The Social Cost of Carbon with Economic and Climate Risks

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Overview

Introduction

- This paper presents dynamic stochastic integration of climate and the economy (DSICE)
- Extend the scope of IAMs by adding uncertainties and risks
- Incorporates economic and climate risks into models where economic agents have rational expectations concerning the future of the economy and of the climate
- Explicit treatment of economic and climate risks significantly changes the results
- The impact of carbon emissions on society is measured by the social cost of carbon (SCC), defined as the marginal economic loss caused by an extra metric ton of atmospheric carbon.

Introduction

- Economic risks imply that there is great uncertainty about the future SCC and the value of future climate change policies.
- While the SCC today is sensitive to parameter choices regarding preferences, this paper does arrive at a robust finding that the SCC is nontrivial, with 40–100 dollar/tC being the range implied by the various opinions regarding dynamic preferences
- There is no simple discounting rule to apply to climate change policy decisions
- Their model: dynamic stochastic integration of climate and the economy (DSICE) examines cases where both economic and climate risks are present and shows that the results differ significantly from a separate examination of these two sources of risk

The Climate Model

- The Carbon System
- The Temperature System
- A Third System that models other climate conditions (e.g. sea level)

Carbon System

Total Emissions: $E_t = E_{Ind,t} + E_{Land,t}$

The authors follow DICE-2007 and aggregate the distribution of carbon in the world into three "boxes"—atmosphere, upper ocean, and lower ocean: $M_t = (M_{AT,t}, M_{UO,t}, M_{LO,t})$.

The carbon concentrations evolve over time according to the physics of diffusion and are represented by the linear dynamical system $M_{t+1} = \Phi_M M_t + (E_t, 0, 0)^T$, where

$$\Phi_{\mathrm{M}} = \begin{bmatrix} 1 - \phi_{12} & \phi_{21} & 0 \\ \phi_{12} & 1 - \phi_{21} - \phi_{23} & \phi_{32} \\ 0 & \phi_{23} & 1 - \phi_{32} \end{bmatrix}$$

Temperature System

The temperature is represented by the vector $T_t = (T_{AT,t}, T_{OC,t})^T$

The system evolves according to $\mathsf{T}_{t+1} = \Phi_{\mathrm{T}} \mathsf{T}_t + \left(\xi_1 \mathcal{F}_t\left(M_{\mathrm{AT},t}\right), 0\right)^\top$.

where

$$\Phi_{\mathrm{T}} = \begin{bmatrix} 1 - \varphi_{21} - \xi_2 & \varphi_{21} \\ \varphi_{12} & 1 - \varphi_{12} \end{bmatrix}$$

ξ_2 represents is the rate of cooling arising from infrared radiation to space, and ξ_1 represents heating due to radiative forcing.

We have

$$\mathcal{F}_t\left(M_{\mathrm{AT},t}\right) = \eta \log_2\left(\frac{M_{\mathrm{AT},t}}{M^*_{\mathrm{AT}}}\right) + F_{\mathrm{EX},t}$$

where M^*_{AT} is the he preindustrial atmospheric carbon concentration and *eta* is the radiative-forcing parameter.

Tipping Element System

Let J represent some feature of the climate other than temperature or carbon. It has a finite set of possible values and represents the state of a tipping element; the authors refer to J as the tipping state. Changes in J are modeled by a Markov chain where transition probabilities depend on the vector of all climate states, (T, M, J). The Markov transition process is denoted as

$$J_{t+1} = g_J(T_t, M_t, J_t, w_{J,t}),$$

where $w_{J,t}$ is one serially independent stochastic process.

The key properties of any tipping element include the likelihood of tipping events, the expected duration of the tipping process, the mean and variance of the long-run impacts on economic productivity, and how all of these depend on (T, M, J).

Comparison with Other IAM Climate Systems

In DSICE, the timing of a tipping event is unknown, even conditional on knowing the full state of the climate system, the timing of the transitions after the tipping event is unknown, and—furthermore— the impact of the Markov chain is unknown before the tipping event.

DSICE relies on expert opinion (Lenton et al. 2008; Kriegler et al. 2009) to calibrate its tipping elements and assumes that a tipping event is a random event with probability depending on the state of the climate system, assuming that the hazard rate of the tipping-point event is increasing with global warming.

The Economic Model

- Predamge Output
- Damage Function and Emissions
- Epstein-Zin Preferences

Predamage Output

The economic side of DSICE is a simple stochastic growth model where production produces greenhouse gas emissions and output is affected by the state of the climate: discrete time, K_t is the world capital, L_t is the population.

CB Production function:

$$f\left(K, L, \tilde{A}_t\right) = \tilde{A}_t K^{\alpha} L^{1-\alpha}$$

$$\tilde{A}_t \equiv \zeta_t A_t$$

$$A_t = A_0 \exp\left(\frac{\alpha_1\left(1 - e^{-\alpha_2 t}\right)}{\alpha_2}\right)$$

where α_1 is the 2005 growth rate and α_2 is the decline rate of the growth rate.

Predamage Output

The authors add a stochastic component, ζ_t, to the productivity process so that we can examine how uncertainty about productivity affects climate change policies. For computing purpose, the authors construct a time-dependent, finite-state Markov chain for (ζ_t, χ_t) with parameter values implying conditional and unconditional moments of consumption processes observed in market data. The Markov transition processes are denoted

$$\zeta_{t+1} = g_\zeta\left(\zeta_t, \chi_t, \omega_{\zeta,t}\right)$$
$$\chi_{t+1} = g_\chi\left(\chi_t, \omega_{\chi,t}\right)$$

where $\omega_{\zeta,t}$ and $\omega_{\chi,t}$ are two serially independent stochastic processes.

Damage Function and Emissions

DSICE models two potential ways in which output is affected by the climate: global average temperature T_{AT} and the Markov chain state denoted by J.

$$Y_t \equiv \Omega\left(T_{\mathrm{AT},t}, J_t\right) f\left(K_t, L_t, \zeta_t A_t\right)$$

where

$$\Omega\left(T_{\mathrm{AT},t}, J_t\right) = \Omega_{\mathrm{T}}\left(T_{\mathrm{AT},t}\right) \Omega_J\left(J_t\right) = \frac{1}{1 + \pi_1 T_{\mathrm{AT},t} + \pi_2\left(T_{\mathrm{AT},t}\right)^2}\left(1 - D\left(J_t\right)\right)$$

Annual industrial emissions equal $E_{\mathrm{Ind},t} = \sigma_t\left(1 - \mu_t\right) f\left(K_t, L_t, \zeta_t A_t\right)$
The authors assume that industrial emissions are proportional to output, with the proportionality factor σ_t, which is referred to as the carbon intensity of output. The social planner can mitigate (i.e., reduce) emissions by a factor $0 \leq \mu_t \leq 1$.

Damage Function and Emissions

The cost of mitigation level μ_t is $\Psi_t = \theta_{1,t}\mu_t^{\theta_2} Y_t$.

World Production: $Y_t = C_t + \Psi_t + I_t$

Capital law of motion: $K_{t+1} = (1-\delta)K_t + I_t$

Epstein-Zin Preferences

Let C_t be the stochastic consumption process. Epstein-Zin preferences recursively define social welfare as

$$U_t = \left[(1-\beta)u\left(C_t, L_t\right) + \beta\left(\mathbb{E}_t\left\{U_{t+1}^{1-\gamma}\right\}\right)^{[1-(1/\psi)]/(1-\gamma)}\right]^{1/[1-(1/\psi)}$$

where

$$u\left(C_t, L_t\right) = \frac{\left(C_t/L_t\right)^{1-1/\psi}}{1-1/\psi} L_t$$

The Dynamic Programming Problem

Let $\mathsf{S} \equiv (K, \mathsf{M}, \mathsf{T}, \zeta, \chi, J)$ denote the nine-dimensional state variable vector, and let S_+ denote its next period's state vector. By a change of variables, we get the following Bellman equation:

$$
\begin{aligned}
V_t(\mathsf{S}) &= \max_{C,\mu} u\left(C_t, L_t\right) + \beta\left(\mathbb{E}_t\left\{\left(V_{t+1}\left(\mathsf{S}_+\right)\right)^{(1-\gamma)/(1-1/\psi)}\right\}\right)^{(1-1/\psi)/(1-\gamma)} \\
\text{such that} \quad K^+ &= (1-\delta)K + Y_t - C_t - \Psi_t \\
\mathsf{M}^+ &= \Phi_{\mathrm{M}}\mathsf{M} + \left(E_t, 0, 0\right)^\top \\
\mathsf{T}^+ &= \Phi_{\mathrm{T}}\mathsf{T} + \left(\xi_1 \mathcal{F}_t\left(M_{\mathrm{AT}}\right), 0\right)^\top \\
\zeta^+ &= g_\zeta\left(\zeta, \chi, \omega_\zeta\right) \\
\chi^+ &= g_x\left(\chi, \omega_\chi\right) \\
J^+ &= g_J\left(\mathsf{T}, \mathsf{M}, J, \omega_J\right),
\end{aligned}
$$

This is a large problem, but the use of parallel programming methods and hardware makes it tractable.

The SCC

The authors define the SCC as the marginal rate of substitution between atmospheric carbon concentration and capital:

$$\mathrm{SCC}_t = \frac{-1,000\,(\partial V_t / \partial M_{\mathrm{AT},t})}{\partial V_t / \partial K_t}$$

The SCC will often be the optimal carbon tax. The optimal carbon tax is the tax on carbon that would equate the private and social costs of carbon.

The social planner in DSICE chooses mitigation μ_t, which is equivalent to choosing a carbon tax equal to $\frac{1{,}000\theta_{1,t}\theta_2\mu_t^{\theta_2-1}}{\sigma_t}$ in units of dollars per ton of carbon.

If $\mu_t < 1$, then the carbon tax equals SCC. However, if $\mu_t 1$, its maximum value, then the carbon tax equals only that level that will drive emissions to zero and may be far less than the SCC.

The SCC with Stochastic Growth

Here we exclude **tipping elements** so that we can focus on the impact of productivity risk.

We present an analysis of a benchmark example based on parameter specifications, which we call *stochastic growth benchmark* case.

The **stochastic growth benchmark** case assumes Epstein-Zin parameter values:

- Measure for Intertemporal Elasticity of Substitution (IES)

$$\psi = 1.5$$

- Measure for Risk Aversion

$$\gamma = 10$$

The Stochastic Growth Benchmark

Figures 1 and 2 display features of the solution to the Bellman equation (15)

$$V_t(\mathsf{S}) = \max_{C,\mu} u\left(C_t, L_t\right) + \beta \left(\mathbb{E}_t\left\{\left(V_{t+1}\left(\mathsf{S}_+\right)\right)^{(1-\gamma)/(1-1/\psi)}\right\}\right)^{(1-1/\psi)/(1-\gamma)}$$

for the stochastic growth benchmark case.

We display results from two deterministic cases of DICE-CJL:

- DICE-CJL with $\psi = 0.5$ (solid red line) represents the DICE-2007 choice of ψ
- and DICE-CJL with $\psi = 1.5$ (dashed red line) represents the choice in our *stochastic growth benchmark*.

And we plot the gray area which represents the 1st–99th percentiles of the SCC paths (for stochastic growth).

The Stochastic Growth Benchmark

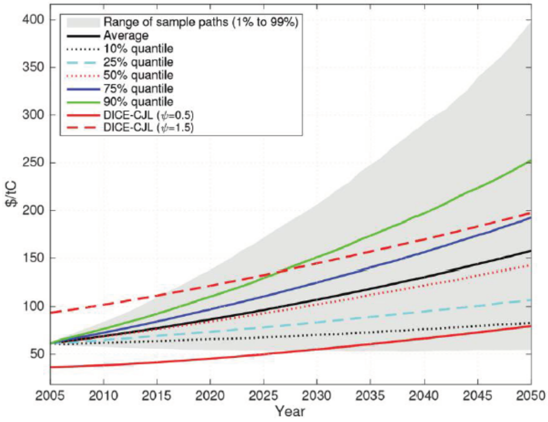


Figure 1: SSC($/tC):2005-50

Figure 1 displays the SCC process for 2005–50.

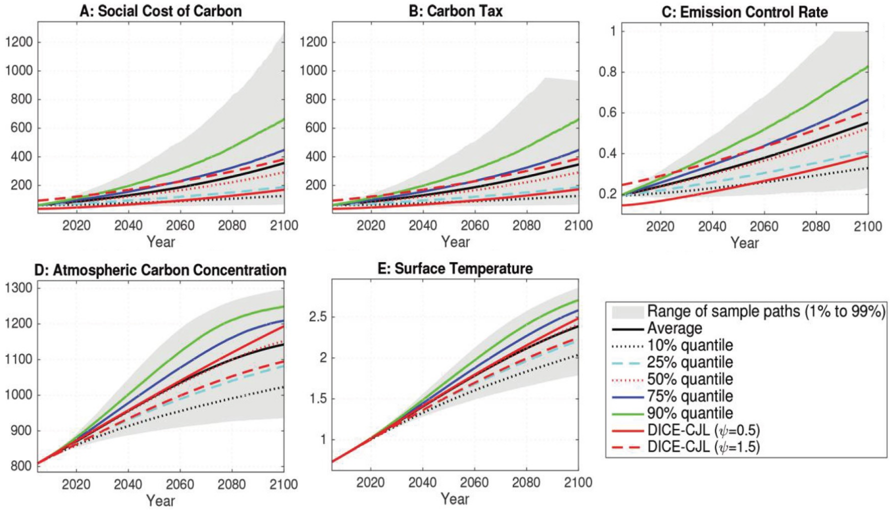
- Moving from $\psi = 0.5$ to $\psi = 1.5$ substantially increases the SCC.
- Adding uncertainty with $\gamma = 10$ decreases SCC to $61/tC.
- No-risk line (dashed red line) exceeds the average SCC (black line) by about $50/tC in long-run.

The productivity risk substantially increases the range of the SCC:

- By 2050, there is a 25% chance of the SCC being almost $200/tC or greater
- and a 10% chance of it exceeding $250/tC.

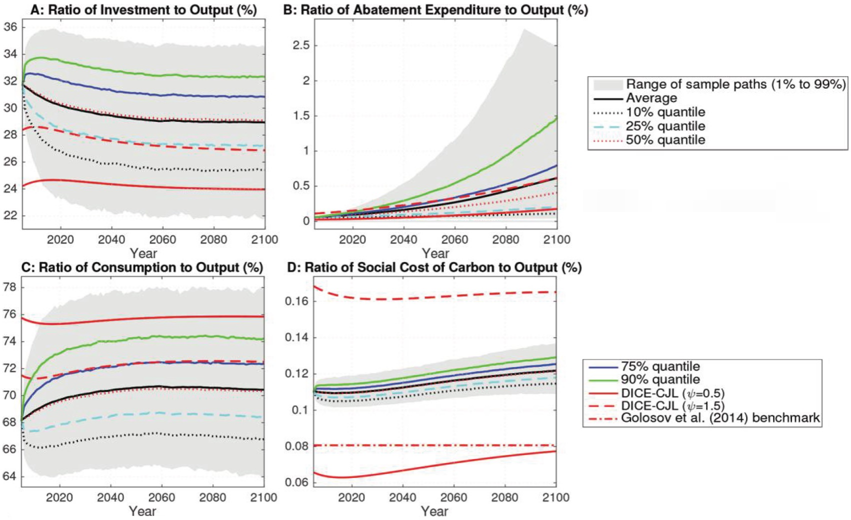
The Stochastic Growth Benchmark

Figure 2: Simulation results of the stochastic growth benchmark—climate system and policies.



The Stochastic Growth Benchmark

Figure 3: Simulation results of the stochastic growth benchmark—ratios to gross world output.



The SCC with Stochastic Climate Tipping

Here we analyze how a **tipping element** in the climate system may affect the SCC in the absence of any economic uncertainty.

It is obvious that adding a tipping element to DICE will increase the SCC.

The question is - **how much the SCC is increased, given the magnitude of the tipping-point damages?**.

$\Longrightarrow$ Figure 4 will help address that issue.

$\Longrightarrow$ The analysis is based on computing the BAU (Business as Usual) case with and without tipping.

The SCC with Stochastic Climate Tipping

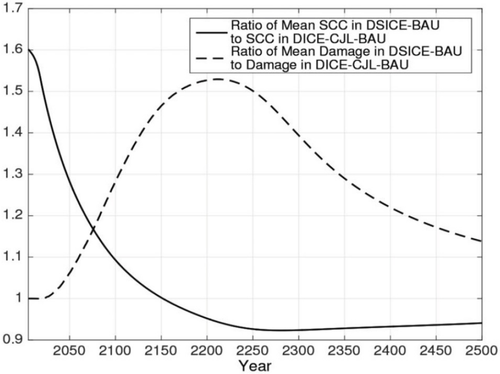


Figure 4: Comparison of DSICE and DICE-CJL with $\psi = 1.5$ under business as usual (BAU)

The dashed line shows:

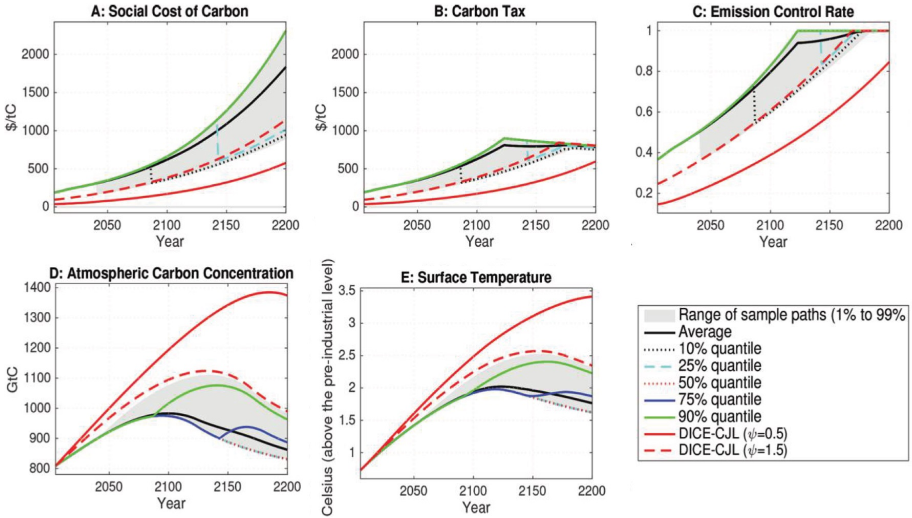
- The relative increase in damage when we add the tipping element.
- The increase is negligible until 2050 and peaks in around 2200 at 53%.

The solid line shows:

- The impact of tipping on the marginal SCC.
- That the marginal damage of carbon rises by 60 percent in 2005.

The SCC with Stochastic Climate Tipping

Figure 5: Simulation results for the climate tipping benchmark—climate system and policies.



The SCC with Stochastic Growth and Climate Tipping

The real world system includes both uncertainties, and in this section we present the results of DSICE in the presence of long-run risk in both:

- economic growth
- and the climate tipping process.

The optimal policy will now have to balance the need to delay the triggering of the tipping-point process with:

- the **accumulation of additional capital** in the face of stochastic growth
- and with the desire to **smooth our consumption patterns**.

The SCC with Stochastic Growth and Climate Tipping

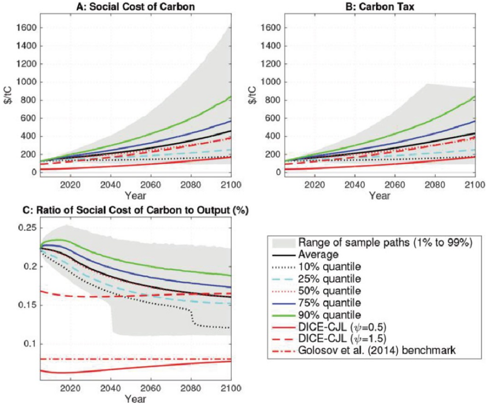


Figure 6: Simulation results for the stochastic growth and climate tipping

The SCC in 2100 ranges from \$100/tC (the 1 percent quantile) to \$1,700/tC (the 99 percent quantile).

Carbon tax, is also more likely to hit its upper bound after 2072 than in either of the single-risk benchmarks.

There is a probability of about 7.5% that mitigation policies will have reached the limit of their effectiveness by 2100.

Compared to the deterministic version of the model, SCC_t/Y_t is about three times larger in 2005, while at 2100 it is expected to be about twice as large.

Summary and Conclusion

- The incorporation of long-run risk shows that the SCC is itself a stochastic process with considerable uncertainty.

- Climate change policy has to recognize the uncertainty about the future SCC and be prepared to consider policies.

- An examination of parameter uncertainty also shows that the range of plausible SCC values is much larger than implied by other integrated assessment analyses.

- The threat of a tipping element leads to significant and immediate increases in the SCC.

- The SCC can be very high, even without assuming catastrophic climate change events.