# Climate Jumps, Fat Tails and Non-linear Carbon Uptake

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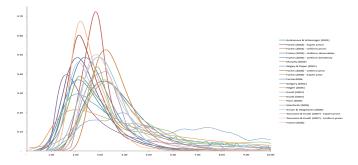
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Introduction	Deterministic version of model	Empirical Evidence	Implications
	Motivation		

- Recent interest in "fat tails" in distribution over temperatures
- one motivation: survey of published scientific work (Weitzman)
- subjective appraisals of key parameters, unclear these are independent

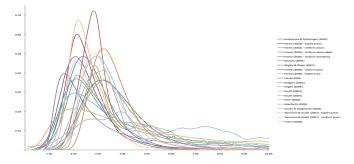
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can we say something using current climate data?

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Current economic literature typically assumes:

- damages based on carbon stock not temperature
- exponential decay of carbon stock (linear uptake)
- stylized [quadratic] representation of link between climate and damages
- deterministic or simple stochastic representation

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#### each of these assumptions is suspect

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Combined, these assumptions imply downward bias in social cost of carbon

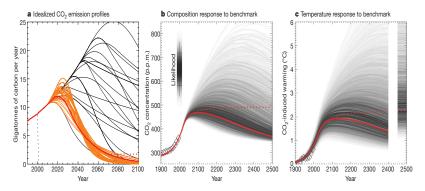
- > relating damages to carbon stocks only sensible if direct relation
- ► climate scientists recently observed some carbon (≈ 20%) stays in atmosphere virtually indefinitely ⇒ concave (non linear) uptake
- quadratic damages  $\Rightarrow$  focus on mean & variance
  - ▷ higher-order moments not relevant

Empirical Evidence

Implications

### carbon stock vs. temperature

- temperature changes linked to carbon stock
- carbon stock changes linked to emissions
- suggests 2<sup>nd</sup> order relation between temperature and accumulated emissions



### carbon stock dynamics

- relating damages to carbon stocks only sensible if direct relation
- Physicists typically assume "three box model"
- 3 state variables, related to different time frames
  - ▷ C<sub>3</sub> reflects 'long term equilibrium ' stock
  - $\triangleright$  C<sub>2</sub> reflects medium term variations around C<sub>3</sub>
  - $\triangleright$  C<sub>1</sub> represents shorter term variations
- ▶ importantly, gases depreciate from C<sub>3</sub> so slowly as to be negligible
- implies some carbon ( $\approx$  20%) stays in atmosphere virtually indefinitely
- temperature changes linked to carbon stock
- carbon stock changes linked to emissions
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Thr	ee box model		

$$\begin{array}{rcl} \dot{C}_2 &=& a_0 E - b_2 C_2 \\ \dot{C}_3 &=& b_3 C_3 \end{array}$$

- concave relation in  $\dot{C}$ ... approximate with quadratic decay?
- analogous to the logistic growth component in modern fisheries models

$$\dot{C} = a_1 E - U(C) = a_1 E - C(b_0 - b_1 C)$$

- *U*(*C*) is "uptake"
- interpretation of coefficient on  $C^2$ : "carrying capacity"
- maximum ability of sinks to uptake carbon
  - ▷ oceans
  - ▷ forest stocks

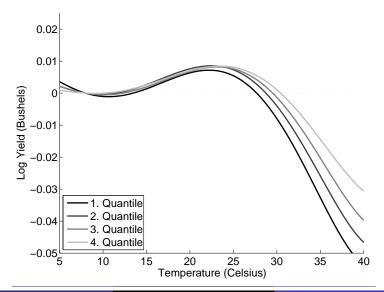
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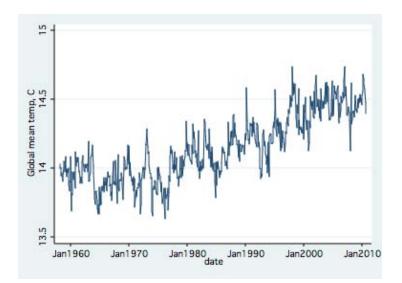
### Linear marginal damage?



Empirical Evidence

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## stochastic temperatures?



Empirical Evidence

### Control model

- ► PDV of payoffs at time  $t = [\pi(E) D(T)]e^{-\rho t}$ ,
  - $\triangleright$   $\pi$ : net benefits from unabated emissions [GDP net of seq'n, abatem't costs]
  - ▷ D: temperature-related damages
  - ρ: discount rate

• 
$$\pi'(E) > 0$$
 for small  $E, \pi''(E) < 0$ 

► iso-elastic form  $\pi(E) = AE^{\theta+1}$  has received significant attention

> elasticity 
$$\theta = \frac{\pi'(E)}{E\pi''(E)}$$

define Current-value Hamiltonian

$$\mathbf{H} = \pi(E) - D(T) + \mu[a_1E - C(b_0 - b_1C)] + \nu[\alpha \ln(\frac{C}{C_0}) - \beta T]$$

 $\triangleright$   $\mu$  is co-state variable (shadow value) associated with state variable *C* 

 $\triangleright$  v is co-state variable (shadow value) associated with state variable T

Empirical Evidence

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### Maximum principle

Necessary conditions for solution:

$$0 = \pi'(E^*) + a_1\mu$$
  

$$\dot{\mu} = \rho\mu - \partial \mathbf{H} / \partial C = (\rho + b_0)\mu - 2b_1C\mu - \frac{\alpha}{C}\nu$$
  

$$\dot{\nu} = \rho\nu - \partial \mathbf{H} / \partial T = (\rho + \beta)\nu + D'(T)$$

#### Time-differentiate equation first condition to obtain

$$0 = \pi''(E^*)\dot{E}^* + a_1\dot{\mu} = \pi''(E^*)\dot{E}^* + a_1[(\rho + b_0)\mu - 2b_1C\mu - \frac{\alpha}{C}\nu], \text{ or }$$

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$$\dot{E}^* = (\rho + b_0 - 2b_1C)\frac{\pi'(E^*)}{\pi''(E^*)} - \frac{a_1\alpha}{\pi''(E^*)C}\nu \leftrightarrow$$

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$$\dot{E}^* = (\rho + b_0 - 2b_1C)\frac{\pi'(E^*)}{\pi''(E^*)} - \frac{a_1\alpha}{\pi''(E^*)C}\nu \leftrightarrow$$
$$\frac{\dot{E}^*}{E^*} = U'(C)\theta - \frac{a_1}{E^*\pi''(E^*)}\frac{\alpha\nu}{C}$$

Empirical Evidence

## Simpler model

Consider 'conventional' assumption  $T(t) = \phi(C(t))$ 

- damages are then  $d(C) \equiv D(\phi(C))$
- state equation on T becomes irrelevant to the dynamic optimization problem
- optimality condition for E is as above
- equation of motion for the (lone remaining) co-state variable is

$$\dot{\mu} = (\rho + b_0)\mu - 2b_1C\mu + d'(C)$$

differential equation governing the path of optimal emissions becomes

$$rac{\dot{E}}{E} = U'(C) heta - rac{a_1}{E \pi''(E)} d'(C)$$

• replace the component  $\frac{\alpha v}{C}$  with  $d'(C), E^*$  with E



- Temperature: monthly global mean temperature, Centigrade
- Carbon stocks: monthly readings at Mauna Loa, ppm
- March 1958 August 2011
- Global emissions: annual observations, 1958 2007
  - 'conventional' emissions
  - emissions related to land use change
- data sources: NOAA, CDIAC, EIA

### Stochastic temperatures, cont.

- now represent temperature state equation as stochastic
- how to model? GBM? jump process?
- ► regress  $ln(C_{t-1})$ ,  $T_{t-1}$  on  $T_t T_{t-1}$  (=  $\Delta T$ )
  - $\triangleright$  alternative 1: if C drives T then  $\Delta C$  drives  $\Delta T$
  - alternative 2: perhaps outliers
  - ▷ alternative 3: endogeneity in carbon?

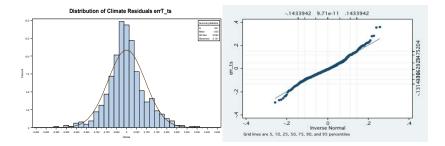
variable	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
$T_{t-1}$	1634**	1639**	0403**	1587**	1647**
	(.0217)	(.0219)	(.0114)	(.0196)	(.0223)
$\ln(C_t)$	.5167**	.5167**	_	.5058**	.5361**
	(.0787)	(.0789)	_	(.0711)	(.0834)
$C_t - C_{t-1}$		.0029	.0308*		_
	_	(.0167)	(.0135)	_	
$D_{out0}$	_			0957**	_
	_		_	(.0019)	_
$D_{out1}$	_			.1075**	_
			_	(.0019)	
constant	9647**	9560	.7767**	9699**	-1.0943**
	(.3368)	(.3394)	(.2198)	(.3038)	(.3604)
R-squared	.082	.082	.020	.256	.082

Dependent variable:  $T_t - T_{t-1}$ number of observations = 640

Empirical Evidence

Implications

### Normally distributed residuals?



kurtosis = 4.285

probability this does not differ from 3 (Normal) < .01</li>

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	~~~?		

- Jumps?
- allow for probability of jump =  $\lambda$
- distribution of jump sizes
- mean θ, variance δ<sup>2</sup>
- means and variance of residuals when no jump obtains:  $\mu, \sigma^2$
- similar qualitative results to kurtosis test

coefficient	estimate	std. err.	restricted estimate	restricted std.err.
μ	1209	.043	0001	.040
σ	.4196**	.049	.9206**	.026
λ	.5816	.069	_	_
θ	.2076*	.089	_	_
δ	1.0661**	.060	_	_

Chi-squared test statistic = 54.87 p-value < .0001 \*: significant at 5% level \*\*: significant at 1% level

### **Carbon Decay**

- annual data on forest stocks 1990-2008
- use land use data to predict forest stocks going back to 1958
  - $\triangleright$  use this synthetic data to create a proxy *D* for deforestation
  - ▷ D represented relative to 1958 (% of land deforested)
- use changes in CO2 stock, total emissions to construct variable representing 'uptake'
- regress uptake on C, C<sup>2</sup> and perhaps interactions with forest stocks
   H<sub>0</sub>: coefficients on C<sup>2</sup> are statistically unimportant

Empirical Evidence

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### Uptake results

Regression results: carbon uptake analysis

variable	coefficient	std. err.	t-stat
С	1.2460	.4369	2.85
$C^2$	00851	.00370	2.30
FC	-1.0483	.4953	2.12
$FC^2$	.00314	.00146	2.16
constant	536.95	290.24	1.85

 $R^2$  = .803 Durbin-Watson stat = 1.909 F-stat on  $H_0$ : 5.465 (1% critical value = 5.149)

Empirical Evidence

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## Theoretical considerations

DP approach: solve for V(C,T) using Fundamental eq'n of optimality

Deterministic modeling approach:

$$\max_{x_t} \left\{ \pi_t e^{-rt} + \dot{C} \frac{\partial V}{\partial C} + \dot{T} \frac{\partial V}{\partial T} \right\} = \rho V.$$

Stochastic variant:

$$\max_{x_t} \left\{ \pi_t e^{-rt} + \dot{C} \frac{\partial V}{\partial C} + \frac{1}{dt} E \left[ dT \right] \frac{\partial V}{\partial T} \right\} = \rho V.$$

Expand Ito operator:

$$\frac{1}{dt}E[dT] = \underbrace{\alpha ln(C/C_0) - \beta T}_{\text{deterministic ingredients}} + \underbrace{\chi(\mu, \sigma^2, \lambda, \theta, \delta)}_{\text{stochastic ingredients}}$$

## Concluding thoughts

- Important to shift focus from carbon stock to temperature
  - leads to more complicated, subtler, effects
- some evidence of relatively fat tails in residuals associated with temperature changes
  - > suggests fatter-tailed distribution than Brownian motion
  - ▷ possible role for unanticipated rapid changes (jumps)
- evidence of non-linear decay in carbon stocks
  - ▷ important in both ocean and forest sinks
  - ▷ forest sinks absorb less rapidly, non-linear effect enters less rapidly