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).

Our contribution

- Transition risk is usually evaluated with Integrated assessment model scenarios (Net Zero 2050, Delayed Transition, Disorderly Transition, etc.)

- These scenarios are static (chosen at time 0) and assume perfect knowledge of the scenario by the agent

$\Rightarrow$ We build a stochastic layer on top of the IAM to introduce dynamic scenario uncertainty and progressive learning of the scenario by the agent

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

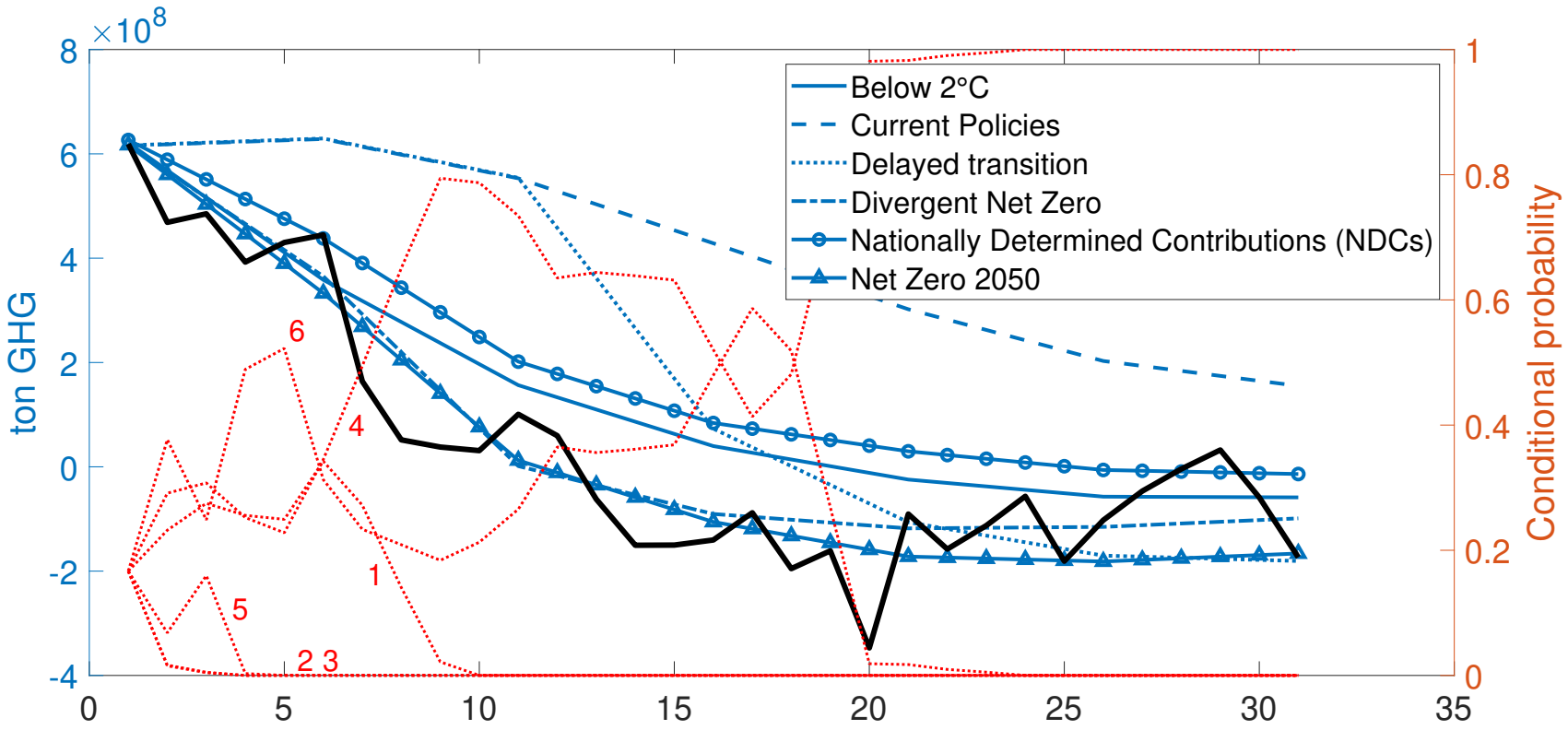
$$y_t = \mu^i_{y,t} + \sigma_y \eta_t \,, \qquad \text{with} \quad \eta_t \sim N(0,1) \text{ i.i.d.}$$

- 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)

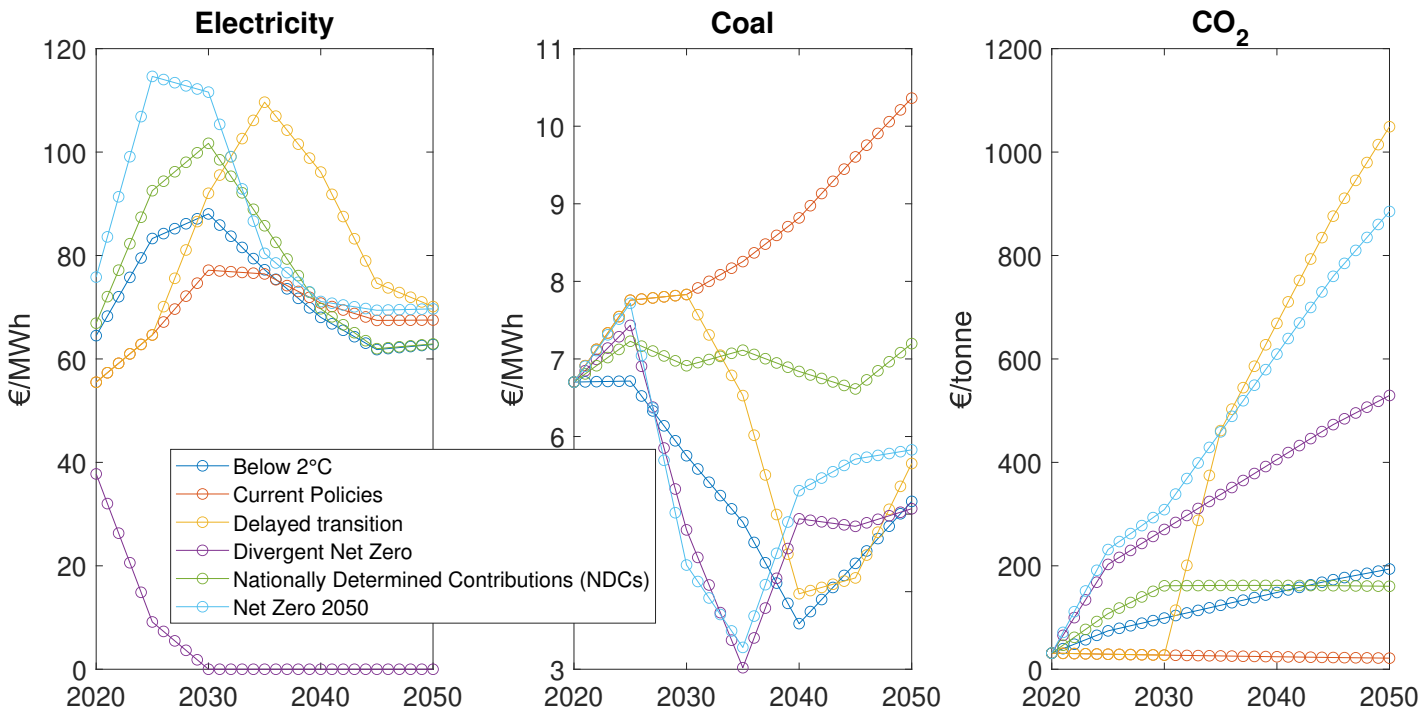
- IAMs include feedbacks between the global economy, the energy system and the climate system
- They are the convenient tool to analyze the economic impacts of climate change and climate change mitigation measures.
- IAMs are used to generate scenarios of evolution of the economy consistent with given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

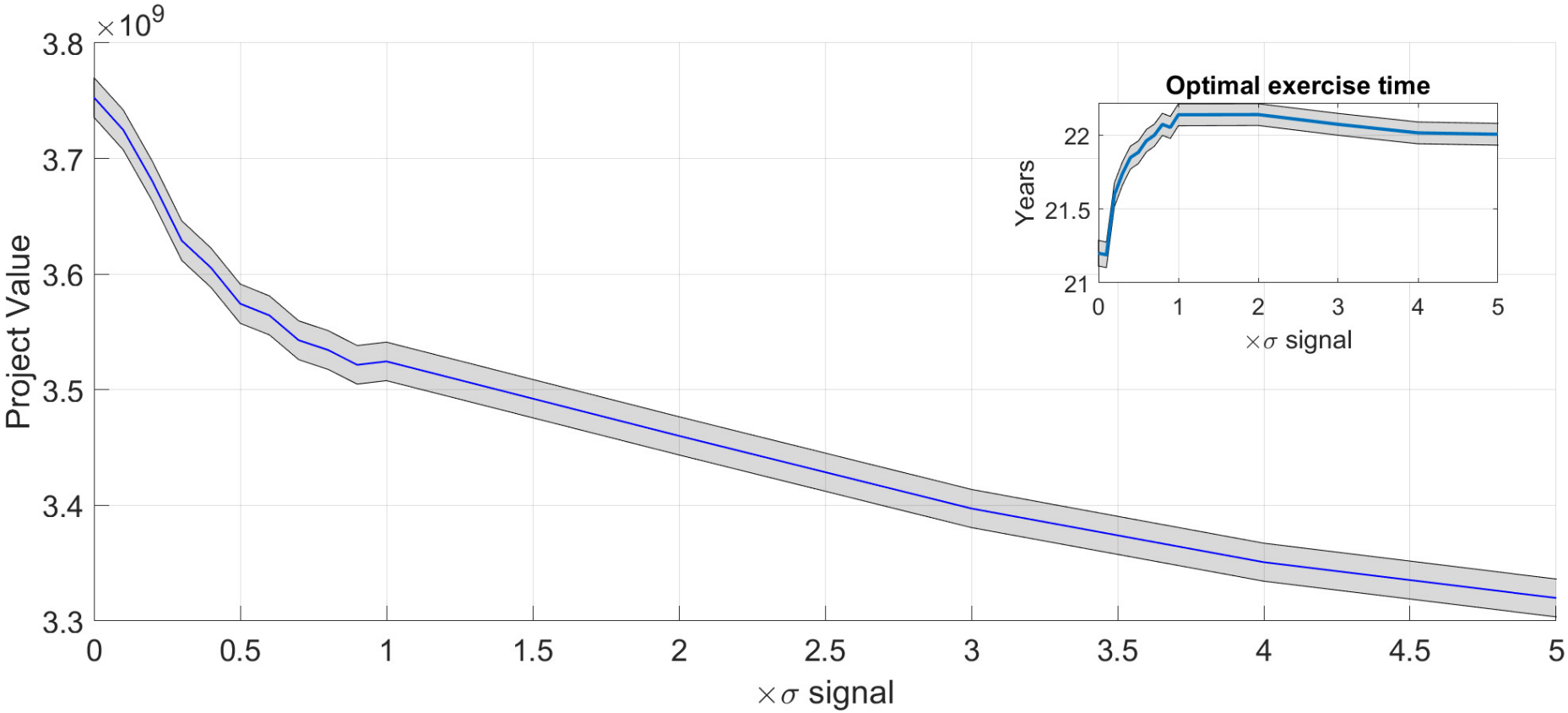
Optimal exit problem

- 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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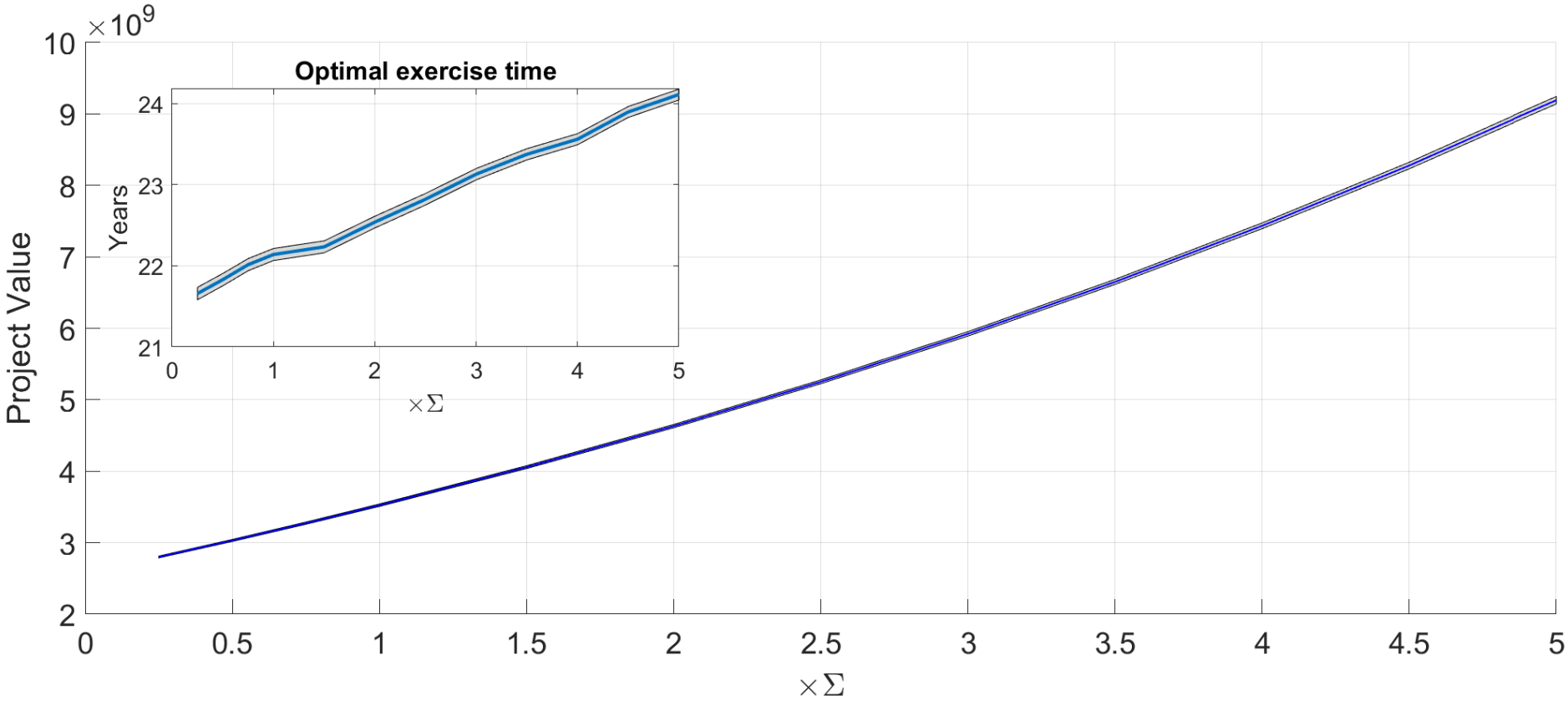
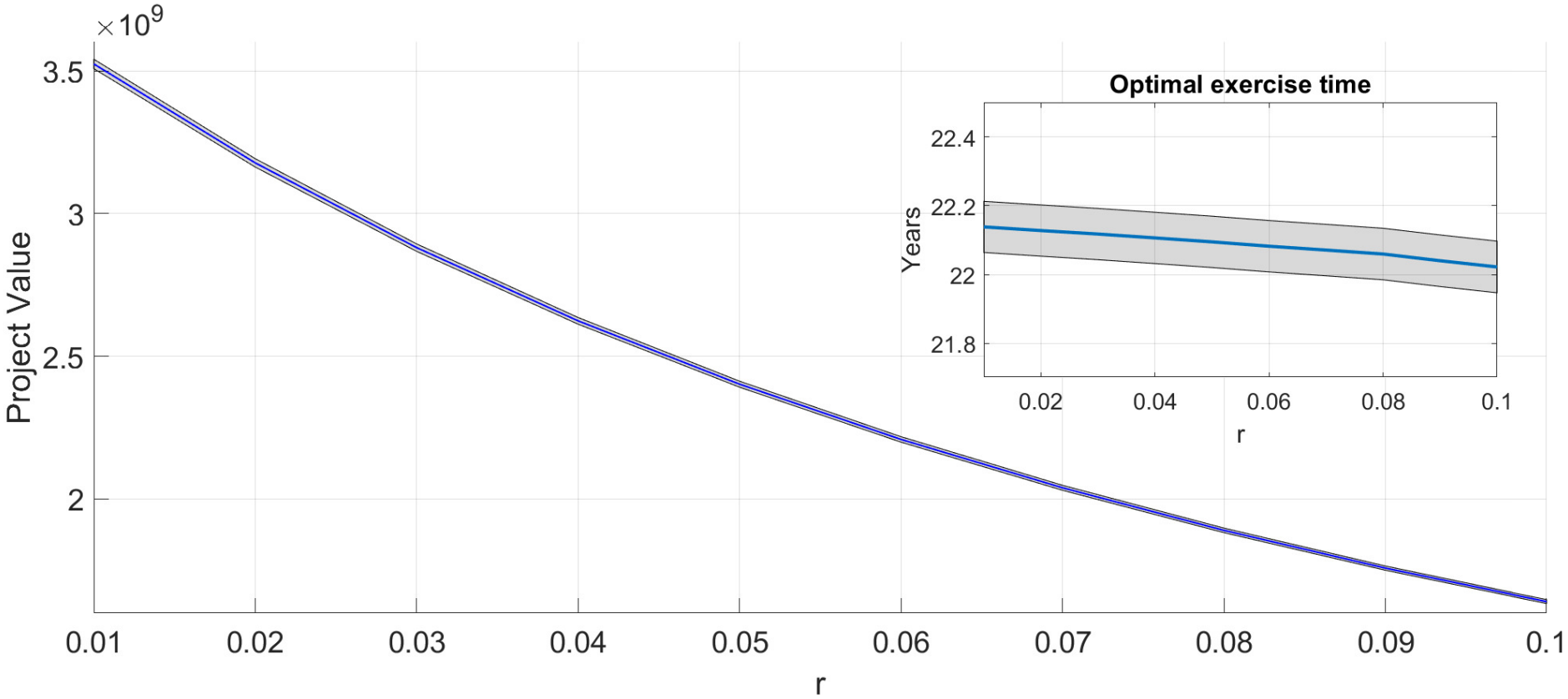
Optimal exit problem: Results

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

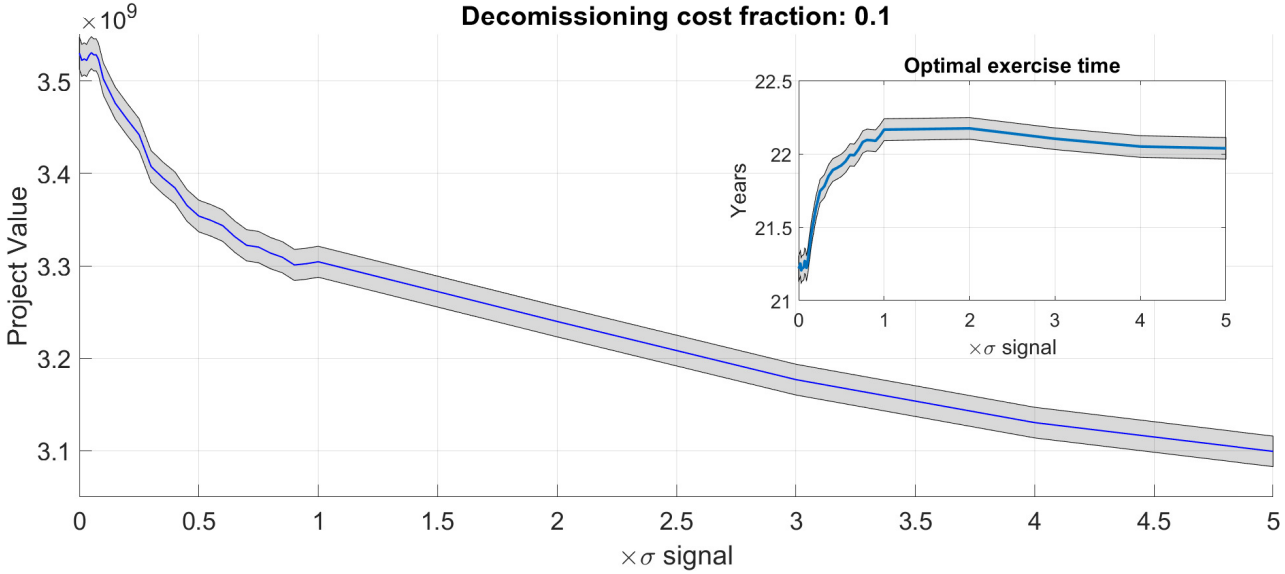


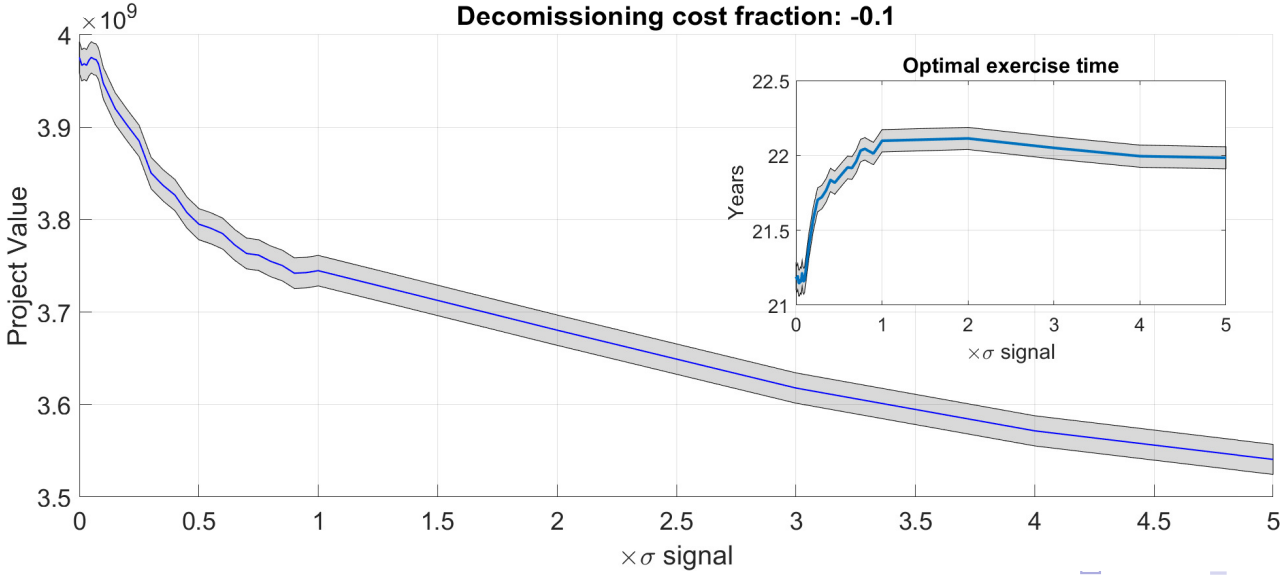
Optimal exit problem: Results

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



Optimal exit problem: Results





Conclusions

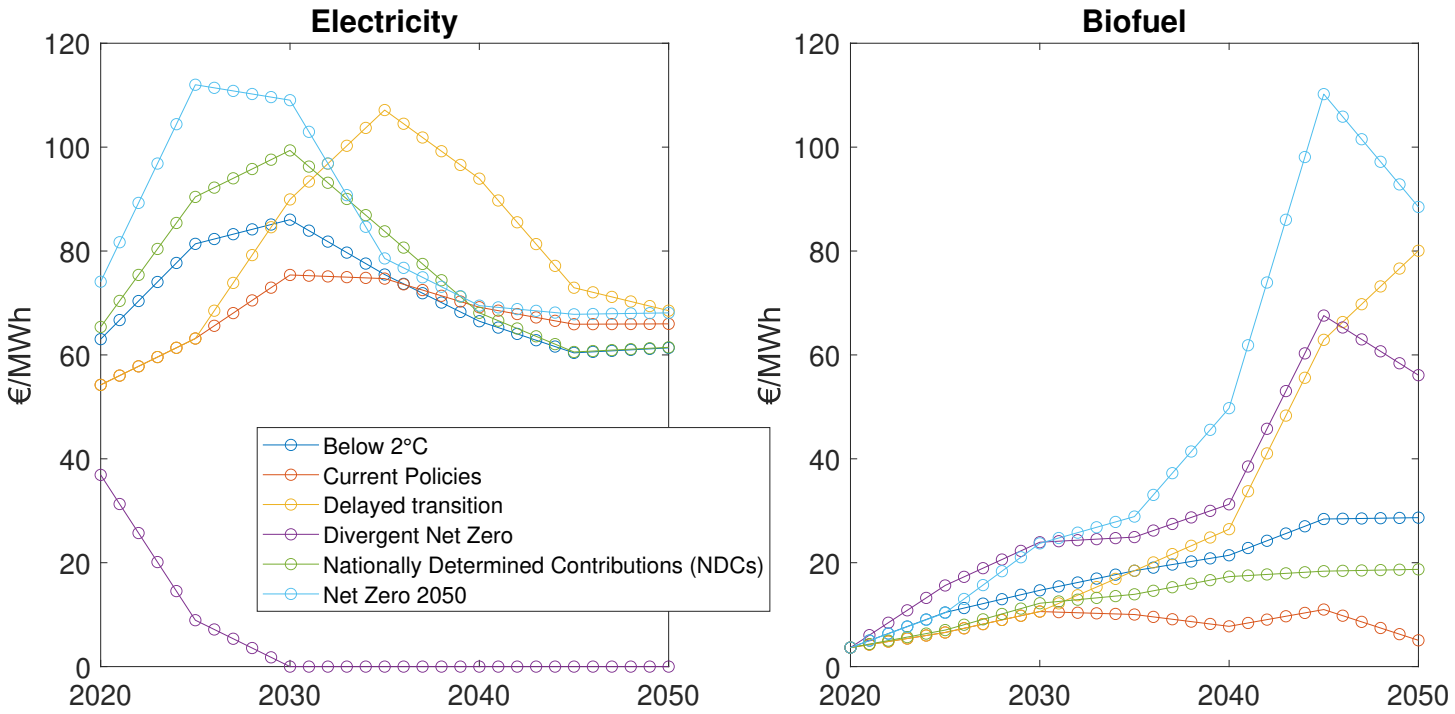
- We present a new strategy for evaluating investment projects, based on a combination of standard real options techniques with a macroeconomic approach for climate transition analysis
- The agent continuously observes a noisy climate-related signal, and forms a belief relative to the likelihood of the possible current macroeconomic climate scenarios
- We show there is value in the learning process of the agent and that the progressive resolution of scenario uncertainty is essential for precise valuation of energy projects

Thank you for your attention!

maria.flora@ensae.fr

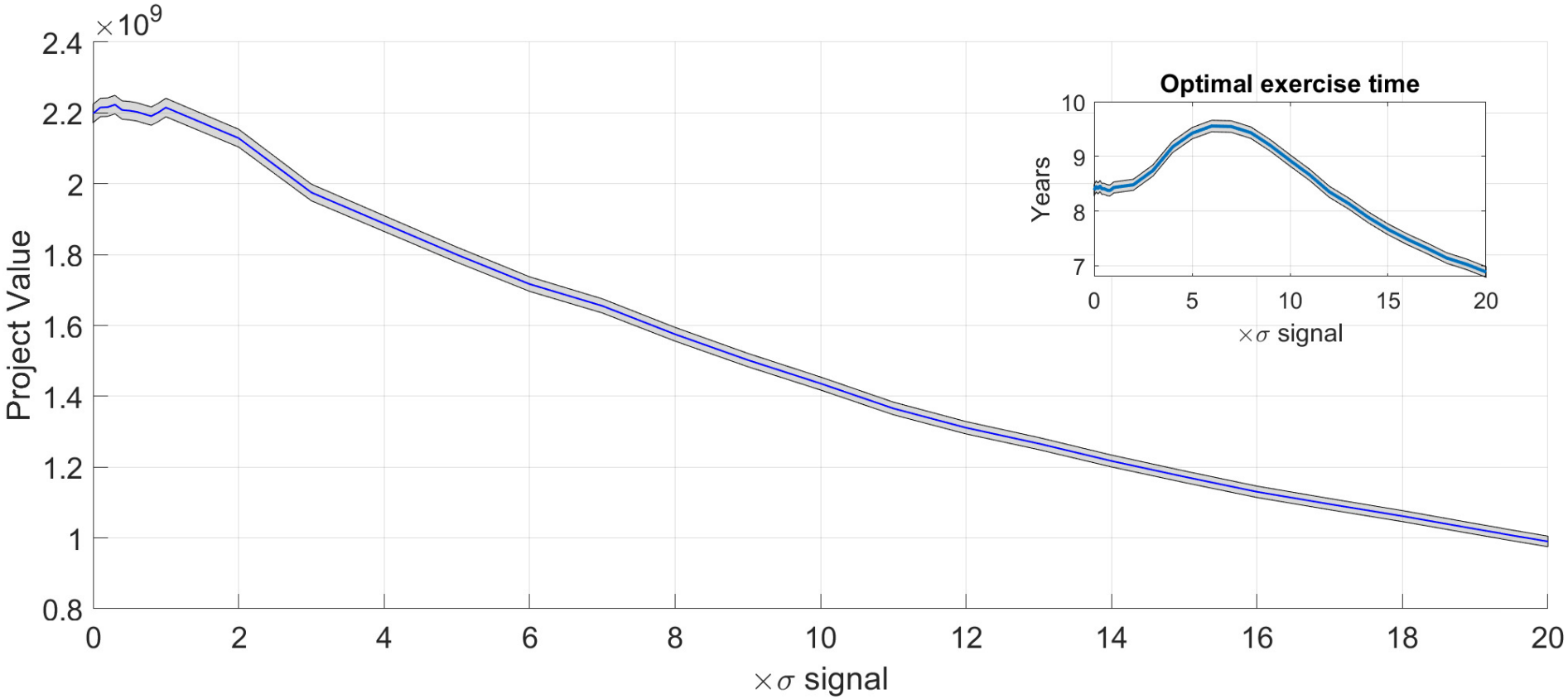
Optimal entry problem

- 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



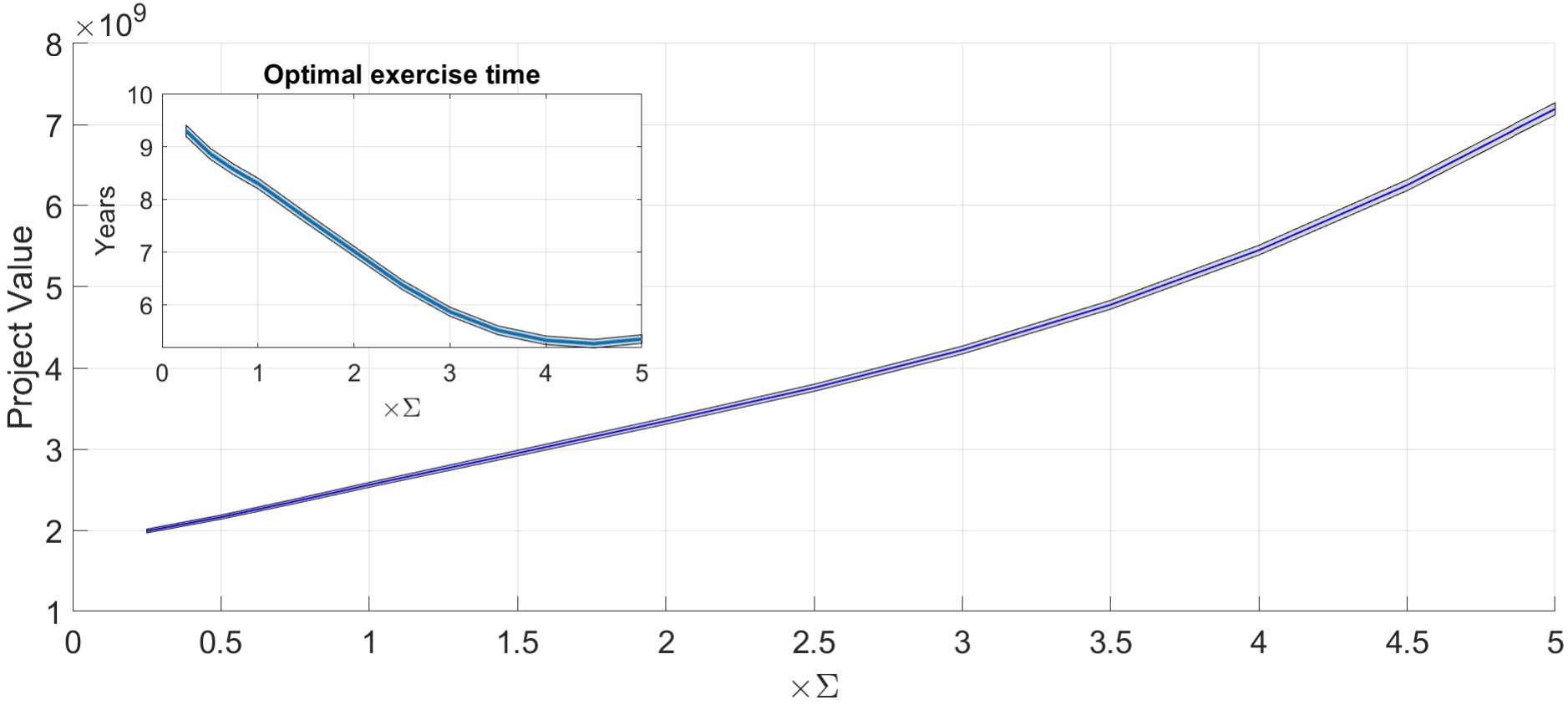
Optimal entry problem: Results

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



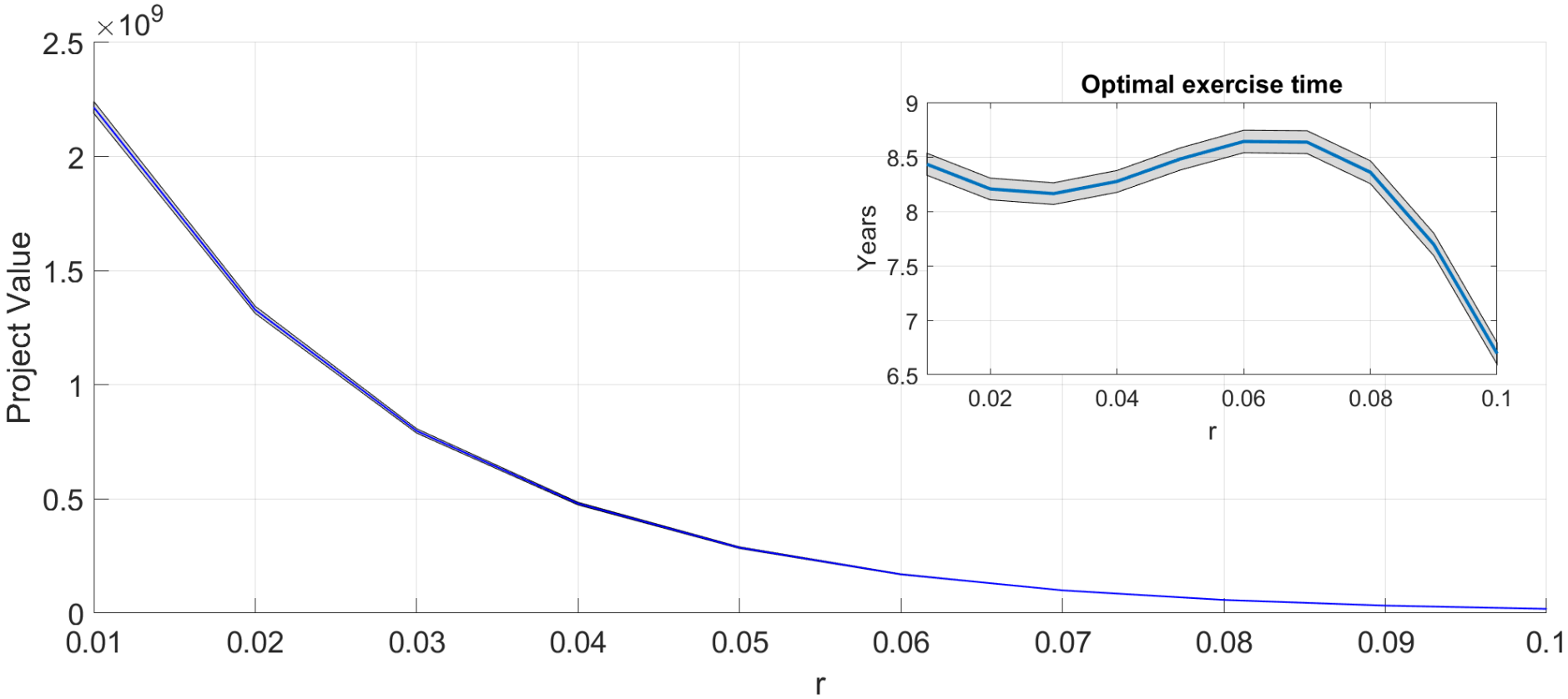
Optimal entry problem: Results

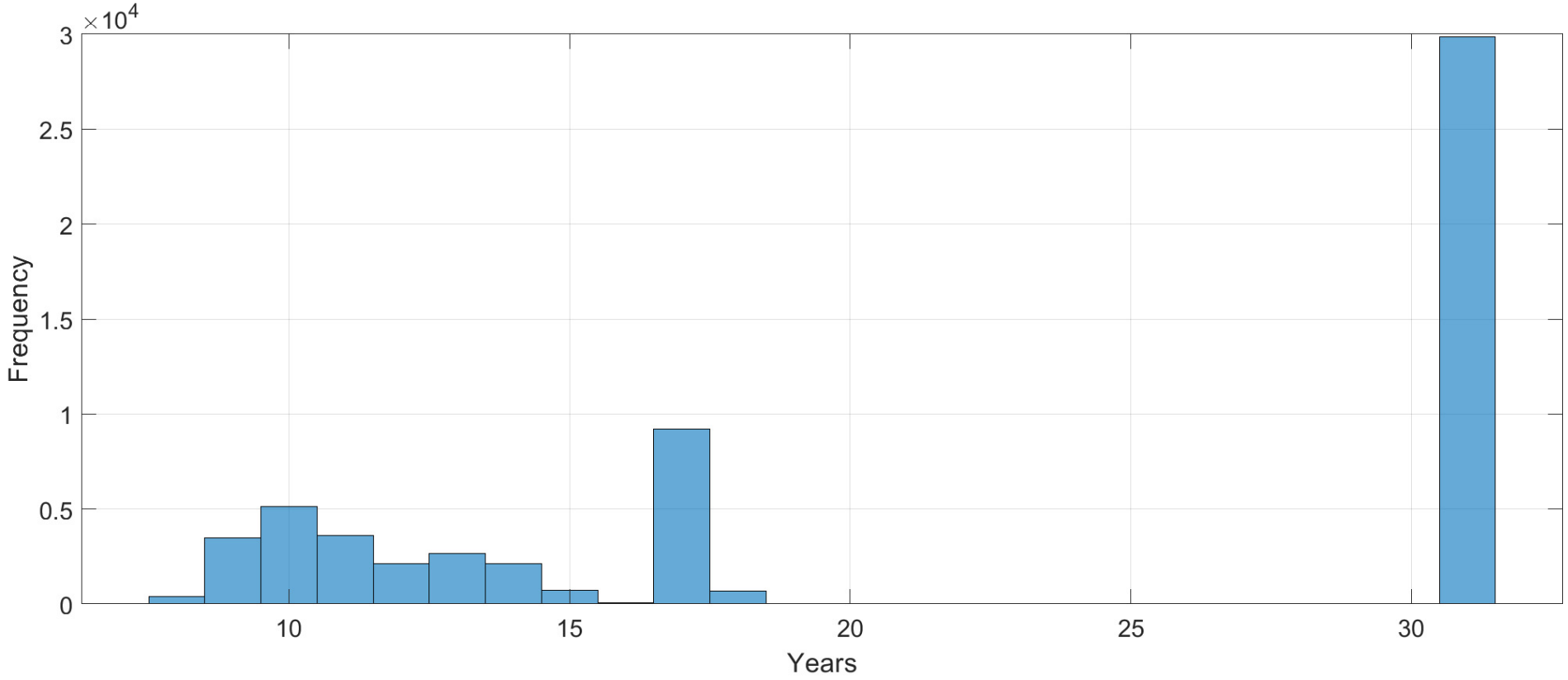
- Sensitivity of the RO value to the volatility of risk factors Σ (signal: carbon price)



Optimal entry problem: Results

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





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