CARBON PRICES, PREFERENCES, AND THE TIMING OF UNCERTAINTY
(work in progress)

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SOCIAL COST OF CARBON SCC

~$40 revised July 2015 Social Cost of CO_2, from "Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866." (U. S. Government Interagency Working Group on Social Cost of Carbon, 2016)

Based on 3% constant discount rate, and an average of 3 climate-economy models, including DICE

Table 2: Social Cost of CO_2, 2010 – 2050 (in 2007 dollars per metric ton of CO_2)

Year	5% Average	**3% Average**	2.5% Average	High Impact (95th Pct at 3%)
2010	10	**31**	50	86
2015	11	**36**	56	105
2020	12	**42**	62	123
2025	14	**46**	68	138
2030	16	**50**	73	152
2035	18	**55**	78	168
2040	21	**60**	84	183
2045	23	**64**	89	197
2050	26	**69**	95	212

Significant increase over 2010 figures: $36 up from $24

Our definition, mirroring U.S. Government's:

- The present value of the damages from the marginal emission of a ton of CO_2.
  - Can be defined for an arbitrary trajectory.
  - Definition here of SCC utilizes an "optimal" trajectory.
  - In a distortion-free economy the optimal SCC defines the optimal carbon tax.
  - Focus here is on the global SCC.
- Requires an Integrated Assessment Model (IAM).
  - DICE, FUND, PAGE were used by the U.S. Interagency Working Group on SCC.
  - The DICE (Dynamic Integrated Climate-Economy) model provides an important focus.

"..,to look only at Nordhaus's own studies with DICE is to understate its contribution hugely, because, by virtue of its simple and transparent unification of growth theory with climate science (not to mention Nordhaus's considerable efforts to make the model code publicly available), it has come to be very widely used by others. The uses to which it has been put are too numerous to cover in a comprehensive manner."
(Dietz & Stern, 2015, p. 577)

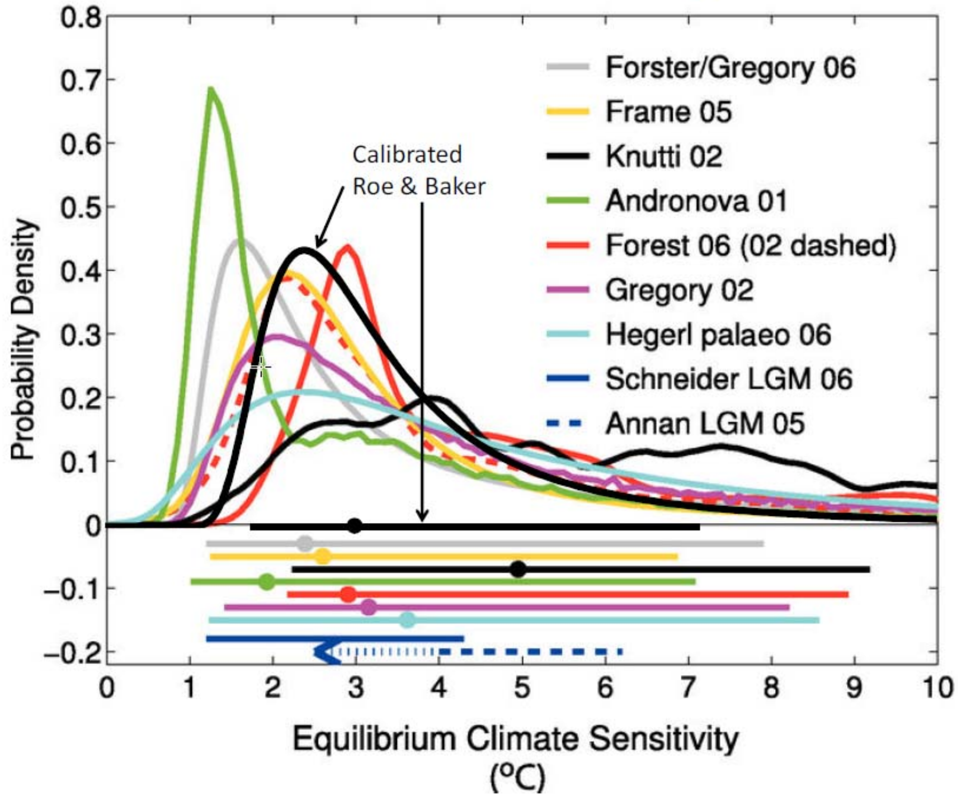
The SCC is a central element of the application and interpretation of IAMs. There is a large literature and the topic has been the subject of extensive scrutiny and evaluation.

- **US Government Assessment and Regulatory Policy.** “Technical Support Document: Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866.” (U. S. Government Interagency Working Group on Social Cost of Carbon, 2016)
- **Electric Power Research Institute.** “Understanding the Social Cost of Carbon: A Technical Assessment.” (Rose et al., 2014)
- **National Academy Studies.** “Valuing Climate Changes: Updating Estimates of the Social Cost of Carbon.” (National Academy of Sciences, 2017)
    - Framework of IAMs.
    - Economic Model.
    - Climate Model.
    - Damage Functions and Tipping Points.
    - Discounting.
    - Uncertainty.
    - Modularity of (future) IAMs.
- **Outstanding issues:**
    - Timing of Uncertainty,
    - Characterization of Preferences,
    - Damage functions in context of timing and preferences.

The Equilibrium Climate Sensitivity (ECS) is uncertain and skewed with a long upper tail.

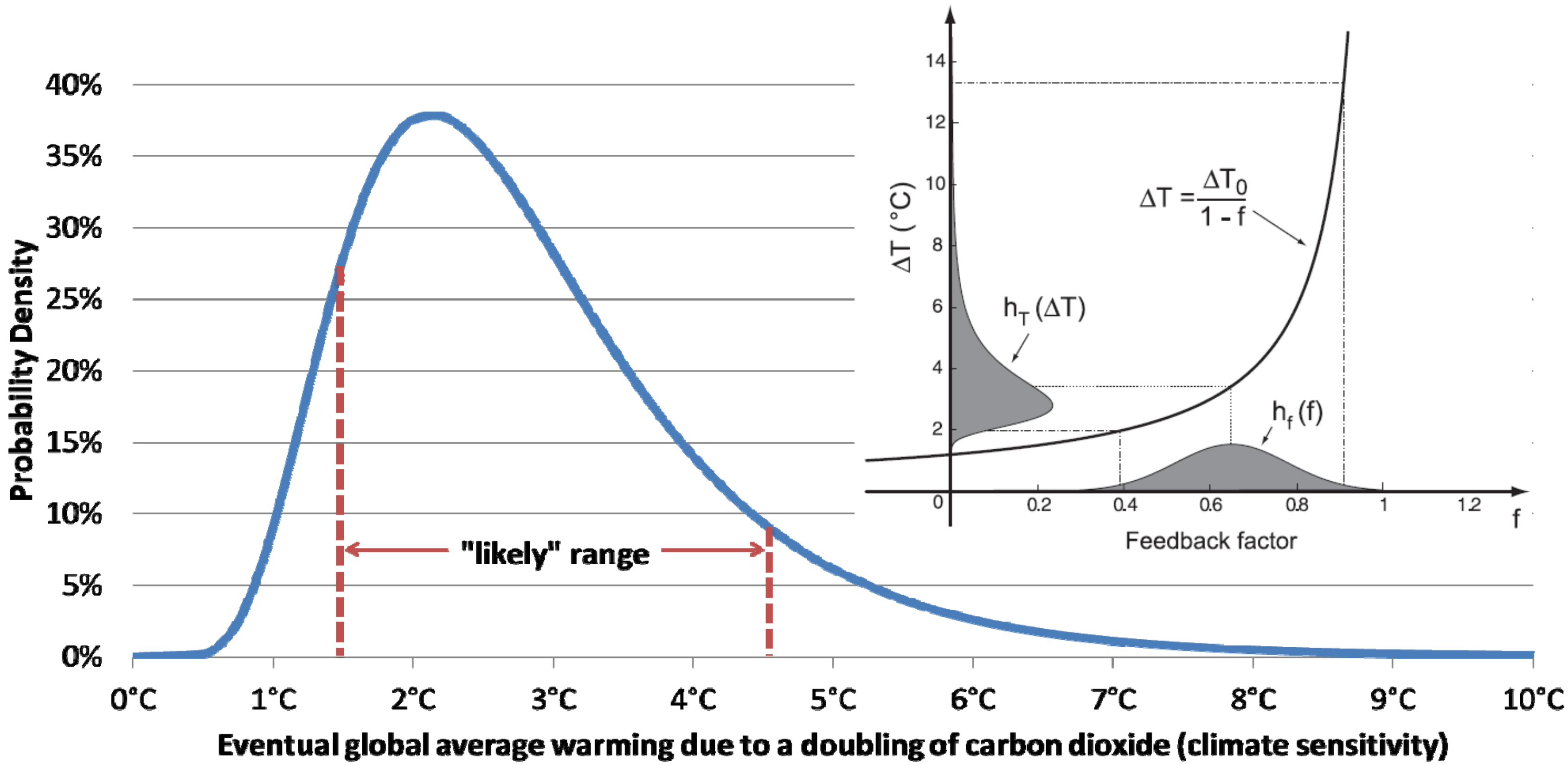
"Climate sensitivity—the long-term response of global-mean, annual-mean surface temperature to a doubling of the atmospheric carbon dioxide concentration above pre-industrial values—has long been a benchmark by which to compare different estimates of the planet's climatic response to changes in radiative forcing." (Roe & Bauman, 2013, p. 648)

Figure 2: Estimates of the Probability Density Function for Equilibrium Climate Sensitivity (°C)



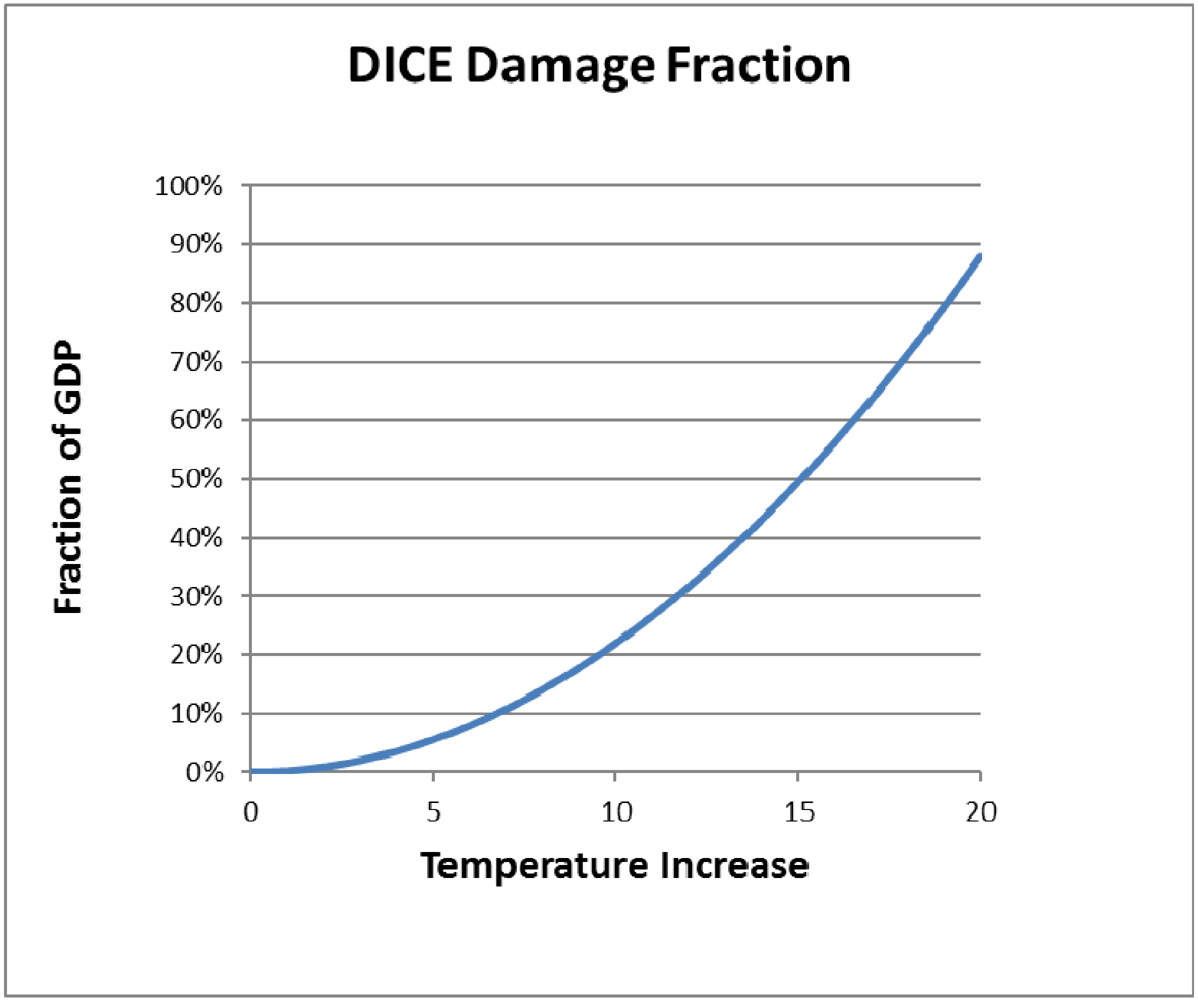
(U. S. Government Interagency Working Group on Social Cost of Carbon, 2010)

IPCC's "likely" range 1.5-4.5°C. 'Heavy-tailed' climate sensitivity calibration using log-normal, mirroring feedback effects of (Roe & Baker, 2007). Equal mass below and above "likely" range likely conservative assumption.



(Wagner & Weitzman, 2015)

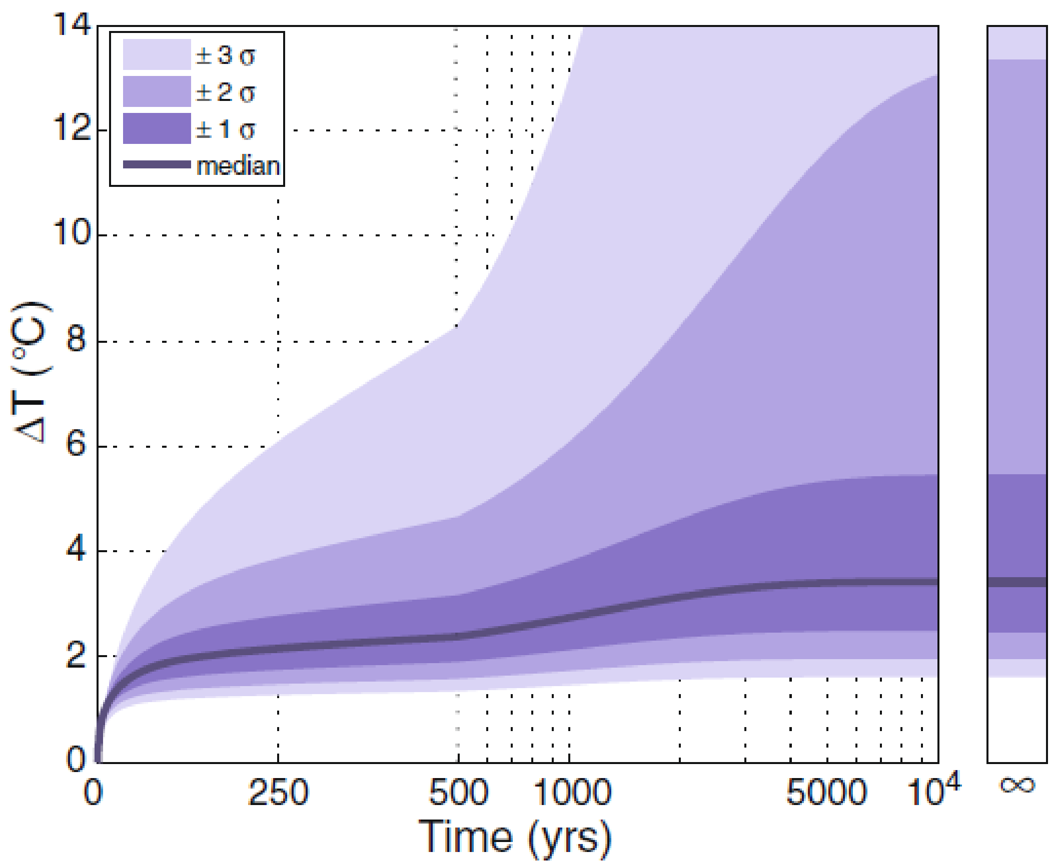
In the DICE model, the damage function follows an inverse quadratic function. (Nordhaus & Sztorc, 2013)



The Roe-Bauman critique of "fat tails" argument: "Climate sensitivity: should the climate tail wag the policy dog?". (Roe & Bauman, 2013) (Johnston, 2015)

"The time evolution of uncertainty in global temperature in response to an instantaneous doubling of CO2 at t = 0, and for standard parameters. The shading reflects the range of feedbacks considered (symmetric in feedbacks, but not in climate response), as explained in the text. Note the change to a logarithmic x-axis after t = 500 yr. The panel illustrates that for high climate sensitivity it takes a very long time to come to equilibrium." (Roe & Bauman, 2013, p. 651)

The NAS study reports on the importance of consistency in evaluating the ECS and the associated dynamics. (National Academy of Sciences, 2017, p. 133)

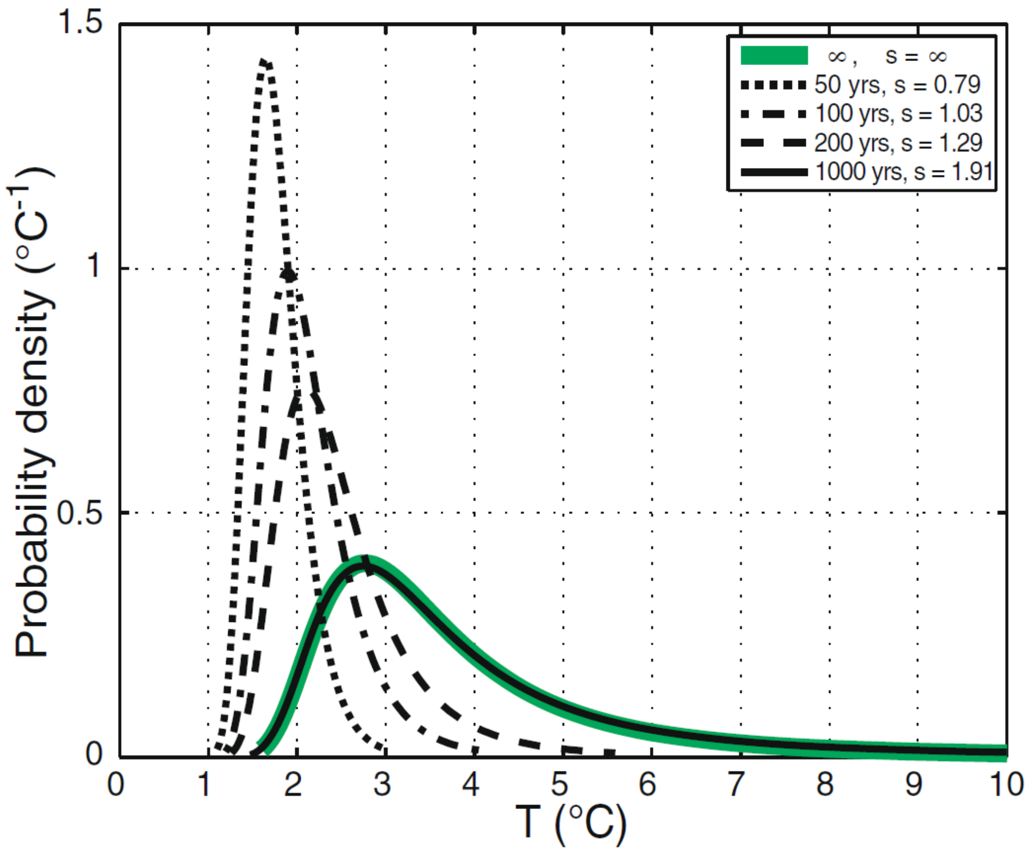


" there are important physical constraints on the climate system that limit how fast temperatures can rise ….even for a planet that is formally headed to[ward] oblivion, it can take a very long time to get there." (Roe & Bauman, 2013, pp. 649–652)

"The shape of the [climate sensitivity] distribution at particular times. The skewness of the distributions are also shown in the legend; as described in the text, the upper bound on possible temperatures is finite at finite time, limiting the skewness." (Roe & Bauman, 2013, p. 651)

The Roe-Baker paper has 501 Google Scholar citations. The IAWG (U. S. Government Interagency Working Group on Social Cost of Carbon, 2016) cites and applies the Roe-Baker asymptotic distribution.

The Roe-Bauman paper has 14 cites. (Google scholar last checked 4/24/17)



The equations of the DICE model can be modified to approximate the Roe-Bauman temperature dynamics.

In the DICE model, given the radiative forcing $F(t)$ derived from the climate concentration, the temperature follows the model:

$$T_{AT}(t) = T_{AT}(t-1) + \xi_1 \left\{ F(t) - \xi_2 T_{AT}(t-1) - \xi_3 \left[T_{AT}(t-1) - T_{LO}(t-1) \right] \right\}$$
$$T_{LO}(t) = T_{LO}(t-1) + \xi_4 \left[T_{AT}(t-1) - T_{LO}(t-1) \right].$$

"$T_{AT}(t)$ and $T_{LO}(t)$ represent respectively the mean surface temperature and the temperature of the deep oceans. Note that the equilibrium temperature sensitivity is given by $\Delta T_{AT} = \Delta F(t) / \xi_2$." (Nordhaus & Sztorc, 2013, p. 17)

Adaptation to the Roe-Bauman dynamics can be approximated by changing the parameters benchmarked for the DICE climate sensitivity, ΔT_{DICE}, to a different sensitivity, $\Delta T'$. The range of ECS candidates comes from the equilibrium distribution of (Roe & Baker, 2007) as approximated in (Ackerman, Stanton, & Bueno, 2013).

For each ECS scenario, we set the time when the doubling reaches the 63% temperature threshold, scaled as the square relative to the time this threshold is reached at the baseline 3.1 degree climate sensitivity in the DICE model. (Roe & Bauman, 2013, p. 649) Choose the parameters $\xi_1', \xi_3' \text{ and } \xi_4'$ to minimize the squared deviations from the DICE parameters.

The basic model is:

$$\frac{T(ECS, p)}{T(3.1, p)} = \left(\frac{ECS}{3.1} \right)^2.$$

Here $T(.,.)$ is the time to reach percentage p of the ECS. We read the time for the DICE-2016 model and compute the time for other values of the ECS.

Application of the approximation method incorporates the Roe-Bauman dynamics on the basic DICE model temperature transitions.

The revised DICE climate dynamic model would be as:

$$T_{AT}(t) = T_{AT}(t-1) + \xi_1' \left\{ F(t) - \xi_2' T_{AT}(t-1) - \xi_3' \left[T_{AT}(t-1) - T_{LO}(t-1) \right] \right\}$$

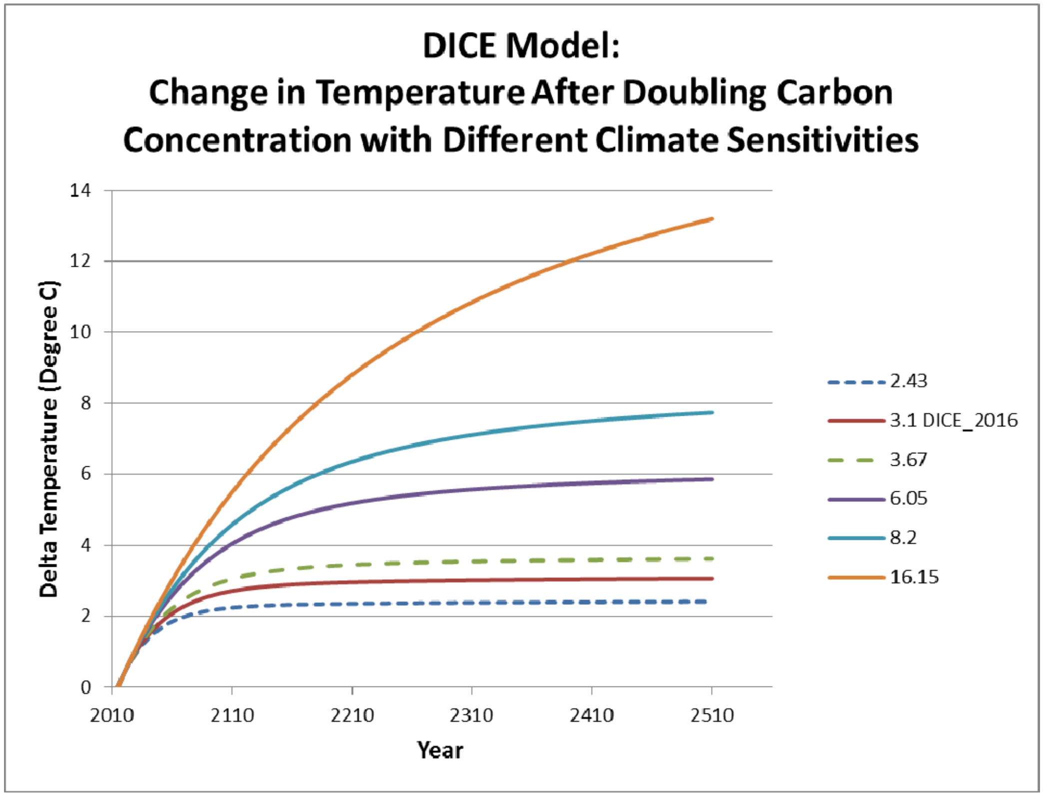
$$T_{LO}(t) = T_{LO}(t-1) + \xi_4' \left[T_{AT}(t-1) - T_{LO}(t-1) \right].$$

Here $\xi_2' = \xi_2 \left(\frac{\Delta T'}{\Delta T_{DICE}} \right)^{-1}$, for alternative equilibrium temperature sensitivities $\Delta T'$.

	Approximate Roe-Bauman Parameters					
ECS(°C)	2.43	3.1	3.67	6.05	8.20	16.15
ξ_1'	0.1229	0.1029	0.0910	0.0565	0.0444	0.0296
ξ_3'	0.0870	0.0879	0.0886	0.0906	0.0912	0.0901
ξ_4'	0.0251	0.0250	0.0248	0.0225	0.0197	0.0199

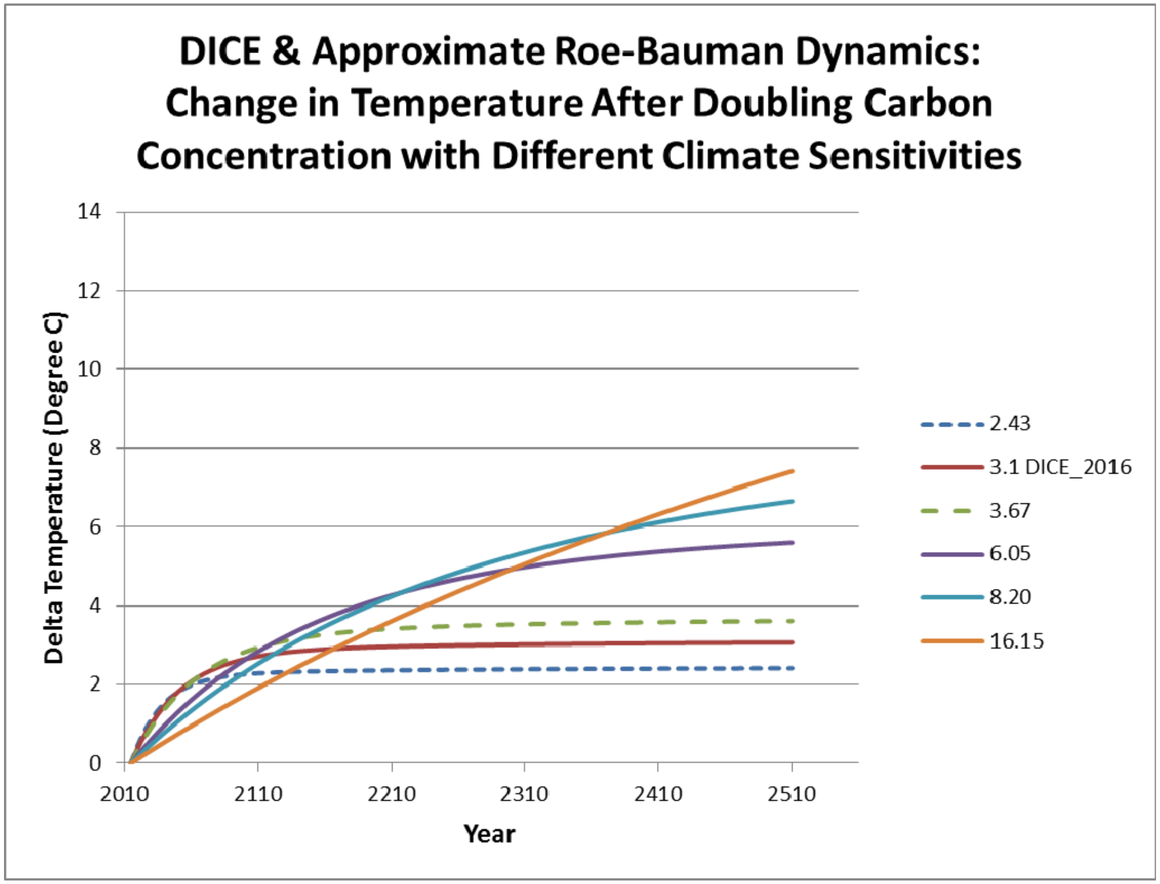
Source: Hogan & Wagner (Mimeo)

Using the different long-run climate sensitivities from (Ackerman et al., 2013), but ignoring the Roe-Bauman dynamics produces DICE temperature trajectories with roughly proportional rates of change after a shock that doubles the concentration of carbon in the atmosphere.



Source: Hogan & Wagner (Mimeo)

Use of the approximate Roe Bauman trajectories with the same asymptotic ECS has a significant effect on the first few centuries of the DICE projections.



Source: Hogan & Wagner (Mimeo)

Introduction of uncertainty highlights interesting questions about the representation of preferences across different outcomes within periods and between periods.

The DICE model applies a long-standing approach of expected utility based on a power function of consumption.

$$U = \sum_t \left(1+\delta\right)^{-1} \frac{c_t^{1-\eta}}{1-\eta}$$

This familiar and convenient model leads to questions about the implicit structure of preferences. (Kreps & Porteus, 1978) (Epstein & Zin, 1989) (Weil, 1990)

- Utility is time-separable, which imposes restrictions on how the timing of the resolution of uncertainty affects choices.
- There is a single parameter to characterize risk and intertemporal tradeoffs. “This form assumes a constant elasticity of the marginal utility of consumption, η. (In the limiting case where $\eta = 1$, the utility function is logarithmic.) The elasticity parameter is best thought of as aversion to generational inequality. Put differently, the elasticity represents the diminishing social valuations of consumption of different generations. If η is close to zero, then the consumptions of different generations are close substitutes, with low aversion to inequality; if η is high, then the consumptions are highly differentiated, and this reflects high inequality aversion. Often, η will also be used to represent risk aversion, but these are strictly speaking quite distinct concepts and should not be confused (see Epstein and Zin 1989, 1991). Additionally, the elasticity is distinct from the personal behavioral characteristics. We calibrate η in conjunction with the pure rate of time preference [δ] as is discussed below.” (Nordhaus & Sztorc, 2013, p. 7)

An alternative representation of preferences responds to these issues.

> "An important limitation of this approach is that η conflates risk aversion and the intertemporal elasticity of substitution. While the latter is our main focus here, future research could explore alternative formulations that relax this restriction, such as along the lines of the Epstein-Zin preferences (Epstein and Zin, 1989, 1991; Ackerman et al., 2013)." (U. S. Government Interagency Working Group on Social Cost of Carbon, 2016)

The Epstein-Zin (E-Z) recursive preference model developed to address the related but distinct issues of time separability, intertemporal tradeoffs, and intratemporal risk aversion. The E-Z preference model is a minimalist isoelastic implementation of the underlying principles with non-separability that allows distinctions for substitution across time and substitution across outcomes at the same time. (Backus, Routledge, & Zin, 2004)

The basic E-Z formulation, as in the notation in (Ackerman et al., 2013), is

$$U_t = \left[(1-\beta) c_t^{\rho} + \beta \left(\mu_t \left[U_{t+1} \right]^{\rho} \right) \right]^{1/\rho}$$

$$\mu_t \left[U_{t+1} \right] = \left(E_t \left[U_{t+1}^{\alpha} \right] \right)^{1/\alpha}$$

Here $\mu_t \left[U_{t+1} \right]$ has the interpretation of the certainty-equivalent of future utility. The assumption in this formulation is that the c_t is known with certainty at the start of each period.

Here β is the discount factor for utility; the rate of pure time preference is $\delta = (1-\beta)/\beta$. (In DICE2016, $\delta = 1.5\%/yr.$) Time preference is also affected by ρ; the elasticity of intertemporal substitution (EIS) is $\Psi = 1/(1-\rho)$. Risk aversion is measured by α; the coefficient of relative risk aversion is $\gamma = (1-\alpha)$. (Ackerman et al., 2013, p. 75) Under the restrictions of the DICE utility function, $\eta = \gamma = 1/\Psi$. But for E-Z this restriction does not apply. $\left[EIS \equiv -\partial \log\left(\frac{c_{t+1}}{c_t} \right) \Big/ \partial \log\left(\frac{\partial U / \partial c_{t+1}}{\partial U / \partial c_t} \right) \right]$

Anticipation of uncertainty and the timing the resolution of uncertainty affect choices now and in the future. A challenge is to incorporate the sequential interaction between the events and decisions. (A S Manne & Richels, 1991)

The problem leads to a decision tree, or a stochastic dynamic programming (SDP) formulation.

$$V_t\left(s_t\right) = \underset{x_t \in X_t\left(s_t\right)}{Max}\left[f\left(x_t\right) + \beta E_s\left(V_{t+1}\left(s_{t+1}\left(x_t, s_t\right)\right)\right)\right]$$

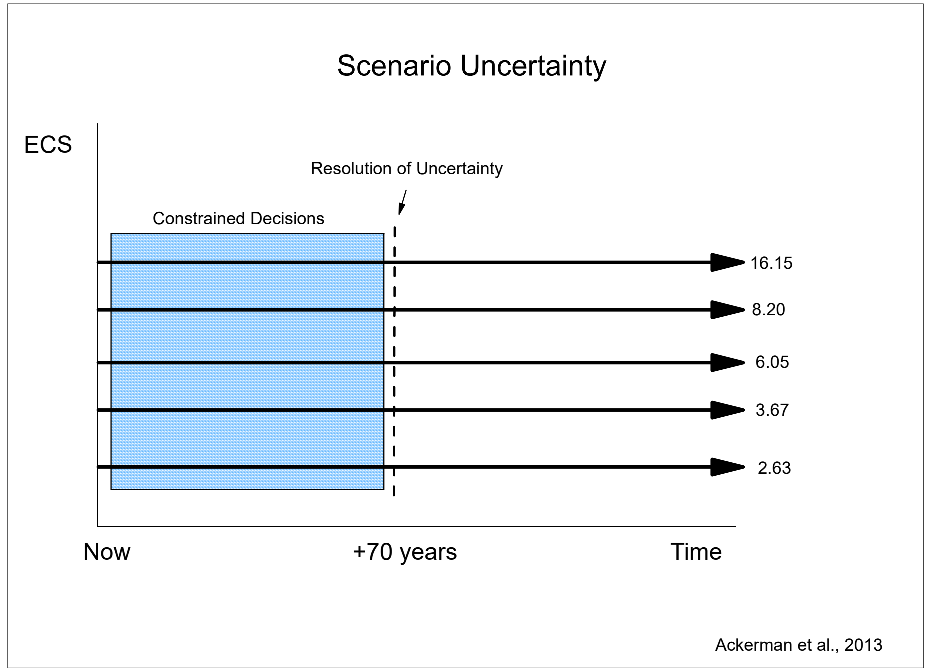
Many alternative formulations confront the "curse of dimensionality" with too many branches on the tree.

- **Simplify the Underlying Model.** Applications of E-Z to the climate problem with simplified representations of DICE and the decision tree include (Ha-Duong & Treich, 2004) (Crost & Traeger, 2011) (Traeger, 2014) (Crost & Traeger, 2014) (Belaia, Funke, & Glanemann, 2017)
- **Full SDP.** An implementation with full SDP and focused on the analysis of tipping points using E-Z and a close approximation of DICE is in (Cai, Lenton, & Lontzek, 2016).
    - o Computationally complex. "We solve the model with parallel dynamic programming methods on 312,500,000 approximation nodes for the ten-dimensional continuous state space and degree-4 complete Chebyshev polynomials for each of the five discrete state vectors. It takes about 3 h to solve the model for a single set of parameter values on 10,560 cores at the Blue Waters supercomputer."
    - o Roe-Bauman critique. The application focus is on tipping point analysis, but does not incorporate the Roe-Baker ECS uncertainty or the Roe-Bauman critique. Incorporating a delay in the resolution of ECS uncertainty raises a type of hidden variables problem (Gerlagh & Liski, 2016) that complicates the SDP assumption that the current known state is a sufficient statistic for the future. See also (Powell, 2011, pp. 185–186), (Špačková & Straub, 2016).

An alternative approach follows the application of a constrained scenario structure that allows full utilization of the DICE model.

The application in (Ackerman et al., 2013) approximates the Roe-Baker ECS distribution using five scenarios.

- Each scenario is almost a parallel application of DICE.
- For the early decisions, only the long-run ECS distribution is known. Hence, the key emission control rate and investment decisions are constrained to be the same.
- All ECS uncertainty is resolved after 70 years, permitting different decisions for future periods.
- The E-Z utility is applied only for the first period!



The scenario formulation greatly simplifies the problem, but the restriction to applying E-Z utility only in the first period is inconsistent with the timing of the resolution of uncertainty. However, the timing issue was part of the motivation for the development of E-Z preferences.

A modification of the scenario model allows more flexibility in the resolution of uncertainty at the cost of a little more complexity in the implementation of E-Z preferences.

Here application of the E-Z preference model employs expectations in each period conditioned by the resolution of uncertainty.

The constraints on decisions are for the emissions control rate and the savings rate.

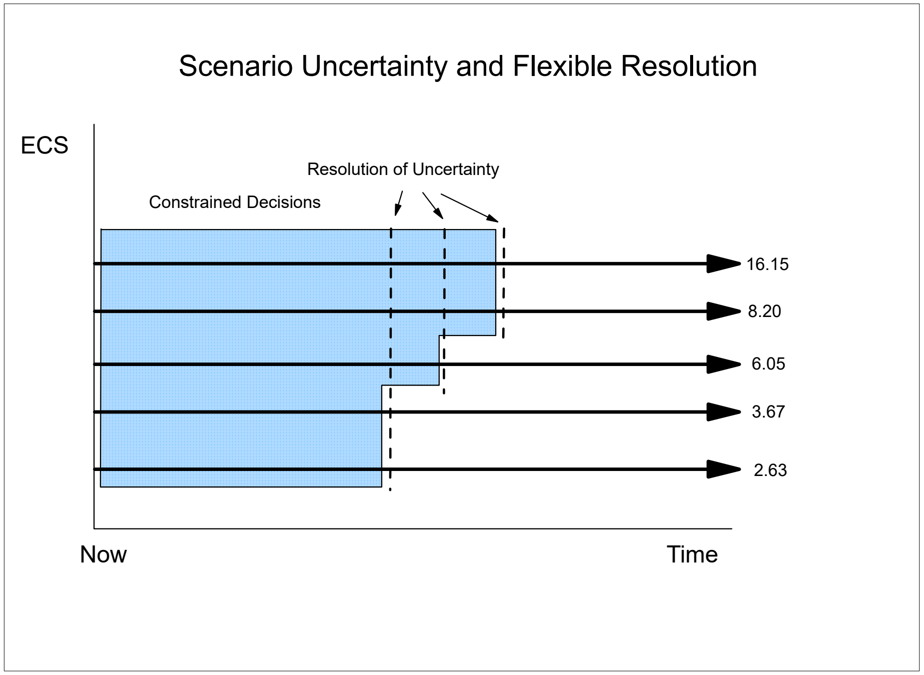
This requires a modification of E-Z to account for the unknown state at the time that decisions are made, implying that the current period consumption is uncertain when the decisions are made. See also (Anthoff & Emmerling, 2016).

The modified E-Z model for per capita consumption of a representative agent becomes:

$$U_t = \left[(1-\beta)\mu_t(c_t)^\rho + \beta\left(\mu_t\left[U_{t+1}\right]^\rho\right) \right]^{1/\rho}$$

$$\mu_t\left[U_{t+1}\right] = \left(E_t\left[U_{t+1}^\alpha\right]\right)^{1/\alpha}$$

$$\mu_t\left[c_t\right] = \left(E_t\left[c_t^\alpha\right]\right)^{1/\alpha}$$



The version here of DICE-Epstein-Zin with Roe-Bauman (DICE-EZ-RB) includes a preference function weighted by the DICE labor supply (population) projections.

The DICE model weights intertemporal utility by the respective population projections. Here we follow (Ha-Duong & Treich, 2004) in the logic of recursive application of population (L_t) weighting relative to the asymptotic population (L_N) according applied to the equivalent consumption of next periods utility.

$$U_t = \left[(1-\beta) \frac{L_t}{L_N} \mu_t (c_t)^\rho + \beta \left(\frac{L_{t+1}}{L_t} \right)^\rho \left(\mu_t [U_{t+1}]^\rho \right) \right]^{1/\rho}$$

$$\mu_t [U_{t+1}] = \left(E_t \left[U_{t+1}^\alpha \right] \right)^{1/\alpha}$$

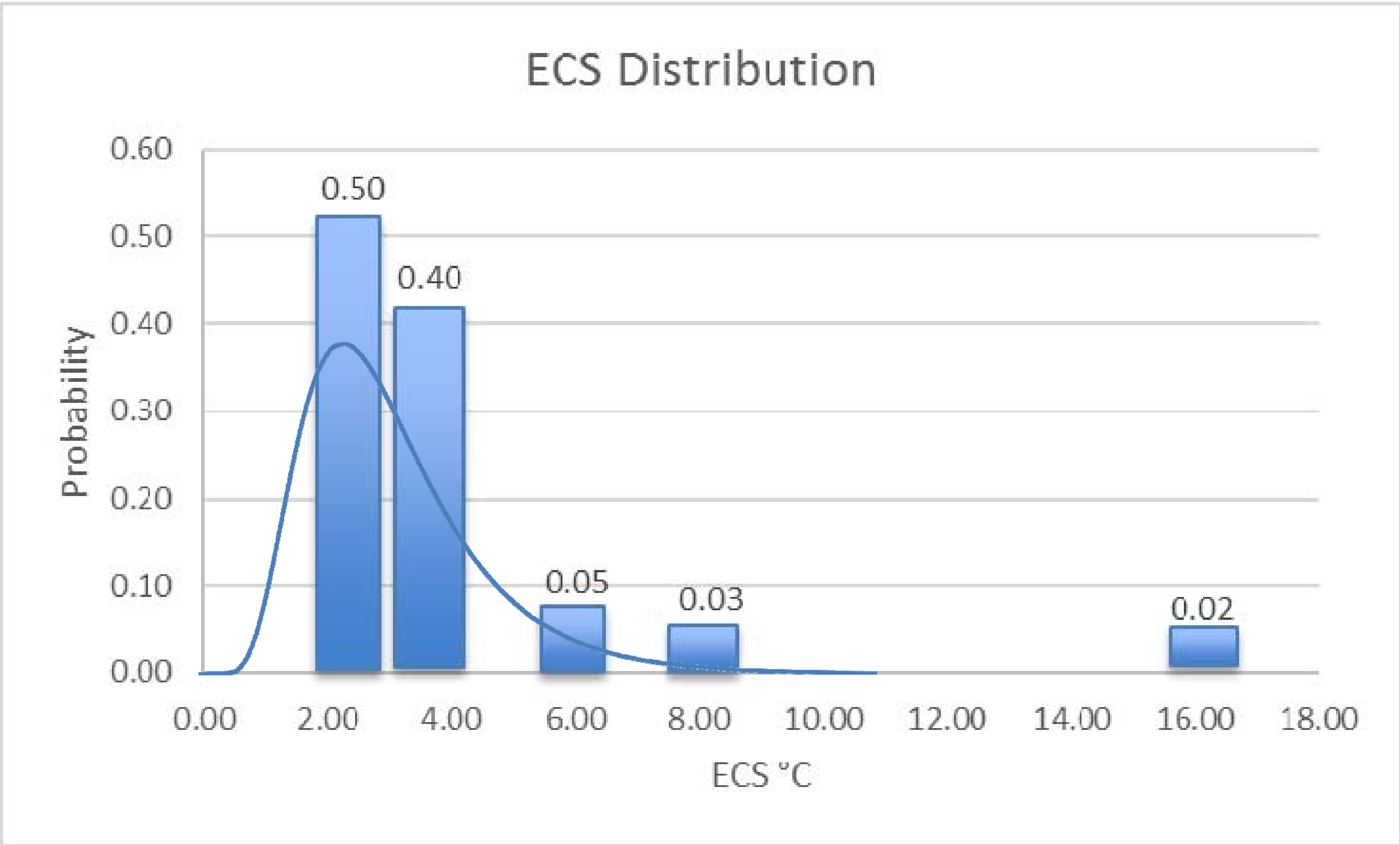
$$\mu_t [c_t] = \left(E_t \left[c_t^\alpha \right] \right)^{1/\alpha}$$

Before the resolution of uncertainty, the emission control rate and saving rate are constrained across scenarios. The expectation in each period is taken as common across constrained scenarios, but reduces to a single scenario after the resolution of uncertainty.

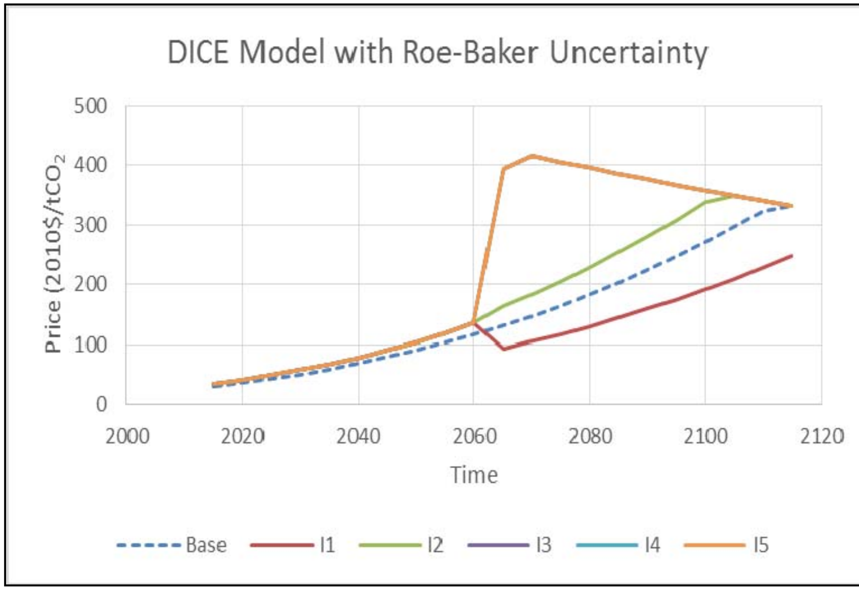
The approximate Roe-Bauman ECS timing and the discrete approximation of the Roe-Baker distribution apply.

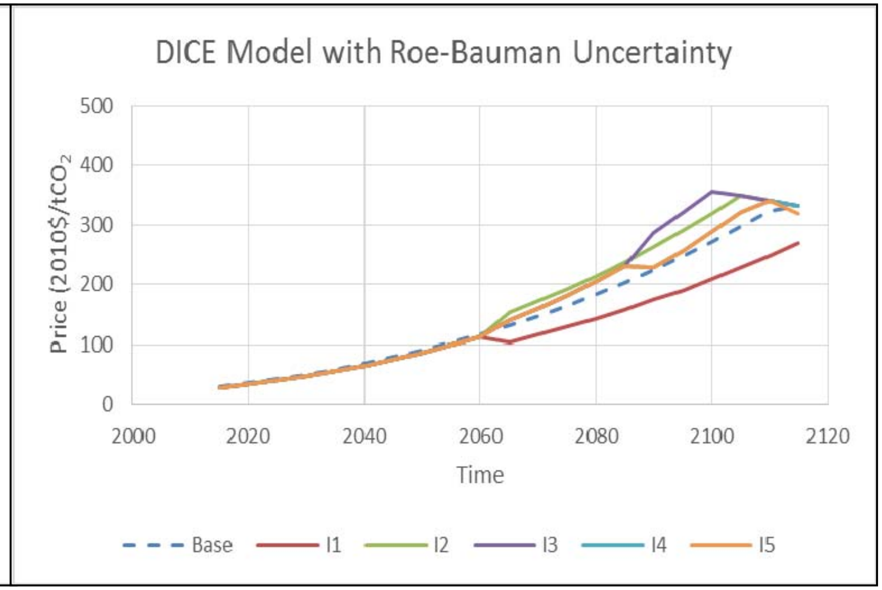
The objective function is to maximize U_0 by choosing emission control and savings rates subject to all the other constraints and relationships in the 2016 DICE model.

The Equilibrium Climate Sensitivity (ECS) is uncertain and skewed with a long upper tail. The scenario approximation follows the characterization of the Roe-Baker distribution as applied in (Ackerman et al., 2013)**.**



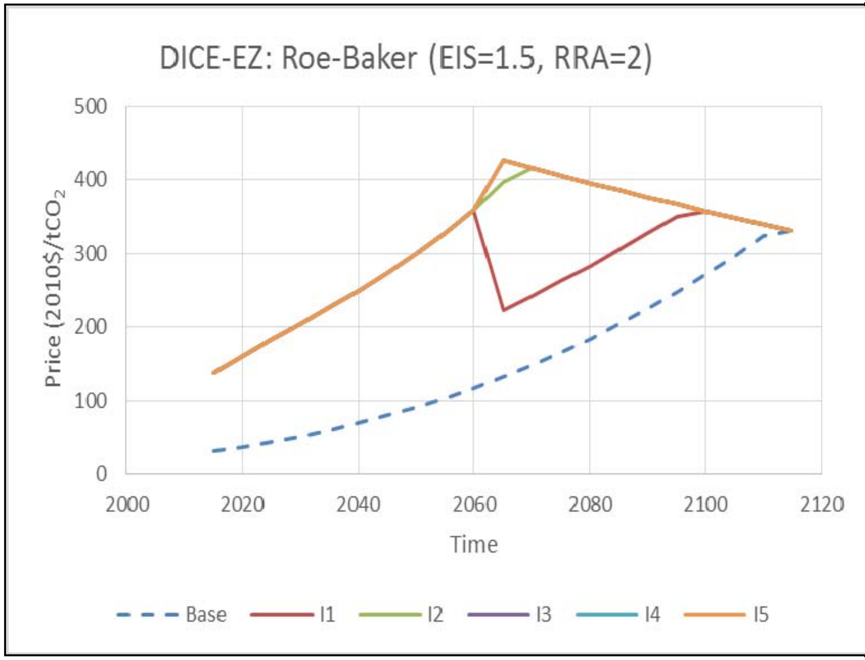
Introduction of ECS uncertainty produces a small effect on the price of carbon, compared to the DICE base case with no uncertainty. Application of the Roe-Bauman dynamics virtually eliminates the difference until the uncertainty is resolved. This is before including E-Z preferences.

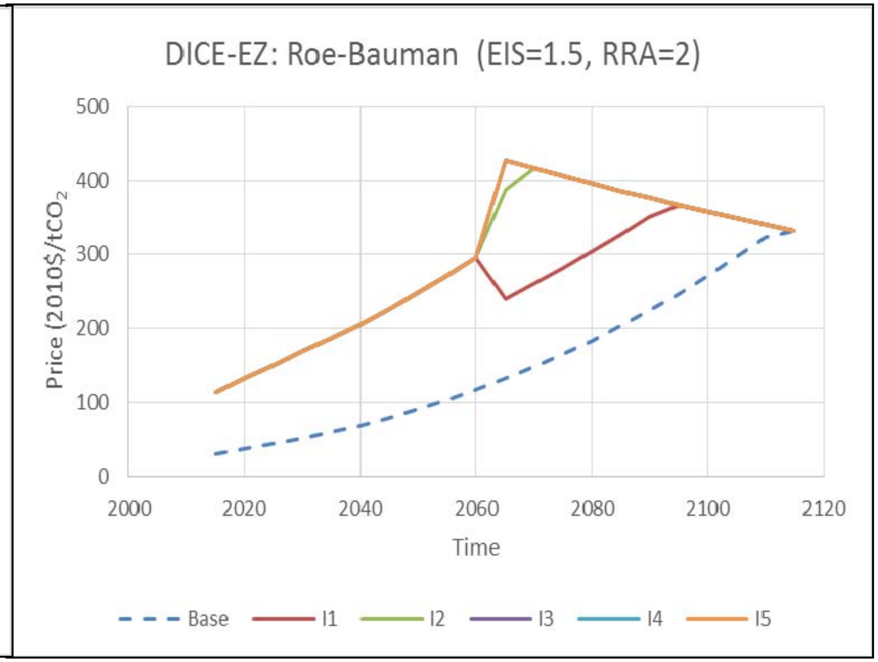




Source: Hogan & Wagner (Mimeo)

Including EZ preferences with an EIS=1.5 produces or more substantial impact from the treatment of uncertainty.





Source: Hogan & Wagner (Mimeo)

SOCIAL COST OF CARBON — DICE-EZ-RB

Introducing the Epstein-Zin preferences illustrates the importance of the EIS. The initial price of carbon is affected by the treatment of uncertainty (Roe-Bauman versus no Roe-Bauman), but the EIS is much more important.

2015 Price of Carbon (SCC, $2010/t CO2)								
	RRA							
DEZRB	1.45		2		4		6	
EIS	Baker	Bauman	Baker	Bauman	Baker	Bauman	Baker	Bauman
0.69	$30	$26	$31	$26	$31	$26	$33	$26
1.50	$137	$114	$138	$114	$143	$115	$148	$115

EIS more important than RRA and Roe-Bauman (“Bauman”) vs No-Roe-Bauman (“Baker”)?

(Source: Hogan & Wagner, Mimeo)

DICE	Base	Baker	Bauman
	$31	$35	$29

Applications of EZ preferences and Roe Baker ECS uncertainty apply high values of the EIS.

- **Examples with EIS 1.5 or more.**
  - (Ackerman et al., 2013). Roe-Baker ECS uncertainty and EIS=1.5 increases initial SCC by over 400%. See also (Belaia et al., 2017) with an explicit Atlantic Thermohaline Circulation risk.
  - (Cai et al., 2016). Roe-Baker ECS uncertainty not addressed. A multiple tipping point analysis raises the initial SCC by over 600%. The support for EIS=1.5 cites (Pindyck & Wang, 2013). However, Pindyck and Wang emphasize the inability to separately identify the EIS and the pure rate of time preference δ. The rate of time preference in (Pindyck & Wang, 2013, p. 319) is 4.98%, compared to the use of the DICE value of 1.5%.
- **Examples with EIS above and below 1.0.**
  - (Cai, Judd, & Lontzek, 2015) Incorporates uncertainty in economic growth, and separate analysis that includes stochastic tipping points. There is no Roe-Baker ECS uncertainty. The results uncertainty in economic growth with different EIS=Ψ and RRA=γ.

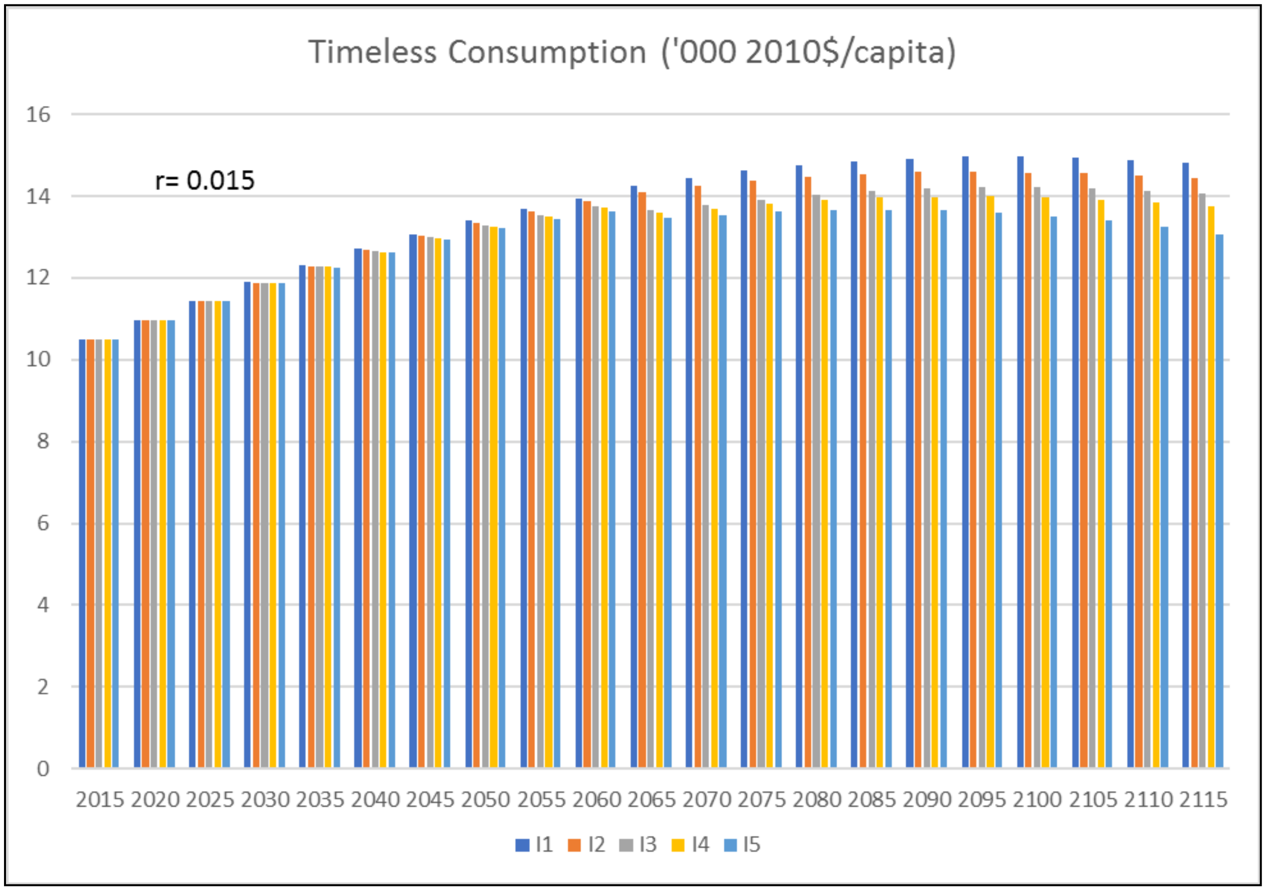
ψ	Deterministic Growth Case	γ				
		0.5	2	6	10	20
0.5	37	35	39	52	61	69
0.75	54	53	55	58	60	62
1.25	82	83	77	65	61	56
1.5	94	95	85	68	61	55
2.0	111	115	97	71	62	54

Initial social cost of carbon ($ per ton of carbon) under stochastic growth

The value of the applied in E-Z models allow for a change in EIS and RRA. The change induced is large.

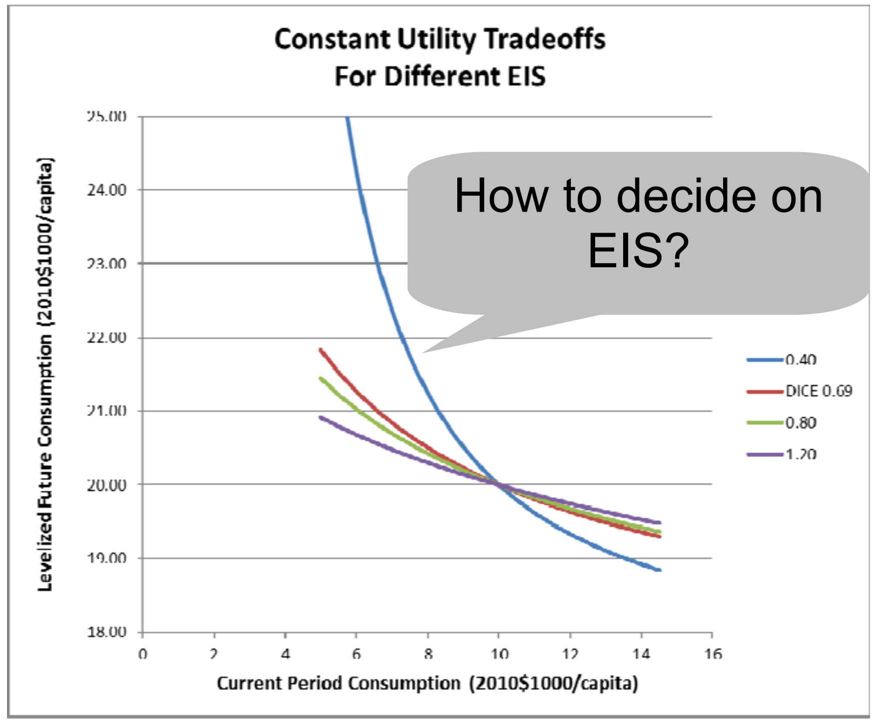
- **Addressing the CRRA formulation,** (Gollier & Hammitt, 2014) **describes a soft consensus across a dozen studies.**
  - "…a degree of relative risk aversion of between 1 and 4 is more representative of a soft consensus among economists." Thus $1 \leq \eta \leq 4$.
  - Common values for the E-Z applications have EIS=1.5. This translates into $\eta = 0.67$.
- **The defects of the CRRA formulation are not fatal, and not removed with the E-Z model.**
  - "Virtually every assumption underlying the DU model has been tested and found to be descriptively invalid in at least some situations." (Frederick, Loewenstein, & O'donoghue, 2002, p. 352). But the basic framework is pervasive as an approximation of a more complicated problem. (Deaton, 1992, p. 20)
  - "Disagreement about the level of [inequality aversion] comes from the fact that this parameter plays many different roles in the discounted expected utility (DEU) model. For example, under the Rawlsian veil of ignorance, the level of inequality aversion should be equal to the degree of relative risk aversion of the representative consumer, thereby transforming an ethical parameter into a descriptive one." (Gollier & Hammitt, 2014, p. 281)
  - The review in (Epstein, Farhi, & Strzalecki, 2014) suggests that the widely cited approach of (Bansal & Yaron, 2004) for estimating the E-Z parameters, and addressing the equity premium puzzle with CRRA, creates its own puzzle about the willingness to pay to resolve uncertainty.

Discounting consumption based only on the pure rate of time preference illustrates the relative unimportance of ECS uncertainty. The intertemporal tradeoffs driven by inequality aversion should be more important. (DICE projection with Roe-Baker ECS uncertainty.)



A critical parameter in the DICE-EZ-RB application is the EIS. How can we determine the appropriate value?

- The intertemporal tradeoff determination replaces the discount rate debate with another conundrum. How to determine EIS?
- A recent EIS survey concludes: "**What is the true value of the EIS? Hard to say.** … The discussion seems to have moved away from *zero or positive?* in the 1980s to *below or above one?* today. … What is a reasonable choice of the EIS in representative agent models? That depends on the model. If the model is sought to explain stock returns and their joint behavior with consumption innovations, one should try to represent preferences of the average stock market participant which is likely to have a higher EIS than the average consumer. The common choice of 1.5 seems pretty reasonable after all. However, for models that assume that the representative agent consumes a single nondurable consumption good, it seems difficult to argue against values that are considerably lower and clearly below one." (Thimme, 2017)



Source: Hogan & Wagner (Mimeo)

Estimation of the definition of the EIS and the relation to inequality aversion is neither obvious nor determined by the available empirical studies.

"…the EIS is defined as the negative ratio of changes in log consumption growth and log growth of marginal utility of consumption." (Thimme, 2017, p. 226)

$$EIS \equiv -\partial \log\left(\frac{c_{t+1}}{c_t}\right) \Big/ \partial \log\left(\frac{\partial U/\partial c_{t+1}}{\partial U/\partial c_t}\right)$$

In the CRRA formulation, $EIS = 1/\eta$ **, and we have the fundamental discounting equation for the discount rate on consumption under certainty.**

$$r = \delta + \eta g \text{ .}$$

This discounting equation has several interpretations:

- **Instantaneous discount rate with one period growth g.**
- **Real rate of interest at the optimal solution in a Ramsey model.**
- **Average discount rate over a long period with average growth g.**
- **1+r is the ratio of a certain exchange of consumption that preserves utility.**

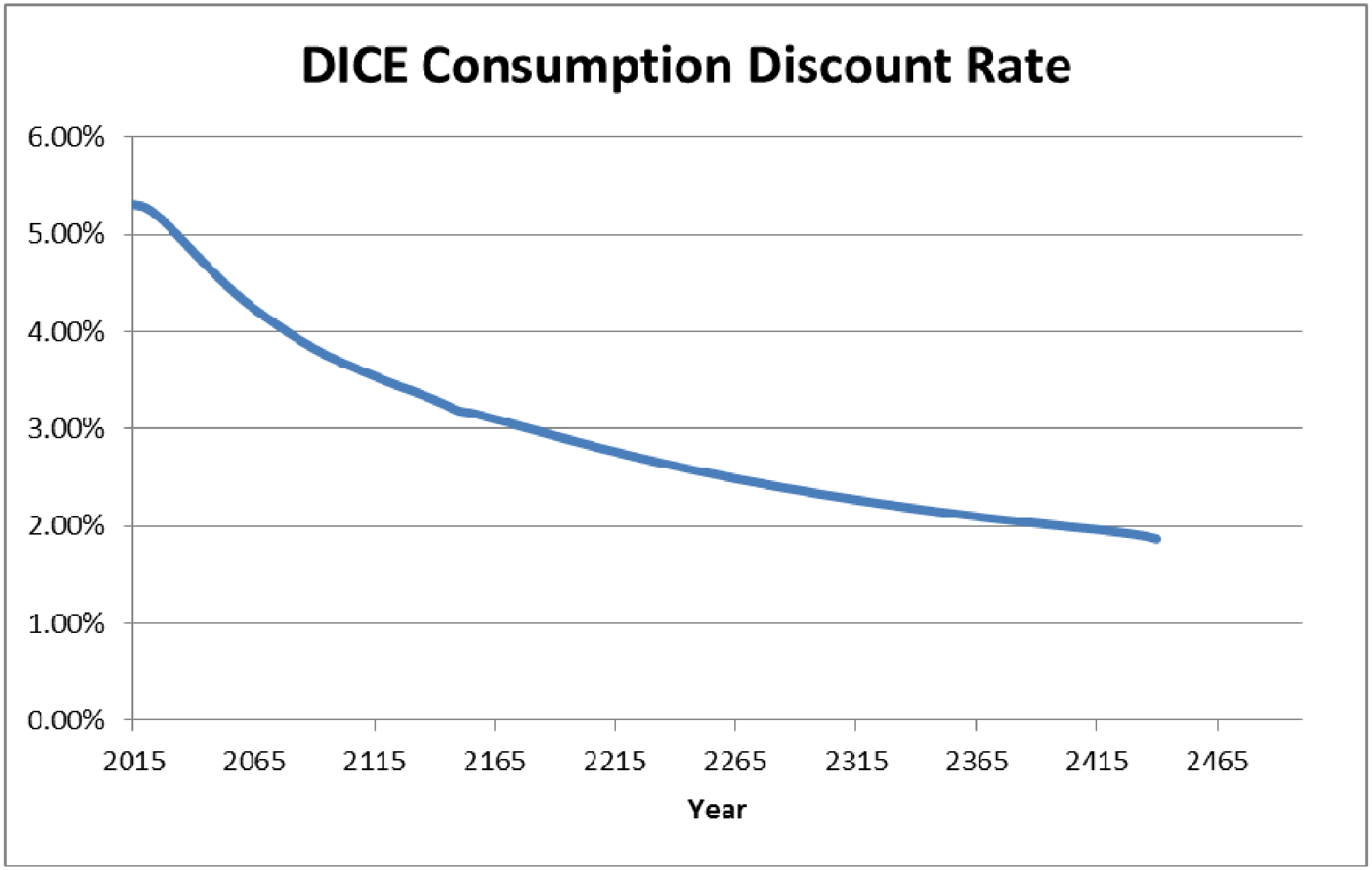
The miracle of compounding applies. (DICE2016 has $\delta = 0.015, \eta = 1.45, g = 1.9\%$.) See also (National Academy of Sciences, 2017, p. 256)**.**

$$r = \delta + \eta g$$

Equivalent Consumption Ratio							
η	δ	**Growth_t**	**t**	***g***	***r***	**Ratio_1**	**Ratio_t**
0	0.015	6.65	100	1.91%	1.50%	1.015	4.43
1	0.015	6.65	100	1.91%	3.41%	1.034	28.67
1.5	0.015	6.65	100	1.91%	4.37%	1.044	71.97
2	0.015	6.65	100	1.91%	5.33%	1.053	179.18
0	0.001	6.65	100	1.91%	0.10%	1.001	1.11
1	0.001	6.65	100	1.91%	2.01%	1.020	7.34
1.5	0.001	6.65	100	1.91%	2.97%	1.030	18.65
2	0.001	6.65	100	1.91%	3.93%	1.039	47.01

DICE2016 has $\delta = 0.015, \eta = 1.45, g = 1.9\%$. The consumption growth rate declines in the base case, which produces a declining discount rate.

$$r = \delta + \eta g$$



Does the Roe-Bauman critique matter?

- Re-optimizing DICE, using Roe-Bauman's parameterization, does not simply add time delay on top of existing optimized paths.
- Uncertainty matters, but the Roe-Bauman dynamics materially reduce the effect of ECS uncertainty on near term decisions.

Does the separation of risk and time a la Epstein-Zin matter?

- Investigating Epstein-Zin in DICE context for ECS uncertainty shows relative unimportance of intratemporal risk aversion.
- The key parameter is the EIS and the inequality aversion across generations.

What about the combination of the two?

- Roe-Bauman dynamics *decrease* SCC in the E-Z case by >15%.
- The E-Z extensions in the literature often apply EIS=1.5, driving the results that produce high SCCs.
- The debate returns to the appropriate parameters for the pure rate of time preference and the measure of inequality aversion that dominate the discount rate. (Alan S. Manne, 1995) (Nordhaus, 2007) (National Academy of Sciences, 2017)

Future work:

- Comparison of influence of EIS vs damage function?
  - Tipping points?
  - RICE?
- Other?

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