FAERE
French Association
of Environmental and Resource Economists

Working papers

Social Cost of Carbon under stochastic tipping points: when does risk play a role?

Nicolas Taconet - Céline Guivarch
Antonin Pottier

WP 2019.11

Suggested citation:

N. Taconet, C. Guivarch, A. Pottier (2019). Social Cost of Carbon under stochastic tipping points: when does risk play a role? *FAERE Working Paper, 2019.11.*

ISSN number: **2274-5556**

www.faere.fr

Social Cost of Carbon under stochastic tipping points: when does risk play a role?

Nicolas Taconet[a,*], Céline Guivarch[a], Antonin Pottier[b]

[a] *CIRED, ENPC, 45 bis, avenue de la Belle Gabrielle, 94736 Nogent-sur-Marne Cedex, France*
[b] *EHESS, Paris*

Abstract

Carbon dioxide emissions impose a social cost on economies, owing to the damages they will cause in the future. In particular, emissions increase global temperature that may reach tipping points in the climate or economic system, triggering large economic shocks. Tipping points are uncertain by nature, they induce higher expected damages but also dispersion of possible damages, that is risk. Both dimensions increase the Social Cost of Carbon (SCC). However, the respective contributions of higher expected damages and risk have not been disentangled. We develop a simple method to compare how much expected damages explain the SCC, compared to the risk induced by a stochastic tipping point. We find that expected damages account for more than 90% of the SCC with productivity shocks lower than 10%, the high end of the range of damages commonly assumed in Integrated Assessment Models. It takes both high productivity shock and high risk aversion for risk to have a significant effect. Our results also shed light on the observation that risk aversion plays a modest role in determining the SCC (the *risk aversion puzzle*): they suggest that too low levels of damages considered in previous studies could be responsible for the low influence of risk aversion.

Keywords: Climate change; Tipping points; Expected utility; Integrated Assessment Models; Risk; Social Cost of Carbon

JEL Classification: C61, H41, Q54

Acknowledgement: The authors would like to thank an anonymous referee from the FAERE.

*Corresponding author
Email address: taconet@centre-cired.fr (Nicolas Taconet)

1. Introduction

There is a consensus that climate change will induce damages in the future, although the range of possible levels for these damages is uncertain. Some consider climate change to be worrysome because damages will be high, others because there is a small chance they could be catastrophic. In the former case, optimal climate policy arises from a simple intertemporal cost-benefit analysis, while in the latter case, emissions reductions result from a precautionary approach as an insurance against the risk of disastrous impacts.

This tension between two potential sources for the harmfulness of climate change can be found in the categorization of the "Reasons for Concerns" (RFC) by the Intergovernmental Panel on Climate Change. How much do "Aggregate impacts" (RFC 4) play a role, compared to the "Risk of large-scale singular events" (RFC 5), such as the breakdown of the thermohaline circulation? The latest assessment of the severity of each Reason for Concern (O'Neill et al., 2017) shows that additional risk due to climate change jumps from moderate to high around the same temperature for both of these Reasons for Concern, suggesting that they contribute by the same magnitude to making climate change worrisome.

However, the balance between both Concerns is not a done deal among climate economists. For instance, Pindyck (2013) and Weitzman (2009) argue that catastrophic outcomes should be the primary driver of climate mitigation. Broome (2010), wondering "whether the most important thing about climate change is the harm it is likely to cause or alternatively the utter catastrophe that it may possibly – though very improbably – cause", gave an opposing view. On the one hand, previous literature emphasizes the impact of the level of expected damages on optimal emissions (Weitzman, 2012; Pizer, 2003; Dumas and Ha-Duong, 2005; Ackerman and Stanton, 2012; Wouter Botzen and van den Bergh, 2012), with some arguing that damage estimates should be revised upward (Dietz and Stern, 2015; Weitzman, 2012). Indeed, estimates of climate damages are subject to numerous uncertainties and limitations (see Diaz and Moore (2017) for a recent review). On the other hand, other authors put forward this uncertainty as a reason to dismiss the use of deterministic damage functions to represent the impacts of climate change (Pindyck, 2013). Thus, damage functions have been criticized both for the difficulty to determine the best-guess expected damages, and that to model the risk of catastrophic outcomes.

This question of "level" versus "risk" is particularly salient in the case of non-marginal or abrupt changes referred to as "tipping points" (Lenton et al., 2008; Alley et al., 2003; Steffen et al., 2018). Examples of such phenomena include the shutdown of thermohaline circulation, the melting of the Arctic sea-ice or the die back of the Amazonian rainforest, but it could also come from the limited ability of social and economic systems to cope with climate conditions beyond some threshold.

Tipping points have mostly been modeled in a stochastic framework (Mastrandrea and Schneider, 2001; Keller et al., 2004; Lemoine and Traeger, 2014b; Lontzek et al., 2012). Studies found that introducing a tipping point has a significant effect on optimal policy. Because they compare cases with and without tipping points, these studies report the full effect of tipping points. But this effect is composed of both an increase in expected damages and the risk induced by their stochastic nature. When integrating tipping points into a model, authors have not separated changes due to higher level of expected damages from those coming from the dispersion of damages, that is the risk introduced by the tipping point.

We propose to disentangle whether tipping points matter from a level or risk perspective. We will use the Social Cost of Carbon–the present social value of damage from an additional ton of CO_2 released in the atmosphere–as the output on which the influence of the tipping point will be evaluated. The relative importance of the level vs. risk effect also informs us on the modeling apt to compute the SCC in the presence of a tipping point. If tipping points have mostly a level effect, it means that a deterministic model using expected damages is a good proxy for calculations of the SCC. This was the intuition of Nordhaus (1994) when, in his initial calibration of the DICE model, he increased the mean damage estimates by 30% as a way to account for risk of catastrophic outcomes. If the risk effect is substantial, it means that a full-fledged stochastic modelling is necessary. Since the damage function is the least-grounded aspect of Integrated Assessment Models, and it has a strong impact on the SCC, it is essential to build rigorous methodologies that compare how different representations of damages affect the SCC (Pottier et al., 2015; Guivarch and Pottier, 2018). Disentangling the risk vs. level effet of tipping points helps to compare two representations, either a change of the expected damage function, or explicit modelling.

In this article, we analyze the respective contribution of level (expected damages) and risk in the case of a stochastic tipping point triggering a productivity shock. We use an Integrated Assessment Model to calculate the SCC under two settings: one with a stochastic tipping point, and one with a deterministic damage function, tailored to capture the supplementary expected damages due to the tipping point. That way, we are able to highlight how much expected damages drive the SCC, and under which conditions deterministic approaches lead to underestimate the SCC. We analyze the influence of preferences of the decision maker (i.e. risk aversion, elasticity of marginal utility) and the size of the shock triggered by the tipping point on our results.

We find that explicit modeling of the tipping point and the approach relying on expected damages lead to similar values for the SCC, suggesting that expected damages explain most of the value for the SCC. This results holds as long as we stay within the range of productivity shocks usually considered in the literature. However, under both high productivity shocks and high risk aversion, precaution to avoid the tipping point drives abatement, so that using a deterministic method underestimates the SCC, and becomes ill-suited to compute its value.

Our findings offer a possible explanation for the so-called *risk aversion puzzle*. Previous literature found that risk aversion played a modest role in IAMs like DICE, even when using Epstein-Zin preferences (Ackerman et al., 2013), and in the case of non-linear threshold (Belaia et al., 2014). Our results suggest that too low levels of damages considered in these studies could be responsible for the low influence of risk aversion.

We begin by laying out the model and methodology we use to model catastrophes and build a deterministic equivalent (section 2). Results using different welfare specifications are discussed in section 3. Section 4 concludes.

2. Methodology

We use a simple Integrated Assessment Model to calculate the Social Cost of Carbon. We present in section 2.1 the climate-economy interactions and in section 2.2 the two social preferences. We then explain our methodology to assess how expected damages and risk contribute to the SCC (section 2.3), and the values we explore for the parameters of the model (section 2.4).

2.1. The climate-economy model

An Integrated Assessment Model is meant to capture the main crossed interactions between the economy and the climate system. On the one hand, growth and technological choices drive the level of greenhouse gas emissions causing changes in the climate system, which affect back the economy. This allows to derive optimal emissions path from the point of view of a social planer balancing costs of mitigation and damages of climate change, and to calculate the marginal damages caused by emissions – the SCC.

We use a classical DICE-like model, building on the Ramsey-Caas-Koopmans framework (Guivarch and Pottier, 2018). The economy produces a single good in quantity Q_t using two factors, capital K_t and labour L_t through a Cobb-Douglas function. The productivity is affected by climate change via a damage factor[1] Ω_t depending on temperature T_t, so that final production Q_t writes:

$$Q_t = \Omega(T_t) A_t K_t^{\alpha} L_t^{1-\alpha} \tag{1}$$

The production induces emissions, which can be mitigated at a certain cost. The social planner trades off between consumption, mitigation costs (which represents a share Λ_t of production), and investment in capital (share s_t of production)

$$C_t = Q_t(1 - \Lambda_t - s_t) \tag{2}$$

$$\Lambda_t = \theta_1(t)\mu_t^{\theta_2} \tag{3}$$

$$K_{t+1} - K_t = -\delta.K_t + Q_t.s_t \tag{4}$$

where δ is capital depreciation, and μ_t the abatement rate. $\theta_1(t)$ measures total mitigation costs and decreases exogenously due to technical progress.

The difference with DICE equations concerns the climate system. There is growing evidence that temperature change depends linearly on cumulated emissions (Allen et al., 2009; Matthews et al., 2009; Goodwin et al., 2015), owing to the fact that effects from oceanic absorption of heat and carbon compensate. Modeling the temperature response to cumulated emissions with a linear function is common specification in the literature (Dietz, 2011; Lemoine and Traeger, 2014a), and it reduces computational burden of dynamic programming.

$$T_t = \beta.(CE_0 + \sum_{s=0}^{t} E_s) \tag{5}$$

[1] For notational convenience, we use damage factor Ω instead of damage function D. The correspondance is simply $\Omega = 1 - D$.

where T_t is the global temperature increase at time t, CE_0 are cumulated emissions up to the first period of the model and E_s the emissions at time s.

$$E_t = \sigma_t(1-\mu_t)Q_t \tag{6}$$

where σ_t is the carbon content of production that decreases exogenously over time, and μ_t the abatement rate.

Crossing the tipping point is a stochastic phenomenon leading to a productivity shock, in line with van der Ploeg and de Zeeuw (2013); Lontzek et al. (2015), because our purpose is to remain as general as possible. Such a change in the damage function can potentially apply to a large range of tipping points inducing larger damages than expected. It can be direct impact on the economy either caused by melting of ice caps, leading to severe sea-level rise; a slowing down of thermohaline circulation; or a social tipping point beyond which adaptation is no longer possible. Some studies consider that the tipping point can also affect climate variables such as climate sensitivity or depreciation rate of atmospheric carbon dioxide to reflect saturation of sinks (Lemoine and Traeger, 2014a). Before the tipping point, the damage factor is:

$$\Omega_1(T) = \frac{1}{1+\pi T^2} \tag{7}$$

Once the tipping point has been crossed, damages write:

$$\Omega_2(T) = \frac{1-J}{1+\pi T^2} \tag{8}$$

J is the strength of the productivity shock, comprised between 0 and 1.

To model the crossing of the tipping point as a stochastic event, we assume that the location of the tipping point is unknown. The initial prior is that the tipping point is uniformly distributed between $T_{\min}$ and $T_{\max}$. At each time $t-1$ with temperature T_{t-1}, the decision maker learns whether the tipping point has been crossed or not. If it has not been crossed, this means that it is located above T_{t-1} so that the decision maker updates prior for the next period. Hence the probability to cross the tipping point at t conditional to non-crossing at $t-1$ is given by:

$$h_t(T_t, T_{t-1}) = \begin{cases} 0 & \text{if } T_t \leq T_{t-1} \text{ or } T_t \leq T_{\min} \\ \frac{T_t - \max(T_{\min}, T_{t-1})}{T_{\max} - \max(T_{\min}, T_{t-1})} & \text{if } T_t > T_{t-1} \text{ and } T_{\min} \leq T_t \leq T_{\max} \\ 1 & \text{if } T_t > T_{t-1} \text{ and } T_t \geq T_{\max} \end{cases} \tag{9}$$

The learning enables the decision maker to prevent the crossing from being unavoidable, unlike in other works (van der Ploeg and de Zeeuw, 2013; Lontzek et al., 2015). With learning, mitigation actions can avoid the tipping point, if temperatures stabilize. In some other settings, mitigation actions only delay the expected time of crossing the tipping point, and there is no hedging strategy.

Our modelling is equivalent to a stochastic process with an endogenous hazard rate given by $h_t(T_t, T_{t-1})$. Note that the marginal hazard rate tends to increase (i.e. $\partial_2\partial_1 h_t \geq 0$), as visited temperatures get warmer.

2.2. The social welfare functions

The model seeks the welfare-maximizing path for two state variables, capital and cumulated emissions, choosing the path for the two control variables, the saving rate s_t and the abatement rate μ_t. We study two social preferences: the classical expected utilitarianism with Constant Relative Risk Aversion (CRRA), and Epstein-Zin preferences. In the CRRA representation, time and risk preferences are embedded in a single parameter, which gives both resistance to intertemporal substitution and risk aversion. However, both can induce opposing-directions effects in the presence of risks (Ha-Duong and Treich, 2004): while resistance to substitution favors the consumption of present generations, risk aversion encourages more abatement in the present to lower the risk of triggering the tipping point. For this reason, we also apply Epstein-Zin preferences, which is common in the literature, which allow to disentangle intertemporal substitution and risk aversion.

Welfare after time t, U_t, is defined recursively:

- For classical expected utility preferences

$$U_t = \left(1 - \frac{1}{1+\rho}\right) u_t + \frac{1}{1+\rho}\mathbb{E}[U_{t+1}] \tag{10}$$

  where ρ is the pure time preference rate, and utility at each time step is given by:

$$u_t = L_t \frac{(C_t/L_t)^{1-\eta}}{1-\eta} \tag{11}$$

  η is the elasticity of marginal utility.

  So that we can define Bellman functions as follows:

$$V_t(x_t) = \max_{y_t} \left[u(x_t, y_t) + \frac{1}{1+\rho}\mathbb{E}[V_{t+1}(G(x_t, y_t))] \right] \tag{12}$$

  where $x_t = (S_t, K_t)$ are state variables, $y_t = (\Lambda, s_t)$ are control variables, and $x_{t+1} = G(x_t, y_t)$ is the transfer function.

- For Epstein Zin preferences:[2]

$$U_t = \left(\left(1 - \frac{1}{1+\rho}\right) u_t + \frac{1}{1+\rho}\mathbb{E}[U_{t+1}^{1-\gamma}]^{\frac{1-\theta}{1-\gamma}}\right)^{\frac{1}{1-\theta}} \tag{13}$$

[2] The formula holds for $\theta<1$. Otherwise when $\theta > 1$ utility function is negative, so that $U_t = -(-(1 - \frac{1}{1+\rho})u + \frac{1}{1+\rho}[\mathbb{E}_t(-U_{t+1})^{1-\gamma}]^{\frac{1-\theta}{1-\gamma}})^{\frac{1}{1-\theta}}$

$$u_t = L_t \frac{(C_t/L_t)^{1-\theta}}{1-\theta} \tag{14}$$

For the sake of clarity we use different notations in the Epstein-Zin case. We denote θ the inverse of the elasticity of intertemporal substitution, and γ the risk aversion parameter.

We can define Bellman functions in order to solve this dynamic program: $V_t = \frac{U_t^{1-\theta}}{1-\frac{1}{1+\rho}}$.

$$V_t(x_t) = \max_{y_t}[u(x_t, y_t) + \frac{1}{1+\rho} f(V_{t+1}(G(x_t, y_t)))] \tag{15}$$

f accounts for the decision maker's attitude toward the risk of tipping.[3]. $f(V_{t+1}) = [\mathbb{E}(V_{t+1}^{\frac{1-\gamma}{1-\theta}})]^{\frac{1-\theta}{1-\gamma}}$. It is the same formula as for CRRA preferences, in which $f = \mathbb{E}$.

Using dynamic programming, we first approximate Bellman functions in the post-threshold world, and then in the pre-threshold world using expectations over the location of the tipping point.

2.3. Comparing SCC for a stochastic tipping point with its deterministic equivalent

To investigate how much the Social Cost of Carbon with a tipping point is explained by expected damages, we will compare SCC with stochastic damages due to tipping point with a SCC with "equivalent" deterministic damages. We first present how we compute the SCC for an uncertain tipping point, then how we construct a deterministic equivalent for damages.

A standard way to capture risk is what the literature called the Monte-Carlo approach. For example, Ackerman et al. (2010) and Dietz (2011) have performed exercises on the "fat tail" of climate sensitivity. They draw a value of climate sensitivity from a distribution, compute the SCC with climate sensitivity fixed at that value and take the mean. As a result, they compare the expected value of SCC once the risk on climate sensitivity has been resolved with the SCC with climate sensitivity fixed at its mean. However, the expected value of the SCC given by the Monte-Carlo is not the same as the SCC for a planner that decides before the risk has been resolved, i.e. when, for the planner, the parameter remains unknown (Crost and Traeger, 2013). In our case of a tipping point of unknown location, it is the difference between the SCC with a known tipping point, averaged over all possible locations and the SCC with an unknown tipping point. Following the literature on tipping points (Mastrandrea and Schneider, 2001; Keller et al., 2004; Lemoine and Traeger, 2014b; Lontzek et al., 2012), we take the second as representing the SCC for a stochastic tipping point. We therefore introduce risk in the decision framework and use dynamic programming, as explained above with the Bellman functions. If S is the stock of emissions (the * denotes that control variables y_0

[3] when $0 < \psi < 1$, the recursive formula involves $u_t - \frac{1}{1+\rho} f(-V_{t+1})$

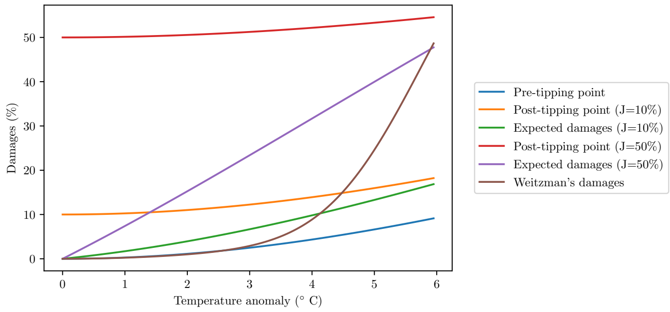


Figure 1: Comparison between different damage functions.

are optimally chosen given x_0.), the Social Cost of Carbon (at initial time) writes in this framework:

$$SCC = -\frac{1}{1+\rho}\frac{\partial_S \mathbb{E}[V_1]|_{x_1}}{\partial_C V_0|_{(x_0,y_0^*)}} \tag{16}$$

To construct the SCC with "equivalent" deterministic damages, we use a modified damage factor $\Omega_d(T)$. This modified damage factor represents the expected damage factor given the prior on the location of the tipping point. Let us note $p(T)$ the prior probability of having crossed the tipping point at temperature T. The expected damage factor writes:

$$\Omega_d(T) = (1 - p(T))\Omega_1(T) + p(T)\Omega_2(T) \tag{17}$$

Damages at a given temperature are set at the expected level of damages given the prior knowledege on the location of the tipping point. Figure 1 shows the resulting damages for two levels of productivity shock ($J = 10\%$ and $J = 50\%$). The sextic damage function proposed in Weitzman (2012) is also pictured for comparison.

The Social Cost Carbon computed with the damage factor Ω_d is the SCC with "equivalent" deterministic damages, noted SCC_d. For each computation of the SCC for a stochastic tipping SCC, we can compute its corresponding deterministic equivalent SCC_d. The SCC in a stochastic setting represents the full effect of the tipping point whereas we take SCC_d as representing the level effect of the tipping point. Indeed, in building the deterministic equivalent SCC_d, we have kept the same level of expected damages and we have canceled the risk element. Comparing SCC and SCC_d tells us how much of the SCC of a stochastic tipping point is explained by the level of expected damages versus by risk. More precisely, we take the ratio SCC_d/SCC as being the part of the SCC that is explained by expected damages. The closer to one the ratio, the more expected damages explain the SCC. Its complement is of course the part of the SCC that is due to a pure risk effect.

2.4. Calibration of the parameters

We use typical range of possible values for parameters related to attitude toward risk and time. Pure rate of time preference (ρ) can take two values: 0.5% and 1.5%. In the CRRA case, elasticity of marginal utility (η) ranges from 0.5 to 3. For the Epstein-Zin case, concerning the intertemporal substitution ($1/\theta$), θ is between 0.5 and 3, while γ ranges from 0.5 to as high as 20.

For the parameters describing the tipping point, we acknowledge that the impacts of such a phenomenon are very difficult to quantify and could be very large. We thus explore a large window for the productivity shock J, from 0 to 50%. The location of the tipping point is uncertain, and could be anywhere between current temperature and $T_{\max}$. We assume $T_{\max} = 7°\text{C}$. Starting from an initial temperature increase of 0.8°C compared to pre-industrial times, this means for instance that a 2°C increase is associated with a 19% probability of triggering the tipping point. For robustess checks on this assumption, see Supplementary Information.

3. Results and discussion

In this section, we present the results first when using CRRA preferences, then with Epstein-Zin preferences, where risk aversion and the inverse of the elasticity of intertemporal substitution differ.

3.1. With CRRA preferences

We compute the SCC for a stochastic tipping point for η, J in the range specified in section 2.4. We also compute the part of this SCC explained by expected damages, that is the ratio SCC_d/SCC.

Figure 2 (bottom panel) plots contour lines for the SCC, in the plane of elasticity of marginal utility and shock due to tipping point. That is to say, a line in represents pairs of η, J resulting in the same level of SCC. We can see that SCC increases with the size of the shock J, as expected. The role of the elasticity of marginal utility η is *a priori* ambiguous. Indeed, CRRA preferences conflate intermporal trade-offs and risk aversion and η has opposing effects on the SCC. On the one hand, a higher η favors present consumption relative to future consumption of wealthier generations (intertemporal substitution), which decreases the SCC. On the other hand, it encourages mitigation of emissions to reduce the risk created by the tipping point (risk aversion), which increases the SCC. We find that the intertemporal substitution effect outweighs the risk aversion effect: for a given J, the SCC decreases when η increases.

Regarding the part of the SCC explained by expected damages, we plot contour lines for the ratio SCC_d/SCC in the plane (η, J) (figure 2, top panel). The ratio decreases as J increases. It was expected, as a higher J means potential exposure to very high damages – a higher risk. As we have discussed, SCC decreases with η. The deterministic equivalent SCC_d also decreases with η as there is only the intertemporal substitution effect at play and not the countervailing risk aversion effect. As a consequence SCC_d decreases faster with η than SCC: the ratio SCC_d/SCC decreases as η increases, expected damages explain less the SCC when the elasticity of marginal utility increases.

We find that it takes both high productivity shocks and high elasticity of marginal utility for the deterministic equivalent to significantly underestimate SCC. In fact, expected damages explain more than 90% of the SCC, as long as the productivity shock is inferior to 10%, whatever the value for risk aversion in the range explored. Only with productivity shocks higher than 40% jointly with elasticity of marginal utility higher than 2 does risk contribute to half or more of the SCC. Though lower pure time preference rate (ρ) significantly raises the level of the SCC, it does so with similar magnitudes in the stochastic case and its deterministic equivalent, so that the part of the SCC explained by expected damages is similar in the case of lower ρ (see graph 7 in Annex).

The conclusion that it takes both high productivity shocks and high elasticity of marginal utility for the deterministic equivalent to significantly underestimate SCC is robust to changes in the value of time preference. Outside these cases, the effet of tipping point on SCC is mostly a level effect that can be captured in a deterministic setting.

It is important to separate the level effect from the risk effect to appreciate for what reason tipping points are important. For example, at $\eta = 2$, introducing a tipping point with a shock of $J = 10\%$ triples the SCC from 34 to 103 $/t$CO_2$. However this increases is not related to risk but to the simple fact that expected damages have increased. Indeed, the deterministic equivalent SCC is 97 $/t$CO_2$. A mere 6 percent of the SCC is due to a pure risk effect.

3.2. With Epstein-Zin preferences

We perform the same exercise when disentangling risk aversion and elasticity of intertemporal substitution, using Epstein-Zin preferences. We present our results in the plane of risk aversion parameter and damages due to the tipping point (γ, J) for $\theta = 1.5$ and $\rho = 1.5\%$ in figure 3 (graphs for different values of θ and ρ can be found in Appendix as a sensitivity check).

Bottom panel of figure 3 plots contour lines for the SCC for a stochastic tipping point. As expected, the SCC increases with the productivity shock J. For a given productivity shock, the SCC increases with the risk aversion γ, as expected since it has an intuitive influence in a single direction.

The part of SCC explained by expected damages has a pattern similar to CRRA preferences. Figure 3, top panel plots the ratio SCC_d/SCC in the plane γ, J. As expected, the ratio decreases with risk aversion γ and producticity shocks J. Values are somewhat similar to the CRRA preferences (with a correspondance $\eta \sim \gamma$) but as we explore a much larger range in risk aversion, the part explained by expected damages for the whole range is much lower. For instance, for a productivity shock equal to 10%, 90% of the SCC is explained by expected damages up to a risk aversion of 4 (as in the CRRA case), but the part explained is only 60% when $\gamma = 15$. Productivity shocks higher than 25%, combined with risk aversion higher than 5, lead to the ratio SCC_d/SCC being under 50%. Expected damages explain less than half of the SCC and the risk effect of the tipping point dominates. For a productivity shock equal to 40% and a risk aversion parameter equal to 5, the level effect makes only 20% of the SCC.

Graphs in Annex (8, 9, 10) show the same results for alternative values of the pure time preference rate ($\rho = 0.5$) and of the elasticity of intertemporal substitution ($\theta = 0.5,\ 1.5$). A decrease in the elasticity of substitution (a higher θ) tends to decrease the

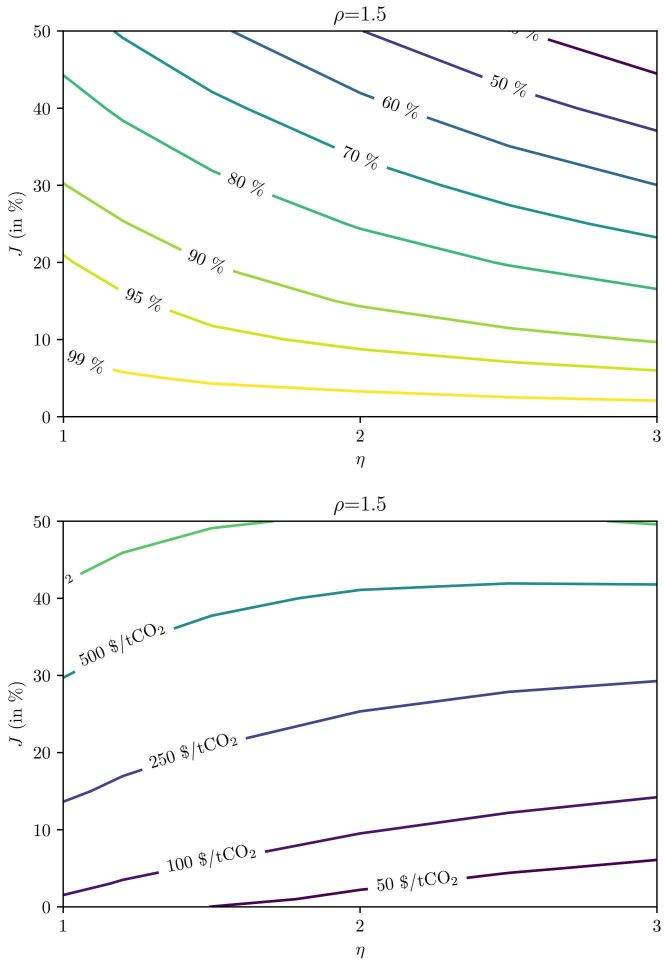


Figure 2: CRRA preferences. Top panel: Contour of share of SCC explained by expected damages (ratio of SCC deterministic on SCC stochastic). Bottom panel: SCC for stochastic runs (in US $2005).

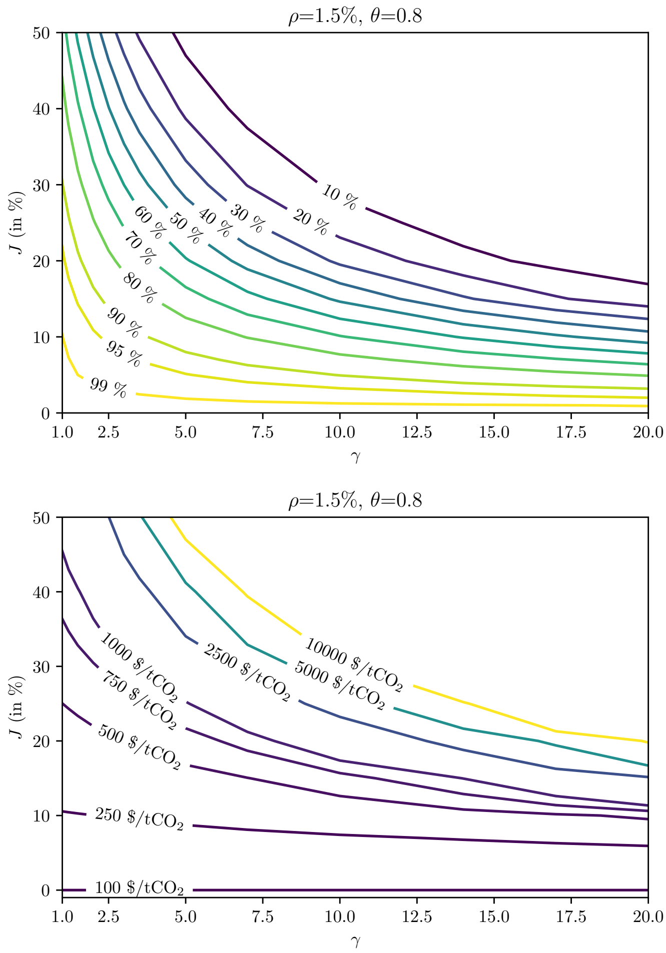


Figure 3: Epstein-Zin preference. Top panel: contour plot of the share of SCC explained by expected damages (ratio of SCC deterministic on SCC stochastic). Bottom panel: SCC for stochastic runs (in US $2005).

SCC, but it does not affect the part of the SCC explained by expected damages. Indeed, θ plays a similar role in both deterministic and stochastic setting, as it governs the trade-off between future and present consumption. This is a strong indication that our construction of the deterministic equivalent has correctly isolated the level effect of the tipping point. It is graphically confirmed with top panel of figure 4, where the iso-lines for the ratio SCC_d/SCC are almost flat in the θ direction. For the same reason, changes in pure time preference rate (ρ) do not affect much the shape or position of the contours of the ratio.

4. Discussion and Conclusion

Climate change is an issue in terms of inter-temporal distribution of welfare because of the damages it will impose on future generations. The difficulty is compounded because these damages are uncertain. They impact climate policies through their expected level but also through the risk on welfare they induce. Disentangling these two effect has so far not been carried out for stochastic tipping points.

What makes these damages remarkable is that they are uncertain: is it their expected level or the uncertainty surrounding them that warrants undertaking mitigation actions? This question has been studied for many types of uncertainty, for instance regarding climate sensitivity or other critical aspects of the climate-economy system, but has not been applied to damage function and tipping points. Authors considering tipping points in Integrated Assessment Models have not studied how explicit modeling of these phenomena differed from standard treatment of uncertainty via expected damage.

In this article, we have developed a methodology to evaluate how expected damages versus dispersion of damages contribute to the Social Cost of Carbon. We compare a setting with explicit modeling of a stochastic tipping point to a deterministic setting using an equivalent damage function. This cancels out the effect of increased expected damages and difference of SCC between the two methods can be attributed to the effect of risk.

Using conventional CRRA preferences, it takes high productivity shocks and risk aversion for a deterministic approach to underestimate SCC. Even when using Epstein-Zin preferences, the share of SCC attributable to risk aversion remains limited (less than 10%) under shocks affecting 10% of production and risk aversion of 10.

Productivity shock of 10% are in the range typically considered in the literature. For instance, in Lontzek et al. (2015), with a similar framework, authors consider the case of $J = 10\%$. Other modeling choices, in Lemoine and Traeger (2014a), make a tipping point induce a change from a quadratic to a sextic damage function, i.e. Weitzman's damage function that relies on an expert panel that explicitly considered physical tipping points. At 4°C, this corresponds to a change of damage factor from $\Omega_1 = 0.96$ to $\Omega_2 = 0.91$ (a loss of less than 10% of Gross World Product). This makes the productivity shock at $J = 1 - \Omega_2/\Omega_1 = 5.2\%$. Our results suggest that the increase of SCC found in these studies are mostly due to a raise in expected damages, and that tipping points are rather a 'level' than a 'risk' problem.

Finally, our work sheds some light on the *risk aversion puzzle*, found in previous work, that is that risk aversion had a surprisingly little effect in Integrated Assessment Models (Ackerman et al., 2013), even in the case of tipping points (Belaia et al., 2014). We show that risk aversion only plays a role when the tipping point triggers high productivity shock, with the risk of losing several tenths of production. Below these levels, an IAM is sensitive to expected damages, so that risk aversion plays a moderate role. Thus, we think that too low levels of possible damages considered in the literature explain the *risk aversion puzzle*. As a matter of comparison, Belaia et al. (2014) only considers productivity shocks below 4.5% when thermohaline circulation collapses.

Deterministic approaches using best-guess expected damages (together with sensitivity analyzes) are currently used to set a value for the SCC for regulations evaluations, and they have lower computational burden than a full-fledged stochastic model. Knowing when deterministic approaches can be used as a good proxy for computing SCC under risk can guide policy making. Our results show that the Social Cost of Carbon comes primarily from the expected level of damages, when the shock induced by a potential tipping point remains lower than 10% or so. In that case, effects of tipping points are well captured in a deterministic setting by updating the damage function to account for higher expected damages.

A very small number of studies explore the possibility of such large shocks, as large as 90 % of consumption (Dietz, 2011), possible extinction (Méjean et al., 2017), though with very low probability. This article clarified which approach is appropriate when the size of the shock is known. Further research is needed to delinate the plausible values of such shocks.

Bibliography

Ackerman, F., Stanton, E., 2012. Climate risks and carbon prices: Revising the social cost of carbon. Economics: The Open-Access, Open-Assessment E-Journal 6, 10.

Ackerman, F., Stanton, E.A., Bueno, R., 2010. Fat tails, exponents, extreme uncertainty: Simulating catastrophe in DICE. Ecological Economics 69, 1657–1665.

Ackerman, F., Stanton, E.A., Bueno, R., 2013. Epstein–Zin utility in DICE: Is risk aversion irrelevant to climate policy? Environmental and Resource Economics 56, 73–84.

Allen, M.R., Frame, D.J., Huntingford, C., Jones, C.D., Lowe, J.A., Meinshausen, M., Meinshausen, N., 2009. Warming caused by cumulative carbon emissions towards the trillionth tonne. Nature 458, 1163–1166.

Alley, R.B., Marotzke, J., Nordhaus, W.D., Overpeck, J.T., Peteet, D.M., Pielke, R.A., Pierrehumbert, R.T., Rhines, P.B., Stocker, T.F., Talley, L.D., 2003. Abrupt climate change. science 299, 2005–2010.

Belaia, M., Funke, M., Glanemann, N., 2014. Global Warming and a Potential Tipping Point in the Atlantic Thermohaline Circulation: The Role of Risk Aversion. Environmental and Resource Economics , 1–33.

Broome, J., 2010. The most important thing about climate change, in: Public policy: Why ethics matters. Australian National University Press, pp. 101–116.

Crost, B., Traeger, C.P., 2013. Optimal climate policy: uncertainty versus Monte Carlo. Economics Letters 120, 552–558.

Diaz, D., Moore, F., 2017. Quantifying the economic risks of climate change. Nature Climate Change 7, 774.

Dietz, S., 2011. High impact, low probability? An empirical analysis of risk in the economics of climate change. Climatic Change 108, 519–541.

Dietz, S., Stern, N., 2015. Endogenous Growth, Convexity of Damage and Climate Risk: How Nordhaus' Framework Supports Deep Cuts in Carbon Emissions. The Economic Journal 125, 574–620.

Dumas, P., Ha-Duong, M., 2005. An abrupt stochastic damage function to analyze climate policy benefits, in: The Coupling of Climate and Economic Dynamics. Springer, pp. 97–111.

Goodwin, P., Williams, R.G., Ridgwell, A., 2015. Sensitivity of climate to cumulative carbon emissions due to compensation of ocean heat and carbon uptake. Nature Geoscience 8, 29–34.

Guivarch, C., Pottier, A., 2018. Climate Damage on Production or on Growth: What Impact on the Social Cost of Carbon? Environmental Modeling & Assessment 23, 117–130.

Ha-Duong, M., Treich, N., 2004. Risk aversion, intergenerational equity and climate change. Environmental and Resource Economics 28, 195–207.

Keller, K., Bolker, B.M., Bradford, D.F., 2004. Uncertain climate thresholds and optimal economic growth. Journal of Environmental Economics and Management 48, 723–741.

Lemoine, D., Traeger, C., 2014a. Watch your step: Optimal policy in a tipping climate. American Economic Journal: Economic Policy 6, 137–166.

Lemoine, D., Traeger, C.P., 2014b. "Playing the climate dominoes: Tipping points and the cost of delaying policy. Technical Report. Working paper.

Lenton, T.M., Held, H., Kriegler, E., Hall, J.W., Lucht, W., Rahmstorf, S., Schellnhuber, H.J., 2008. Tipping elements in the Earth's climate system. Proceedings of the National Academy of Sciences 105, 1786–1793.

Lontzek, T.S., Cai, Y., Judd, K.L., 2012. Tipping points in a dynamic stochastic IAM .

Lontzek, T.S., Cai, Y., Judd, K.L., Lenton, T.M., 2015. Stochastic integrated assessment of climate tipping points indicates the need for strict climate policy. Nature Climate Change 5, 441–444.

Mastrandrea, M.D., Schneider, S.H., 2001. Integrated assessment of abrupt climatic changes. Climate Policy 1, 433–449.

Matthews, H.D., Gillett, N.P., Stott, P.A., Zickfeld, K., 2009. The proportionality of global warming to cumulative carbon emissions. Nature 459, 829.

Méjean, A., Pottier, A., Zuber, S., Fleurbaey, M., 2017. Intergenerational equity under catastrophic climate change .

Nordhaus, W.D., 1994. Managing the global commons: the economics of climate change. volume 31. MIT press Cambridge, MA.

O'Neill, B.C., Oppenheimer, M., Warren, R., Hallegatte, S., Kopp, R.E., Pörtner, H.O., Scholes, R., Birkmann, J., Foden, W., Licker, R., 2017. IPCC reasons for concern regarding climate change risks. Nature Climate Change 7, 28.

Pindyck, R.S., 2013. The climate policy dilemma. Review of Environmental Economics and Policy 7, 219–237.

Pizer, W.A., 2003. Climate change catastrophes. Resources for the Future.

van der Ploeg, F., de Zeeuw, A., 2013. Climate policy and catastrophic change: Be prepared and avert risk. Technical Report. Oxford Centre for the Analysis of Resource Rich Economies, University of Oxford.

Pottier, A., Espagne, E., Fabert, B.P., Dumas, P., 2015. The comparative impact of integrated assessment models' structures on optimal mitigation policies. Environmental Modeling & Assessment 20, 453–473.

Steffen, W., Rockström, J., Richardson, K., Lenton, T.M., Folke, C., Liverman, D., Summerhayes, C.P., Barnosky, A.D., Cornell, S.E., Crucifix, M., Donges, J.F., Fetzer, I., Lade, S.J., Scheffer, M., Winkelmann, R., Schellnhuber, H.J., 2018. Trajectories of the Earth System in the Anthropocene. Proceedings of the National Academy of Sciences 115, 8252–8259. doi:10.1073/pnas.1810141115.

Weitzman, M.L., 2009. On modeling and interpreting the economics of catastrophic climate change. The Review of Economics and Statistics 91, 1–19.

Weitzman, M.L., 2012. GHG targets as insurance against catastrophic climate damages. Journal of Public Economic Theory 14, 221–244.

Wouter Botzen, W.J., van den Bergh, J.C.J.M., 2012. How sensitive is Nordhaus to Weitzman? Climate policy in DICE with an alternative damage function. Economics Letters 117, 372–374. doi:10.1016/j.econlet.2012.05.032.

Appendix A Appendix

A.1 Additional graph

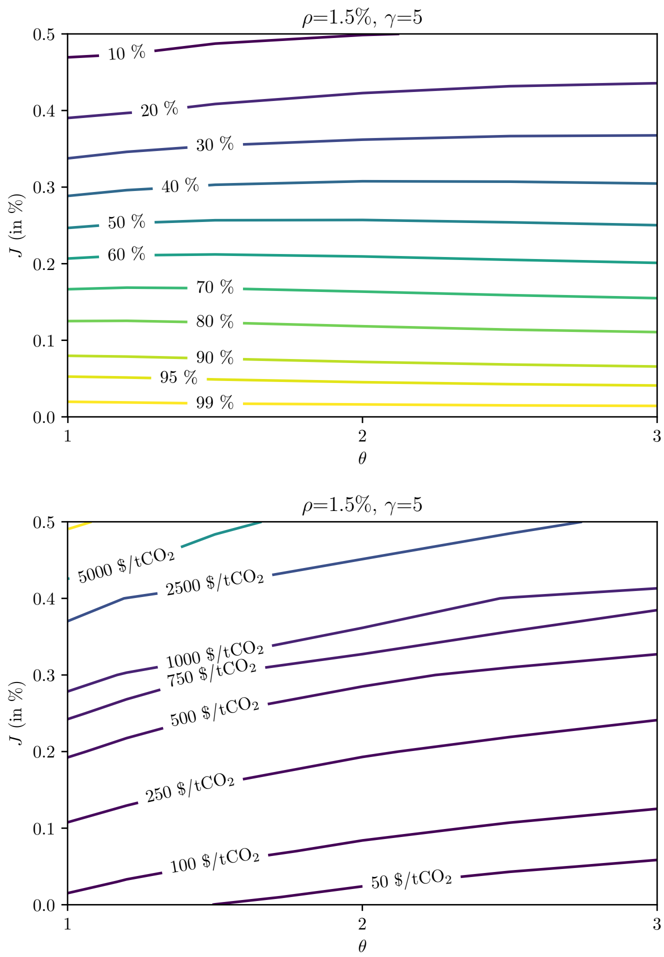


Figure 4: Epstein-Zin preferences: influence of θ. Top panel: Contour of share of SCC explained by expected damages (ratio of SCC deterministic on SCC stochastic). Bottom panel: SCC for stochastic runs (in US $2005).

Two parameters are involved in welfare evaluation at each time step: risk aversion (γ) and resistance to intertemporal substitution (θ). In the main text, we have analyzed the influence of risk aversion combined with the value of the shock. On figure 4, we display how resistance to intertemporal substitution affects the comparison of determinsitic and stochastic methods. A change in θ does not affect the share of the SCC explained by expected damages, the contour lines on the graph are horizontal.

A.2 Robustness checks

We perform a sensitivity analysis on several parameters of the model:

- The maximum temperature threshold for the tipping point T_{max}. We look at $T_{max} = 10$ instead of 7.
- Pure rate of time preference ρ. We run the model for lower ρ (0.5%)
- Elasticity of intertemporal substitution ($1/\theta$) in the Epstein-Zin case. We consider $\theta = 0.5$ and $\theta = 1.5$.

The graphs show that the shapes of the curves are not affected by a change in these parameters, and our finding that most of the SCC is still explained by expected damages as long as the shock remain under 10%.

A.2.1 Parameter T_{max}

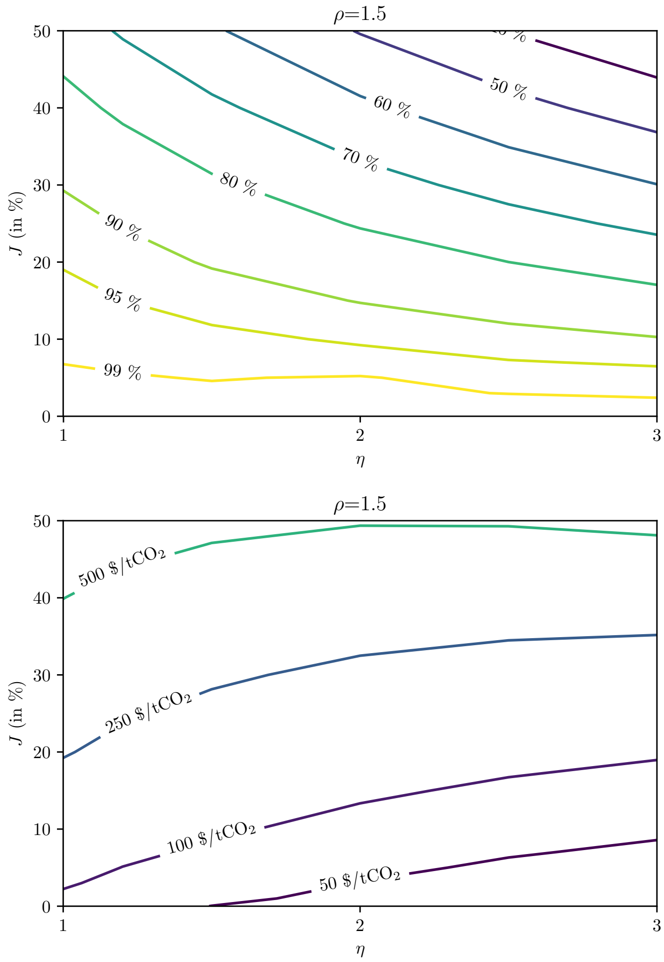


Figure 5: CRRA preferences. Sensitivity analysis for $T_{max} = 10°C$. Top panel: Contour of share of SCC explained by expected damages (ratio of SCC deterministic on SCC stochastic). Bottom panel: SCC for stochastic runs (in US \$2005).

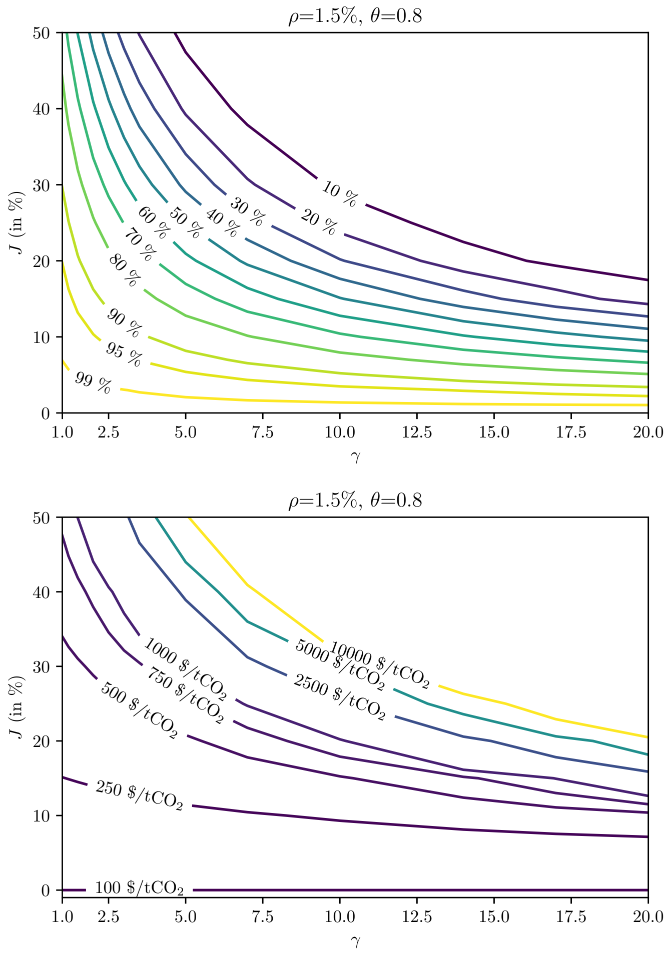


Figure 6: Epstein-Zin preferences. Sensitivity analysis for $T_{max} = 10°C$. Top panel: Contour of share of SCC explained by expected damages (ratio of SCC deterministic on SCC stochastic). Bottom panel: SCC for stochastic runs (in US \$2005).

A.2.2 Parameter ρ

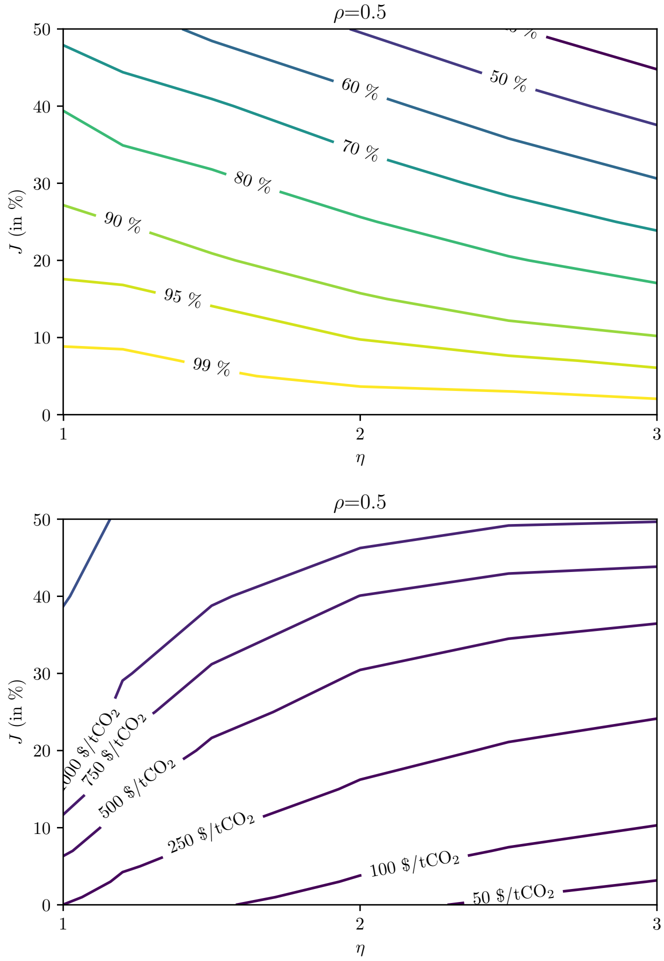


Figure 7: CRRA preferences. Sensitivity analysis for $\rho = 0.5\%$. Top panel: Contour of share of SCC explained by expected damages (ratio of SCC deterministic on SCC stochastic). Bottom panel: SCC for stochastic runs (in US \$2005).

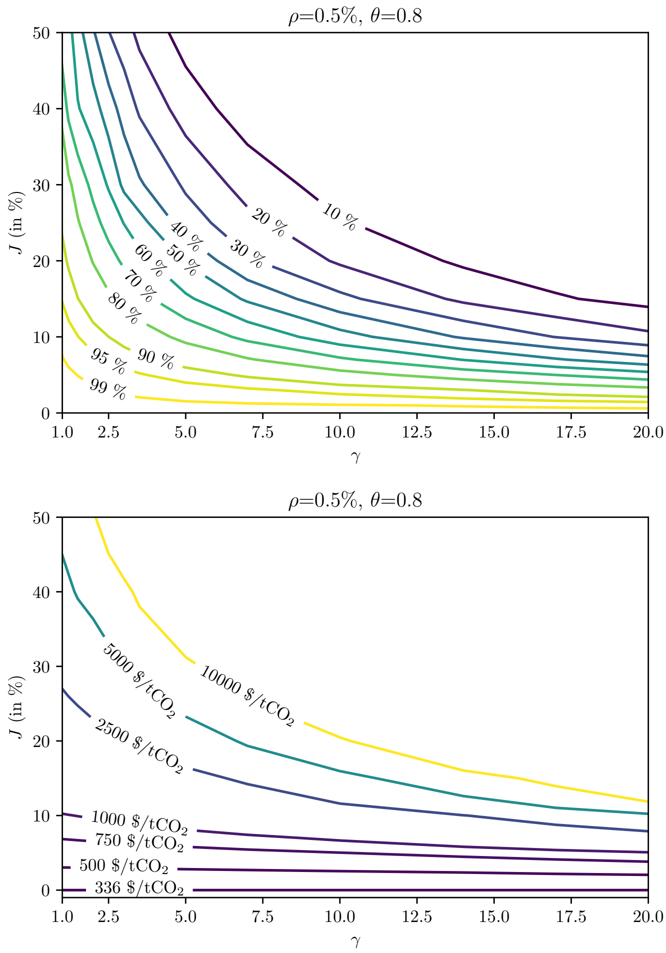


Figure 8: Epstein-Zin preferences. Sensitivity analysis for $\rho = 0.5\%$. Top panel: Contour of share of SCC explained by expected damages (ratio of SCC deterministic on SCC stochastic). Bottom panel: SCC for stochastic runs (in US \$2005).

A.2.3 Parameter θ

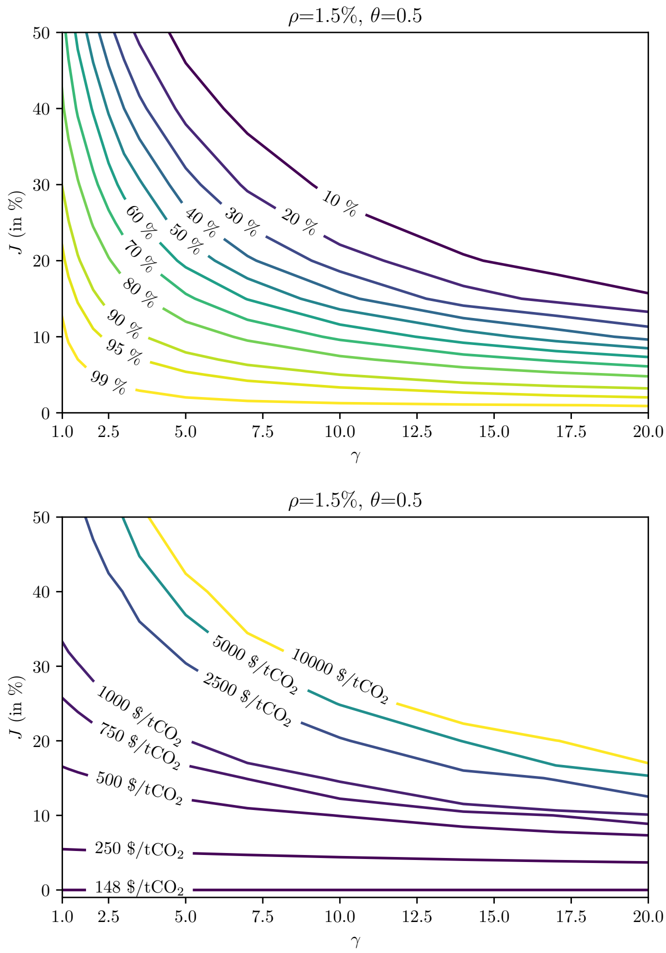
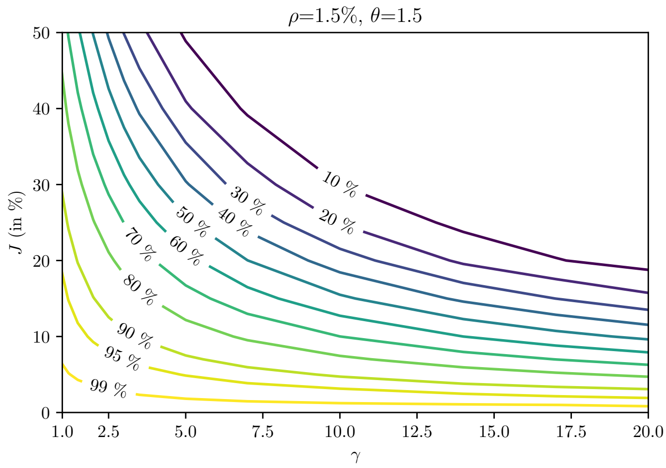


Figure 9: Epstein-Zin preferences. Sensitivity analysis for $\theta = 0.5$. Top panel: Contour of share of SCC explained by expected damages (ratio of SCC deterministic on SCC stochastic). Bottom panel: SCC for stochastic runs (in US \$2005).



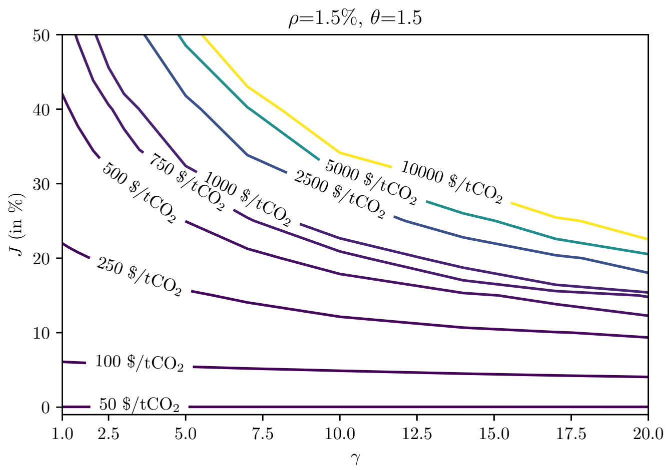


Figure 10: Epstein-Zin preferences. Sensitivity analysis for $\theta = 1.5$. Top panel: Contour of share of SCC explained by expected damages (ratio of SCC deterministic on SCC stochastic). Bottom panel: SCC for stochastic runs (in US \$2005).