Green investment and asset stranding under transition scenario uncertainty

Maria Flora[1] Peter Tankov[2]

[1]CREST, CNRS, IP Paris

[2]CREST, ENSAE, IP Paris

Motivation

- The need for a major decarbonisation of the energy system has become evident
- Climate change impacts are expected throughout the energy system itself

Traditional risk management approaches are no longer sufficient to evaluate energy-related assets and investment projects

Our contribution

We develop a flexible investment project valuation model that combines :

1. Integrated assessment modeling (IAM): the scenarios in the IAM help the economic agent get a sense of transition scenario uncertainty

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2. Bayesian learning: the agent progressively forms a belief about the state of the system from the observations of a signal (e.g., carbon price).

Asset stranding and green investment

- We consider two different project valuation problems:

1. Optimal exit: an agent owns a brown plant and wants to understand when it is optimal to decommission (or sell) the plant (with P&L function $h^b(\mathbf{P}_t)$ in year t)

The value function of the agent is of the form

$$\sup_{\tau \in \mathcal{T}_t} \mathbb{E}\left[\sum_{s=t+1}^{\tau} \beta^{(s-t)} h^b(\mathbf{P}_s) - \beta^{\tau-t} K(\tau) \,\middle|\, (\mathbf{P}_t, \hat{\boldsymbol{\pi}}_t) = (\mathbf{P}, \hat{\boldsymbol{\pi}})\right]$$

2. Optimal entry: an agent wants to understand when it is optimal to invest in a green energy project (with P&L function $h^g(\mathbf{P}_t)$ in year t)

The value function of the agent is of the form

$$\sup_{\tau \in \mathcal{T}_t} \mathbb{E}\left[\sum_{s=\tau}^{\tau+T} \beta^{(s-\tau)} h^g(\mathbf{P}_s) - \beta^{\tau-t} K(\tau) \,\middle|\, (\mathbf{P}_\tau, \hat{\boldsymbol{\pi}}_\tau) = (\mathbf{P}, \hat{\boldsymbol{\pi}})\right]$$

Modeling the risk factors

- The agent is exposed to different risk factors (state variables), based on the type of project she wants to divest/undertake
- The risk factors P_k (e.g. electricity price, fuel price, carbon emission allowances price) follow an autoregressive dynamics with mean-reversion rate ϕ_k, volatility σ_k, and scenario-dependent mean $\mu^i_{k,t}$:

$$P_{k,t} = \mu^i_{k,t} + AR^k_t \, ,$$

where AR^k is an autoregressive component such that

$$AR^k_t = \phi_k AR^k_{t-1} + \sigma_k \varepsilon^k_t \, ,$$

and (ε^k_t) are i.i.d. standard Gaussian.

Bayesian learning approach

- The information the agent has about the scenario is encoded in a vector π_t containing the subjective probabilities of scenarios, which are updated dynamically by the agent.
- The Bayesian update is triggered by the observation of a climate-related signal
- It may also be triggered by other events (e.g., subjective perception changes)

Bayesian learning approach

- The signal (e.g. carbon price, tons of GHG emissions) is normally distributed with mean $\mu^i_{y,t}$ and volatility σ_y, that is

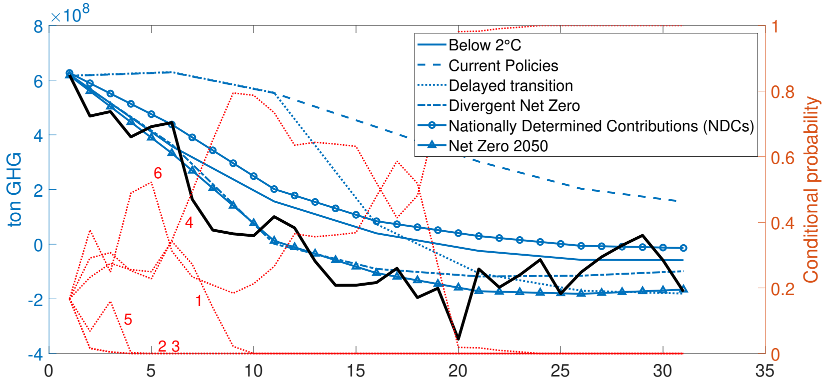
$$y_t = \mu^i_{y,t} + \sigma_y \eta_t \,, \qquad \text{with} \quad \eta_t \sim N(0,1) \text{ i.i.d.}$$

- Denote by π^i_t the conditional probability of i-th scenario given the observations of a signal y up to date t:

$$\pi^i_t = \mathbb{P}[I = i | \mathcal{F}_t], \quad \mathcal{F}_t = \sigma(y_s, s \leq t)\,.$$

Bayesian learning approach

- Given $\mathcal{F}_{t-1}$, we can define the joint law of π_t and y_t, and thus obtain simulated paths for the signal y_t and for the resulting conditional probabilities π_t



Pricing the real option

- We can then simulate paths of the relevant price variables $\mathbf{P}_t$, given their law

$$\mathbb{P}[\mathbf{P}_t|\mathcal{F}_{t-1}] = \sum_{i=1}^{N} \pi_{t-1}^{i} \mathbb{P}\left[\mathbf{P}_t|I = i, \mathcal{F}_{t-1}\right] \ \ldots$$

- ...and through the dynamic programming principle we can derive the Bellman equation of the agent's value function.

- Now, the value of the project can be computed by backward induction similarly to the value of an American option, using Least Squares Monte Carlo

Least Squares Monte Carlo

- The algorithm works by backward induction
- At each point in time, it compares the convenience of immediate exercise with that of delaying the decision
- The continuation value from keeping the option alive at each possible exercise point is computed from a least squares cross-sectional regression using the simulated paths
- In such a way, we obtain both the value of the real option and the optimal exercise time

Integrated Assessment Models (IAMs)

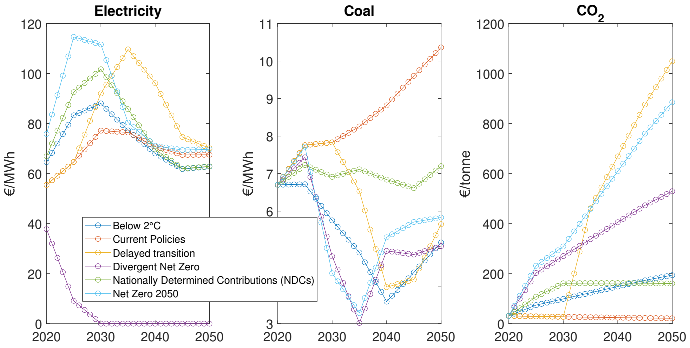
- IAMs include feedbacks between the global economy, the energy system and the climate system
- They are the convenient tool to analyze the economic impacts of climate change and climate change mitigation measures.
- IAMs are used to generate scenarios of evolution of the economy consistent with given climate objectives, based on a set of assumptions
- In this work, we employ a NFGS IAM, namely REMIND 2.1

REMIND 2.1: 6 alternative scenarios

1. **Current Policies :** existing climate policies remain in place
2. **Nationally Determined Contributions (NDCs) :** currently pledged unconditional NDCs are implemented fully, and respective targets on energy and emissions in 2025 and 2030 are reached in all countries;
3. **Delayed Transition (Disorderly) :** there is a "fossil recovery" from 2020 to 2030; Only thereafter countries with a clear commitment to a specific net-zero policy target at the end of 2020 are assumed to meet the target
4. **Below 2°C :** the 67-percentile of warming is kept below 2°C throughout the 21st century
5. **Divergent Net Zero (Disorderly) :** median temperature below 1.5°C in 2100, after a limited temporary overshoot
6. **Net Zero 2050 :** global CO_2 emissions are at net-zero in 2050

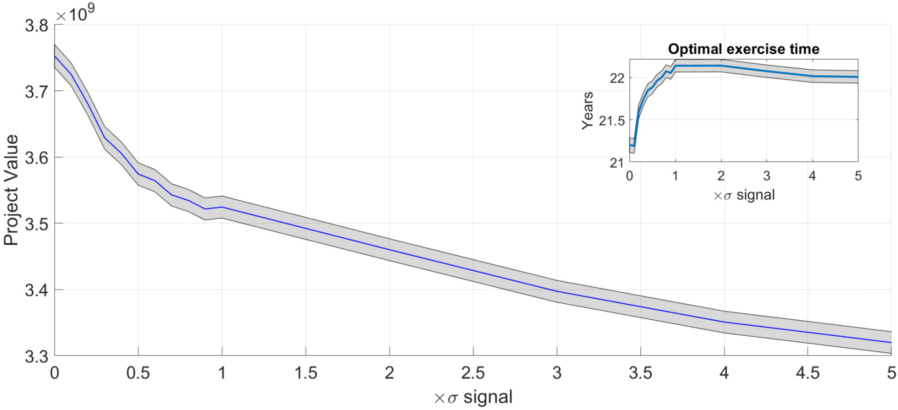
Optimal exit problem

- We consider an integrated coal gasification plant without CCS technology, located in Germany
- The plant presents 3 risk factors, namely the price of electricity, the price of coal and the price of carbon



Optimal exit problem: Results

- Sensitivity of the RO value to the volatility of the signal σ_y (signal: total GHG emissions)



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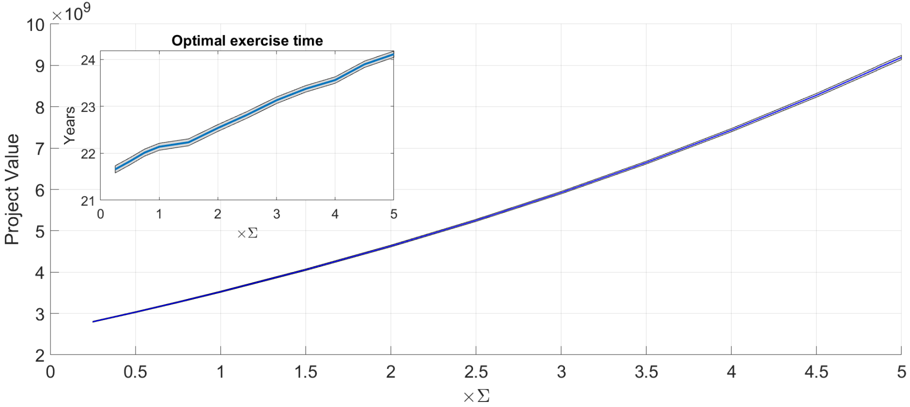
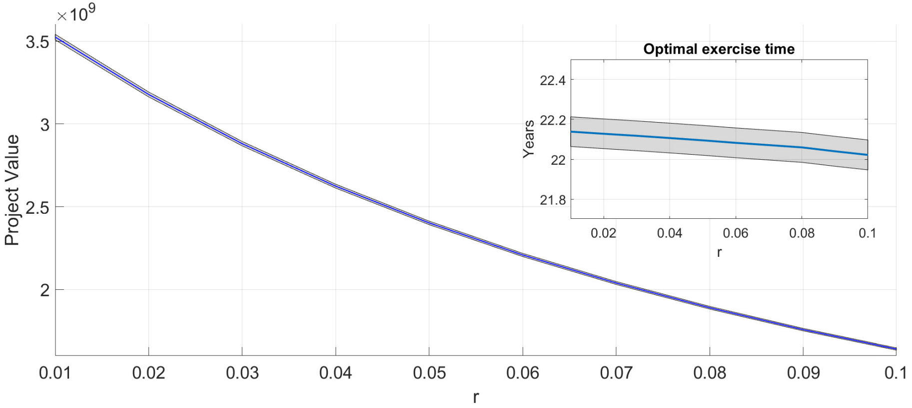
Optimal exit problem: Results

- Sensitivity of the RO value to the volatility of risk factors Σ (signal: total GHG emissions)

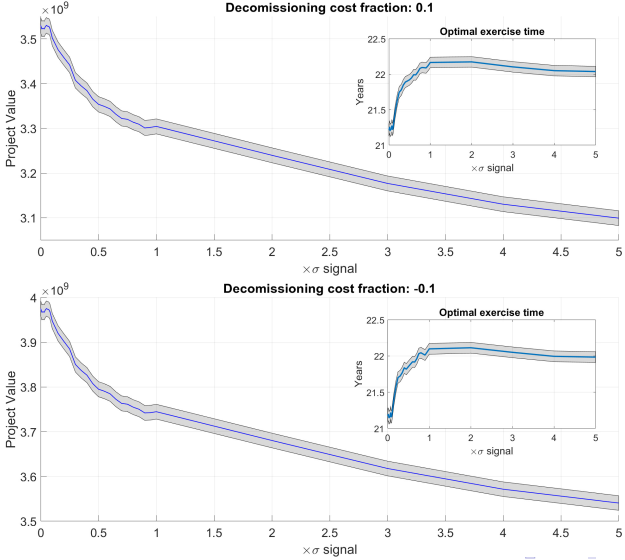


Optimal exit problem: Results

- Sensitivity of the RO value to the risk-adjusted discount rate r (signal: total GHG emissions)

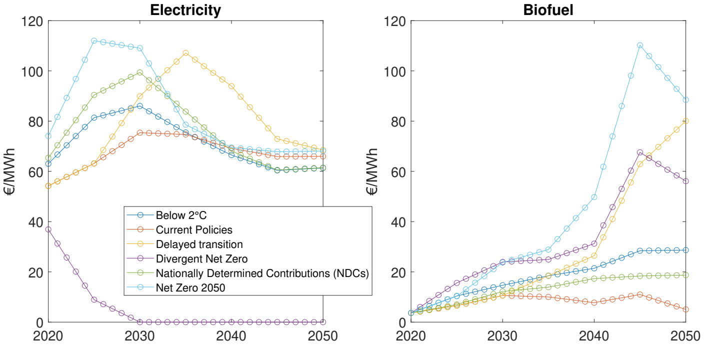


Optimal exit problem: Results



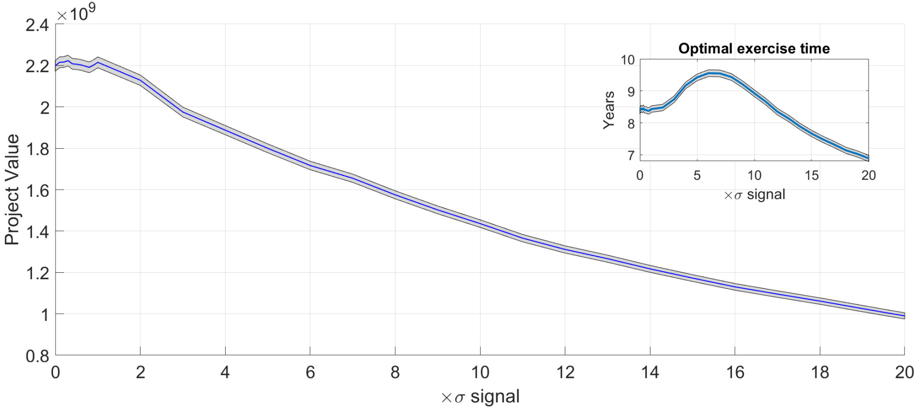
Optimal entry problem

- We consider an integrated biomass power plant with CCS technology, located in Germany
- The plant presents 2 risk factors, namely the price of electricity, and the price of biofuel



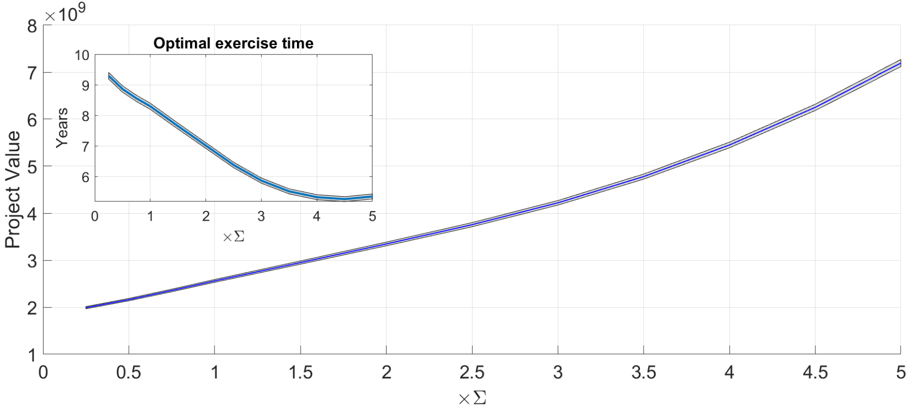
Optimal entry problem: Results

- Sensitivity of the RO value to the volatility of the signal σ_y (signal: carbon price)



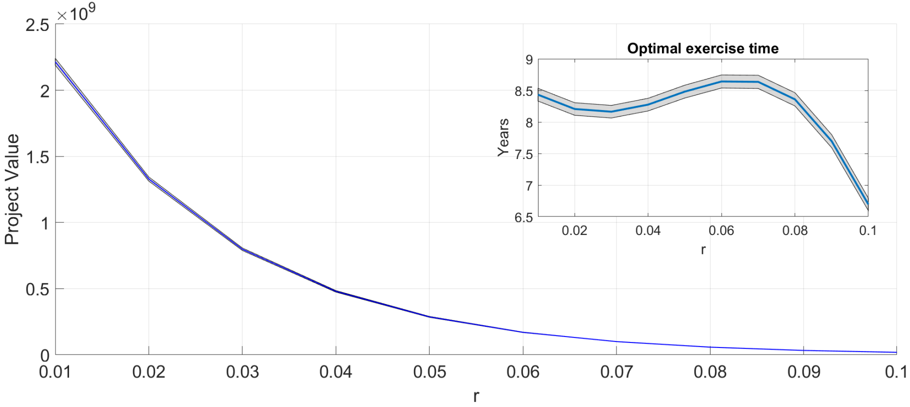
Optimal entry problem: Results

- Sensitivity of the RO value to the volatility of risk factors Σ (signal: carbon price)



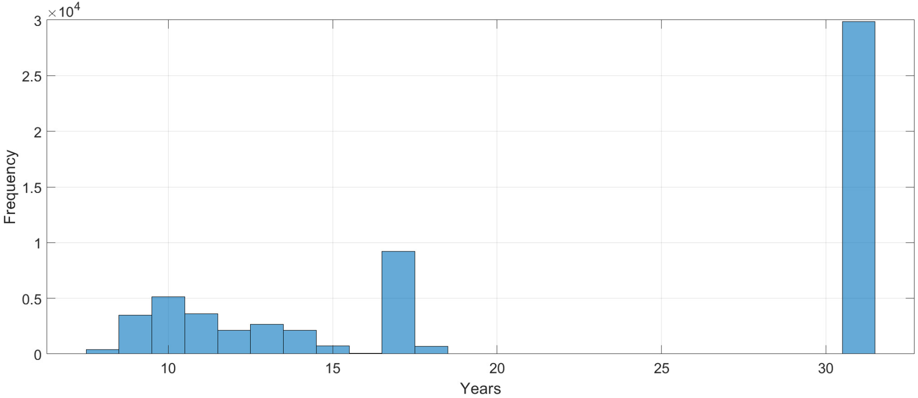
Optimal entry problem: Results

- Sensitivity of the RO value to the risk-adjusted discount rate r (signal: carbon price)



Thank you for your attention!

maria.flora@ensae.fr



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