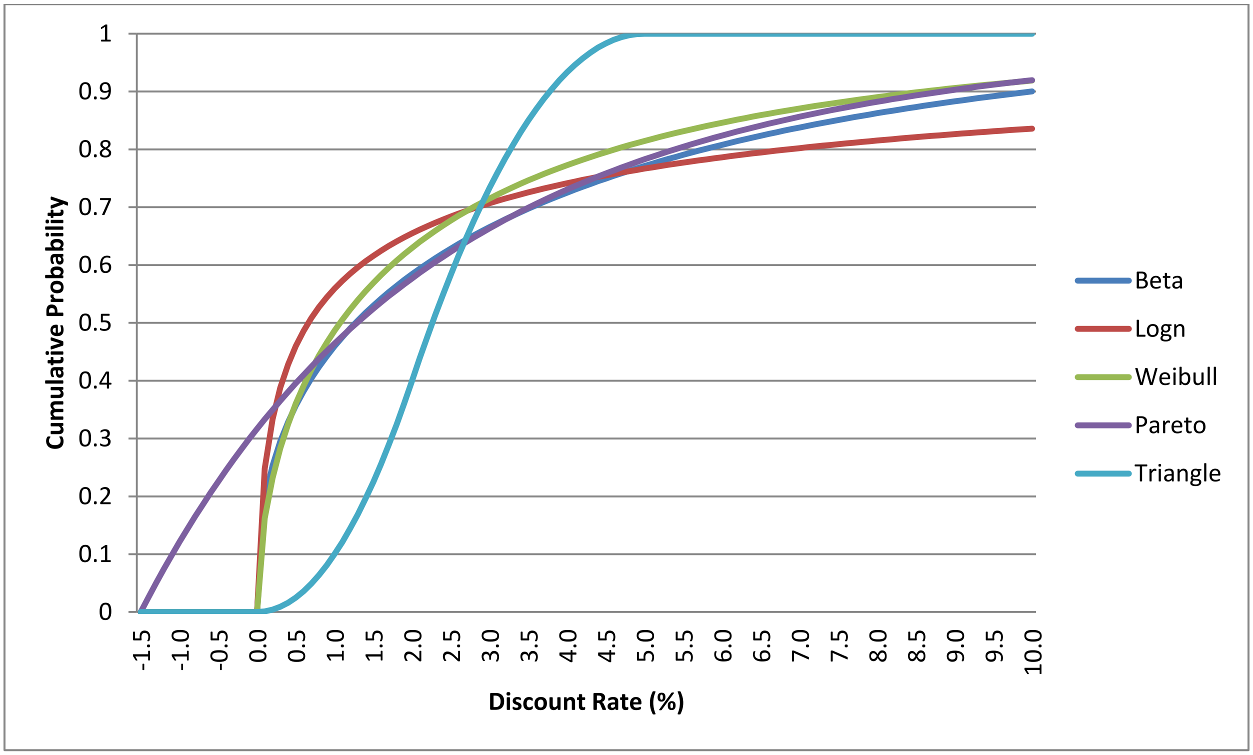


Figure 15b: Cumulative Distribution Functions of Discount Rates Trimming at 1th and 99th Percentile

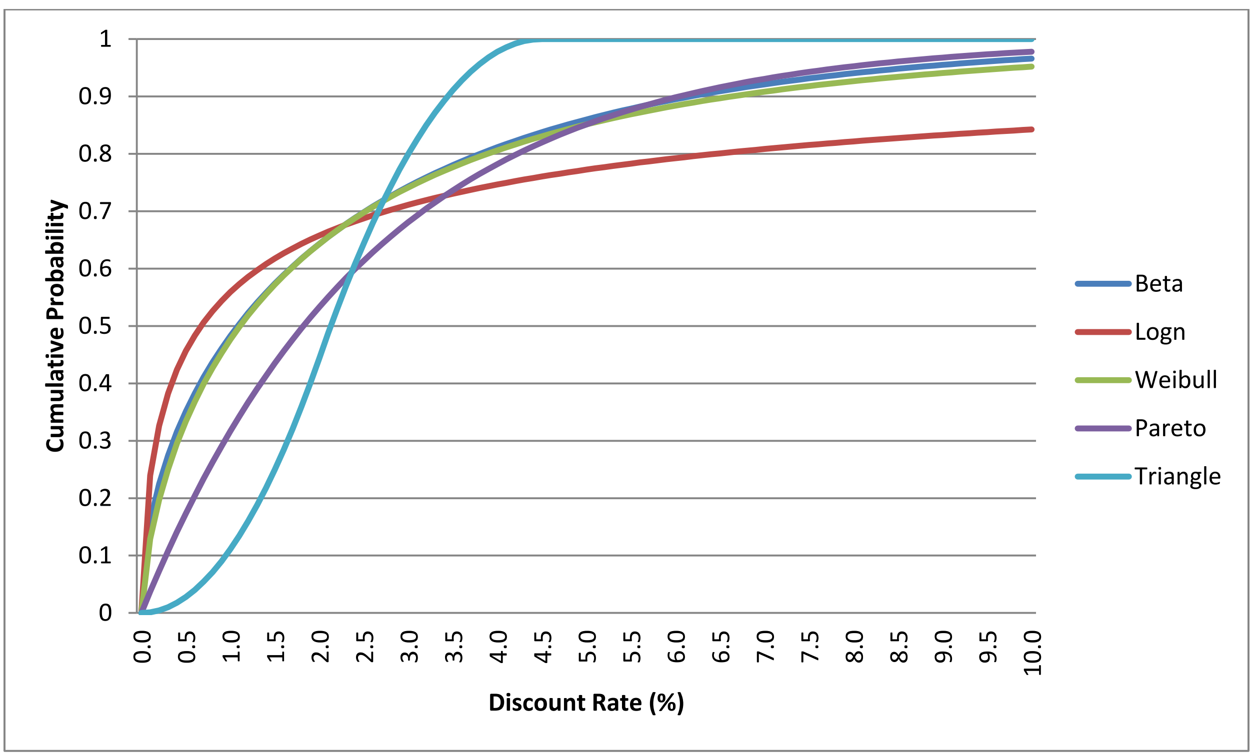
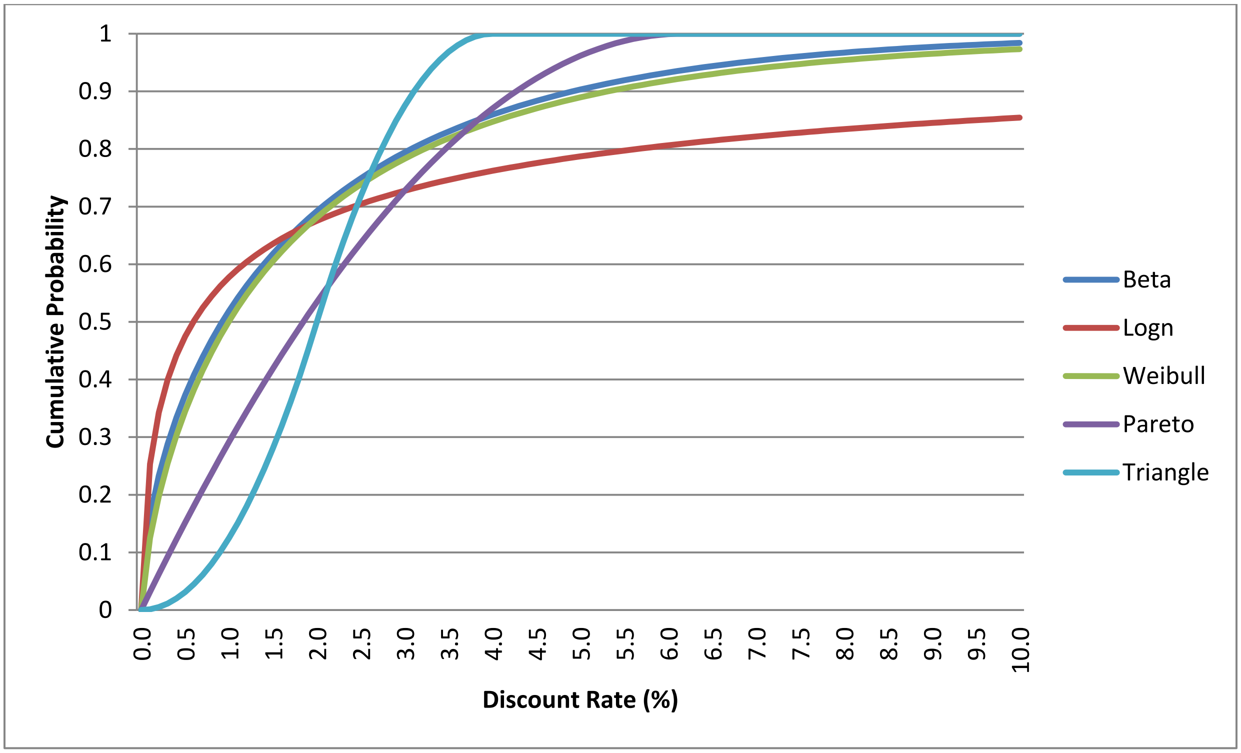


Figure 15c: Cumulative Distribution Functions of Discount Rates Trimming at 5th and 95th Percentile



[1] Chris Hope uses author discretion to combine various damage estimates, consisting mostly of earlier damage estimates of DICE and FUND (Howard, 2014).

[2] Specifically, Pindyck (2015) states that "the ad hoc equations that go into most IAMs are no more than reflections of the modeler's own 'expert' opinion…determining plausible outcomes and probabilities, and the emission reductions needed to avert these outcomes, would mean relying on 'expert' opinion. For an economist, this is not very satisfying…But remember that the inputs to IAMs (equations and parameter values) are already the result of 'expert' opinion; in this case the modeler is the 'expert'…If effect, we would use expert opinion to determine the inputs to a simple, transparent and easy-to-understand model."

[3] This is not really a calculation of the SCC. Instead, it should be interpreted as the average benefit of avoiding catastrophic impacts of climate change. In other words, the average social cost of carbon.

[4] The disadvantage of meta-analysis is specification error, small samples, and the inability to address omitted impacts in a transparent way. Furthermore, a meta-analysis of global impact estimates does not allow the IWG to break down impacts by region or sector, making this methodology primarily useful for IAMs with one aggregate damage function like DICE. Alternatively, a meta-analysis of regional and sector damage estimates is possible, though much more time intensive.

[5] In the latter case, using responses to Scenario A, Nordhaus calibrated a discrete distribution of the amount of climate damages that occurs for a 2.5 °C increase (i.e., the value climate damage coefficient in quantiles) to use in Monte Carlo simulation.

[6] Specifically, Weitzman (2001) asked: "Taking all relevant considerations into account, what real interest rate do you think should be used to discount over time the (expected) benefits and (expected) costs of projects being proposed to mitigate the possible effects of global climate change?"

[7] In addition to non-respondents, Weitzman (2001) also struck from the record any extreme responses, i.e., below 0.5% or above 12%, for which a reasonable justification was not supplied upon follow up.

[8] We used the response rate definition from the 2011 AAPOR's *Standard Definitions* (R6 on page 45). See AAPOR (2011).

[9] We chose the 1994 date for several reasons: this cutoff includes the vast majority of papers on climate change; it matched the cutoff used in the 2009 Institute for Policy Integrity survey; and it was 20 years before the beginning of this project.

[10] This broad definition of "climate change" is consistent with the approach used in Holladay et al, 2009.

[11] Our economics journal rankings came from Kalaitzidakis et al. (2003) and Kalaitzidakis et al. (2011). Our environmental economics journal rankings came from Rousseau (2008) and Rousseau et al. (2009).

[12] Our environmental journal rankings together revealed five publications with the highest ratings. One journal, the *Journal of Environmental Economics and Management (JEEM)*, appeared in both the economics and environmental economics rankings. We classified JEEM as an environmental economics journal.

[13] A small portion of the respondents in our sample are not Ph.D. economists (14%); a third of which are natural scientists, 16% are inter-disciplinary, and 14% are engineers. We chose to include all those who have authored a publication in a leading economics or environmental economics journal, even if their credentials are in another discipline, or they have not received a Ph.D. We believe this criterion was appropriate for demonstrating expertise in the economics of climate change, even if a small number of respondents are not professional economists.

[14] For example, the group that received the survey included authors who proposed an economic model that predicted a potentially positive effect on global agriculture from climate change, and others who subsequently criticized that model and approach.

[15] We launched our survey on April 30, 2015 and closed it 18 days later.

[16] Though it is unclear from the academic literature what an "acceptable" response rate entails (Anderson et al., 2011), our general response rate was roughly in line with the average for online surveys in recent periods. Our overall effective response rate (RR6) is slightly lower than the 37% average found across 31 studies summarized in Sheehan (2001). However, there is strong evidence that e-mail survey response rates have been declining over time (Sheehan, 2001; Fan and Yan, 2010). For example, Sheehan's (2001) response rates over the 1998 and 1999 period average to 31%; these numbers are similar to our response rates in this survey. Similarly, Manfreda et al.

(2008) find that the average response rate for 45 web survey was 11% (Fan and Yan, 2010). With regards to these studies, our response rates are above or close to average.

[17] In addition to helping us understand our respondent base (given that all responses were anonymous), this question allowed us to disaggregate responses by group—for instance, we could see if those who had published on the economic risks from climate change viewed those risks differently than other respondents. This analysis is available in Howard and Sylvan (2015).

[18] These nine respondents published papers that met our criteria for contributing to the discussion on climate economics. However, based on their responses to this question, these authors apparently did not view their papers as publications on climate change. Nevertheless, they completed the survey and we chose to include them in our sample, given that they met our definition for subject matter expertise.

[19] We chose this scenario both because it approximates a business-as-usual emissions path and because it matches the main scenario from Nordhaus' 1994 survey, allowing us to compare our data directly. As a point of reference, the newest version of FUND predicts a 3.3°C increase by 2090 and a 3°C increase by 2083. DICE-2013 predicts a 3.1°C increase by 2080 and 3.5 °C by 2090. The scenario we used is also similar to the A1B scenario from IPCC (2007) and assumes a bit more emissions mitigation than the A2 scenario. However, the temperature change predicted in our scenario is lower than the latest IPCC (2013, page 90) BAU prediction of 3.7 °C by 2100 under the RCP 8.5 scenario. Given that damages tend to be higher for temperature increases that occur earlier (Nordhaus, 1994), our damage estimates represent a lower bound relative to these alternative scenarios.

[20] Policymakers and journalists, including those who advocate for climate change policies, often use rhetoric and examples that focus almost exclusively on how climate change will affect future generations. Some examples can be found in Stecker (2013) and Walsh (2013).

[21] To calculate the mean impact year, we assign the central year in a particular bin (i.e., "by 2025" implies a central value of 2020 given "already having an impact" implies an impact by 2015) as its value. We then drop the seven responses that believe no negative impact will ever occur, and then assign 1982.5 (central value between 1950 and 2015) and 2150 as the values for the "climate change is already having a negative effect on the global economy" and "After 2100" bins, respectively.

[22] Schauer (1995) used the following scenario: a 2.5 degree Celsius increase relative to pre-industrial temperature.

[23] See Howard (2014) and Howard and Sterner (2016) for additional details.

[24] The variance was 665.6%, resulting in a wide 90th percentile of 0.8% and 60%, respectively. These results do not differ between the 95th and 99th percentiles.

[25] Nordhaus (1994) found mean and median probabilities of 0.5% and 4.8% for a 25% drop in GDP. Our results are not directly comparable with Nordhaus because (1) we ask for a probability of a 25% or greater loss in GDP instead of a 25% decline specifically, and (2) we analyze a large group of economic experts, while he analyzed a select group of economists, other social scientists, and natural scientists.

[26] Unlike earlier versions of DICE, the DICE-2013 damage function captures only non-catastrophic climate impacts.

[27] DICE-2013R assumes that the 2015 social cost of carbon equals the value of consumption necessary to offset the social welfare loss from an additional unit of emissions in 2015. Thus, it is equal to marginal social welfare with respect to emission $\left(\frac{\partial U}{\partial E}\right)$ divided by marginal social welfare with response to consumption $\left(\frac{\partial U}{\partial C}\right)$, such that $SCC = \left(\frac{\partial U}{\partial E} / \frac{\partial U}{\partial C}\right) = \frac{\partial C}{\partial E}|_{U=\bar{U}}$ where U is the social welfare function, E is the amount of carbon emissions, C is per capita consumption in dollar terms, and $\bar{U}$ is the level of social welfare before adding the marginal emission.

[28] We solve two simultaneous equations: $0 = \alpha_1 + \alpha_2$ and $D = 3\alpha_1 + 9\alpha_2$ where α_1 and α_2 are the coefficients corresponding to temperature and temperature squared and D is the impact estimates drawn from responses to question 13 of our survey.

[29] Due to our assumed quadratic functional form, allowing for initial benefits has two impacts on the social cost of carbon: (1) the SCC decreases as an additional unit of emissions allows climate benefits to be enjoyed sooner, and (2) the SCC decreases as the increasing portion of the damage function (which is steeper than when we exclude initial benefits) is also reached earlier. Given our parameter values, the latter effect dominates.

[30] Given that we asked in question 15 for the probability of a 25% or greater GDP decline, a higher impact could have been chosen. However, we chose 25% in order to estimate a lower bound on catastrophic impacts and to correspond to the calibration method used in Nordhaus and Boyer (1999).

[31] The first four distributions are chosen because they are characterized by two parameters and allow for a positive skew as observed in the responses to questions 13 and 15; see Figures 3 and 4. The triangular distribution is chosen because it is a popular distribution in the IAM literature, and it both allows initial benefits from climate change and it limits impacts to a maximum amount.

[32] Unlike the other distributions, the triangular distribution has three parameters: the minimum impact *a*, the maximum impact *b*, and the mode of the distribution *c*. Using the average responses to questions 13 and 15, only allows us to calibrate the value of *b* and a relationship between *a* and *c*. We calibrate the remaining two parameters by assuming that the median response to question 13 equals *c*.

[33] Numerically, this is necessary because the domains of these distributions are restricted to greater than zero.

[34] For example, an inconsistent responses would be an individual who states that the most likely outcome for a 3 °C by 2090 is a 10% decline in GDP (response to question 13) and who states that there is a 60% change of a 25% or more decline in GDP (response to question 13). The inconsistency arises because both of these responses cannot be simultaneously true.

[35]Inconsistent responses are most common for economic experts publishing in environmental economic journals and those identified using multiple publications. Alternatively, those publishing in economics journals and on integrated assessment models had lower inconsistent response rates.

[36] Because the triangular distribution is characterized by three parameters, it cannot be calibrated for each individual.

[37] In Figures 12a to 12e, we also employed the first methodology using only consistent responses – i.e., a trimmed-group methodology. For all impact levels, the trimmed-group distribution assigns a lower cumulative probability to each impact level; this occurs because experts that provided inconsistent results tended to provide more pessimistic results as well. However, consistent pessimistic survey responses have greater weight when averaging across individuals implying higher probabilities of cataclysmic impacts (i.e., extreme high GDP damages) for distributions corresponding to the "trimmed-individual" methodology.

[38] Alternative assumptions are possible, including that the initial benefits match the non-catastrophic impacts estimated in the previous sub-section.

[39] In cases where we do not limit the damages, the DICE model still never reaches 100% of GDP.

[40] For the Pareto and log-normal distributions calibrated using untrimmed data and all distributions calibrated using trimmed data, the social cost of carbon followed a U-shape over time. This may partially result from our failure to include constraints requiring a minimum level of consumption.

[41] For the triangular distribution, we can allow for a quadratic benefit curve where a random draw implies initial benefits from climate change because its domain is not limited like the other distributions. Therefore, we calculate the SCC using the triangular distribution assuming that the climate impacts must be damages – aka "triangular (zeroed)" - and assuming that climate change can have a positive impact for all temperature increases – aka "triangular".

[42] Because the Ramsey discount rate increases with GDP per capita and most IAMs assume that per capita GDP declines over time, IAMs implicitly assume a declining discount rate over time. Only IAMs that assume a risk neutral central planner (i.e., a risk aversion parameter of zero) avoid this equivalence.

[43] This assumes the definition of expertise used in our survey: all those who have published an article related to climate change in a highly ranked, peer-reviewed economics or environmental economics journal

[44] If the an analyst adopts the normative perspective to discount rates, economists have demonstrated that an extended Ramsey rule arises under uncertainty implying a declining discount rate when (1) the growth rate of per capita consumption is stochastic, and (2) consumption shocks are positively correlated over time (or their mean or variances are uncertain) (Arrow et al. (2013); Arrow et al. (2014); Gollier and Hammitt, 2014; Cropper et al. (2014)). While a constant adjustment downwards (known as the precautionary effect) – that captures a preference for consumption smoothing – can be theoretically correct when growth rates are independent and identically distributed (Cropper et al., 2014), empirical evidence supports the two above assumptions for the United States implying a declining discount rate (Cropper et al., 2014, Arrow et al., 2014; IPCC, 2014).

[45] It is well known in the finance literature due to the equity-premium and the risk-free rate puzzles (Ackerman and Stanton, 2013; Traeger, 2014a; Traeger, 2014b) that current derivation of the Ramsey equation implies an overly simplistic social welfare function with regards to an identical aversion to current risk (Arrow-Pratt relative risk),

intra-generational inequality (distributive society within time periods), and inter-generational inequality (distributive society between periods).

[46] In the case of discount rates where normative and positive approaches currently differ, such a convergence may not happen due to differing subjective opinions (Freeman and Groom, 2001). Potentially, the introduction of more complex and realistic Ramsey equations from the finance literature may result in convergence.

[47] However, in climate change, we are dealing with a phenomenon is still unfolding, making the derivation of a seed variable difficult.

[48] We utilize our survey results with respect to damages to calibrate the DICE-2013R damage function – a model that assumes that climate change decreases consumption levels without affecting economic growth rates. Thus, by utilizing the DICE model, we implicitly assume that climate change will not have a long-term negative impact on the growth rate of the global economy. However, this assumption contradicts an additional finding from our survey (corresponding to question 6): 78% of respondents believed that climate change is likely to have a long-term negative impact on the growth rate of the global economy, compared to 5% who thought this unlikely. These responses are consistent with empirical literature identifying such an impact (Bansal and Ochoa, 2011; Dell et al., 2012; Burke et al., 2015). Given the compounding impact of growth, ignoring its effects could greatly underestimate the SCC (Dietz and Stern, 2015; Moyer et al., 2014; Moore and Diaz, 2015; Roson and van der Mensbrugghe, 2010)

[49] Uncertainty over the climate sensitivity parameter is not driving these catastrophic impacts, given that we can hold the temperature constant in our scenario.

Appendix A
List of Journals Used in Survey

Economics Journals
American Economic Review
Econometric Theory
Econometrica
Economic Journal
Economic Theory
Economics Letters
European Economic Review
Games and Economic Behavior
International Economic Review
Journal of Applied Econometrics
Journal of Business and Economic Statistics
Journal of Development Economics
Journal of Econometrics
Journal of Economic Dynamics and Control
Journal of Economic Literature
Journal of Economic Theory
Journal of Financial Economics
Journal of Human Resources
Journal of International Economics
Journal of Labor Economics
Journal of Labor Economics
Journal of Monetary Economics
Journal of Money, Credit, and Banking
Journal of Political Economy
Journal of Public Economics
Journal of the European Economic Association
NBER Macroeconomics Annual
Quarterly Journal of Economics
Rand Journal of Economics
Resource and Energy Economics
The Journal of Economic Perspectives
The Review of Economic Studies

Environmental Economics Journals
American Journal of Agricultural Economics
Ecological Economics
Environment and Resource Economics
Journal of Environmental Economic Management
Land Economics

Appendix B
Survey Questions

Survey on Economics and Climate Change (2015)

The Institute for Policy Integrity at New York University School of Law is conducting a survey to examine the opinions of expert economists on climate change policy and uncertainty. This survey is only being sent to economists who have published a climate change-related article in a top economic journal.

The survey should take less than 15 minutes to complete. The aggregate results of this survey will be used in academic research and potentially distributed to media members, but individual responses will be anonymous and confidential.

Respondent Information

1. You have published on the following topics *(check all that apply)*:
   ❑ Climate Change Risks
   ❑ Estimated Damages from Climate Change
   ❑ Global Climate Strategies
   ❑ International Agreements/Game Theory
   ❑ Greenhouse Gas Control Mechanisms
   ❑ Integrated Assessment Models / Social Cost of Carbon
   ❑ Climate Change Adaptation
   ❑ Other Climate-Related Topics
   ❑ None

Climate Change Risks

2. Which of the following best describes your view about climate change?
   ❑ Immediate and drastic action is necessary
   ❑ Some action should be be taken now
   ❑ More research is needed before action is taken
   ❑ This is not a serious problem

3. If nothing is done to limit climate change in the future, how serious of a problem do you think it will be for the United States?
   ❑ Very serious
   ❑ Somewhat serious
   ❑ Not so serious
   ❑ Not serious at all
   ❑ No opinion

4. The following domestic economic sectors are likely to be negatively affected by climate change *(check all that apply)*:
   - ❑ Agriculture
   - ❑ Mining/Extractive Industries
   - ❑ Fishing
   - ❑ Forestry
   - ❑ Real Estate
   - ❑ Insurance
   - ❑ Construction
   - ❑ Transport
   - ❑ Manufacturing
   - ❑ Health Services
   - ❑ Tourism/Outdoor Recreation
   - ❑ Utilities (Electricity, Water, Sanitation, etc.)
   - ❑ Other (please specify)

5. During what time period do you believe the net effects of climate change will first have a negative impact on the global economy? (Please assume a business-as-usual path for emissions, with no major new climate policies implemented.)
   - ❑ Climate change is already having a negative effect on the global economy
   - ❑ By 2025
   - ❑ By 2050
   - ❑ By 2075
   - ❑ By 2100
   - ❑ After 2100
   - ❑ Climate change will not have a negative effect on the global economy

6. What is the likelihood that climate change will have a long-term, negative impact on the *growth rate* of the global economy? (Please assume a business-as-usual path for emissions, with no major new climate policies implemented.)
   - ❑ Extremely likely
   - ❑ Likely
   - ❑ Not clear
   - ❑ Unlikely
   - ❑ Extremely unlikely

Domestic Greenhouse Gas Control Mechanisms

7. The U.S. Environmental Protection Agency's "Clean Power Plan" will set carbon dioxide emission targets for each individual state's electricity sector. What would be the most efficient way to implement these targets?
   - ❑ Performance standards and programs that prioritize cleaner fuels and energy efficiency, *implemented within each individual state*
   - ❑ Performance standards and programs that prioritize cleaner fuels and energy efficiency, *coordinated among states at a regional level*
   - ❑ Market-based mechanisms (trading programs or carbon taxes) *implemented at the individual state level*
   - ❑ Market-based mechanisms *coordinated at a regional or national level* (such as a regional/national trading program or carbon tax)
   - ❑ No opinion

Global Climate Strategy and International Agreements

8. The United States may be able to strategically induce other countries to reduce their greenhouse gas emissions (or enter into an emissions reduction agreement) by adopting policies to reduce U.S. emissions.
   - ❑ Strongly agree
   - ❑ Agree
   - ❑ Neutral
   - ❑ Disagree
   - ❑ Strongly disagree
   - ❑ No opinion

9. The U.S. government should commit to reducing greenhouse gas emissions:
   - ❑ Regardless of the actions other countries have taken thus far
   - ❑ Only if it can enter into a multilateral emissions reduction agreement with some countries
   - ❑ Only if other major emitters enact policies to reduce their emissions
   - ❑ Only if every country commits to reducing emissions through a global agreement
   - ❑ Under no circumstances
   - ❑ No opinion

Social Cost of Carbon

(For questions in this section, please assume business-as-usual climate and socioeconomic scenarios.)

10. The global "social cost of carbon" (SCC) is the marginal cost to society of carbon dioxide emissions. Specifically, it is the present value of all future damages to the global society of one additional metric ton of carbon dioxide-equivalent greenhouse gasses emitted today.

    In 2013, a U.S. government Interagency Working Group adopted $37 (in 2007 USD) as its central estimate for the SCC (this figure estimates the economic damages of a unit of 2015 emissions, with a 3% discount rate).

    What is your opinion of this estimate:
   - ❑ Strongly believe the SCC is higher than $37
   - ❑ Believe the SCC is higher than $37
   - ❑ $37 is a likely estimate
   - ❑ Believe the SCC is lower than $37
   - ❑ Strongly believe the SCC is lower than $37
   - ❑ No opinion

11. How should the benefits to future generations of climate change mitigation be evaluated/discounted?
   - ❑ By using a constant discount rate calibrated using market rates
   - ❑ By using a constant discount rate calibrated using ethical parameters
   - ❑ By using a declining discount rate calibrated using market rates
   - ❑ By using a declining discount rate calibrated using ethical parameters
   - ❑ No opinion
   - ❑ Other (please specify)

12. If benefits to future generations are to be discounted using a constant discount rate, the appropriate discount rate to use when calculating the social cost of carbon is:
(Please enter a percentage) __________

Climate Impact Estimates

(For questions in this section, please assume business-as-usual climate and socioeconomic scenarios.)

13. Imagine this scenario:
Global mean temperature *increases by 3°C* relative to the pre-industrial era (i.e., a 2.1°C increase from the current period) *by approximately 2090*.

    What is your best guess (median/50th percentile estimate) of the impact on global output, as a percentage of GDP? Please include non-market and market impacts, and factor in adaptation to climate change.

    Please provide your answer as a % of global GDP. If you believe these impacts will increase GDP rather than decrease it, please indicate this with a (+). __________

14. Climate change is likely to affect both market goods (e.g., food and fiber, service sector, and manufacturing) and non-market goods (e.g., environmental amenities, ecosystems, and human health). Market goods should be thought of as all goods and services traditionally included in national accounts, i.e., GDP.

    What is your best guess of the percentage of total impacts (market plus non-market) that will be borne by the market sector? Please provide the % of impacts in the market sector. (Assume a 3°C rise by 2090.) __________

15. Some people are concerned about a low-probability, high-consequence outcome from climate change, potentially caused by environmental tipping points. Assume by "high-consequence" we mean a 25% loss or more in global income indefinitely. (Global output dropped by approximately 25% during the Great Depression.)

    What is your median/50th percentile estimate of the probability of such a high-consequence outcome if global average temperature were to increase 3°C by 2090? __________

16. [Optional] Please comment on any of the above questions. We are especially interested in the approach you used for your estimates, any sources you found helpful, your level of confidence in the answers you provided, issues with question clarity, etc. ____