

Super-Hedging under Transaction Costs

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Introduction

Mathematical Tools

Main steps

Choose Your Moves Wisely!

You hold a portfolio that should be worth 1000 in 3 months.

- You want to hedge the risk of market movements.
- You plan to adjust your position at several dates.
- But each trade comes with **transaction costs.**



Key question:

*What is the **minimal initial price** I need today to hedge my portfolio safely?*

- Discrete-time financial market:

$$(\Omega, (\mathcal{F}_t)_{t=0}^T, \mathbb{P})$$

- A riskless bond with price: $S_t^0 = 1$ (zero interest rate).
- A risky asset with price process:

$$S = (S_t)_{t=0}^T.$$

- Transaction costs represented by proportional rates:

$$(k_t)_{t=0}^{T-1}.$$

- **Investment strategy:** $\theta = (\theta_t)_{t=0}^{T-1}$, representing the portfolio adjustments at each trading date.

□ Motivation:

- Transaction costs are considered.
- No specific assumption on how prices evolve (no fixed model).
- The portfolio can be adjusted at an arbitrary number of dates.

Self-Financing Portfolio with Transaction Costs

We define a **self-financing portfolio** $(V_t)_{t=0}^T$ with the following dynamics:

$$\Delta V_t = \theta_{t-1} \Delta S_t - \underbrace{k_{t-1} |\Delta \theta_{t-1}| S_{t-1}}_{\triangle \text{Transaction costs}}$$

- V_t is interpreted as a **super-hedging price** at time t for a given payoff ξ_T if

$$V_T \geq \xi_T \quad \text{almost surely.}$$

Solve the superhedging problem:

- Define the set of admissible strategies and values:

$$\mathcal{V} = \{(V, \theta) : V_T \geq g(S_T)\}$$

where g is a **convex payoff function**.

- Compute the minimal initial capital required to superhedge:

$$P_0^* = \text{ess inf}\{V_0(\theta) : (V, \theta) \in \mathcal{V}\}$$

Approach:

- Use conditional supports of the relative prices.
- Rely on conditional essential supremum / infimum.
- Apply Fenchel conjugate and biconjugate tools.

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Definition: Let X be an \mathbb{R}^d -valued random variable on $(\Omega, \mathcal{F}, \mathbb{P})$, and let $\mathcal{G} \subseteq \mathcal{F}$ be a sub- σ -algebra. The *conditional support* of X given \mathcal{G} , denoted $\text{supp}_{\mathcal{G}}(X)$, is the smallest \mathcal{G} -measurable closed set-valued map $C : \Omega \rightarrow 2^{\mathbb{R}^d}$ such that

$$\mathbb{P}(X \in C \mid \mathcal{G}) = 1 \quad \text{a.s.}$$

Conditional Essential Supremum

Definition (Cardaliaguet et al., 2003): Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space, and let $\mathcal{G} \subseteq \mathcal{F}$ be a sub- σ -algebra. For a non-empty family \mathcal{A} of \mathcal{F} -measurable random variables, the *conditional essential supremum* of \mathcal{A} given \mathcal{G} , denoted $\text{ess sup}_{\mathcal{G}} \mathcal{A}$, is the unique (a.s.) \mathcal{G} -measurable random variable Z such that:

- $Z \geq X$ a.s. for all $X \in \mathcal{A}$;
- if Y is any other \mathcal{G} -measurable random variable with $Y \geq X$ a.s. for all $X \in \mathcal{A}$, then $Y \geq Z$ a.s.

Properties of Conditional Essential Supremum

- **Tower Property:** If $\mathcal{H} \subseteq \mathcal{G} \subseteq \mathcal{F}$, then

$$\text{ess sup}_{\mathcal{H}} \text{ess sup}_{\mathcal{G}} \mathcal{A} = \text{ess sup}_{\mathcal{H}} \mathcal{A} \quad \text{a.s.}$$

- **Monotonicity:** If $\mathcal{A} \subseteq \mathcal{B}$, then

$$\text{ess sup}_{\mathcal{G}} \mathcal{A} \leq \text{ess sup}_{\mathcal{G}} \mathcal{B} \quad \text{a.s.}$$

- **Stability under \mathcal{G} -measurable shifts:** For any $Z \in L^0(\Omega, \mathcal{G})$,

$$\text{ess sup}_{\mathcal{G}} \{X + Z : X \in \mathcal{A}\} = \text{ess sup}_{\mathcal{G}} \mathcal{A} + Z \quad \text{a.s.}$$

Reference: E. N. Barron, P. Cardaliaguet, and R. Jensen, *Conditional Essential Suprema with Applications*, Applied Mathematics and Optimization, 48(3):229–253, 2003.

Proposition

Let $X \in L^0(\mathbb{R}, \mathcal{F})$ and $h : \Omega \times \mathbb{R} \rightarrow \mathbb{R}$ be $\mathcal{G} \otimes \mathcal{B}(\mathbb{R})$ -measurable and lower semicontinuous in x . Then

$$\text{ess sup}_{\mathcal{G}} h(X) = \sup_{x \in \text{supp}_{\mathcal{G}}(X)} h(x) \quad \text{a.s.}$$

Fenchel Conjugate and Biconjugate

Definition: Let $f : \mathbb{R}^d \rightarrow \mathbb{R} \cup \{+\infty\}$ be a function. Its *Fenchel (convex) conjugate* f^* is defined by:

$$f^*(y) := \sup_{x \in \mathbb{R}^d} \{\langle x, y \rangle - f(x)\}.$$

The *biconjugate* f^{**} is the conjugate of f^* :

$$f^{**}(x) := \sup_{y \in \mathbb{R}^d} \{\langle x, y \rangle - f^*(y)\}.$$

Fenchel Moreau Theorem: If f is proper, lower semicontinuous, and convex, then:

$$f = f^{**}.$$

Reference: Rockafellar, *Convex Analysis*, 1970.

Lemma

Let f be a function from \mathbb{R} to $[-\infty, \infty]$ such that $f = \infty$ on \mathbb{R}_- . For every real-valued convex function φ , $f^* \circ \varphi$ is a convex function.

Let \mathcal{A} denote the class of all affine functions defined on \mathbb{R} .

Lemma

Let $\gamma \in \mathcal{A}$, $\gamma(x) := ax + b$, and φ be a bijection. Then, $(\gamma^* \circ \varphi)^*$ is an affine function given by $(\gamma^* \circ \varphi)^*(x) := \varphi^{-1}(a)x + b$ and we have $(\gamma^* \circ \varphi)^{**} = \gamma^* \circ \varphi$.

Lemma (*)

Suppose that f is a function defined on \mathbb{R} with values in $] -\infty, \infty]$ such that $f = \infty$ on \mathbb{R}_- . Then, for every bijection Φ such that Φ^{-1} is real-valued and convex, there exists a unique lower semi-continuous convex function h such that $h^* \circ \Phi$ is lower semi-continuous, convex and $f^{**} = (h^* \circ \Phi)^*$. Moreover,

$$\begin{aligned} h &= [(h_1^* \circ \Phi)^{**} \circ \Phi^{-1}]^*; \\ h_1(x) &:= \sup\{(\gamma^* \circ \Phi^{-1})^*(x), \gamma \in \mathcal{A} \text{ and } \gamma \leq f\}. \end{aligned}$$

Introduction

Mathematical Tools

Main steps

- The super-hedging problem is first solved between time $T - 1$ and T for an European claim $\xi_T = g_T(S_T)$ where $g_T \geq 0$ is a convex function.

Super-Hedging Prices at Time $T-1$

We denote by:

$$\mathcal{P}_{T-1}(g_T) := \mathcal{P}_{T-1}(g_T, \theta_{T-2})$$

the set of all super-hedging prices of the contingent claim $\xi_T = g_T(S_T)$.

We show that

$$\mathcal{P}_{T-1}(g_T) = \bar{\mathcal{P}}_{T-1}(g_T) + L^0(\mathbb{R}_+, \mathcal{F}_{T-1}),$$

where:

$$\bar{\mathcal{P}}_{T-1}(g_T) = \left\{ f_{T-1}^*(-\theta_{T-1}) + \theta_{T-1}S_{T-1} + k_{T-1}|\Delta\theta_{T-1}|S_{T-1} : \theta_{T-1} \in L^0(\mathbb{R}, \mathcal{F}_{T-1}) \right\},$$

$$f_{T-1}(x) = -g_T(x) + \delta_{\text{supp } \mathcal{F}_{T-1}(S_T)}(x).$$

Where for a (random) set $I \subseteq \mathbb{R}$:

$$\delta_I(z) := (+\infty) \cdot 1_{\Omega \setminus I}.$$

Main idea: Use the self-financing definition.

The infimum price of g_T at time $T-1$ is given by:

$$p_{T-1}(g_T) = - \left(f_{T-1}^* \circ \Phi_{\theta_{T-2}}^{-1} \right)^* (S_{T-1}),$$

where the function $\Phi_{\theta_{T-2}}$ is defined as:

$$\Phi_{\theta_{T-2}}(x) := x - k_{T-1} |x + \theta_{T-2}|.$$

Key Tool:

Let f be a \mathcal{H} -normal integrand on \mathbb{R} . Then:

$$\operatorname{ess\,inf}_{\mathcal{H}} \left\{ f(A) : A \in L^0(\mathbb{R}, \mathcal{H}) \right\} = \inf_{a \in \mathbb{R}} f(a).$$

Proof Outline

$$\begin{aligned} p_{T-1}(g_T) &= \operatorname{ess\,inf} \mathcal{P}_{T-1}(g_T) \\ &= \inf_{z \in \mathbb{R}} [f_{T-1}^*(-z) + zS_{T-1} + k_{T-1}|z - \theta_{T-2}|S_{T-1}] \\ &= -\sup_{z \in \mathbb{R}} [-f_{T-1}^*(-z) - zS_{T-1} - k_{T-1}|z - \theta_{T-2}|S_{T-1}] \\ &= -\sup_{z \in \mathbb{R}} [-f_{T-1}^*(z) + zS_{T-1} - k_{T-1}|z + \theta_{T-2}|S_{T-1}] \\ &= -\sup_{z \in \mathbb{R}} [S_{T-1}\Phi_{\theta_{T-2}}(z) - f_{T-1}^*(z)] \\ &= -\sup_{z \in \mathbb{R}} [S_{T-1}z - f_{T-1}^* \circ \Phi_{\theta_{T-2}}^{-1}(z)] \\ &= -\left(f_{T-1}^* \circ \Phi_{\theta_{T-2}}^{-1}\right)^*(S_{T-1}). \end{aligned}$$

Dual Representation of the Infimum Price

Theorem

Let g_T be a continuous convex function. Then there exists a unique lower semi-continuous convex function h_{T-1} such that:

$$p_{T-1}(g_T) = -h_{T-1}(S_{T-1}).$$

Moreover, h_{T-1} admits the representation:

$$h_{T-1} = \left[(\bar{h}_{T-1}^* \circ \Phi_{\theta_{T-2}})^{**} \circ \Phi_{\theta_{T-2}}^{-1} \right]^*,$$

where

$$\bar{h}_{T-1}(x) := \sup \left\{ (\gamma^* \circ \Phi_{\theta_{T-2}}^{-1})^*(x) : \gamma \in \mathcal{A}, \gamma \leq f_{T-1} \right\}.$$

Proof of Theorem

Since $f_{T-1} = \infty$ on \mathbf{R}_- and $\Phi_{\theta_{T-2}}$ is a bijection such that $\Phi_{\theta_{T-2}}^{-1}$ is convex, Lemma (*) is in force hence there exists a unique lower semi-continuous convex function denoted h_{T-1} such that

$f_{T-1}^* = h_{T-1}^* \circ \Phi_{\theta_{T-2}}$. Therefore,


$$\begin{aligned} p_{T-1}(g_T) &= -(f_{T-1}^* \circ \Phi_{\theta_{T-2}}^{-1})^*(S_{T-1}) \\ &= -(h_{T-1}^* \circ \Phi_{\theta_{T-2}} \circ \Phi_{\theta_{T-2}}^{-1})^*(S_{T-1}) \\ &= -h_{T-1}(S_{T-1}). \end{aligned}$$

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$$\begin{aligned} p_{T-1}(g_T) &= -(f_{T-1}^* \circ \Phi_{\theta_{T-2}}^{-1})^*(S_{T-1}) \\ &= -(h_{T-1}^* \circ \Phi_{\theta_{T-2}} \circ \Phi_{\theta_{T-2}}^{-1})^*(S_{T-1}) \\ &= -h_{T-1}(S_{T-1}). \end{aligned}$$

 The random function $h_{T-1}(\cdot)$ may depend on S_{T-1} so that the mapping $S_{T-1} \mapsto h_{t-1}(S_{T-1})$ could be non convex.

Notations

- Denote C_{T-1} the conditional support of S_T w.r.t. the σ -algebra \mathcal{F}_{T-1} .
- Assume that C_{T-1} is a random compact interval of the form $[m_{T-1}, M_{T-1}]$, where $m_{T-1}, M_{T-1} \in L^0(\mathbf{R}_+, \mathcal{F}_{T-1})$ satisfy $m_{T-1} < M_{T-1}$ a.s..

We define: $y_{T-1} := g_T(m_{T-1})$, $Y_{T-1} := g_T(M_{T-1})$

m_{T-1}^+	m_{T-1}^-	M_{T-1}^+	M_{T-1}^-
$\frac{m_{T-1}}{1+k_{T-1}}$	$\frac{m_{T-1}}{1-k_{T-1}}$	$\frac{M_{T-1}}{1+k_{T-1}}$	$\frac{M_{T-1}}{1-k_{T-1}}$

- The discrete-time delta-hedging strategy at time $T-1$ is given by:

$$a_{T-1}^0 := \frac{Y_{T-1} - y_{T-1}}{M_{T-1} - m_{T-1}}.$$

Explicitly!

The infimum super-replicating price of g_T at time $T - 1$ satisfies:

$$\text{If } a_{T-1}^0 \leq \theta_{T-2},$$

$$\begin{aligned} p_{T-1}(g_T) &= -\infty, \quad S_{T-1} < m_{T-1}^+ \text{ or } S_{T-1} > M_{T-1}^-, \\ &= y_{T-1} + \theta_{T-2}(S_{T-1} - m_{T-1}), \quad m_{T-1}^+ \leq S_{T-1} < m_{T-1}^-, \\ &= y_{T-1} + a_{T-1}^0(S_{T-1} - m_{T-1}) + k_{T-1}(\theta_{T-2} - a_{T-1}^0)S_{T-1}, \quad m_{T-1}^- \leq S_{T-1} \leq M_{T-1}^-. \end{aligned}$$

$$\text{If } a_{T-1}^0 \geq \theta_{T-2},$$

$$\begin{aligned} p_{T-1}(g_T) &= -\infty, \quad S_{T-1} < m_{T-1}^+ \text{ or } S_{T-1} > M_{T-1}^-, \\ &= y_{T-1} + a_{T-1}^0(S_{T-1} - m_{T-1}) + k_{T-1}(a_{T-1}^0 - \theta_{T-2})S_{T-1}, \quad m_{T-1}^+ \leq S_{T-1} < M_{T-1}^+, \\ &= y_{T-1} + a_{T-1}^0(S_{T-1} - m_{T-1}) + (M_{T-1} - S_{T-1})(a_{T-1}^0 - \theta_{T-2}), \quad M_{T-1}^+ \leq S_{T-1} \leq M_{T-1}. \end{aligned}$$

Absence of Immediate Profit (AIP)

- An immediate profit at time $t - 1$ relative to the payoff function g_t at time t is an infimum price $p_{t-1}(g_t)$ such that we have $\mathbb{P}(p_{t-1}(g_t) = -\infty) > 0$.

Definition (AIP)

We say that the relative AIP condition holds for g_t at time $t - 1$ if there is no immediate profit at time $t - 1$ relative to the payoff function g_t .

Corollary

The following statements are equivalent:

- 1) AIP holds at time $T - 1$,
- 2) $m_{T-1}^+ \leq S_{T-1} \leq M_{T-1}^-$, a.s.,
- 3) $p_{T-1}(\theta_{T-2} = 0, g_T) \geq 0$, a.s..

Corollary

The following statements are equivalent:

- 1) AIP holds at time $T - 1$,
- 2) $m_{T-1}^+ \leq S_{T-1} \leq M_{T-1}^-$, a.s.,
- 3) $p_{T-1}(\theta_{T-2} = 0, g_T) \geq 0$, a.s..

Corollary

Suppose that $m_{T-1} = \alpha_{T-1}S_{T-1}$ and $M_{T-1} = \beta_{T-1}S_{T-1}$ where $0 \leq \alpha_{T-1} < \beta_{T-1}$ are deterministic. Then, AIP holds at time $T - 1$ if and only if $\alpha_{T-1} \leq 1 + k_{T-1}$ and $\beta_{T-1} \geq 1 - k_{T-1}$.

Minimum Super-Hedging Price at Time $T - 1$

Let g_T be a continuous convex function and let $\theta_{T-2} \in L^0(\mathbf{R}, \mathcal{F}_{T-2})$ be given. Suppose:

- $m_{T-1} = \alpha_{T-1}S_{T-1}$ and $M_{T-1} = \beta_{T-1}S_{T-1}$,
- where $0 \leq \alpha_{T-1} < \beta_{T-1}$ are deterministic,
- and that **AIP holds at time $T - 1$.**

Then, the infimum super-hedging price $p_{T-1}(g_T) \in \mathcal{P}_{T-1}(g_T)$ is given by:

$$p_{T-1}(g_T) = y_{T-1} + (1 - \alpha_{T-1})a_{T-1}^0 S_{T-1} + \delta_{T-1} |a_{T-1}^0 - \theta_{T-2}| S_{T-1}$$

where:

$$\delta_{T-1} = \begin{cases} \min(k_{T-1}, 1 - \alpha_{T-1}) & \text{if } a_{T-1}^0 \leq \theta_{T-2}, \\ \min(k_{T-1}, \beta_{T-1} - 1) & \text{if } a_{T-1}^0 \geq \theta_{T-2}. \end{cases}$$

Optimal strategy

Moreover, an **optimal strategy** is:

$$\theta_{T-1}^{\text{opt}} = a_{T-1}^0 \mathbf{1}_{B_{T-1}^l} + \theta_{T-2} \mathbf{1}_{B_{T-1}^r}$$

with:

$$\begin{aligned} B_{T-1}^l &= \left(\{k_{T-1} \leq 1 - \alpha_{T-1}\} \cap \{a_{T-1}^0 \leq \theta_{T-2}\} \right) \\ &\quad \cup \left(\{k_{T-1} \leq \beta_{T-1} - 1\} \cap \{a_{T-1}^0 \geq \theta_{T-2}\} \right), \\ B_{T-1}^r &= \left(\{k_{T-1} \geq 1 - \alpha_{T-1}\} \cap \{a_{T-1}^0 \leq \theta_{T-2}\} \right) \\ &\quad \cup \left(\{k_{T-1} \geq \beta_{T-1} - 1\} \cap \{a_{T-1}^0 \geq \theta_{T-2}\} \right). \end{aligned}$$

To summarize:

- The super-hedging problem is first solved between time $T - 1$ and T for an European claim $\xi_T = g_T(S_T)$ where $g_T \geq 0$ is a convex function.

⚠ Absence of Immediate Profit assumption.

👉 Under the assumption that the conditional supports of the relative prices $\frac{S_{t+1}}{S_t}$ are deterministic intervals, we show that at time $T - 1$,

- There exists minimal super-hedging prices

$$P_{T-1}^* = P_{T-1}^*(\theta_{T-2})$$

⚠ Depends on the strategy θ_{T-2} chosen at time $T - 2$.

We get a specified form $g_{T-1}(\theta_{T-2}, S_{T-1}) = P_{T-1}^*(\theta_{T-2})$.

★ Note that g_{T-1} is still a convex function in S_{T-1} .

Second Step:

The dependence of g_t , $t \leq T - 1$, w.r.t. θ_{t-1} is iteratively identified so that the second step consists in solving the **unusual** super-hedging price problem of the form

$$V_{t-1} + \theta_{t-1} \Delta S_t - k_{t-1} |\Delta \theta_{t-1}| S_{t-1} \geq g_t(\theta_{t-1}, S_t). \quad (3.1)$$

Our assumption is the following:

- The payoff function g_t at time t is of the form:

$$g_t(\theta_{t-1}, x) = \max_{i=1, \dots, N} g_t^i(\theta_{t-1}, x) \quad (\star)$$


- The mapping $x \mapsto g_t^i(\theta_{t-1}, x)$ is **convex**.
- $g_t^i(\theta_{t-1}, x) = \hat{g}_t^i(x) - \hat{\mu}_t^i \theta_{t-1} x$


$(\hat{\mu}_t^i)_{i=1}^N$ are deterministic such that $1 + \hat{\mu}_t^i > 0$.

Third Step:

- Check the propagation property to ensure the infimum super-hedging price remains a payoff function of the underlying asset in the conjectured form.
- The AIP condition is required at each step to avoid negative infinite prices.

Main idea!

$$\begin{aligned}V_{t-1} &\geq g_t(\theta_{t-1}, S_t) - \theta_{t-1} \Delta S_t + k_{t-1} |\theta_{t-1} - \theta_{t-2}| S_{t-1}, \\&\geq \underbrace{\text{ess sup}_{\mathcal{F}_{t-1}} (g_t(\theta_{t-1}, S_t) - \theta_{t-1} S_t)}_{\text{red bracket}} + \theta_{t-1} S_{t-1} + k_{t-1} |\Delta \theta_{t-1}| S_{t-1}.\end{aligned}$$


$$\text{ess sup}_{\mathcal{F}_{t-1}} (g_t(\theta_{t-1}, S_t) - \theta_{t-1} S_t) = \max_{i=1, \dots, N} \underbrace{\text{ess sup}_{\mathcal{F}_{t-1}} (g_t^i(\theta_{t-1}, S_t) - \theta_{t-1} S_t)}_{\text{magenta bracket}}$$


$$\begin{aligned}\text{ess sup}_{\mathcal{F}_{t-1}} (g_t^i(\theta_{t-1}, x) - \theta_{t-1} S_t) &= \sup_{z \in \text{supp}_{\mathcal{F}_{t-1}}(S_t)} (\hat{g}_t^i(z) - \hat{\mu}_t^i \theta_{t-1} z - \theta_{t-1} z) \\&= \sup_{x \in K_{t-1}^i} (\bar{g}_t^i(x) - \theta_{t-1} x) \\&= \sup_{x \in \mathbb{R}} (-\theta_{t-1} x - \bar{f}_t^i(x)) \\&= (\bar{f}_t^i)^*(-\theta_{t-1}).\end{aligned}$$

- V_{t-1} is a super-hedging price if and only if

$$V_{t-1} \geq \underbrace{f_t^*(-\theta_{t-1}) - \theta_{t-1}S_t + \theta_{t-1}S_{t-1} + k_{t-1}|\Delta\theta_{t-1}|S_{t-1}}_{V_{t-1}(\theta_{t-1})}$$

- The set of all super-hedging prices at time $t - 1$ is given by

$$\mathcal{V}_{t-1}(g_t) = \{V_{t-1}(\theta_{t-1}) : \theta_{t-1} \in L^0(\mathbb{R}, \mathcal{F}_{t-1})\} + L^0(\mathbb{R}_+, \mathcal{F}_{t-1})$$

- The infimum super-hedging price is defined as:

$$p_{t-1}(g_t) = \text{ess inf } \mathcal{V}_{t-1}(g_t)$$

Theorem

The infimum super-hedging price at time $t - 1$ satisfies the following:

$$p_{t-1}(g_t) = -(f_{t-1}^* \circ \Phi_{\theta_{t-2}}^{-1})^*(S_{t-1})$$

⚠ Distorted Legendre-Fenchel biconjugate makes computations more complicated.

Proposition

The AIP condition holds at time $t - 1$ relatively to the payoff function g_t if and only if

$$k_{t-1} \geq \max(\alpha_{t-1}^1 - 1, 1 - \beta_{t-1}^N).$$

$$\text{supp}_{\mathcal{F}_{t-1}} S_t / S_{t-1} = [\alpha_{t-1}, \beta_{t-1}]$$

Theorem

Suppose that AIP condition holds. The infimum super-hedging price at time $t - 1$ satisfies $p_{t-1}(g_t) = g_{t-1}(\theta_{t-2}, S_{t-1})$ where g_{t-1} is a payoff function of the form (\star) with t replaced by $t - 1$.

Proposition

Suppose that $k_{t-1} \geq |\alpha_{t-1}^1 - 1|$. Suppose that g_t is a convex payoff function satisfying the form (\star) . Then, the infimum superhedging price $p_{t-1}(g_t)$ at time $t - 1$ satisfies ¹

$$g_{t-1}(\theta_{t-2}, S_{t-1}) = \max_{(i,j) \in \Lambda_1} g_{t-1}^{i,j}(\theta_{t-2}, S_{t-1}) \vee \max_{i \in \Lambda_2} g_{t-1}^{1,i}(\theta_{t-2}, S_{t-1}),$$

where

$$\begin{aligned} g_{t-1}^{i,j}(\theta_{t-2}, x) &= \hat{g}_{t-1}^{i,j}(x) - \hat{\mu}_{t-1}^{i,j} \theta_{t-2} x, \quad (i, j) \in \Lambda_1, \\ \hat{g}_{t-1}^{i,j}(x) &= \lambda_{t-1}^{i,j} \tilde{g}_t^i(x) + (1 - \lambda_{t-1}^{i,j}) \tilde{g}_t^j(x), \quad (i, j) \in \Lambda_1, \\ g_{t-1}^{1,i}(\theta_{t-2}, x) &= \hat{g}_{t-1}^{1,i}(x) - \hat{\mu}_{t-1}^{1,i} \theta_{t-2} x, \quad i \in \Lambda_2, \\ \hat{g}_{t-1}^{1,i}(x) &= \epsilon_{t-1}^i \tilde{g}_{t-1}^1(x) + (1 - \epsilon_{t-1}^i) \tilde{g}_{t-1}^i(x), \quad i \in \Lambda_2. \end{aligned}$$

¹We adopt the convention $\max(\emptyset) = -\infty$.

Parameter	Expression
ϵ^1	1
ϵ_{t-1}^i	$1 - \frac{\rho_{t-1}}{\alpha_{t-1}(\hat{\mu}_t^i - \hat{\mu}_t^1)} \leq 1, \quad i = 2, \dots, N$
ϵ_{t-1}^i	$1 - \frac{\rho_{t-1}}{\beta_{t-1}^{i-N} - \alpha_{t-1}^1} \leq 1, \quad i = N+1, \dots, 2N$
ρ_{t-1}	$(1 + k_{t-1}) - (1 + \hat{\mu}_t^1)\alpha_{t-1} \geq 0$

Sets:

$$\Lambda_1 = \left\{ (i, j) \in \{1, \dots, 2N\}^2 : \epsilon_{t-1}^i \leq 0, \epsilon_{t-1}^j > 0 \right\},$$

$$\Lambda_2 = \left\{ j \in \{1, \dots, 2N\} : \epsilon_{t-1}^j > 0 \right\}.$$

Associated Quantities:

$$\lambda_{t-1}^{i,j} = \frac{|\epsilon_{t-1}^j|(1 - \epsilon_{t-1}^i)}{|\epsilon_{t-1}^j - \epsilon_{t-1}^i|} \in [0, 1], \quad (i, j) \in \Lambda_1,$$

$$\hat{\mu}_{t-1}^{i,j} = k_{t-1} + \frac{\epsilon_{t-1}^i \rho_{t-1}}{1 - \epsilon_{t-1}^i} \cdot \mathbf{1}_{\{j=1\}} > -1, \quad (i, j) \in \Lambda_1,$$

$$\hat{\mu}_{t-1}^{1,i} = (\rho_{t-1} - k_{t-1})\mathbf{1}_{\{i=1\}} + k_{t-1}\mathbf{1}_{\{i \neq 1\}} > -1, \quad i \in \Lambda_2.$$

Proposition

Let g_t be a convex payoff function of the form (\star) . Suppose that $k_{t-1} \geq |\alpha_{t-1}^1 - 1|$, then an optimal strategy associated to the minimal super-hedging price $p_{t-1}(g_t)$ is

$$\theta_{t-1}^{opt} = a_{t-1}(\alpha_{t-1}^*) 1_{\{\theta_{t-2} < a_{t-1}(0)\}} + \theta_{t-2} 1_{\{\theta_{t-2} \geq a_{t-1}(0)\}},$$

where α_{t-1}^* is solution to the following minimization problem:

$$\alpha_{t-1}^* \in \arg \min_{E \in I_{t-1}} |A_{t-1}^{(1)}(E) - p_{t-1}(g_t)|,$$

$$I_{t-1} = \{I_{i,j} : i \neq j, s_{t-1}^i \leq 0 \text{ and } s_{t-1}^j \geq 0\}.$$

Parameters:

$$\begin{array}{l|l}
 p_{t-1}^i = \bar{p}_{t-1}^{\sigma(i)} & \bar{p}_{t-1}^j = \frac{1}{(\alpha_{t-1}^j - \alpha_{t-1}^1)S_{t-1}}, \quad j = 2, \dots, N \\
 b_{t-1}^i = \bar{b}_{t-1}^{\sigma(i)} & \bar{b}_{t-1}^j = \bar{p}_{t-1}^j \left(\hat{g}_t^j(\alpha_{t-1}S_{t-1}) - \hat{g}_t^1(\alpha_{t-1}S_{t-1}) \right) \\
 & \bar{p}_{t-1}^j = \frac{1}{(\beta_{t-1}^{j-N} - \alpha_{t-1}^1)S_{t-1}}, \quad j = N+1, \dots, 2N \\
 & \bar{b}_{t-1}^j = \bar{p}_{t-1}^j \left(\hat{g}_t^{j-N}(\beta_{t-1}S_{t-1}) - \hat{g}_t^1(\alpha_{t-1}S_{t-1}) \right)
 \end{array}$$

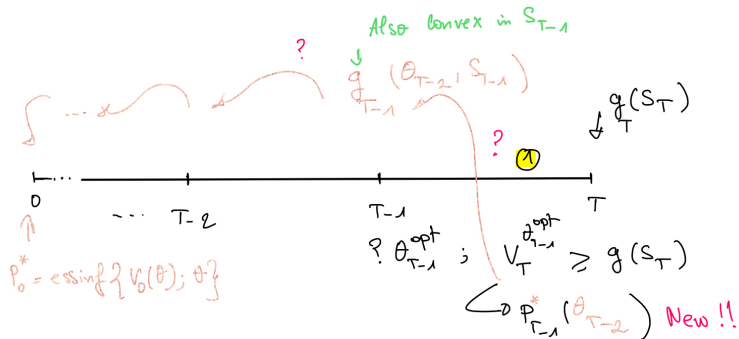
$$a_{t-1} := \max_{i=2, \dots, 2N} (b_{t-1}^i - p_{t-1}^i \alpha)$$

Auxiliary Quantities:

$$\begin{aligned}
 d_{t-1}^1 &= \theta_{t-2}(1 - \alpha_{t-1}^1)S_{t-1}, \quad s_{t-1}^1 = 1, \\
 d_{t-1}^i &= (1 - \alpha_{t-1}^1)S_{t-1}b_{t-1}^i, \quad s_{t-1}^i = 1 - (1 - \alpha_{t-1}^1)S_{t-1}p_{t-1}^i, \quad i = 2, \dots, \\
 A_{t-1}^i(\alpha) &= d_{t-1}^i + s_{t-1}^i \alpha, \quad i = 1, \dots, 2N.
 \end{aligned}$$

$$\begin{aligned}
 I_{i,j} \text{ solves } A_{t-1}^i(I_{i,j}) &= A_{t-1}^j(I_{i,j}), \\
 A_{t-1}^{(1)} &= \max_{i=1, \dots, 2N} A_{t-1}^i.
 \end{aligned}$$

To sum up..!



Thank you For your attention !

- Lepinette, E., Omrani, A. (2025). Beyond the Leland strategies. arXiv preprint arXiv:2503.02419.

