# Optimal business model adaptation plan for a company under an energy transition scenario

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# Context

- Climate change:
  - Caused by human activities: [Stern and Kaufmann, 2014];
  - Requires cutting carbon emissions to Net Zero as soon as possible: the Energy Transition.
- Transition Risk:
  - *"The financial risks which could result from the process of adjustment towards a lower-carbon economy*" (see [Carney, 2015]);
  - Long-term risk: The tragedy of horizons.
  - Need to assess this risk in a forward-looking manner: Climate Stress-Tests [Bank of England, 2019, Autorité de Contrôle Prudentiel et de Résolution, 2020].
- Climate Stress-Tests modelling challenges:
  1. Finer granularity to bypass the lack of historical data,
  2. Longer time horizon,
  3. Dynamicity of the bank's positions and balance sheet.
- Here we focus on transition risk and corporate credit risk stress testing.

# Our Contribution

**Question**

How to model a company's business model adaptation to the energy transition in a given transition scenario for credit risk climate stress tests ?

- Many individual pathways that lead to the same aggregated results.
- Micro-Macro Simulation: The company's characteristics determine how much adaptation is needed.
- Existing approaches:
  - Deterministic : econometric regressions on historical data [Alogoskoufis et al., 2021, Emambakhsh et al., 2023]), same slope or target as scenario [Barclays PLC, 2021];
  - Rely mainly on carbon price increases and omit costs.
- We need a stochastic approach that captures all different transmission channels of transition risk (policy, technology, sentiment see [Basel Committee on Banking Supervision, 2021]).

We propose an approach by stochastic control optimization.

# The model

# The Business model indicator

## Assumptions

- $(\Omega, \mathcal{F}, \mathbb{P})$
- Management period : $[0, T]$ where $T$ is the end of the scenario.
- $N$ fixed decision dates $i = 0 : N-1$ with constant time step $\delta$.
- Let $\Delta\varepsilon_i^I$ and $\Delta\varepsilon^S$ be the bounded time-increments of random iid processes such that $corr(\Delta\varepsilon_i^I, \Delta\varepsilon_i^S) < 0$ for any $i = 0 : N$ with canonical filtration $\mathcal{F}$.

- Business model indicator / State variable : $(X_i)_{i=0:N} := (I_i, S_i)_{i=0:N}$.
- Sales Revenues Emissions Intensity

$$X_i^{(1)} = I_i = I_{i-1} e^{-\gamma_{i-1}\delta} \times e^{\sigma_I \Delta\varepsilon_i^I - \psi_i^I(\sigma_I)}. \tag{3.1}$$

- Intensity reduction rate: $\gamma_i \in [0, \gamma_{max}] \quad \forall i = 0 : N-1$.
- $\psi_i^I$ the log moment generating function of $\Delta\varepsilon_i^I$: $e^{\psi_i^I(\sigma_I)} = \mathbb{E}\left[e^{\sigma_I \Delta\varepsilon_i^I}\right]$.

# The sales revenues

The company's sales revenues between $i-1$ and $i$:

- Sales Revenues

$$X_i^{(2)} = S_i = S_{i-1} \frac{\bar{S}_i}{\bar{S}_{i-1}} e^{-\kappa\left(I_{i-1} - I_{i-1}^{\mathrm{ref}}\right)\delta} \times e^{\sigma_S \Delta\varepsilon_i^S - \psi_i^S(\sigma_S)}. \tag{3.2}$$

- with $\bar{S}$ the sales revenues of the reference market, $I^{\mathrm{ref}}$ the market reference for the intensity and $\kappa \geq 0$ and $\psi_i^S$ the log moment generating function of $\Delta\varepsilon_i^S$ .
- We take into account: Cost pass-through, Reputation (consumer sentiment) and Demand-price elasticity shocks ([Basel Committee on Banking Supervision, 2021]).

By definition of the sales emissions intensity we have:

$$\text{Emissions :} \quad E_i = I_i \times S_i$$

# The costs functions

- At each date, the company will pay a carbon tax : $\mathrm{cp}_i \times E_i$ with $\mathrm{cp}_i$ the carbon price given by the scenario.
- Investment costs : $I^C$; is a positive, increasing and convex function of the emissions reduction rate [Grubb et al., 1993, McKinsey et al., 2009].

$$I^C(i, S, \gamma) = S \times c \times \alpha^{i\delta} \times \frac{\left(1 - e^{-\gamma\delta}\right)^{\beta}}{\beta}, \tag{3.3}$$

where $c > 0$ is the unit abatement cost of emissions in $USD$, $\alpha \in [0.8, 1]$ the factor of autonomous cost decrease over time, and $\beta \geq 2$ the exponent of the emissions reduction rate $1 - e^{-\gamma\delta}$. Indeed, the proactive emissions reduction rate is obtained as follows:

$$\begin{aligned} \Delta E_i &= E_i - E_i e^{-\gamma_i \delta} \\ &= I_i S_i (1 - e^{-\gamma_i \delta}) \end{aligned}$$

# Statement of the problem

Similarly to [Liang and Huang, 2021], we assume that the company will choose the intensity reduction strategy $\pi = (\gamma_0, \dots, \gamma_{N-1})$ that minimizes its total discounted costs.

## Stochastic control problem

$$J^*(0,x) = \inf_{\pi \in \Pi} \mathbb{E}\left[ \sum_{i=0}^{N-1} \frac{\mathrm{cp}_i X_i^{(1)} X_i^{(2)} + I^C(i, X_i^{(2)}, \gamma_i)}{(1+r\delta)^i} + \frac{\mathcal{C}_N(X_N)}{(1+r\delta)^N} \mid X_0 = x \right] \tag{3.4}$$

$$= \inf_{\pi \in \Pi} \mathbb{E}\left[ \sum_{i=0}^{N-1} \frac{\mathcal{C}_i(X_i, \gamma_i)}{(1+r\delta)^i} + \frac{\mathcal{C}_N(X_N)}{(1+r\delta)^N} \mid X_0 = x \right]. \tag{3.5}$$

where $\Pi$ is the set of admissible strategies, meaning $\mathcal{F}$-adapted and such that $\gamma_i \in [0, \gamma_{max}] \quad \forall i = 0 : N-1$.

# Resolution

## Theorem: Existence of an optimal control (see [Bertsekas and Shreve, 1978])

1. If the following assumption is satisfied:

$$\mathbb{E}\left[\max\left(0, -\mathcal{C}_i(X,\gamma)\right)\right] < \infty, \quad \forall i = 0:N, \quad \gamma \in [0,\gamma_{max}], \tag{$F^+$}$$

2. and if the infimum in:

$$\inf_{\gamma\in[0,\gamma_{max}]}\{\mathcal{C}_i(x,\gamma) + \frac{1}{1+r\delta}\mathbb{E}_\gamma\left[J^*(i+1,X_{i+1}) \mid X_i = x\right]\}, \quad i = 0:N-1,$$
$$x \in \mathbb{R}^+ \times \mathbb{R}^+,$$

is attained for all $x \in \mathbb{R}^+ \times \mathbb{R}^+$ with $J^*(N,x) = \mathcal{C}_N(x)$, then an optimal nonrandomized Markov strategy $\pi^*(x)$ exists. This strategy is given by the dynamic programming algorithm:

$$\gamma_i : x \longmapsto \arg\min_{\gamma\in[0,\gamma_{max}]}\{\mathcal{C}_i(x,\gamma) + \frac{1}{1+r\delta}\mathbb{E}_\gamma\left[J^*(i+1,X_{i+1}) \mid X_i = x\right]\}. \tag{4.1}$$

# Numerical Resolution by Backward Sampling

## Goal

Find by backward induction $\forall i = N-1:0$:

$$\gamma_i^*(x) = \arg\min_{\gamma\in[0,\gamma_{max}]}\{\mathcal{C}_i(x,\gamma) + \frac{1}{1+r\delta}\mathbb{E}_\gamma\left[J^*(i+1,X_{i+1}) \mid X_i = x\right]\}. \tag{4.2}$$

ISSUES:

- How to compute $J^*(i,x) := \inf_{\pi_i\in\Pi_i} J_{\pi_i}(i,x)$ ?
- How to minimize $\mathbb{E}_\gamma\left[J^*(i+1,X_{i+1}) \mid X_i = x\right]$ w.r.t $\gamma$ ? (i.e. write it as an explicit function of $\gamma$)

# The backward sampling trick

- $X_j^{\pi^{(0)}_{0:i}}(0, X_0)$: the value for the state variable at $j$ starting in $X_i^{\pi^{(0)}_{0:i}}$ at date $i$ and computed with a reference Markovian strategy $\pi^{(0)}_{i:j}$.
- Let $X_j^{\pi_{i:j}}(i, X_i^{\pi^{(0)}_{0:i}})$: the value for the state variable at $j$ starting in $X_i^{\pi^{(0)}_{0:i}}$ at date $i$ and computed with admissible strategy $\pi_{i:j}$.

Thanks to the exponential form of the state variable, we can hop between any two trajectories computed with different admissible strategies (keeping noise constant).

$$I_j^{\tilde{\pi}_{i:j}}(i, X_i^{\pi^{(0)}_{0:i}}) = I_j^{\pi^{(0)}_{i:j}}(i, X_i^{\pi^{(0)}_{0:i}}) \exp\left(-\sum_{q=i}^{j-1}(\tilde{\gamma}_q - \gamma_q^{(0)})\delta\right), \tag{4.3}$$

$$S_j^{\tilde{\pi}_{i:j}}(i, X_i^{\pi^{(0)}_{0:i}}) = S_j^{\pi^{(0)}_{i:j}}(i, X_i^{\pi^{(0)}_{0:i}}) \exp\left(-\kappa\sum_{q=i}^{j-1}\left(I_q^{\tilde{\pi}_{i:q}}(i, X_i^{\pi^{(0)}_{0:i}}) - I_q^{\pi^{(0)}_{i:q}}(i, X_i^{\pi^{(0)}_{0:i}})\right)\delta\right). \tag{4.4}$$

This allows us to compute the best trajectory starting in date $i$ (and the corresponding reward) without resampling data.

# Backward Sampling Algorithm

1. Simulate $M$ paths for $(X_i^{\pi_{0:i}}(0, X_0^{\pi^{(0)}_{0:0}}))_{i=0:N}$ to get controlled trajectories with an arbitrarily chosen admissible deterministic strategy $\pi^{(0)}_{0:N}$.
2. For i=N-1:0:
   1. Set $J^*(i+1, X_{i+1}^{\pi^{(0)}_{0:i+1}}) =$
   $$\mathbb{E}\left[\sum_{j=i+1}^{N-1} \frac{\mathcal{C}_j\left(X_j^{\tilde{\pi}_{i+1:j}}(i+1, X_{i+1}^{\pi^{(0)}_{0:i+1}}), \tilde{\gamma}_j(X_j^{\tilde{\pi}_{i+1:j}}(i+1, X_{i+1}^{\pi^{(0)}_{0:i+1}}))\right)}{(1+r\delta)^{j-i-1}} + \frac{\mathcal{C}_N\left(X_N^{\tilde{\pi}_{i+1:N}}(i+1, X_{i+1}^{\pi^{(0)}_{0:i+1}})\right)}{(1+r\delta)^{N-i-1}} \mid X_{i+1}^{\pi^{(0)}_{0:i+1}}\right].$$
   2. Approximate $J^*$ using Least Squares on $L$ basis functions $\phi = \{\phi_l\}_{l=1,\dots,L}$.
   $$\hat{J}^*(i+1, X_{i+1}) := \sum_{l=1}^{L} \hat{\alpha}_l^i \phi_l(X_{i+1}), \tag{4.5}$$
   3. Compute $\mathbb{E}_\gamma\left[\hat{J}^*(i+1, X_{i+1}) \mid X_i = x\right] \approx \mathbb{E}_\gamma\left[\sum_{l=1}^{L} \hat{\alpha}_l^i \phi_l(F(x,\gamma))\right]$ as a double integral using the conditional p.d.f. of $(\Delta\varepsilon^I_{i+1}, \Delta\varepsilon^S_{i+1})$ w.r.t $X_i$ and the set of simulated points $\{X_i^{\pi^{(0)}_{0:i}}\}$, then update the rest of the trajectory.
   4. Get $\gamma_i^*(X)$ using a minimization algorithm on the set of simulated $X_i$ points and by regression. Then update trajectories.
3. Repeat until stability of results.

# Application

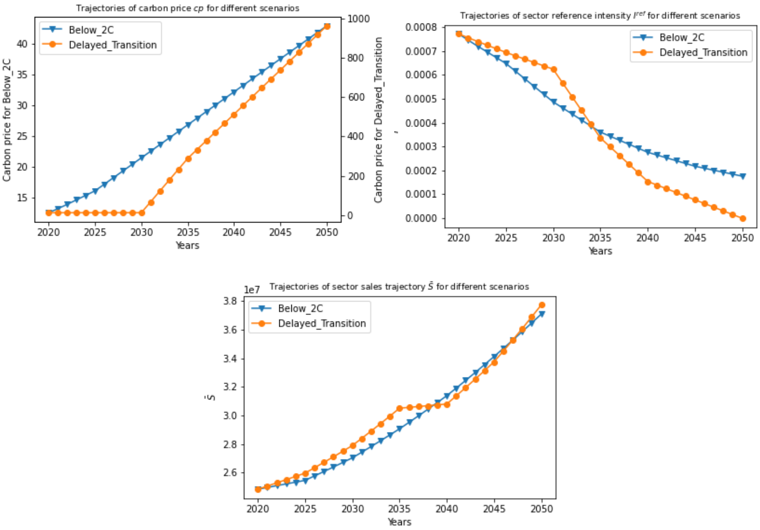


Figure: Trajectories for carbon price $\text{cp}_i$, reference market intensity $I^{\text{ref}}$ and market sales $\bar{S}$ for scenarios Below 2C and Delayed transition for D35 - Electricity Steam and Gas - France (source : NGFS)

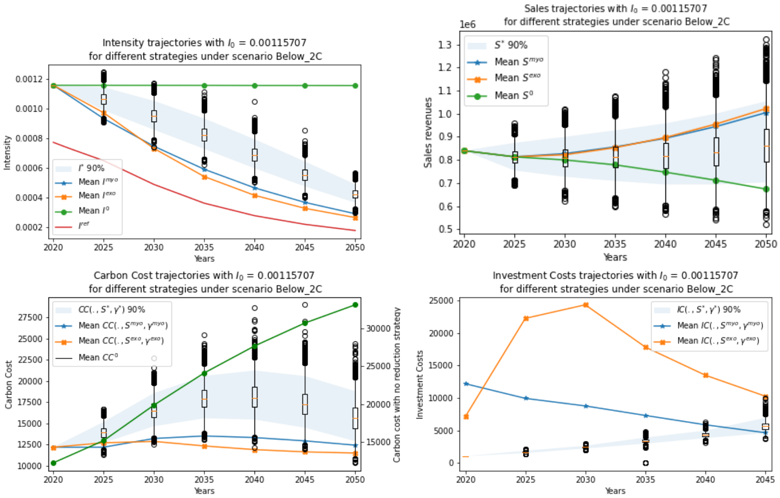


Figure: Simulated results for the **brown company** with the optimal strategy (boxplots) and benchmark strategies (myopic = stars, exogenous = squares, no strategy = dots) in scenario B2C. From top LHS to bottom RHS : Intensity, Sales Revenues, Carbon Cost and Investment Costs.

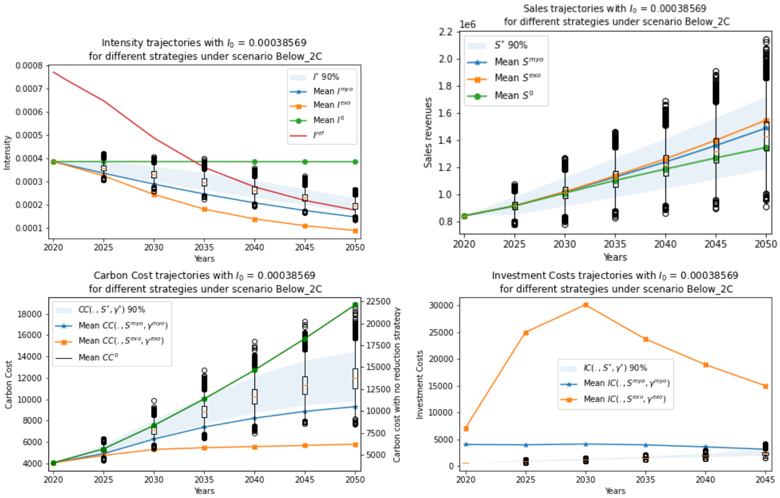


Figure: Simulated results for the **green company** with the optimal strategy (boxplots) and benchmark strategies (myopic = stars, exogenous = squares, no strategy = dots) in scenario B2C. From top LHS to bottom RHS : Intensity, Sales Revenues, Carbon Cost and Investment Costs.

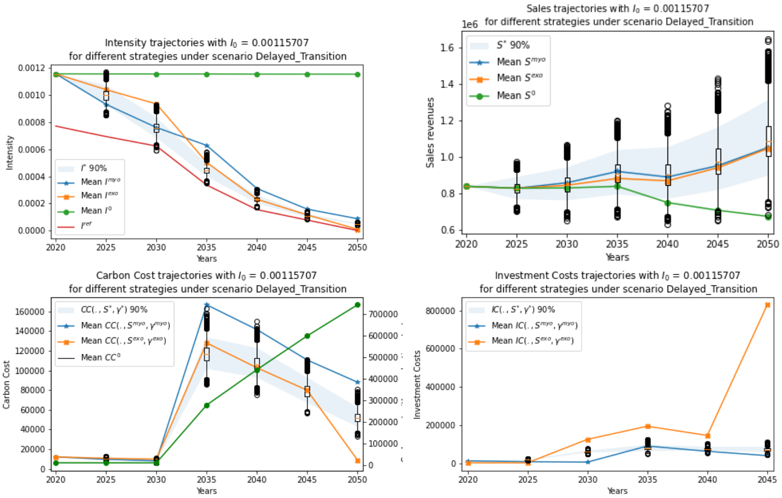


Figure: Simulated results for the **brown company** with the optimal strategy (boxplots) and benchmark strategies (myopic = stars, exogenous = squares, no strategy = dots) in scenario DT. From top LHS to bottom RHS : Intensity, Sales Revenues, Carbon Cost and Investment Costs.

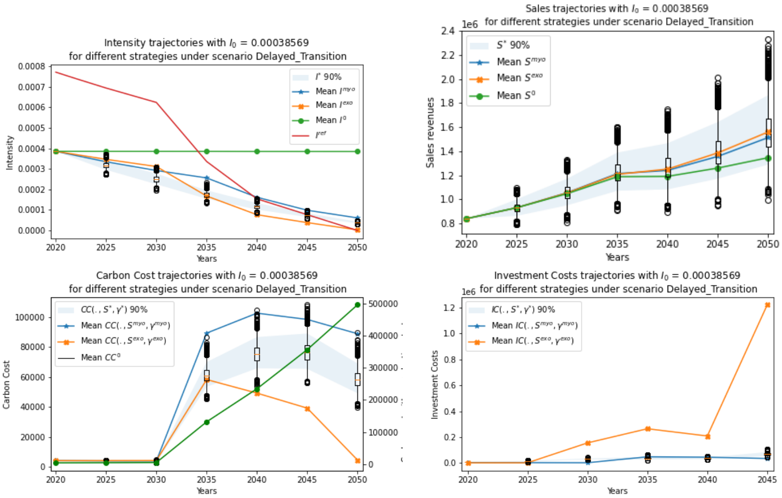


Figure: Simulated results for the **green company** with the optimal strategy (boxplots) and benchmark strategies (myopic = stars, exogenous = squares, no strategy = dots) in scenario DT. From top LHS to bottom RHS : Intensity, Sales Revenues, Carbon Cost and Investment Costs.

# Conclusion

- Not adapting the company's relative emissions is ill-advised for long-term credit risk assessment (carbon tax costs largely supersedes the investment economies, and loss in Sales).
- The often used exogenous strategy is overpriced for little gain in sales and carbon tax reduction.
- Myopic strategy's lack timing/anticipation can be costly, especially in disorderly transition scenarios (decreasing investment costs, carbon price shocks). (Perfect foresight assumption in stress tests)
- In general, it's best for the company to pay more tax and invest less because of the convexity of the investment costs (negligible loss in sales compared to other strategies).
- Green companies are likely to rest on their laurels and put little effort in the transition.

# Thank you for your attention

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