Policy Responses to Climate Change in a Dynamic Stochastic Economy[1]

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Climate Change Policy Analysis

What should be the policy response to global warming in the face of uncertainty?

- Economists analyze simple stylized models of pieces of the system
  - Deterministic: economic actors know perfectly the economic and climate systems
  - Myopic: ignore known future events (such as *WARMING*) and policies
  - Bad physics: e.g., CO2 emitted in 2020 causes warming in 2010 (DICE2007, IWG)
- We create dynamic and stochastic integrated models of climate and economy (DSICE)
  - uncertain (random) economic growth
  - parameter uncertainty
  - allow future warming and policies affect decisions today

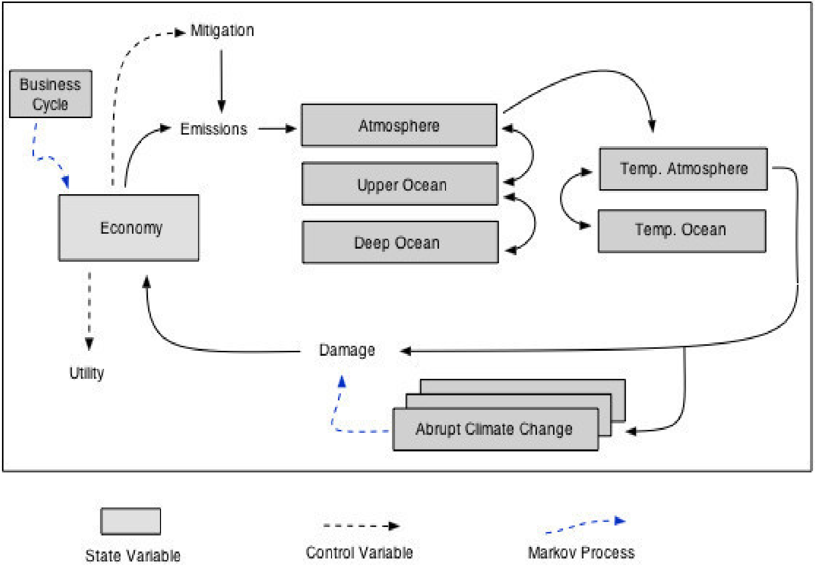
Economics Is Stuck in the “Stone” (Laptop) Age

- Federal Reserve Models
  - are linear (or nearly so)
  - run on laptops in a few minutes
  - have temporal resolution of three months
  - have spatial resolution greater than 1000 km
  - code authors do not know numerical analysis – no LU, no AD, ...
  - written in Matlab and Eviews: “This allows you solve the problem and graph the results in one program.”
- Federal Reserve economists
  - run the US and world monetary policy
  - I know them; some took my course in numerical methods
  - have no interest in doing better
- We develop computational methods of general value in economics; Climate change policy analysis is an application

Risks

- Economic risks: taste shocks, uncertain technological advances (e.g., quantum computers), financial crisis
- Climate risks: Antarctic and Greenland ice sheet melting (sea level rise, IPCC 2014)
- Two kinds of risk and uncertainty
- Example: Brownian motion
  - We may know the drift and variance parameters
  - We do not know the future position of a particle following a Brownian motion
- In climate change policy work, "uncertainty" usually just means uncertainty about parameters.
- We examine both parameter uncertainty and intrinsic stochasticity
- Economic productivity follows a Brownian motion, its parameters have been estimated by statistical methods, and we incorporate these estimates in our model of the economy and climate.

DSICE Framework



Dynamic Optimization Problem

- Epstein-Zin Preferences: recursive utility function
  - $u_t(c) = \frac{c^{1-1/\psi}}{1-1/\psi} L_t$: utility flow per period
  - ψ: dynamic consumption flexibility
  - γ: risk aversion
  - $\Gamma = \frac{1-\gamma}{1-1/\psi}$: composite factor
- State: $\mathbf{S} = (K, \mathbf{M}, \mathbf{T}, \mathbf{J}, \mathbf{I})$
  - ten continuous state variables
  - like 10D parabolic HJB PDE
- Bellman equation

$$
\begin{aligned}
V_t(\mathbf{S}) = \mathfrak{F}_t V_{t+1}(\mathbf{S}^+) \equiv \max_{c,\mu} \quad & u_t(c_t) + \beta \left[\mathbb{E}_t \left\{ \left(V_{t+1} \left(\mathbf{S}^+ \right) \right)^{\Gamma} \right\} \right]^{1/\Gamma}, \\
\text{s.t.} \quad & \mathbf{S}^+ = \mathbf{F}_t(\mathbf{S}, c_t, \mu_t, \epsilon_t)
\end{aligned}
$$

Parallelization of DSICE

- The value function $V_t(\mathbf{S})$ represents system at time t as a function of $\mathbf{S}$
- The value function $\hat{V}(\mathbf{S};\mathbf{b}^t)$ approximates $V_t(\mathbf{S})$ with polynomials with coefficients $\mathbf{b}^t$
- Solve backwards in time, like Hamilton-Jacobi-Bellman PDEs
- For each time t, solve the Bellman equation in parallel
  - Step 1. Maximization step: Compute (in parallel)

    $$v_i = \mathfrak{F}_t \hat{V}(\mathbf{S}_i^+;\mathbf{b}^{t+1}),$$

    for approximation nodes $\mathbf{S}_i$
  - Step 2. Fitting step: compute coefficients $\mathbf{b}^t$ such that $\hat{V}(\mathbf{S};\mathbf{b}^t)$ fits $(\mathbf{S}_i, v_i)$ data.

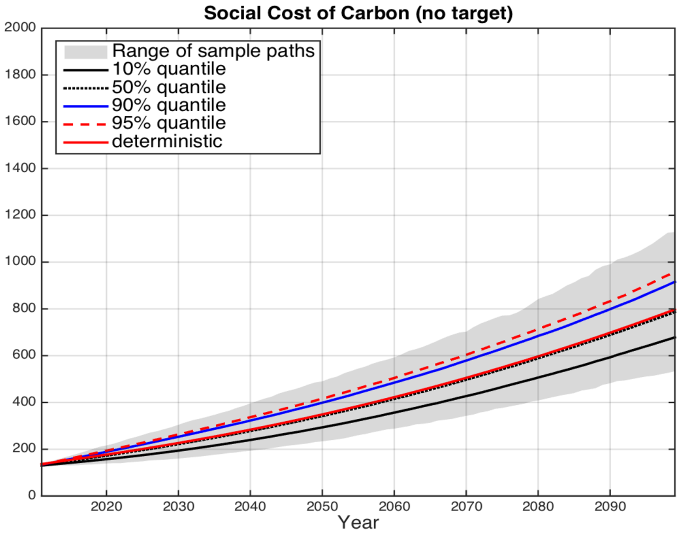
Example	# of Optimization problems	#Cores	Wall Clock Time	Total CPU Time
1	94 billion	10K	3 hours	4 years
2	372 billion	84K	8 hours	77 years

- Strong scaling: linear over 1K cores to 100K cores

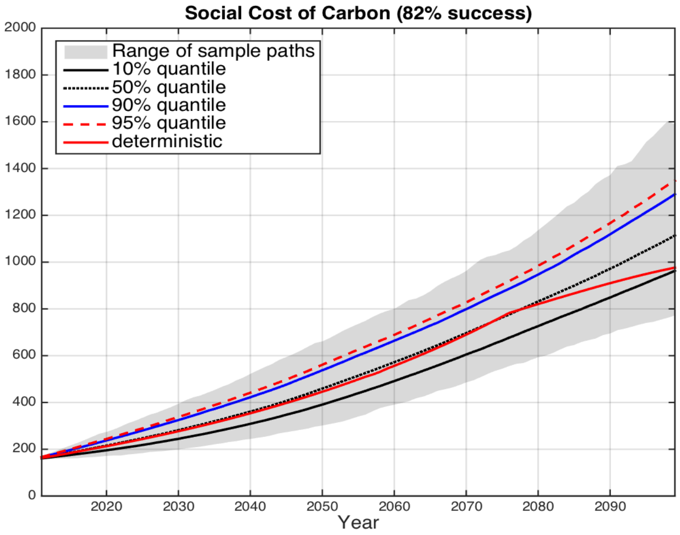
Application: Optimal Carbon Tax

- What should the tax ($ per metric ton of C) be in order to limit warming?
- Must balance concerns for economic well-being over
  - space
  - time
  - possible evolution of economic productivity

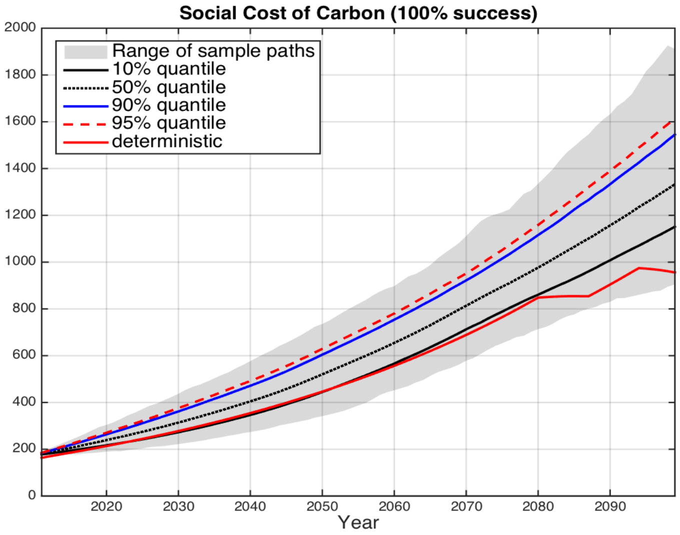
No Target


Social Cost of Carbon (no target)
2000
1800
1600
1400
1200
1000
800
600
400
200
0
Range of sample paths
10% quantile
50% quantile
90% quantile
95% quantile
deterministic
2020
2030
2040
2050
2060
2070
2080
2090
Year

Two-Degree Target with 82% Success

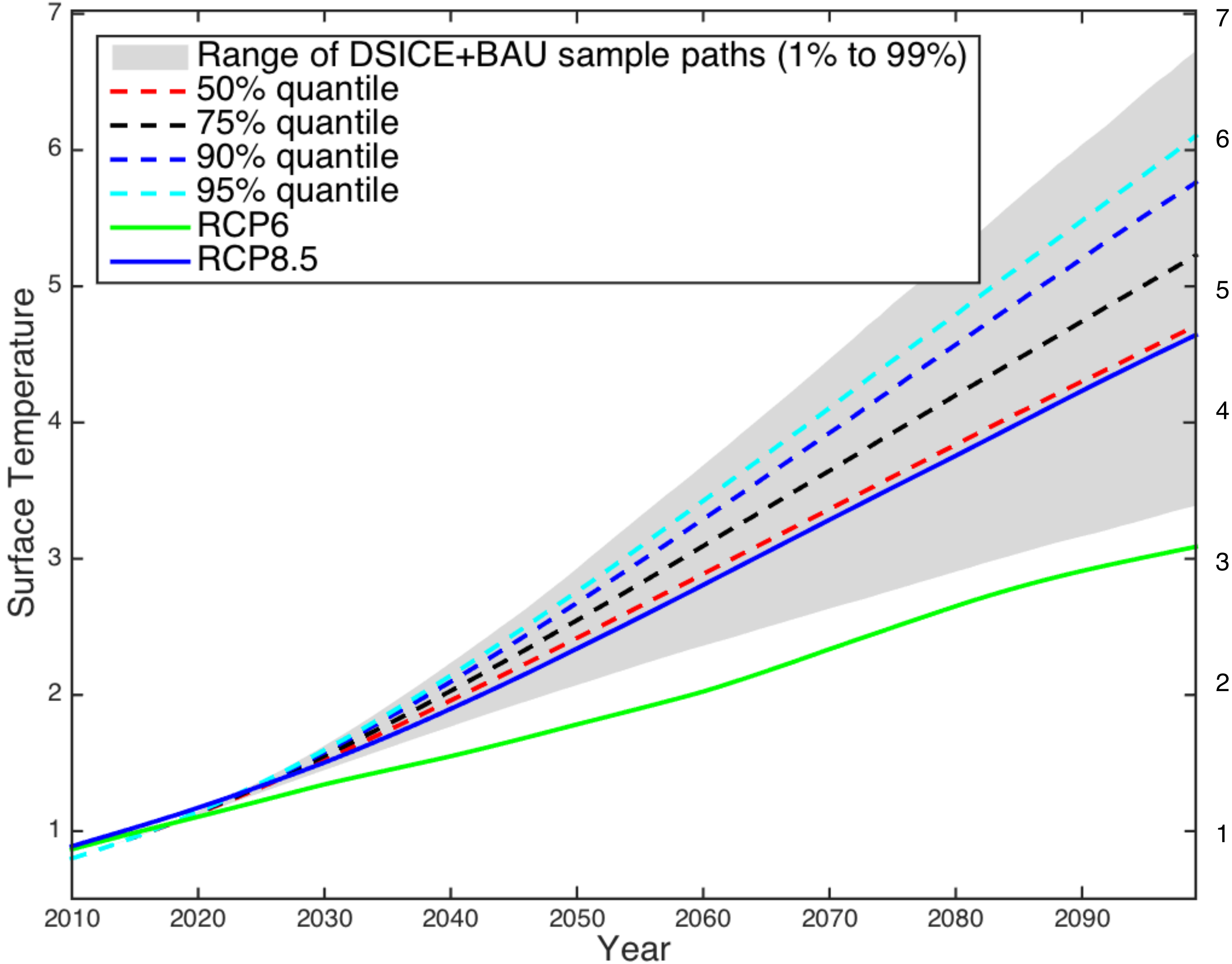


Two-Degree Target with 100% Success



Application: Range of possible warming

- Climate studies use economic models to predict what could happen if there is no serious mitigation policy.
- DSICE shows that the range is much larger when you include economic uncertainty in analysis
- The upper tail of potential temperature is of most interest
- IPCC-style analysis misses the upper tail



Range of DSICE+BAU sample paths (1% to 99%)
50% quantile
75% quantile
90% quantile
95% quantile
RCP6
RCP8.5
Surface Temperature
Year
2010
2020
2030
2040
2050
2060
2070
2080
2090
1
2
3
4
5
6
7

Work in Progress Using Blue Waters

- Spatial-DSICE
  - the polar regions have more warming
  - developing countries (most in the tropical regions) suffer more economic loss from warming
  - sea level rise has different damage in different regions
- DSICE with multiple tipping events

Publications Using Blue Waters

- Cai, Y., T.M. Lenton, and T.S. Lontzek (2016). Risk of multiple climate tipping points should trigger a rapid reduction in CO2 emissions. *Nature Climate Change* 6, 520–525.
- Cai, Y., K.L. Judd, and J. Steinbuks (2016). A nonlinear certainty equivalent approximation method for stochastic dynamic problems. *Quantitative Economics*, `http://www.qeconomics.org/ojs/forth/533/533-3.pdf`.
  - Introduce a new method that can approximately solve up to 400-dimensional dynamic stochastic problems
- Lontzek, T.S., Y. Cai, K.L. Judd, and T.M. Lenton (2015). Stochastic integrated assessment of climate tipping points calls for strict climate policy. *Nature Climate Change* 5, 441–444.
- Cai, Y., K.L. Judd, T.M. Lenton, T.S. Lontzek, and D. Narita (2015). Risk to ecosystem services could significantly affect the cost-benefit assessments of climate change policies. *Proceedings of the National Academy of Sciences*, 112(15), 4606–4611.

Working Papers Using Blue Waters

- Cai, Y., K.L. Judd, and T.S. Lontzek (2015). The social cost of carbon with economic and climate risks. Under R&R in *Journal of Political Economy*, arXiv preprint arXiv:1504.06909.
- Yeltekin, S., Y. Cai, and K.L. Judd (2015). Computing equilibria of dynamic games. Under R&R in *Operations Research*.
- Cai, Y., J. Steinbuks, J.W. Elliott, and T.W. Hertel (2014). The effect of climate and technological uncertainty in crop yields on the optimal path of global land use. The World Bank Policy Research Working Paper 7009, under R&R in *Journal of Environmental Economics and Management*.
- Cai, Y., K.L. Judd, and T.S. Lontzek (2015). Numerical dynamic programming with error control: an application to climate policy.

Impact

A White House (2014) report:

- "The cost of delaying action to stem climate change" is high
- Incorporated our paper's conclusion that high SCC can be justified without assuming the possibility of catastrophic events

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- We thank the Blue Waters Support team for their always fast and helpful responses
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Summary

- Global warming could have huge and uncertain damage
- DSICE provides a powerful tool with the Blue Waters support for policy analysis in the face of risks and uncertainty
- DSICE shows that the social cost of carbon with risks is significantly higher that the one in the deterministic model
- With the Blue Waters support, our work has made impact to academia, society and government