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EMPIRICALLY-CONSTRAINED CLIMATE SENSITIVITY AND THE SOCIAL COST OF CARBON

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Abstract: Integrated Assessment Models (IAMs) require parameterization of both economic and climatic processes. The latter includes Equilibrium Climate Sensitivity (ECS), or the temperature response to doubling CO_2 levels, and Ocean Heat Uptake (OHU) efficiency. ECS distributions in IAMs have been drawn from climate model runs that lack an empirical basis, and in Monte Carlo experiments may not be constrained to consistent OHU values. Empirical ECS estimates are now available, but have not yet been applied in IAMs. We incorporate a new estimate of the ECS distribution conditioned on observed OHU efficiency into two widely-used IAMs. The resulting Social Cost of Carbon (SCC) estimates are much lower than those from models based on simulated parameters. In the DICE model the average SCC falls by 30-50% depending on the discount rate, while in the FUND model the average SCC falls by over 80%. The span of estimates across discount rates also shrinks substantially.

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1 INTRODUCTION

Integrated Assessment Models (IAMs) emerged in the 1990s and have become central to the analysis of global climate policy, especially for estimating the social cost of carbon (SCC)[1] or the marginal damages of an additional unit of carbon dioxide (CO_2) emissions. A particularly influential application has been through the US InterAgency Working Group (IWG 2010, 2013) which estimated SCC rates for use in US climate and energy regulations. IAMs operate at a high level of abstraction and require extensive parameterization of both climatic and economic processes. Among the economic parameters, the most influential are the discount rate and the coefficients of the damages function (Marten 2011). A key climate parameter is equilibrium climate sensitivity (ECS), which represents the long term temperature change from doubling atmospheric CO_2. It is either included explicitly or implicitly in the IAM functions determining temperature responses to CO_2 accumulation.

Optimal SCC estimates depend strongly on the damage function, which in turn is strongly influenced by the ECS parameter (e.g. Webster et al 2008, Ackerman et al. 2010, Wouter Botzen and van den Bergh 2012). ECS uncertainty has multiple dimensions, beginning with the wide range of point estimates within the major IAMs (van Vuuren et al. 2011). The interaction between ECS and ocean heat uptake (OHU) efficiency is an important but largely-overlooked source of uncertainty because it affects the time-to-equilibrium which affects SCC estimates via the role of discounting (Roe and Bauman 2013; see below). A number of authors have studied how quickly ECS uncertainty

[1] Various reviews of IAMs exist, each highlighting or criticizing different aspects, such as Parson and Fisher-Vanden (1997), Stanton et al. (2009) and Pindyck (2013).

may be reduced over time via Bayesian learning as new information become available (Kelly and Kolstand 1999, Leach 2007). Interestingly, Webster et al (2008) find that learning is slowest in the low ECS case while Urban et al. (2014) find it slowest in the high ECS case, with the difference being due to the role of OHU efficiency.[2]

IWG (2010, 2013) represented ECS uncertainty by modifying three standard IAMs[3] to include a probability density function (PDF) parameterized to fit a range of estimates from climate modeling simulations, which then gave rise to a distribution of marginal damages. The choice of ECS distribution can strongly influence the average SCC if it has a large upper tail, which pulls up both the median and mean values. The IWG used a PDF from a graph in Roe and Baker (2007, herein RB07) which does have a long upper tail. RB07 was an exploration of why uncertainties over ECS have not been reduced despite decades of effort, with the explanation centering on the amplified effect of uncertainties in the value of the climate feedback parameter *f* on final temperatures, due to its position in the denominator of the equation for ECS. To illustrate the point they fitted a curve to a small selection of ECS estimates published between 2003 and 2007, yielding an ECS curve that

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[2] The representation of uncertainty itself can introduce uncertainty. Crost and Traeger (2013) argue that averaging Monte Carlo runs of deterministic models rather than using a stochastic dynamic programming (SDP) framework yields inaccurate and potentially incoherent results. But Traeger (2014) finds that applying SDP in the DICE framework causes problems of dimensionality which necessitate introducing new simplifications elsewhere, including in the representation of OHU efficiency.

[3] The three IAMs are called DICE (Nordhaus 1993), FUND (Tol 1997) and PAGE (Hope 2006).

had a long upper tail even though there was no unbounded source of uncertainty in the underlying model.

The reliance by IWG on RB07 is questionable for two reasons. First, as Roe and Bauman (2013) pointed out, the distribution in RB07 was not directly applicable in the context of IAM simulations because the wideness of the tails is a function of the time span to equilibrium, which depends heavily on the assumed OHU efficiency, and the time span associated with the fat upper tail is not relevant to SCC calculations. In the real world, CO_2 doubling is not instantaneous, the transition to a new equilibrium state is exceedingly slow, and the oceans absorb huge amounts of heat along the way depending on OHU efficiency. In simplified climate models, time-to-equilibrium goes up with the square of ECS, so an upward adjustment of the ECS parameter outside the range consistent with the assumed OHU efficiency parameter can yield distorted present value damage estimates. In particular, the higher the ECS, the slower the adjustment process, making the fat upper tail of realized warming physically impossible for even a thousand years into the future (Roe and Bauman 2013, p. 653). An ECS distribution applicable to the real world must therefore be conditioned on a realistic OHU efficiency estimate.

Second, RB07 predated a large literature on empirical ECS estimation. As was common at the time, they fitted a distribution to a small number of simulated ECS distributions derived from climate models. It is only relatively recently that sufficiently long and detailed observational data sets have been produced to allow direct estimation of ECS using empirical energy balance models. A large number of studies have appeared since 2010 estimating ECS on long term climatic data (Otto et al. 2013, Ring et al. 2012, Aldrin et al. 2012, Lewis 2013, Lewis & Curry 2015, Schwartz 2012, Skeie et al 2014, Lewis 2016, etc.). This literature has consistently yielded median ECS values near or even below the low end of the range taken from climate model studies. General circulation models (GCMs) historically yielded sensitivities in the range of 2.0 – 4.5 ^{o}C, and (based largely on GCMs) RB07 yields a central 90 percent range of 1.72 – 7.14 ^{o}C with a median of 3.0 ^{o}C and a mean of 3.5 ^{o}C (see comparison table in IWG 2010, p. 13). But the median of recent empirical estimates has generally been between 1.5 and 2.0 ^{o}C, with 95% uncertainty bounds below the RB07 average.

This inconsistency has attracted growing attention in the climatology literature (Kummer and Kessler 2014, Marvel et al. 2015). It is also discussed in the documentation for Nordhaus' DICE model[4] where it is cited as a reason for a slight downward revision in the ECS parameter. However, that change was based on early evidence published prior to 2008, whereas all the studies discussed herein were published after 2010.

For the most part, however, the inconsistency between empirical and model-simulated ECS estimates has been ignored in the climate economics literature. But, as we will show herein, it has potentially massive policy implications. We replicate the IWG's SCC estimates using the EPA's modified versions of two IAMs (FUND and DICE),[5] then we re-do the calculations using an observational ECS distribution from a recent study (Lewis and Curry 2015, herein LC15) that controls for observed OHU efficiency, thereby yielding an empirically-constrained climate sensitivity distribution. The resulting SCC values drop dramatically compared to those reported in

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[4] See http://aida.wss.yale.edu/~nordhaus/homepage/documents/DICE_Manual_100413r1.pdf pp. 17-18.

[5] We did not use a third model, PAGE, because its code is unavailable for independent usage.

the IWG (2010, 2013). Using DICE with the model-based RB07 ECS distribution at a 3 percent discount rate yields a mean SCC for the year 2020 of $37.73, in line with the IWG estimates that currently guide US policymaking. Substituting the empirical ECS distribution from LC15 yields a mean 2020 SCC of $19.52, a drop of 48%. The same exercise using FUND yields a mean SCC estimate of $19.33 based on RB07 and $3.33 based on the LC15 parameters—an 83% decline. Furthermore the probability of a negative SCC (implying CO_2 emissions are a positive externality) jumps dramatically using an empirical ECS distribution. Using the FUND model, which allows for productivity gains in agricultural and forestry from higher temperatures and elevated CO_2, under the RB07 parameterization at a 3% discount rate there is only about a ten percent chance of a negative SCC through 2050, but using the LC15 distribution, the probability of a negative SCC jumps to about 40%. Remarkably, in the FUND model, replacing simulated climate sensitivity values with an empirical distribution calls into question whether CO_2 is even a negative externality. The lower SCC values also cluster more closely together across difference discount rates, diminishing the importance of this parameter.

The paper proceeds as follows. Section 2 explains the roles of ECS and OHU parameterization in climate submodels, and reviews the empirical literature over the past half-decade. Section 3 presents SCC calculations using DICE and FUND, and Section 4 presents conclusions.

2 IAM Parameterization

ECS is defined as the average increase in temperatures around the world as a result of CO_2 doubling, after the deep ocean has adjusted to the increased forcing. While data on historical temperatures and CO_2 concentrations are available, it is not straightforward to estimate ECS empirically. Rising levels of CO_2 and other greenhouse gases must be translated into units of "radiative forcing" which maps their effect on radiation into a common measure by which the effects of all types of drivers of climate change on temperature change may be compared. The warming effect of CO_2 and other greenhouse gases is partially offset by the potential cooling effect of aerosols which are sometimes released by the same processes responsible for CO_2. However, compared to the warming effect of CO_2, the direct and indirect aerosol cooling effects, and the related negative aerosol forcing, are much more uncertain and difficult to quantify, in part because of their interactions with cloud formation (IPCC 2013 ch. 8, Kiehl 2007, Schwartz et al 2007). Hence there is a range of possible forcing values consistent with the historical CO_2 record, based on how strong the offsetting aerosol forcing is taken to be.

If cooling by aerosol forcing is strongly negative, it will offset much of the positive, warming, forcing from greenhouse gases; if it is weak it will offset little of it. The net forcing, in turn, affects temperature according to the magnitude of ECS. Since the historical temperature record is fixed, there must be an offsetting relationship between ECS and estimated forcing: for a given temperature change, greater net historical forcing implies lower ECS and vice-versa. This inverse relationship is reflected across the suite of climate models. For instance, models that translate historical greenhouse gas and aerosol levels into a relatively strong positive forcing must have lower ECS, etc. (Kiehl 2007).

The treatment within a model of OHU efficiency also affects the ECS that corresponds to observed warming. The higher OHU efficiency is, and thus the larger the amount of heat sequestered in the oceans over the past century, the more the historical climate record understates the total amount of warming that will ultimately occur (Roe and Bauman 2013). Consequently, estimates of ECS for use in real-world policy simulations need to make use of information on aerosol forcing and OHU efficiency as well as CO_2 and temperature records. The problem with inserting into IAMs an ECS distribution fitted to data generated by unconstrained climate models is that the range of values is not necessarily consistent with the scenario time span as represented in the IAM. The spread of model ECS measures taken in isolation may be misleading if applied in an IAM without simultaneously adjusting the IAM's OHU efficiency estimates or, if the OHU parameters are held fixed, limiting the ECS values to a range consistent with those values.

The latter approach is implicit when an empirical energy balance model is estimated using historical aerosol forcing and ocean heat content estimates to condition the ECS distribution. This is the approach taken in LC15. They used the 1750-2011 forcing and OHU estimates from the then-most recent IPCC report (IPCC 2014), yielding a median ECS of 1.64 ^{o}C and a 5—95 % uncertainty range of 1.05 – 4.05 ^{o}C. This is in line with empirical estimates from Otto et al. (2013), Ring et al. (2012), Aldrin et al. (2012) and Lewis (2013), but is in clear contrast to the customary IAM parameterization using RB07, since the central value in LC15 falls below the 5% lower bound of the ECS distribution used in IWG (2010, 2013). Not surprisingly, this implies that empirically unconstrained SCC estimates are skewed too high.

One proposal for resolving the discrepancy between model-based and empirical ECS estimates is to use so-called "efficacies" to adjust forcing values for different feedback responses (Kummer and Dessler, 2014, Marvel et al. 2015). The underlying argument is that two different types of climate forcing agents, each with equivalent initial forcing, may still generate different eventual temperature impacts, particularly if they are not well-mixed and the spatial variation induces differing local feedbacks. Hansen (2005) introduced the term "efficacy" to capture this concept, with the unit of measurement a ratio of overall temperature response to that of CO_2. If a species of, say, greenhouse gas has an efficacy of 1.5 this means that if its atmospheric concentration were to increase by an amount corresponding to the same additional effective radiative forcing (ERF) as a doubling of CO_2 levels, the eventual temperature response would be 1.5 times larger, due to the different feedback processes involved. Hansen (2005) found in GCM simulations that most efficacies were close to unity so the spatial and other variations did not matter much at the global level. Marvel et al. (2015) analyse simulated data from a different model (GISS-E2-R) and found that aggregate efficacy of forcings operating over the historical period was below one, due *inter alia* to aerosol forcing (which is negative) having a high efficacy. They argued that this meant empirical estimates of ECS were biased down. However, Marvel et al. mistakenly left out land-use forcing, and their revised uncertainty bounds are so wide that most single-forcing efficacies for ERF encompass unity (Marvel et al. 2016 Table S1), though the aggregate efficacy remained below unity. More generally, Marvel et al. (2015) is a study of the behavior of a particular GCM, and it has not been established whether forcing efficacy differences among climate models translates into empirically-relevant real-world effects. Otto et al. (2013), for instance, used forcing estimates that implicitly incorporated efficacy variations and they obtained an ECS distribution nearly identical to that in LC15.

3 SCC CALCULATIONS USING EMPIRICAL PARAMETERS

We obtained the code for DICE and FUND[6] as used for the IWG (2010, 2013) studies from the US Environmental Protection Agency. We first replicated the SCC estimates that would have been used in IWG (2013) from both the DICE and FUND models based on the RB07 ECS distribution. The damage paths are contingent on the emissions scenarios so five scenarios are used and the results are averaged.[7] As we did not include the PAGE model in our work (due to the unavailability of the code) we cannot directly compare our results with the IWG tables since they are averaged over all three models. IWG (2013) Table A5 lists separate results for FUND and DICE for 2020 and we were able to check our results against those. Since the calculations are probabilistic it is not guaranteed that we will reproduce the exact SCC estimates as shown in IWG (2013), but our replication is quite close. Table 1 shows the DICE and FUND SCC estimates for 2020 compared with our replications ("Repl") for three discount rates. Apart from a slight under-estimation of the FUND results under the lower discount rates the match is extremely good.

3.1 DICE MODEL

Table 2 shows the mean SCC estimates for four discount rates, applying the RB07 and LC15 ECS distribution to the DICE model. The final row shows the percentage change for the 2020 estimates (all years exhibit about the same percentage changes). Under the widely-used RB07 distribution, the SCC ranges from $3.88 to $89.26 depending on the discount rate and the future year. Under the

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[6] Model authors' source code is available at http://www.econ.yale.edu/~nordhaus/homepage/ (DICE) and http://www.fund-model.org/ (FUND). We are grateful to the EPA for providing us with the MATLAB code they used which contains the modifications for the IWG analysis.

[7] The scenarios are called Image, Merge Optimistic, Message, MiniCAM, and 5th Scenario.

LC15 parameter distributions the SCC ranges from $2.39 to $46.00. For the year 2020 the largest proportional drop—nearly 50 percent—is observed in the low discount rate case. The high discount rate case yields a drop of just under 40 percent.

These reductions are primarily due to the LC15 distribution containing a smaller upper tail and therefore greater probability mass at lower temperatures. Table 3 shows the average standard deviations of the two sets of estimates. The largest reduction, about 24 percent, again occurs at the lowest discount rate, compared to only seven percent at the highest discount rate. The LC15 distribution provides uniformly more certainty for the SCC for all years and all discount rates. These results are in line with previous research performing similar computations by applying the Otto et al (2013) ECS distribution in the DICE model (Dayaratna and Kreutzer 2013).

3.2 FUND Model

Tables 4 and 5 present the same results as Tables 2 and 3, but for the FUND model. A number of differences are notable. The mean SCC estimates are lower under both parameterizations, and under the empirical LC15 coefficients they are, on average, mostly negative at 5 percent or higher discount rates out past 2030. A negative value implies that carbon dioxide emissions are a positive externality, so that an optimal policy would require subsidizing emissions. Also, in contrast to the DICE model, use of the LC15 coefficients increases the average standard deviation, indicating higher uncertainty compared to the RB case.[8] The increased uncertainty includes a much larger lower tail,

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[8] ECS is the only stochastic parameter in DICE so the reduction in variance between RB07 and LC15 leads automatically to a corresponding reduction in the SCC variance. By contrast, dozens of parameters in FUND

implying a larger probability of a negative SCC. DICE is constrained to a single quadratic global damage function so damages cannot be negative regardless of temperature change. FUND allows the gains for regions that benefit from moderate warming to potentially outweigh the costs in other regions so some scenarios can yield negative net costs at the global level. Table 6 shows that, under the RB07 parameterization, at a 2.5 percent discount rate the probability of carbon dioxide emissions being a positive externality is only 7.1 percent in 2050. But using the LC15 parameters this probability jumps to over 35 percent.

Figure 1 shows frequency histograms of SCC calculations for the Merge Optimistic scenario at 2.5 percent discounting as of 2030. The height of each bar is equal to the probability of selecting an observation within that bin interval, and the height of all of the bars sums to 1. The bin width for RB07 is 5, the bin width of LC15 is 3. Comparing the top and bottom panels we see that model simulation of ECS introduces uncertainty not found in observations by creating an extended upper tail.

These results are in line with previous simulations using other ECS distributions that have smaller upper tails than RB07, namely Otto et al (2013) and Lewis (2013); see Dayaratna and Kreutzer (2014).

Figure 2 summarizes the calculations by comparing the mean of DICE- and FUND-computed SCC values from 2010 to 2050 at a 3 percent discount rate using the simulated (black, upper line) and

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are stochastic so reduction in the mean and variance of ECS interacts in a more complex way with the rest of the model. The net effect, as shown is to increase the spread of SCC estimates.

the empirical (gray, lower line) ECS values. As of 2050 the empirically-constrained value ($18.87) is still below the 2010 value ($23.47) based on simulated ECS.

4 DISCUSSION AND CONCLUSION

Model-based ECS distributions are misleading for use in SCC calculations because they are not conditioned on OHU efficiency rates relevant to IAM timelines and because they are skewed high relative to the current empirical evidence. The model-observational discrepancy in ECS estimation is not attributable simply to a specific empirical methodology, as similar results have been found by Otto et al. (2013), Ring et al. (2012), Aldrin et al. (2012) and others using a variety of methods. Nor is it an artifact of selecting a specific estimation period, as LC15 showed their results were robust to numerous variations on the choice of base and final periods (LC15, Table 4).

We incorporated the Lewis and Curry (2015) ECS distribution, which is conditioned on updated forcings and OHU data, into the DICE and FUND models. This reduces the estimated Social Cost of Carbon in both, regardless of discount rates. Using a 3 percent discount rate and the RB07 ECS distribution, DICE yields an average SCC ranging from about $30 to $60 between now and 2050, but this falls in half to the $15 to $30 range using the LC15 ECS estimate. The corresponding average SCC in FUND falls from the $17 to $27 range to the $3 to $5 range. Moreover FUND, which takes more explicit account of potential regional benefits from CO_2 fertilization and increased agricultural productivity, yields a substantial (about 40 percent) probability of a negative SCC through the first half of the 21st century, putting into question whether CO_2 is even a net social cost or benefit.

A further way in which use of empirically-constrained parameters reduces uncertainty is the shrinking of the SCC range across discount rates. In the DICE model under the RB07 parameterization, the mean SCC estimates span about $50 as of 2010 depending on choice of discount rate, with the span rising to about $80 as of 2050. This span shrinks to the $20 to $40 range under the LC15 parameterization. Using the FUND model, the uncertainty range associated with the choice of discount rate is from about $30 to $40 under the RB07 parameterization, falling to $4 to $8 range under the LC15 parameterization. Thus, use of well-constrained empirical parameters makes a substantial contribution also to reducing uncertainty associated with the choice of discount rate.

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6 TABLES

	2.5%		3.0%		5.0%	
	IWG	**Repl**	**IWG**	**Repl**	**IWG**	**Repl**
DICE	$57	$57	$38	$38	$12	$12
FUND	$36	$33	$21	$19	$3	$3

Table 1: Replication of IWG (2013) SCC estimates for DICE and FUND models for 2020, under three discount rate assumptions. Replications done herein denoted “Repl”.

	Mean Social Cost of Carbon – DICE Model							
	Using Simulated ECS				Using Empirical ECS			
Discount rates	**2.50%**	**3.00%**	**5.00%**	**7.00%**	**2.50%**	**3.00%**	**5.00%**	**7.00%**
2010	$46.87	$29.96	$8.62	$3.88	$23.72	$15.50	$4.91	$2.39
2020	$57.34	$37.73	$11.85	$5.66	$29.07	$19.52	$6.70	$3.43
2030	$67.13	$45.18	$15.04	$7.43	$34.20	$23.45	$8.48	$4.47
2040	$77.82	$53.45	$18.74	$9.53	$39.86	$27.84	$10.56	$5.71
2050	$89.26	$62.38	$22.90	$11.94	$46.00	$32.65	$12.90	$7.13
% Chg at 2020					-49.3%	-48.3%	-43.5%	-39.3%

Table 2: Mean Social Cost of Carbon estimates by year under four discount rates from the DICE Model, for both the simulated (RB07) and empirical (LC15) ECS distributions. Last row shows the percent change as of 2020.

	Average Standard Deviation – DICE Model							
	Using Simulated ECS				Using Empirical ECS			
Discount rates	**2.50%**	**3.00%**	**5.00%**	**7.00%**	**2.50%**	**3.00%**	**5.00%**	**7.00%**
2010	$25.73	$14.88	$3.28	$1.15	$19.34	$11.36	$2.72	$1.09
2020	$31.29	$18.74	$4.59	$1.75	$23.74	$14.32	$3.78	$1.62
2030	$36.64	$22.62	$6.00	$2.41	$27.97	$17.17	$4.83	$2.17
2040	$42.22	$27.00	$7.79	$3.25	$32.61	$20.26	$6.06	$2.86
2050	$47.71	$31.00	$9.82	$4.25	$37.51	$23.64	$7.50	$3.64
% Chg at 2020					-24.2%	-23.6%	-17.6%	-7.4%

Table 3: Average standard deviation of SCC estimates by year under four discount rates from the DICE Model, for both the simulated (RB07) and empirical (LC15) ECS distributions. Last row shows the percent change as of 2020.

	Mean Social Cost of Carbon – FUND Model							
	Using Simulated ECS				Using Empirical ECS			
Discount rates	**2.50%**	**3.00%**	**5.00%**	**7.00%**	**2.50%**	**3.00%**	**5.00%**	**7.00%**
2010	$29.69	$16.98	$1.87	-$0.53	$5.25	$2.78	-$0.65	-$1.12
2020	$32.90	$19.33	$2.54	-$0.37	$5.86	$3.33	-$0.47	-$1.10
2030	$36.16	$21.78	$3.31	-$0.13	$6.45	$3.90	-$0.19	-$1.01
2040	$39.53	$24.36	$4.21	$0.19	$7.02	$4.49	-$0.18	-$0.82
2050	$42.98	$27.06	$5.25	$0.63	$7.53	$5.09	$0.64	-$0.53
% Chg at 2020					-82.2%	-82.8%	-118.5%	-197.3%*

Table 4: Mean Social Cost of Carbon estimates by year under four discount rates from the FUND Model, for both the simulated (RB07) and empirical (LC15) ECS distributions. Last row shows the percent change as of 2020. * Change from -$0.37 to -$1.10 is, arithmetically, a positive number, but is shown here as negative to indicate that it is a change to a larger negative magnitude.

	Average Standard Deviation – FUND Model							
	Using Simulated ECS				Using Empirical ECS			
Discount rates	**2.50%**	**3.00%**	**5.00%**	**7.00%**	**2.50%**	**3.00%**	**5.00%**	**7.00%**
2010	$64.24	$31.45	$5.19	$2.24	$67.60	$42.54	$8.07	$2.52
2020	$32.90	$35.68	$6.28	$2.79	$80.17	$52.61	$11.27	$3.51
2030	$36.16	$40.24	$7.48	$3.40	$93.86	$64.26	$15.69	$5.02
2040	$39.53	$45.14	$8.78	$4.05	$108.03	$77.23	$21.75	$7.37
2050	$42.98	$50.31	$10.22	$4.76	$121.20	$90.55	$29.76	$11.04
% Chg at 2020					+143.7%	+47.4%	+71.2%	+25.8%

Table 5: Average standard deviation of SCC estimates by year under four discount rates from the FUND Model, for both the simulated (RB07) and empirical (LC15) ECS distributions. Last row shows the percent change as of 2020.

	Probability of Negative Social Cost of Carbon – FUND Model							
	Using Simulated ECS				Using Empirical ECS			
Discount rates	**2.50%**	**3.00%**	**5.00%**	**7.00%**	**2.50%**	**3.00%**	**5.00%**	**7.00%**
2010	0.087	0.121	0.372	0.642	0.416	0.450	0.601	0.730
2020	0.084	0.115	0.344	0.601	0.402	0.432	0.570	0.690
2030	0.080	0.108	0.312	0.555	0.388	0.414	0.536	0.646
2040	0.075	0.101	0.282	0.507	0.371	0.394	0.496	0.597
2050	0.071	0.093	0.251	0.455	0.354	0.372	0.456	0.542

Table 6: Probability of a negative Social Cost of Carbon under four discount rates in the FUND Model.

7 FIGURES

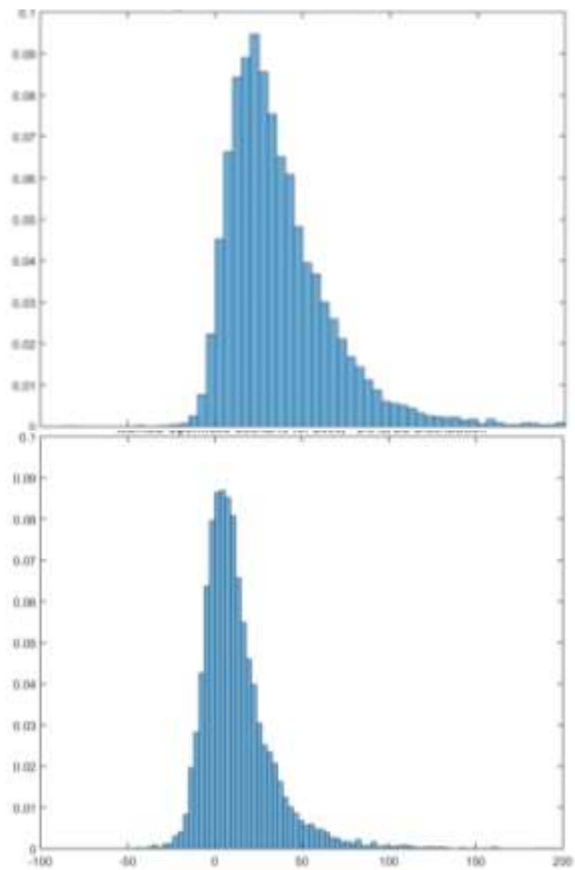

Figure 1. Frequency histograms of SCC computations in FUND under different ECS distributional assumptions. Top panel: Using MERGE 'Optimistic' scenario with 2.5 percent discount rate, as of 2030, SCC rate on horizontal axis and number of times observed on vertical axis, ECS follows Roe-Baker (2007) distribution. Bottom panel: same but ECS follows Lewis-Curry (2015) distribution.

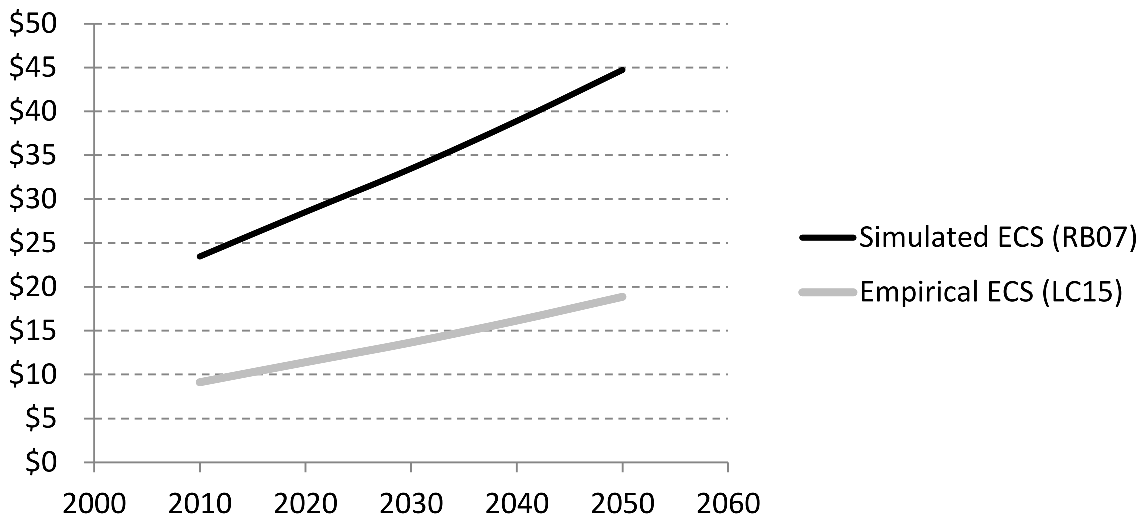

Figure 2. Social Cost of Carbon Estimates, 2010 – 2050, average of DICE and FUND models applying a 3 percent discount rate. Top (black) line using simulated ECS parameter distribution. Bottom (gray) line using empirical ECS parameter distribution.