

Uncertainty, Social Valuation, and Climate Change Policy

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How proactive should we be in the face of uncertainty?

To answer this question, we confront two uncertainty trade-offs:

- How much weight do we assign to:
 - best guesses
 - potentially bad outcomes

when designing policy?

- Do we **act now**, or do we **wait** until we learn more?

We explore which among **multiple channels** of uncertainty are **most important** to the design of policy.

For today's talk

- I use a family of models sufficiently rich to
 - investigate **uncertainty trade-offs**
 - explore simultaneous and separate **channels** through which uncertainty impacts climate policy.
- Our models uses deliberately stark **simplifications**, as do most macro and finance models, to reveal
 - internal mechanisms **transparently**
 - nonlinear and durable transition dynamics using **global solution** methods.

*“The economic consequences of many of the complex risks associated with climate change **cannot**, however, currently **be quantified**. ... these unquantified, poorly understood and often **deeply uncertain** risks can and **should be included** in economic evaluations and decision-making processes.”*

Rising, Tedesco, Piontek, Stainforth, 2022

What are the uncertainties?

Four channels of uncertainty:

- **productivity**: capital investment today alters future output
- **geosciences**: CO_2 emissions today impact the future climate
- **economics**: climate change in the future alters economic opportunities and social well-being
- **technology**: research and development invested today may eventually lead to economically viable technologies

What are the consequences of the uncertainties?

Two policy levers:

- **reduce** fossil fuel **emissions**
- **invest** in the **discovery** of new technologies that are **clean replacements**

Decision theory seeks to develop and justify approaches that are “**rational**” or perhaps better described as “**prudent**.”

- allows for a **broad perspective** on uncertainty
 - **risk** - unknown outcomes with known probabilities
 - **ambiguity** - unknown weights to assign to alternative probability models - **prior uncertainty**
 - **misspecification** - unknown ways in which a model might give flawed probabilistic predictions - **likelihood uncertainty**
- includes formulations that are **dynamic** and **tractable**

Formulate a recursive **max-min** game instead of a single-agent maximization problem where we:

- **minimize** over the possible probability distributions subject to a penalization and maximize over the possible decision processes.
- use the minimizing probability to provide an **uncertainty adjustment** pertinent for representing **policies** and the associated **valuations**.

- Borrow insights from derivative claims pricing and from robust Bayesian theory to:
 - deduce a “**worst-case**” probability distribution isolating where potential misspecification is most concerning;
 - use this as an **uncertainty-adjusted probability** measure for social (in place of market) valuation.

Our primary focus will be on potential misspecification.

Uncertainty quantification and decomposition I

- Use the decision problem to assess where uncertainty is **most consequential**.
- As an external analyst, **explore sensitivity** of prudent decisions to the degree of **uncertainty aversion**.
- Quantify the **most important channel** of uncertainty by:
 - ▷ solving **four decision** problems by restricting the uncertainty to one of four channels at a time: i) productivity; ii) geo-scientific, iii) economic damages, and iv) technology;
 - ▷ comparing the outcomes to a decision solution when all four are **simultaneously** considered.

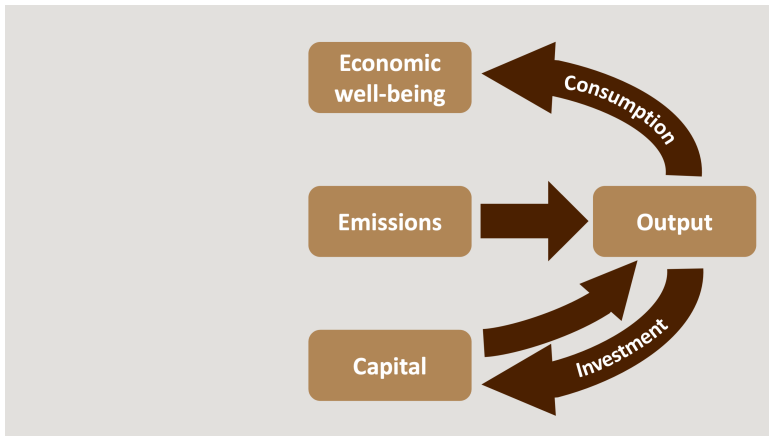
Uncertainty quantification and decomposition II

- Depict **prudent decisions** as dependent on **marginal valuations**.
- Represent **marginal valuations** as **asset prices** with uncertain payoffs.
- Split marginal valuations into **distinct components** based on alternative contributions to the payoffs.

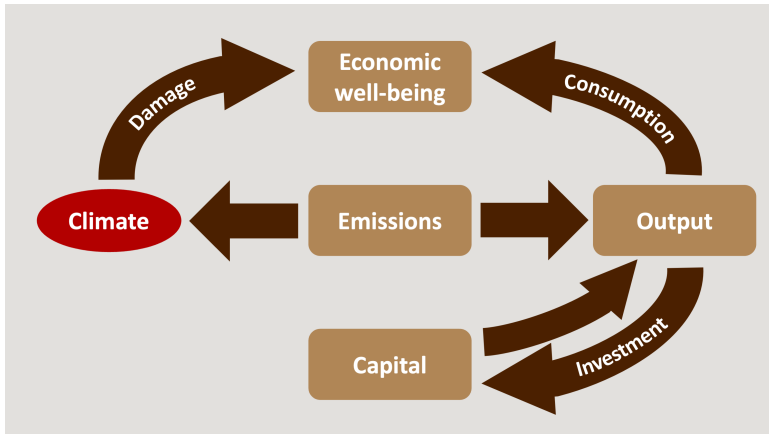
In the case of climate change, two marginal valuations are relevant:

- social cost of **global warming**
- social value of **research and development**.

Modeling framework without climate change

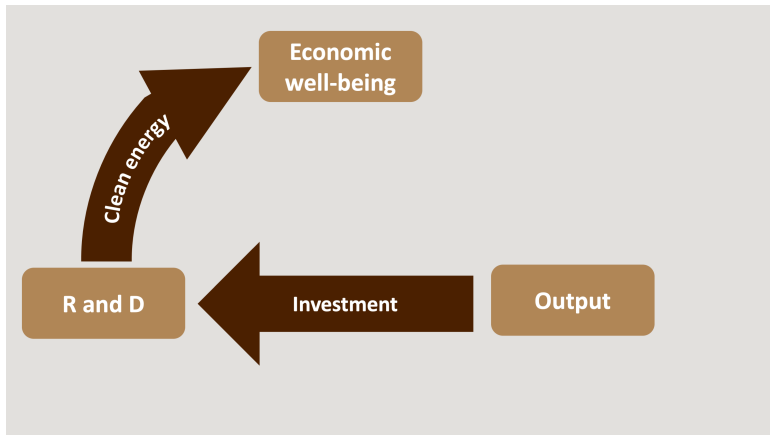


Modeling framework including climate change



Equivalently, the damage could be to the productive capacity of the economy.

Modeling framework with research and development



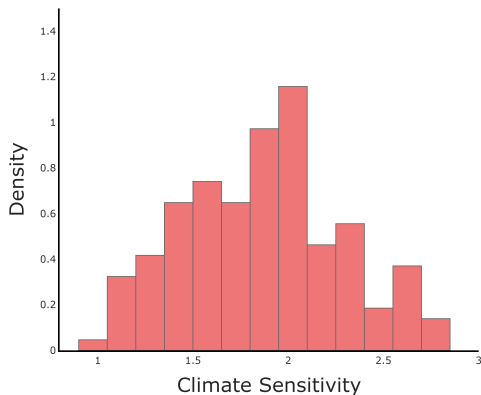
Diffusion process:

$$dY_t = \mathcal{E}_t[\theta(m)dt + \varsigma dW_t]$$

where

- Y is the temperature anomaly
- \mathcal{E} is emissions
- W is a Brownian motion
- $\theta(m)$ is the response implied by model m .

Divergent model predictions



Histograms for the exponentially weighted responses of temperature to an emissions pulse from 144 different models

- consumption
- investment in capital - increases future output
- investment in R&D - increases the stock of knowledge that could generate a technological solution to climate change

- capital
- fossil-fuel based energy

We model technological success for R&D investment as a Poisson event that replaces fossil fuels with an **entirely clean and economically viable** alternative.

- stock of productive **capital**, K , evolves as

$$dK_t = K_t \left[-\mu_k + \left(\frac{I_t^k}{K_t} \right) - \frac{\kappa}{2} \left(\frac{I_t^k}{K_t} \right)^2 \right] dt + K_t \sigma_k dW_t$$

where investment, I^k , contributes new capital subject to an adjustment cost captured by the curvature parameter κ

- the stock of **knowledge** induced by R & D, J , evolves as

$$dJ_t = -\zeta J_t dt + \psi_0 \left(I_t^j \right)^{\psi_1} \left(J_t \right)^{1-\psi_1} dt + J_t \sigma_j dW_t$$

where $0 < \psi_1 < 1$ and I_t^j is an investment in R & D

- **output** constraint

$$C_t + I_t^k + I_t^j = \alpha K_t \left[1 - \phi_0 \left(\frac{\iota_t}{\beta_t \alpha K_t} \right)^{\phi_1} \right]$$

for $\phi_1 \geq 2$ and $0 < \phi_0 \leq 1$, where C is consumption and

$$\iota_t = (\beta_t \alpha K_t - \mathcal{E}_t) \mathbf{1}_{\mathcal{E}_t < \beta_t \alpha K_t}$$

- **technological change**

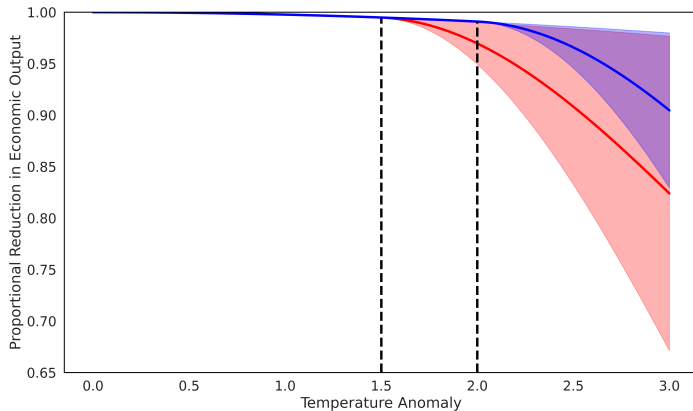
$$\beta_t = \bar{\beta} > 0,$$

and β eventually jumps to zero with an intensity that is proportional to J_t .

Poisson jump process

- jump intensity **increases substantially** over the temperature anomaly degree interval $[1.5, 2]$
- at the time of the jump, the **damage curvature** from that point forward **is revealed** where the tail curvature coefficient takes on one of twenty values

Damage curves

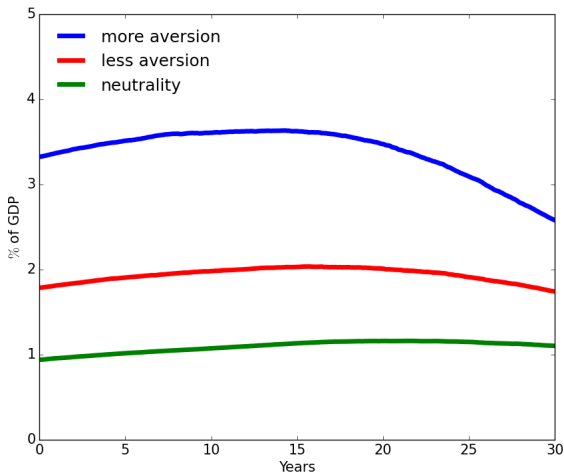


Range of possible damage curves for two cases with different jump thresholds.

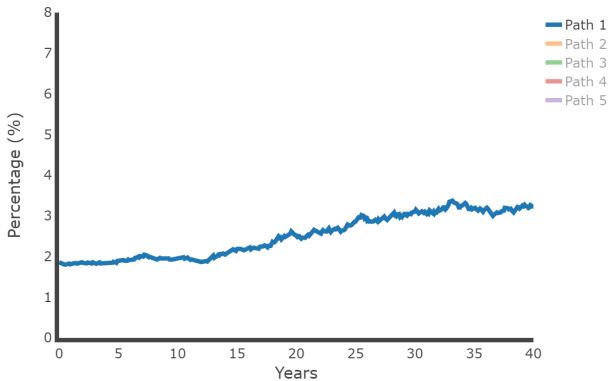
Our initial research shows that:

- the unknown timing of the success of the **R&D investment** is the most potent contributor to uncertainty for climate-economics policy;
- this source of uncertainty leads to doing **more** green R&D investment;
- **reduce emissions** in the short term to allow for **R&D** to have a chance to be successful, even though this response is less sensitive to uncertainty.

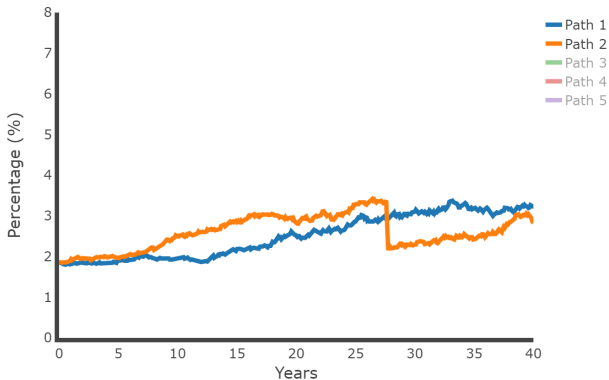
Expected R&D investment



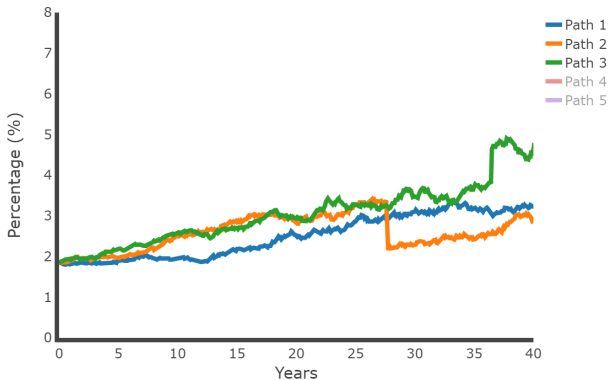
The trajectories are simulated under the baseline transition dynamics averaging over Brownian and jump shocks.



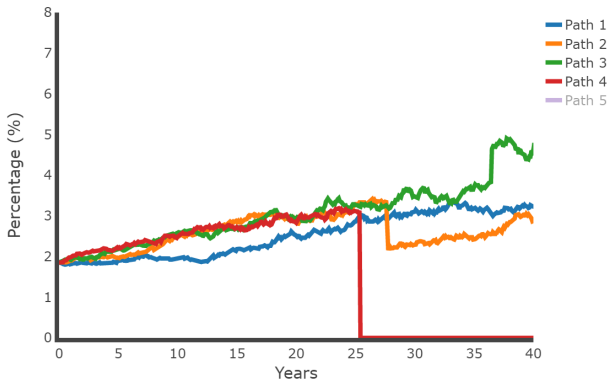
Stochastic simulations



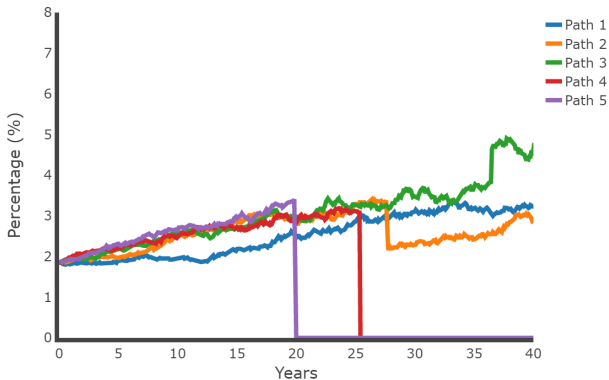
Stochastic simulations



Stochastic simulations

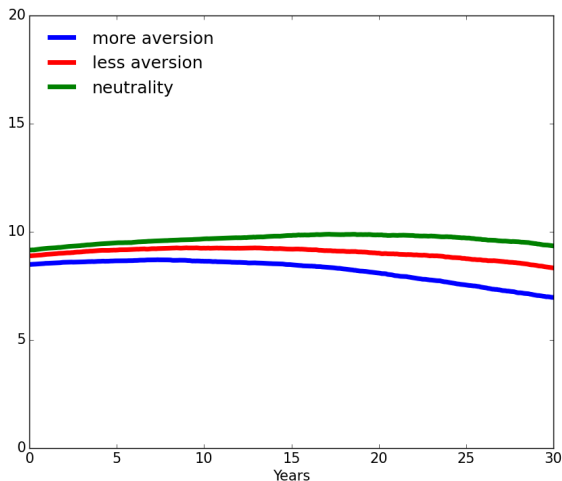


Stochastic simulations



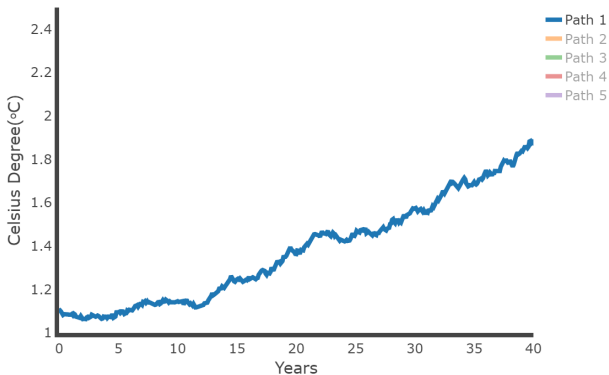
Stochastic simulations

Expected fossil fuel emissions



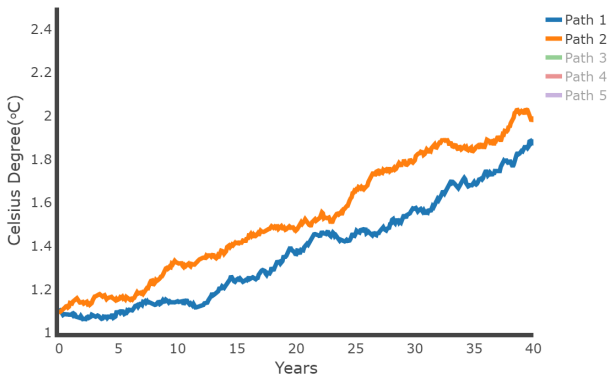
The trajectories are simulated under the baseline transition dynamics averaging over Brownian and jump shocks.

Robust Temperature Anomaly



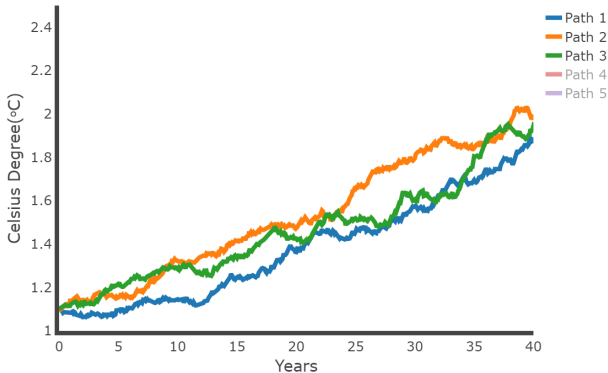
Stochastic simulations

Robust Temperature Anomaly



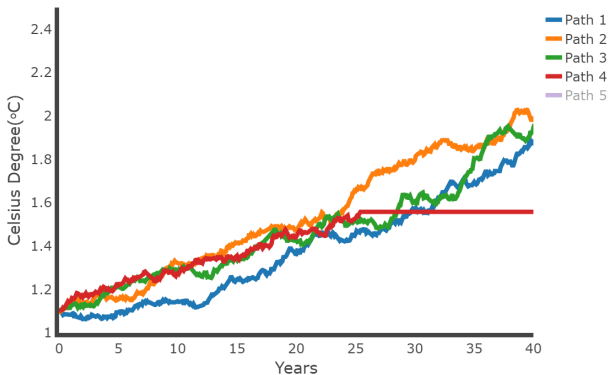
Stochastic simulations

Robust Temperature Anomaly



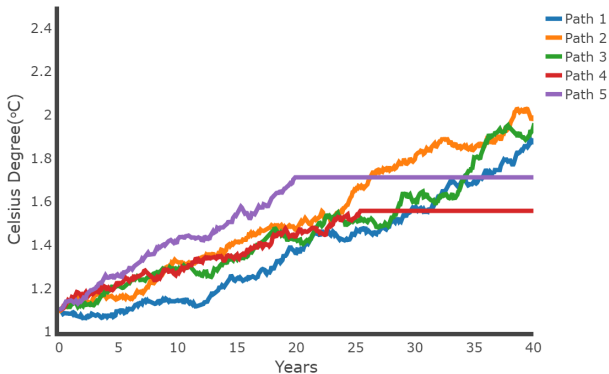
Stochastic simulations

Robust Temperature Anomaly



Stochastic simulations

Robust Temperature Anomaly



Stochastic simulations

Uncertainty-adjusted probabilities

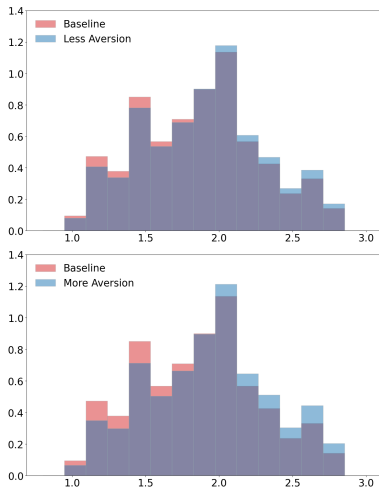


Figure: Altered climate model distribution.

Uncertainty-adjusted probabilities

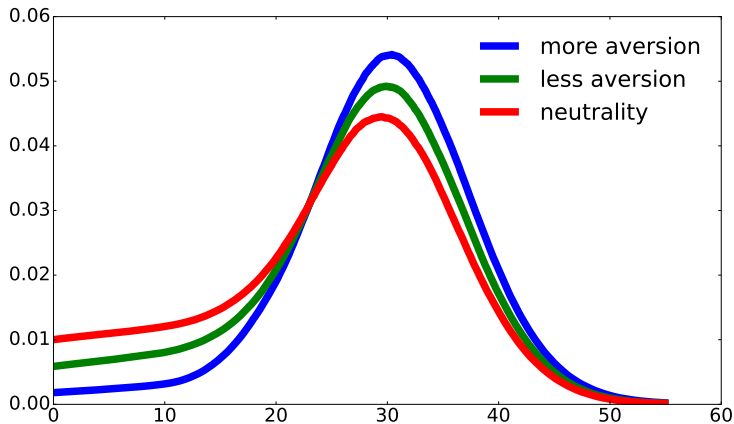


Figure: Densities for the initial jump

Uncertainty-adjusted probabilities

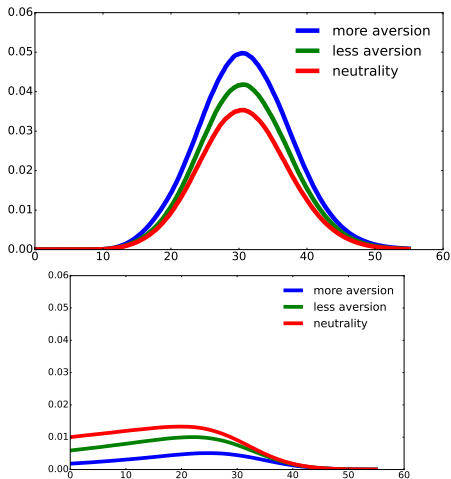


Figure: Two components to the jump densities. Top: damage jumps. Bottom: technology jump.

Why more R&D investment?

Competing forces:

- Uncertainty-adjusted distribution is **more pessimistic** about the R&D timing (**delayed success**).
- Value to a **technological success** is **higher**.

To gain a better understanding, we want to view the **social value of research and development** as an “**asset price**.”

Initially, consider diffusion dynamics:

$$dX_t = \mu(X_t)dt + \sigma(X_t)dW_t$$

where X is a Markov diffusion and W is a multivariate standard Brownian motion.

We will construct a “stochastic” impulse response to measure the impact of a marginal change in a state.

- Form the (first) **variational process**, M , that gives the marginal impact on future X of a marginal change in one of the initial states.
- **Initialize** the process at one of the **coordinate vectors** to specify the initial state of interest.
- Stochastic evolution that depends on X .

- The process M^i evolves as:

$$dM_t^i = (M_t)' \frac{\partial \mu_i}{\partial x}(X_t) dt + (M_t)' \frac{\partial \sigma_i}{\partial x}(X_t) dW_t.$$

where M^i is the i^{th} component of M .

- Stack all of the M^i 's and study the joint dynamics (X, M) .
- Linear VAR (vector autoregression) counterpart is obtained with a drift $\mu(x)$ that is linear in x and a Brownian exposure matrix σ that is constant. M not stochastic.
- M is stochastic in general.

- **Solve for a value function**, V , associated with a discounted objective by
 - imposing the maximizing controls (investments and emissions) and the minimizing probability measure;
 - characterizing its dependence on state variables.
- **Investigate** marginal values computed as partial derivatives that capture small changes in the endogenous state variables including temperature and the stock of knowledge.

A revealing formula

Represent the **partial derivatives** as **asset prices**:

$$\begin{aligned} & \frac{\partial V}{\partial x}(X_0) \cdot M_0 \\ &= \delta \int_0^{\infty} \exp(-\delta t) E \left[\frac{\partial U}{\partial x}(X_t) \cdot M_t \mid X_0, M_0 \right] dt. \end{aligned}$$

where δ is the subjective rate of discount and U is the utility contribution to the value function.

- Initializing M_0 at alternative coordinate vectors gives the derivatives of interest.
- $\frac{\partial U}{\partial x}(X_t)$ is **marginal utility contribution** in the future.
- M is the vector of **stochastic impulse responses**.

Analyze the problem from a “pre-jump” perspective.

- Let $\mathcal{J}^\ell(x)$ denote the jump intensity to jump type ℓ , for $\ell = 1, 2, \dots, L$.
- Let V^ℓ denote the state dependent continuation value for type ℓ .

Jump contributions

- Alter **discount rate** to adjust for a damage curve revelation jump or a technology discovery jump:

$$\delta + \sum_{\ell=1}^L \mathcal{J}^{\ell}(X_t).$$

- Additional **flow** contributions:
 - marginal impact of a jump:

$$M_t \cdot \sum_{\ell=1}^L \left[\frac{\partial \mathcal{J}^{\ell}}{\partial x}(X_t) \right] [V^{\ell}(X_t) - V(X_t)];$$

- marginal impact when you jump:

$$M_t \cdot \sum_{\ell=1}^L \mathcal{J}^{\ell}(X_t) \left[\frac{\partial V^{\ell}}{\partial x}(X_t) \right].$$

Uncertainty adjustment to the decision problem

- Change the **probability** of the **first jump**. (discount factor)
- Change the **continuation value functions** including those that conditioned on the jump types (technology discovery and damage curve realization). (flow terms to be discounted)
- Change the **uncertainty exposure** to the possible jumps. (additional flow term)

Why is R&D investment more attractive?

There are **offsetting impacts** of uncertainty aversion that we study with our **asset pricing representation**:

- the **uncertainty-adjusted** probability measure **pushes** the prospects for **successful R&D** into the **more distant future**;
- the change in continuation values associated with jumps become **substantially larger**.

The **second impact** dominates over a range of uncertainty aversion that we find to be interesting.

- Sometimes the **best response** to uncertainty is to be more **proactive**.
- The approaches I described to characterizing the **impacts of uncertainty** have more **general applicability** to the study of dynamic models.
- This research is part of a larger agenda to explore uncertainty impacts on both **private** and **public sector** decision making.