

# Pricing Uncertainty Induced by Climate Change\*

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## Abstract

Geophysicists examine and document the repercussions for the earth's climate induced by alternative emission scenarios and model specifications. Using simplified approximations, they produce tractable characterizations of the associated uncertainty. Meanwhile, economists write simplified damage functions to assess uncertain feedbacks from climate change back to the economic opportunities for the macroeconomy. How can we assess both climate and emissions impacts, as well as uncertainty in the broadest sense, in social decision-making? We provide a framework for answering this question by embracing recent decision theory and tools from asset pricing, and we apply this structure with its interacting components in a revealing quantitative illustration.

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# 1 Introduction

Global efforts to mitigate climate change are guided by projections of future temperatures. But the eventual equilibrium global mean temperature associated with a given stabilization level of atmospheric greenhouse gas concentrations remains uncertain, complicating the setting of stabilization targets to avoid potentially dangerous levels of global warming. Allen et al. (2009)

Our ambition, like that of other researchers, is to understand better the macroeconomic consequences of climate change and conversely how the economic activity will alter the climate in the future. We see this challenge as a problem for which aggregate uncertainty is a first-order consideration and not just a second-order afterthought as it often is in quantitative macroeconomic analyses. To develop a modeling framework that could support policy discussions requires that we quantify the associated uncertainty and assess its impacts on policy design. To address this problem requires a structural model in the sense of Hurwicz (1966) because we will be compelled to assess possibilities that are not well represented by historical evidence. Economic dynamics necessarily play a central role. To design, say, an optimal carbon tax compels us to use measurements of the mechanism by which human activity today will impact climate in the future and an assessment of the resulting damages to human welfare. Uncertainty prevails in both the transmission mechanism and the resulting social damages. While much of the economics literature has focused on quantifying social damages, climate science investigates the transmission mechanism by which carbon emissions alter the environment. As is reflected in the Allen et al. (2009) quote, climate science quantifications embed uncertainty both across models and within any given model. This paper pays particular attention to the interaction of the climate impacts and their economic consequences.

We build and assess *dynamic structural* economic models using:

- a) *decision theory under uncertainty*
  - axiomatic defenses
  - recursive representations
- b) *nonlinear impulse response functions*
- c) *dynamic valuation via asset pricing*

In terms of item a), we use a formal decision problem as a way to conduct a meaningful sensitivity analysis. While much of decision theory within economics is typically axiomatic in nature, for us the resulting recursive representations are also of vital importance for implementation. In terms of item b), changes in emissions today have impacts on the climate and hence economic damages in current and future time periods. Our interest in the shadow price of the human-induced externality on the climate leads us to use nonlinear counterparts to impulse response functions familiar in macroeconomics and climate science. In terms of item c), we use asset pricing methods not only to impute market valuations but also social valuations. Our asset pricing vantage point leads us to view the shadow prices of interest as discounted expected values of the impulse responses. As we know, asset prices are “marginal” in nature. In a private market setting, they depend on the stochastic intertemporal marginal rates of substitutions of investors. Since our interest is in social valuation, the prices of interest use the marginal rates of substitution of the preferences of the fictitious planner for stochastic discounting and the pertinent relative prices. In turn these are sensitive to the formulation of decision theory under uncertainty that we use to represent these preferences. We provide mathematical characterizations of the probability measures that adjust for *ambiguity* over how much emphasis to place on the alternative models and for the potential impact of model *misspecification*. Indeed, we use tools from items a, b and c in ways that are intertwined. While our main focus is to apply these tools in social valuation to represent Pigouvian taxes that confront externalities in socially efficient manners, an analogous approach can be developed to study the local impacts of policy changes from socially inefficient allocations.

In this paper, we use the “social cost of carbon” as a target of measurement. Featuring this entity as a tax on an externality is an overly simplified solution to a complex policy problem, both politically and economically. Two challenges in implementing such a tax are i) what happens to the tax revenues and ii) how do existing distortionary taxes alter an idealized choice of a carbon tax? These challenges carry with them a variety of ramifications for implementation, from determining how best to offset any undesirable distributional consequences to ensuring that proceeds are allocated in ways that are not socially wasteful.<sup>1</sup> Of course, there are questions about how to coordinate any such policy across a variety of political venues. These are all vital questions that are part of actual policy discourse, but not ones that we address in this particular paper. Our aim is to assess what sources of uncertainty matter the most. We use implications for the social cost of carbon to guide

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<sup>1</sup>Kevin Murphy and Bob Topel have emphasized these points in direct communication.

those discussions, although we suspect that some of the key uncertainty considerations here should also contribute to other more complex and pragmatic approaches to policy.

Our analysis targets “sensitivity” to uncertainty and potential misspecification. We approach this in two ways. First, we take a preliminary stab at exploring the uncertainty in the transmission mechanism from carbon emissions to the climate (captured by us as temperature changes). Second, we show that the “details” of the economic model can really matter, by conducting our analysis within some different economic configurations of technology and preferences.

In this paper, we feature continuous-time models and corresponding pricing methods that are familiar to financial economists. We will exploit the continuous-time recursive representations of preferences to produce revealing formulas for how alternative uncertainty components are reflected in valuation. While the continuous-time diffusion model gives some pedagogically revealing formulas, our approach has direct extensions to discrete-time models and models with jump components, although we do not develop such connections here.

## 2 Uncertainty and approximation

We find it advantageous to explore three components to uncertainty:

- *risk* - uncertainty *within* a model: uncertain outcomes with known probabilities
- *ambiguity* - uncertainty *across* models: unknown weights for alternative possible models
- *misspecification* - uncertainty *about* models: unknown flaws of approximating models

The first of these components is captured in scientific discourse by introducing random shocks or impulses into models. With known distributions, this modeling approach captures *risk*. Economists often discuss risk and aversion to that risk. We frame this discussion as one in which outcomes are not known, but probabilities are. For instance economic agents “inside” rational expectation models confront risk. The literature on long-run risk assumes investors have preferences that respond to the intertemporal composition of risk using the recursive formulation originally proposed by Kreps and Porteus (1978). The long-run-risk literature uses this framework in conjunction with uncertainty in macroeconomic growth rates. See, for instance, Bansal and Yaron (2004). As many previous researchers have

noted, the human impact on the climate is a potentially important source of uncertainty that could play out over long horizons. See for instance, Jensen and Traeger (2014), Cai et al. (2015), Nordhaus (2017), Hambel, Kraft, and Schwartz (2018) and especially Cai, Judd, and Lontzek (2017).

The second of these components, *ambiguity*, reflects the fact that there are multiple models at the disposal of decision makers motivating the question of how much weight to assign to each of these models in terms of their credibility. This is addressed by subjective probabilities within a Bayesian framework. The robust Bayesian approach explores sensitivity to subjective inputs. Historical data alone has only limited insights in terms of how we conceptualize climate change uncertainty. Some of the potential adverse climate outcomes seem best understood by using climate models designed to help us think through the long-term consequences of human inputs into the climate system. For an example of within model ambiguity, consider the findings reported in Olson et al. (2012) for what they call the climate sensitivity parameter. Figure 3 of their paper reports Bayesian posteriors using an uninformative prior and compares this to an informative prior documenting substantial sensitivity, suggesting the importance of the subjective prior in the analysis. This is not a parameter for which “the evidence speaks for itself.” More generally, the interplay between models and evidence seems vital if we are to think through the consequences of uncertainty, broadly-conceived. There are now a variety of climate models, with differing implications so that how to confront cross-model uncertainty seems pertinent to an assessment of uncertainty.

In this paper, we consider two approaches to model ambiguity. One builds from the research of Chen and Epstein (2002) recursive implementation of max-min utility model axiomatized by Gilboa and Schmeidler (1989). The origins of this approach come from the initial formalization of decision theory due to Wald (1950). The other applies the Hansen and Miao (2018) recursive implementation of the smooth ambiguity model originally proposed and axiomatized by Klibanoff, Marinacci, and Mukerji (2005). The smooth ambiguity model provides a differential preferential response to the uncertainty about models that is distinct from risk. Examples motivated by climate science are given in Millner, Dietz, and Heal (2013) and Lemoine and Traeger (2016), although their analyses are not motivated by robustness considerations. Such considerations for subjective probabilities have played an important role in Bayesian inferences. For instance, see Berger (1984), Hansen and Sargent (2007) and Hansen and Miao (2018) provide a link between the smooth ambiguity model and a recursive robust prior model.

This third component to uncertainty, potential *model misspecification*, is necessitated by the underlying complexity of the environment to be understood through the guises of insightful models. The climate environment, like the economic one, is complex. Models that we constructed of their interactions are necessarily abstractions designed to help us understand the underlying phenomenon under consideration. They are necessarily misspecified because of our desire for simplicity, and because our understanding of some of the features of the environment is limited. Other model shortcomings may be hard to pinpoint *ex ante*. Interestingly, some well known climate models are themselves sufficiently complicated that researchers construct simplified approximations typically called emulators that capture some broad features using relatively simple time series models. See, for instance, Li and Jarvis (2009) and Castruccio et al. (2014). Considerations like these lead us to consider potential model misspecification as an important source of uncertainty.

Hansen and Sargent (2001) and Anderson, Hansen, and Sargent (2003) draw on insights from the robust control theory literature (*e.g.*, see James (1992) and Petersen, James, and Dupuis (2000) ) and incorporate model specific concerns about potential misspecification in a recursive way. Hansen and Sargent (2019b) then show how to combine the Chen and Epstein (2002) formulation of ambiguity aversion across “structured models” with model-specific concerns about misspecification. As an alternative approach, Hansen and Miao (2018) extends the analysis of Hansen and Sargent (2007) by taking a continuous-time limit with an interpretable representation thereby combining smooth ambiguity preferences with model specific concerns about misspecification. As we will show, these approaches give revealing continuous-time formulas for pricing uncertainty components.

The remainder of the paper is organized as follows. In Section 3 we describe formally the economic model that we use for our computations. We explore the construction and implications of Hamilton-Bellman-Jacobi (HJB) equations for our analysis and deduce revealing asset pricing formulas for the social cost of carbon (SCC) for in Section 4. Asset prices are appropriately discounted cash flows where the form of the discounting is dictated by the uncertainty in the cash flow. In representing the externality components of SCC, the counterparts of the cash flows are nonlinear impulse response of damages to the economic environment. The analysis in Section 4 features only the risk component to uncertainty. In Section 5, we show formally how to incorporate ambiguity aversion over models and concerns about potential model misspecification into the analysis. This broader perspective on uncertainty impacts the preferences of the fictitious social planner preferences used as a device to compute the social cost of carbon. Moreover, it leads us to alter the prob-

ability measure used in conjunction with stochastic discounting for social valuation. We discuss some additional characterizations of uncertainty in the climate dynamics in Section 7. Finally, we provide some concluding remarks in Section 8.

### 3 A Stochastic Growth Model with Reserves and Climate Damages

Our model consists of an information structure, the evolution of endogenous state variables including reserves, cumulative emissions, capital and environmental damages along with societal preferences. Figure 1 depicts the economic model components without climate impacts and environmental damages. This model has a Brownian motion information structure and, like many in macroeconomics, is highly stylized. We use it to illustrate a framework for doing dynamic policy analysis in the presence of uncertainty in a setting that is numerically tractable. But we are cognizant of its limitations and hope to add some complexity in future research. The continuous time, Brownian information structure simplifies some of the implications for social valuation, but it is not essential to the overall approach.<sup>2</sup>

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<sup>2</sup>Our continuous-time diffusion model is similar in some respects to two prior contributions. Hambel, Kraft, and Schwartz (2018) build and analyze a DICE-type model and consider damage specifications in technology and in technology growth. Our production specification is different including, in particular, our inclusion of reserves as a state variable. The structure of our model, net of climate change, bears some similarity to the Eberly and Wang (2009) analysis of two productive capital stock technologies with adjustment costs. Our two stocks, however, produce distinct outputs with one being the stock of reserves.

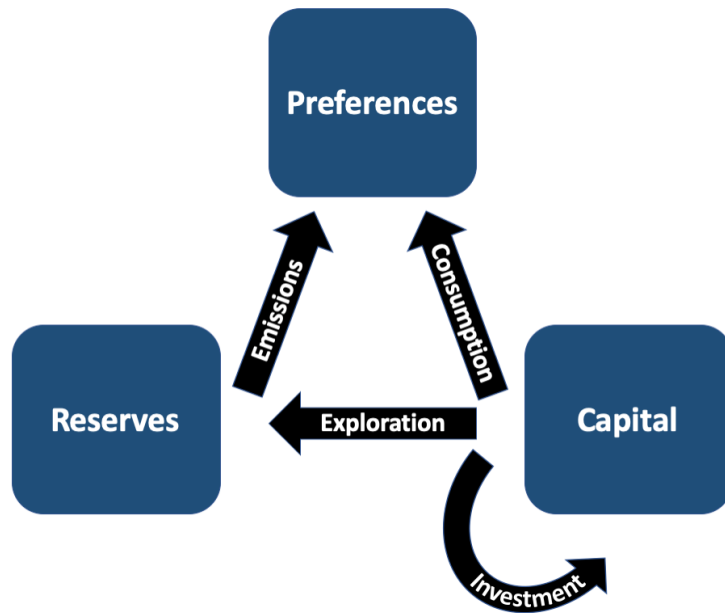


Figure 1: This figure depicts the economic model in the absence of economic and climate damages. The model includes Brownian increment shocks, adjustment costs in capital accumulation and curvature in how investment in discovery increases the stock of new reserves.

### 3.1 Information

To assist some of our characterizations, we presume a Brownian information structure where  $W \doteq \{W_t : t \geq 0\}$  is a  $m$ -dimensional standard Brownian motion and  $\mathfrak{F} \doteq \{\mathfrak{F}_t : t \geq 0\}$  is the corresponding Brownian filtration with  $\mathfrak{F}_t$  generated by the Brownian motion between dates zero and  $t$ .

In what follows we let  $Z \doteq \{Z_t : t \geq 0\}$  be an exogenously specified, stochastically stable, multivariate forcing process. We write its evolution equation stochastically as:

$$dZ_t = \mu_Z(Z_t)dt + \sigma_Z(Z_t)dW_t.$$

In our examples  $Z$  will be Ornstein-Uhlenbeck or Feller type processes with affine mean dynamics and either constant or linear volatility dynamics.



## 3.2 State variable evolution

We consider an extended version of a model used by Brock and Hansen (2018). Capital  $K$  evolves as:

$$dK_t = K_t \left[ \zeta_K(Z_t)dt + \phi_0 \log \left( 1 + \phi_1 \frac{I_t}{K_t} \right) dt + \sigma_K \cdot dW_t \right].$$

where  $I_t$  is investment and  $0 < \phi_0 < 1$  and  $\phi_1 > 1$ . For computational purposes, we will use the evolution for  $\log K$

$$d \log K_t = \zeta_K(Z_t)dt + \phi_0 \log \left( 1 + \phi_1 \frac{I_t}{K_t} \right) dt - \frac{|\sigma_K|^2}{2}dt + \sigma_K \cdot dW_t.$$

where the third  $dt$  term is the local lognormal adjustment implied by Ito's Lemma.

Output is constrained by an AK model:

$$C_t + I_t + J_t = \alpha K_t$$

where  $C_t$  is consumption,  $I_t$  is new investment in productive capital,  $J_t$  is investment in new reserves and  $\alpha > 0$  is a productivity parameter.

**Remark 3.1.** *So far, we imposed the adjustment costs in the capital evolution. Alternatively, we could posit the adjustment costs in the output constraint. This model is sufficiently streamlined so that it allows for both interpretations. To see this define an alternative investment/capital ratio equal to:*

$$\frac{\tilde{I}_t}{K_t} = \phi_0 \log \left( 1 + \phi_1 \frac{I_t}{K_t} \right)$$

*Substituting into the capital evolution give us:*

$$dK_t = K_t \mu_K(Z_t)dt + \tilde{I}_t dt + K_t \sigma_K \cdot dW_t.$$

*Inverting this relationship we have that:*

$$\frac{I_t}{K_t} = \frac{\exp \left( \frac{\tilde{I}_t}{\phi_0 K_t} \right) - 1}{\phi_1}.$$

Now the output equation can be written with convex adjustment costs as:

$$C_t + K_t \left[ \frac{\exp\left(\frac{\tilde{I}_t}{\phi_0 K_t}\right) - 1}{\phi_1} \right] + J_t = \alpha K_t.$$

The stock of reserves,  $R_t$ , can be at least partially replenished and evolves according to:

$$dR_t = -E_t dt + \psi_0 (R_t)^{1-\psi_1} (J_t)^{\psi_1} dt + R_t \sigma_R \cdot dW_t$$

where  $\psi_0 > 0$  and  $0 < \psi_1 < 1$  and  $E_t$  is the emission of carbon. For computational purposes, we use the implied evolution for  $\log R$ :

$$d \log R_t = - \left( \frac{E_t}{R_t} \right) dt + \psi_0 \left( \frac{J_t}{R_t} \right)^{\psi_1} dt - \frac{|\sigma_R|^2}{2} dt + \sigma_R \cdot dW_t$$

**Remark 3.2.** *This model of reserves has some features in common with others in the literature. The well known Hotelling (1931) specification is a special case in which  $J_t$  is constrained to be zero and  $\sigma_R = 0$ . To elaborate, let*

$$R_t = \int_0^{+\infty} E_{t+s} ds$$

*be a total stock of reserves available from date  $t$  forward. Then:*

$$dR_t = -E_t dt,$$

*or*

$$d \log R_t = - \frac{E_t}{R_t} dt$$

*While the Hotelling constraint gives us some pedagogical simplicity and is a revealing platform for illustration, historically the stock of reserves has been increasing over time because of new discoveries, which would have to be included in the Hotelling constraint. Moreover, there is little empirical evidence for the Hotelling price impacts.*

*Another special case is when  $\psi_1 = 1$ . With this specification, a nonnegativity constraint on  $J_t$  may bind for a substantial fraction of time in the solution to the planners problem. A similar model with these features was analyzed by Casassus, Collin-Dufresne, and Routledge (2018). They treated the counterpart of  $J_t$  as an “impulse control problem” whereby  $J_t$  is*

optimally set to zero over time segments determined endogenously. While we view this as an interesting special case, we choose not to address it in this paper.

As a third example, Bornstein, Krusell, and Rebelo (2017) have an industry model of reserves with a counterpart to investment  $J_t$  with diminishing returns. They allow for richer dynamics by including an additional state variable they call exploration, whose evolution depends on  $J_t$ . Exploration increases the reserve stock in a proportional manner. In contrast, we conserve on state variables by having oil reserve investment augment the reserve stock. We also allow for the current stock of reserves to alter the productivity of investment  $J_t$  in a manner that preserves a constant-returns-to-scale specification.

None of these three papers used their reserve model to explore adverse social implications of carbon admissions. While many previous researchers have imposed a Hotelling (1931)-type constraint, we are particularly interested in the impact on oil reserve investment.

### 3.3 Damages

Climate literature suggests an approximation that can simplify discussions of uncertainty and its impact. Matthews et al. (2009) and others have purposefully constructed a simple “approximate” climate model:

$$T_t - T_0 \approx \beta \int_0^t E_s ds = \beta F_t. \quad (1)$$

where the  $F$  evolution pertinent to this approximation is:

$$dF_t = E_t dt$$

Within this framework, emissions today have a permanent impact on temperature in the future where  $\beta$  is a climate sensitivity parameter.

Of course, this is rather stark approximation of a complex climate system, and we will entertain some alternatives. There is a substantial literature in climate science assessing for what purposes this is a revealing approximation, which we will discuss subsequently. There are transient components to temperature fluctuations not explicitly connected to emissions that are needed to capture a more complete characterization of temperature dynamics. These could be captured by an exogenous transient process added to  $\beta F_t$  in our analysis.

We focus on the component that the Matthews et al. approximation is meant to capture. Thus while actual temperature has transient departures, the contribution to temperature

change that might be most pertinent to our analysis of the economic impact of climate change could be the increment  $\beta E_t$ . Even with a richer specification of the climate dynamics, it could be advantageous to feature the longer-term temperature changes induced by human activity as it is not obvious why the transient components should be included when quantifying damages induced by an externality induced by carbon emissions. In this paper we use cumulative emissions,  $F$ , and not temperature,  $T$ , as the pertinent state variable.

The simplicity of the Matthews et al. approximation is sometimes used to reframe policy questions in terms of a carbon budget. Given knowledge of the parameter  $\beta$ , a maximal allowable change in temperature implies an intertemporal constraint on the amount of emissions and in effect could be used to justify a Hotelling-type constraint on cumulative emissions. But when there is substantial uncertainty about the climate sensitivity coefficient,  $\beta$ , there is corresponding uncertainty about what constraint to impose on emissions. This uncertainty is depicted in Figure 2, which provides a histogram and a smoothed density based on evidence reported by MacDougall, Swart, and Knutti (2017). They find that the cross model mean value to be 1.72 degrees centegrade per one trillion tons of carbon (TtC). The .05 quantile value is 0.88, which is about half the mean value; and the .95 quantile is 2.52. showing the extensive range of parameter values. When there is substantial uncertainty about  $\beta$ , there is uncertainty about what constraint to impose on emissions. As an alternative, we could impose the constraint on the realized temperature change or on the admissible augmentation of carbon concentration.

# Climate Sensitivity Uncertainty

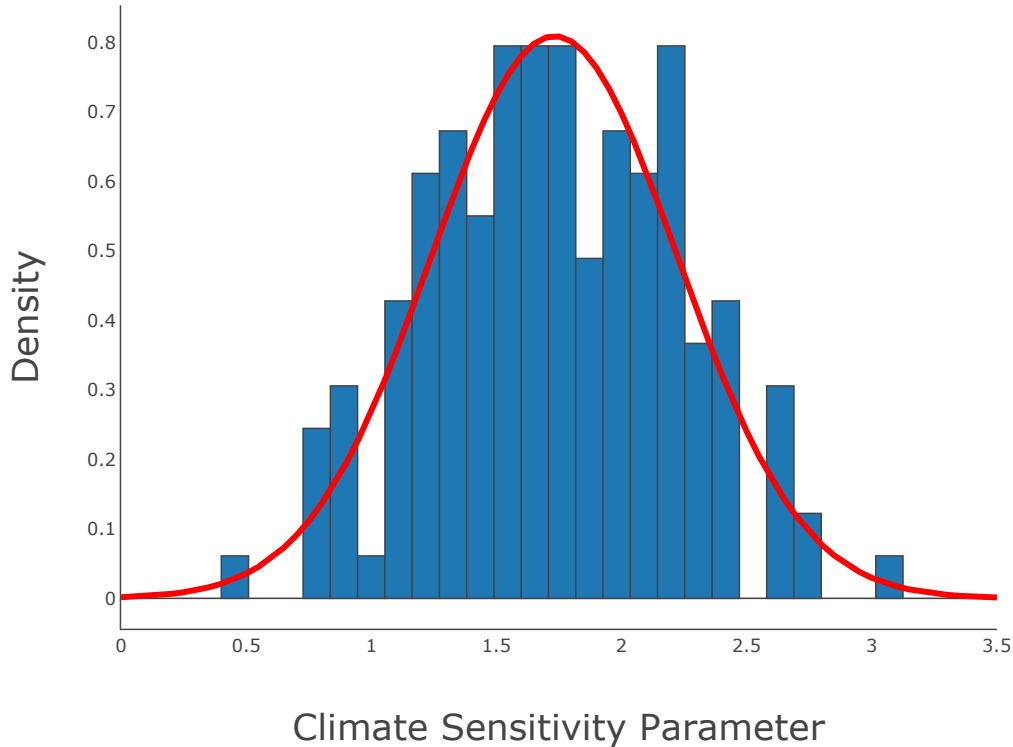


Figure 2: Histogram and normal density approximation for the climate sensitivity parameter  $\beta$  across models. The climate sensitivity parameter is in units degrees centigrade per teraton carbon. Evidence is from MacDougall, Swart, and Knutti (2017).

Given our limited understanding of how to model damages and long-term uncertainty associated with the impact that emissions might have on the economy, some scholars have doubted the value of building so called integrated assessment models with *ad hoc* specifications of economic or social damages. Instead some have suggested that the social policy objectives should be framed in terms of temperature increases induced by of carbon concentration targets. For recent such arguments, see Morgan et al. (2017) and Pezzey (2019). Imposing admissible temperature or concentration bounds can be represented as an extreme form of damage or penalization function with infinite damages or penalties when a threshold is exceeded. We could use this as our damage function, but instead we follow much of the economics-climate literature by penalizing large temperature changes through a so-called damage function specified exogenously. Consistent with a more general view of

carbon budgeting, this damage function could be taken to be a penalty function instead of a hard constraint where the magnitude of the penalty is dictated, at least in part, by the implied climate outcomes. Recall that our aim is to assess what aspects of uncertainty have the most adverse consequences, and we see value in the modeling formalism. On the other hand, we share concerns about the literal interpretation of ours and others of the computed social costs of carbon.

In this paper, we follow much of the previous literature in economics by positing an *ad hoc* damage process to capture negative externalities on society imposed by carbon emissions. Just as in the case of the climate approximation, the damage specification we use is an obvious simplification. The economics literature has explored alternative damage specifications typically expressed as functions of temperature. By positing such an evolution we refrain from modeling formally any dynamics associated with adaptation including responses in advance of future temperature increases.<sup>3</sup> While this model is overly simplistic, the evolution of damages captures two forms of uncertainty that interest us, one from damages that we as depict as uncertainty in the function  $\Gamma$  and the other from climate uncertainty parameter  $\beta$ .

### 3.4 Preference-based Damages

In this specification, the instantaneous contribution to preferences is:

$$\delta(1 - \kappa) (\log C_t - \log D_t) + \delta\kappa \log E_t$$

where  $\delta > 0$  is the subjective rate of discount and  $0 < \kappa < 1$  is a preference parameter that determines the relative importance of emissions in the instantaneous utility function. While damages enter the utility function in this specification, we may equivalently think of this as a model with proportional damages to production along the lines suggested by Brock and Hansen (2018).

We model the logarithm of damages,

$$\log d = \Gamma(\beta f) + \zeta_D(z) \cdot \begin{bmatrix} f \\ 1 \end{bmatrix}.$$

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<sup>3</sup>While the literature on modeling adaptation to climate change is limited, for a recent example focused on agriculture, see and Keane and Neal (2018).

where  $\zeta_D$  is a two-dimensional vector. With this specification,  $\zeta_D(z) \cdot \begin{bmatrix} f \\ 1 \end{bmatrix}$  potentially captures two forms of uncertainty in damage/climate sensitivity by adding an exogenous shifter to the logarithm of damages. One component is deliberately proportional to the temperature anomaly. The other component could capture a distinct role for more transient changes in temperature on damages or other technological contributions that could impact damages. As we will see, this exogenous component opens the door to possible model misspecification that is at least partially disguised by the Brownian increments  $dW_t$ . The other component could capture a distinct role for more transient changes in temperature on damages or other technological contributions that could impact damages. The implied evolution for  $\log D$  is

$$d \log D_t = [\nabla \Gamma](\beta F_t) \beta E_t dt + d\zeta_D(Z_t) \cdot \begin{bmatrix} F_t \\ 1 \end{bmatrix} + \zeta_D(Z_t) \cdot \begin{bmatrix} E_t \\ 0 \end{bmatrix} dt \quad (2)$$

where  $[\nabla \Gamma]$  is the first derivative of the function  $\Gamma$ .

In our subsequent illustration we parameterize  $\Gamma$  as

$$\Gamma(y) = \begin{cases} \gamma_1 y + \frac{1}{2} \gamma_2 y^2 & 0 \leq y < \bar{\gamma} \\ \gamma_1 y + \frac{1}{2} \gamma_2 y^2 + \frac{1}{2} \gamma_2^+ (y - \bar{\gamma})^2 & y \geq \bar{\gamma} \end{cases} \quad (3)$$

where  $\gamma_2^+ \geq 0$ . To illustrate the impact of damage uncertainty, we focus on the parameter  $\gamma_2^+$ . For a low damage specification, we set this parameter to zero and for a high damage specification we set it to be a positive number. By setting  $\gamma_2^+$  to an arbitrarily large number, we approximate a carbon budget constraint by penalizing damages in excess of  $\bar{\gamma}$ . While the construction of  $\bar{\gamma}$  is suggestive of a “tipping point,” previous literature has focused explicitly on tipping points with uncertain consequences. Of course, other damage functions are also of interest.

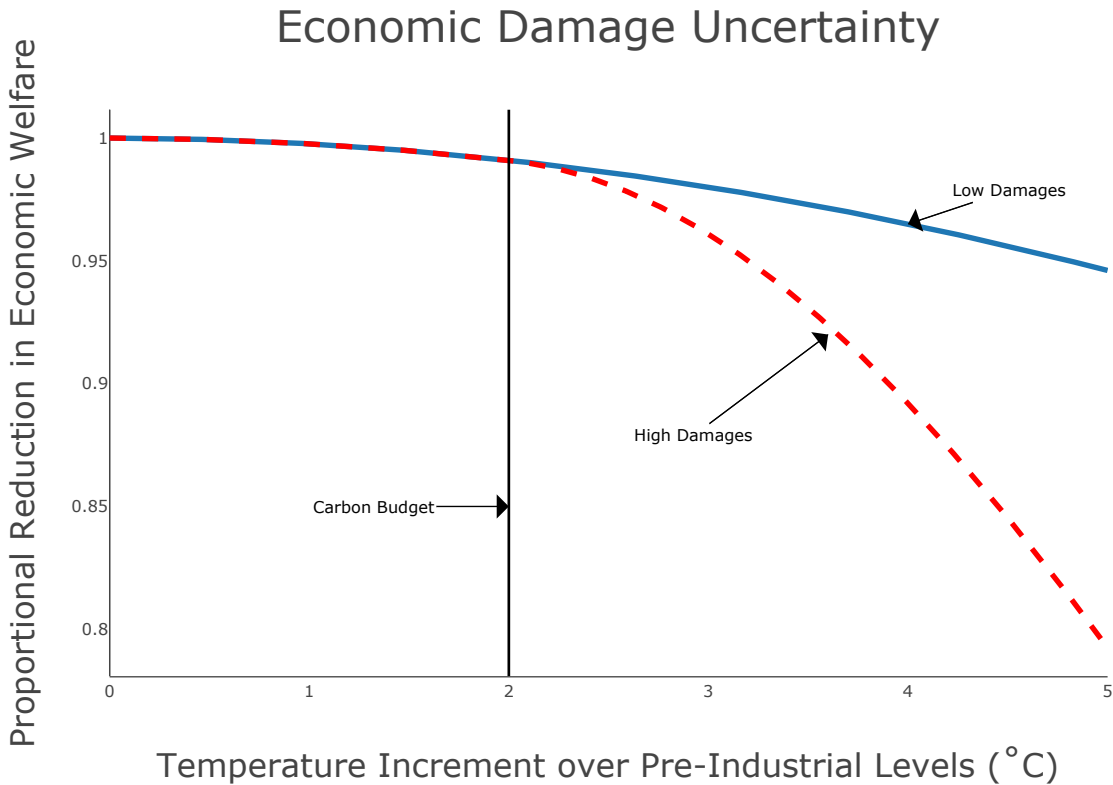


Figure 3: Two alternative economic damage configurations. The two curves plot  $D$  as a function of the temperature net of pre-industrial levels. The vertical axis gives the corresponding damage percentage.

In our computation example, we use the two damage functions depicted in Figure 3. The low damage specification is implemented by setting  $\gamma_2^+ = 0$ . In terms of the previous environmental economics literature, we imagine the case in which  $\gamma_2^+ = 0$  as an approximation to Nordhaus (2018). One can see from this figure that our 3 degrees C percentage loss is approximately the same as that of Nordhaus and Moffatt (2017) who say,

the estimated impact is -2.04 (+ 2.21) % of income at 3 C warming. We also considered the likelihood of thresholds or sharp convexities in the damage function and found no evidence from the damage estimates of a sharp discontinuity or high convexity.

Weitzman (2012) argues for a steeper degradation in the damages and motivates his construction of an alternative damage function on the basis of uncertainty considerations.



Rather than simply impose an approximation to Weitzman’s damage function we illustrate an uncertainty adjustment by positing an alternative even steeper function over some of the temperature increment region and consider the impact of weighting the two possibilities. This allows us to characterize the uncertainty contribution explicitly. In the extreme case in which  $\gamma_2^+$  is arbitrarily large, we may think of  $\bar{\gamma}$  as a hard carbon budget constraint. While the construction of  $\bar{\gamma}$  is suggestive of a “tipping point,” previous literature has focused explicitly on tipping points with uncertain consequences.

There are two interconnected forms of uncertainty in the evolution of damages that we will capture in conjunction with equation (2), one from the specification of the damage function  $\Gamma$  and the other from climate uncertainty parameter  $\beta$ .

### 3.4.1 Damages to macroeconomic growth

Alternatively, suppose that damages diminish growth in the capital evolution:<sup>4</sup>

$$d \log K_t = \zeta_K(Z_t)dt - \Gamma(\beta F_t)dt - \zeta_D(Z_t) \cdot \begin{bmatrix} F_t \\ 1 \end{bmatrix} dt + \phi_0 \log \left( 1 + \phi_1 \frac{I_t}{K_t} \right) dt - \frac{|\sigma_K|^2}{2} dt + \sigma_K \cdot dW_t.$$

Not surprisingly, and as discussed in previous literature (see, for instance, the recent discussion in Diaz and Moore (2017)), this difference can have an important impact on computations of the social cost of carbon.<sup>5</sup> Examples of empirical analyses that seek to bear on this issue are Dell, Jones, and Olken (2012) and Burke, Hsiang, and Miguel (2015), which have different perspectives on the importance of heterogeneity and nonlinearity based on reduced-form panel data evidence. From our perspective, this reinforces the notion of damage rate uncertainty.

Several researchers have looked empirically at the relation between macro growth and temperature including Dell, Jones, and Olken (2012), Burke, Hsiang, and Miguel (2015), Burke, Davis, and Diffenbaugh (2018) and Colacito, Hoffmann, and Phan (2019) among

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<sup>4</sup>Bansal, Kiku, and Ochoa (2017) and Hambel, Kraft, and Schwartz (2018) give alternative stochastic models of damages to macroeconomic growth. Both use a recursive utility specification for preferences with a risk-based approach where the decision-maker knows the probabilities.

<sup>5</sup>The material in Section 9 of Diaz and Moore (2017) Supplementary Online Material speaks directly to this point. An early entrant into this discussion is Moyer et al. (2014), where they illustrate that modifying a DICE-type model to include damages to the growth rate of productivity could have a big impact on the implied social cost of carbon.

others. Dell, Jones, and Olken explore cross country evidence including lagged effects. They document the largest impacts of temperature on macroeconomic growth occur for low income countries. While they find evidence for a long term impact the quantitative magnitude of the impact is much reduced. The climate-economic system potentially has feedbacks in both directions and a single equation approach may be a flawed way empirically to deduce the long-term impacts. The heterogeneity in the impacts across economies at different stages of economic development does seem to be both empirically and substantively important. Unfortunately our simplified analysis in this paper is not designed to confront this heterogeneity, although the consequences of uncertainty will remain for a more refined analysis.

## Macroeconomic Growth-Rate Damages

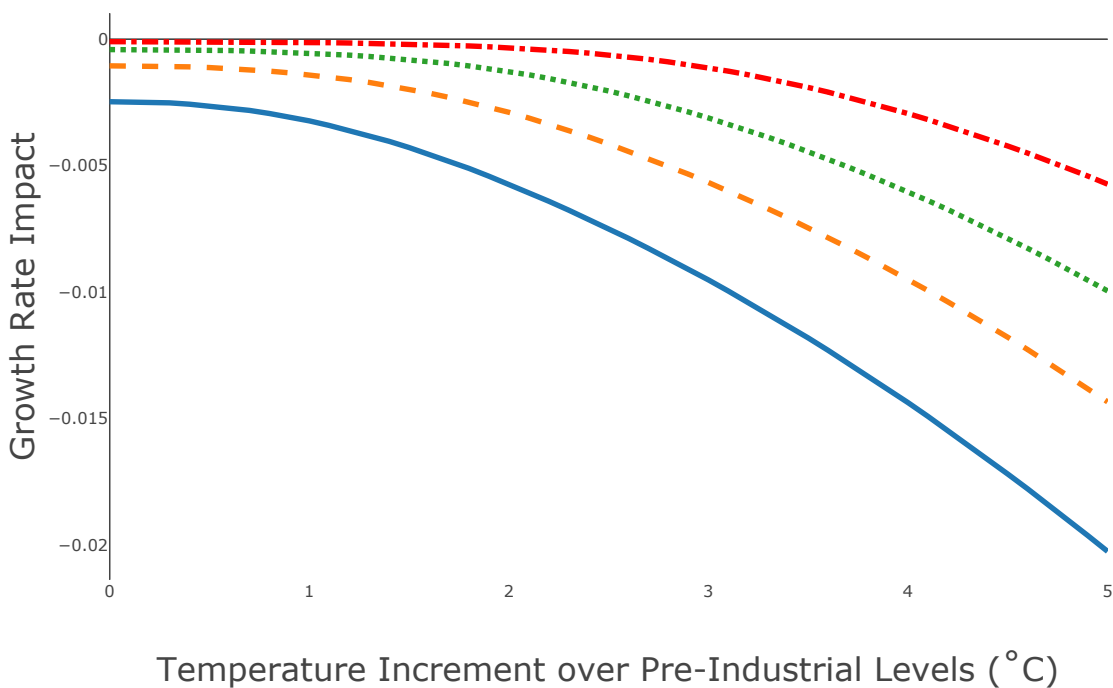


Figure 4: Macroeconomic growth rate damages and the corresponding quintiles based on estimation from Burke, Davis, and Diffenbaugh (2018). The blue solid line is the probability .2 quintile and the red dot-dashed line is the .8 quintile. The intermediate curves are the .4 and .6 quintiles.

In Figure 4 we use reported evidence from Burke, Davis, and Diffenbaugh (2018) ex-

ploiting cross country variation in development and temperature exposure. They report cross country evidence with temperature and its square regressors (in addition to fixed effects.)<sup>6</sup> Their featured econometric has a homogeneous growth response to temperature and abstracts from more lagged impacts that might emerge through adaptation.

Our growth damage function is constructed from the estimated coefficients from Burke, Davis, and Diffenbaugh (2018). Our  $\gamma_1$  and  $\gamma_2$  roughly correspond to the linear and quadratic temperature effects, respectively, on economic growth in their global effect regression (Figure 1a and estimated Equation 1 in Methods section coefficients  $\beta_1$  and  $\beta_2$ ). There are nontrivial issues in converting this evidence to single region, say world, model, leading us to make some *ad hoc* choices in how we report and subsequently use their evidence.<sup>7</sup>

As we will see this quadratic specification of temperature on economic damages will have rather dramatic implications for the policy implications of our climate-economic model, we include this in large part to illustrate the impact of damage uncertainty. We have some skepticism as to how far one can go in using developing country responses to quantify more generally global responses to temperature changes by extrapolating from lower income countries in locations with higher temperature.<sup>8</sup> Moreover, given historical evidence alone it is likely to be challenging to extrapolate climate impacts on a world scale to ranges in which many economies have yet to experience. Both richer dynamics and alternative nonlinearities may well be essential features of the damages that we experience in the future due to global warming. Burke, Davis, and Diffenbaugh (2018) give a thoughtful treatment of the impact of parameter uncertainty that we exploited when constructing Figure 4 and that we draw on in our computations that follow.<sup>9</sup>

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<sup>6</sup>Relatedly, Burke, Hsiang, and Miguel (2015) show how a quadratic specification for the temperature impact on growth can capture the heterogenous temperature responses documented previously by Dell, Jones, and Olken and others.

<sup>7</sup>The pre-industrial level of temperature corresponds to a value of approximately thirteen degrees Celsius in temperature levels as measured by historical records. We use thirteen degrees as the baseline for the construction of the temperature anomaly values that arise in our model. This value is in line with the median no damage temperature value estimated in Burke, Davis, and Diffenbaugh (2018). We thank Marshall Burke for answering our questions about their work and directing us to the GitHub repository with the full set of parameter estimates and corresponding variance-covariance matrices from their estimations. Neither he nor his co-authors bear responsibility for how we used their very interesting evidence.

<sup>8</sup>These studies do include fixed country and time effects.

<sup>9</sup>While cross-country differences in the long-term impact of temperature on growth is likely to be pronounced, interestingly Colacito, Hoffmann, and Phan (2019) also find that seasonal differences are important in an advanced economy like that of the United States. These are masked in the use of annual data.

## 4 Implications of Hamilton-Jacobi-Bellman equations

We start by deducing the relatively standard optimization implications of our model in the absence of ambiguity and model misspecification concerns. The following notation will be used in setting up social planner Hamilton-Jacobi-Bellman (HJB) equations. Let the state vector  $X_t$  include  $\log K_t, \log R_t, \log D_t, F_t, Z_t$ , and let the action vector  $A_t$  include  $\frac{I_t}{K_t}, \frac{J_t}{K_t}$  and  $\frac{E_t}{R_t}$ . Write the composite state equation as:

$$dX_t = \mu_X(X_t, A_t)dt + \sigma_X(X_t)dW_t$$

where  $\sigma_X(x)' \sigma_X(x)$  is nonsingular  $m$  by  $m$  matrix. Let  $n$  denote the number of states. In what follows we use lower-case letters to denote potential realized values. For instance,  $d$  is a possible realization of  $\log D_t$ ,  $k$  is a possible realization of  $\log K_t$  and  $r$  is a potential realized value of  $\log R_t$ . In terms of the actions,  $i$  and  $j$  are possible realizations of the investment ratios  $\frac{I_t}{K_t}$  and  $\frac{J_t}{K_t}$  and  $e$  is a possible realization of emissions  $\frac{E_t}{R_t}$ . For our alternative model specifications, some of the state variables enter into value functions in ways that we can exploit for computational simplicity.

### 4.1 Preference Damages

The HJB equation for this setup abstracting from robustness is

$$\begin{aligned} 0 = \max_{a \in \mathbb{A}} & -\delta V(x) + \delta(1 - \kappa) [\log(\alpha - i - j) + k - d] + \delta\kappa(\log e + r) \\ & + \frac{\partial V}{\partial x}(x) \cdot \mu_X(x, a) + \frac{1}{2} \text{trace} \left[ \sigma_X(x)' \frac{\partial^2 V}{\partial x \partial x'}(x) \sigma_X(x) \right] \end{aligned} \quad (4)$$

where  $\mathbb{A}$  is a constraint set for the realized action or decision  $a$ . As part of a guess and verify approach, the implied value function coefficient for the logarithm of damages is  $\kappa - 1$ . The pertinent terms for the first-order conditions for the actions or controls are:

$$\begin{aligned} & \delta(1 - \kappa) [\log(\alpha - i - j)] + \delta\kappa \log e + (\kappa - 1) \left( [\nabla \Gamma](\beta f)\beta + \zeta_D(z) \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right) e \exp(r) \\ & + V_f(x) e \exp(r) + V_k(x) \phi_0 \log(1 + \phi_1 i) + V_r(x) (-e + \psi_0 \exp[\psi_1(k - r)]) j^{\psi_1} \end{aligned}$$

The first-order conditions for  $i$ ,  $j$  and  $e$  are:

$$-\frac{\delta(1-\kappa)}{\alpha-i-j} + \frac{\phi_0\phi_1 V_k(x)}{1+\phi_1 i} = 0 \quad (5)$$

$$-\frac{\delta(1-\kappa)}{\alpha-i-j} + V_r(x) (\psi_0\psi_1) j^{\psi_1-1} \exp[\psi_1(k-r)] = 0 \quad (6)$$

$$\frac{\delta\kappa}{e} + V_f(x) \exp(r) - V_r(x) + (\kappa-1) \left( [\nabla\Gamma](\beta f)\beta + \zeta_D(z) \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right) \exp(r) = 0 \quad (7)$$

We denote the solution for the investment-capital ratio as  $i^*(x)$  and for the exploration-capital ratio as  $j^*(x)$ . The first-order conditions for the two investments can be solved separately from first-order condition for emissions. Moreover, there is a further simplification as the first-order conditions for investment in capital imply the affine relationship (conditioned on state variables)

$$\phi_0\phi_1 V_k(x) (\alpha - i^* - j^*) = \delta(1-\kappa)(1 + \psi_1 i^*),$$

which can be exploited in computation.

#### 4.1.1 Relative prices of capital and reserves

As is typical in the investment literature, we define the relative price  $q^*$ , sometimes referred to as Tobin's  $q$ , as the marginal rate of substitution between capital and consumption:

$$q^*(x) = V_k(x) \left[ \frac{\alpha - i^*(x) - j^*(x)}{\delta(1-\kappa)} \right] = \frac{1 + \phi_1 i^*(x)}{\phi_0\phi_1} \quad (8)$$

where the second relation follows from the first-order conditions (5) for investment in new capital. While the first-order conditions are for the investment-capital ratio, the value function argument is the logarithm of capital. These two adjustments net out in our construction of  $q^*$ .

Analogously, we define the relative price  $p^*$  as the marginal rate of substitution between the reserve stock and consumption:

$$p^*(x) = V_r(x) \left[ \frac{\alpha - i^*(x) - j^*(x)}{\delta(1-\kappa)} \right] = \frac{j^*(x)^{1-\psi_1} \exp[\psi_1(r-k)]}{\psi_0\psi_1}$$

where the second equality is implied by the first-order conditions (6) for investment in new

reserves.

#### 4.1.2 Social cost of carbon

The social marginal rate of substitution between emissions and consumption is commonly referred to as the social cost of carbon (SCC). Thus it is a shadow price of the resource allocation problem for a hypothetical planner. It could be implemented via a Pigouvian tax that would correct the private shadow price for the externality, although we use this way to assess the impact of uncertainty, when conceived broadly. Following previous literature, we start by representing this social cost in terms of partial derivatives of the value function of the social planner. We then apply an asset pricing perspective to interpret components to this social cost. This follows in part discussions in Golosov et al. (2014). Cai, Judd, and Lontzek (2017) have a more ambitious exploration of the risk consequences for the social cost of carbon. We also embrace an asset pricing interpretation, but we will show how to extend the analysis to include forms of uncertainty other than risk. Our purpose in making this asset pricing link goes beyond the particular example economy that we posited. This same perspective also allows researchers to understand better the components to the social cost applicable in more general settings.

The marginal utility of emissions as a function of the state vector is given by:

$$\frac{\delta \kappa}{e^* \exp(r)} = \frac{V_r(x)}{\exp(r)} - V_f(x) + (1 - \kappa) \left( [\nabla \Gamma](\beta f) \beta + \zeta_D(z) \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right)$$

where the second equality follows from the first-order conditions (7). Dividing by the marginal utility of consumption gives:

$$scc(x) = \left[ \frac{V_r(x)}{\exp(r)} - V_f(x) + (1 - \kappa) \left( [\nabla \Gamma](\beta f) \beta + \zeta_D(z) \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right) \right] \left[ \frac{\alpha - i^*(x) - j^*(x)}{\delta(1 - \kappa)} \right]$$

As with the constructions of  $q^*$  and  $r^*$ , the scaling by capital nets out when forming the marginal rate of substitution used in the social cost of carbon construction.

In the construction of these prices, we use the marginal utility of consumption. Depending on the interpretation of the model, an alternative would be to think of  $C_t/D_t$  as “damaged consumption” and that the planner’s preferences are expressed in terms of the logarithm of damage consumption. Under this alternative, we replace the term  $\frac{\alpha - i^*(x) - j^*(x)}{\delta(1 - \kappa)}$  with  $\frac{\alpha - i^*(x) - j^*(x)}{\delta(1 - \kappa) \exp(d)}$  in the price constructions.

The social cost induced by the externality is captured by the two terms:

$$ecc(x) = -V_f(x) + (1 - \kappa) \left( [\nabla\Gamma](\beta f)\beta + \zeta_D(z) \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right) \quad (9)$$

scaled by the current period marginal utility for consumption. As we will now show, both of these can in turn be expressed as expected discounted values of future social damages. To motivate this representation, consider impulse response functions for the logarithm of damages in the future induced by a marginal change in emissions today. This is necessarily a nonlinear impulse response and hence will be state-dependent. The marginal emissions change induces an impact on  $\log D_{t+u}$  given by:<sup>10</sup>

$$\left( [\nabla\Gamma](\beta F_t)\beta + \zeta_D(Z_t) \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right) + \int_0^u [\nabla^2\Gamma](\beta F_{t+\tau})\beta^2 E_{t+\tau} d\tau$$

The first contribution occurs on impact, and the second one accumulates through its effect on current emissions on the state variable  $f$ .

Damages enter the utility function discounted and multiplied by  $\delta(1 - \kappa)$ . Doing some simple accounting and exploiting the exponential discounting, we combine all the date  $\tau$  contributions appropriately integrated to get

$$\exp(-\delta\tau)(1 - \kappa)[\nabla^2\Gamma](\beta F_{t+\tau})\beta^2 E_{t+\tau}$$

along with the initial term:<sup>11</sup>

$$\exp(-\delta\tau)\delta(1 - \kappa) \left( [\nabla\Gamma](\beta F_t)\beta + \zeta_D(Z_t) \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right).$$

Thus the external part to the social cost of carbon expressed in terms of expected realized state and control variables is:

$$\begin{aligned} & \delta(1 - \kappa) \left( [\nabla\Gamma](\beta F_t)\beta + \zeta_D(Z_t) \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right) \int_0^\infty \exp(-\delta\tau) d\tau \\ & + E \left[ \int_0^\infty \exp(-\delta\tau)(1 - \kappa)[\nabla^2\Gamma](\beta F_{t+\tau})\beta^2 E_{t+\tau} d\tau \mid X_t = x \right] \end{aligned} \quad (10)$$

<sup>10</sup>Following our earlier notational convention,  $[\nabla^2\Gamma]$  denotes the second derivative of  $\Gamma$ .

<sup>11</sup>Formally, we exchange orders of integration.

divided by the date  $t$  marginal utility of consumption.

By integrating the exponential function in the first expression, the  $\delta$  drops out resulting in:

$$(1 - \kappa) \left( [\nabla\Gamma](\beta F_t)\beta + \zeta_D(Z_t) \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right)$$

which is one of the two terms in formula (9) for *ecc*.

Since the second term is a discounted expected value, it solves a so-called Feynman-Kac (FK) equation. Formally, we are interested in the solution  $\Phi$  to the forward-looking equation:

$$\begin{aligned} \Phi(X_t) &= \mathbb{E} \left[ \int_0^\infty \exp(-\delta\tau) \Psi(X_{t+\tau}) d\tau \mid X_t \right] \\ &= \exp(\delta t) \int_t^\infty \exp(-\delta\tau) \mathbb{E} [\Psi(X_\tau) \mid X_t] d\tau \end{aligned} \quad (11)$$

for a pre-specified  $\Psi$ . Specifically, let:

$$\Psi(x) = (1 - \kappa) [\nabla^2\Gamma](\beta f) \beta^2 e^*(x) \exp(r).$$

To provide a heuristic reminder of form and rationale for the FK equation, we obtain the drift of the process  $\{\Phi(X_t) : t \geq 0\}$  of the left-hand hand side of (11) via Ito's formula for  $X_t = x$  as:

$$\frac{\partial\Phi}{\partial x}(x) \cdot \mu_X[x, a^*(x)] + \frac{1}{2} \text{trace} \left[ \sigma_X(x)' \frac{\partial^2\Phi}{\partial x \partial x'}(x) \sigma_X(x) \right]$$

where  $a^*$  is the maximizing decision rule. Differentiating the right-hand side of (11) with respect to  $t$  gives an alternative formula for this drift by computing a time derivative:

$$\delta\Phi(x) - \Psi(x).$$

By equating these, we obtain the FK or (more generally) resolvent equation:

$$-\delta\Phi(x) + \frac{\partial\Phi}{\partial x}(x) \cdot \mu_X[x, a^*(x)] + \frac{1}{2} \text{trace} \left[ \sigma_X(x)' \frac{\partial^2\Phi}{\partial x \partial x'}(x) \sigma_X(x) \right] + \Psi(x) = 0. \quad (12)$$

Notice that this equation is just the special case of an HJB equation, but one that abstracts from optimization.

By differentiating the HJB equation with respect to  $f$  and applying the “Envelope



Theorem,” it can be shown that the solution  $\Phi$  to the FK equation satisfies

$$\Phi(x) = -V_f(x)$$

This gives us the following interpretation of  $-V_f(x)$ , which is the second component of *ecc* in formula (9):

$$-V_f(x) = (1 - \kappa)E \left[ \int_0^\infty \exp(-\delta\tau) [\nabla^2 \Gamma](\beta F_{t+\tau}) \beta^2 E_{t+\tau} d\tau \mid X_t = x \right]$$

Thus *ecc* is an expected discounted impulse response of marginal damages induced by current period emissions divided by the current period marginal utility of consumption. The discounting here is with respect to the subjective rate of discount because we are working with marginal utilities. This overall approach of representing the *ecc* as a discounted expected value to more complex models of climate dynamics. But so far, we have presumed knowledge of the climate dynamics when constructing this cost. We will have much more to say about uncertainty adjustments and the implied “stochastic discounting” in the next section.

## 4.2 Damages to Macroeconomic Growth

We briefly describe the corresponding set of calculations of the model in which there are damages to capital evolution. In this specification, we no longer make reference to an explicit damage state variable. The pertinent terms from the HJB equation for optimization are given by:

$$\begin{aligned} & \delta(1 - \kappa) \log(\alpha - i - j) + \delta\kappa \log e + V_k(x)\phi_0 \log(1 + \phi_1 i) \\ & + V_r(x) [-e + \psi_0 \exp[\psi_1(k - r)] j^{\psi_1}] + V_f(x)e \exp(r) \end{aligned}$$

Even with the modifications, the first order conditions for  $i$  and  $j$  remain the same. The value function and its derivatives are different, however, as is the first-order condition for  $e$ :

$$\frac{\delta\kappa}{e} + V_f(x) \exp(r) - V_r(x) = 0$$

Thus the implied marginal utility for emissions satisfies.

$$\frac{\delta\kappa}{e^* \exp(r)} = \frac{V_r(x)}{\exp(r)} - V_f(x)$$

We now think of  $-V_f$  divided by the marginal utility of consumption to be the external contribution to the social cost of carbon. The period utility cost induced by a marginal change in  $e$  is given by:

$$\Psi(x) = -V_k(x) [\nabla\Gamma(\beta f)\beta]$$

Thus  $-V_f$  has an intuitively appealing interpretation as the expected discounted marginal contribution to growth rate damages multiplied by the marginal utility of capital in the respective time periods. Changing the numeraire at each date from utils to consumption entails replacing  $V_k$  by the relative price  $q^*$  as given by formula (8) so that the social costs being discounted weight marginal damages by  $q^*$ .

## 5 Incorporating Additional Uncertainty Components

As formulated so far, the planner's problem only features risk and not other components of uncertainty. We now explore multiple ways to capture a broader notion of uncertainty, beyond just risk, that exploit some simplifications that emerge from our continuous-time formulation. In what follows, we capture ambiguity and model misspecification concerns conveniently with two parameters  $(\xi_p, \xi_m)$  following an approach suggested by Hansen and Sargent (2007) and extended to continuous time by Hansen and Miao (2018). From a computational/mathematical perspective, they act as penalization parameters that restrain the sensitivity analysis of alternative models  $(\xi_p)$ , and the exploration of the potential misspecification of those models  $(\xi_m)$ . An outcome of the computation will be an alternative probability measure that reflects aversions to model ambiguity and to the potential misspecification of each of models under consideration by the social planner. In constructing such a measure, we borrow convenient mathematical tools used extensively for pricing derivative claims. The measure emerges as part of our solution to an HJB equation for the planner who designs policies that are aimed to be sensibly robust in the presence of this uncertainty. In effect, this probability is an uncertainty-based pricing measure. In this section, we derive this adjusted probability measure under various settings of uncertainty and its implications for social valuation, and in Section 6 we illustrate its impact in a

quantitative example.

## 5.1 Discounting, Uncertainty and Pricing

Before plunging into our analysis, we remark on how an asset pricing perspective adds new twists to the environmental economics literature. Discussions of the questions “what should the discount rate be for social valuation?” have been extensive in the environmental economics literature to date. This discourse sometimes alludes to *ad hoc* uncertainty adjustments. A detailed version of such an exploration is provided in Gollier (2013), including references to ambiguity aversion as a motivation for wanting to alter discount rates. The discussion of discount rates often includes both a subjective discount rate contribution,  $\delta$  in our model, and a growth rate adjustment. While our formulas for the SCC only include the former, this is because we expressed the costs to discounting in utility units. Had we used instead a consumption numeraire, a consumption growth adjustment would have been present in our analysis as well. But even here, the theory of asset pricing typically uses a *stochastic* discount factor process when there are shocks to the macroeconomy. Differential exposure to these shocks should be discounted in different ways as encoded conveniently in stochastic discount factors. It is perhaps more germane to ask “what should the social *stochastic* discount factor be for social valuation?” Producing interest rate counterparts over alternative horizons depends on both the price of uncertainty and the exposure to that uncertainty, but these adjustments are a feature of the joint properties of the stochastic discounting and the uncertain social costs to be discounted. Consistent with Gollier’s reference to forward rates, the compounding of stochastic discount factors over multiple periods of time can have substantively important valuation consequences giving rise to a potentially important term structure for risk prices.

We next provide an overview of how we incorporate a broad notion of uncertainty into valuation. In a nutshell, our uncertainty measures adds an important dimension to stochastic discounting and the remainder of this section shows how to construct this measure.

## 5.2 An Overview

We purposely limit our exploration of alternative probability measures to those that are “disguised” from the planner and not trivially revealed through observations.<sup>12</sup> Roughly

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<sup>12</sup>We accomplish this formally considering only alternative probability measures that are absolutely continuous over finite intervals of time.

speaking, consider alternative probabilities that can be represented as likelihood ratios. Since we focus on models with Brownian information structures, it is most convenient to use changes of measures familiar in mathematical finance justified mathematically by the Girsanov Theorem. As is well known from the theorem, the implied change of probability measure includes a possibly history-dependent drift distortion within the Brownian increment. That is, under the alternative probability measure:

$$dW_t = H_t dt + dW_t^H \tag{13}$$

with  $dW_t^H$  a Brownian increment under the change of measure and  $H = \{H_t : t \geq 0\}$  is a history-dependent drift distortion process. The drift distortion allows for considerable flexibility, but this formulation is not “without loss of generality.”<sup>13</sup> It is a restriction enforced by the likelihood ratio formulation.

To implement concerns about misspecification, we necessarily penalize or constrain the corresponding drift distortions. For our alternative ways to depict ambiguity aversion and model misspecification, we show the corresponding adjustments to the Hamilton-Jacobi-Bellman (HJB) equation of the robust social planner. These adjustments introduce a minimization problem to the HJB equation formulation so that the planner solves a max-min, or equivalently a two-player, zero-sum game specified recursively rather than only a maximization problem. The minimization is over alternative probabilities represented conveniently as drift distortions. We then use the minimization problem to construct a specific probability measure that gives the valuation adjustment that we are looking for. For adding specificity, we start by describing more formally the resulting preferences.

### 5.3 Continuation Values

We use continuation values to define the preferences recursively. Continuation values are prospecti and computed by solving a forward stochastic differential equation. As in dynamic programming, a terminal value along with a forward-looking evolution equation imply continuation value processes for each hypothetical decision or action process. Looking forward, for Markov decision problems of the type we consider for a social planner, the equation for the continuation value evolution alters the HJB equations previously described.

Let  $U = \{U_t : t \geq 0\}$  denote the continuation value process posed in continuous time.

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<sup>13</sup>While there are ways to further generalize some of the formulations which follow, these are beyond the scope of this paper.

Write:

$$dU_t = \mu_{U,t}dt + \sigma_{U,t} \cdot dW_t$$

where a recursive representation of the value function implies the restriction:

$$0 = \mu_{U,t} + v_t - \delta U_t. \tag{14}$$

This representation of preferences translates into an HJB equation once we use the Markov structure and the Ito formula to depict the drift  $\mu_{U,t}$  in terms of value function derivatives and the local evolution of the Markov state. For an action or decision process  $A$  and value function  $V$ , the local dynamic coefficients for the continuation value process are:

$$\begin{aligned} \mu_{U,t} &= \frac{\partial V}{\partial x}(X_t) \cdot \mu_X(X_t, A_t) + \frac{1}{2} \text{trace} \left[ \sigma_X(X_t)' \frac{\partial^2 V}{\partial x \partial x'}(X_t) \sigma_X(X_t) \right] \\ \sigma_{U,t} &= \left[ \frac{\partial V}{\partial x}(X_t) \right]' \sigma_X(X_t). \end{aligned}$$

The instantaneous utility  $v_t$  depends on the action as a function of the state. Optimization leads us to include the maximization as in (4).

Under the (local) change of measure captured by (13), this is modified to be:

$$0 = \mu_{U,t} + v_t + \sigma_{U,t} \cdot H_t - \delta U_t \tag{15}$$

Alternative specifications of aversions to uncertainty will lead us to restrain the drift distortion processes  $H$  in different ways.

## 5.4 Model Misspecification

Initially, we explore model misspecification for a single model. Allowing for arbitrary misspecification leads to a degenerate outcome. Instead we consider ways of penalizing distortions using a well-studied construct in the applied probability literature called “relative entropy.” The approach has been used previously in the literature on robust control theory. For instance, see Jacobson (1973) for an initial entry to the literature and James (1992) for a continuous-time formulation. We use the adaptation and extension by Hansen and Sargent (2001), Anderson, Hansen, and Sargent (2003), and Hansen et al. (2006). With the Brownian motion information structure, this approach is straightforward to implement by introducing a quadratic penalization term in the Hamilton-Jacobi-Bellman equation.

Anderson, Brock, and Sanstad (2018) used a discrete-time formulation of this approach to study an alternative energy climate model with concerns for model misspecification.<sup>14</sup>

As shown by Hansen and Sargent (2019b), this formulation can be viewed as a special case of the recursive variational decision theory axiomatized by Maccheroni, Marinacci, and Rustichini (2006). This approach introduces a quadratic penalty in (15)

$$0 = \min_{h \in \mathbb{R}^m} \mu_{U,t} + v_t + \sigma_{U,t} \cdot h - \delta U_t + \frac{\xi_m}{2} h \cdot h = \mu_{U,t} + v_t - \delta U_t - \frac{1}{2\xi_m} \sigma_{U,t} \cdot \sigma_{U,t} \quad (16)$$

where the minimized value is:

$$H_t^* = -\frac{1}{\xi_m} \sigma_{U,t}$$

Here  $\xi_m$  determines how much the planner is concerned about misspecification. Large values of  $\xi_m$  capture low concern about misspecification, while for small values of  $\xi_m$  this concern is much more pronounced. By taking limits of (16) as  $\xi_m$  goes to  $\infty$ , the outcome of the minimization recovers (14).

Recall that the damage evolution equation (2) includes a term

$$\begin{bmatrix} F_t & 1 \end{bmatrix} \cdot d\zeta_D(Z_t)$$

which contributes a Brownian increment to this equation. Let  $\sigma_D(Z_t)dW_t$  denote the Brownian component to  $d\zeta_D(Z_t)$ . Then the implied Brownian increment for the damage evolution is:

$$\begin{bmatrix} F_t & 1 \end{bmatrix} \sigma_D(Z_t) dW_t$$

Under a change of probability measure this becomes:

$$\begin{bmatrix} F_t & 1 \end{bmatrix} \sigma_D(Z_t) H_t dt + \begin{bmatrix} F_t & 1 \end{bmatrix} \sigma_D(Z_t) dW_t^H.$$

Notice that if  $\sigma_D$  does not depend on the exogenous state,  $Z_t$ , then constant choices of  $H$  can be thought of as a change in the composite function  $[\nabla\Gamma](\beta f)\beta$  when  $[\nabla\Gamma]$  is linear. Fluctuations in  $H$  could proxy for unmodelled time variation in the coefficients. Given the flexibility in the construction of  $H$ , other forms of misspecification are also entertained.

Next, we describe a more structured approach to parameter uncertainty.

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<sup>14</sup>They show that the resulting robust policy design shows a remarkable lack of sensitivity to how much the baseline model reflects climate changes.

## 5.5 Parameter Ambiguity

Dynamic models typically have unknown parameters for which theory and data are only partially informative. Recall from Figure 2, that there is substantial uncertainty in the climate sensitivity parameter  $\beta$  used in the Matthews et al. approximation. Similarly, Figures 3 and 4 illustrate uncertainty in the specification of damages. There may be very little reason to commit to a specific measure of central tendency in the case of Figures 2 and 4 or an arbitrary weighting of the high and low damage specifications in Figure 4 when solving the model. We could perform calculations based on imposing alternative values on the fictitious social planner and check for sensitivity of the analysis. Here, we suggest an alternative strategy whereby the planner confronts parameter ambiguity and model specification with caution in one of two alternative ways.

Let  $\theta$  denote a possible parameter configuration unknown to the planner in a set  $\Theta$ . For each possible parameter realization  $\theta$ , there is dynamic evolution given by:

$$dX_t = \mu_X(X_t, A_t | \theta)dt + \sigma_X(X_t)dW_t.$$

For a value function  $V$  and a decision process  $\{A_t : t \geq 0\}$

$$\mu_{U,t}(\theta) = \frac{\partial V}{\partial x}(X_t) \cdot \mu_X(X_t, A_t | \theta)$$

Let  $P_t(d\theta)$  be a date  $t$  reference prior/posterior over a set of possible values of  $\Theta$  conditioned on date  $t$  information. In a dynamic setting, the distinction between a prior and posterior becomes blurred as “yesterday’s posterior” is “today’s prior”. The values of  $\theta$  can index unknown parameters or a discrete set of models or both. Rather than fully embrace this posterior, the planner explores deviations. Let  $Q_t(\theta)$  be a relative density that satisfies:

$$\int_{\Theta} Q_t(\theta)P_t(d\theta) = 1$$

used to alter the posterior distribution. Let  $G_t(\theta)$  be a drift distortion that can depend on the unknown parameter. We use this to capture potential model specific misspecification. Then the drift distortion that interests us is an  $H_t$  that satisfies

$$\sigma_X(X_t)H_t = \left( \int_{\Theta} [\mu_X(X_t, A_t | \theta) + \sigma_X(X_t)G_t(\theta)] Q_t(\theta)P_t(d\theta) \right)$$

$$- \int_{\Theta} \mu_X(X_t, A_t | \theta) P_t(d\theta), \quad (17)$$

as a possible drift distortion for the Brownian motion. Notice that if  $Q_t$  is identically one, then  $H_t = \int G_t(\theta) P_t(d\theta)$  solves this equation. Before proceeding, there is one technical restriction that we must impose on how the drift depends on the unknown parameter vector.

**Remark 5.1.** *Recall that we allow for  $\sigma_X$  to be singular (e.g.  $m < n$ ). Instead, we restrict the  $m$  by  $m$  matrix  $(\sigma_X)' \sigma_X$  to be nonsingular. Allowing  $\sigma_X$  to have more rows than columns requires some explanation because there may not exist a solution  $H_t$  to the equation. We rule this problem out by requiring that the local learning dynamics not be degenerate. Suppose there is some (potentially conditional) linear combination of the  $n$ -dimensional state vector that has locally predictable dynamics for which the Brownian exposure is zero. We restrict the implied drift for this linear combination to be independent of  $\theta$ . In effect, we restrict the parameter vector to be fully disguised by the local dynamics. For example, in our model there is no diffusion component to the state dynamics for  $F$ . These same dynamics do not depend on an unknown parameter.*

*In terms of (17), premultiply both sides by an  $n$ -dimensional row vector  $\mathbf{r}'$  with the same number of coordinates as there are states and that is orthogonal to all of columns of  $\sigma_X$ . Then the left-hand side is zero and the right-hand side is:*

$$\int_{\Theta} \mathbf{r}' \mu_X(X_t, A_t | \theta) Q_t(\theta) P_t(d\theta) - \int_{\Theta} \mathbf{r}' \mu_X(X_t, A_t | \theta) P_t(d\theta).$$

*This expression will be zero if  $\mathbf{r}' \mu_X$  does not depend on  $\theta$  as then the choice of what probability measure to use in the integration is inconsequential.*

To accommodate this structured uncertainty, in restricting the local mean of the continuation value, we now alter minimization problem (16) along the lines suggested in the Hansen and Miao (2018):

$$\begin{aligned} 0 = & \min_{q, \int q(\theta) P_t(d\theta) = 1} \min_{g(\theta) \in \mathbb{R}^m} -\delta U_t + v_t \\ & + \int_{\Theta} \left[ \mu_{U,t}(\theta) + \sigma_{U,t} \cdot g(\theta) + \frac{\xi_m}{2} g(\theta) \cdot g(\theta) \right] q(\theta) P_t(d\theta) \\ & + \xi_p \int_{\Theta} [\log q(\theta)] q(\theta) P_t(d\theta) \end{aligned} \quad (18)$$



where we have penalized the choice of density distortion  $q$  with a scaled version of the relative entropy divergence:

$$\int_{\Theta} [\log q(\theta)] q(\theta) P_t(d\theta),$$

which has been used extensively in the applied probability and statistics literature. Letting  $q$  be one makes this divergence zero, and letting the parameter  $\xi_p$  become arbitrarily large restricts the posterior distortion  $q$  to be arbitrarily close to unity.

This minimization has a very tractable quasi-analytical solution, which is important for numerical implementation. The minimizing  $g(\theta)$  does not depend on  $\theta$  and has a solution that analogous to that for minimizing  $h$  for the model misspecification problem:

$$G_t^*(\theta) = -\frac{1}{2\xi_m} \sigma_{U,t}$$

The minimizing density distortion

$$Q_t^*(\theta) = \frac{\exp\left[-\frac{1}{\xi_p} \mu_{U,t}(\theta)\right]}{\int_{\Theta} \exp\left[-\frac{1}{\xi_p} \mu_{U,t}(\theta)\right] P_t(d\theta)}$$

which tilts the resulting posterior towards  $\theta$ 's for which the value function drift is relatively low. Substituting these solutions in to the objective in (18) gives:

$$-\delta U_t + v_t - \xi_p \log \int_{\Theta} \exp\left[-\frac{1}{\xi_p} \mu_{U,t}(\theta)\right] P_t(d\theta) - \frac{\xi_m}{2} \sigma_{U,t} \cdot \sigma_{U,t} \quad (19)$$

**Remark 5.2.** *This approach, absent model misspecification, can be viewed as a continuous-time version of a “smooth ambiguity” model. Klibanoff, Marinacci, and Mukerji (2005) represent uncertainty as a two-stage lottery whereby one stage is used to capture risk conditioned on a model  $\theta$  which for us is depicted as a Brownian increment; and another stage to depict ambiguity over models (indexed by  $\theta$ ). They suppose that there are distinct preference representations of aversions associated with this two-stage lottery. This two-stage perspective permits the ambiguity aversion over models to play a more featured role in the decision problem. In this paper, we follow Hansen and Miao (2018) in our use of a continuous-time formulation along with the robustness interpretation. To connect our formulation to that of Klibanoff, Marinacci, and Mukerji, notice that the outcome of the minimization problem*

depicted in (19) includes a term given on the left-hand side of the inequality

$$-\xi_p \log \int_{\Theta} \exp \left[ -\frac{1}{\xi_p} \mu_{U,t}(\theta) \right] P_t(d\theta) \leq \int_{\Theta} \mu_{u,t}(\theta) \cdot P_t(d\theta)$$

The term on the left is recognizable as the exponential certainty equivalent and less than the posterior mean  $\int_{\Theta} \mu_{u,t}(\theta) P_t(d\theta)$ . Hansen and Miao (2018) derive this as a continuous-time limit of recursive smooth ambiguity preferences.

**Remark 5.3.** As an alternative ambiguity adjustment in a continuous-time Brownian setting, Chen and Epstein (2002) propose an instant-by-instant restriction on the potential subjective probabilities  $Q_t(\theta)P_t(d\theta)$  assigned to the alternative models. The decision maker is uncertain about  $Q_t$  but instead restricts it to be in the convex set that can be state-dependent. The Chen and Epstein (2002) preference specification is a recursive implementation of the max-min utility formulation axiomatized by Gilboa and Schmeidler (1989). Hansen and Sargent (2019b) motivate state dependence in the date-by-date constraint set as a form of time variation in parameters and show how to construct such an ambiguity set using a refinement of relative entropy. The formulation in Hansen and Sargent (2019a,b) combines this approach with concerns that each of the models in the ambiguity set might be misspecified. This amalgam is very much analogous to the extension of the smooth ambiguity formulation we proposed here. The asset pricing methods that we describe in what follows are also applicable to the uncertainty averse preferences proposed in Hansen and Sargent (2019b).

## 5.6 Parameter Learning

Learning adds state variables to the the analysis. For sufficiently simple examples, there could be sufficient statistics that make learning recursions straightforward and tractable to implement recursively. These sufficient statistics would need to be included among the set of state variables and the drift distortions to the underlying Brownian motion would alter their evolution. Also, depending on what coefficients are uncertain, the choice of action could impact the learning and the social planner problem as we have posed it here, as the social planner might have incentives to “experiment.” To the extent such a channel exists, designing a policy with this incentive in mind would add controversy to the analysis, as

it does in macroeconomic policy in other settings.<sup>15</sup> For some key climate parameters, learning can happen at best very slowly. In our computations we will omit the learning channel altogether. While this will substantially simplify our calculations, there are also convincing reasons from climate science to embrace this approximation. For instance, Roe and Baker (2007) write:

The envelope of uncertainty in climate projections has not narrowed appreciably over the past 30 years, despite tremendous increases in computing power, in observations, and in the number of scientists studying the problem. ... foreseeable improvements in the understanding of physical processes, and in the estimation of their effects from observations, will not yield large reductions in the envelope of climate sensitivity.

This perspective is consistent with the Bayesian computations of Olson et al. (2012) for what they call the climate sensitivity parameter that we mentioned earlier.

## 5.7 HJB Equation and Implications

We now propose a modified HJB equation for the social planner that includes concerns about model misspecification and ambiguity. In light of this evidence of very slow learning, we use a time invariant probability  $P$  in place of  $P_t$  as an approximation. The value function dynamics given in equation (18) imply a counterpart HJB equation to (4) with damages entering preferences (or equivalently scaling consumption):

$$\begin{aligned}
0 = \max_{a \in \mathbb{A}} \min_{q > 0, \int q P(d\theta) = 1} \min_{g \in \mathbb{R}^m} & -\delta V(x) + \delta(1 - \kappa) [\log(\alpha - i - j) + k - d] + \delta\kappa(\log e + r) \\
& + \frac{\partial V}{\partial x}(x) \cdot \left[ \int_{\Theta} \mu_X(x, a \mid \theta) q(\theta) P(d\theta) + \sigma_X(x)g \right] \\
& + \frac{1}{2} \text{trace} \left[ \sigma_X(x)' \frac{\partial^2 V}{\partial x \partial x'}(x) \sigma_X(x) \right] \\
& + \frac{\xi_m}{2} g'g + \xi_p \int_{\Theta} [\log q(\theta)] q(\theta) P(d\theta).
\end{aligned} \tag{20}$$

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<sup>15</sup>For example, see Cogley et al. (2008) for a discussion of robustness and experimentation in a monetary policy setting with learning.

See Appendices A and B for more details on our numerical implementation.

This max-min problem provides a state-dependent action  $a^*$  as well as state-dependent density  $q^*$  and a drift distortion  $g^*$ . We now show how to use these latter two objects to construct an uncertainty adjusted probability by constructing a corresponding drift for the state dynamics. The ambiguity-adjusted probability over the parameter space  $\Theta$  is  $q^*(\theta | x)P(d\theta)$  and the drift as a function of the Markov state is given by:

$$\mu^*(x) = \int_{\Theta} \mu_X[x, a^*(x) | \theta] q^*(\theta | x) P(d\theta) + \sigma_X(x) g^*(x) \quad (21)$$

In section 4, we represented the external contribution to the social cost of carbon as expected discounted future marginal damages induced by a marginal change in emissions for all future time periods where the time  $t + \tau$  contribution is:

$$(1 - \kappa)[\nabla^2 \Gamma](\beta F_{t+\tau}) \beta^2 E_{t+\tau} + \delta(1 - \kappa) \left( [\nabla \Gamma](\beta F_t) \beta + \zeta_D(Z_t) \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right).$$

scaled by the marginal utility of consumption. This same logic extends once we incorporate the alternative uncertainty sources, but with qualification. This gives us the following counterpart to formula (9):

$$ecc^*(x) = -V_f(f) + (1 - \kappa) \int_{\Theta} \left( [\nabla \Gamma](\beta f) \beta + \zeta_D(z) \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right) q^*(\theta | x) P(d\theta)$$

where the  $\theta$  integration is over  $\beta$  and the unknown parameter of  $\Gamma$ . The term  $-V_f$  continues to equal to an expected discounted value of the following social cost contributions at future dates,

$$(1 - \kappa)[\nabla^2 \Gamma](\beta F_{t+\tau}) \beta^2 E_{t+\tau}$$

where the states and emissions are the ones implied by the solution for the HJB equation (20). The expectation, however, is now computed using the conditional *ambiguity-adjusted probability measure*. The argument for this conclusion is essentially the same as before but it recognizes that the minimization problem alters the stochastic evolution of the state

variable. The FK equivalent computation of  $-V_f$  again applies with:

$$\Psi^*(x) = (1 - \kappa) \int_{\Theta} [\nabla^2 \Gamma](\beta f) \beta^2 e^* \exp(r) q^*(\theta | x) P(d\theta).$$

This FK computation opens the door to a novel characterization of the impact of uncertainty on the SCC. As an alternative to evaluating the discounted value using the ambiguity-adjusted probability, suppose we use the original unadjusted probabilities to evaluate the expected discounted value of the future marginal social costs. Call this  $\overline{ecc}(x)$ . We take the difference between the two discounted expected values

$$ucc^*(x) = [ecc^*(x) - \overline{ecc}(x)]$$

divided by the marginal utility of consumption or its damaged counterpart to be the uncertainty component to the SCC of carbon, inclusive of both model ambiguity and model misspecification adjustments.

We compute  $\overline{ecc}$  and hence  $ucc^*$  as follows:

i) integrate:

$$(1 - \kappa) \int_{\Theta} \left( [\nabla \Gamma](\beta f) \beta + \zeta_D(z) \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right) P(d\theta);$$

ii) integrate:

$$\overline{\Psi}(x) = (1 - \kappa) \int_{\Theta} [\nabla^2 \Gamma](\beta f) \beta^2 e^* \exp(r) P(d\theta);$$

iii) solve FK to produce the function  $\overline{\Phi}$ ;

iv) add the solution from part i) to the solution  $\overline{\Phi}$  from part iii) to form  $\overline{ecc}$ .

We apply the analogous approach for the model in which damages alter economic growth. The basic construct is much more generally applicable including to models with richer climate dynamics.

The altered probability is not meant to represent the beliefs of the social planner. This constructed probability gives the planner a way to confront more general forms of uncertainty other than risk. Conveniently, the outcome of our robustness analysis to alternative probabilities can be captured and computed by specifying two parameters that serve as preference parameters for the decision maker,  $\xi_p$  and  $\xi_m$ . While we do not dictate what these should be, we find it revealing to look at the implied ambiguity-adjusted probabilities

and the corresponding relative entropies to assess what probabilities are of most concern to the decision maker. See Anderson, Hansen, and Sargent (2003), Anderson, Brock, and Sanstad (2018), and Hansen and Sargent (2019a) for alternative ways to link the parameter  $\xi_m$  to entropy measures and to so-called detection error probabilities used to assess how close statistically the ambiguity-adjusted probability measure is to the reference or baseline probability.

**Remark 5.4.** *Since the writing of Good (1952), robust Bayesians have suggested that an implied “worst-case probability” under which the decision maker optimizes is worthy of careful inspection. The ambiguity-adjusted probability measure that emerges from the HJB equation is arguably hard to interpret in this light because it depends on endogenous state variables. To construct this worst-case probability, we appeal to a result from two-player, zero-sum differential games. Just like in dynamic programming, there is a date zero static game that the HJB equation provides a solution for. Provided that a so-called Bellman-Isaacs condition is satisfied, the orders of maximization and minimization can be exchanged as of date zero without altering the implied value to the game. See Fleming and Souganidis (1989) for a formal discussion. To compute the worst-case probability, exchange orders in the static game by first maximizing conditioned on the probability and then minimizing over probabilities subject to penalization. The outcome of this static minimization with the order of extremization reversed gives the worst-case probability from a robust Bayesian perspective. For further discussion, see Hansen et al. (2006).<sup>16</sup>*

**Remark 5.5.** *The term social cost of carbon can have different meanings depending on the context. While we featured the Pigouvian taxation interpretation, there is another construct that may more pertinent to current usage by governments, say as is reflected in the Green Book prepared by HM Treasury (2018). Consider a marginal change in emissions from an existing equilibrium that may not be socially efficient. To formalize this with a similar perspective, we would impose the stochastic evolution of the pertinent economic state variables specified exogenously in our HJB equation formulation. For instance, we could solve for a competitive equilibrium abstracting from climate impacts and then impose the resulting actions on the planners problem. Instead of computing the action “a” as in HJB equation (20), we would dispense with the maximization and impose the solution for the action from the competitive problem. We would continue to solve the minimization problem to produce an ambiguity adjusted probability to use for social valuation. With this*

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<sup>16</sup>The material in Appendix D is particularly relevant on this topic.

*approach, we would still compute the social marginal rate of substitution of emissions and consumption as an alternative measure of the social cost of carbon. This cost also can be represented as the valuation of a social cash flow for the implied economic damages using the ambiguity adjusted probability measure from the altered HJB equation.*

## 6 An Illustration

In this section, we illustrate our analysis. To provide a basic understanding of the economic model, we start by investigating a steady state version of our model without climate impacts. Given the homogeneity imposed, this version of the model possesses a steady state in the appropriate ratios of variables. This was by design. We use these relations to gain an initial understanding of our baseline parameter configuration and to set the stage for assessing how the efficient allocation is altered by incorporating the climate externality. We then we introduce a climate/damage externality and show how uncertainty alters emissions and the social cost of carbon. As we will illustrate, the damage specification acts similarly to a Hotelling-like constraint on emissions.

### 6.1 Steady state without climate impacts

To illustrate “how the model works” we start with a deterministic version of the model without damages and investigate the steady state implications.

Table 1 lists the technology parameters, Table 2 gives our choice of preference parameters. and Table 3 gives the steady values associated with our parameters. The economic model at this level of abstraction is hard to calibrate in a fully convincing way. Thus, this table is not the outcome of a formal moment matching approach sometimes used in the macro calibration literature. In addition to its simplicity, the notion of capital in our setup should be broad based in including human capital and forms of intangible capital in addition to physical capital. Similarly, the reserves in our models could include both oil and coal.<sup>17</sup> See Appendix C for more details.

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<sup>17</sup>We did formally impose two steady state targets in our parameter settings, one on the reserves to capital ratio and the other on the growth rate of capital.

Table 1: Technology

parameter	value
$\alpha$	.115
$\phi_1$	16.7
$\phi_0$	.060
$\bar{\mu}_K$	-.035
$\psi_0$	.113
$\psi_1$	.143

Table 2: Preferences

parameter	value
$\delta$	.010
$\kappa$	.032

Table 3: Steady States (without climate impacts)

variable	value
investment/capital <sup>a</sup> : $i$	.090
growth rate of capital <sup>a</sup>	.020
marginal value of capital <sup>a</sup> : $q$	2.50
emissions/reserves <sup>a</sup> : $e$	.015
reserves/capital <sup>a</sup> : $\exp(r - k)$	.980
exploration/capital: $j$	$2.72 \times 10^{-4}$
consumption/capital: $c$	.0247
marginal value of reserves: $p$	.0545

<sup>a</sup>Imposed when setting the parameters.

Since the emissions trajectory implicit in this fixed point ignores the climate externality in perpetuity, the outcome will be essentially will be to “fry the planet.” Absent climate impacts, by design our model has sufficient homogeneity whereby there is steady growth implying a fixed point in ratios. Under the Matthews et al. (2009) approximation, temperature will grow without bound. In the competitive steady state associated with our parameter settings, emissions grow at two percent while the subjective discount factor is one percent. This implies that log damages will grow at roughly four percent given our quadratic specification of log damages. This means that the discounted future social costs will be infinite at the deterministic steady state. The solution to the social planner’s problem will avoid this extreme outcome as it will be desirable to limit the growth of emissions and keep the damage integral finite.



## 6.2 Consequences of climate and damage uncertainty

Our first set of results are computed using the smooth ambiguity specification of preferences applied to both climate sensitivity and to the damage uncertainty depicted in Figure 3. In particular, we make the following modeling simplifications:

- i)  $\xi_m = \infty$ ,
- ii)  $\zeta_D(Z_t) \cdot \begin{bmatrix} F_t \\ 1 \end{bmatrix} = \zeta_{D,2}(Z_t)$ .

In regards to item i), we do not mean to diminish the importance of model misspecification and plan to do comparative analysis of the distinct consequences of both uncertainty components in future research. We impose the restriction in item ii), to simplify computation, though it also removes a potentially interesting source of variation for emissions. Moreover, as we discussed in Section 5.4, activating both would open an interesting additional channel for model misspecification concerns to impact prudent climate/economics policy.

As we discussed previously, associated with this ambiguity adjustment are altered probabilities assigned to the alternative damage specifications and altered densities for the climate sensitivity parameter  $\beta$ . As we see no easy way to give a “primitive interpretation” for the magnitude of the smooth ambiguity parameter  $\xi_p$ , we instead look at the distributional consequences of this parameter setting. With this in mind, we begin by looking at the implied densities and probabilities.

We start by assigning baseline probabilities of one half to each of the damage specifications. Once we introduce damages, there is no even approximate stochastic steady state that is of interest. As a result, this induces state dependence in the worst-case or adjusted probabilities that is reflected prominently in the dynamic evolution of state variables. The dependence on the state variable  $f$  that measures cumulative emissions turns out to have a particularly pronounced impact on the worst-case densities. The altered probabilities become greater as the emissions trajectories push towards relatively higher damages towards the region where the two damage specifications depicted in Figure 3 diverge. This pattern is evident in the second column of Table 4, where we report entropies for a deterministic path simulated from the state initialization that matches the steady states from the competitive model without climate impacts. The entropies only start to have notable distortions on this path, 50 years out. Prior to this date, altering probabilities has little impact on the decision problem because the two damage specifications agree. The simulated path for

the state variables is from the solution to the planner’s problem in which emissions are relatively modest. Exposure to large environmental degradation is delayed until well into the future under this trajectory.

year	weighted damage (low damage prob)	low damage (mean, std dev)	high damage
0	.006 (.50)	.012 (1.81, .503)	.005
25	.012 (.50)	.040 (1.87, .512)	.010
50	.041 (.49)	.067 (1.91, .517)	.027
75	.168 (.45)	.088 (1.94, .521)	.124
100	.254 (.41)	.105 (1.95, .523)	.210

Table 4: Entropies relative to the baseline normal density with a mean of 1.73 and a standard deviation of .493. For the “weighted damage” specification, the baseline probabilities are one half for each damage specification in Figure 3. The implied worst-case probabilities for the low damage specification are given in parentheses. For the “low damage” specification, probability one is placed on the low damage specification. The worst-case means and standard deviations are reported in parentheses. For the “high damage” specification, probability one is placed on the high damage specification. The value used for  $\xi_p$  is  $\frac{1}{4500}$ .

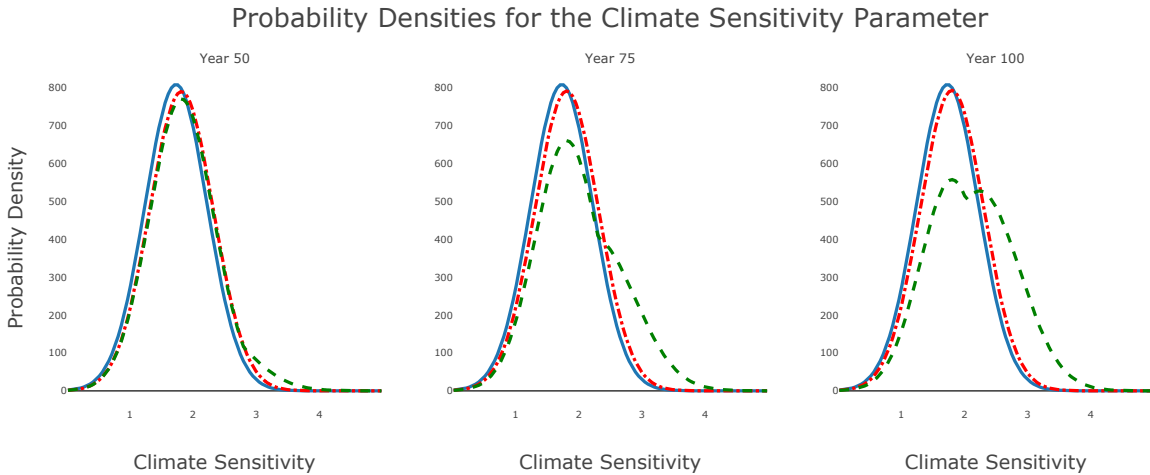


Figure 5: Weighted damage configuration. The blue solid curve is the baseline probability density, the red dot-dashed curves are the ambiguity-adjusted density conditioned on the low damage model and the green dashed curves are the ambiguity-adjusted densities conditioned on the high damage model.

The distorted climate sensitivity densities that condition on each of the damage function specifications are depicted in Figure 5. This figure gives three densities for the climate sensitivity parameter  $\beta$ . One reproduces the normal approximation from Figure 2 and the other two are the ambiguity adjusted densities conditioned on each of the two damage specifications. These are shifted to the right to capture the caution implicit in the ambiguity adjusted probabilities. The distortions are notably larger conditioned on the high-damage specification, which is to be expected. The high damage specification is of most concern to the planner while the adjusted weights reported in Table 4 even up to one hundred years are modest. Conditioned on the high damage specification the adjusted density for  $\beta$  loads up probability in the right-tail with the second mode of the density becoming more prominent.

## Social Cost of Carbon Decomposition

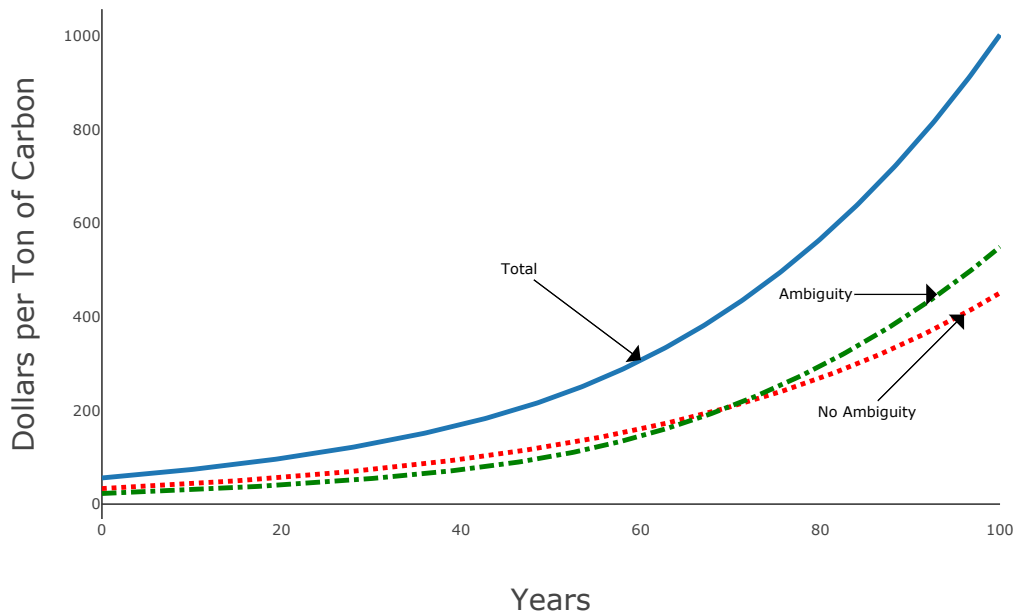


Figure 6: Social cost of carbon decomposition. The units are 2010 US dollars per ton of carbon. The costs are computed at the socially efficient allocation. The private contribution is negligible relative to the other components and is not plotted. The green dot-dashed curve gives the uncertainty contribution and the red dotted curve gives the external contribution computed under the baseline probabilities. The sum of these two components is essentially the total social cost of carbon given by the blue solid curve.

In Figure 6, we plot the implied social cost of carbon over a hundred year time horizon. This figure also includes a contribution that quantifies the impact of the uncertainty-adjusted probability measure. The private contribution to this cost is relatively speaking, very small and can safely be ignored. In contrast, the uncertainty component is substantial and accounts for roughly half of the social cost of carbon for this example. Not surprisingly, given our depiction of the adjusted densities in Figure 5, the relative importance of the uncertainty adjustment becomes more prominent at say one hundred years out than at zero. The units are 2010 US dollars per ton of carbon.

## Emissions Comparison

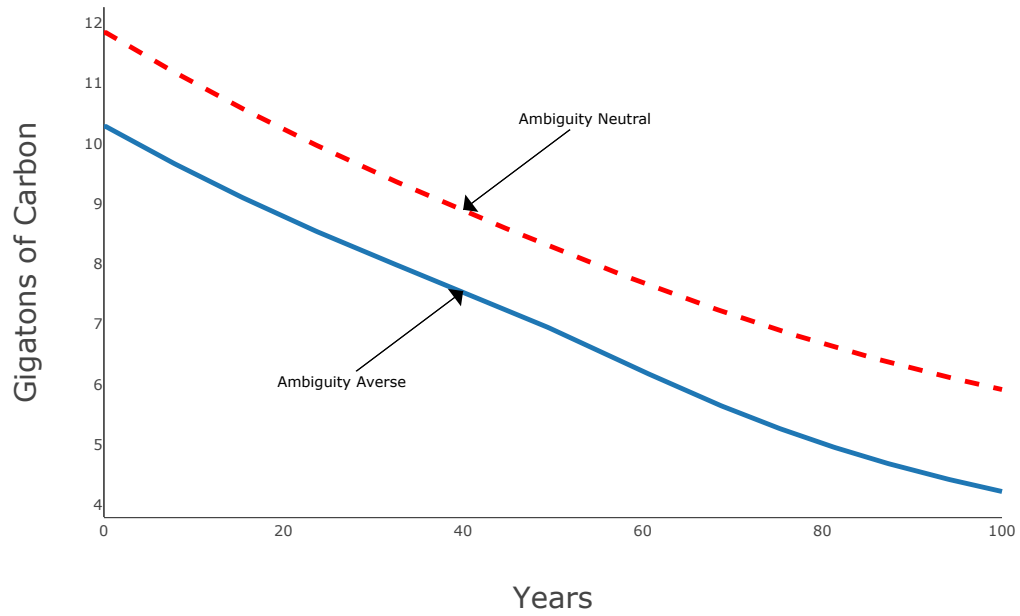


Figure 7: Emissions paths under ambiguity aversion (blue solid line) and ambiguity neutrality (red dashed line). In each case, the socially efficient allocations are used under the respective ambiguity preferences.

## Social Cost of Carbon Comparison

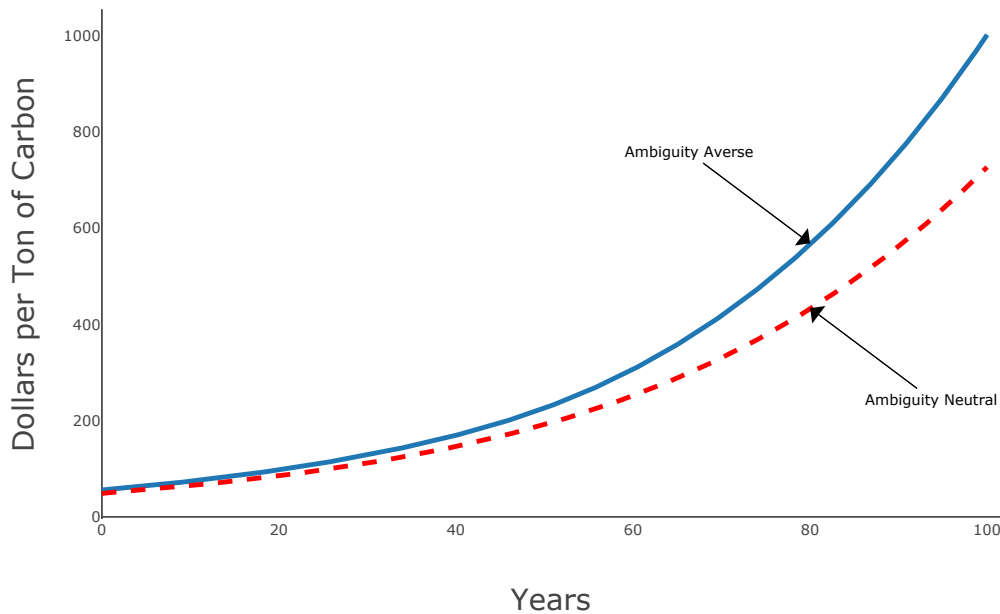


Figure 8: Social cost of carbon trajectories computed under ambiguity aversion (blue solid line) and under ambiguity neutrality (red dashed line). In each case the socially efficient allocations are used under the respective ambiguity preferences. The units are 2010 US dollars per ton of carbon.

Figure 7 gives two emissions trajectories, one computed when we abstract from ambiguity aversion and the other from the same social planners problem as was used in the Table 4 and Figure 5. Both trajectories decay much like in a Hotelling exhaustible resource allocation problem. However, this outcome is not induced by the potential exhaustion of the resource because our model allows for investment in new reserves. Instead, the potential for severe damages restrain the emissions for the fictitious planner because of the presence of the climate externality.<sup>18</sup> While the curves in Figure 6 hold fixed the emissions and other allocations implied by the model, in Figure 8, we report the total social cost of carbon with and without the ambiguity averse preferences. Both trajectories grow like the

<sup>18</sup>Note that the initial value of emissions is actually higher here than in our steady state ignoring climate impacts. Apparently this finding emerges because the initial decrease in the marginal social value of holding reserves increases emissions over that in the steady-state economy. While at the outset this impact offsets the additional climate-induced social costs, but this is only a transient phenomenon. In models such as this one, the alternative potential intertemporal trajectories of damages can have subtle and surprising effects on the corresponding paths of emissions as revealed in our computations.

resource price in a Hotelling model, but not surprisingly, the social cost of carbon is higher when the planner is averse to ambiguity.

We next report results from a “sensitivity to the prior” type analysis familiar in robust Bayesian methods. We change rather substantially the *ex ante* weights to the two damage specifications by focusing on two extremes. In the first one, we simply embrace the “low damage” specification by assigning probability one to this specification while continuing to focus on climate sensitivity. In the second one, we feature the “high damage” specification by assigning all of the weight on this specification.

In making these comparisons, we hold fixed the parameter  $\xi_p$ . Alternatively we might hold fixed relative entropies at perhaps some date and adjust the  $\xi_p$  parameter accordingly. This becomes an issue because for the fixed  $\xi_p$  the relative entropies differ across damage function specifications as is evident in Table 4. Consistent with the computation we reported earlier, for the “high damage” configuration, the distortions become quite pronounced with a fatter right-hand tail for the climate sensitivity for longer time periods in the future. The consequences for emissions and the social cost of carbon are depicted in Figures 10 and 11, respectively.

# Probability Densities for the Climate Sensitivity Parameter (special cases)

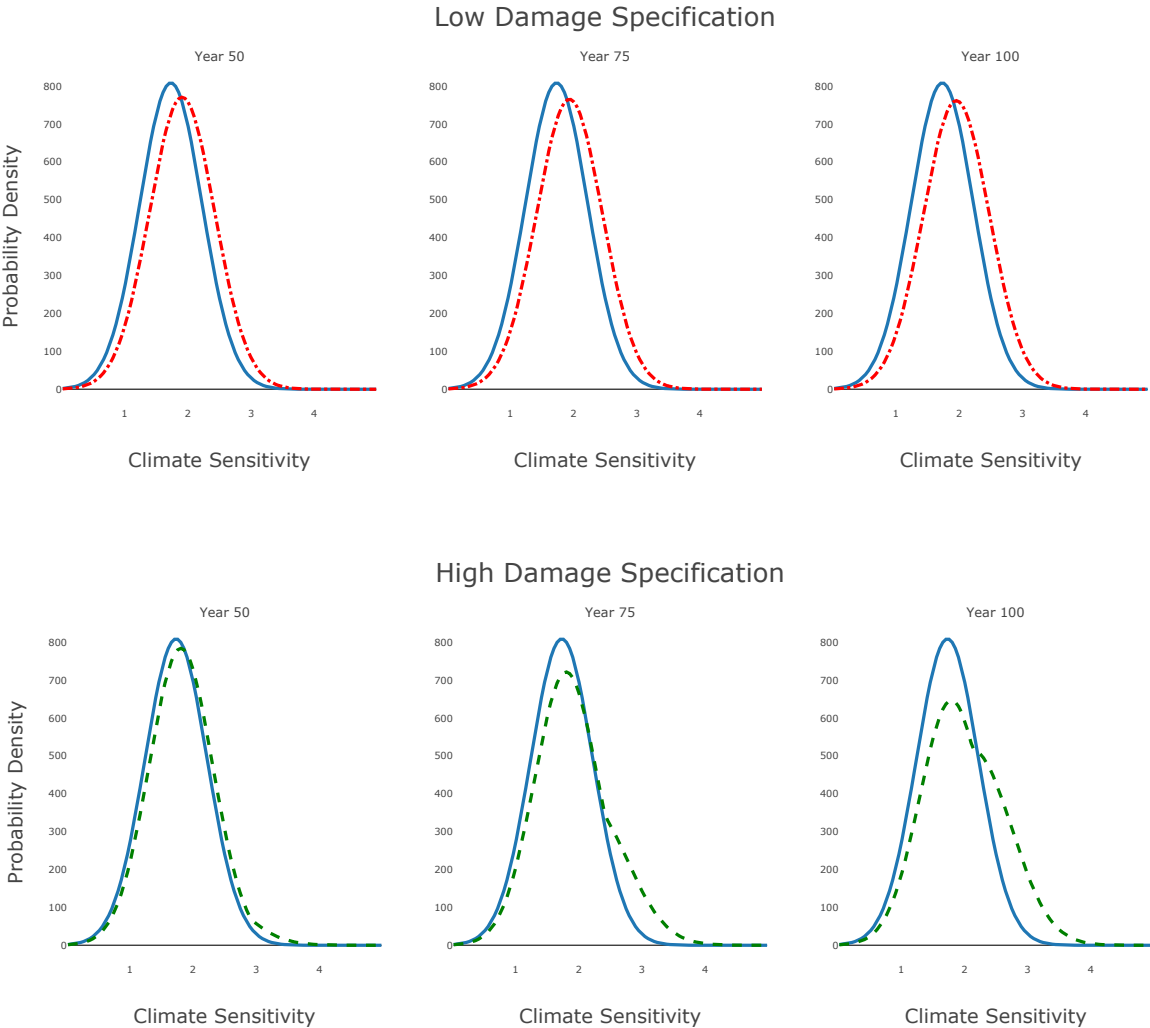


Figure 9: Top panel places probability one on the low damage specification and bottom panel on the high damage specification. The blue solid curve is the baseline probability density, the red dot-dashed curves are the ambiguity-adjusted densities for the low damage specification, and the green dashed curves are the ambiguity-adjusted densities for the high damage specification.



## Emissions Comparison

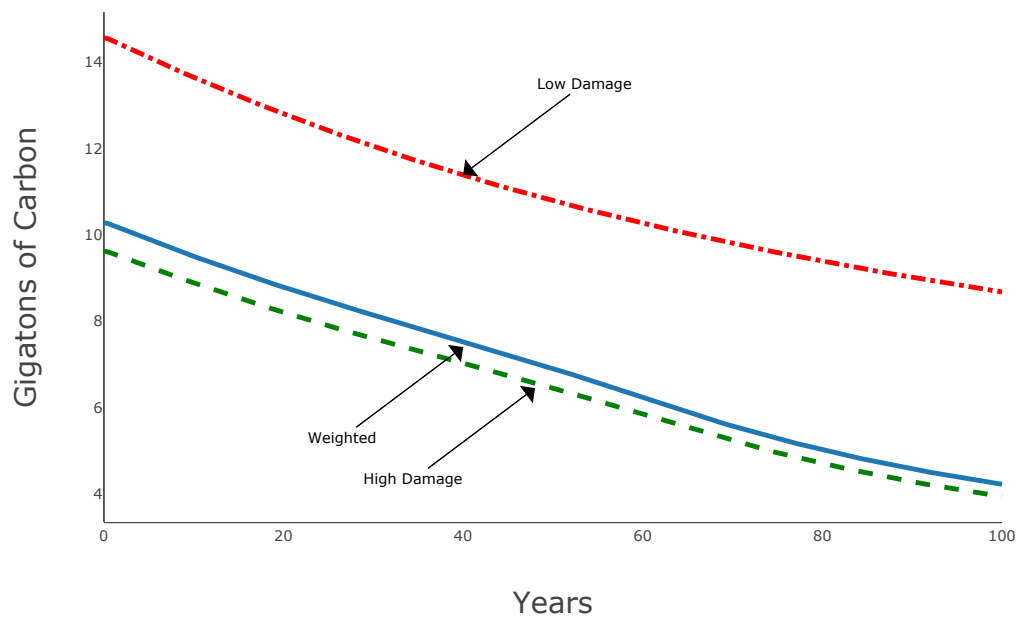


Figure 10: The values are computed at the socially efficient allocation simulated along a deterministic path.

## Social Cost of Carbon Comparison

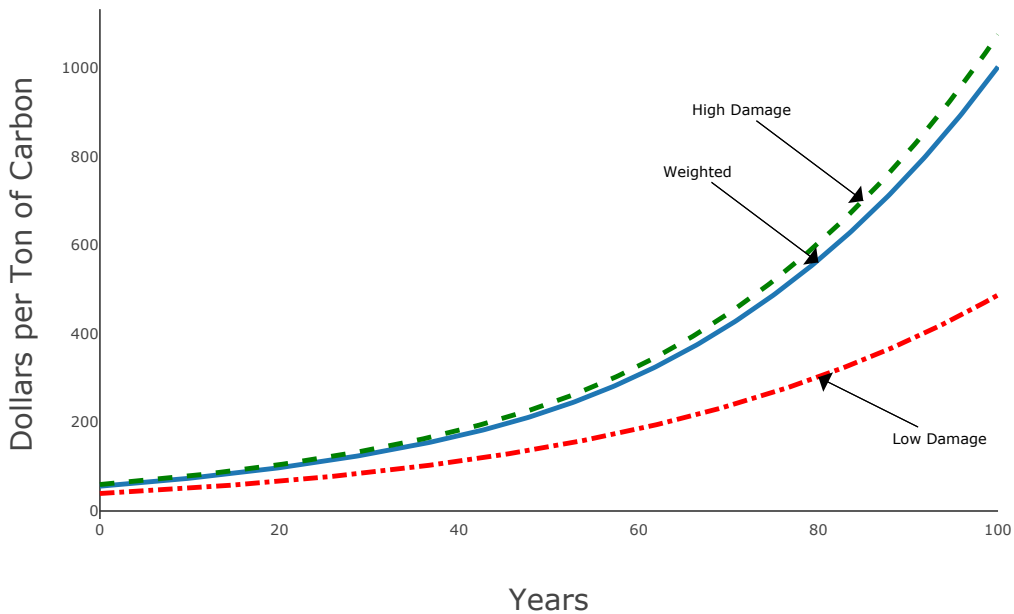


Figure 11: The values are computed at the socially efficient allocations simulated along deterministic paths. The units are 2010 US dollars per ton of carbon.

The emissions and social cost of carbon trajectories when the *ex ante* one half weights are used are quite similar to those that emerge when we feature only the high damage specification. In contrast, the emissions trajectory is higher and the social cost of carbon lower when entertaining only the low damage specification. This finding is explicitly tied to our parameter  $\xi_p$ . A larger relative entropy penalty pushes the one-half/one-half outcomes closer to an intermediate location. Figure 8 illustrates this for the limiting case in which the ambiguity/robustness parameter is infinite.

To understand the plotted outcomes it is revealing to compare the adjusted probability densities. Of particular interest are the green densities reported in Figure 5 and the corresponding ones reported in the bottom of panel of Figure 9. For instance, consider what happens at year one hundred. In Figure 5, the density for the climate sensitivity parameter conditioned on the high damage specification is even more substantial than the corresponding curve in lower panel of Figure 9 where only the high damage specification is entertained by the planner. But in the *ex ante* one-half/one-half case, the marginal density for the climate sensitivity parameter averages over the two damage specifications and adjustments

conditioned on the low damage configuration are much smaller than those that condition on the high damage specification. About 40 percent of the ambiguity-adjusted weight goes to the low damage specification, making it important in the low damage contribution in the marginal density for the climate sensitivity parameter. More generally, the marginal densities are similar for the different time periods even though the densities conditioned on the high damage specification differ in ways that are quantitatively important. Consistent with the similarities in the ambiguity-adjusted densities, there is an overall similarity in trajectories for both the emissions and the social cost of carbon.

### 6.3 Climate Change and Growth Damages

For the macroeconomic growth damage specification, we incorporate estimates of Burke, Davis, and Diffenbaugh (2018) used as in the construction of Figure 4. The results from this growth specification of damages are much more extreme than those displayed in the previous figures. What follows are the impacts observed in emissions and the external and uncertainty contributions to the social cost of carbon.

Table 5 provides the implications for emissions and the social cost of carbon along a simulated deterministic path for one hundred years. As before, the initial states for this path match the steady states from the competitive model without climate impacts. For these comparisons, we hold fixed relative entropies at time 100 to be close to those in the preference damage ambiguity averse setting. Given the specification differences, this compels us to adjust the  $\xi_p$  parameter.

Ambiguity Neutral: $\xi_p = \infty$				
Year	Emissions	SCC - external	SCC - uncertainty	Entropy
0	2.4	239	0	0
50	2.0	707	0	0
100	1.8	1991	0	0
Ambiguity Averse: $\xi_p = .005$				
Year	Emissions	SCC - external	SCC - uncertainty	Entropy
0	1.3	201	255	.21
50	1.1	515	649	.24
100	1.0	1280	1608	.26

Table 5: Emissions and social cost of carbon external and uncertainty contributions. The values are computed at the socially efficient allocations for deterministic pathways. The top panel gives the values at 0, 50, and 100 years for the ambiguity-neutral setting of the growth damages model. The bottom panel gives the values at 0, 50, and 100 years for the ambiguity-averse setting of the growth damages model.

The socially efficient emissions are remarkably small and the social cost of carbon remarkably high even under ambiguity neutrality. The uncertainty adjustment is substantial, making the numbers all the more extreme.

As we noted earlier, using growth damages from tropical, underdeveloped regions may well overstate damages to growth for other economies for reasons many economists have discussed (for example, see Sachs (2001).) We conjecture that, to use this evidence in a more revealing way, it requires explicit regional heterogeneity coupled with a more complete accounting the economic differences in the regions. Distinguishing long-run from short-run growth responses could also change the nature of the evidence as suggested in the earlier work of Dell, Jones, and Olken (2012).<sup>19</sup> Hence we view our growth analysis as a call for more serious probes into the sources and consequences of economic damages.

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<sup>19</sup>Dell, Jones, and Olken (2012) consider only linear specification for temperature on macroeconomic growth rates. Nonlinearity could well alter their short-run/long-run decomposition.

## 6.4 Discussion and Extensions

We have shown how uncertainty can potentially matter for the social cost of carbon. Our model is very stylized, and our calculations are no doubt sensitive to some of the modeling details. Whenever one engages, like we have, in quantitative story-telling, the outcome is in part about the model and in part about the social problem that it addresses. We constructed the framework explicitly to include multiple “stories.” In what follows, we conjecture about potential extensions of our analysis.

Our social costs of carbon, and in particular, the uncertainty components, are sensitive to the parameter  $\xi_p$ . Our particular choice of  $\xi_p$  is made for sake of illustration, but by conveniently using relative entropy, we have reduced the ambiguity aversion representation to a single parameter. Instead of being committed to a single parameter value, we may think of our framework as providing a disciplined way to perform a prior/posterior sensitivity analysis for uncertain damage and climate sensitivity parameters indexed by the choice of  $\xi_p$ .

The discount rate choice  $\delta$  will matter as it does in other discussions of climate policy. Changing the subjective discount rate will certainly alter our emissions and cost numbers. Moreover, stochastic discounting in social valuation depends on both the subjective rate of the discount in preferences and the ambiguity-adjusted probability measure that we characterized. Along a similar vein, we find it revealing and advantageous to focus on distinct contributions to valuation as well as quantifying their overall impact. While our example economy is special, the decomposition we propose has much more general applicability.

One familiar observation about Hotelling-type models is that as the price rises, backstop technologies become viable, which can give an upper bound on the price. The analogous observation applies in our setting with the potential for green energies to become profitable in the future. While such a technology is absent in our model, extensions that incorporated this will also place a new source of uncertainty and a new channel by which uncertainty impacts the economic performance in future time periods. While the model would have to change and the computations would be altered, we suspect that uncertainty, broadly-conceived, would continue to play an important role in a quantitative investigation. Relatedly, as carbon presents more of a challenge for society in the future and as technology advances, carbon sequestration may become an attractive form of mitigation. The potential for this and other forms of mitigation to become socially productive would certainly alter our quantitative findings, but they would also open the door to new sources of uncertainty.

While the computations in this section focused on model ambiguity, as we argued earlier in the paper, potential model misspecification is also a concern. This misspecification may be disguised by the Brownian increments making it difficult for the planner to detect model deviations. In future work, we hope to investigate misspecification concerns as a third component to the uncertainty pertinent to climate change.

In this paper, we abstracted from active learning and its impact on the uncertainty adjustments. While learning about carbon sensitivity may be modest in the current environment, if we experience more rapid climate change in the future, learning could also be more pronounced. This is absent from our model, but it could be an important consideration. This form of learning, however, occurs in times of potentially high economic damages making it costly for society to defer action while waiting to learn more. This said, we believe learning to be an interesting extension of our analysis.

## 7 Impulse Response Approximation to Climate Dynamics

Recall that a central component to the social cost of carbon is the response function or trajectory for damages to an emissions impulse. A variety of papers in the climate science literature have used transfer function and impulse response methods to approximate the much more complex output that emerges from climate models. This approach aims to provide useful summaries of model implications or syntheses to support tractable emulation and facilitate model comparison. Some examples include Li and Jarvis (2009), Joos et al. (2013) and Castruccio et al. (2014). The Matthews et al. (2009) approximation is a particularly simple version of such a linearized response function. That paper shows differences across models for alternative horizons that interest us. In what follows, we describe some more recent model comparisons that we find to be particularly revealing. We present this evidence to suggest further important research to be done that incorporates model uncertainty from climate science and to suggest some of the challenges that embracing this evidence entails.

Carbon-climate dynamics are often represented in two component parts, the dynamic response of  $CO_2$  concentration to a change in emissions and the dynamic response of temperature to a change in  $CO_2$  concentration via radiative forcing. Combining the two, as in the Matthews et al. approximation, entails a convolution of these response trajectories.

Nonlinearity plays a role connecting the two components as it is typically the logarithm of ratio of current concentration to the pre-industrial counterpart that determines radiative forcing that is used as an input into the dynamic mapping from  $CO_2$  concentration to temperature. See, for instance, Pierrehumbert (2014).

Impulse response and transfer functions, while pedagogically and computationally convenient, are inherently linear tools of analysis. As discussed in Joos et al. (2013), there is a nontrivial issue over what range of inputs might serve as a good approximation.

Non-linearities arise from the non-linearity of the carbonate chemistry in the ocean, from changes in ocean circulation with global warming that affect the surface-to-deep transport of excess anthropogenic  $CO_2$  as well as from other effects such as non-linear dependencies of terrestrial productivity or soil overturning rates on climate and atmospheric  $CO_2$ . ... In conclusion, the IRF (impulse response function) and thus also the AGWP (absolute global warming potential) for  $CO_2$  depends on the details of the experimental setup (background concentration, pulse size) as well as on the characteristics of the carbon cycle climate model used for its determination.<sup>20</sup>

The impulse response functions that contribute to the social cost of carbon can accommodate nonlinearity by allowing for explicit state dependence in the responses and by calculating local approximations evaluated at the stochastic outcome of the planner's problem. Indeed, a small change in emissions in a nonlinear stochastic system with uncertain random consequences in the future can be pertinent to the social valuation. Given a nonlinear stochastic diffusion evolution, these responses could be computed recursively using what is called the first variation of the process. Such computations, while they have conceptual appeal, would seem to be tractable only for small scale nonlinear stochastic systems. Perhaps nonlinear emulation methods would be valuable inputs into studies like ours.

Here, we report findings using the impulse response approximations from Joos et al. (2013) that illustrate cross-model heterogeneity and speaks to the potential importance of model ambiguity in decision making. Figure 12 shows the responses for long-term changes in carbon concentration. In looking at the left panel, all models agree that the impact of a change in emissions decays, but not to zero, and that the decay is very slow. After one hundred years, alternative models have substantial differences in terms of their implications

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<sup>20</sup>This discussion is from page 2797 of Joos et al. (2013).

for carbon concentration. The impact of emissions continues to decline over future centuries, but this additional decay is remarkably slow. While there are considerable similarities in the pattern of the responses, there is substantial variation in the magnitudes of the responses.<sup>21</sup> The corresponding temperature responses display more erratic behavior as reported in Joos et al. (2013) for the reasons they describe. Castruccio et al. (2014) provide further evidence for cross model differences in temperature responses to changes in radiative forcing.

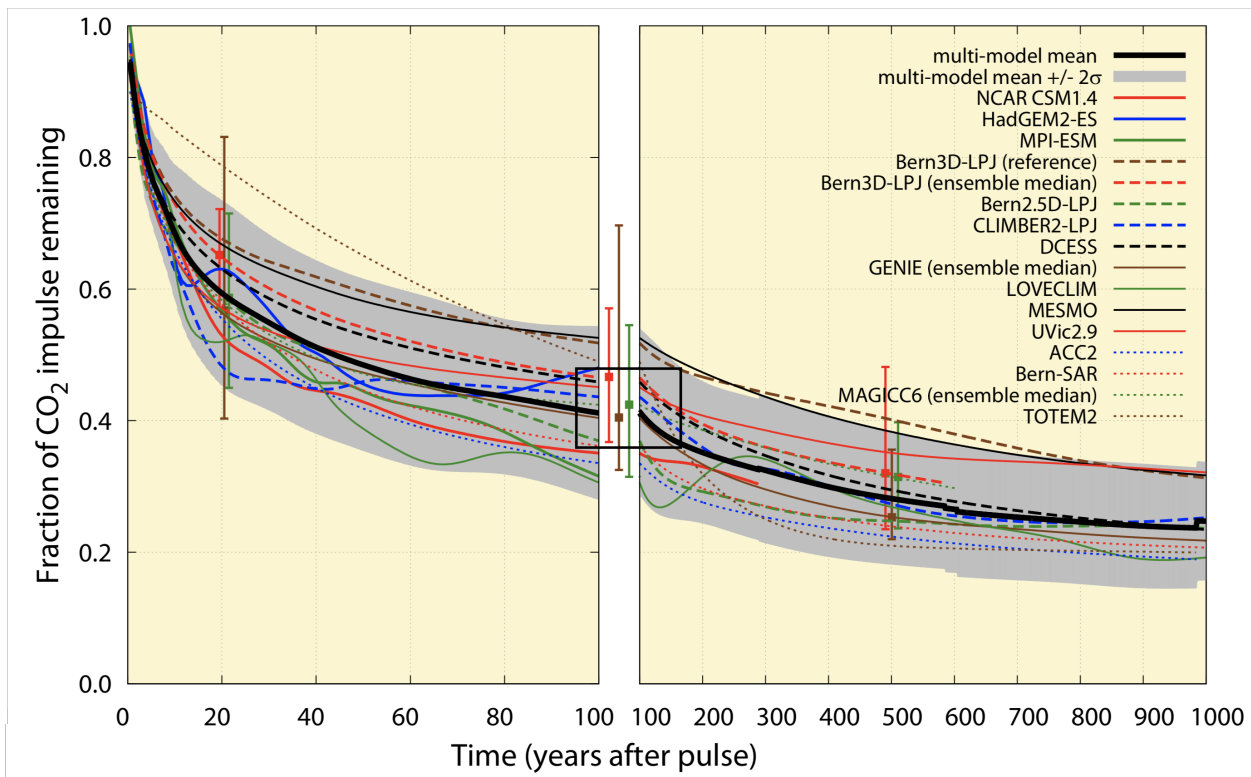


Figure 12: This figure shows the cross model heterogeneity in carbon-climate responses. It reproduces Figure 1a of Joos et al. (2013).

We present this evidence to suggest further important research to be done that incorporates model uncertainty from climate science and to suggest some of the challenges that embracing this evidence entails.

<sup>21</sup>We invite the reader to inspect other figures in Joos et al. (2013) that illustrate model heterogeneity of responses of surface temperature, ocean temperature, sea level rise and other variables of interest to emission pulses of  $CO_2$ .



## 8 Conclusion

We have shown how to apply continuous-time decision theory and asset pricing tools to confront multiple components of uncertainty for the purposes of social valuation. The framework we developed incorporates both concerns about model uncertainty and model misspecification. The resulting methods allow for these broader notions of uncertainty to be integrated formally into decision-making. We apply these tools to study the economic impacts of climate change through the lens of the social cost of carbon.

While the methods are more generally applicable, our example illustrates the impact of the interacting uncertainty components coming from climate and economic modeling. In effect, the impact of these uncertainties is multiplicative: and when both are large, together their impact can be truly substantial. As a result, the social cost of carbon shows notable increases when both sources of uncertainty are acknowledged. This aspect of the analysis is particularly pertinent when the decision maker is averse to ambiguity over models and to potential model misspecification. Just as risk aversion is theory of “caution,” so too are preference-based concerns about ambiguity and misspecification.<sup>22</sup> We believe these components to be particularly relevant for assessing the economic impacts of climate change, and we expect them to be pertinent for social valuation applied in other settings.

We are sympathetic to concerns that readers might have of our seemingly simplistic use of the social cost of carbon. Yet, for the purposes of this paper, the social cost of carbon serves as a metric to guide our assessment of what components of uncertainty are most impactful. The development of richer models of the underlying economy that include research aimed at mitigation or for the development of viable green technologies are appealing extensions of our analysis.

For quantifying the consequences of uncertainty in revealing ways, we suspect that we have scratched the surface so-to-speak. For purposes of illustration, we have imposed overly simplified specifications of climate and economic dynamics. Moreover, the approximate climate models we consider potentially understate the importance of nonlinearities in the climate dynamics. Within the confines of risk analyses, important research on climate tipping points has been done by Lenton et al. (2008), Cai et al. (2015), Cai, Lenton, and Lontzek (2016), and Cai, Judd, and Lontzek (2017). We suspect that adopting a broader perspective on uncertainty could contribute productively to this line of research.

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<sup>22</sup>Even within the study of financial markets, what is typically called risk aversion may be better conceived as investor concerns about these other components to uncertainty. For example, see Hansen and Sargent (2019a).

## A Numerical Method

To solve the nonlinear partial differential equations that characterize the HJB equations for the planner's problems from our model, we use a so-called implicit, finite-difference scheme and a conjugate gradient method.<sup>23</sup> We briefly outline the steps to this numerical solution method below.

Recall that the HJB equation (20) includes both minimization and maximization. We proceed recursively as follows:

- i) start with a value function guess  $\tilde{V}(x)$  and a decision function  $\tilde{a}(x)$ ;
- ii) solve the minimization problem embedded in the HJB equation and produce an exponentially tilted density  $\hat{q}$  and drift distortion  $\hat{g}$  conditioned on  $x$  and given  $(\tilde{V}, \tilde{a})$  using the quasi-analytical formulas in Section 5.
- iii) compute the implied relative entropy from the change in prior:

$$\hat{\mathbb{I}}(x) = \int_{\Theta} [\log \hat{q}(\theta)] \hat{q}(\theta) P(d\theta).$$

- iv) solve the following maximization problem by choice of  $a = (i, j, e)$ :

$$\begin{aligned} & \delta(1 - \kappa) \log(\alpha - i - j) + \delta\kappa \log e \\ & + \frac{\partial V}{\partial x}(x) \cdot \int_{\Theta} \mu_X(x, a \mid \theta) \hat{q}(\theta \mid x) P(d\theta) \end{aligned}$$

- v) use the minimization output from step ii) and maximization output from step iv) and construct an adjusted drift using the following formula, which is the analog to formula (21):

$$\hat{\mu}(x) = \int_{\Theta} \mu_X(x, \hat{a} \mid \theta) \hat{q}(\theta \mid x) P(d\theta) + \sigma_X(x) \hat{g}(x)$$

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<sup>23</sup>Consultations with Joseph Huang, Paymon Khorrami and Fabrice Tourre played an important role in the software implementation.

vi) construct the linear equation system for a new value function  $V = \hat{V}$

$$\begin{aligned} 0 = & -\delta V(x) + \delta(1 - \kappa) \left( \log \left[ \alpha - \hat{i}(x) - \hat{j}(x) \right] + k - d \right) + \delta\kappa [\log \hat{e}(x) + r] \\ & + \frac{\partial V}{\partial x}(x) \cdot \hat{\mu}(x) + \frac{1}{2} \text{trace} \left[ \sigma_X(x)' \frac{\partial^2 V}{\partial x \partial x'}(x) \sigma_X(x) \right] \\ & + \frac{\xi_m}{2} \hat{g}(x) \cdot \hat{g}(x) + \xi_p \hat{\mathbb{I}}(x) \end{aligned}$$

vii) modify this equation by adding a so-called “false transient” to the left-hand side:

$$\begin{aligned} \frac{V(x) - \tilde{V}(x)}{\epsilon} = & -\delta V(x) + \delta(1 - \kappa) \left( \log \left[ \alpha - \hat{i}(x) - \hat{j}(x) \right] + k - d \right) + \delta\kappa [\log \hat{e}(x) + r] \\ & + \frac{\partial V}{\partial x}(x) \cdot \hat{\mu}(x) + \frac{1}{2} \text{trace} \left[ \sigma_X(x)' \frac{\partial^2 V}{\partial x \partial x'}(x) \sigma_X(x) \right] \\ & + \frac{\xi_m}{2} \hat{g}(x) \cdot \hat{g}(x) + \xi_p \hat{\mathbb{I}}(x) \end{aligned} \tag{22}$$

viii) solve linear system (22) for  $V = \hat{V}$  using a conjugate-gradient method.

ix) set  $\tilde{V} = \hat{V}$  and  $\tilde{a} = \hat{a}$  and repeat steps ii) - viii) until convergence.

A conjugate gradient method used in viii) is a well known iterative algorithm designed to solve a minimization problem of the form:  $\frac{1}{2}y'\Lambda'y - y'\Lambda'\lambda$  for a nonsingular matrix  $\Lambda$  and vector  $\lambda$ . The  $y$  that minimizes this expression satisfies the linear equation  $\Lambda y = \lambda$  as the first-order condition for the minimization problem. The matrix  $\Lambda$  and vector  $\lambda$  come from the numerical approximation of equation (22).

The choice of  $\epsilon$  in step vii) is made by trading off increases in speed of convergence, achieved by increasing its magnitude, and enhancing stability of the iterative algorithm, achieved by decreasing its magnitude.

We solved the specification with damages to the growth rate with the same steps applied to the corresponding HJB equation.

## B Computing Ambiguity-Adjusted Probabilities

In our implementations, we presume a discrete number of possible damage function specifications along with a normal distribution for the climate sensitivity  $\beta$ .

We consider two cases:

- i) Each possible  $\Gamma$  is a quadratic function. In this case, we proceed as follows: we deduce the implied  $q$  by first determining the probability distribution for  $\beta$  conditioning the  $\Gamma$  specification. It is straightforward to show that these conditional distributions are normal with altered means and variances. We also have a quasi-analytic formula for the implied relative entropy conditioned on the  $\Gamma$  specification since both the baseline and altered distributions for  $\beta$  are normal. We then deduce the implied discrete weights on the alternative  $\Gamma$  specifications and produce the full measure of entropy inclusive of these discrete components.
- ii) One of the  $\Gamma$ 's is not a quadratic function. This is true for the high damage specification acting through the preferences. In this case, we must do numerical integration to compute the implied  $q$ 's, the relative entropies, and the resulting ambiguity adjusted drift coefficient. We use Gaussian-Legendre quadrature in our computations.

For the growth specification, we construct nine models for  $\Gamma$  as follows. We take the approximating normal distribution from Burke, Davis, and Diffenbaugh (2018) for their linear and quadratic coefficient estimates. In effect, this treats their asymptotic approximation as a prior for our analysis. We take a Cholesky decomposition of the covariance matrix and the corresponding linear transformation of the coefficients so as to obtain a bi-variate standard normal distribution. With three point Gaussian-Hermite quadrature for each dimension, we generate nine implied models for  $\Gamma$  with the Gaussian-Hermite weights scaled to sum to one as the baseline probabilities. Had the SCC not been so substantial, we would have been more concerned about “lopping off tails” with so few points of approximation.

## C Calibration: Steady states without climate impacts

While we view our model as an illustration, given its level of abstraction, we seek to provide numerical results that are importantly revealing in understanding the dynamics of pricing and allocations. To do this, we choose parameters by first looking at the steady state of the no climate version of the model.<sup>24</sup>

In this model, it is most convenient to transform the state vector to be  $y = r - k$  and  $k$  rather than  $r$  and  $k$ . With the transformation, the value function separates with a linear term in  $k$  with a unit coefficient and nonlinear term in  $y$ . To compute the steady state numerically, use the first-order conditions as three of the equations to be solved

$$\begin{aligned} -\frac{\delta(1-\kappa)}{\alpha-i-j} + \frac{\phi_0\phi_1(1-\nu)}{1+\phi_1i} &= 0 \\ -\frac{\delta(1-\kappa)}{\alpha-i-j} + \nu(\psi_0\psi_1)j^{\psi_1-1}\exp(-\psi_1y) &= 0 \\ \frac{\delta\kappa}{e} - \nu &= 0. \end{aligned}$$

where  $\nu$  is the co-state corresponding to state  $y$  and is equal to the derivative of the value function with respect to  $y$  evaluated at steady-state values. Note that  $\nu$  is also the co-state for state  $r$  and  $1 - \nu$  is the implied co-state for state  $k$ . The steady-state first-order conditions are solved along with the contribution from the state equation:

$$0 = -e + \psi_0 [j^{\psi_1} \exp(-\psi_1y)] - \bar{\mu}_K - \phi_0 \log(1 + \phi_1i), \quad (23)$$

and from the co-state equation

$$0 = \delta\kappa - \nu [\psi_0\psi_1j^{\psi_1}\exp(-\psi_1y) + \delta]. \quad (24)$$

Finally, let  $\rho$  be the growth rate in the economy, which satisfies:

$$\rho = \bar{\mu}_K + \phi_0 \log(1 + \phi_1i) \quad (25)$$

steady state  $q$

$$q = (1 - \nu) \left[ \frac{\alpha - i - j}{\delta(1 - \kappa)} \right] \quad (26)$$

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<sup>24</sup>John Wilson and Jieyao Wang made valuable contributions to this appendix.

and the output constraint:

$$c + i + j = \alpha. \tag{27}$$

Thus we have three first-order conditions, a state equation, (23), a co-state equation, (24), a growth-rate equation, (25), a relative price equation, (26), and an output equation, (27).

## C.1 Backing Out Parameters

Our approach to calibration is to invert the previous equations taking the steady states for  $(i, e, y, q)$  and the growth rate  $\rho$  as inputs for determining  $(\nu, c, j)$  along with the production parameters. There is a nice recursive structure, which we exploit in the following steps.

- i) Compute  $(c, \nu)$  from the first-order conditions for  $e$  and the formula for  $q$ :

$$\frac{\delta\kappa}{e} = \nu = 1 - \left[ \frac{\delta(1 - \kappa)}{c} \right] q$$

- ii) Given  $(i, q)$  and  $\rho$ , we solve for the capital evolution parameters.

- a) From the first-order conditions for investment, solve

$$q = 1 + \phi_1 i,$$

solve for  $\phi_1$  where we have set  $\phi_0 \phi_1 = 1$ .

- b) From the growth equation (25) and  $\rho$ , solve for  $\bar{\mu}_K$ .

- iii) Given  $(\nu, c, y, e)$ , we have three equations for the three unknowns  $(\psi_0, \psi_1)$  and  $\log j$  based on the first-order conditions for  $j$ , the state equation for reserves, equations (23) and (25), and the co-state equation for reserves, equation (24):

$$\log \left[ \frac{\delta(1 - \kappa)}{c} \right] = \log \nu + \log \psi_0 + \log \psi_1 + (\psi_1 - 1) \log j - \psi_1 y$$

$$\log(\rho + e) = \log \psi_0 + \psi_1 \log j - \psi_1 y,$$

$$\log(e - \delta) = \log \psi_0 + \log \psi_1 + \psi_1 \log j - \psi_1 y.$$

It is most convenient to transform this equation system.

a) By subtracting the first and third equations,

$$\log \left[ \frac{\delta(1 - \kappa)}{c} \right] - \log(e - \delta) = \log \nu - \log j,$$

which we use to solve for  $\log j$ .

b) Substituting  $\log j$  into the second equation gives a linear equation for  $\psi_1$  expressed in terms of  $\log \psi_0$ .

c) Substituting this expression for  $\psi_1$  into the third equation gives us a single equation to solve in a single unknown,  $\log \psi_0$ .

iv) Given  $(c, i, j)$  determine  $\alpha$  from the output constraint by adding them together. It may be verified that  $\alpha = i + \delta q$ .

## C.2 Some Empirical Evidence

Our model is highly stylized making it challenging to find precise inputs to use as calibration targets. To implement the approach in Section C.1, we set the growth rate  $\rho$  at two percent, and the reserve capital ratio at .98. We will return to this second number later when we discuss initial conditions. Our number for the emissions-to-reserves ratio is .015. While this ratio is less than that used by Bornstein, Krusell, and Rebelo (2017), theirs is only based on oil. (Their ratio is between .026 to .028.) We use a smaller number to incorporate coal, based in part on numbers from BP (2018) and Figueres et al. (2018).<sup>25</sup>

There are four preference parameters that are pertinent  $(\delta, \kappa, \xi_p, \xi_m)$  to our analysis. In our reported computations, we abstracted from model misspecification concerns and effectively set  $\xi_m = \infty$ . In the Section 5.1, we discussed discounting in valuation for which the subjective discount rate,  $\delta$ , is only part of the story. Stochastic growth and uncertainty aversion, which we feature, are important contributors. In Section 6, we argued that the implied worst-case probabilities or their relative entropies are easier to interpret than the numerical value of  $\xi_p$ . The actual numerical values for  $\xi_p$  are  $\frac{1}{4500}$  for the damages in preferences specification and  $\frac{1}{200}$  for the damages to growth rates specification. Finn (1995) and Leduc and Sill (2004) use (.04) as the value of the energy input share which we deflate by 80 percent based on the approximate proportion of energy consumption that comes from

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<sup>25</sup>Specifically, we choose an initial period emissions target of about 10 GtC/yr in our calibrations to match the most recent number from Figueres et al. (2018).

fossil fuels. For instance, see data from the International Energy Agency (IEA) Statistics database. Thus, we use  $\kappa = .032$  in our computations.

Consider next the technology parameters for capital accumulation and productivity. For such a stylized model, there is no agreed upon way to fit parameters to measured counterparts of steady states. We agree with Pindyck and Wang (2013) that capital within this model should be interpreted broadly to include both human, intangible as well as organizational capital. Even for more narrow views of capital, there is a rather substantial range for the magnitude of the adjustment costs. We set the steady state  $q = 2.5$  and the investment-capital ratio to be  $.9$ . Although not critical to computation, the implied investment-capital ratio is sensitive to whether the costs are presumed on the input or output side of the capital evolution. See Remark 3.1.

The capital and oil reserves volatility  $\sigma_K, \sigma_R$  are chosen to match the empirically measured annual changes in the time series of GDP and reserves from the World Bank database and BP (2018).

Table 6: Initial Values

$Y_0$	80
$K_0^a$	666.67
$R_0$	650
$F_0$	290

<sup>a</sup> $K_0$  is derived from  $K_0 = Y_0/\alpha$

The initial values for the model solution simulations are given in Table 6. The value for GDP comes from the World Bank database and the capital value is implied by the assumed productivity parameter  $\alpha$  and this GDP value. The value for reserves comes from estimates of existing recoverable reserves of oil and coal from the Energy Information Agency and BP (2018) and within the range of empirical measures of reserves cited by McGlade and Ekins (2015) (who provide further details on this data) and earlier research by Rogner (1997). By construction, the ratio of the initial reserves to capital matches the steady state value used in setting the steady state target  $y$ . The initial value of cumulative emissions or atmospheric carbon concentration comes from the NOAA dataset. We use anomaly from the pre-industrial level, where the pre-industrial level we use is 580, in line with the IPCC Fourth Assessment Report (2007) for concentrations around 1800. The Carbon Dioxide Information Analysis Center (CDIAC) provides a conversion factor to convert the NOAA



and IPCC concentrations values from parts per million (ppm) to gigatons of carbon (GtC).

The exogenous stochastic component to damages, as introduced in our example, plays a very passive role in the analysis. We presume this component is present to disguise the parameter and model uncertainty. It only contributes an additive component to the value function that is pertinent for stochastic simulations of the model, but it does not alter the decision rules computed in their absence. The simulations we report are deterministic in nature and hence not impacted by how we specify this exogenous contribution.

The simulations for the damages-in-preferences model used consumption and not damaged consumption as the numeraire. Had we used damaged consumption, the time path for damages inclusive of an initialization would have been an input into the SCC trajectory. Our “back-of-the-envelope” calculations suggests that this difference is minor over the time horizons we reported.

## References

- Allen, M. R., D. J. Frame, C. Huntingford, C. D. Jones, J. A. Lowe, M. Meinshausen, and N. Meinshausen. 2009. Warming Caused by Cumulative Carbon Emissions Towards the Trillionth Tonne. *Nature* 458:1163–6. doi:10.1038/nature08019.
- Anderson, E. W., W. A. Brock, and A. Sanstad. 2018. Robust Consumption and Energy Decisions. In V. V. Chari and R. Litterman, eds., *Climate Change Economics: the Role of Uncertainty and Risk*. Wiley. doi:10.2139/ssrn.2844980.
- Anderson, E. W., L. P. Hansen, and T. J. Sargent. 2003. A Quartet of Semigroups for Model Specification, Robustness, Prices of Risk, and Model Detection. *Journal of the European Economic Association* 1:68–123. doi:10.1162/154247603322256774.
- Bansal, R., D. Kiku, and M. Ochoa. 2017. Price of Long-Run Temperature Shifts in Capital Markets. Working Paper, NBER Working Paper.
- Bansal, R., and A. Yaron. 2004. Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles. *Journal of Finance* 59:1481–509.
- Berger, J. O. 1984. The Robust Bayesian Viewpoint. In J. B. Kadane, ed., *Robustness of Bayesian Analysis*, vol. 4 of *Studies in Bayesian Econometrics*, 63–124. North-Holland, Amsterdam.
- Bornstein, G., P. Krusell, and S. Rebelo. 2017. Lags, Costs, and Shocks: An Equilibrium Model of the Oil Industry. NBER Working Paper 23423, National Bureau of Economic Research, Inc.
- BP. 2018. *Statistical Review of World Energy*, vol. 67. BP.
- Brock, W. A., and L. P. Hansen. 2018. Wrestling with Uncertainty in Climate Economic Models. In V. V. Chari and R. Litterman, eds., *Climate Change Economics: the Role of Uncertainty and Risk*. Wiley.
- Burke, M., W. M. Davis, and N. S. Diffenbaugh. 2018. Large Potential Reduction in Economic Damages Under UN Mitigation Targets. *Nature* 557:549–53. doi:10.1038/s41586-018-0071-9.
- Burke, M. B., S. M. Hsiang, and E. M. Miguel. 2015. Global Non-linear Effect of Temperature on Economic Production. *Nature* 527:235–9.

- Cai, Y., K. L. Judd, T. M. Lenton, T. S. Lontzek, and D. Narita. 2015. Environmental Tipping Points Significantly Affect the Cost-Benefit Assessment of Climate Policies. *Proceedings of the National Academy of Sciences* 112:4606–11. ISSN 0027-8424. doi: 10.1073/pnas.1503890112.
- Cai, Y., K. L. Judd, and T. S. Lontzek. 2017. The Social Cost of Carbon with Climate Risk. Working Paper, Hoover Institution, Stanford, CA.
- Cai, Y., T. M. Lenton, and T. S. Lontzek. 2016. Risk of Multiple Interacting Tipping Points Should Encourage Rapid CO<sub>2</sub> emission Reduction. *Nature Climate Change* 6:520–5. doi: 10.1038/nclimate2964.
- Casassus, J., P. Collin-Dufresne, and B. R. Routledge. 2018. Equilibrium Commodity Prices With Irreversible Investment and Non-Linear Technologies. *Journal of Banking and Finance* 95:128–47. doi:10.1016/j.jbankfin.2018.04.001.
- Castruccio, S., D. J. McInerney, M. L. Stein, F. Liu Crouch, R. L. Jacob, and E. J. Moyer. 2014. Statistical Emulation of Climate Model Projections Based on Precomputed GCM Runs. *Journal of Climate* 27:1829–44.
- Chen, Z., and L. Epstein. 2002. Ambiguity, Risk, and Asset Returns in Continuous Time. *Econometrica* 70:1403–43.
- Cogley, T., R. Colacito, L. Hansen, and T. Sargent. 2008. Robustness and U.S. Monetary Policy Experimentation. *Journal of Money, Credit and Banking* 40. doi:10.1111/j.1538-4616.2008.00176.x.
- Colacito, R., B. Hoffmann, and T. Phan. 2019. Temperature and Growth: A Panel Analysis of the United States. *Journal of Money, Credit and Banking* 51:313–68.
- Dell, M., B. F. Jones, and B. A. Olken. 2012. Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics* 4:66–95.
- Diaz, D., and F. Moore. 2017. Quantifying the Economic Risks of Climate Change. *Nature Climate Change* 7:774–82.
- Eberly, J. C., and N. Wang. 2009. Reallocating and Pricing Illiquid Capital: Two Productive Trees. In *AFA 2010 Atlanta Meetings Paper*.

- Figueres, C., C. Le Quéré, A. Mahindra, O. Bäte, G. Whiteman, G. Peters, and D. Guan. 2018. Emissions Are Still Rising: Ramp Up the Cuts. *Nature* 564:27–30.
- Finn, M. G. 1995. Variance Properties of Solow’s Productivity Residual and Their Cyclical Implications. *Journal of Economic Dynamics and Control* 19:1249–81.
- Fleming, W. H., and P. E. Souganidis. 1989. On the Existence of Value Functions of Two-Player, Zero-Sum Stochastic Differential Games. *Indiana University Mathematics Journal* 38:293–314.
- Gilboa, I., and D. Schmeidler. 1989. Maxmin Expected Utility with Non-Unique Prior. *Journal of Mathematical Economics* 18:141–53.
- Gollier, C. 2013. *Pricing the Planet’s Future: The Economics of Discounting in an Uncertain World*. Princeton University Press.
- Golosov, M., J. Hassler, P. Krusell, and A. Tsyvinski. 2014. Optimal Taxes on Fossil Fuel in General Equilibrium. *Econometrica* 82:41–88. doi:10.3982/ECTA10217.
- Good, I. J. 1952. Rational Decisions. *Journal of the Royal Statistical Society. Series B (Methodological)* 14.
- Hambel, C., H. Kraft, and E. Schwartz. 2018. Optimal Carbon Abatement in a Stochastic Equilibrium Model with Climate Change. Working Paper 21044, National Bureau of Economic Research. doi:10.3386/w21044.
- Hansen, L. P., and J. Miao. 2018. Aversion to Ambiguity and Model Misspecification in Dynamic Stochastic Environments. *Proceedings of the National Academy of Sciences* 115:9163–8. doi:10.1073/pnas.1811243115.
- Hansen, L. P., and T. J. Sargent. 2001. Robust Control and Model Uncertainty. *The American Economic Review* 91:60–6.
- . 2007. Recursive Robust Estimation and Control without Commitment. *Journal of Economic Theory* 136:1–27. doi:10.1016/j.jet.2006.06.010.
- . 2019a. Macroeconomic Uncertainty Prices when Beliefs are Tenuous. Working Paper, SSRN Working Paper.

- . 2019b. Structured Uncertainty and Model Misspecification. Working Paper, SSRN Working paper.
- Hansen, L. P., T. J. Sargent, G. Turmuhambetova, and N. Williams. 2006. Robust control and model misspecification. *Journal of Economic Theory* 128:45–90. doi:10.1007/s11149-006-0008-3.
- HM Treasury. 2018. *The Green Book: Central Government Guidance on Appraisal and Evaluation*. London: National Archives.
- Hotelling, H. 1931. The Economics of Exhaustible Resources. *Journal of Political Economy* 39:137–75. doi:10.1007/BF02464433.
- Hurwicz, L. 1966. On the Structural Form of Interdependent Systems. In P. S. Ernest Nagel and A. Tarski, eds., *Logic, Methodology and Philosophy of Science Proceeding of the 1960 International Congress*, vol. 44 of *Studies in Logic and the Foundations of Mathematics*, 232–9. Elsevier. doi:http://dx.doi.org/10.1016/S0049-237X(09)70590-7.
- Jacobson, D. H. 1973. Optimal Stochastic Linear Systems with Exponential Performance Criteria and Their Relation to Deterministic Differential Games. *IEEE Transactions for Automatic Control* AC-18:1124–31.
- James, M. R. 1992. Asymptotic Analysis of Nonlinear Stochastic Risk-Sensitive Control and Differential Games. *Mathematics of Control, Signals and Systems* 5:401–17.
- Jensen, S., and C. Traeger. 2014. Optimal Climate Change Mitigation under Long-Term Growth Uncertainty: Stochastic Integrated Assessment and Analytic Findings. *European Economic Review* 69:104–25.
- Joos, F., R. Roth, J. S. Fuglestvedt, G. P. Peters, I. G. Enting, W. Von Bloh, V. Brovkin, E. J. Burke, M. Eby, N. R. Edwards, T. Friedrich, T. L. Frölicher, P. R. Halloran, P. B. Holden, C. Jones, T. Kleinen, F. T. Mackenzie, K. Matsumoto, M. Meinshausen, G. K. Plattner, A. Reisinger, J. Segschneider, G. Shaffer, M. Steinacher, K. Strassmann, K. Tanaka, A. Timmermann, and A. J. Weaver. 2013. Carbon Dioxide and Climate Impulse Response Functions for the Computation of Greenhouse Gas Metrics: A Multi-Model Analysis. *Atmospheric Chemistry and Physics* 13:2793–825. doi:10.5194/acp-13-2793-2013.

- Keane, M. P., and T. Neal. 2018. The Impact of Climate Change on U.S. Agriculture: The Roles of Adaptation Techniques and Emissions Reductions. *UNSW Business School Research Paper* .
- Klibanoff, P., M. Marinacci, and S. Mukerji. 2005. A Smooth Model of Decision Making Under Uncertainty. *Econometrica* 73:1849–92.
- Kreps, D. M., and E. L. Porteus. 1978. Temporal Resolution of Uncertainty and Dynamic Choice. *Econometrica* 46:185–200.
- Leduc, S., and K. Sill. 2004. A Quantitative Analysis of Oil-Price Shocks, Systematic Monetary Policy, and Economic Downturns. *Journal of Monetary Economics* 51:781–808.
- Lemoine, D., and C. P. Traeger. 2016. Ambiguous Tipping Points. *Journal of Economic Behavior & Organization* 132:5–18.
- Lenton, T. M., H. Held, E. Kriegler, J. W. Hall, W. Lucht, S. Rahmstorf, and H. J. Schellnhuber. 2008. Tipping Elements in the Earth’s Climate System. *Proceedings of the National Academy of Sciences* 105:1786–93. doi:10.1073/pnas.0705414105.
- Li, S., and A. Jarvis. 2009. Long Run Surface Temperature Dynamics of an A-OGCM: the HadCM3 4 x CO2 Forcing Experiment Revisited. *Climate Dynamics* 33:817–25.
- Maccheroni, F., M. Marinacci, and A. Rustichini. 2006. Dynamic Variational Preferences. *Journal of Economic Theory* 128:4–44. doi:10.1016/j.jet.2005.12.011.
- MacDougall, A. H., N. C. Swart, and R. Knutti. 2017. The Uncertainty in the Transient Climate Response to Cumulative CO2 Emissions Arising from the Uncertainty in Physical Climate Parameters. *Journal of Climate* 30:813–27. doi:10.1175/JCLI-D-16-0205.1.
- Matthews, H. D., N. P. Gillett, P. A. Scott, and K. Zickfeld. 2009. The Proportionality of Global Warming to Cumulative Carbon Emissions. *Nature* 459:829–32.
- McGlade, C., and P. Ekins. 2015. The Geographical Distribution of Fossil Fuels Unused When Limiting Global Warming to 2C. *Nature* 517:187–90. doi:10.1038/nature14016.
- Millner, A., S. Dietz, and G. Heal. 2013. Scientific Ambiguity and Climate Policy. *Environmental and Resource Economics* 55:21–46. doi:10.1007/s10640-012-9612-0.

- Morgan, M. G., P. Vaishnav, H. Dowlatabadi, and I. L. Azevedo. 2017. Rethinking the Social Cost of Carbon Dioxide. *Issues in Science and Technology* 33.
- Moyer, E. J., M. D. Woolley, N. J. Matteson, M. J. Glotter, and D. A. Weisbach. 2014. Climate Impacts on Economic Growth as Drivers of Uncertainty in the Social Cost of Carbon. *The Journal of Legal Studies* 43:401–25. doi:10.1086/678140.
- Nordhaus, W. 2018. Projections and uncertainties about climate change in an era of minimal climate policies. *American Economic Journal: Economic Policy* 10:333–60. doi:10.1257/pol.20170046.
- Nordhaus, W. D. 2017. Revisiting the Social Cost of Carbon. *Proceedings of the National Academy of Sciences* 114:1518–23. doi:10.1073/pnas.1609244114.
- Nordhaus, W. D., and A. Moffatt. 2017. A Survey of Global Impacts of Climate Change: Replication, Survey Methods, and a Statistical Analysis. Working Paper, SSRN. doi:10.2139/ssrn.3009427.
- Olson, R., R. Sriver, M. Goes, N. M. Urban, H. D. Matthews, M. Haran, and K. Keller. 2012. A Climate Sensitivity Estimate using Bayesian Fusion of Instrumental Observations and an Earth System Model. *Journal of Geophysical Research Atmospheres* 117:1–11. doi:10.1029/2011JD016620.
- Petersen, I. R., M. R. James, and P. Dupuis. 2000. Minimax Optimal Control of Stochastic Uncertain Systems with Relative Entropy Constraints. *IEEE Transactions on Automatic Control* 45:398–412.
- Pezzey, J. C. V. 2019. Why the Social Cost of Carbon Will Always Be Disputed. *Wiley Interdisciplinary Reviews: Climate Change* 10:e558–. doi:10.1002/wcc.558.
- Pierrehumbert, R. T. 2014. Short-Lived Climate Pollution. *Annual Review of Earth and Planetary Science* 42:341–79.
- Pindyck, R. S., and N. Wang. 2013. The economic and policy consequences of catastrophes. *American Economic Journal: Economic Policy* 5:306–99. doi:10.1257/pol.5.4.306.
- Roe, G. H., and M. B. Baker. 2007. Why is Climate Sensitivity so Unpredictable? *Science* 318:629–32. doi:10.1126/science.1144735.

- Rogner, H.-H. 1997. An Assessment of World Hydrocarbon Resources. *Annual Review of Energy and the Environment* 22:217–62. doi:10.1146/annurev.energy.22.1.217.
- Sachs, J. D. 2001. Tropical Underdevelopment. Working Paper, National Bureau of Economic Research.
- Wald, A. 1950. *Statistical Decision Functions*. New York: John Wiley and Sons.
- Weitzman, M. L. 2012. GHG Targets as Insurance Against Catastrophic Climate Damages. *Journal of Public Economic Theory* 14:221–44. doi:10.1111/j.1467-9779.2011.01539.x.