Modeling Uncertainty in Climate Change:
A Multi-Model Comparison

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Modeling Uncertainty Project

A systematic study of uncertainty in a set of IAMs:

- Determine the differences among models in the uncertainties.

- Provide benchmark pdfs for major parameters.

- Highlight areas where reducing uncertainties would have a high payoff.

Related Literature

- MIPs that have explored similar topics (e.g RoSE MIP: 3 IAMs, Pop, TFP, Resources)

- Meta analysis of IAM scenarios (Repetto, Tavoni and Tol, Drouet et. al)

- Multi model global sensitivity analysis on energy technologies (Bosetti et al. 2014: GCAM, WITCH, MARKAL US)

Participating Models

Six well-known IAMs for their participation:

- MIT IGSM (John Reilly)

- JGCRI GCAM (Haewon McJeon & Jae Edmonds)

- EPRI MERGE (Geoff Blanford)

- Yale DICE (William Nordhaus)

- Tol/Antoff FUND (David Anthoff)

- FEEM WITCH (Valentina Bosetti & Giacomo Marangoni)

    – In feasibility study: PHOENIX and PAGE

Three Uncertain Input Variables

Modeling teams first ran a set of "feasibility runs":

– An emissions pulse, a pulse of global TFP, increase of global TFP growth, increased climate sensitivity, increased population, and a carbon tax.

Decision to focus on three that all models could handle:

- TFP growth
- Population growth
- Climate sensitivity (ECS)

For all three, a baseline and carbon tax run

Output (Results) Variables

We choose output variables that capture key features relevant to climate change that (most) models output:

- Consumption
- Emissions
- CO_2 concentrations
- Global mean surface temperature
- Damages/Social cost of carbon (subset of models)

We calculate an output pdf for each for each model

Methodology: Two-track Procedure

<u>Track 1</u>. Perform calibration runs and estimate a surface response function (SRF) for each model

<u>Track 2</u>. Develop pdfs of uncertain variables

Schematic Outline of Two-Track Method

Assume y = output variables; u = input parameters; H^m = model mapping for model m.

Steps:

1. Choose uncertain variables: ECS, TFP, Pop.
2. Model calibration runs: $y = H^m(u)$. Lattice Diagrams.
3. Fit "Surface response function," $y = R^m(u)$.
4. Derive pdfs for u variables, f(u).
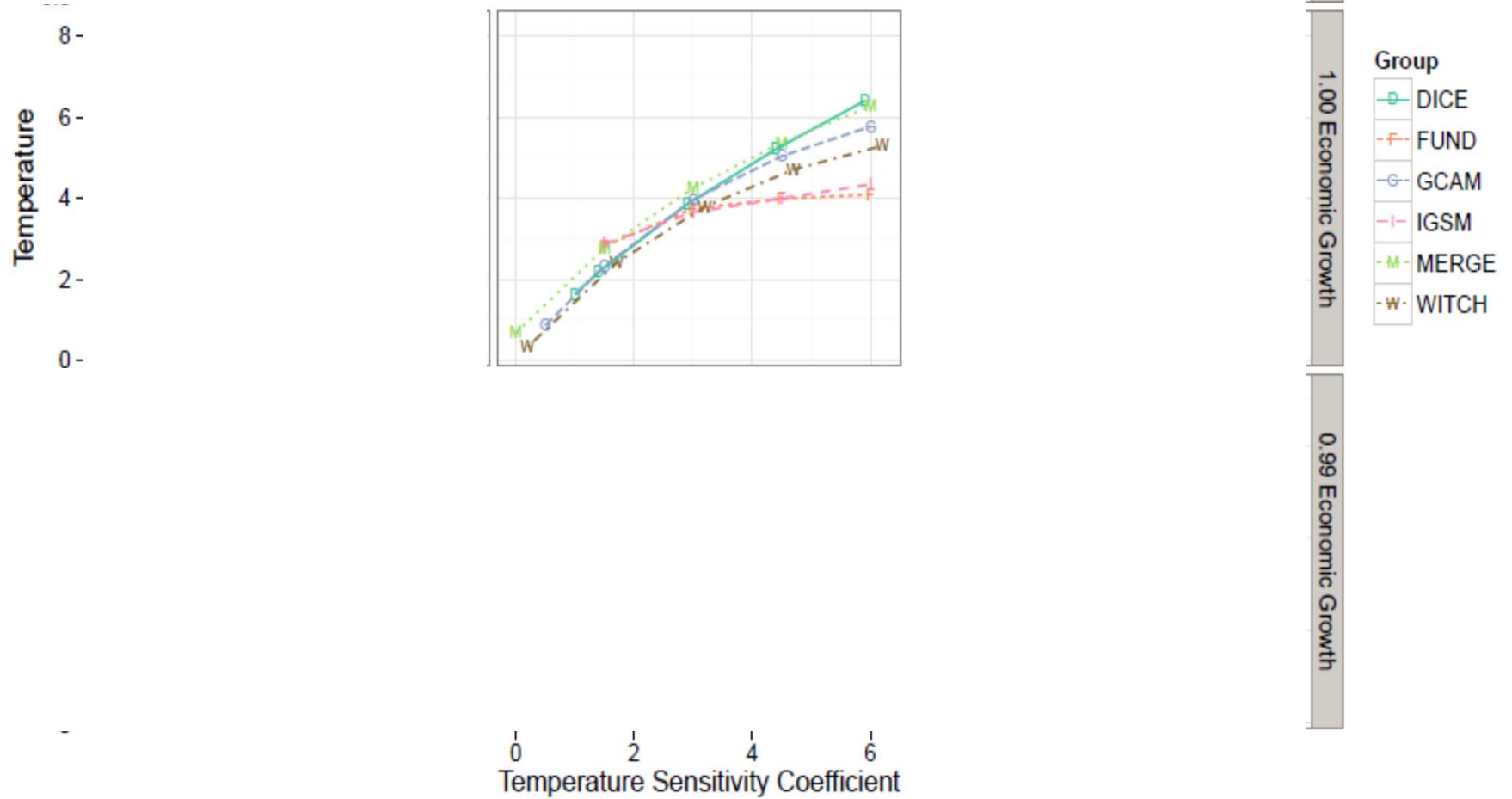5. Perform Monte Carlo analysis for distribution of output variables, obtaining the pdf $g^m(y)$ for output variables.

$$g^m(y) = \int R^m(u) f(u) du$$

Track I: Calibration Runs and SRFs

- Calibration model runs on a 5 x 5 x 5 grid
  - The middle point of the grid is the modeler's baseline
  - The other points add and subtract from the baseline
  - Visualize results with a "lattice diagram"

- Run a baseline and carbon tax case for each grid

- Estimate the surface response functions
  - Find linear quadratic with interactions works well.

Base, Temperature, 2100

1.00 Population Growth

1.01 Economic Growth

1.00 Economic Growth

0.99 Economic Growth

Temperature

Temperature Sensitivity Coefficient

Group
- DICE
- FUND
- GCAM
- IGSM
- MERGE
- WITCH

SRF (temperature and log output)

Temperature change, 2100								
	ECS	ECS	TFP	TFP	Pop	Pop	1-R2	1-R2
	L	LQI	L	LQI	L	LQI	L	LQI
DICE	0.9801	1.0403	62.96	60.14	70.40	67.31	0.0239	0.0007
FUND	0.2888	0.4004	58.80	59.83	60.03	61.09	0.0878	0.0053
GCAM	0.9173	0.9744	53.78	52.60	135.05	132.11	0.0788	0.0042
IGSM	0.3296	0.3951	67.28	66.36	48.99	48.18	0.0256	0.0028
MERGE	0.9359	0.9359	57.35	57.35	56.99	56.99	0.0505	0.0039
WITCH	0.8190	0.7883	5.73	28.03	9.69	47.38	0.0911	0.0090

log Output, 2100								
	ECS	ECS	TFP	TFP	Pop	Pop	1-R2	1-R2
	L	LQI	L	LQI	L	LQI	L	LQI
DICE	-0.0411	-0.0371	81.16	81.51	84.95	85.34	0.0018	0.0001
FUND	-0.0016	-0.0023	88.06	88.05	89.72	89.71	0.0000	0.0000
GCAM	0.0000	0.0000	86.74	86.74	88.96	88.96	0.0000	0.0000
IGSM	0.0000	0.0000	89.27	89.27	66.61	66.61	0.0035	0.0002
MERGE	0.0000	0.0000	89.21	89.21	78.44	78.44	0.0006	0.0000
WITCH	0.0000	0.0000	18.38	89.59	17.65	85.63	0.6082	0.0093

The coefficients for ECS are zero in the output equation because there is no feedback
from ECS to output in the model.

ECS = temperature sensitivity coefficient

TFP = total factor productivity growth

POP = population growth

linear (L) and liner-quadratic-interactions (LQI) specifications

Robustness of Extrapolation

- For population and the ECS: calibration runs cover at least 99.9 % of the range of the pdfs

- For TFP, calibration runs only extend as far as the 83 percentile at the upper

- Reliability test of 2 models: SRF will show a thinner tail than the one generated by the SRF estimated over the calibration runs.

Track II: Develop PDFs

1. **Population Growth**
   - Using pdfs from IIASA's demography group
   - Cross-check with UN and Berkeley estimates

2. **Temperature Sensitivity**
   - Base our pdf on the literature referenced in the IPCC AR5

3. **Total factor productivity**
   - No evidence in the literature
   - Created our own expert survey

Phase II: Developing PDFs

- This study focuses on the three uncertain variables:
  1. Population growth
  2. *Temperature Sensitivity*
  3. Total factor productivity growth

Climate Sensitivity PDF

- Equilibrium climate sensitivity (ECS) or temperature sensitivity coefficient (TSC).
  - The change (in degrees C) in the global mean surface temperature with a sustained doubling of CO_2 concentrations, *after* the climate equilibrates to the new CO2 concentrations (relative to the pre-industrial CO2 concentration).

Olson et al. (2012)
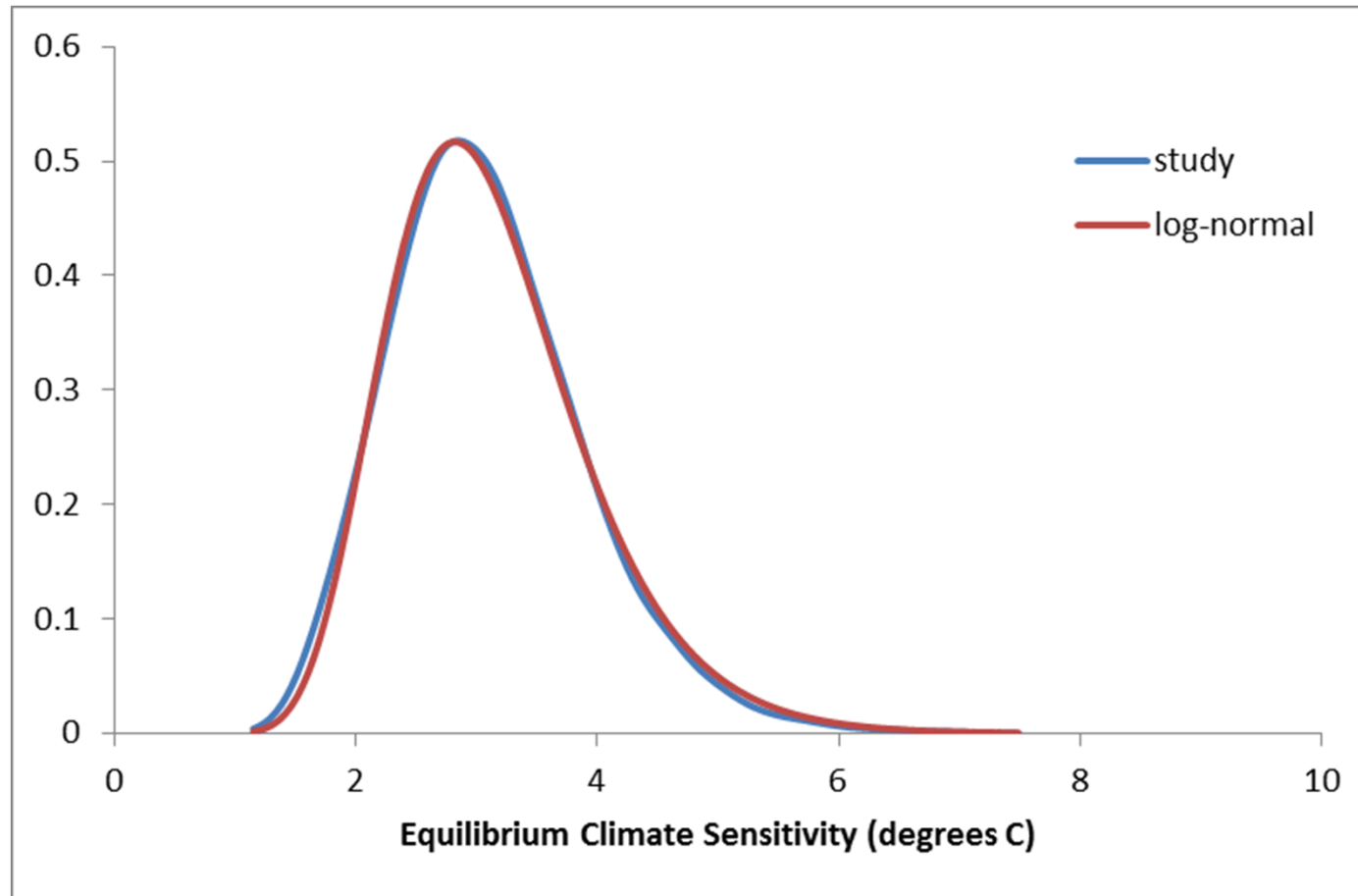
Olson et al. (2012)

Representative of the literature in using a Bayesian approach:

- Prior based on previous studies
- Likelihood based on instrumental/modeled data
 - Using University of Victoria ESCM climate model

Three Reasons for this Choice

1. It was recommended to us in personal communications with climate scientists.

2. It is fairly representative of the studies in the IPCC AR5 and falls into the middle range of the different estimates.

3. Sensitivity analysis of the effect on aggregate uncertainty of changing the std. dev. of the Olson et al. indicates that the sensitivity is small.

Phase II: Developing PDFs

- This study focuses on the three uncertain variables:

    1. Population growth
    2. Temperature Sensitivity
    3. *Total factor productivity growth*

Individual and combined pdfs: annual growth rates of output per capita, 2010 – 2100 (average annual percent per year)
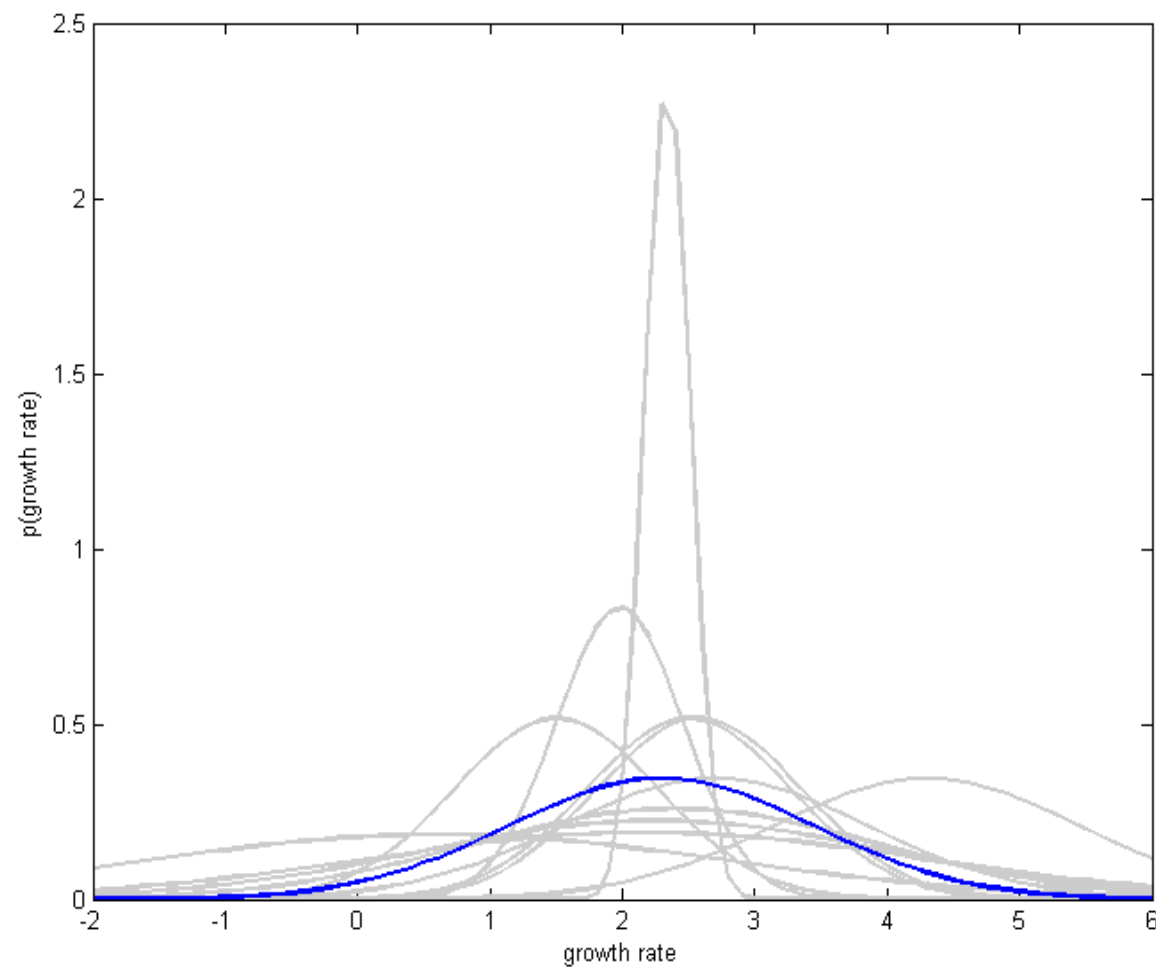
Six Overall Key Findings

1. Central projections (modelers' baselines) are remarkably similar, but models diverge at extremes for the parameters.

2. The pdfs of most key output variables are remarkably similar across models (in the baseline).

3. The climate-related output variables are characterized by lower uncertainty than the economic variables.

4. There is much greater parametric uncertainty than structural uncertainty (in the baseline).
   - The one exception is for the social cost of carbon.

5. Lack of evidence for fat tails in the current models.

6. Uncertainty in TFP growth has a dominant effect on output uncertainty, overwhelming uncertainty in ECS or population.

Monte Carlo Results (1 million draws)

- Results of Monte Carlo simulations for averages of all models.
- The table shows the values of all variables for 2100, except for the social cost of carbon, which is for 2020. Damages and SCC are for three models (WITCH, DICE, and FUND).

Variable	Linear				Linear-quadratic-interactions				
	Mean	Standard deviation	10-90 %ile	99 %ile	Mean	Standard deviation	10-90 %ile	99 %ile	Coeff of Variation
CO2 concentrations	888	233	597	1,429	895	247	595	1,672	0.28
Temperature	3.60	0.89	2.26	5.89	3.87	0.89	2.25	6.29	0.23
Output	583	533	1,368	1,825	649	637	1,370	2,975	0.98
Output (log)	664	807	1,343	3,878	664	807	1,343	3,878	1.21
Emissions	112.56	73.10	187.51	282.59	115.12	80.82	187.16	381.98	0.70
Population	12,142	2,378	6,094	17,661	10,245	2,401	6,092	16,816	0.23
Radiative Forcings	7.40	1.60	4.11	11.13	7.40	1.63	4.12	11.81	0.22
Damages	27.41	32.96	84.51	104.36	32.39	41.88	84.90	191.91	1.29
SCC	16.26	7.05	17.68	35.43	13.30	6.95	16.16	36.19	0.52

Note: All dollars values are in terms of real 2005 dollars.

Temperature Change

- Distribution of 2100 Temperature change in the base case (degrees C above pre-industrial).

Temperature	0.1 %ile	1 %ile	5 %ile	10%ile	25%ile	50%ile	75%ile	90%ile	95%ile	99%ile	99.9%ile
DICE	1.60	1.97	2.38	2.64	3.12	3.76	4.51	5.29	5.80	6.88	8.28
FUND	1.96	2.30	2.63	2.83	3.19	3.64	4.17	4.74	5.12	5.92	6.96
GCAM	1.59	2.02	2.46	2.73	3.23	3.86	4.56	5.27	5.73	6.64	7.79
IGSM	1.30	1.82	2.31	2.58	3.05	3.58	4.13	4.65	4.97	5.58	6.29
MERGE	2.20	2.56	2.93	3.16	3.61	4.20	4.90	5.63	6.12	7.13	8.46
WITCH	1.83	2.21	2.60	2.82	3.22	3.71	4.23	4.72	5.01	5.58	6.22

Model differ in the tails

Temperature Change

- Box plot of 2100 Temperature change in the base case (degrees C above pre-industrial)

Temperature increase, 2100 (deg C)

DICE   FUND   GCAM   IGSM   MERGE   WITCH
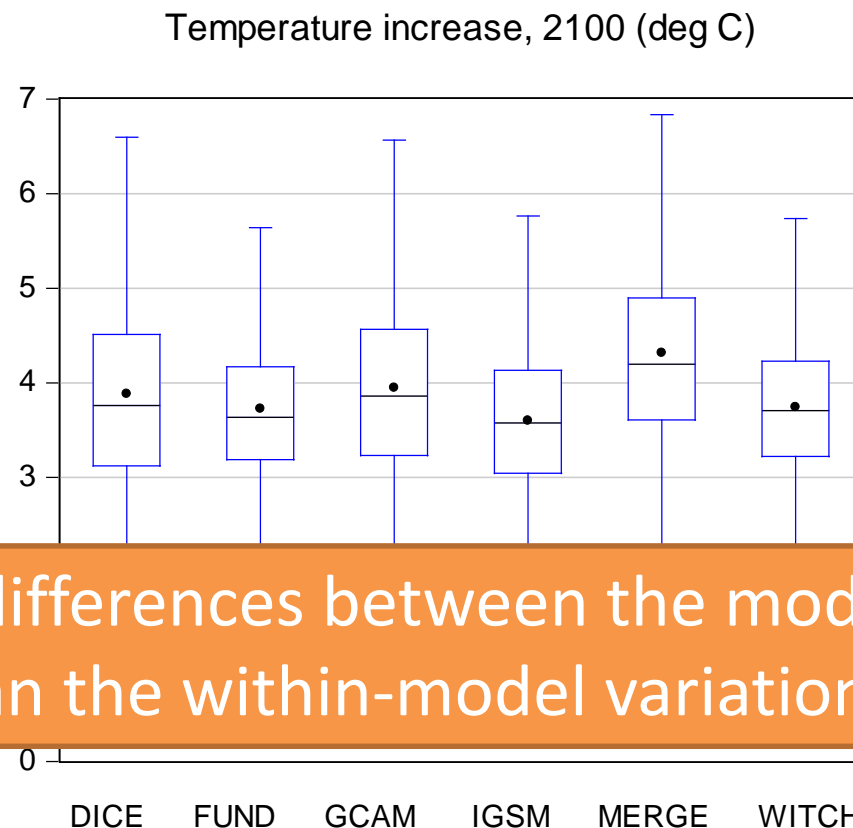
While there are differences between the models, they are much smaller than the within-model variation.

Fat Tails?

- Informal Test: ratio of the values of the output variables at the 99th and 99.9th percentile

- the maximum ratio is 1.56: tail is slightly fatter than the normal distribution, but falls far short of the slope associated with an infinite-variance Pareto process.

- CAVEAT! Models omit discontinuities or sharp non-linearities AND our assumed pdfs are too thin-tailed, we may underestimate the thickness of the tails.
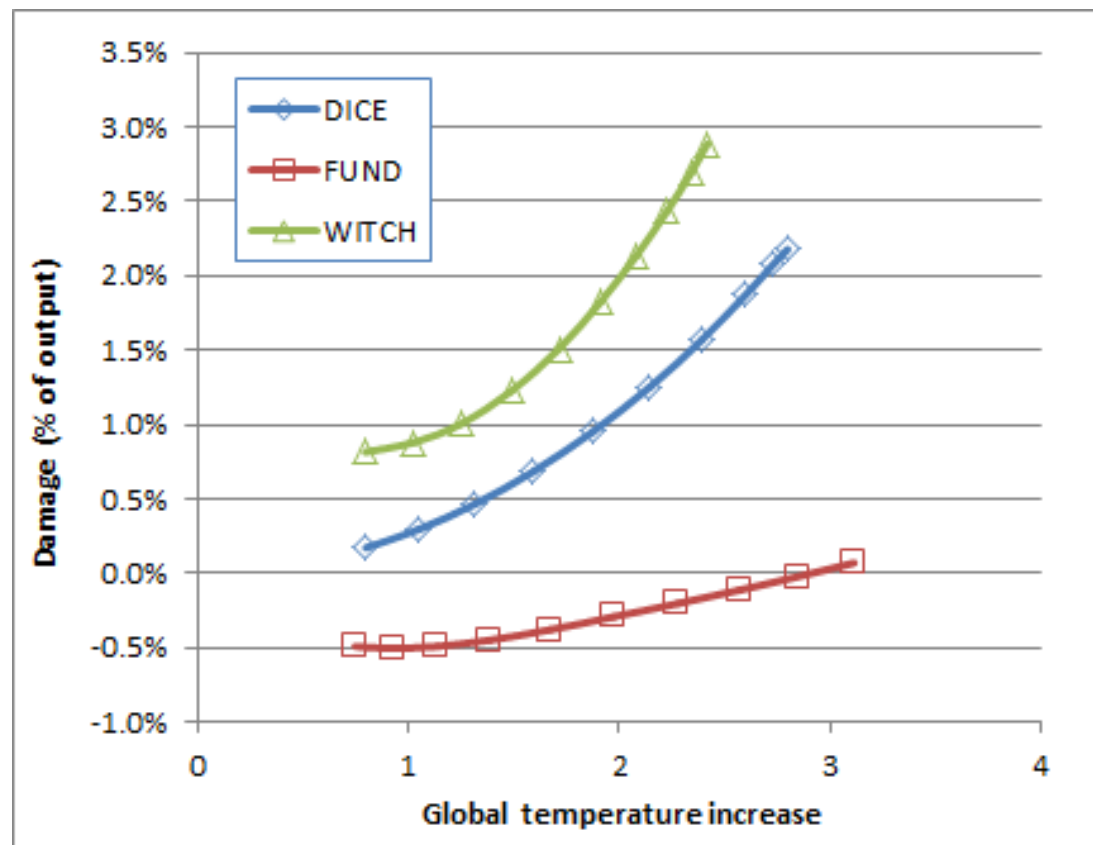
Increase standard deviation of each of the pdfs by a factor of 2

- Uncertainty in GDP growth dominates the uncertainty in emissions.

Variation	CO2 Conc	Temp	Output	Emissions	Population	Rad Forc
Base	1.00	1.00	1.00	1.00	1.00	1.00
Pop x 2	1.11	1.06	1.07	1.11	2.07	1.12
TFP x 2	2.16	1.62	2.68	2.23	1.00	1.99
ETS x 2	1.00	1.40	1.00	1.00	1.00	1.01
All x 2	2.24	1.97	2.74	2.31	2.06	2.07

Illustrative quasi-damage functions

- Implied quasi-damage functions plot damages against the total temperature increase over time (in base case).

What comes next

Main components

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Model	47 (0) 42 – 50	27 (1) 21 – 33	42 (1) 35 – 45	48 (1) 38 – 52	50 (1) 39 – 55	53 (1) 39 – 59	52 (1) 37 – 60	50 (1) 37 – 59	48 (1) 37 – 58
Policy implementation	9 (0) 7 – 11	18 (0) 17 – 21	21 (1) 18 – 28	25 (1) 21 – 31	25 (1) 22 – 31	23 (1) 21 – 29	23 (0) 20 – 29	23 (0) 20 – 29	21 (0) 16 – 26
Climate category	6 (0) 4 – 8	11 (0) 10 – 14	23 (1) 20 – 33	26 (1) 23 – 33	28 (0) 25 – 34	23 (1) 20 – 32	22 (1) 19 – 30	23 (0) 19 – 28	22 (0) 17 – 26
Baseline	15 (1) 10 – 19	11 (0) 8 – 15	10 (0) 6 – 16	11 (1) 6 – 19	12 (1) 7 – 26	14 (1) 9 – 29	17 (1) 10 – 32	17 (1) 11 – 31	17 (1) 11 – 28

η^2 [%]   0   25   50   75   100

Drouet et al. 2015

Communicating Uncertainty

- Performing Uncertainty Analysis makes sense if we are understood when we communicate

  ➢ You asked for a bike, now you must ride it

Some Lessons

- Use natural language AND numbers to express probabilities

- People have prior, they will update rather than consider your numbers their posteriors

- Use Box plots

- Users do not really care/understand the difference between parametric and model uncertainty

Trust, Understanding and Uncertainty

- Users are different in their desire for probabilistic information

- Advocacy versus science communication

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