Optimal Carbon Policy with Business Cycle and Climate Risks

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Climate Change Policy Analysis

Question: What can and should be the policy response to rising CO2 concentrations?

We build a dynamic and stochastic integrated framework for models of climate and the economy (DSICE)

- Economic risk
  - uncertain economic growth with persistence in growth rates
  - flexible preferences that represent risk aversion (Epstein–Zin)
- Climate risk
  - damages interact with economic shocks
  - climate events are stochastic; e.g., glaciers melting, THC collapse
- Model uncertainty
  - We do not know what models for economy and climate are best
  - We do not exactly know key parameters in any specific model

Climate Change Policy Analysis

Results

- 2020 SCC (Social Cost of Carbon) and optimal carbon tax are generally higher when one includes uncertainty
  - SCC is a stochastic process similar to a random walk
  - Variance of SCC is increases substantially over time
- There is no single "discount rate" to use when valuing GHG policies
  - Discounting should be based on consumption CAPM, stochastic asset pricing kernel
  - For damages proportion to output
    - use consumption discount rate
    - treat mitigation expenses like investment
  - For damages due to tipping events
    - use safe rate
    - treat mitigation expenses like insurance
- It is possible to combine the best macro models with canonical models of the climate

Why Should Other Economists be Interested?

- Economies are complex systems
- Networks of interacting economies are even more complex
- Economic modeling typically ignores this
  - Economists analyze simple stylized models of pieces of economies
  - Economists love tractable models requiring little math and low-level computational tools (even Excel)
  - Economists ignore uncertainty in our knowledge of key parameters
- My collaborators and I are trying to change that
  - Create robust and general tools that can use state-of-the art numerical methods on modern computer architectures
  - Economists must recognize model uncertainty
  - Climate change policy is the application; analysis of any other policy can use the same tools.
  - Many non-economists would like to participate in this effort

I: Current State of Integrated Assessment Modeling

IAMs are simple, unreliable

Economic models are from 30+ years ago

- Many have "myopic expectations", no foresight
- Many have a single state variable
- None have economic and climate uncertainty, multiple sectors, multiple countries, etc.

Climate science models use lastest algorithms and hardware; economists use laptops

Economists' numerical "methods" are flawed

- IWG 2010 report used a simple model to get estimate of SCC
- We showed that their SCC numbers were 20-40% too high because of "time-traveling CO2" (Lesson: the code can be different from equations in documents)
- One IAM did post their code; a friend of mine tried to run it and the code failed to converge

IAM Literature is not Open Science

Example 1

- Request: "Could you send me the system of equations you solved in the CGE modeling in the paper?"
- Response: "Modern CGE analysis uses software that doesn't require one to explicitly write down all equations"

Example 2

- I asked author for economic details used in his paper; he refused.
- I reported this to the journal's editors, hoping they would enforce transparency rules
- Response from one editor: "I personally have concluded that you are really trying to rip off people's hard earned intellectual property"

The lack of openness is particularly bad in the case of US-based projects. Europeans have better practices.

My Views: See CIM-EARTH & RDCEP

These efforts contained up my view of where IAMs, and economic policy analysis in general, should go

- CIM-EARTH Framework (**C**ommunity **I**ntegrated **M**odel for **E**nergy and **R**esource **T**rajectories for **H**umankind)
  - "An environment for economic modeling and simulation"
  - Goal: "provide open source ... tools that incorporate the most modern computational methods, to increase ... quality and transparency of integrated assessment modeling"
    - "Framework", not just a single model
    - Incorporate uncertainties and risks
  - Funded by MacArthur Foundation
- **R**obust **D**ecision Making on **C**limate and **E**nergy **P**olicy (RDCEP)
  - Expansion of CIM-EARTH: Added PIs Hansen and Munson
  - NSF/SBE funded – $6M (2010-2015); renewed for $2.6M (2015-2020)
- Dynamic scoring was a special case of the project goal.
- The goals were
  - Build modern computational tools for economic modelling
  - Make it easy for economists to use them for their own models
  - Analogy with past: economists use to write their own statistical code, but then came TSP, RATS, etc.

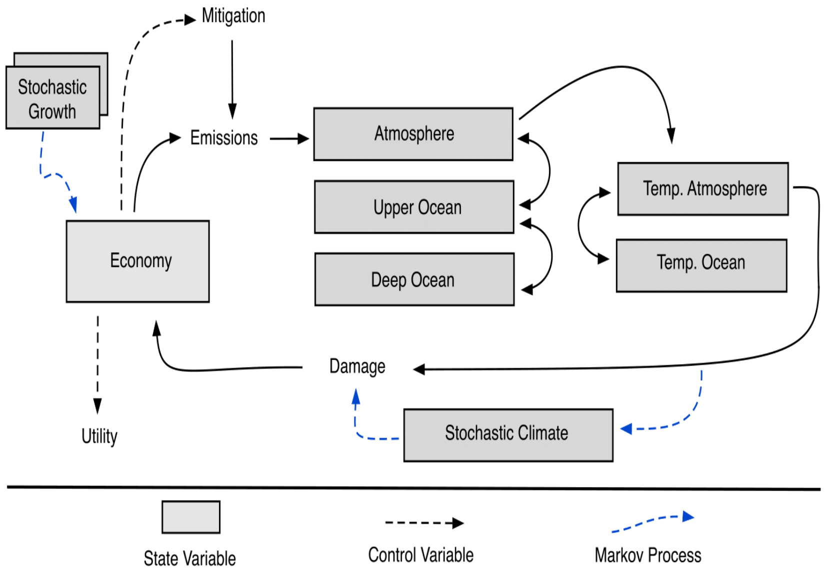
Validation, Verification, and Uncertainty Quantification (VVUQ)

- We do not know actual values of parameters
  - Standard errors in estimation
  - Disagreements over data, estimation procedures, models
- Applied physicists and engineers have the same problems
  - US nuclear weapons stockpile stewardship
  - Engineering design
  - Motivation for supercomputing development
- VVUQ methods developed in engineering and applied physics areas
  - Validation: Is the model true?
  - Verification: Is the code solving the model?
  - Uncertainty Quantification: How much do the results depend on parameters?

II: The DSICE Framework

We build on Nordhaus DICE model
It is the most widely used model
A useful benchmark which allows us to determine how adding uncertainty and risk affects results from well-known analyses

Dynamic Stochastic Integration of Climate and Economy



Climate System for Temperature and GHG – DICE

- Carbon concentration: $\mathbf{M} = (M_{\mathrm{AT}}, M_{\mathrm{UO}}, M_{\mathrm{LO}})^\top$

$$\mathbf{M}_{t+1} = \Phi_M \mathbf{M}_t + (E_t, 0, 0)^\top$$

  - E_t: emissions from biological and economic activity
  - Φ_M: transition matrix of carbon cycle
- Temperature: $\mathbf{T} = (T_{\mathrm{AT}}, T_{\mathrm{OC}})^\top$

$$\mathbf{T}_{t+1} = \Phi_T \mathbf{T}_t + \left(\xi_1 \mathcal{F}_t \left(M_{\mathrm{AT},t}\right), 0\right)^\top$$

  - $\mathcal{F}_t$: radiative forcing
  - Φ_T: transition matrix of temperature system

Climate Tipping State – Innovation of DSICE

- Climate Tipping State: J_t
  - irreversible damage in output
- Examples of climate tipping elements
  - West Antarctic ice sheet melting
  - Greenland ice sheet melting
  - collapse of Atlantic themohaline circulation
- Net-of-damage output factor: $\Omega\left(T_{\mathrm{AT},t}, J_t\right)$

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

Economic System – DICE plus LRR

- Production:

$$f(K_t, L_t, \widetilde{A}_t) = \widetilde{A}_t K_t^{\alpha} L_t^{1-\alpha}$$

  - K_t: capital; L_t: world population
  - A_t: deterministic trend
  - ζ_t: productivity shock with long-run risk

$$\log(\zeta_{t+1}) = \log(\zeta_t) + \chi_t + \varrho\omega_{\zeta,t}$$

$$\chi_{t+1} = r\chi_t + \varsigma\omega_{\chi,t}$$

  - $\widetilde{A}_t$: stochastic productivity, $\widetilde{A}_t \equiv \zeta_t A_t$

- Output:

$$Y_t = \Omega\left(T_{\mathrm{AT},t}, J_t\right) f\left(K_t, L_t, \widetilde{A}_t\right)$$

- Next-year capital with investment I_t:

$$K_{t+1} = (1 - \delta)K_t + I_t$$

- Market clearing condition:

$$Y_t = I_t + C_t + \Psi_t$$

  - C_t: consumption
  - Ψ_t: mitigation expenditure depending on output and emission control rate μ_t

Carbon Emission and Abatement – DICE

- Emissions depend on nature, economic output, and emission control

$$E_t = E_{\mathrm{Ind},t} + E_{\mathrm{Land},t}$$

$$E_{\mathrm{Ind},t} = \sigma_t(1-\mu_t)f\left(K_t, L_t, \widetilde{A}_t\right)$$

  - σ_t: carbon intensity of output at time t, representing technical change
  - μ_t: emission control at time t
- Cost of Mitigation

$$\Psi_t = \theta_{1,t}\mu_t^{\theta_2} Y_t$$

  - $\theta_{1,t}$: efficiency of mitigation technology
  - θ_2: exceeds unity, representing convexity in cost

III: Economic Policy Evaluation

Epstein–Zin Preferences

Preferences: recursive utility function

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

- ψ: inter-temporal elasticity of substitution (IES): desire for consumption smoothing
- γ: risk aversion parameter
- $u(C_t, L_t)$: annual world utility function

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

DICE (and most work) assumes either $\gamma = 1/\psi$, or no uncertainty (in which case, γ is irrelevant)

Bellman Equation

- Bellman equation for the dynamic stochastic problem:

$$
\begin{aligned}
V_t(\mathbf{S}) = \max_{C,\mu} \quad & u_t(C, L_t) + \beta \left[\mathbb{E}_t \left\{ \left(V_{t+1}\left(\mathbf{S}^+\right) \right)^{\frac{1-\gamma}{1-\frac{1}{\psi}}} \right\} \right]^{\frac{1-\frac{1}{\psi}}{1-\gamma}}, \\
\text{s.t.} \quad & K^+ = (1-\delta)K + Y_t - C - \Psi_t, \\
& \mathbf{M}^+ = \Phi_M \mathbf{M} + (E_t, 0, 0)^\top, \\
& \mathbf{T}^+ = \Phi_T \mathbf{T} + \left(\xi_1 \mathcal{F}_t\left(M_{\mathrm{AT}}\right), 0\right)^\top, \\
& \zeta^+ = g_\zeta(\zeta, \chi, \omega_\zeta), \\
& \chi^+ = g_\chi(\chi, \omega_\chi), \\
& J^+ = g_J(J, \mathbf{T}, \omega_J)
\end{aligned}
$$

- Nine-dimensional state vector: $\mathbf{S} = (K, \mathbf{M}, \mathbf{T}, \zeta, \chi, J)$
- Two control variables: C, μ
- 600-year horizon; annual time steps; terminal value function

Epstein-Zin Preference Parameters

We recognize the wide range of beliefs about IES and RA

	IES	RA
Bansal & Yaron (2004)	1.5	10
Bansal and Ochoa (2011)	1.5	10
Vissing-Jørgensen and Attanasio (2003)	1.23	[5, 17]
Barro (2009)	2	4
Pindyck and Wang (2013)	1.5	3.066
Constantinides Ghosh (2011)	1.41	9.43 (2.94)
Schorfheide et al. (2014)	1.6	10
Epstein et al. (2014)	1.5	7.5
Belleer and Campbell (2011)	1.5	10
Gruber (2013)	2 (0.8)	0.5
Jensen and Traeger (2014)	1.5	10

␣

Note: DSICE is constructed to handle any recursive preference specification – robust optimization, habits, Campbell-Cochrane, ambiguity – because it is written to solve difference equations in Banach spaces

Calibration for stochastic productivity

- Choose productivity process so that the implied consumption process matches empirical data on the moments of per-capita consumption growth rates

	Observed Data	DSICE		
Variable	Estimate	Median	5%	95%
$\mathbb{E}(g_c)$	0.019	0.013	0.002	0.025
$\sigma(g_c)$	0.022	0.023	0.019	0.028
order-1 autocorrelation	0.48	0.43	0.19	0.64
order-2 autocorrelation	0.17	0.37	0.13	0.59
autoregression coef Λ	0.46	0.48	0.24	0.68
autoregression sd $\sigma(\epsilon)$	0.0179	0.0203	0.0177	0.023

Computational Method

- DSICE:
  - six-dimensional continuous state variables $\mathbf{x} \equiv (K, \mathbf{M}, \mathbf{T})$
  - three-dimensional discrete state variables $\theta \equiv (\zeta, \chi, J)$ with $91 \times 19 \times 16$ time-dependent values
- Solve backwards in time
  - A value function $V_t(\mathbf{S})$ represents economic system at time t as a function of $\mathbf{S} = (\mathbf{x}, \theta)$
  - Terminal condition: $V_T(\mathbf{S})$ known for time T
  - Decisions today depend on expectations of what will be done tomorrow
  - Backward induction:

$$V_t = \mathfrak{F}_t V_{t+1}$$

Numerical Dynamic Programming

- *Initialization.*
  - *Choose the approximation nodes,* $\mathbb{X}_t = \{x_{i,t} : 1 \le i \le m_t\}$ *for every* $t < \mathcal{T}$*,*
  - *Choose a functional form for* $\hat{V}(x, \theta; \mathbf{b})$*, where* $\theta \in \Theta_t$*.*
  - *Let* $\hat{V}(x, \theta; \mathbf{b}_{\mathcal{T}}) \equiv V_{\mathcal{T}}(x, \theta)$*.*
- *For* $t = \mathcal{T} - 1, \mathcal{T} - 2, \ldots, 0$*, iterate through steps 1 and 2.*
- *Step* ***1.*** *Maximization step (in parallel). Compute*

$$\begin{aligned} v_{i,j} = \max_{a \in \mathcal{D}(x_i, \theta_j, t)} \quad & u_t(x_i, a) + \beta \mathcal{H}_t \left(\hat{V} \left(x^+, \theta_j^+; \mathbf{b}_{t+1} \right) \right) \\ \text{s.t.} \quad & x^+ = F(x_i, \theta_j, a), \\ & \theta_j^+ = G(x_i, \theta_j, \omega), \end{aligned}$$

  for each $\theta_j \in \Theta_t$*,* $x_i \in \mathbb{X}_t$*,* $1 \le i \le m_t$*.*
- *Step* ***2.*** *Fitting step. Using an appropriate approximation method, compute the* $\mathbf{b}_t$ *such that* $\hat{V}(x, \theta_j; \mathbf{b}_t)$ *approximates* $(x_i, v_{i,j})$ *data for each* $\theta_j \in \Theta_t$*.*

Computational Challenges and Parallelization

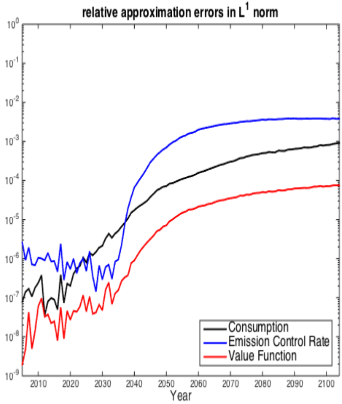
- Computational Challenges
  - 100:1 ratio in maximum to minimum capital stock over next 200 years
  - substantial range in climate state variables
  - value function is strongly nonlinear
- Size of computation
  - Approximation: 1.5 billion approximation nodes
  - Optimization: 372 billion optimization problems
- Massive Parallelization in DSICE

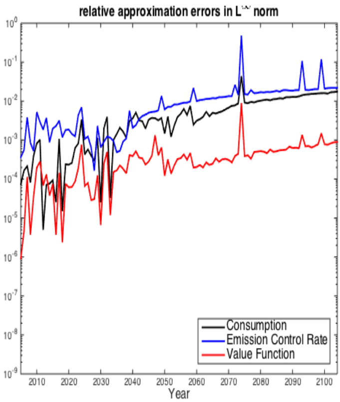
	Parallelization	No Parallelization
Number of cores	84K	1
Running time	8 hours	77 years

- Speed can be improved by 10-100x

Verification of Results

Standard practice: Trust numerical results, don't verify
We follow VVUQ: At each iteration, we compute approximation errors with an "out of sample test"





IV: Results

Social Cost of Carbon–Productivity Risk

SCC is also the optimal carbon tax
Nordhaus model is upper left corner – 37
Adding LRR and using "more plausible" parameter values implies substantially larger SCC
Our results don't just "add noise" to DICE results

ψ	Deterministic Growth Case	γ 2	6	10	20
0.5	37	39	52	61	69
0.75	54	55	58	60	62
1.25	82	77	65	61	56
1.5	94	85	68	61	55
2.0	111	97	71	62	54

Table: 2010 social cost of carbon ($ per ton of carbon) under stochastic growth

Discount Rate for Damages

- Discount rate, ρ, of marginal expected damages, $dSSC_0$, per marginal unit of emission, dD_t, is defined by:

$$d\mathrm{SCC}_0 = \sum_{t=0}^{T} (1+\rho)^{-t} dD_t$$

- Damages from risky climate events should be discounted less than damages from damages proportional to output
- Paying carbon tax to prevent tipping is like paying insurance
- Consumption CAPM
- Conclusion: There is no one discount rate
- Future work: incorporate multiple sectors with differing income elasticity of demand and compute sector-specific discounting of sector-specific damages

Damages:	Tipping (DSICE)	Output (DICE)
Discount rate:	0.5%	3.8%

Uncertainty Quantification

Uncertainty Quantification versus Economics

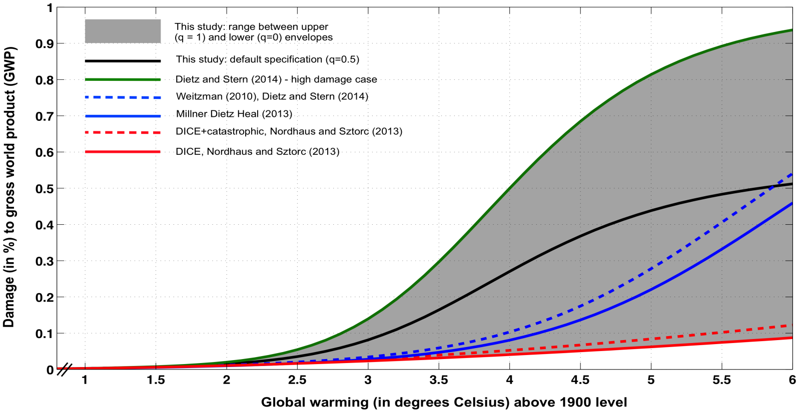
- Dominant methodology in economics is
  - examine empirical literature
  - choose the "best" value for each parameter
  - solve model for that case *only*
  - ignore parameter sensitivity
- Most journals accept this; some demand this

How much do we know?

- Pindyck: "[IAMs] create a perception of knowledge ... that is illusory"
- I agree; in fact, this is true of most economic analyses
- My response: use Uncertainty Quantification
  - Specify range of plausible values for a parameter
  - Display how results differ across parameter values
  - Display how parameters interact in producing results

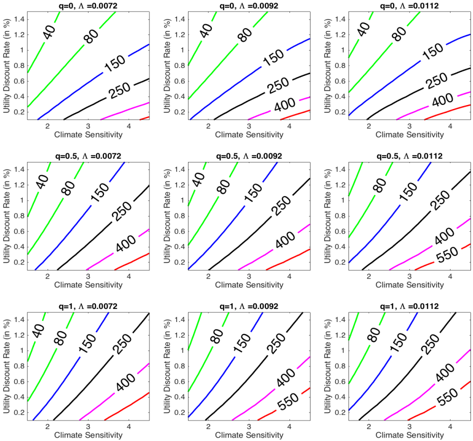
Damage and Growth Uncertainty

- We do not know the mean growth rate Λ: let
- People have different opinions on damage as function of temperature



Four-D Uncertainty Quantification with Macro Risk

- Four parameters: damage, mean growth rate, utility discount rate, climate sensitivity



Lessons from our 4D UQ

Damage function and trend growth rate don't matter much
Climate sensitivity is important – a task for climate modelers
Utility discount rate is important– a task for economists

- Nordhaus approach is internally coherent – planner uses actors' discount rates
- Stern approach is internally incoherent – the planner uses a low discount rate
  - BUT ignores the actors discount rates (or, assuming that moral suasion will change it)
  - If Stern recognized difference in planner and actors' discounting, he would get different results
    - high discounters save less, implying less output and emissions in the future
    - if planner wants to impose low discounting on everything, then he would have to subsidize capital formation

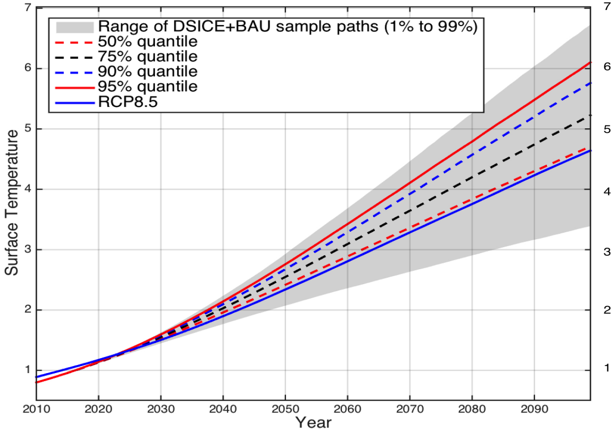
Bayesian learning about climate sensitivity

Climate sensitivity is uncertain, but of critical importance
Policy should incorporate uncertainty about climate sensitivity
First papers on Bayesian made nonsense assumptions that an uncertain parameter could be expressed as being drawn from a Gaussian random variable – physics tells us that the support is not infinite
We have incorporated this into DSICE in a manner which allowed us to use basic Kalman filtering but kept all random variables bounded.
Preliminary results say that current SCC is not much affected.

Scenarios

IPCC presents consensus scenarios for emissions and temperature impacts
RCP8.5 represents the "Business as usual" scenario – that is, little if any policy intervention
IPCC models ignore uncertainty in economic growth
DSICE reexamines the scenarios but adding LRR

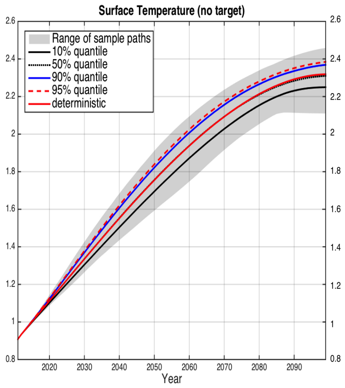
Scenarios: DSICE vs. RCP8.5

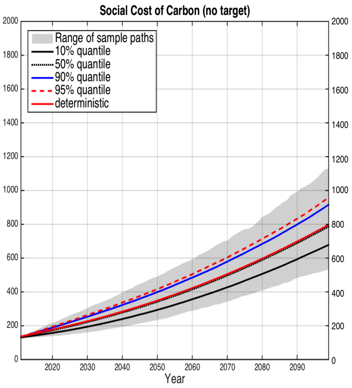


Two-Degree Target

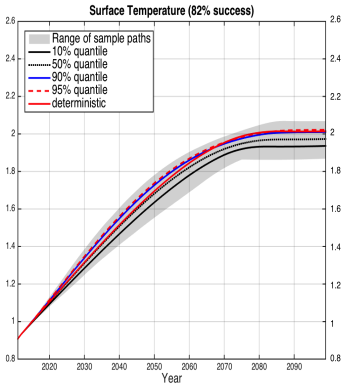
Many argue for a two-degree target
Researchers use models like DICE
Uncertainty ignored
DSICE computes two-degree target policies when policymakers recognize economic fluctuations

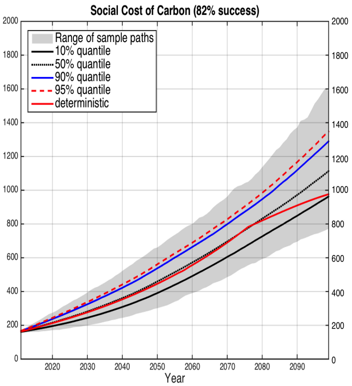
Temperature and no target



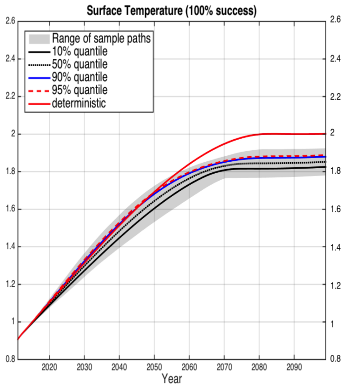


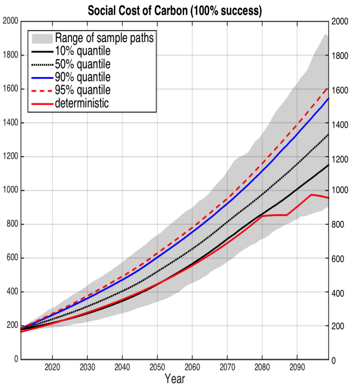
Temperature and 82% successful target





Temperature and 100% successful target





Conclusions: IAMs (and economics!) can be far more realistic

DSICE shows that

- It is possible to add both climate and economic risk to climate change policy and impact analyses
- It is possible to add sector and/or international disaggregation
- It is possible to incorporate economic uncertainty into dynamic scoring of tax proposals

Changes are necessary to implement the potential

- Economists need to think about leaving their laptops, Excel, Matlab, EViews, and other second millenium tools
- Economists need to collaborate with computational scientists – like everyone else is!