Carbon Prices, Preferences,

and the Timing of Uncertainty

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Uncertainty is persistent features of climate economics. Two prominent recent manifestations are an emphasis on tail risks and on Epstein-Zin (EZ) preferences. We explore both numerically in the DICE model and find that neither escapes decades-old discounting debates. The greater are climate sensitivity tail risks, the longer it takes to reach equilibrium temperatures, bringing discounting back to the fore. Similarly, our numerical EZ explorations show the importance of the elasticity of intertemporal substitution relative to risk aversion, pointing back to the crucial role of normative judgments around discounting far-distant futures. There appears to be no escaping economics' philosophical roots. (JEL D62, D81, H43, Q54, Q58*)*

The question of how to price one ton of carbon dioxide (CO_2) released into the atmosphere has haunted climate economists for decades. Call it the "mother of all benefit-cost analyses."[1] That highlights the enormous burden on those who attempt

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[1] Climate change invokes colorful—superlative—language. Stern (2006) calls it "the greatest market failure the world has ever seen," Tol (2009) "the mother of all externalities."

the feat, and also magnifies the credit due to economists like Bill Nordhaus, who, in the early 1990s, introduced the Dynamic Integrated Climate-Economy (DICE) model to answer just that question, and has maintained it ever since (Nordhaus, 1992, 2017a, 2018). The outcome of this global, multi-century benefit-cost analysis is the social cost of carbon dioxide (SC-CO_2).[2]

It is easy to find faults. Many have.[3] DICE's simplicity, one of its most important features, lends itself to instant criticism. A mere 20 main equations describe the climate-economy system, with three describing the entire climate system (Nordhaus and Sztorc, 2013). The simplicity makes DICE well-suited to test how key inputs and structural assumptions affect the SC-CO_2. Two such fundamental assumption are the discount rate and the model's treatment of uncertainty.

Valuing climate damages is beset with pervasive, oft deeply seated uncertainties. One of DICE's important contributions is capturing the entire climate-economic chain from economic output to how climate damages affect economic well-being. That chain includes several crucial links along the way: from output to CO_2 emissions, from emissions to atmospheric CO_2 concentrations, from concentrations to global average temperatures, and from temperatures to climate damages, with damages reducing economic consumption and, thus, economic well-being. Three steps, in particular, come with considerable uncertainties. The first step of forecasting economic growth alone is highly uncertain (Christensen, Gillingham and Nordhaus, 2018); translating output into emissions projections adds yet another layer of uncertainty. The final step of translating climate changes into damage

[2] The SC-CO_2 is often known as the social cost of carbon (SCC), most prominently because of U.S. Government Interagency Working Group on the Social Cost of Carbon (2010; 2016). The SCC, too, is typically denoted in dollars per ton of CO_2 emitted. Neither the SC-CO_2 or the SCC, meanwhile, necessarily denote the optimal CO2 price, as they could be calculated as the marginal price on today's emissions trajectory, which is hardly optimal. We here utilize an optimal trajectory for the SC-CO_2.

[3] Rose et al. (2014; 2017) shows how the three main climate-economy models, including DICE, used in the U.S. Government Interagency Working Group on the Social Cost of Carbon (2010; 2016) have, in part, wildly different assumptions and inputs, while still leading to relatively similar answers for the resulting social cost figure. See Burke et al (2016) and especially NAS (2017) for a comprehensive critique and set of recommended improvements.

estimates is similarly fraught. DICE has assumed a quadratic damage function since the very beginning (Nordhaus, 1992, 2018), with the most recent empirical advances having yet to find their way into the model (Burke *et al.*, 2016; Hsiang *et al.*, 2017; NAS, 2017; Stoerk, Wagner and Ward, 2018). We here focus on uncertainties in the link from concentrations to temperatures.

Weitzman (2009a, 2011, 2014) has highlighted some of the stark implications, developing what he calls the "Dismal Theorem": Even a small chance of catastrophe loosely defined dwarfs any results derived by focusing on expected values. Intuitively, any ever-so-small probability $\epsilon > 0$, multiplied by infinitely bad outcomes, results in expected infinite costs. More formally, any fat-tailed equilibrium climate sensitivity (ECS) distribution, the crucial link between atmospheric greenhouse-gas concentrations and eventual global average temperatures, makes calculating expected values mathematically impossible. Such a result would render DICE all but useless. The debate between Nordhaus and Weitzman continues to this day.[4]

We here take Weitzman's Dismal Theorem seriously, while exploring the implications of the timing of uncertainty. Roe and Bauman (2013) argue convincingly how "there are important physical constraints on the climate system that limit how fast temperatures can rise" (p. 649). The farther out on the tail of the ECS distribution one goes, the longer it takes to get there.[5] To be clear, none of that is of particular news to climate scientists. Roe and Bauman (2013) are hardly the first to make that point in the climate literature. See, for example, Baker and Roe (2009). In any case, the time element would be scant comfort to some, like Heal

[4] Nordhaus (2009) responds directly to Weitzman (2009a), who, in turn, replies in equally strong terms (Weitzman, 2009b). Nordhaus (2011) and Weitzman (2010, 2011) present a further evolution of the debate, followed by Weitzman (2015) reviewing Nordhaus's (2013) *Climate Casino* with an eye toward its treatment of uncertainty, and Nordhaus (2015) returning the favor in reviewing Wagner and Weitzman (2015). Pindyck (2011) sides with Nordhaus, while Heal (2017), in a broad review of the literature, lends support to Weitzman's thesis and the need to look toward alternative decision criteria.

[5] NAS (2017) similarly reports on the importance of consistency in evaluating the ECS and the associated dynamics (p. 133). Johnston (2015) explores further implications for the optimal carbon price.

(2017) and Heal and Millner (2014), seeking alternative decision criteria altogether. Within an expected utility framework, however, timing matters, highlighting the importance of discounting.

The debate around which discount rate to use in the presence of persistent uncertainties has led to a number of important theoretical (e.g., Gollier and Weitzman, 2010), empirical (e.g., Giglio, Maggiori and Stroebel, 2015), and philosophical (e.g., Dasgupta, 2008) contributions, leading to a widely held consensus around the need for declining discount rates (Arrow *et al.*, 2013, 2014).[6] This consensus is, in part, reflected in the work of the U.S. Government Interagency Working Group on the Social Cost of Carbon (2010; 2016) under President Barack Obama's administration. While its central estimate uses a constant 3% discount rate, it justifies a constant 2.5% as its lower bound by having it be a proxy for a rate that begins at 3% today and declines over time (NAS, 2017). Meanwhile, Nordhaus's (2017a) preferred discount rate over the years has been around 4.25%, declining only slowly to slightly over 4%. This difference in discount rate to a large extent explains the difference in SC-CO_2 estimates between DICE and the U.S. Government Interagency Working Group on the Social Cost of Carbon (Nordhaus, 2017b).

The importance of the discount rate highlights another recent frontier in climate economics: those arguing that discount rates ought to be the output of a careful calibration exercise rather than a free parameter chosen by the analyst. Around the same time when Nordhaus developed DICE, based on a Ramsey (1928)-Cass (1965)-Koopmans (1963)-style economic growth model, financial economists began considering more flexible, recursive preference structures. First introduced by Kreps and Porteus (1978) and later popularized by Weil (1990) and, in particular,

[6] By one count, over 600 economists wrote papers on discounting in the highest-ranked 100 economic journals in only the first 15 years of this century (Drupp *et al.*, 2015).

Epstein and Zin (1989, 1991), recursive preference structures have become standard tools used by financial economists. They allow for a separation of risk aversion across states of nature from discounting across time. Epstein-Zin (EZ) preferences have since found their way into climate-economic models, including DICE.[7]

We modify DICE to include both EZ preferences and the Roe-Bauman (RB) time component vis-à-vis ECS uncertainty, creating DICE-EZ-RB. The model allows us to explore the relative importance of both modifications, leading us to conclude that there is no escaping the debate around how to discount the (distant) future in the presence of potentially large uncertainties.

I. The DICE-EZ-RB Model

DICE provides a framework for capturing key tradeoffs inherent in climate economics. One is between consumption today and future climate damages. That puts projected damages and discounting front and center. What might appear like catastrophically large climate damages might be insignificant to today's decision-making, if those damages were discounted away. Conversely, in the 'standard' model using typical discount rates, only truly catastrophic damages centuries hence would necessitate significant climate action today.

A. Climate Uncertainty

We focus on uncertainties governing equilibrium climate sensitivity (ECS), defined as what happens to global average surface temperatures eventually, due to a doubling of atmospheric CO_2 concentrations. The key word here is "eventually."

[7] Most implementations of EZ preferences in climate-economic models focus on DICE (Ha-Duong and Treich, 2004; Crost and Traeger, 2011, 2014; Ackerman, Stanton and Bueno, 2013; Traeger, 2014; Belaia, Funke and Glanemann, 2017). A few explore a full stochastic dynamic programming formulation (Cai, Judd and Lontzek, 2013, 2015; Golosov *et al.*, 2014; Cai, Lenton and Lontzek, 2016), with Daniel, Litterman and Wagner (2016) attempting to provide a simplified version. Lemoine and Rudik (2017a) survey the literature focused on EZ implementations in DICE.

While geologists refer to ECS as "fast" climate sensitivity—distinct from "Earth system sensitivity" that considers long-run feedbacks over many centuries and millennia that could more than double ECS estimates (Knutti and Hegerl, 2008; Proistosescu and Huybers, 2017)—ECS, too, plays out over decades and centuries.[8] How long it takes for temperatures to reach their equilibrium value depend crucially on how high it is. ECS, meanwhile, has been persistently uncertain.

The Intergovernmental Panel on Climate Change (IPCC) has concluded that the ECS is "likely" in the range of 1.5–4.5°C (IPCC, 2013). While the definition of "likely" has become more precise over the years—it is now defined as having a 66% probability of occurring—the range itself has not changed since Charney *et al* (1979).[9] The overall distribution is skewed to the right. Roe and Baker (2007) provide perhaps the most prominent explanation for why. They calibrate what has become known as the "Roe-Baker" distribution, which, in turn, is qualitatively similar to a log-normal distribution first used by Weitzman (2009a) in an economic context. Roe and Bauman (2013) take the Roe-Baker ECS distribution and add the all-important time element: the higher the value of ECS, the longer it takes for global average temperatures to reach their equilibrium value. In particular, "the upper bound on possible temperatures is finite at finite time, limiting the skewness" (Roe and Bauman, 2013, fig. 2).[10]

[8] Confusingly, describing ECS as "fast" climate sensitivity relative to Earth system sensitivity is distinct from more recent conversations around "fast" versus "slow" climate responses from a pulse of CO_2 emitted today. There, "fast" refers to current climate responses playing out typically within a decade, pointing to "cumulative emissions models" as a potentially superior way of looking at the climate impact of one ton of CO_2 emitted today (Matthews *et al.*, 2009; Matthews, Solomon and Pierrehumbert, 2012). See Nordhaus (1991) and Lemoine and Rudik (2017b) for general discussions of the role of time in climate-economy models. See Moreno-Cruz, Wagner, and Keith (2018) for an explicit discussion of a cumulative emissions model in a climate-economic context.

[9] The IPCC's range has been the same ever since 1990 (IPCC, 1990, 1995, 2001). The one exception was when IPCC (2007) narrowed it to 2–4.5°C, only for IPCC (2013) to revert again to 1.5–4.5°C. The overarching point is simply that ECS is evidently difficult to pin down precisely (Freeman, Wagner and Zeckhauser, 2015). A prominent recent study attempts to constrain the ECS based on global temperature variability and calculates a 66% "likely" range of 2.2-3.4°C, with no appreciable upper tail (Cox, Huntingford and Williamson, 2018). Wagner and Weitzman's (2018) reply argues how the shortened upper tail is largely a result of the assumptions of Cox et al's analysis.

[10] Roe and Bauman (2013) are hardly the first to do so. See, for example, Figure 4 in Baker and Roe (2009).

We here take Roe and Bauman's (2013) temperature dynamics as given and modify DICE to approximate their time path. Nordhaus and Sztorc (2013) present two temperature equations, 17 and 18, for mean surface aka "atmospheric" (T_{AT}) and deep ocean aka "lower ocean" (T_{LO}) temperatures, respectively:

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

(2) $$T_{LO}(t) = T_{LO}(t-1) + \xi_4\left[T_{AT}(t-1) - T_{LO}(t-1)\right],$$

where $F(t)$ is cumulative radiative forcing of anthropogenic greenhouse gases. The standard DICE 2016R calibration employs an ECS of 3.1°C. We approximate Roe-Bauman temperature dynamics by adjusting DICE's implied temperature sensitivity, represented by $\Delta T_{AT} = \Delta F(t)/\xi_2$ via equation (1), to account for the time to reach each ECS value. Following Ackerman, Stanton and Bueno (2013), and previewing our desire to integrate EZ preferences, we modify DICE's standard calibration around ECS = 3.1°C and instead calibrate our model to the five other ECS values represented in Table 1, choosing ξ_1', ξ_3', and ξ_4' to minimize the squared deviations from DICE's parameters and replace their respective parameters in equations (1) and (2). For each ECS scenario, we calculate time *t* when temperatures have reached percentage *p* of the particular ECS value, scaled as the square relative to the time this threshold is reached for the ECS = 3.1°C baseline:

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

To reflect the asymptotic nature of the temperature equilibrium process (Roe and Bauman, 2013, p. 649) we set $p = 63\%\ \left(\sim 1 - \frac{1}{e}\right)$. Table 1 represents the resulting parameters ξ_1', ξ_3', and ξ_4', with ξ_2' derived directly via the implied temperature sensitivity calculation, such that $\xi_2' = \xi_2 \frac{\Delta T_{AT}}{\Delta T'_{AT}}$ for alternative values of $\Delta T'_{AT}$.

TABLE 1—DICE PARAMETERS REFLECTING ROE-BAUMAN CALIBRATION

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
Probability	0.50	(base case)	0.40	0.05	0.03	0.02

Notes: Probabilities represent assumed probabilities for five different ECS values assumed by Ackerman, Stanton and Bueno (2013) to approximate the Roe-Baker ECS distribution.
Source: Authors' calculations, minimizing the squared deviations from DICE's parameters, setting $p =$ 63% $\left(\sim 1 - \frac{1}{e}\right)$ in equation (3).

The implications of the Roe-Bauman calibration become most evident when contrasting surface temperature time paths. Figure 1 shows the standard DICE time path using difference ECS values from Ackerman, Stanton and Bueno (2013), while ignoring RB dynamics. The resulting temperature trajectories are roughly proportional to eventual ECS values.

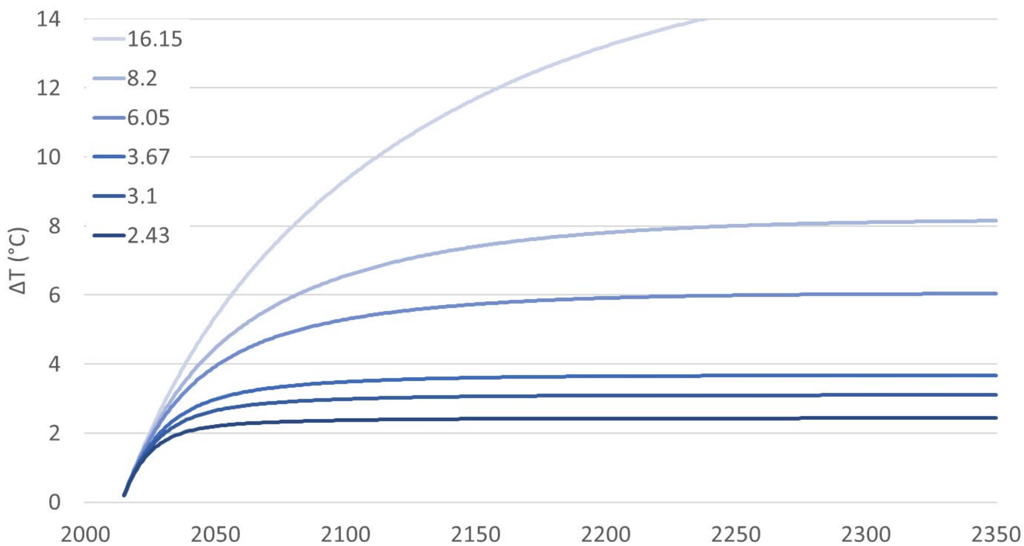

FIGURE 1. CHANGE IN SURFACE TEMPERATURE AFTER DOUBLING ATMOSPHERIC CO_2 CONCENTRATIONS WITH DIFFERENT CLIMATE SENSITIVITIES ASSUMING STANDARD DICE DYNAMICS

Notes: Authors' calculations, based on ECS values used by Ackerman, Stanton and Bueno (2013) and standard DICE parameters for ECS = 3.1°C.

Figure 2, by contrast, employs Roe-Bauman dynamics, showing significantly lower temperature changes in the first few decades and centuries. The differences are particularly important for extremely high ECS values. While the path for ECS = 2.43°C is almost identical, temperatures do not rise above 4.5°C within the first century even for ECS = 16.15°C. Without Roe-Bauman dynamics, DICE would project temperature to rise over twice as quickly by 2100.

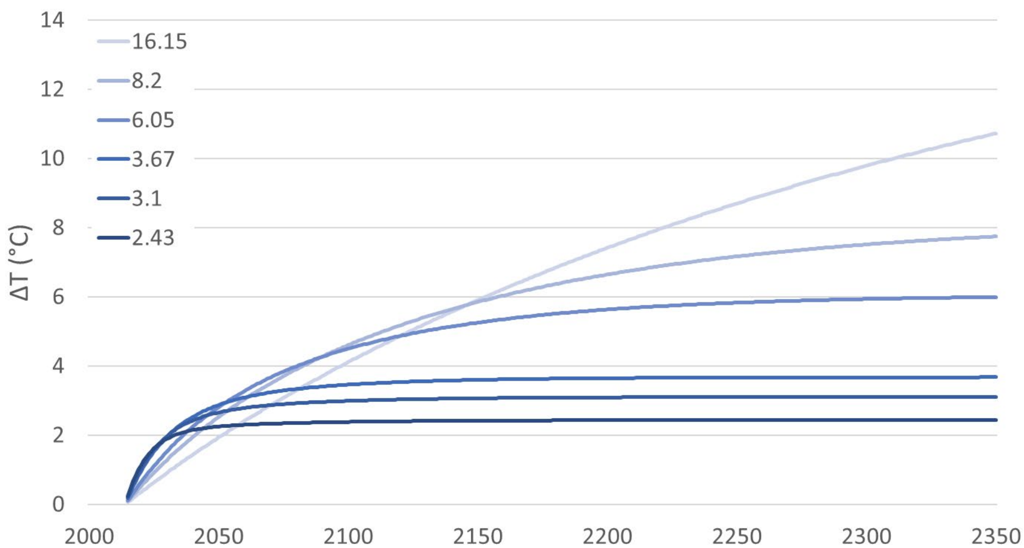

FIGURE 2. CHANGE IN SURFACE TEMPERATURE AFTER DOUBLING ATMOSPHERIC CO_2 CONCENTRATIONS WITH DIFFERENT CLIMATE SENSITIVITIES ASSUMING ROE-BAUMAN DYNAMICS

Notes: Authors' calculations, based on ECS values used by Ackerman, Stanton and Bueno (2013) and DICE parameters from Table 1.

Our modeling seemingly extreme ECS value well outside the IPCC's "likely" range of 1.5-4.5°C is merely an attempt, following Ackerman, Stanton and Bueno (2013), to approximate the Roe-Baker ECS distribution. To do so, we weigh the five ECS scenarios as given in the final row in Table 1.

The presence of high-impact, low-probability ECS values also highlights the importance of a second important modification to DICE: the use of EZ preferences. We do not claim that any such extreme ECS values are "likely." They are not.

Employing EZ preferences allows us to consider them nonetheless in our model, in an effort to take seriously the potential impacts of extreme risk.

B. Epstein-Zin (EZ) Preferences

The DICE model applies a standard economic growth approach of reliant on expected utility equal to the discounted stream of consumption over time, c_t:

$$U_t = \sum_t (1+\delta)^{-1} \frac{c_t^{1-\eta}}{1-\eta} \tag{4}$$

While standard, this approach is also limiting in one important way: a single parameter, η, characterizes both intertemporal tradeoffs and risk across different states of nature. This limitation has long been recognized in the financial literature (Kreps and Porteus, 1978; Epstein and Zin, 1989, 1991; Weil, 1990). Nordhaus, too, acknowledges the limitations of the standard approach, emphasizing how η represents both "aversion to generational inequality" and "often" also risk aversion (Nordhaus and Sztorc, 2013, p. 7). The same goes for the U.S. Government Interagency Working Group on the Social Cost of Carbon (2010; 2016) and the National Academy of Sciences (2017) reviewing the government's efforts. All reference Epstein and Zin (1989, 1991). None goes beyond the standard expected utility framework, leaving that step to an increasing number of other researchers (e.g., Lemoine and Rudik, 2017a). The climate-economic literature is hardly alone here. Deaton (1992), for example, discusses the restrictive nature of the expected utility framework (p. 20) before continuing to use it throughout the book.[11]

[11] Deaton (2007), meanwhile, questions the underlying expected utility assumptions himself. In a response to the Stern (2006), he asks: "Are we really entirely comfortable with the essentially arbitrary functional form assumptions that allow us to link risk aversion, intertemporal preferences, and the treatment of rich people versus poor people?"

Epstein and Zin (1989, 1991) and Weil (1990) developed what has since become known as Epstein-Zin (EZ) recursive preferences to address related but distinct issues of time separability, intertemporal tradeoffs, and intratemporal risk aversion. The EZ preference model is a minimalist isoelastic implementation of the underlying principles that allows distinctions for substitution across time and substitution across outcomes at the same time (Backus, Routledge and Zin, 2004).

Ackerman, Stanton and Bueno (2013) were among the first to introduce EZ preferences into DICE, employing recursive preferences of the form:

$$(5) \qquad U_t = \left[(1-\beta)c_t^{\rho} + \beta\left(\mu_t\left[U_{t+1}\right]^{\rho}\right)\right]^{1/\rho},$$

with the certainty-equivalent of future utility defined as:

$$(6) \qquad \mu_t\left[U_{t+1}\right] = \left(E_t\left[U_{t+1}^{\alpha}\right]\right)^{1/\alpha}.$$

This formulation separates time and risk preferences. The utility discount factor β determines the pure rate of time preference $\delta = \frac{1-\beta}{\beta}$. Time preference is also affected by ρ, which, in turn, determines the elasticity of intertemporal substitution:

$$(7) \qquad EIS \equiv -\frac{\partial ln\left(\frac{c_{t+1}}{c_t}\right)}{\partial ln\left(\frac{\partial U/\partial c_{t+1}}{\partial U/\partial c_t}\right)},$$

which here equals $\frac{1}{1-\rho}$. Risk aversion, meanwhile, is measured by α, which, in turn, determines the coefficient of relative risk aversion $\gamma = 1 - \alpha$.

Under DICE's standard expected utility function, $\eta = \gamma = \frac{1}{EIS}$, with the latter equality holding because $\alpha = \rho$ and indicating the rigid, and inverse, relationship between risk aversion and time preference.

While this recursive preference structure is clearly more flexible, it still embeds a number of key assumptions. For example, equation (5) assumes that c_t is known with certainty at the start of each period. This would be fine to assume in a model where each period is sufficiently short and of equal length across scenarios—e.g. one year. However, a full-fledged stochastic dynamic programming formulation with a large number of decision tree nodes creates complex computational challenges. Cai, Lenton and Lontzek (2016) build a model with over 300 million decision nodes that requires a supercomputer with over 10,000 cores three hours to solve. That has led many to greatly simplify the implementation of EZ preferences, limiting the number of decision points and extending each period from single years to decades or longer.[12] Doing so, however, points to the importance of the timing of the resolution of uncertainty, a problem first identified as such by Manne and Richels (1991), themselves among the first to model climate policy as a risk mitigation problem. More specifically, expanding the length of periods while assuming that each period's consumption c_t is known throughout each period raises a type of hidden variables problem (Gerlagh and Liski, 2016). Incorporating a delay in the resolution of ECS uncertainty complicates the assumption embedded in stochastic dynamic programming formulations that the current known state is a sufficient statistic for the future (Powell, 2011, pp. 185–6; Špačková and Straub, 2017). Ackerman, Stanton and Bueno (2013), for example, approximate the Roe-Baker ECS distribution using five scenarios. In doing so, ECS uncertainty is resolved after the first period 70 years hence. They, thus, only apply EZ utility for

[12] See footnote 7 for references.

the first period. This assumption greatly simplifies the problem, but the restriction to applying EZ utility only in the first period is inconsistent with the timing of the resolution of uncertainty, which was part of the motivation for the development of EZ preferences in the first place.

While looking to Ackerman, Stanton and Bueno (2013) for guidance in the choice of our six ECS scenarios (Table 1), we modify the implementation of EZ preferences to allow for a more flexible resolution of uncertainty. Equation (5) now becomes:

$$U_t = \left[(1-\beta)\mu_t\left[c_t\right]^{\rho} + \beta\left(\mu_t\left[U_{t+1}\right]^{\rho}\right)\right]^{1/\rho}, \tag{8}$$

with:

$$\mu_t\left[c_t\right] = \left(E_t\left[c_t^{\alpha}\right]\right)^{1/\alpha}, \tag{9}$$

and $\mu_t\left[U_{t+1}\right]$ as in equation (6). This formulation, following Weil's (1990) more flexible EZ framework relative to Epstein and Zin (1989, 1991), first adopted in a climate-economy model by Ha-Duong and Treich (2004), accounts for the unknown state of the world at the time that decisions are made. Here that implies allowing for uncertain c_t at the beginning of each decision period (Anthoff and Emmerling, 2016), which itself might be of unequal length, dependent on the ECS value itself. A higher ECS engenders more uncertainty for longer.[13]

One further complicating factor of note is population growth (Ha-Duong and Treich, 2004). As c_t represents our representative agent's *per capita* consumption,

[13] Note that while ECS differs across our five scenarios, expectations over eventual ECS values are taken as common across scenarios until the resolution of uncertainty. Only then do scenarios differ in their assumed ECS values.

we need to weigh the preference function by DICE's population projections. Population, in DICE equal to labor supply L_t, modifies equation (8) relative to the asymptotic population L_N as follows:

$$U_t = \left[(1-\beta)\frac{L_t}{L_N}\mu_t\left[c_t\right]^\rho + \beta\left(\frac{L_{t+1}}{L_t}\right)^\rho\left(\mu_t\left[U_{t+1}\right]^\rho\right)\right]^{1/\rho}, \tag{10}$$

with $\mu_t\left[U_{t+1}\right]$ and $\mu_t\left[c_t\right]$ continuing to be given by equations (6) and (9), respectively.

C. Optimization

Our objective is to maximize U_0, defined by equation (10), by choosing emissions control and savings rates subject to all other constraints and relationships specified in Nordhaus's 2016R version of DICE.[14] Besides employing EZ preferences, the only other modification in our DICE-EZ-RB model is to use Roe-Bauman parameters specified in Table 1 to replace parameters in DICE's temperature equations (1) and (2).

Everything else is standard. This allows us to focus exclusively on our two modifications of interest: the switch to EZ preferences, and the impact of RB time dynamics.

[14] See Nordhaus (2017a) for a brief description of modifications since Nordhaus and Sztorc (2013). Nordhaus (2018) introduces a further evolution in form of DICE 2016R2. In it he introduces a small uncertainty analysis around damage function parameters in the base-case code. Whereas the base-case damage coefficient in DICE 2016R was 0.0236% for loss in global income per degrees Celsius squared (Y/°C²), 2016R2 now tests five cases, with the mean value at the slightly lower 0.227% for Y/°C². We here use 2016R, helping us to isolate ECS uncertainty.

II. Results

Moving from regular DICE dynamics and an assumed ECS = 3.1°C to an approximation of a Roe-Baker distribution produces a small effect on the SC-CO_2 (Figure 3). The price in 2015, for example, changes from $31 to $35, rising at a rate slightly faster than the DICE base case, until prices diverge considerably after 2060, when ECS uncertainty is assumed to be resolved.

Moving to "DICE-RB," after applying the Roe-Bauman time dynamics, virtually eliminates the difference until uncertainty is resolved, and dramatically reduces diverging SC-CO_2 numbers thereafter (Figure 4). This is before including EZ preferences.

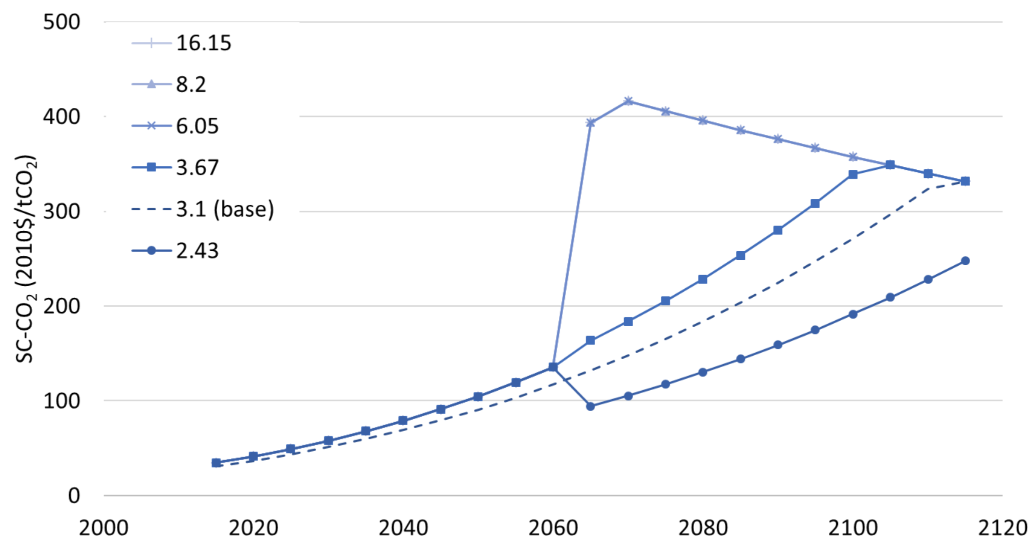

FIGURE 3. SOCIAL COST OF CARBON DIOXIDE (SC-CO_2) WITH ROE-BAKER ECS UNCERTAINTY AND STANDARD DICE 2016R DYNAMICS

Notes: Authors' calculations, based on ECS values used by Ackerman, Stanton and Bueno (2013) and standard DICE parameters for ECS = 3.1°C. Price paths for ECS = 16.15, 8.2, and 6.05°C coincide fully.

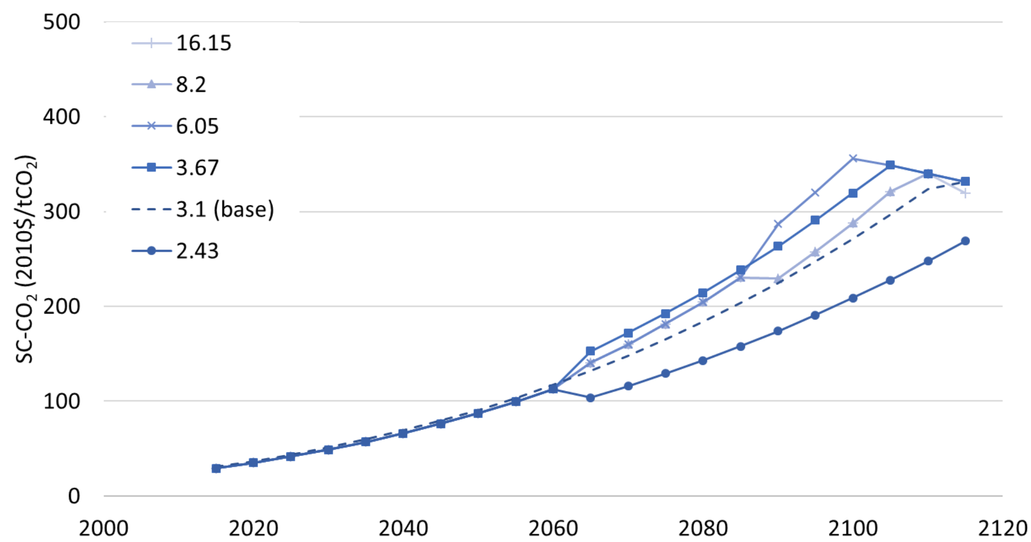

FIGURE 4. SOCIAL COST OF CARBON DIOXIDE (SC-CO_2) UNDER DICE 2016R WITH ROE-BAUMAN ECS UNCERTAINTY ("DICE-RB")

Notes: Authors' calculations, based on ECS values used by Ackerman, Stanton and Bueno (2013) and DICE parameters from Table 1 following Roe and Bauman (2013).

Moving from standard DICE preferences to EZ produces a more substantial impact on the SC-CO_2. That goes both for standard DICE dynamics (Figure 5) and for Roe-Bauman, leading to the full-fledged DICE-EZ-RB model (Figure 6).

The introduction of Roe-Bauman time dynamics still matters as well, depressing the SC-CO_2 through 2060, when ECS uncertainty is assumed to be resolved, though the rate of change of those prices through 2060 remains the same. Note also that—like in the non-EZ case for Roe-Bauman price dynamics (Figure 3) and unlike in the DICE-RB case (Figure 4)—the SC-CO_2 for ECS = 16.15, 8.2, and 6.05°C are so large after resolution of uncertainty, that they all run up against DICE's boundary conditions, leading to declining SC-CO_2 from 2065 onward. In addition, the SC-CO_2 for ECS = 3.67°C now also runs up against those same constraints beginning in 2070, fully coinciding with the other price paths.

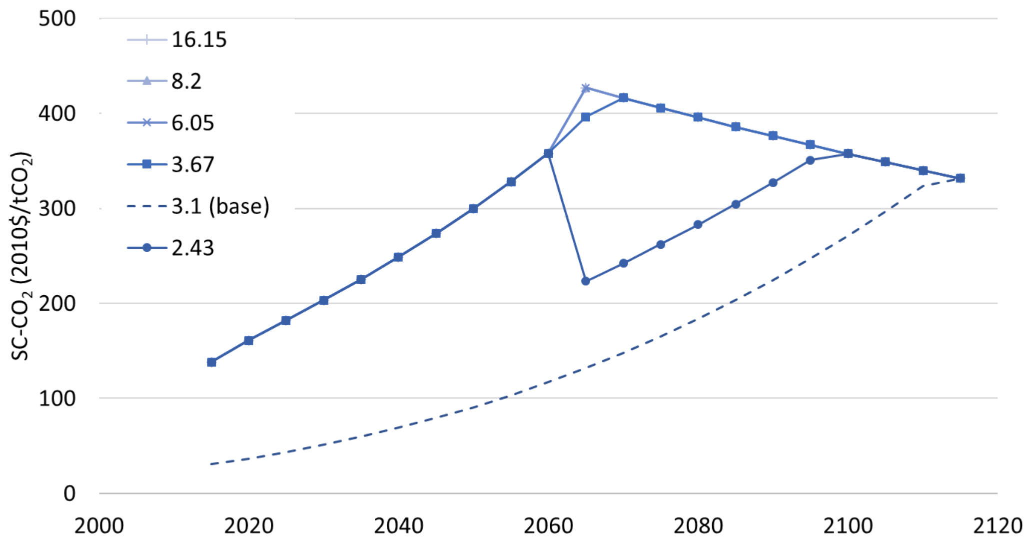

FIGURE 5. SOCIAL COST OF CARBON DIOXIDE (SC-CO_2) UNDER STANDARD DICE 2016R DYNAMICS WITH EPSTEIN-ZIN PREFERENCES AND ROE-BAKER ECS UNCERTAINTY ("DICE-EZ")

Notes: Authors' calculations, based on ECS values used by Ackerman, Stanton and Bueno (2013) and standard DICE parameters for ECS = 3.1°C. The EZ calibration assumes an Elasticity of Intertemporal Substitution (EIS) = 1.5 and a coefficient of relative risk aversion (γ) = 2. Price paths for ECS = 16.15, 8.2, and 6.05°C coincide fully, that for ECS = 3.67°C coincides with the former beginning in 2070.

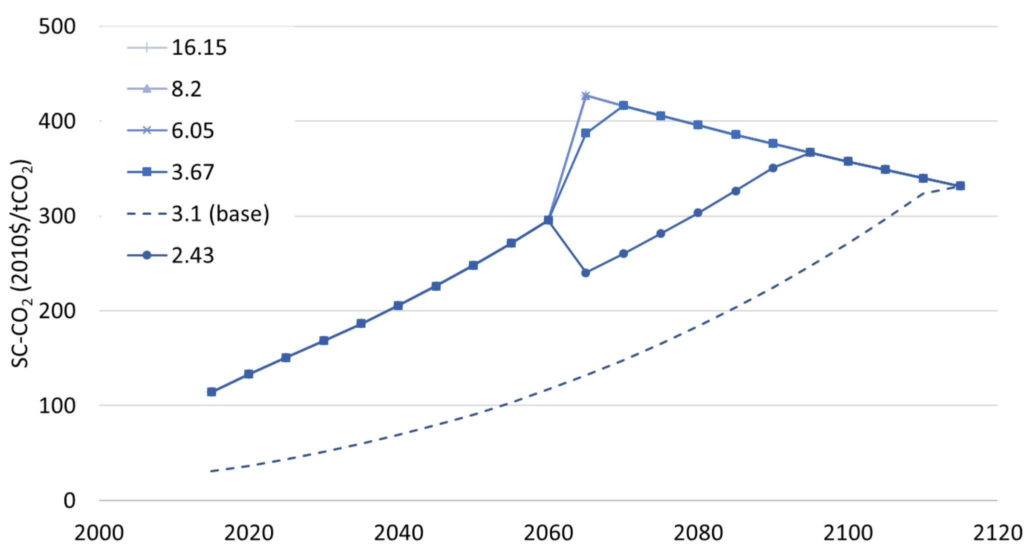

FIGURE 6. SOCIAL COST OF CARBON DIOXIDE (SC-CO_2) UNDER DICE 2016R WITH EPSTEIN-ZIN PREFERENCES AND ROE-BAUMAN ECS UNCERTAINTY ("DICE-EZ-RB")

Notes: Authors' calculations, based on ECS values used by Ackerman, Stanton and Bueno (2013) and DICE parameters from Table 1 following Roe and Bauman (2013). The EZ calibration assumes EIS = 1.5 and $\gamma = 2$. Price paths for ECS = 16.15, 8.2, and 6.05°C coincide fully, that for ECS = 3.67°C coincides with the former beginning in 2070.

III. Discussion

A. The Importance of the Timing of Climate Uncertainty

Our results clearly show two points: The climate system's time dynamics, emphasized by Baker and Roe (2009) and, most importantly for our application, Roe and Bauman (2013) though all-but-ignored by the climate-economic literature, are a crucial component of any climate risk and uncertainty conversation. DICE-RB shows an impact of tail risk on the SC-CO_2 relative to DICE (Figure 4), but that impact is smaller than an uncritical use of a Roe-Baker ECS distribution ignoring the time component might suggest (Figure 3).

All this suggest that the "Weitzman critique" of climate-economic treatments that ignore ECS tail risk may not be as important as oft-stated, both by Weitzman (2009a, 2011, 2014) and many others, including a co-author of Weitzman's and this present analysis (Wagner and Weitzman, 2015, 2018). In short, discounting reigns supreme.[15]

B. The Importance of the Elasticity of Intertemporal Substitution (EIS)

That is where a move to EZ preferences appears more important than one integrating tail risk alone. DICE-EZ-RB implies a significantly higher price path than DICE or DICE-RB alone (Figure 6). However, note the key assumption in our

[15] There, too, Weitzman has made important contributions, including Gollier and Weitzman (2010). See also Arrow et al. (2013, 2014) and further citations in footnote 6 and the text around it. None of this implies that climate damages are unimportant, especially since the most recent damages literature has increasingly identified larger damages than previously expected

application of EZ preferences: an assumed Elasticity of Intertemporal Substitution (EIS) = 1.5, combined with a coefficient of relative risk aversion (γ) = 2.

Arguments for a move to EZ preferences are typically accompanied by calls for avoiding treating discount rates as something to be "chosen" and instead as a parameter that can and, thus, ought to be "calibrated"—a call for moving away from "prescriptivism" and toward "descriptivism." We do not question that logic and the well-established finance literature employing EZ preferences here.[16] We simply proceed to probe it further.

One immediate implication is the importance of the EIS. Table 2 shows the 2015 $SC\text{-}CO_2$ under both standard DICE and Roe-Bauman ECS time dynamics, various γ values, and for two EIS values: 1.50 and 0.69 $\sim\frac{1}{1.45}$. Given that EIS = $\frac{1}{\gamma}$ under DICE's standard expected utility function, EIS = 0.69 an $\gamma = 1.45$d most closely approximates DICE's standard assumptions, using DICE-EZ-RB. The two are indeed comparable. Calculating the $SC\text{-}CO_2$ with DICE directly results in $31 (ECS = 3.1°C base case), $35 ("DICE"), and $29 ("RB"), while the latter two numbers for DICE-EZ-RB with EIS = 0.69 and $\gamma = 1.45$ are $30 and $26, respectively. However, even though the 2015 $SC\text{-}CO_2$ is affected by the treatment of uncertainty ("DICE" versus "RB") and, to a lesser extent, γ, the EIS appears most important in this comparison.

[16] See, for example, Kelleher and Wagner (2018) for a deeper exploration of prescriptivism versus descriptivism and its importance in economic discounting debates.

TABLE 2—2015 SC-CO_2 FOR DICE-EZ-RB

γ / EIS	1.45		2		4		6	
	DICE	RB	DICE	RB	DICE	RB	DICE	RB
0.69	$30	$26	$31	$26	$31	$26	$33	$26
1.50	$137	$114	$138	$114	$143	$115	$148	$115

Notes: All prices in 2010$. Based on ECS values used by Ackerman, Stanton and Bueno (2013). "DICE" uses DICE parameters from Table 1 following Roe and Bauman (2013).
Source: Authors' calculations using DICE-EZ-RB.

What then is the true EIS value? Thimme (2017), in a recent review of the literature, concludes that it is "hard to say." Havránek (2015) agrees. Both emphasize the importance of model choice for calculating the EIS. While the discussion has long moved on from early household studies estimating EIS values close to zero (Hall, 1988), support for any single other EIS estimate is tenuous at best. The perhaps most-cited calibration effort within an EZ framework comes from Bansal and Yaron (2004) in a model with persistent consumption shocks. Their headline figure is an EIS = 1.5. Thimme (2017), while arguing that there is no single correct EIS value, also concludes by suggesting 1.5 as a reasonable choice. EIS values of 1.5 and above, in turn, have been taken up by many climate-economy EZ calibration efforts (e.g., Ackerman, Stanton and Bueno, 2013; Cai, Lenton and Lontzek, 2016; Belaia, Funke and Glanemann, 2017).[17]

Moving from the standard expected utility framework and equation (4) to EZ preferences then appears to simply move the problem of thinking about intergenerational tradeoffs from one about "picking" the right discount rate to one about "picking" the right EIS. Estimating the EIS, defined by equation (7), is neither obvious nor determined by the available empirical studies. None of that means that fixing EIS = $\frac{1}{\gamma}$ is the correct answer, but it is unclear to see which other

[17] Some of the justifications for EIS = 1.5 appear to be less solid than they might appear at first. Cai, Lenton and Lontzek (2016), for example, cite Pindyck and Wang (2013) for support for their EIS choice. The latter, meanwhile, emphasize the inability to separately identify the EIS and the pure rate of time preference, δ. While the standard DICE calibrations assumes $\delta = 1.5\%$ (Nordhaus and Sztorc, 2013), Pindyck and Wang (2013, p. 319) use $\delta = 4.98\%$ in conjunction with EIS = 1.5.

number is any more correct. Figure 7 constructs a thought experiment of trading \$10,000 in this period versus twice as much in the next. Simple introspection reveals how difficult it is to distinguish among wildly differing EIS values to decide which slope would be most appropriate. That, however, is precisely the tradeoff an analyst pinning down the EIS is trying to calibrate.

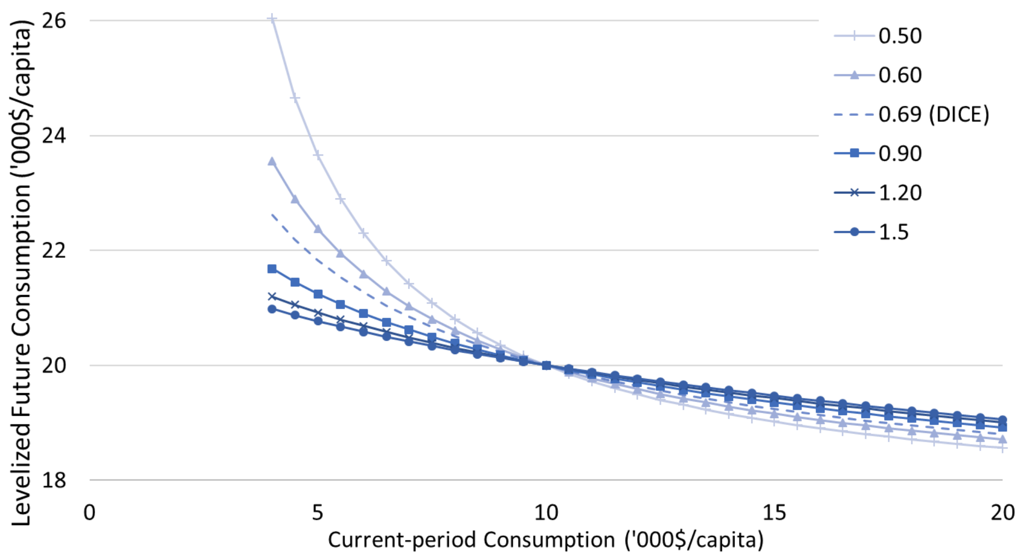

FIGURE 7. CONSTANT-UTILITY TRADEOFFS FOR DIFFERENT EIS VALUES

Notes: Authors' calculations, assuming the utility equivalence of c_t=\$10,000 and c_{t+1} = \$20,000.

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There appears to be no easy solution. Epstein, Farhi and Strzalecki (2014), for example, suggest that a Bansal-Yaron-style approach for estimating EZ parameters, and thus addressing the equity premium puzzle by adjusting γ, creates its own puzzle about the willingness to pay to resolve uncertainty. Should that be the death knell for EZ preferences? Not necessarily. But it calls for an open exploration of the role of EIS.

Our own review of climate-economic papers employing EZ preferences shows that a deeper probing of the impact of EIS is rare (Lemoine and Rudik, 2017a), though it is not unprecedented. Cai, Judd and Lontzek (2015) look at the impact of uncertain economic growth and present the resulting SC-CO_2 under various assumed EIS and γ combinations, confirming our findings of large variations of SC-CO_2 with changing EIS (Table 3, p. 28).

Is a move from standard expected utility to EZ preferences worth the investment? Yes, and no. Yes, as it is clear that tying time and risk preferences to each other is a restrictive assumption. Relaxing it, for example, allows for an explanation of the equity premium puzzle (Mehra and Prescott, 1985; Weil, 1989). But it is hardly the only such possible explanation. That also leads immediately to the counterargument.

EZ preferences come with their own restrictions and apparent puzzles. One such restriction is its conflation of individual and social risk aversion on the one hand and of individual and social inequality aversion on the other (Kelleher and Wagner, 2018). There are good reasons to believe that the social rates ought to be different from those of individuals (Dasgupta, 2008). Epstein, Farhi and Strzalecki's (2014) time premium puzzle is important on its own. The puzzle of what the right EIS value is in any particular situation might be more important.

Meanwhile, EZ preferences, are not even necessary to explain the equity premium puzzle they were introduced to explain. Beginning with Rietz (1988), the asset pricing literature has emphasized the importance of extreme events, a path pursued by many others (Barro, 2006; Weitzman, 2007; Martin, 2008, 2012b).[18] Barro (2015) and especially Weitzman (2009a, 2011, 2014) apply the same tail risk logic to pricing climate risk, though without incorporating Roe-Bauman-style time dynamics (see section A).

[18] Some like Barro and Ursua (2008) and Martin (2012a) use both extreme events and EZ preferences. Other explanations include habit formation (Campbell and Cochrane, 1999) and time-varying risk aversion (Andries, Eisenbach and Schmalz, 2018).

IV. Conclusion

Valuing climate damages and, thus, calculating the SC-CO_2 has spawned an enormous literature, attesting to the importance of the exercise. Two recent insights have focused on the impacts of deep-seated climatic uncertainty and on separating attitudes toward risk and time a la Epstein-Zin. We here probe both steps further and hope to draw attention to two apparently underappreciated aspects: For one, reaching extreme equilibrium temperatures takes time. This fact, long known to climate scientists, has largely been ignored in the climate-economic literature. Adding this time dimension virtually zeroes out impacts from extreme climatic tail risk on near-term decisions.

Doing so also highlights the importance of the second step: a proper calibration of attitudes toward risk and time. While the standard model conflates the two, applying Epstein-Zin preferences shows the relative unimportance of intratemporal risk aversion relatively to preferences over time. The key parameter appears to be the elasticity of intertemporal substitution (EIS), all but driving results in the literature that find high SC-CO_2 numbers.

A high SC-CO_2 may well be correct, but it is clear that deriving it depends on assumptions around EIS that put a burden on the analyst that goes well beyond a purely descriptivist exercise. Calibrating models to derive an EIS and subsequently the SC-CO_2 involves a number of prescriptivist choices. Both incorporating extreme climatic risks and moving to Epstein-Zin preferences—and perhaps especially the combination of the two—involves important ethical decisions.

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