A Backward dual representation for the quantile hedging of Bermudan options

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Problem formulation

$$\cdot$$
 ($\Omega, \mathcal{F}, \mathbb{F}, \mathbb{P}$), $\mathbb{F} := \{\mathcal{F}_t, 0 \leq t \leq T\}$ and W a *d*-dim. BM,

$$\forall (t,x) \in [0,T] \times (0,\infty)^d, \ T > 0 \text{ and for } s \ge t:$$
$$X_s^{t,x} = x + \int_t^s \mu(r, X_r^{t,x}) \mathrm{d}r + \int_t^s \sigma(r, X_r^{t,x}) \mathrm{d}W_r ,$$

with

 $\mu: [0, T] imes (0, \infty)^d o \mathbb{R}^d$ and $\sigma: [0, T] imes (0, \infty)^d o \mathbb{M}^d$ Lipschitz continuous,

 $\cdot \ \sigma \, {\rm is \ invertible \ and } \, \lambda := \sigma^{-1} \mu \, \, {\rm is \ bounded},$

 $\cdot \mathbb{Q}_{t,x} \sim \mathbb{P}$ is unique and is s.t. $\frac{\mathrm{d}\mathbb{P}}{\mathrm{d}\mathbb{Q}_{t,x}} = Q_{t,x,1}$ where for $s \geq t$:

$$\mathrm{d} Q_{t,x,1}(s) = \lambda(s, X_{t,x}(s)) Q_{t,x,1}(s) \mathrm{d} W^{\mathbb{Q}_{t,x}}_s \in (0,\infty),$$

 $Q_{t,x,1}(t) = 1.$

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Problem formulation (cont.)

 An admissible financial strategy is a *d*-dimensional predictable process ν s.t.

$$\mathbb{E}^{\mathbb{Q}_{t,x}}\left[\int_t^T |\nu_r^{\top}\sigma(r,X_r^{t,x})|^2 dr\right] < \infty,$$

and the corresponding wealth process

$$Y^{t,x,y,\nu} := y + \int_t^{\cdot} \nu_r^{\top} \mathrm{d} X_r^{t,x} \ge 0, \text{ on } [t,T],$$

given (t, x) and $y \ge 0$.

• $U_{t,x,y}$ is the collection of admissible financial strategies.

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Problem formulation (cont.)

Fix a finite collection of times

 $\mathbb{T}_t := \{t_0 = 0 \leq \cdots \leq t_i \leq \cdots \leq t_n = T\} \cap (t, T],$

together with non-negative payoff functions

 $x \in (0,\infty)^d \mapsto g(t_i,x)$, Lipschitz continuous for all $i \leq n$.

The quantile hedging problem is

 $v(t, x, p) := \inf \Gamma(t, x, p),$

where

$$\Gamma(t, x, p) \\ := \left\{ y \ge 0 : \exists \nu \in \mathcal{U}_{t,x,y} \text{ s.t. } \mathbb{P}\left[\bigcap_{s \in \mathbb{T}_t} \{Y_s^{t,x,y,\nu} \ge g(s, X_s^{t,x})\} \right] \ge p \right\}.$$

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Problem formulation (cont.)

Remark (Preliminary remarks)

• Meaning of $v(t, \cdot, 1)$...

$$m{v}(t,x,1) \;\; = \;\; \mathbb{E}^{\mathbb{Q}_{t,x}}[(m{v} \lor g)(t_{i+1},X^{t,x}_{t_{i+1}},1)]\,, \; ext{for} \; t \in [t_i,t_{i+1})\,,$$

with i < n and

$$g(t, x, p) := g(t, x) \mathbb{1}_{\{0 1\}}, \ \ ext{for} \ p \in \mathbb{R}$$

• $p \mapsto v(\cdot, p)$ is non-decreasing.

• $v(\cdot, p) = 0$ if $p \le p_{\min}(t, x)$ where

$$p_{\min}(t,x) := \mathbb{P}[g(s,X^{t,x}_s)\mathbb{1}_{\{s < \mathcal{T}\}} = 0 \text{ for all } s \in \mathbb{T}_t]$$

 $\mathsf{Hyp:} \ p_{\min}(t,\cdot) < 1 \text{, for } t < \mathcal{T} \Rightarrow \textit{v}(t,x,1) > 0 \,, \text{ for } t < \mathcal{T} \,.$

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What can we find in the literature?

(A) Markovian Framework:

(1) Incomplete market case:

(a) **European Case:** Soner and Touzi in [7] and [8], Bouchard, Elie and Touzi in [2],

(b) American Case: Bouchard and Vu in [3],

(2) Complete market case :

 $\rm (a)$ European Case: Bouchard, Elie and Touzi in [2] and Föllmer and Leukert in [5].

(B) Non-Markovian Framework:

Bouchard, Elie and Reveillac in [1] and Jiao, Klopfenstein and Tankov in [6].

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Problem reduction

Before all reduce the initial problem to a standard stochastic target one (see [2]).....

To this aim introduce the set $\mathcal{A}_{t,p}$ of square integrable predictable processes such that

$$\mathcal{P}^{t,p,\alpha} := p + \int_t^{\cdot} \alpha_r^{\top} \mathrm{d} W_r \in [0,1], \text{ on } [t,T].$$

We denote $\hat{\mathcal{U}}_{t,x,y,p} := \mathcal{U}_{t,x,y} \times \mathcal{A}_{t,p}$.

Proposition

Fix $(t,x,p)\in [0,T] imes (0,\infty)^d imes [0,1]$, then

$$\Gamma(t,x,p) = \left\{ \begin{array}{l} y \ge 0 : \exists (\nu,\alpha) \in \hat{\mathcal{U}}_{t,x,y,p} \ s.t.\\ Y^{t,x,y,\nu} \ge g(\cdot, X^{t,x}) \mathbb{1}_{\{P^{t,p,\alpha} > 0\}} \ on \ \mathbb{T}_t \end{array} \right\} .$$
(1)

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Problem reduction (cont.)

Proof. Obvious at T. Fix t < T. Let $y \in \overline{\Gamma}(t, x, p)$ with $\overline{\Gamma}$ the RHS in (1) and fix $(\nu, \alpha) \in \mathcal{U}_{t,x,\nu,p}$ s.t. $Y^{t,x,y,\nu} \geq g(\cdot, X^{t,x}, P^{t,p,\alpha})$ on \mathbb{T}_t . Then, $\{Y^{t,x,y,\nu} \geq g(\cdot, X^{t,x})\} \supset \{P^{t,p,\alpha} > 0\}$ on \mathbb{T}_t . Since $P^{t,p,\alpha} \in [0,1]$ and $\mathbb{1}_{\{P^{t,p,\alpha} > 0\}} \ge P^{t,p,\alpha}$, we have $\mathbb{P}\left|\bigcap_{s\in\mathbb{T}}\left\{Y_{s}^{t,x,y,\nu}\geq g(s,X_{s}^{t,x})\right\}\right|\geq\mathbb{P}\left|\bigcap_{s\in\mathbb{T}}\left\{P_{s}^{t,p,\alpha}>0\right\}\right|$ $\geq \mathbb{E}\left[P_T^{t,p,\alpha} \prod_{s \in \mathbb{T}_t \setminus \{T\}} \mathbb{1}_{\{P_s^{t,p,\alpha} > 0\}} \right] \ .$

Noticing that the process $P^{t,p,\alpha}$ is a martingale, for $s \in \mathbb{T}_t$, $\{P_s^{t,p,\alpha} = 0\} \subset \{P_T^{t,p,\alpha} = 0\}$ we obtain $y \in \Gamma(\underline{t}, x, \underline{p})$.

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Problem reduction (cont.)

Proof. (cont.) Fix $y \in \Gamma(t, x, p)$ and choose $\nu \in \mathcal{U}_{t,x,p}$ s.t. $p' := \mathbb{P}\left[\bigcap_{s \in \mathbb{T}_t} \{Y_s^{t,x,y,\nu} \ge g(s, X_s^{t,x})\}\right] \ge p$. By the martingale representation theorem, we can find $\alpha \in \mathcal{A}_{t,p'}$ such that

$$\mathbb{1}_{\bigcap_{s\in\mathbb{T}_{t}}\{Y_{s}^{t,x,y,\nu}\geq g(s,X_{s}^{t,x})\}}=P_{T}^{t,p',\alpha}\geq P_{T}^{t,p,\alpha}$$

Modifying appropriately α we have $\alpha \in \mathcal{A}_{t,p}$. Moreover

$$\mathbb{1}_{\{Y_s^{t,x,y,\nu}\geq g(s,X_s^{t,x})\}}\geq P_T^{t,p,\alpha},\ s\in\mathbb{T}_t.$$

Now take the conditional expectation and use the fact that $P^{t,p,\alpha}$ is a martingale to get

$$\mathbb{1}_{\{Y^{t,x,y,\nu} \ge g(\cdot, X^{t,x})\}} \ge P^{t,p,\alpha} \Leftrightarrow Y^{t,x,y,\nu} \ge g(\cdot, X^{t,x}) \mathbb{1}_{\{P^{t,p,\alpha} > 0\}} \text{ on } \mathbb{T}_t .$$
Hence, $y \in \overline{\Gamma}(t,x,p).$

Dynamic programming Dual backward algorithm

Dynamic programming

A first way to compute the value function v...

Theorem (Dynamic Programming)

Fix $0 \leq i \leq n-1$ and $(t, x, p) \in [t_i, t_{i+1}) \times (0, \infty)^d \times [0, 1]$,

$$v(t, x, p) = \inf_{\alpha \in \mathcal{A}_{t,p}} \mathbb{E}^{\mathbb{Q}_{t,x}} \left[(v \lor g) \left(t_{i+1}, X_{t_{i+1}}^{t,x}, P_{t_{i+1}}^{t,p,\alpha} \right) \right]$$

Standard arguments should lead to a characterization of v as a viscosity solution on each interval $[t_i, t_{i+1})$, i < n of

$$\sup_{\alpha \in \mathbb{R}^{d}} \left\{ \frac{-\partial_{t}\varphi + \alpha^{\top}\lambda D_{p}\varphi}{-\frac{1}{2} \left(\operatorname{Tr}[\sigma\sigma^{\top}D_{xx}^{2}\varphi] + 2\operatorname{Tr}[\alpha^{\top}\sigma^{\top}D_{xp}^{2}\varphi] + |\alpha|^{2}D_{pp}^{2}\varphi \right) \right\} = 0,$$

with the boundary condition

$$v(t_{i+1}-,\cdot)=(v\vee g)(t_{i+1},\cdot).$$

Dynamic programming Dual backward algorithm

Dual backward algorithm: intuition of the main result

As with Bouchard, Elie and Touzi in [2] for n = 1, take the Fenchel transform v^{\sharp} of v, i.e.

$$v^{\sharp}(t,x,q) := \sup_{p \in \mathbb{R}} (pq - v(t,x,p)) ,$$

to deduce that v^{\sharp} should be a viscosity solution of the linear PDE on each interval $[t_i, t_{i+1})$, i < n of

$$-\partial_t \varphi - \frac{1}{2} \left(\operatorname{Tr}[\sigma \sigma^\top D_{xx}^2 \varphi] + 2q \operatorname{Tr}[\lambda^\top \sigma^\top D_{xq}^2 \varphi] + |\lambda|^2 q^2 D_{qq}^2 \varphi \right) = 0,$$

with the boundary condition

$$v^{\sharp}(t_{i+1}-,\cdot)=(v\vee g)^{\sharp}(t_{i+1},\cdot).$$

Dual backward algorithm: intuition of the main result (cont.) and main result

By the Feynman-Kac representation this corresponds to the following backward algorithm for i < n

$$\left\{ \begin{array}{ll} w(T,x,q) &:= & q + \infty \mathbb{1}_{\{q < 0\}}\,, \\ w(t,x,q) &:= & \mathbb{E}^{\mathbb{Q}_{t,x}}\left[(w^{\sharp} \lor g)^{\sharp}(t_{i+1},X^{t,x}_{t_{i+1}},Q^{t,x,q}_{t_{i+1}}) \right] \, t \in [t_i,t_{i+1})\,, \end{array} \right.$$

Main result...

Theorem (Main result)

$$v = w^{\sharp}$$
 on $[0, T] \times (0, \infty)^d \times [0, 1]$.

Aim: Prove the result by relying on dual arguments only!

The backward algorithm as a lower and upper bound

 $\left(1\right)$ The backward algorithm as a lower bound

Proposition

 $v \geq w^{\sharp}$ on $[0, T] \times (0, \infty)^d \times [0, 1]$.

Proof. Use the definition of the Legendre Fenchel transform and argue by induction.

(2) The backward algorithm as a upper bound This is the more involved part...

Proposition $v \le w^{\sharp}$ on $[0, T] \times (0, \infty)^d \times [0, 1].$

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The backward algorithm as a upper bound

Idea of the proof. Fix $0 \le i \le n-1$ and let $(t, x, p) \in [t_i, t_{i+1}) \times (0, \infty)^d \times [0, 1]$.

Step 1. Prove by induction that a convexification in the dynamic programming algorithm holds, i.e.

$$v(t,x,p) = \inf_{\alpha \in \mathcal{A}_{t,p}} \mathbb{E}^{\mathbb{Q}_{t,x}} \left[\operatorname{co}[v \lor g] \left(t_{i+1}, X_{t_{i+1}}^{t,x}, P_{t_{i+1}}^{t,p,\alpha} \right) \right] \,.$$

where for a given function f, co[f] is its closed convex envelope.

Step 2. Prove by induction the probabilistic representation of the dual function, i.e. there exists $\bar{\alpha} \in A_{t,p}$ such that

$$w^{\sharp}(t,x,p) = \mathbb{E}^{\mathbb{Q}_{t,x}} \left[\operatorname{co}[w^{\sharp} \lor g] \left(t_{i+1}, X_{t_{i+1}}^{t,x}, P_{t_{i+1}}^{t,p,\overline{\alpha}} \right) \right] \,.$$

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The backward algorithm as a upper bound (cont.)

- To prove **Step 2.** we have, by proceeding backward, to: (a) prove a decomposition in simple terms of $(w^{\sharp} \lor g)^{\sharp}$ and $(w^{\sharp} \lor g)^{\sharp\sharp}$,
- (b) study the subdifferential of $(w^{\sharp} \lor g)^{\sharp}$.
- (c) find a particular value p in the subdifferential of $w(t_i, \cdot)$,

(d) apply a martingale representation argument between the elements of the subdifferential of $(w^{\sharp} \lor g)^{\sharp}$ at t_{i+1} and p at t_i (cf. European case). Be careful we have to study the limits of w^{\sharp} in p!

The backward algorithm as a upper bound (cont.)

Example: fix $(t, x, p) \in [t_{n-1}, T) \times (0, \infty)^d \times [0, 1]$.

(1) Decomposition We know from (a)

$$egin{aligned} & \mathsf{w}(t,\mathsf{x},q) = \mathbb{E}^{\mathbb{Q}_{t,\mathsf{x}}}[(qQ_T^{t,\mathsf{x},1} - g(T,X_T^{t,\mathsf{x}}))^+] \ &= \mathbb{E}^{\mathbb{Q}_{t,\mathsf{x}}}[g^{\sharp}\left(t_{i+1},X_{t_{i+1}}^{t,\mathsf{x}},qQ_{t_{i+1}}^{t,\mathsf{x},1}
ight)]\,. \end{aligned}$$

(2) Study of the subdifferential

It can be proved using the Lebesgue theorem that

$$D_q^+ w(t, x, q) = \mathbb{P}[qQ_T^{t,x,1} \ge g(T, X_T^{t,x})]$$

 $D_q^- w(t, x, q) = \mathbb{P}[qQ_T^{t,x,1} > g(T, X_T^{t,x})].$

leading to $D_q^+ w(t, x, \cdot) \ge 0$ if $q \ge 0$ and $D_q^- w(t, x, \cdot) \ge 0$ if q > 0, $\lim_{q\uparrow\infty} D_q^+ w(t, x, q) = 1$, $D_q^+ w(t, x, 0) = p_{\min}(t, x)$.

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The backward algorithm as a upper bound (cont.)

(3.a) Martingale representation for $p \in (p_{\min}(t, x), 1)$. From (2) $\exists \tilde{q} \in (0, \infty)$ s.t. $(p_{\min}(t, x), 1)$ lies in the subdifferential of $w(\cdot, \tilde{q})$.

This implies that

$$p = \lambda \mathbb{P}[\tilde{q}Q_T^{t,x,1} \ge g(T,X_T^{t,x})] + (1-\lambda)\mathbb{P}[\tilde{q}Q_T^{t,x,1} > g(T,X_T^{t,x})].$$

with $\lambda \in [0, 1]$, lies in the subdifferential of $w(t, x, \cdot)$ at \tilde{q} . By the martingale representation theorem, $\exists \ \bar{\alpha} \in \mathcal{A}_{t,p}$ s.t.

$$\begin{split} \lambda \mathbb{1}_{\tilde{q}Q_T^{t,x,1} \geq g(\mathcal{T},X_T^{t,x})} + (1-\lambda) \mathbb{1}_{\tilde{q}Q_T^{t,x,1} > g(\mathcal{T},X_T^{t,x})} \\ &= p + \int_t^{t_{i+1}} \bar{\alpha}_s^\top \mathrm{d}W_s =: P_{t_{i+1}}^{t,p,\bar{\alpha}} \,. \end{split}$$

The backward algorithm as a upper bound (cont.)

Applying [4, Chapter I, Proposition 5.1] we have,

$$\begin{split} w^{\sharp}(t,x,p) &= \tilde{q}p - w(t,x,\tilde{q}) \\ &= \mathbb{E}^{\mathbb{Q}_{t,x}} \left[P^{t,p,\bar{\alpha}}_{t_{i+1}} \tilde{q} Q^{t,x,1}_{t_{i+1}} - g^{\sharp} \left(t_{i+1}, X^{t,x}_{t_{i+1}}, \tilde{q} Q^{t,x,1}_{t_{i+1}} \right) \right] \\ &= \operatorname{co}[g] \left(t_{i+1}, X^{t,x}_{t_{i+1}}, P^{t,p,\bar{\alpha}}_{t_{i+1}} \right) \,. \end{split}$$

(3.b) Martingale representation for $p \in [0, p_{\min}(t, x)]$ and $p = \{1\}$. As $[0, p_{\min}(t, x)]$ belongs to the subdifferential of $w(t, x, \cdot)$ at 0 and $p_{\min}(t, x) = D_q^+ w(t, x, 0)$ we can find $\lambda \in [0, 1]$ such that $p = \lambda D_q^+ w(t, x, 0)$. We then proceed as in (3.a). The case p = 1 requires the study of the limit at p = 1 of w^{\sharp} .

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For all the technical details feel free to visit our paper on arXiv: http://arxiv.org/abs/1409.8219

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Thank you!

Géraldine Bouveret Quantile hedging of Bermudan options

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