A stochastic target approach to the granularity problem Journee de la Chaire

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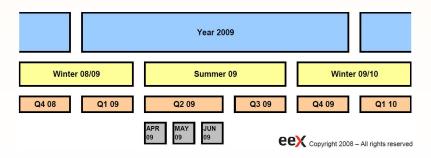
joint work with L. Moreau, N. Oudjane and A. Tamisier

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# Problem

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#### Statement

- The price of  $X^M$  has a structural correlation with  $X^Q$ .
- The market is incomplete.

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### Definition

The granularity is the progressive apparition of traded futures contracts depending on their maturity and delivery period. The futures contracts 'split' in several contracts with shorter delivery period.

#### Statement

- The price of  $X^M$  has a structural correlation with  $X^Q$ .
- The market is incomplete.
- Goal : quantify the premium for a level of loss.
- Approach : the stochastic target problem of Bouchard, Elie and Touzi (2009)

### Introduction of the shaping factor

By absence of arbitrage :

$$X_t^Q = \frac{h^{M_1} X_t^{M_1} + h^{M_2} X_t^{M_2} + h^{M_3} X_t^{M_3}}{h^{M_1} + h^{M_2} + h^{M_3}}$$

with  $h^{M_i}$  = number of hours in month *i* and  $X^{M_i}$  = price of contract covering month *i*.

Let [0, T] be the time interval of hedging,
 and t<sub>0</sub> ∈ (0, T) the time of apparition of the month contract.
 We suppose that

$$X_{t_0}^M = \lambda X_{t_0}^Q$$

with  $\lambda$  a  $\mathcal{F}_{t_0}$ -measurable variable of law J and support E independent of  $X^Q_{t_0}$ .

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## Empirical analysis of the shaping factor

A study on EEX Power Derivatives market (mid-price) :

- Month and Quarter contracts on 7 years (78 occurrences)
- Daily mid-price (non continuous trading strategy)
- ► Goal : hedge and price a call option on month with quarter.

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Relevant results in the Black-Scholes framework :

- $\lambda$  is a random parameter (no clear correlation with the price  $X_{t_0}^Q$ ).
- The hedging error due to the estimation is greater than model or discretization error with an error > 10%.
- A reasonably wrong estimation of  $\lambda$  impacts the price significantly.

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- The hedging error due to the estimation is greater than model or discretization error with an error > 10%.
- A reasonably wrong estimation of  $\lambda$  impacts the price significantly. Conclusion : operational need to take the incompleteness into account

## Dynamics and portfolio

The dynamics :

We denote by X<sub>t,x</sub> the price process on [0, T] starting at (t, x).
 Y<sup>ν</sup><sub>t,x,y</sub> is the portfolio process starting at (t, y) with the strategy ν.

$$\begin{cases} X_{t,x}(r) &= x + \int_t^r \mu_s X_{t,x}(s) ds + \int_t^r \sigma_s X_{t,x}(s) dW_s \\ Y_{t,x,y}^{\nu}(r) &= y + \int_t^r \nu_s dX_{t,x}(s) \end{cases}$$

On  $[0, t_0)$ , X is the price of the quarter contract. On  $[t_0, T]$ ,  $\lambda X$  is the price of the month contract.

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The agent's objective :

• We are endowed with a claim  $g(\lambda X_{t,x}(T))$ .

• We introduce the loss function  $\ell(z) = \frac{(z^{-})^n}{n}$ 

### The stochastic target problem

#### Mathematical formulation :

Let U<sub>t</sub> be the set of controls ν starting at time t.
 For a given threshold p ≤ 0, we want to solve the following problem :

$$v(t,x,p) := \inf \left\{ \begin{array}{l} y \in \mathbb{R} : \exists \nu \in \mathcal{U}_t \text{ such that} \\ \mathbb{E} \left[ -\ell \left( Y_{t,x,y}^{\nu}(T) - g(\lambda X_{t,x}(T)) \right) \right] \ge p \end{array} \right\}$$

### The stochastic target problem

#### Mathematical formulation :

• Let  $\mathcal{U}_t$  be the set of controls  $\nu$  starting at time t.

For a given threshold  $p \leq 0$ , we want to solve the following problem :

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Interpretation :

- ▶ Find the minimal capital controlling the level *p* of loss.
- Focus only on loss with a n moment function (e.g. quadratic asymmetrical error).
- We do NOT hedge the claim but control its impact (if p < 0).
- Advantage : we take into account the risk of  $\lambda$ .

### The complete and half complete market cases

**(HCM)** : we suppose that if  $\lambda$  is known, the market is complete. Standard case : If  $t \ge t_0$ , we know  $\lambda$  and the market is complete.

- ▶ We keep the controlled loss approach (consistency of the strategy).
- What link with perfect replication of  $g(\lambda X_{t,x}(T))$ ?

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The half-complete market :  $\lambda$  is  $\mathcal{F}_{t_0}$ -independent and  $t < t_0$ .

- We study a specific case of claim  $f(X_{t,x}(T),\lambda)$
- Other applications : volume risk, mix finance-insurance claims,...

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  - We study a specific case of claim  $f(X_{t,x}(T),\lambda)$
  - Other applications : volume risk, mix finance-insurance claims,...

Question : can we join the two separated problems?

- If  $t \ge t_0$ , we can write  $\lambda X_{t,x}(r) = X_{t,\lambda x}(r)$ .
- Following Bouchard and al. (2009), the stochastic target problem becomes

$$\mathsf{v}(t,x,p) := \inf \left\{ egin{array}{l} y \in \mathbb{R} \ : \ \exists (
u, lpha) \in \mathcal{U}_t imes \mathcal{A}_t ext{ such that} \ -\ell \Big( Y^{
u}_{t,x,y}(\mathcal{T}) - g(\lambda X_{t,x}(\mathcal{T})) \Big) \geq P^{lpha}_{t,x,p}(\mathcal{T}) \end{array} 
ight\}$$

where  $P_{t,x,p}^{\alpha}(r) = p + \int_{t}^{r} \alpha_{s} P_{t,x,p}^{\alpha}(s) dW_{s}$  and  $A_{t}$  is the set of controls  $\alpha$  independent of  $\mathcal{F}_{t}$ .

•  $P_{t,p}^{\alpha}$  being a martingale, we have

$$\mathbb{E}\left[-\ell\Big(Y_{t,x,y}^{\nu}(T)-g(\lambda X_{t,x}(T))\Big]\geq p\right]$$

Similar to a superreplication problem of function

$$\Psi^{-1}(X_{t,x}(T), P^{\alpha}_{t,p}(T)) = g(X_{t,x}(T)) - (nP^{\alpha}_{t,p}(T))^{1/n}$$

Following Bouchard and al. (2009), we have that v<sub>∗</sub> is a viscosity supersolution on [t<sub>0</sub>, T) × ℝ<sub>+</sub> × ℝ<sub>−</sub> of

$$\begin{cases} -\partial_t \varphi + \sup_{(u,a) \in \mathcal{N}_0} \mathcal{L}^{u,a} \varphi \ge 0 , & \text{ on } [t_0, T) \times \mathbb{R}_+ \times \mathbb{R}_- \\ v_* - [g(x) - (np)^{1/n}] \ge 0 , & \text{ on } \{T\} \times \mathbb{R}_+ \times \mathbb{R}_- \end{cases}$$

with  $\mathcal{N}_0 := \{(u, a) : \sigma_t x u - \sigma_t x \partial_x \varphi - a p \partial_p \varphi = 0\}$ and  $\mathcal{L}^{u, a} \varphi := u x \mu_t - [\mu_t x \partial_x \varphi + \frac{1}{2} \sigma_t^2 x^2 \partial_{xx} \varphi + \frac{1}{2} a^2 p^2 \partial_{pp} \varphi + \sigma_t x a \partial_{xp} \varphi]$ 

 $\triangleright$   $v_*$  being convex in p, we can explicit (u, a) and obtain :

$$-\partial_t \varphi - \frac{1}{2} \sigma_t^2 x^2 \partial_{xx} \varphi + \frac{(\mu_t / \sigma_t \partial_p \varphi - \sigma_t x \partial_{xp} \varphi)^2}{2 \partial_{pp} \varphi} \ge 0$$

Using the Fenchel transform u(t, x, q) = sup<sub>p</sub>(pq - v(t, x, p)) we have that u is a subsolution of

$$\begin{cases} \varphi_t + \frac{1}{2}\sigma_t^2 x^2 \partial_{xx} \varphi + \frac{1}{2}\frac{\mu_t}{\sigma_t} q^2 \partial_{qq} \varphi + \mu_t x q \partial_{xq} \varphi \le 0 , & \text{on } [t_0, T) \\ \varphi(T, x, q) - (1 - \frac{1}{n})q^{\frac{1}{1-n}} - g(x) \le 0 , & \text{on } \{T\} \end{cases}$$

By the Feynman-Kac formula, u is smaller than

$$\begin{split} \bar{u} &:= \mathbb{E}^{Q_{t,x,q}}[(1-\frac{1}{n})q^{\frac{1}{1-n}} - g(X_{t,x}(T))]\\ \text{with} \left\{ \begin{array}{l} dX_{t,x}(s) &= \sigma_t X_{t,x}(s) dW_s^{Q_{t,x,q}}\\ dQ_{t,x,q}(s) &= \frac{\mu_t}{\sigma_t} Q_{t,x,q}(s) dW_s^{Q_{t,x,q}} \text{ and } Q_{t,x,q}(t) = q \end{array} \right. \end{split}$$

Using the Fenchel again, we obtain

$$v(t,x,p) = \mathbb{E}^{Q_{t,x,1}}[g(X_{t,x}(T)] - (-np)^{\frac{1}{n}} \exp\left\{\frac{1}{2(n-1)} \int_{t}^{T} \frac{\mu_{s}^{2}}{\sigma_{s}^{2}} ds\right\}$$

The complete market case allows to obtain explicit formulae for μ and σ constant :

$$P_{t,p}^{\alpha}(s) = p(\frac{X_{t,x}}{x})^{-\frac{n}{\mu}}(n-1)\sigma^2 \exp(\frac{n}{(n-1)}(\frac{n-2}{n-1}-\mu)(s-t))$$

$$u_s = \Delta(s, X_{t,x}(s)) + rac{\mu}{(n-1)x\sigma^2}(-np)^{1/n}\exp(rac{1}{2(n-1)}(rac{\mu^2}{\sigma^2}(T-s)))$$

With a moment loss function, we separate the claim and the level of loss.

- ▶ ⇒ : the diffusion of  $P_{t,p}^{\alpha}$  depends only on  $X_{t,x}$  (not the claim).
- $\blacktriangleright$   $\Rightarrow$  : the value function is the Black Scholes price minus a premium.
- When  $\mu = 0$ , the strategy is the Black Scholes delta hedging.
- The agent can choose judiciously  $n \ge 2$  and  $p \le 0$ .

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#### When the contract appears

Idea : by definition,  $v(t_0^-, x, p)$  shall verify

$$\mathbb{E}\left[-\ell(Y^\nu_{t_0^-,x,\nu(t_0^-,x,p)}(\mathcal{T})-g(\lambda X_{t_0^-,x}(\mathcal{T})))\right]\geq p \text{ for some }\nu\in\mathcal{U}_{t_0^-}$$

so that we shall find  $\nu(\lambda) \in \mathcal{U}_{t_0}$  for each  $\lambda$  such that

$$\mathbb{E}\left[\int_{E} -\ell(Y_{t_0^-,x,v(t_0^-,x,\rho)}^{\nu(\lambda)}(T) - g(\lambda X_{t_0^-,x}(T))J(d\lambda)\right] \geq \rho$$

#### Proposition

For  $(t, x, p) \in [0, t_0) imes \mathbb{R}_+ imes \mathbb{R}^-$ , we have

$$v(t,x,p) = \inf \left\{ y \in \mathbb{R} \ : \ \exists \nu \in \mathcal{U}_t \ s.t. \ \mathbb{E} \left[ \Xi(X_{t,x}(t_0), Y_{t,x,y}^{\nu}(t_0)) \right] \geq p \right\}$$

with  $\Xi(x, y) := \int_E \sup \{ p : v(t_0, \lambda x, p) \le y \} J(d\lambda)$ 

Interpretation : we have a piecewise problem. For  $t < t_0$ , we are in the **(HCM)** framework.

## When the contract appears

#### Facts and hints

- If we compute Ξ from v(t<sub>0</sub>,.), the market is complete and we can use the DPP.
- Here,  $\Xi(x, y)$  has not an explicit solution in general.
- If  $\lambda$  is constant, we retrieve the Black Scholes strategy.
- Otherwise, we weight the strategy by losses induced by  $\lambda$ .

#### Numerical procedure comes now...

- We suppose that  $\lambda$  follows a Beta law.
- We compute the expectation wrt  $J(d\lambda)$  numerically by iid simulations.

### The half complete case

In the case of  $t < t_0$ , we have in our case

▶  $P_{t,p}^{\alpha}$  is an explicit function of  $X_{t,x}$  ( $P_{t,p}^{\alpha}$  is markov if  $\mu, \sigma$  constant).

$$\blacktriangleright \Rightarrow v(s, X_{t,x}(s), P^{\alpha}_{t,p}(s)) = u_0(s, X_{t,x}(s)).$$

regularity assumptions

Dynamic Programming Principle + martingale representation theorem  $\Rightarrow v(t, x, p)$  is the superhedging price of  $u_0(t_0^-, X_{t,x}(t_0^-))$ .

$$\begin{cases} v(s, X_{t,x}(s), P_{t,p}^{\alpha}(s)) = \mathbb{E}[u_0(t_0^-, X_{t,x}(t_0^-)) | X_{t,x}(s)] \\ \\ \nu(s, X_{t,x}(s)) = \frac{\partial \mathbb{E}[u_0(t_0^-, X_{t,x}(t_0^-)) | X_{t,x}(s)]}{\partial X} . \end{cases}$$

# The half complete case

#### Procedure

- We compute numerically  $X_{t,x}(t_0^-)$  and  $v(t_0, \lambda X_{t,x}(t_0), P_{t,p}(t_0))$
- We then obtain  $u_0(t_0^-, X_{t,x}(t_0^-))$  (optimization).
- We compute  $\nu$  (the derivative) with tangent processes.
- We compute the conditional expectations with regressions (on 3 monomials).
- Benchmark : we compare v(0, x, p) to the Black-Scholes approach.
  - on call options price and loss (OTM, ATM, ITM)
  - Black Scholes price is computed with  $\mathbb{E}[\lambda]$ .

# Numerical procedure

Main initial data :

- $\lambda$  has a standard deviation of 0.081.
- $S_0 = 50.89$ .
- Loss function  $\ell(Y g(X)) = ((Y g(x))^{-})^{2}$ .

Simulations :

- 10000 trajectories
- 10000 simulations of  $\lambda$  (Calibrated Beta law).

### Price Vs Loss :ITM

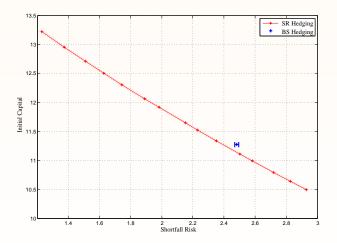


FIGURE: For  $K = 0.80 \times S_0$ . BS price = 11.27 eur.

### Price Vs Loss :ATM

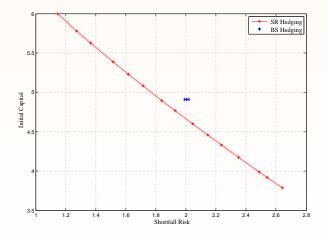
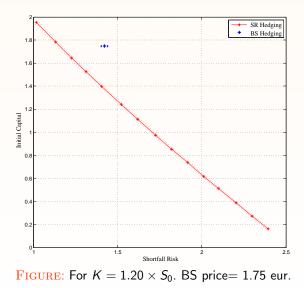


FIGURE: For  $K = S_0$ . BS price= 4.91 eur.

### Price Vs Loss :OTM



## Suming up the results

Loss = % of Loss Reduction with BS Price  $(C^{BS}(X) = v(0, X, p))$ Price = % of Price Reduction compared to BS Loss (same p).

Strike	$(1-20\%)S_0$	$S_0$	$(1+20\%)S_0$
BS price (eur)	11.27	4.91	1.75
Loss	3.49%	8.70%	18.68%
Price	1.16%	5.12%	21.30%

## CVar comparison :ITM

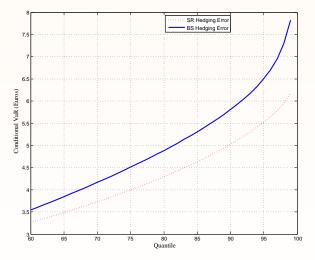


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## CVar comparison :ATM

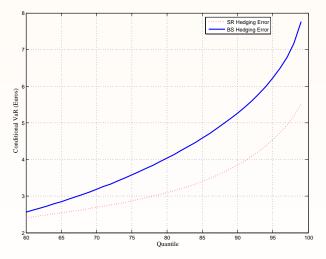


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## CVar comparison :OTM

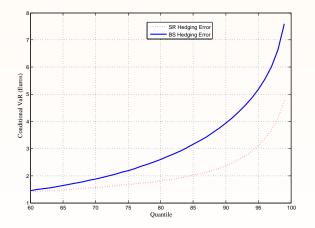


FIGURE: For  $K = 1.20 \times S_0$ . BS price= 1.75 eur.

# Conclusions

The stochastic target approach :

- minimizes a given criteria till a threshold p.
- reduces the CVaR Risk with the same initial capital as BS.
- reduces the initial capital needed to achieve the same Loss as BS.

#### What remains to be done :

- Present results on real data.
- Develop the general continuous semimartingale framework.
- give a comprehensive interpretation of the differences between SR and BS strategy.
- calibrate new objects : p, n (preferences) and  $\lambda$  (statistics).