Modeling Uncertainty Project: Major Results

Snowmass EMF

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Draft, preliminary and not for circulation

Schematic outline of two-track method

Assume y = endogenous variables; u = exogenous or policy variables; H^m = model mapping for model m

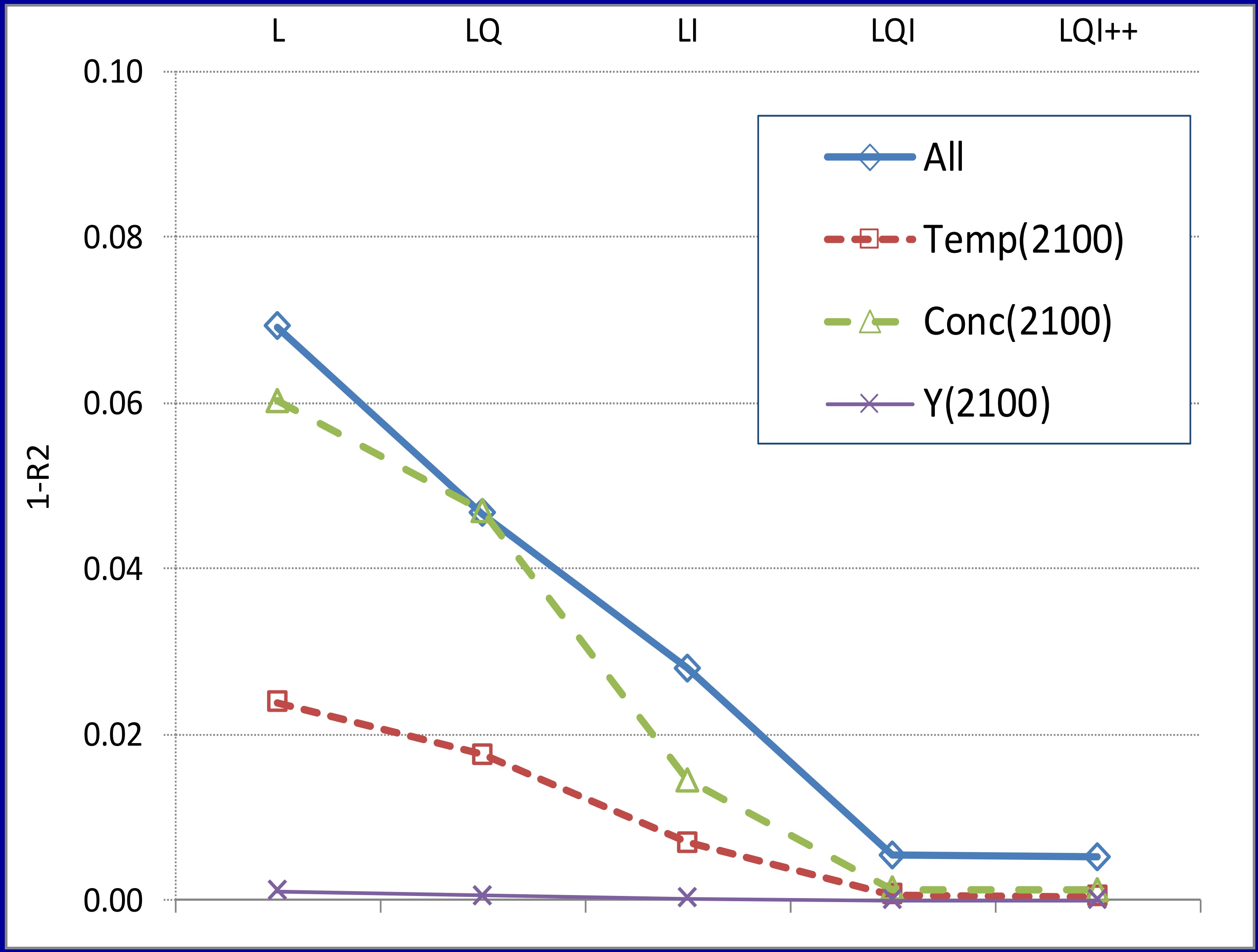
Steps:

1. Choose uncertain variables: $u = [ETS, TFP, Pop]$
2. Model calibration runs: $y = H^m(u)$.
3. Fit surface response functions, $y = R^m(u)$.
4. Derive Pdfs for u variables, $f(u)$.
5. Then do Monte Carlo for distribution of output variables, obtaining the distribution $g^m(y)$ for output variables

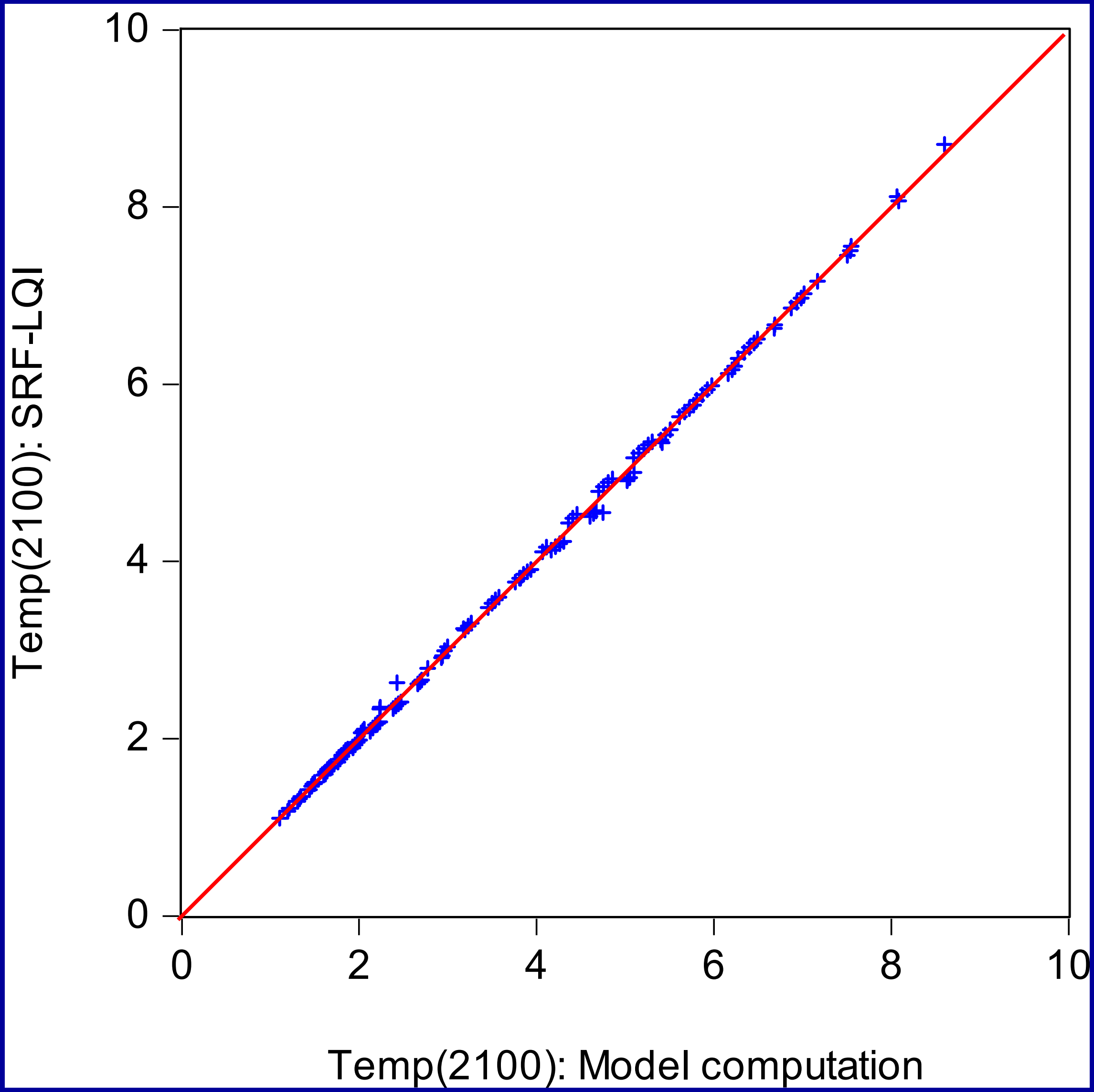
$$g^m(y) = \int f(u) R^m(u) du$$

Surface response function

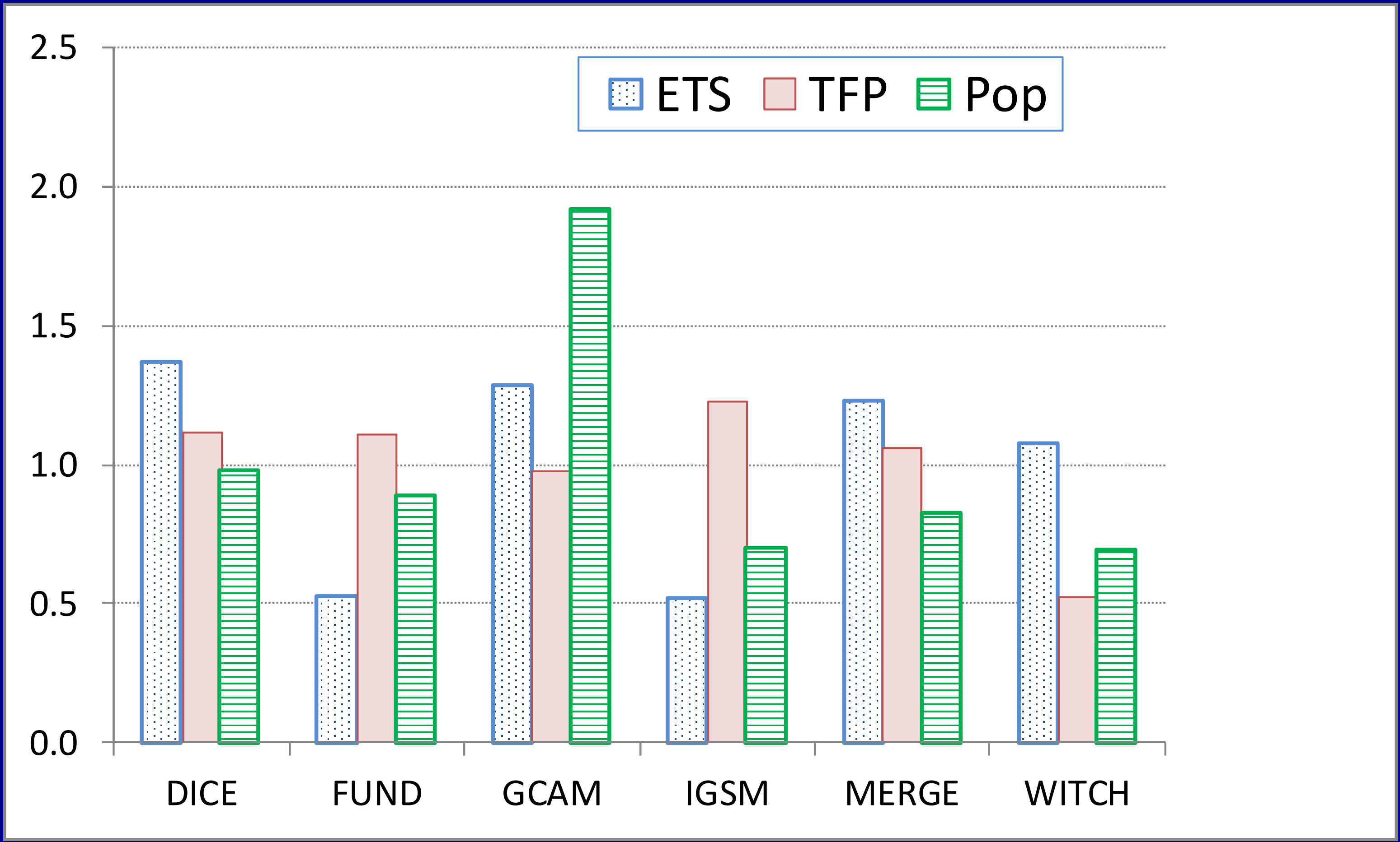
Goodness of fit of different SRF specifications



Surface Response Example: DICE temp



SRF derivatives of temperature by variable and model relative to model average



Estimates are linear term in centered LQI equations. They are normalized to the average of all models (average of 1).

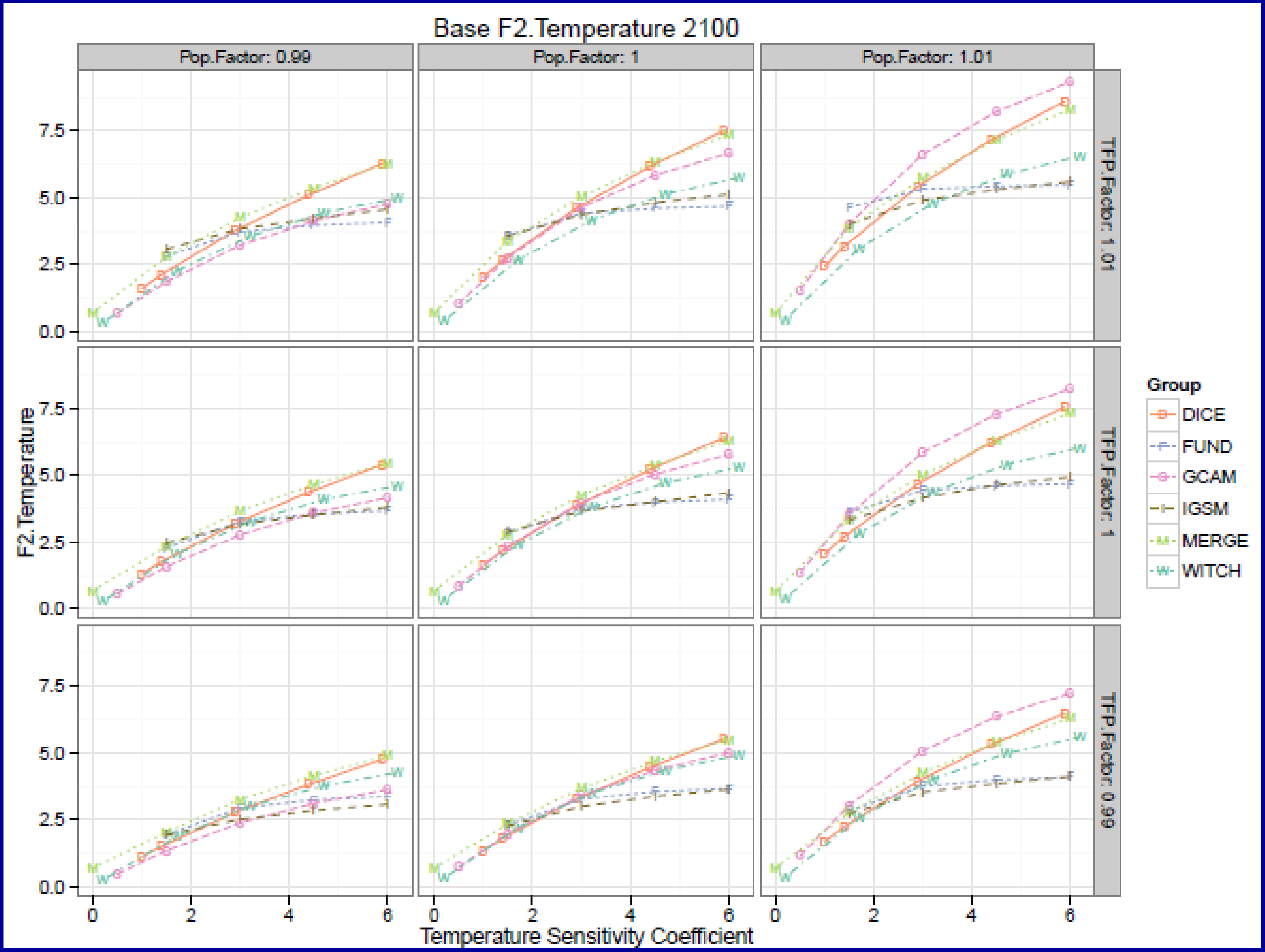
Six major results

1. Comparison of model results
2. Estimates of uncertainty are remarkably similar
3. Uncertainty low for climate variables; high for economic variables
4. Parametric uncertainty much larger than model (ensemble) uncertainty
5. No evidence of fat tails
6. Main sensitivity is to productivity growth

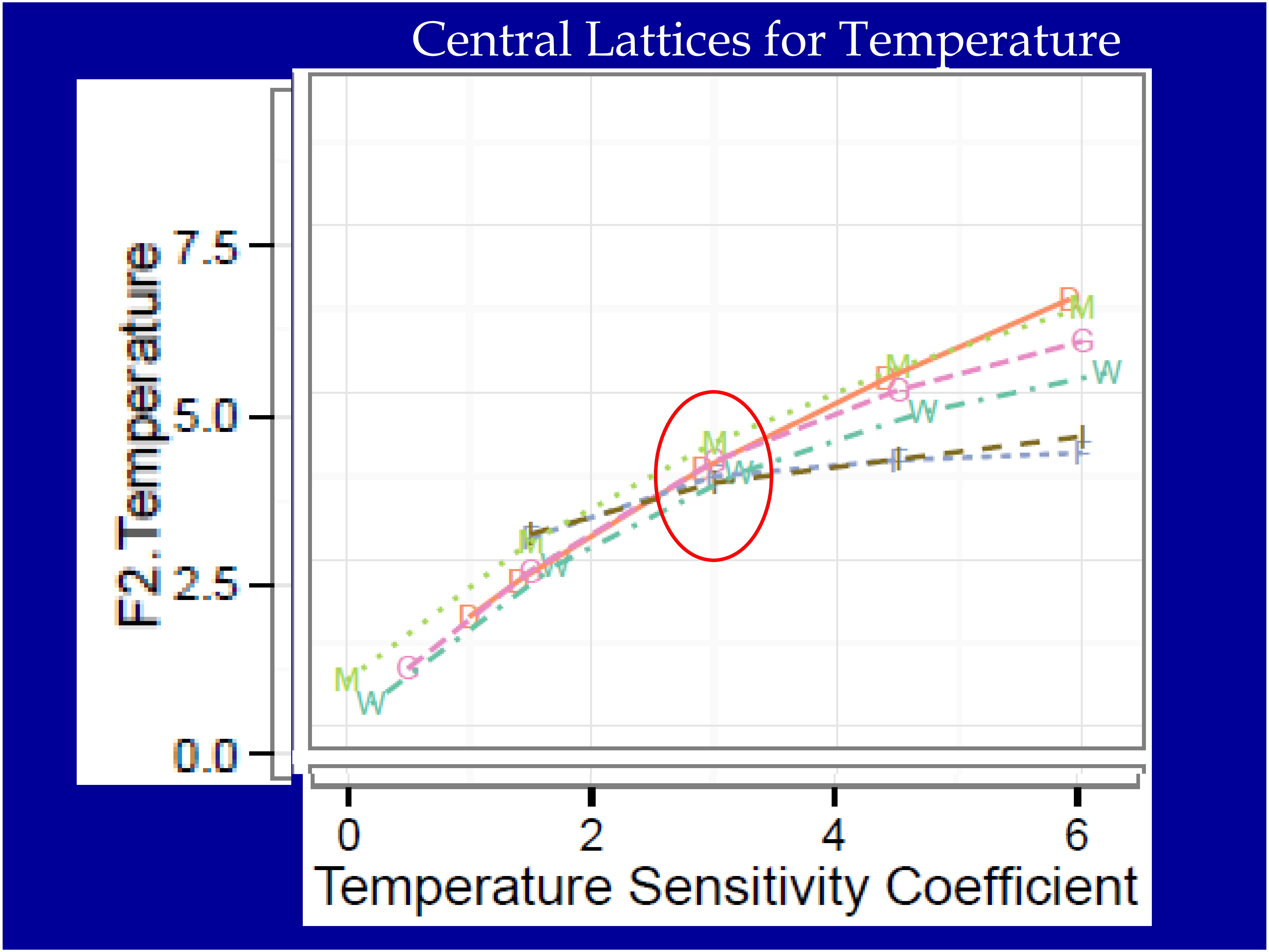
1. General comparison of model results

- First, the central projections of the integrated assessment models (IAMs) are remarkably similar at the modeler's baseline parameters. This result is probably due to the fact that models have been used in model comparisons and may have been revised to yield similar baseline results.

Lattices



Base F2.Temperature 2100
Pop.Factor: 0.99
Pop.Factor: 1
Pop.Factor: 1.01
TFP.Factor: 1.01
TFP.Factor: 1
TFP.Factor: 0.99
F2.Temperature
Temperature Sensitivity Coefficient
0.0
2.5
5.0
7.5
0
2
4
6
Group
DICE
FUND
GCAM
IGSM
MERGE
WITCH

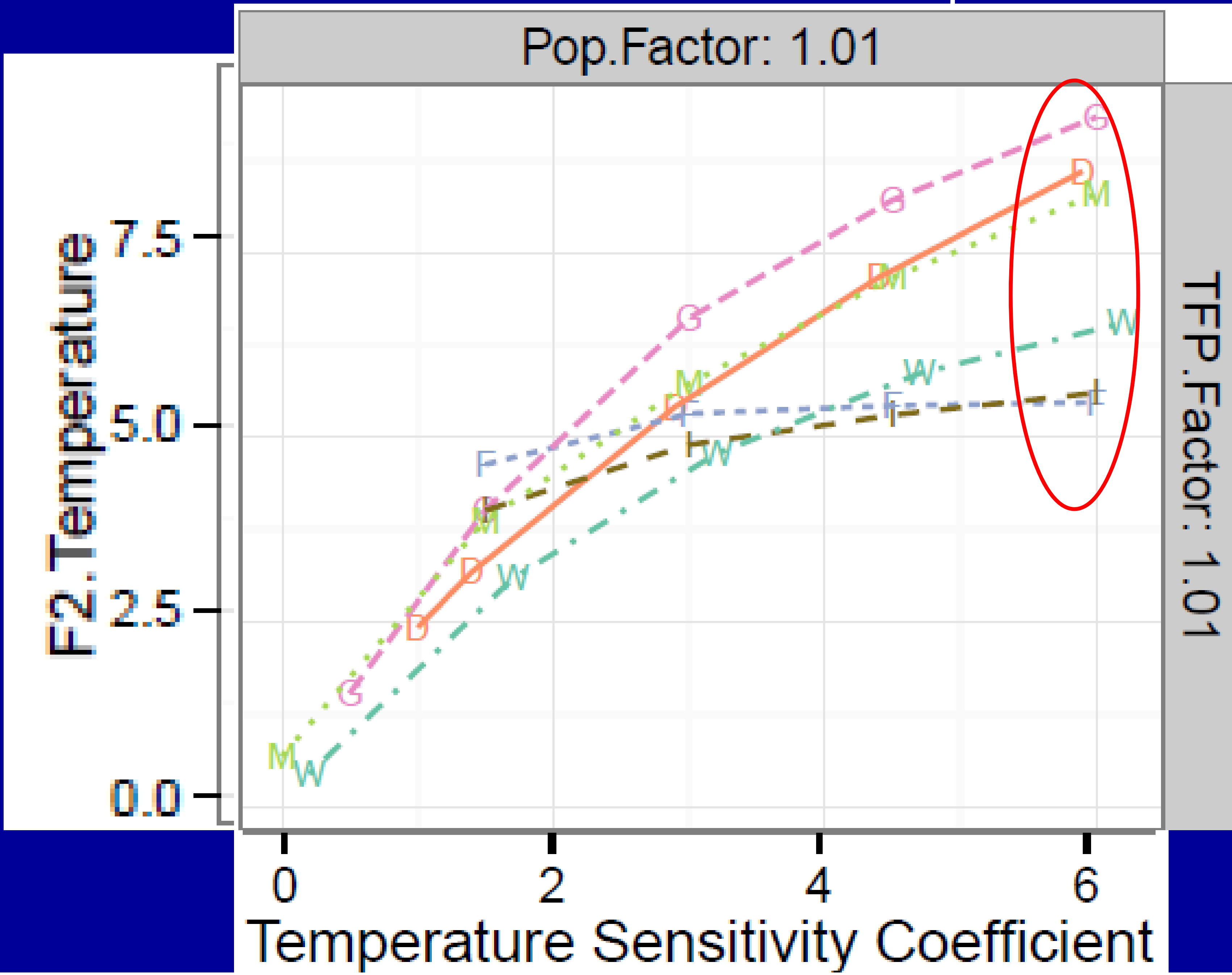


Central Lattices for Temperature
F2.Temperature
7.5
5.0
2.5
0.0
0
2
4
6
Temperature Sensitivity Coefficient
M
W
G
D

General comparison of model results

- First, the central projections of the integrated assessment models (IAMs) are remarkably similar at the modeler's baseline parameters. This result is probably due to the fact that models have been used in model comparisons and may have been revised to yield similar baseline results.
- However, the projections diverge sharply when alternative assumptions about the key uncertain parameters are used, especially at high levels of population growth, productivity growth, and equilibrium climate sensitivity.

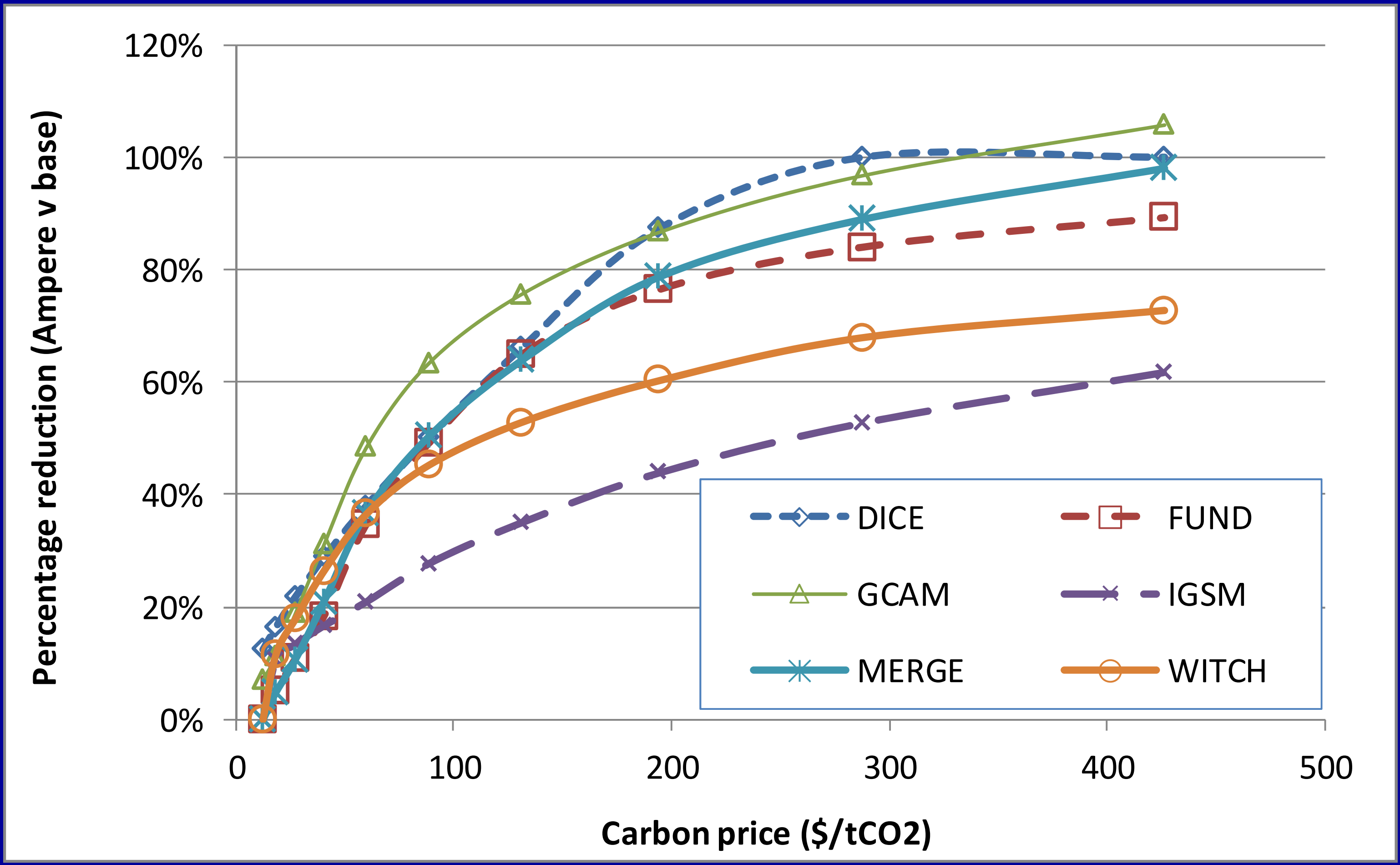
Extreme Lattice for Temperature



Model carbon prices

- Emissions control rates differ greatly at carbon prices by model

Emissions reduction/carbon price curves

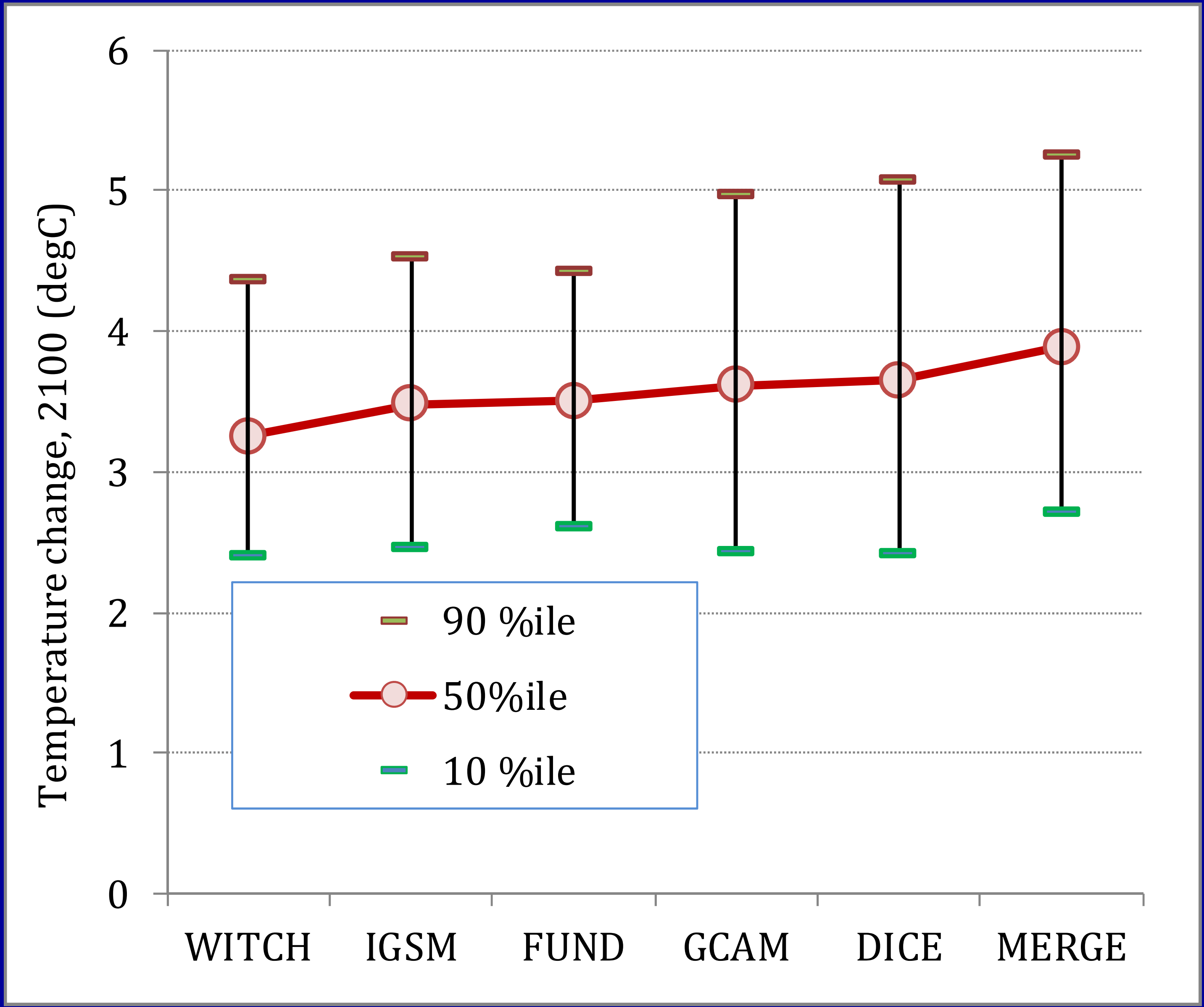


Carbon tax and emissions reductions by model

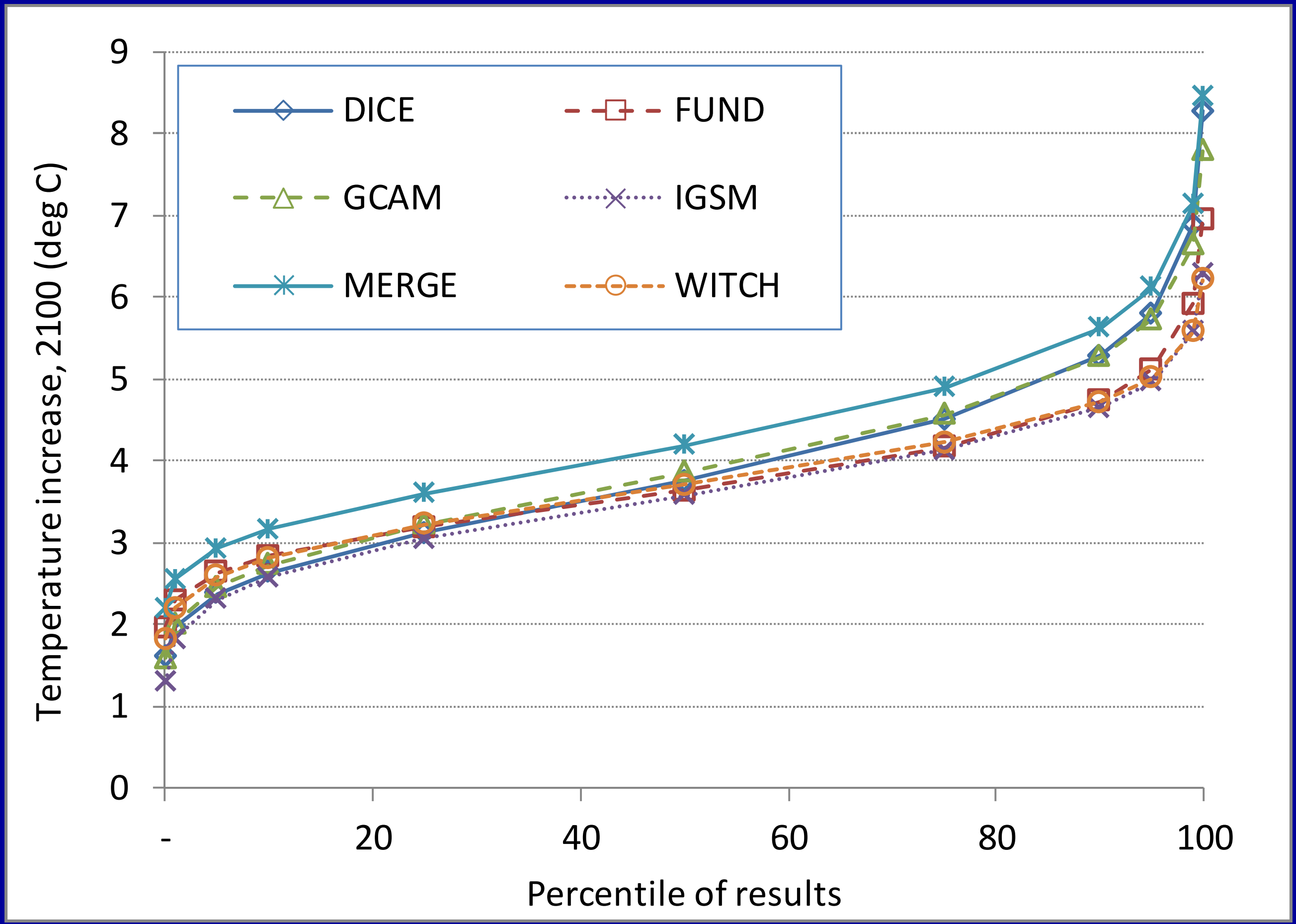
2. Similarity of pdfs of output variables of different models

- Second, despite these differences across models for alternative parameters, the distributions of the key output variables are remarkably similar across models with different structures and levels of complexity.
- To take year 2100 temperature as an example, the quantiles of the distributions of the models differ by less than ½ °C for the entire distribution up to the 95^{th} percentile.

Comparative percentiles for temperature



Temperature distributions

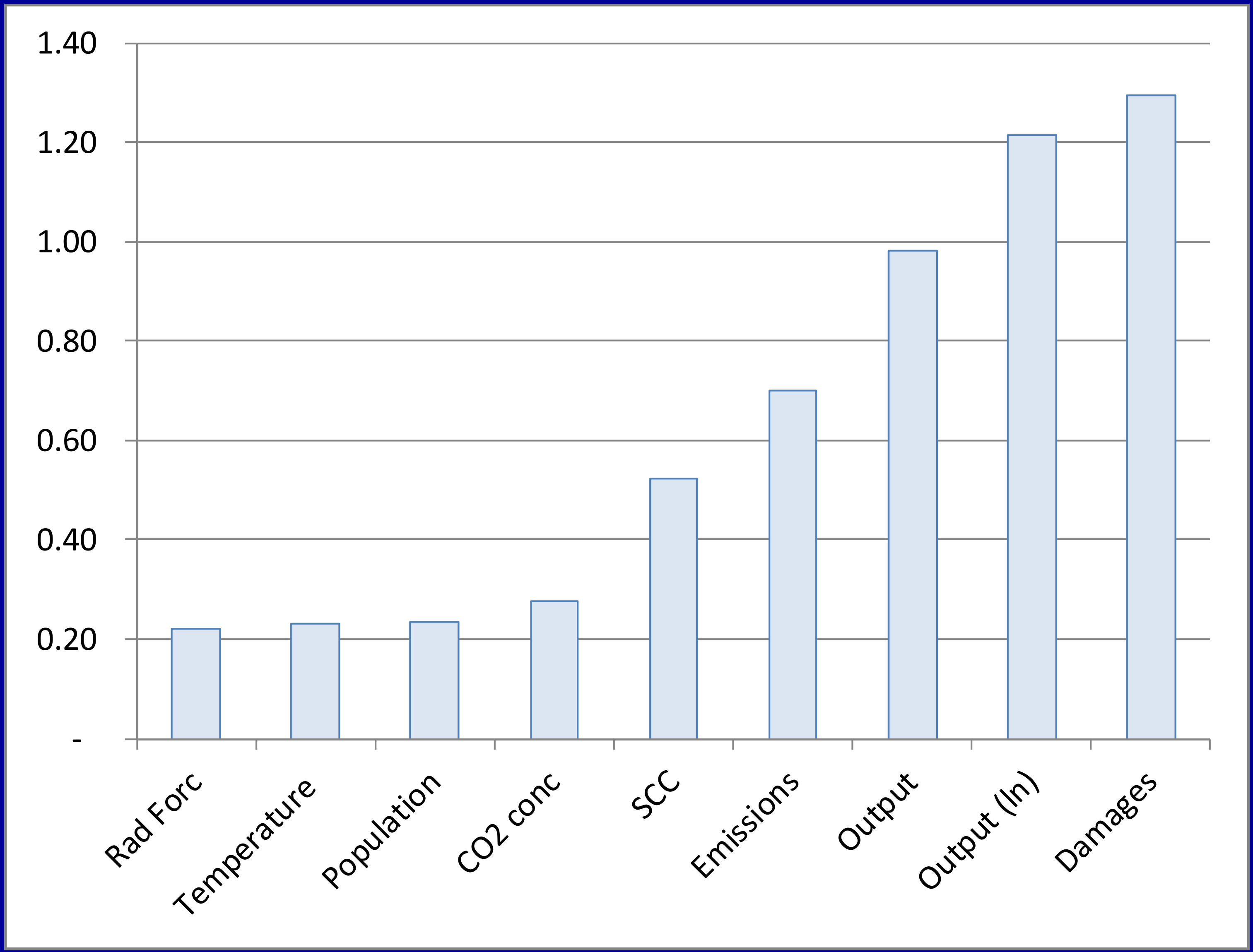


Percentiles of the change in temperature in 2100 across the six models.

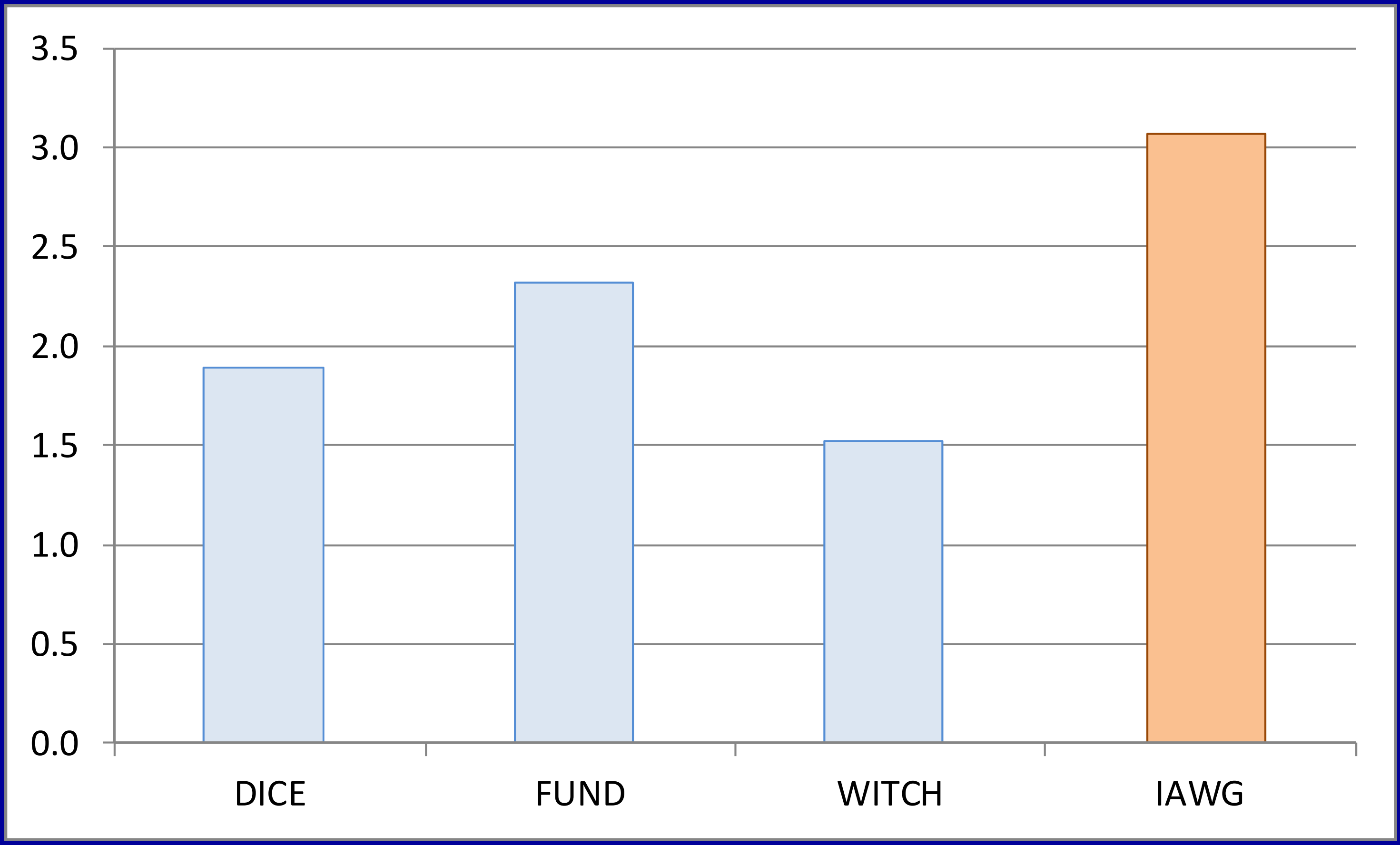
3. Low uncertainty for climate; high uncertainty for economic variables

- Third, we find that the climate-related variables have low uncertainty relative to those relating to most economic variables. For this comparison, we look at the coefficient of variation (CV) of the Monte Carlo simulations.
- CO_2 concentrations, radiative forcings, and temperature (all for 2100) have relatively low CV. Output and damages have relatively high CV.

Coefficient of Variation (parametric uncertainty)



SCC uncertainty comparison with the IAWG: Ratio 95 %ile to Mean



Why? IAWG inputs variables are from scenarios, not distributions.
Also, Roe-Baker has much more dispersion than log-normal.

Major results on uncertainty

Variable	Linear-quadratic-interactions				
	Mean	Standard deviation	10-90 %ile	99 %ile	Coeff of Variation
Radiative Forcings	7.40	1.63	4.12	11.81	0.22
Temperature	3.87	0.89	2.25	6.29	0.23
Population	10,245	2,401	6,092	16,816	0.23
CO2 concentration	895	247	595	1,672	0.28
SCC	13.30	6.95	16.16	36.19	0.52
Emissions	115.12	80.82	187.16	381.98	0.70
Output	649	637	1,370	2,975	0.98
Output (log)	664	807	1,343	3,878	1.21
Damages	32.39	41.88	84.90	191.91	1.29

All variables are for 2100 except SCC, which is 2020.
These are parametric uncertainty only.

4. Parametric uncertainty much more important than model uncertainty

- Fourth, we find much greater parametric uncertainty than structural (across model) uncertainty.
- To show this we calculate the variance of variables for all models and uncertain variables and decompose to parts from model means and parts from uncertainties.

Assume that the model outcome for variable i and model m is and that the uncertain parameters are :

$$Y_i^m = \alpha_i^m + \sum_{i=1}^{3} \beta_i^m u_i + \sum_{j=1}^{3} \sum_{i=1}^{3} \gamma_{i,j}^m u_i u_j$$

For a given distribution of each of the uncertain parameters, the variance of including model variation is:

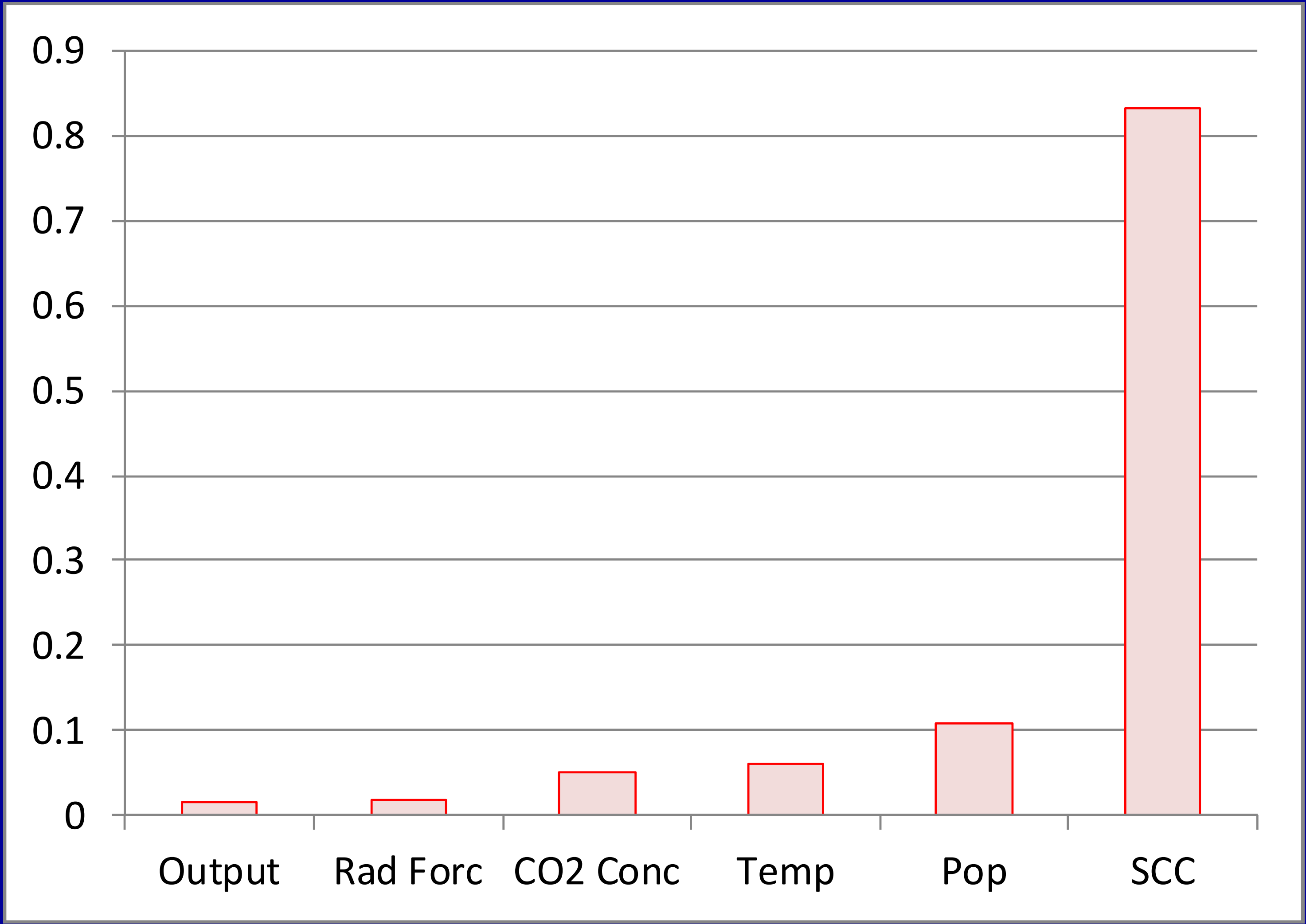
$$\sigma^2(Y_i) = \sigma^2(\alpha_i) + \sum_{i=1}^{3} (\beta_i^m)^2 \sigma^2(u_i) + \sum_{j=1}^{3} \sum_{i=1}^{3} (\gamma_{i,j}^m)^2 \sigma^2(u_i) \sigma^2(u_j)$$

The first term on the right hand side is the variance due to model differences (or ensemble uncertainty),

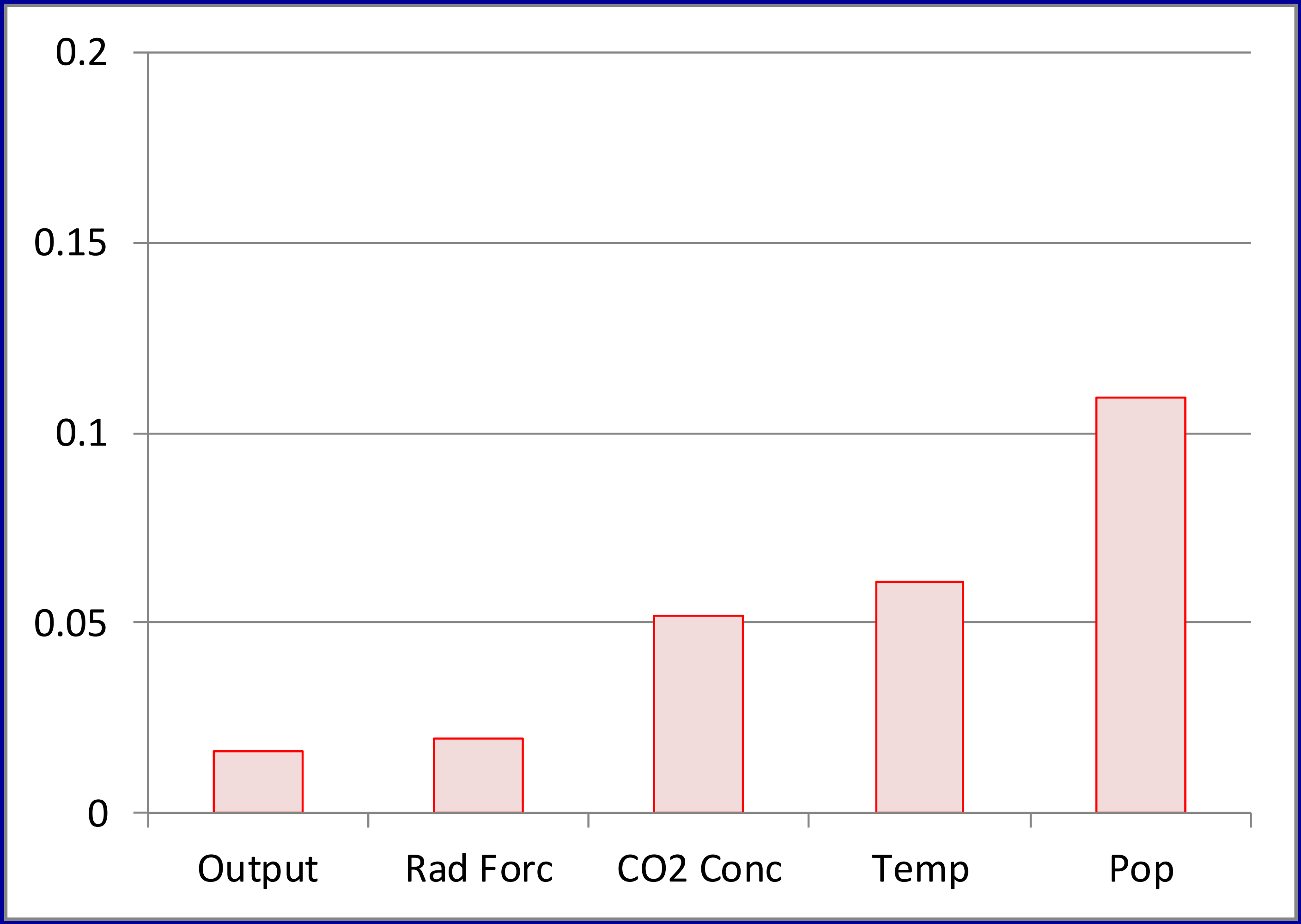
Parametric uncertainty much more important than model uncertainty

- For T 2100, the difference of model means (or the ensemble uncertainty) is approximately one-quarter of the total uncertainty, with the rest driven by parametric uncertainty.
- This result is important because of the widespread use of ensemble uncertainty as a proxy for overall uncertainty.

Percent of variance explained by model differences (ensemble share)



Percent of variance explained by model differences (ensemble share)



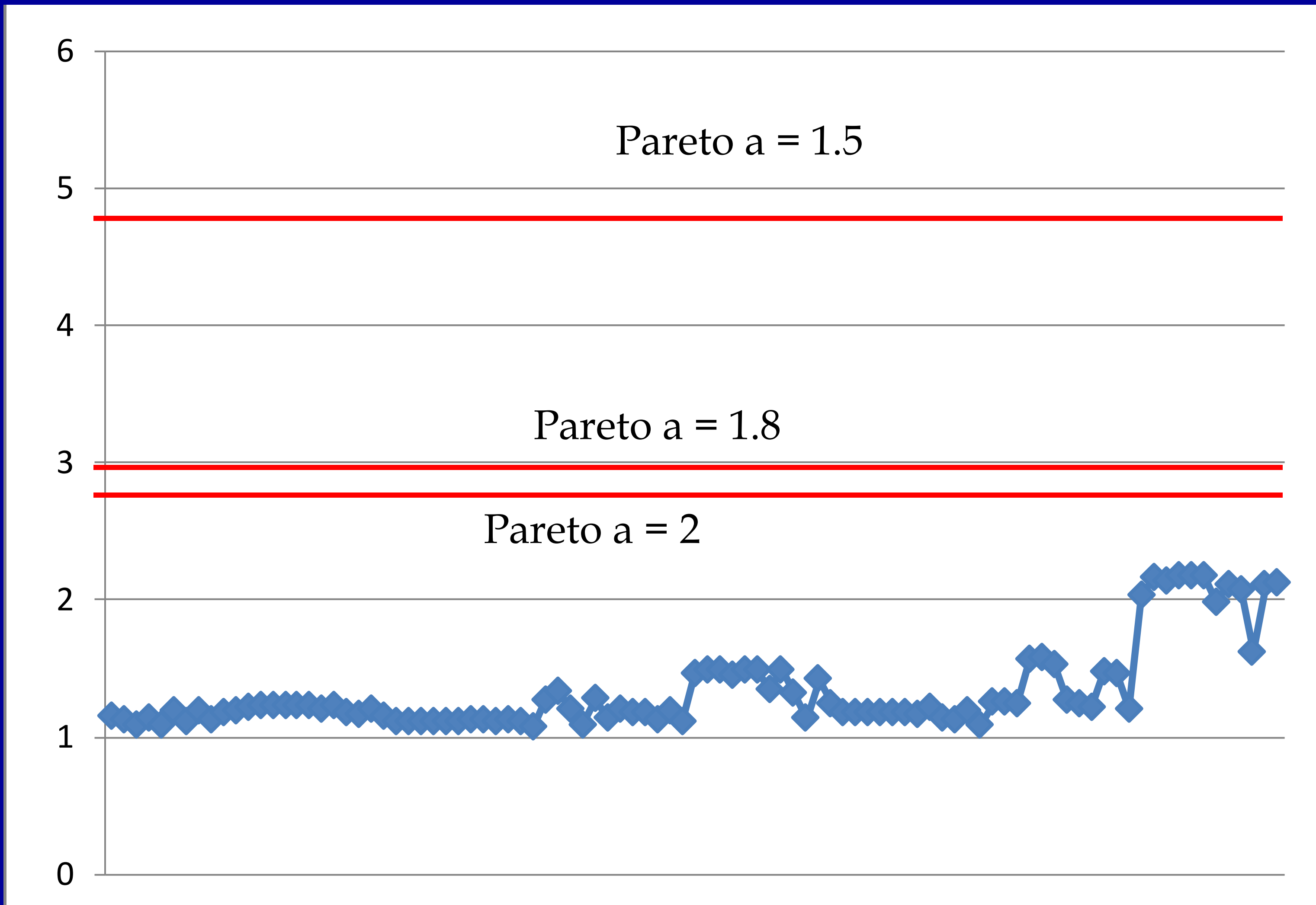
% of variance due to model variation

Variable	Fraction explained by model differences
CO2 concentrations (2100)	0.052
Temperature (2100)	0.061
Output (2100)	0.016
Radiative forcing (2100)	0.020
Population (2100)	0.109
Social cost of carbon (2020)	0.832

5. Fat tails?

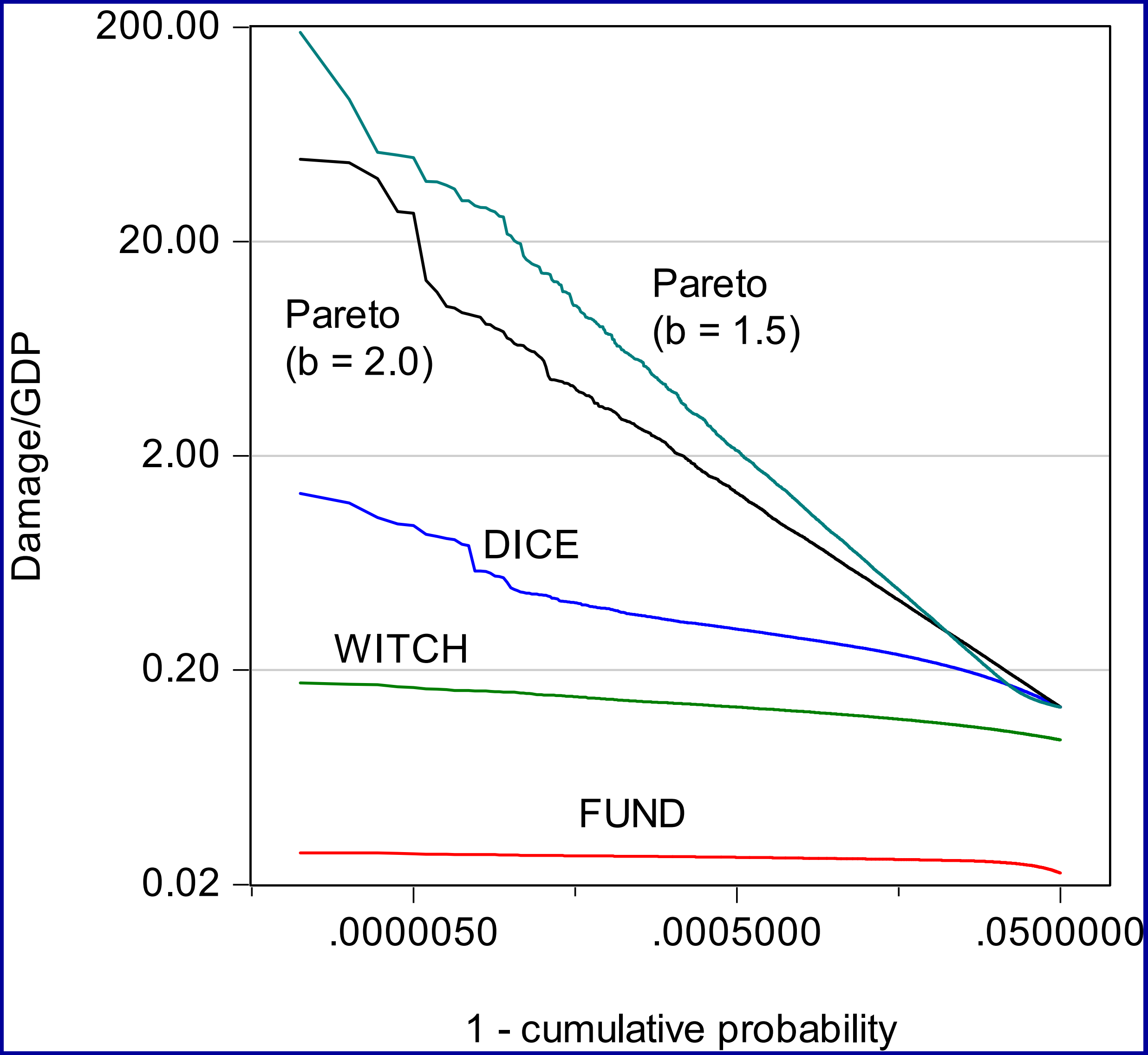
- A fifth interesting finding of this analysis is the lack of evidence in support of fat tails in any variables
- Based on both informal and formal tests, the models as currently constructed find that the tails are relatively thin.
- These results tend to support the use of expected benefit-cost analysis for climate change policy, in contrast to suggestions by some authors that neglect of fat tail events may vitiate standard analyses (Weitzman 2009).

Informal Pareto test: Ratio of 99.9:99 %ile



All variables and models

Damage-GDP ratop



Probability of "catastrophe"

- Define catastrophe as damage ratio of > that 25% of output in 2100 (roughly, a Great Depression forever)

Probability of Catastrophe by 2100			
DICE	2.0%		
FUND	0.0%		
WITCH	0.0%		

Tail of damage ratio

95 %ile of damage ratio	
[Damages/GDP, 2100]	
DICE	13.5%
FUND	2.3%
WITCH	9.5%
Stern	8.5%

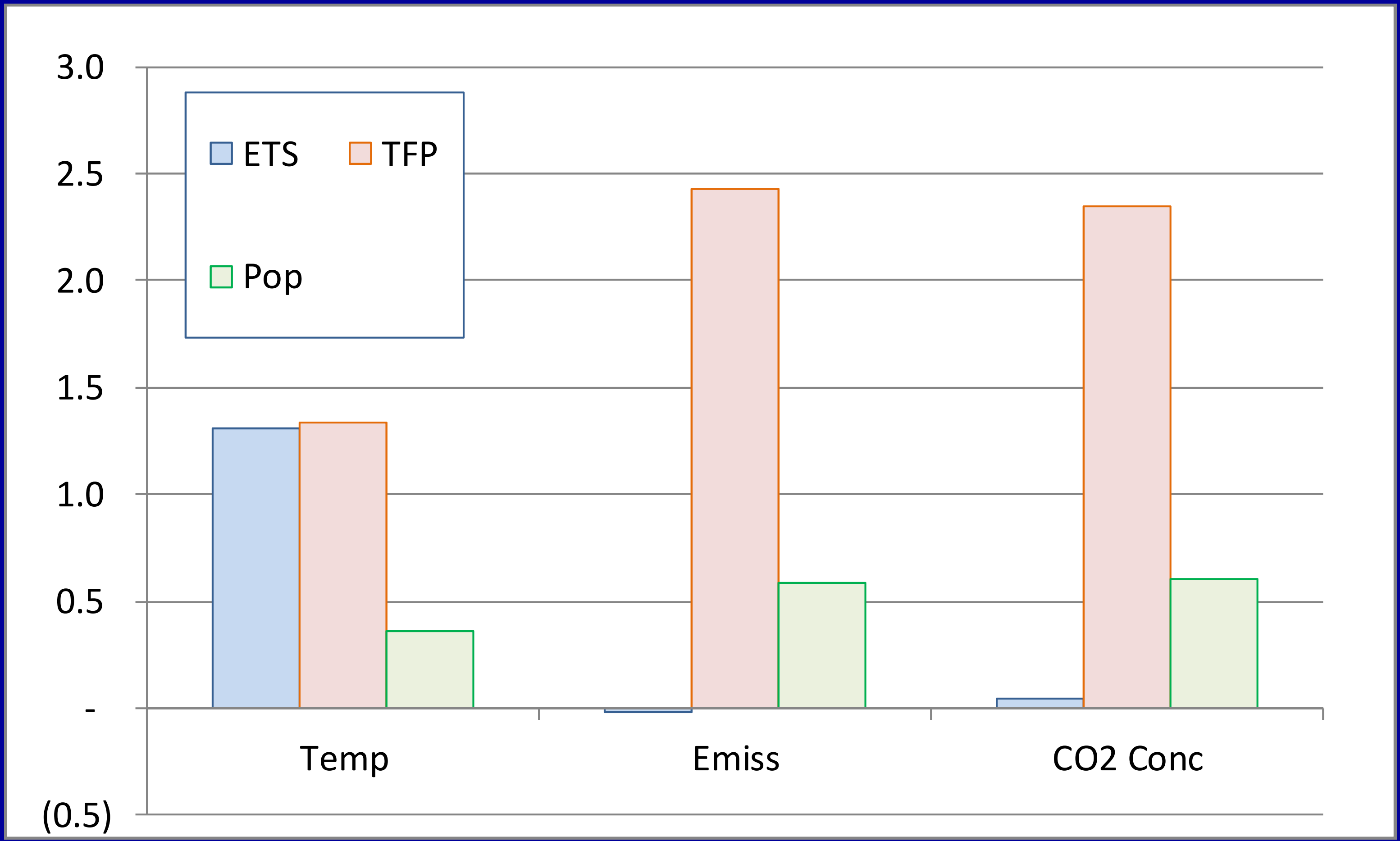
6. Productivity is the main sensitive parameter

- Sixth, sensitivity analysis finds
  - Doubling sigma has little effect for population
  - Doubling ETS has little effect of anything but temperature and T's downstream effects.
- However, uncertainty about productivity growth has a major impact on the uncertainty of all the major output variables.

Sensitivity to change in variability

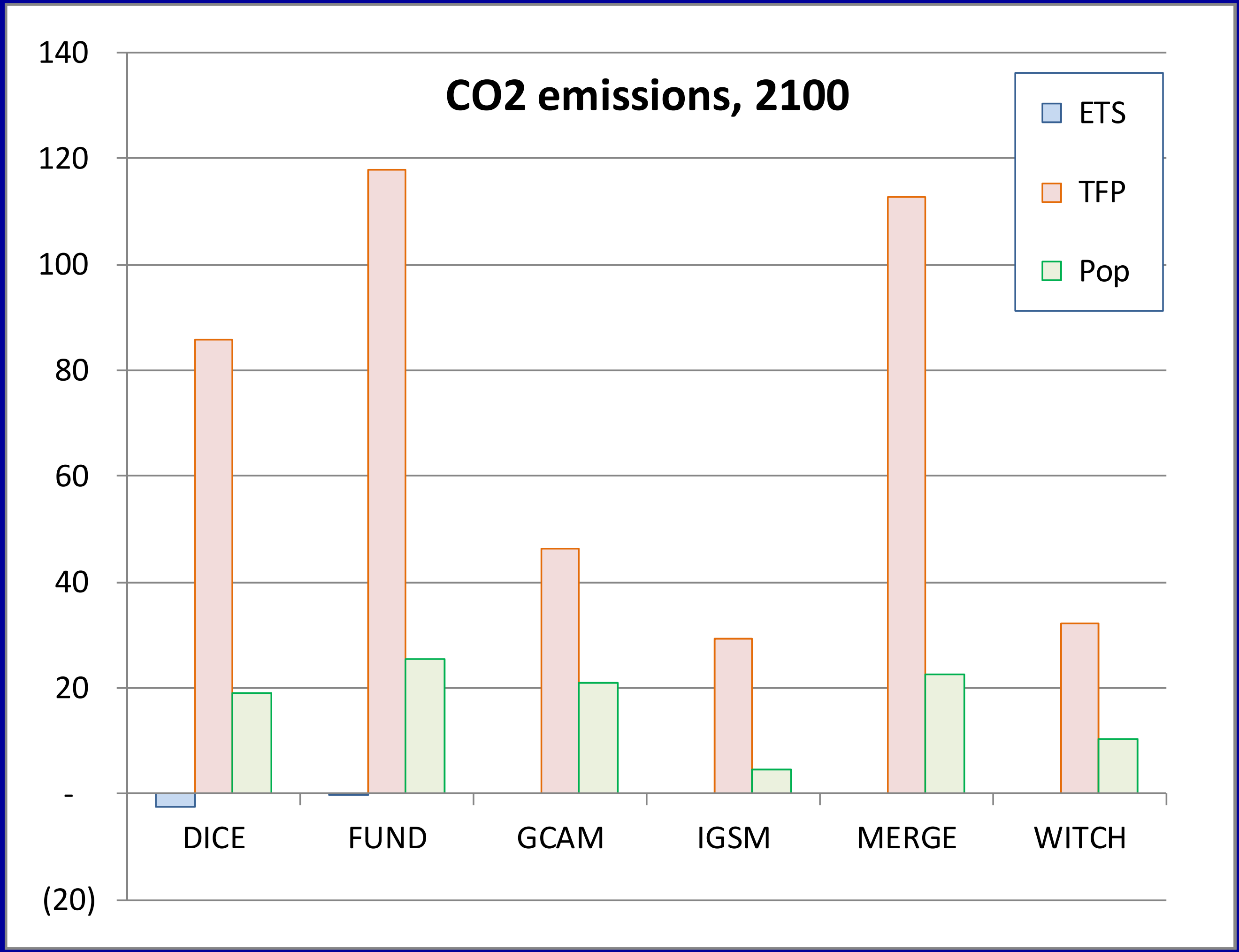
Variation	CO2 Conc	Temp	Output	Emissions	Population	Rad Forc
Base	1.00	1.00	1.00	1.00	1.00	1.00
Pop x 2	1.11	1.06	1.07	1.11	2.07	1.12
TFP x 2	2.16	1.62	2.68	2.23	1.00	1.99
ETS x 2	1.00	1.40	1.00	1.00	1.00	1.01
All x 2	2.24	1.97	2.74	2.31	2.06	2.07

Normalized importance of uncertain variables



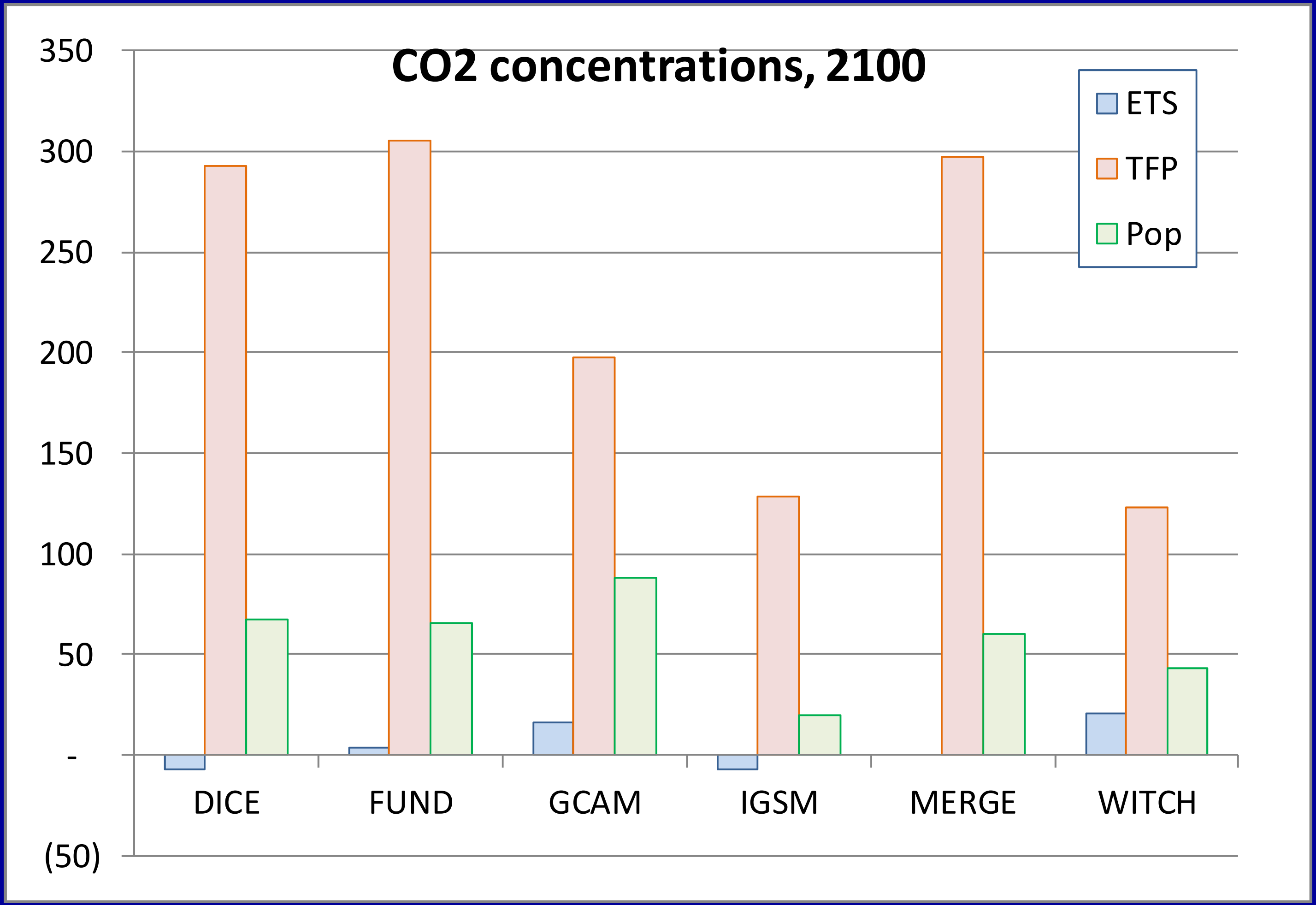
This shows the relative impact of each uncertain variable on the different outcome variables. Note that for second and third set of bars, ETS uncertainty has virtually no impact.

Normalized importance of variables: Emissions



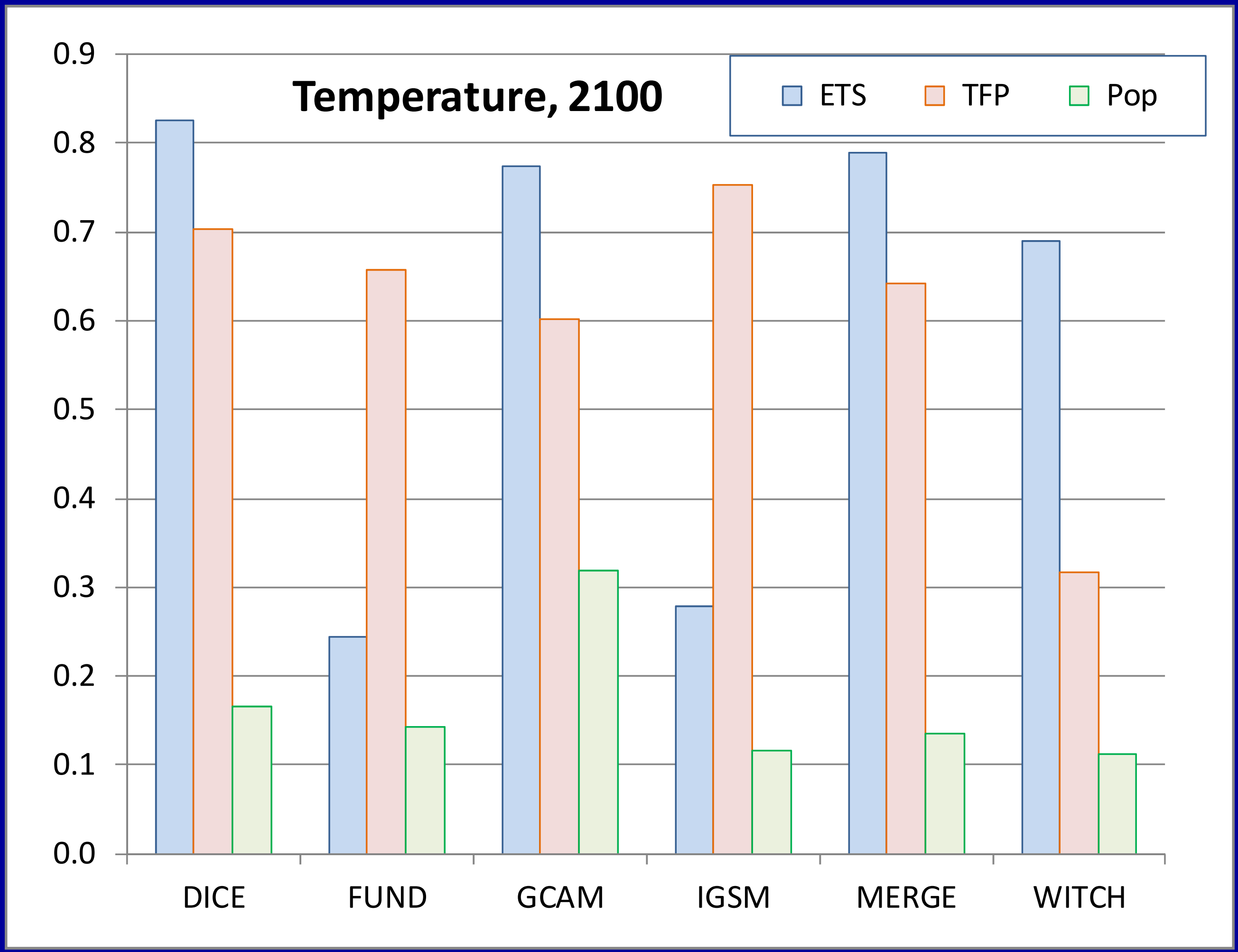
Normalized importance is coefficient of SRF divided by standard deviation of uncertain variable.

Normalized importance of variables: Conc



Normalized importance is coefficient of SRF divided by standard deviation of uncertain variable.

Normalized importance of variables: Temp



Normalized importance is coefficient of SRF divided by standard deviation of uncertain variable.

Productivity main sensitive parameter

- The reason for this is that the uncertainty of productivity growth from the expert survey compounds greatly over the 21st century and induces an extremely large uncertainty about output, emissions, concentrations, temperature change, and damages by the end of the century.

Summary

- The MUP two-track method has proven a flexible approach to model calibration and estimation of uncertainties of major outcomes of climate change.
- Parametric uncertainty appears generally much larger than model (ensemble) uncertainty.
- Uncertainties are much larger for economic outcomes than geophysical outcomes.
- The most important and sensitive uncertain variable is productivity growth.