

INTRODUCTION TO STOCHASTIC CONTROL OF MARKOV DIFFUSIONS

Nizar TOUZI, CREST, Paris, touzi@ensae.fr

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- Conditional expectations and linear parabolic PDE's
- Standard formulation of stochastic control problems
- Dynamic programming principle and HJB equation
- Viscosity solutions

CONDITIONAL EXPECTATIONS AND LINEAR PARABOLIC PDE's

Consider the function :

$$V(t, x) := \mathbb{E}_{t, x} \left[\int_t^T f(X_u) \beta(t, u) du + \beta(t, T) g(X_T) \right]$$

where

$$dX_t = \mu(X_t)dt + \sigma(X_t)dW_t, \quad \beta(t, u) := e^{-\int_t^u k(X_v)dv}$$

and

$$\mu : \mathbb{R}^n \longrightarrow \mathbb{R}^n, \quad \sigma : \mathbb{R}^n \longrightarrow \mathcal{S}_{\mathbb{R}}^n,$$

$$f, g, k : \mathbb{R}^n \longrightarrow \mathbb{R}$$

Second order PDE :

$$(E) \quad \frac{\partial v}{\partial t}(t, x) + F(t, x, v(t, x), Dv(t, x), D^2v(t, x)) = 0, \quad t < T, \quad x \in \mathcal{O} \subset \mathbb{R}^n$$

- (E) is **parabolic** if $F(x, r, p, A)$ is non-increasing in A
- (E) is **linear** if $F(x, r, p, A)$ is linear in (r, p, A)
- v is a classical **super-solution** (resp. **subsolution**) of (E) if $v \in C^{1,2}$ and $\frac{\partial v}{\partial t} + F(t, x, v(t, x), Dv(t, x), D^2v(t, x)) \geq 0$ (resp. ≤ 0) on $[0, t) \times \mathbb{R}^n$

Maximum Principle. Let \mathcal{O} bounded and $F(t, x, r, p, A)$ parabolic strictly increasing in r . Let u (resp. v) be a classical subsolution (resp. super-solution) of (E), with $u \leq v$ on $\partial\{(0, T) \times \mathcal{O}\}$. Then $u \leq v$ on $[0, T] \times \overline{\mathcal{O}}$.

Dynkin operator

$$\mathcal{L}V(t, x) := V_t(t, x) + \mu(x) \cdot DV(t, x) + \frac{1}{2} \text{Tr} [\sigma \sigma^*(x) D^2 V(t, x)]$$

\implies **Tower property** : for any $h > 0$

$$\beta(0, t)V(t, x) = \mathbb{E}_{t, x} \left[\int_t^{t+h} \beta(0, u) f(X_u) du + \beta(0, t+h)V(t+h, X_{t+h}) \right]$$

\implies if V is smooth, then it follows from Itô's lemma

$$\begin{aligned} 0 &= \frac{1}{h} \mathbb{E}_{t, x} \left[\int_t^{t+h} \beta(t, u) (kV - \mathcal{L}V - f)(u, X_u) du + \int_t^T DV(u, X_u) \cdot \sigma(X_u) dW \right] \\ &= \frac{1}{h} \mathbb{E}_{t, x} \left[\int_t^{t+h} \beta(t, u) \{k(X_u)V(u, X_u) - \mathcal{L}V(u, X_u) - f(X_u)\} du \right] \quad ! \end{aligned}$$

send h to zero $\implies V$ solves the **parabolic linear** PDE

$$-\mathcal{L}V(t, x) + k(x)V(t, x) - f(x) = 0$$

Feynman-Kac representation formula

Cauchy problem

$$-\mathcal{L}v(t, x) + k(x)v(t, x) - f(x) = 0 \quad \text{and} \quad v(T, x) = g(x)$$

Theorem *Let v be a classical solution of the above Cauchy problem with $|v(t, x)| \leq C(1 + |x|^p)$. Then*

$$v(t, x) = V(t, x) = \mathbb{E}_{t,x} \left[\int_t^T f(X_u) \beta(t, u) du + \beta(t, T) g(X_T) \right]$$

- Uniqueness
- Important implication for numerical approximation

Cauchy problem can be solved
by means of Monte Carlo method

STANDARD FORMULATION OF STOCHASTIC CONTROL PROBLEMS

- *Control process* $\nu \in \mathcal{U}_0$

ν_t v.a. \mathcal{F}_t – measurable with values in $U \subset \mathbb{R}^k$

- *Controlled process* For $\nu \in \mathcal{U}_0$, define X^ν by

$$\text{EDS}(\nu) \quad dX_t^\nu = b(X_t^\nu, \nu_t)dt + \sigma(X_t^\nu, \nu_t)dW_t \quad \text{and} \quad X_0^\nu \text{ given}$$

where

$$b : \mathbb{R}^n \times U \longrightarrow \mathbb{R}^n, \quad \sigma : \mathbb{R}^n \times U \longrightarrow \mathcal{M}_{\mathbb{R}}^{n,d} \quad \text{Lip in } x \text{ unif. in } u$$

- *Admissible control process* $\nu \in \mathcal{U}$ if

EDS(ν) has a unique solution in L^2 for every initial data $X_0 = x$

REWARD CHARACTERISTICS

$$f, k : \mathbb{R}^n \times U \longrightarrow \mathbb{R} \quad \text{and} \quad g : \mathbb{R}^n \longrightarrow \mathbb{R}$$

with

$$k \geq 0 \quad \text{and} \quad |f(t, x, u)| + |g(x)| \leq C(1 + |x|^2)$$

- f : cont. reward rate
- g : terminal reward
- k : discount rate

STOCHASTIC CONTROL PROBLEM

$$V(t, x) := \sup_{\nu \in \mathcal{U}} J(t, x, \nu)$$

where

$$J(t, x, \nu) := \mathbb{E}_{t,x} \left[\int_t^T \beta^\nu(t, s) f(X_s^\nu, \nu_s) ds + \beta^\nu(t, T) g(X_T^\nu) \right]$$

with the discount factor

$$\beta^\nu(t, s) := e^{-\int_t^s k(X_r^\nu, \nu_r) dr}$$

Goal : characterize the local behavior of V by means of

the *Hamilton-Jacobi-Bellman* equation

SOME VOCABULARY

- $\hat{\nu}$ is an *optimal control* if

$$\hat{\nu} \in \mathcal{U} \text{ and } V(t, x) = J(t, x, \hat{\nu}_{t,x})$$

- $\nu \in \mathcal{U}$ is a *feedback control*

ν is adapted to \mathbb{F}^X

- ν is a *Markov control* if

$$\nu_s = \tilde{u}(s, X_s) \text{ for some measurable function } u$$

- ν is an *open-loop control* if

ν is deterministic

DYNAMIC PROGRAMMING PRINCIPLE

Theorem For any stopping time τ with values in $[t, T]$:

$$V(t, x) = \sup_{\nu \in \mathcal{U}} \mathbb{E}_{t, x} \left[\int_t^\tau \beta^\nu(t, s) f(s, X_s^\nu, \nu_s) ds + \beta^\nu(t, \tau) V(\tau, X_\tau^\nu) \right]$$

- Basic tool of stochastic control / compare with tower property
- *Main ingredient* : concatenation of control processes
- In finite discrete time

$$V(t, x) = \sup_{u \in U} \mathbb{E}_{t, x} \left[f(X_t^\nu, u) + e^{-k(X_t^\nu, \nu_t)} V(t+1, X_{t+1}^\nu) \right]$$

\implies Reduction to a (backward) sequence of finite-dimensional optimization problems

REDUCTION TO MAYER FORM ($f = k \equiv 0$)

Consider new controlled processes (Y, Z) :

$$dY^{\nu_s} = Z_s f(X_s, \nu_s) ds \quad \text{and} \quad dZ^{\nu_s} = -Z_s k(X_s, \nu_s) ds$$

\implies Augmented controlled process

$$\bar{X} := (X, Y, Z)$$

Then $V(t, x) = \bar{V}(t, x, 0, 1)$, where

$$\bar{V}(t, \bar{x}) := \sup_{\nu \in \mathcal{U}} \mathbb{E}_{t,x} \left[\bar{g} \left(\bar{X}_T^{t,x} \right) \right] \quad \text{and} \quad \bar{g}(x, y, z) := y + g(x)z$$

HAMILTON-JACOBI-BELLMAN EQUATION

Denote

$$\mathcal{L}^u v(t, x) := b(x, u) \cdot Dv(t, x) + \frac{1}{2} \text{Tr} [\sigma \sigma^*(x, u) D^2 v(t, x)]$$

$$H(x, r, p, A) := \sup_{u \in U} \left\{ -k(x, u)r + b(x, u) \cdot p + \frac{1}{2} \text{Tr}[\sigma \sigma^*(x, u) A] + f(x, u) \right\}$$

Proposition If $V \in C^{1,2}([0, T], \mathbb{R}^n)$:

$$-\frac{\partial V}{\partial t}(t, x) - H(x, V(t, x), DV(t, x), D^2 V(t, x)) \geq 0$$

i.e. V is a super-solution of the associated HJB equation

Proof of super-solution property. $(t, x) \in [0, T) \times \mathbb{R}^n$, $u \in U$ fixed, constant control $\nu_s = u$, controlled process X^u , and

$$\tau_h := (t + h) \wedge \inf \{s > t : |X_s^u - x| \geq 1\}$$

Dynamic programming and Itô's lemma :

$$\begin{aligned} 0 &\leq \frac{1}{h} \mathbb{E}_{t,x} \left[\beta(0, t)V(t, x) - \beta(0, \tau_h)V(\tau_h, X_{\tau_h}) - \int_t^{\tau_h} \beta(0, r)f(r, X_r, \nu_r)dr \right] \\ &= -\frac{1}{h} \mathbb{E}_{t,x} \left[\int_t^{\tau_h} \beta(0, r)(-kV + V_t + \mathcal{L}^u V + f)(r, X_r, u)dr \right] \\ &\quad - \frac{1}{h} \mathbb{E}_{t,x} \left[\int_t^{\tau_h} \beta(0, r)DV(r, X_r)^* \sigma(X_r, u)dW_r \right] \\ &= -\frac{1}{h} \mathbb{E}_{t,x} \left[\int_t^{\tau_h} \beta(0, r)(-kV + V_t + \mathcal{L}^u V + f)(r, X_r, u)dr \right] \end{aligned}$$

Finally, send h to zero, and use the dominated convergence theorem

Proposition *If $V \in C^{1,2}([0, T], \mathbb{R}^n)$, and H is continuous, then :*

$$-\frac{\partial V}{\partial t}(t, x) - H(x, V(t, x), DV(t, x), D^2V(t, x)) = 0$$

\implies Proof... more technical

In order to complete the characterization of V :

(i) Terminal condition

(ii) Uniqueness result

VERIFICATION RESULT

Theorem $v \in C^{1,2}([0, T], \mathbb{R}^n) \cap C([0, T] \times \mathbb{R}^n)$ with $|v(t, x)| \leq C(1 + |x|^2)$

(i) If $v(T, \cdot) \geq g$ and $-v_t(t, x) - H(t, x, v(t, x), Dv(t, x), D^2v(t, x)) \geq 0$.

Then $v \geq V$

(ii) Assume further that

- $v(T, \cdot) = g$ and $0 = v_t(t, x) + \mathcal{L}^{\hat{u}(t, x)}v(t, x) + f(t, x, u)$
- there is a unique solution for the SDE

$$dX_s = b(X_s, \hat{u}(s, X_s)) ds + \sigma(X_s, \hat{u}(s, X_s)) dW_s \quad \text{for any } X_0 = x$$

- $\hat{v} \in \mathcal{U}$, where $\hat{v}_s := \hat{u}(s, X_s)$

Then $v = V$, et \hat{v} is a (Markov) optimal control

Sketch of the proof

(i) Let $\nu \in \mathcal{U}$, $X = X^\nu$, $X_t = x \implies$ Itô's lemma :

$$\begin{aligned} v(t, x) &= \beta(t, T)v(T, X_T^\nu) \\ &\quad - \int_t^T \beta^\nu(t, r)(-kv + v_t + \mathcal{L}^{\nu(r)}v)(r, X_r^\nu)dr \\ &\quad - \int_t^T \beta^\nu(t, r)Dv(r, X_r^\nu) \cdot \sigma(r, X_r^\nu, \nu_r)dW_r \end{aligned}$$

Since $-v_t + kv - \mathcal{L}^u v - f(\cdot, u) \geq -v_t - H(\cdot, v, Dv, D^2v) \geq 0$:

$$\begin{aligned} v(t, x) &\geq \mathbb{E}_{t,x} \left[\beta^\nu(t, T)v(T, X_T^\nu) + \int_t^T \beta^\nu(t, r)f(X_r^\nu, \nu_r)dr \right] \\ &\geq \mathbb{E}_{t,x} \left[\beta^\nu(t, T)g(X_T^\nu) + \int_t^T \beta^\nu(t, r)f(X_r^\nu, \nu_r)dr \right] \end{aligned}$$

(ii) inequalities are in fact equalities with the control $\hat{\nu}$

ON THE REGULARITY OF THE VALUE FUNCTION

$f = k \equiv 0$ (Mayer's formulation)

Proposition (i) g Lipschitz, then $V(t, \cdot)$ is Lipschitz-continuous

(ii) U bounded, then $V(\cdot, x)$ is $(1/2)$ -Hölder-continuous

Example. Let $U = \mathbb{R}$, $\mathcal{U} := \{\text{bounded predictable processes valued in } U\}$,

$$dX_t^\nu = X_t^\nu \nu_t dW_t \quad \text{and} \quad V(t, x) := \sup_{\nu \in \mathcal{U}} \mathbb{E}_{t,x} [g(X_T^\nu)]$$

where g is l.s.c. and bounded from below. Then

$$V(t, x) = g^{\text{conc}}(x) \quad g^{\text{conc}} \text{ is the concave envelope of } g$$

V not continuous at $t = T$ and not C^1 in x , in general.

VISCOSITY SOLUTIONS

Consider the **elliptic** PDE

$$(E) \quad F(z, v(z), Dv(z), D^2v(z)) = 0 \quad \text{for } z \in \mathcal{O} \text{ open subset of } \mathbb{R}^d$$

$(F(z, r, p, A)$ **non-increasing** in A)

- $v : \mathcal{O} \rightarrow \mathbb{R}$ l.s.c. is a **viscosity super-solution** of (E) if, for every $(z_0, \varphi) \in \mathcal{O} \times C^2(\mathcal{O})$:

$$(v - \varphi)(z_0) = \min_{\mathcal{O}} (v - \varphi) \implies F(z_0, v(z_0), D\varphi(z_0), D^2\varphi(z_0)) \geq 0$$

- $v : \mathcal{O} \rightarrow \mathbb{R}$ u.s.c. is a **viscosity sub-solution** of (E) if, for every $(z_0, \varphi) \in \mathcal{O} \times C^2(\mathcal{O})$:

$$(v - \varphi)(z_0) = \max_{\mathcal{O}} (v - \varphi) \implies F(z_0, v(z_0), D\varphi(z_0), D^2\varphi(z_0)) \leq 0$$

Semi-continuous envelopes :

$$v_*(z) := \liminf_{z' \rightarrow z} v(z') \quad \text{and} \quad v^*(z) := \limsup_{z' \rightarrow z} v(z')$$

finite for locally bounded $v : \mathbb{R}^d \longrightarrow \mathbb{R}$

Proposition (i) *If V is locally bounded, then*

$$-\frac{\partial V_*}{\partial t}(t, x) - H\left(x, V_*(t, x), DV_*(t, x), D^2V_*(t, x)\right) \geq 0$$

i.e. V_ is a super-solution of the associated HJB equation*

(ii) *If in addition H is continuous, then*

$$-\frac{\partial V^*}{\partial t}(t, x) - H\left(x, V^*(t, x), DV^*(t, x), D^2V^*(t, x)\right) \leq 0$$

i.e. V^ is a sub-solution of the associated HJB equation*

UNIQUE CHARACTERIZATION AND CONTINUITY

- Boundary condition :

$V_*(T, x)$ and $V^*(T, x)$ might not be given by the natural BC $g(x)$

(Recall our example)

- If we can prove that $V_*(T, x) \geq V^*(T, x)$ and that Maximum principle in the viscosity sense holds, then :

$$V_* = V^* \text{ on } [0, T] \times \mathbb{R}^n$$

$\implies V$ is the unique **continuous** viscosity solution **in a certain class**.

SUPER-HEDGING UNDER PORTFOLIO CONSTRAINTS

Nizar TOUZI, CREST, Paris, touzi@ensae.fr

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- Problem formulation
- **Dual** formulation
- **Geometric** dynamic programming and HJB equation
- Boundary condition : *face-lifting*
- Explicit solution in the Black-Scholes model

PROBLEM FORMULATION : the financial market

- 1 non-risky asset $S^0 \equiv 1$ ($r = 0$, *change of numéraire*)
- d risky assets S :

$$\frac{dS_t^i}{S_t^i} = \mu_t^i dt + \sum_{j=1}^d \sigma_t^{ij} dW_t^j, \quad i = 1, \dots, d$$

μ , σ and σ^{-1} bounded \mathbb{F} -adapted with values respectively in \mathbb{R}^d and $\mathcal{S}_{\mathbb{R}}^d$

- *Wealth process* $X^{x,\pi}$, under *self-financing* condition, defined by

$$dX_0^{x,\pi} = x \quad \text{and} \quad dX_t^{x,\pi} = \sum_{i=1}^d X_t^{x,\pi} \pi_u^i \frac{dS_u^i}{S_u^i} = X_t^{x,\pi} \pi_u \cdot (\mu_u du + \sigma_u dW_u)$$

- $\pi \in \mathcal{A}$: admissible portfolio if

$$\int_0^T |\sigma_u^* \pi_u|^2 du < \infty$$

PROBLEM FORMULATION, portfolio constraints

Let K be a closed convex (!) subset of \mathbb{R}^d containing 0

- K -admissible portfolio : $\pi \in \mathcal{A}_K$ if

$$\pi \in \mathcal{A} \text{ and } \pi_u \in K \text{ Leb} \otimes \mathbb{P} - \text{a.s.}$$

Example 1 *No short-selling* : $K = \{x \in \mathbb{R}^d : x^i \geq 0\}$

Example 2 *Incomplete market* : $K = \{x \in \mathbb{R}^d : x^{i_0} = 0\}$

Example 3 *No borrowing* : $K = \{x \in \mathbb{R}^d : \sum_i x^i \leq 1\}$

Example 4 *Rectangular constraints* : $K = \{x \in \mathbb{R}^d : m^i \leq x^i \leq M^i\}$

Example 5 *Finite capitalizations* : change model expressing portfolios in terms of number of shares...

PROBLEM FORMULATION, the super-replication problem

- Contingent claim $G : \mathcal{F}_T$ -measurable random variable, we will mainly consider $G = g(S_T)$ with

$$g : [0, \infty) \longrightarrow \mathbb{R} \quad \text{l.s.c. and bounded from below}$$

- Super-replication problem

$$V(0, S_0) := \inf \left\{ x : X_T^{x, \pi} \geq G \text{ a.s. for some } \pi \in \mathcal{A}_K \right\}$$

\implies Stochastic control problem in **non-standard form** !

\implies Connection with backward stochastic differential equations

\implies Very difficult to reach any *a-priori* regularity result

\implies 1st idea : *reduce to the classical setting*, i.e. standard formulation

DUAL FORMULATION : dual characterization of the constraints

Support function of K :

$$\delta(y) := \sup_{x \in K} x \cdot y$$

Effective domain of δ :

$$\tilde{K} := \{y \in \mathbb{R}^d : \delta(y) < \infty\}$$

Lemma Let K be a closed convex subset of \mathbb{R}^n . Then

$$x \in K \iff \delta(y) - x \cdot y \geq 0 \text{ for all } y \in \tilde{K}$$

DUAL FORMULATION : dual variables

Let $\mathcal{D} := \left\{ \text{bounded } \mathbb{F} - \text{adapted processes with values in } \tilde{K} \right\}$

$$\frac{d\mathbb{P}^\nu}{d\mathbb{P}} \Big|_{\mathcal{F}_T} := \exp \left[\int_0^T \sigma_u^{-1} (\nu_u - \mu_u) \cdot dW_u - \frac{1}{2} \int_0^T \left| \sigma_u^{-1} (\nu_u - \mu_u) \right|^2 du \right]$$

By Girsanov's Theorem, the process

$$W_u^\nu := W_u - \int_0^u \sigma_u^{-1} (\nu_u - \mu_u) du \quad 0 \leq u \leq T$$

is a Brownian motion under \mathbb{P}^ν , and

$$d \left(X_t^{x, \pi} e^{-\int_0^t \delta(\nu_u) du} \right) = X_t^{x, \pi} e^{-\int_0^t \delta(\nu_r) dr} \left[-(\delta(\nu_t) - \pi_t \cdot \nu_t) dt + \sigma_u dW_u^\nu \right]$$

\implies The process $\left\{ X_t^{x, \pi} e^{-\int_0^t \delta(\nu_u) du}, 0 \leq t \leq T \right\}$

is a \mathbb{P}^ν -super-martingale for every $\pi \in \mathcal{A}_K$ and $\nu \in \mathcal{D}$

DUAL FORMULATION :

reducing to a standard stochastic control problem

Theorem $V(0, S_0) = \tilde{V}(0, S_0) := \sup_{\nu \in \mathcal{D}} \mathbb{E}^{\mathbb{P}^\nu} \left[G e^{-\int_0^T \delta(\nu_u) du} \right]$

<ElKaroui-Quenez 1995, Cvitanić-Karatzas 1993, Föllmer-Kramkov 1999>

$G = g(S_T)$ and S is a Markov diffusion \implies Girsanov's Theorem

$$V(0, S_0) = \tilde{V}(0, S_0) := \sup_{\nu \in \mathcal{D}} \mathbb{E} \left[g(S_T^\nu) e^{-\int_0^T \delta(\nu_u) du} \right]$$

where

$$S_0^\nu = S_0 \quad \text{and} \quad dS_t^\nu = \text{diag}[S_t^\nu] (\nu_t dt + \sigma(S_t^\nu) dW_t)$$

Stochastic control problem in standard form

DUAL FORMULATION : the HJB equation

From general theory, if V is locally bounded, then

$$-(V_*)_t - \frac{1}{2} \text{Tr} [\bar{\sigma} \bar{\sigma}^*(s) D^2 V_*] - \text{diag}[s] y \cdot DV_* + \delta(y) V_* \geq 0 \quad \text{for all } u \in \tilde{K}$$

in the viscosity sense (super-solution property), where $\bar{\sigma}(s) := \text{diag}[s] \sigma(s)$

Since \tilde{K} is a cone, this is equivalent to

$$\min \left\{ -(V_*)_t - \frac{1}{2} \text{Tr} [\bar{\sigma} \bar{\sigma}^*(s) D^2 V_*], \inf_{y \in \tilde{K}_1} (\delta(y) V_* - \text{diag}[s] y \cdot DV_*) \right\} \geq 0$$

where $\tilde{K}_1 := \{y \in \tilde{K} : |y| = 1\}$

We will see later that this is the HJB equation for our problem

FROM NOW ON : MARKOV MODEL

- Risky assets dynamics :

$$\frac{dS_t^i}{S_t^i} = \mu^i(t, S_t) dt + \sum_{j=1}^d \sigma^{ij}(t, S_t) dW_t^j, \quad i = 1, \dots, d$$

μ and σ Lipschitz, linearly growing, and we will usually forget about the dependence upon t .

- Contingent claim

$$G = g(S_T)$$

for some

$$g : [0, \infty)^d \longrightarrow \mathbb{R} \text{ l.s.c. and bounded from below}$$

GEOMETRIC DYNAMIC PROGRAMMING PRINCIPLE

- *Trivial claim* : Let $(t, s), x, \pi \in \mathcal{A}_K$ be such that $X_T^{x, \pi} \geq g(S_T^{t, s})$. Then

$$X_\tau^{x, \pi} \geq V(\tau, S_\tau) \text{ for every stopping time } \tau \in [t, T] \text{ a.s.}$$

In fact, we have the following *geometric dynamic programming principle* (without dual formulation)

Theorem. For all $(t, s) \in [0, T) \times \mathbb{R}_+$, and stopping time $\tau \in [t, T]$ a.s.

$$V(t, s) = \inf \{x : X_\tau^{x, \pi} \geq V(\tau, S_\tau) \text{ a.s. for some } \pi \in \mathcal{A}_K\}$$

\implies Super-solution property

Proposition $-\frac{\partial V_*}{\partial t} - \frac{1}{2} \text{Tr} [\sigma \sigma^* D^2 V_*] \geq 0$ and $\frac{\text{diag}[s] D V_*}{V_*} \in K$

Sketch of proof (super-solution property)

For simplicity, assume V is smooth and

$$V(t, s) := \underline{\min} \left\{ x : X_T^{x, \pi} \geq g(S_T) \text{ for some } \pi \in \mathcal{A}_K \right\}$$

Then, starting from initial wealth $\hat{x} := V(t, s)$:

$$X_T^{\hat{x}, \hat{\pi}} \geq g(S_T^{t, s}) \text{ for some } \hat{\pi} \in \mathcal{A}_K$$

\implies Geometric dynamic programming

$$X_\tau^{\hat{x}, \hat{\pi}} = V(t, s) + \int_t^\tau X_u^{\hat{x}, \hat{\pi}} \hat{\pi}_u [\mu_u du + \sigma_u dW_u] \geq V(\tau, S_\tau^{t, s})$$

\implies Itô's lemma

$$0 \leq - \int_t^\tau \mathcal{L}V(u, S_u^{t, s}) du + \int_t^\tau \sigma_u \left(X_u^{\hat{x}, \hat{\pi}} \hat{\pi}_u - \text{diag}[S_u] DV(u, S_u) \right) dW_u^0$$

Sketch of proof (super-solution property), continued

$$0 \leq - \int_t^\tau \mathcal{L}V(u, S_u^{t,s}) du + \int_t^\tau \sigma_u \left(X_u^{\hat{x}, \hat{\pi}} \hat{\pi}_u - \text{diag}[S_u] DV(u, S_u) \right) dW_u^0$$

1. Set $\tau_h := (t + h) \wedge \inf \{u > t : |\ln S_u - \ln s| \geq 1\}$, and take expected values $\implies -\mathcal{L}V \geq 0$

2. **Lemma.** (Loc. behavior of stoch. int.) *Let b be a predictable W -integrable process satisfying $\int_0^t b_s \cdot dW_s \geq -C t$, $0 \leq t \leq \tau$, for some $C > 0$ and positive stopping time τ . Then $\liminf_{t \searrow 0} \frac{1}{t} \int_0^t |b_s| ds = 0$ \mathbb{P} -a.s.*

$$\implies \frac{\text{diag}[s] DV}{V} \in K, \text{ or equivalently } \inf_{y \in \tilde{K}_1} \left(\delta(y) - \frac{\text{diag}[s] y \cdot DV}{V} \right) \geq 0$$

CHARACTERIZING THE TERMINAL CONDITION : implications from the HJB equation

We have of course $V(T, s) = g(s)$, by definition. Let

$$\bar{V}(s) := \liminf_{(t', s') \rightarrow (T, s)} V(t, s) \quad [= V_*(T, s)]$$

Lemma *We have $\bar{V} \geq g$ and $\frac{\text{diag}[s]D\bar{V}}{\bar{V}} \in K$.*

The latter condition might not be satisfied by g . Then

$$\bar{V} \neq g \quad \text{in general}$$

Sketch of proof (implications from HJB)

- $g \geq C$ and l.s.c. $\implies V \geq g$ (Fatou's lemma)

- For $t < T$,

$$\delta(y)V(t, s) - y \cdot \text{diag}[s]DV(t, s) \geq 0 \quad \text{for every } y \in \tilde{K}$$

or equivalently,

$$\alpha \longmapsto \ln \bar{V}(se^{\alpha y}) - \delta(y)\alpha \quad \text{is non-decreasing}$$

\implies send t to T ...

CHARACTERIZING THE TERMINAL CONDITION :

face-lifting

Lemma $\bar{V}(s) \geq \hat{g}(s) := \sup_{y \in \tilde{K}} g(se^y) e^{-\delta(y)}$

Proof For every $y \in \tilde{K} : 0 \leq \delta(y)\bar{V}(s) - y \cdot \text{diag}[s]D\bar{V}$

$$\implies 0 \leq \delta(y) - \frac{\partial}{\partial \alpha} \ln \bar{V}(se^{\alpha y})$$

integrate between $\alpha = 0$ and $\alpha = 1$, and recall $\bar{V} \geq g$:

$$\bar{V}(s) \geq \bar{V}(se^y) e^{-\delta(y)} \geq g(se^y) e^{-\delta(y)}$$

y is arbitrary in \tilde{K} ...

CHARACTERIZING THE TERMINAL CONDITION :

properties of the face-lifting operator

- $\hat{g} \geq g$ (\hat{g} majorant of g)
- $\frac{\text{diag}[s]D\hat{g}}{\hat{g}} \in K$ (*satisfies the constraints*)
- $\hat{\hat{g}} = \hat{g}$ ("*projection*" property)
- If h is such that $h \geq g$ and $\frac{\text{diag}[s]Dh}{h} \in K$, then $h \geq \hat{g}$ (*minimality*)

\hat{g} is the smallest majorant of g
which satisfies the constraints

CHARACTERIZING THE TERMINAL CONDITION :

Examples for $d = 1$, $K = [-\ell, u] \ni 0$

European call option $g(s) = (s - \kappa)^+$

$$\hat{g}(s) = \begin{cases} (s - \kappa) & \text{pour } s \geq \frac{\kappa u}{u-1} \\ \frac{\kappa}{u-1} \left(\frac{(u-1)s}{\kappa u} \right)^u & \text{pour } s \leq \frac{\kappa u}{u-1} \end{cases}$$

European put option $g(s) = (\kappa - s)^+$

$$\hat{g}(s) = \begin{cases} (\kappa - s) & \text{pour } s \leq \frac{\kappa \ell}{\ell+1} \\ \frac{s}{\ell+1} \left(\frac{\kappa \ell}{(\ell+1)s} \right)^\ell & \text{pour } s \geq \frac{\kappa \ell}{\ell+1} \end{cases}$$

EXPLICIT RESULT IN THE BLACK-SCHOLES MODEL

<Broadie-Cvitanić-Soner 1998>

Theorem For constant σ , we have $V(t, s) = \mathbb{E}_{t,s}^{\mathbb{P}^0} [\hat{g}(S_T)]$, and the optimal hedging strategy is the classical Black-Scholes hedging strategy of the face-lifted contingent claim $\hat{g}(S_T)$

In the more general *local volatility model* $\sigma(t, s)$:

Theorem Under some conditions, V is the unique (in a certain class) continuous viscosity solution of the associated HJB equation

$$\min \left\{ -V_t - \frac{1}{2} \text{Tr} [\overline{\sigma\sigma^*}(s) D^2 V] , \inf_{y \in \tilde{K}_1} (\delta(y)V - \text{diag}[s]y \cdot DV) \right\} = 0$$

Proof of Broadie-Cvitanić-Soner's result

Denote $w(t, s) := \mathbb{E}_{t,s}^{\mathbb{P}^0} [\hat{g}(S_T)]$

(i) $w(t, s) - V(t, s) \leq \mathbb{E}_{t,s}^{\mathbb{P}^0} [\bar{V}(S_T) - V_*(t, s)] = \mathbb{E}_{t,s}^{\mathbb{P}^0} \left[\int_t^T \mathcal{L}V_*(u, S_u) \right] \leq 0$

(iia) $\delta(y)w(t, s) - y \cdot \text{diag}[s]Dw(t, s) = \mathbb{E}_{t,s}^{\mathbb{P}^0} [\delta(y)\hat{g}(S_T) - y \cdot \text{diag}[S_T]D\hat{g}(S_T)]$
 ≥ 0 for all $y \in \tilde{K}$

(iib) $\mathcal{L}w = 0 \implies$ set $\hat{\pi}_u := \frac{\text{diag}[s]Dw(u, S_u)}{w(u, S_u)}$, and apply Itô's lemma :

$$\begin{aligned} \hat{g}(S_T) &= w(T, S_T) \\ &= w(t, s) + \int_t^T \mathcal{L}w(u, S_u)du + \int_t^T w(u, S_u)\hat{\pi}_u \cdot \text{diag}[S_u]^{-1}dS_u \\ &= w(t, s) + \int_t^T w(u, S_u)\hat{\pi}_u \cdot \text{diag}[S_u]^{-1}dS_u = X_T^{w(t,s), \hat{\pi}} \end{aligned}$$

Since $\hat{g} \geq g$, this implies that $w(t, s) \geq V(t, s)$

PROOF OF SUBSOLUTION PROPERTY IN THE LOCAL VOLATILITY MODEL

Consider the simple case $\text{int}(K) \neq \emptyset$, and show that

$$\min \left\{ -V_t^* - \frac{1}{2} \text{Tr} [\bar{\sigma} \bar{\sigma}^*(s) D^2 V^*], \inf_{y \in \tilde{K}_1} (\delta(y) V^* - \text{diag}[s] y \cdot D V^*) \right\} \leq 0$$

in the viscosity sense. Let $(t_0, s_0) \in [0, T) \times \mathbb{R}_+^d$, $\varphi \in C^2$ be such that

$$0 = (V^* - \varphi)(t_0, s_0) = \text{max (strict)} (V^* - \varphi)$$

and *assume to the contrary* that

$$f(t_0, s_0) := \left(-\varphi_t - \frac{1}{2} \text{Tr} [\bar{\sigma} \bar{\sigma}^* D^2 \varphi] \right) (t_0, s_0) > 0$$

$$\text{and } \hat{\pi}(t_0, s_0) := \frac{\text{diag}[s_0] D \varphi(t_0, s_0)}{\varphi(t_0, s_0)} \in \text{int}(K)$$

PROOF OF SUBSOLUTION PROPERTY, continued (2)

Define the open neighborhood of (t_0, s_0) :

$$\mathcal{N} := \{(t, s) : |(t, \ln s) - (t_0, \ln s_0)| \leq 1, f(t, s) \geq 0 \text{ and } \hat{\pi}(t, s) \in K\}$$

Since (t_0, s_0) is a point of *strict maximum* of $V^* - \varphi$, we have

$$\max_{\partial \mathcal{N}} (\ln V^* - \ln \varphi) =: -3\eta < 0$$

Choose $(t_1, s_1) \in \text{int}(\mathcal{N})$ so that

$$|\ln V(t_1, s_1) - \ln \varphi(t_1, s_1)| \leq \eta$$

Take (t_1, s_1) as initial data for the process S , and define

$$\tau := \inf \{u > t_1 : (u, S_u) \notin \mathcal{N}\}$$

PROOF OF SUBSOLUTION PROPERTY, continued (3)

Consider the initial capital $\hat{x} := V(t_1, s_1)e^{-\eta}$, and compute that

$$\begin{aligned}\ln X_{\tau}^{\hat{x}, \hat{\pi}} - \ln V(\tau, S_{\tau}) &\geq \ln X_{\tau}^{\hat{x}, \hat{\pi}} - \ln V^*(\tau, S_{\tau}) \\ &\geq \ln X_{\tau}^{\hat{x}, \hat{\pi}} - \ln \varphi(\tau, S_{\tau}) + 3\eta \\ &\geq \ln X_{\tau}^{\varphi(t_1, s_1), \hat{\pi}} - \ln \varphi(\tau, S_{\tau}) + \eta\end{aligned}$$

Next observe that

$$\begin{aligned}\frac{d\varphi(t, S_t)}{\varphi(t, S_t)} &= \frac{\mathcal{L}\varphi(t, S_t)}{\varphi(t, S_t)} dt + \hat{\pi}(t, S_t) \cdot \text{diag}[S_t]^{-1} dS_t \\ &= \frac{\mathcal{L}\varphi(t, S_t)}{\varphi(t, S_t)} dt + \frac{dX_t^{\varphi(t_1, s_1), \hat{\pi}}}{X_t^{\varphi(t_1, s_1), \hat{\pi}}}\end{aligned}$$

PROOF OF SUBSOLUTION PROPERTY, continued (4)

Since $\mathcal{L}\varphi \leq 0$ for $t \in [t_1, \tau]$, and $X_{t_1}^{\varphi(t_1, s_1), \hat{\pi}} = \varphi(t_1, s_1)$, this implies that

$$X_{\tau}^{\varphi(t_1, s_1), \hat{\pi}} \geq V(\tau, S_{\tau})$$

Hence, starting from the initial capital $\hat{x} := V(t_1, s_1)e^{-\eta}$, we have

$$\begin{aligned} \ln X_{\tau}^{\hat{x}, \hat{\pi}} - \ln V(\tau, S_{\tau}) &\geq \ln X_{\tau}^{\hat{x}, \hat{\pi}} - \ln V^*(\tau, S_{\tau}) \\ &\geq \ln X_{\tau}^{\hat{x}, \hat{\pi}} - \ln \varphi(\tau, S_{\tau}) + 3\eta \\ &\geq \ln X_{\tau}^{\varphi(t_1, s_1), \hat{\pi}} - \ln \varphi(\theta, S_{\tau}) + \eta \geq \eta \end{aligned}$$

thus *contradicting the geometric dynamic programming*

HEDGING UNDER GAMMA CONSTRAINTS

Nizar TOUZI, CREST, Paris, touzi@ensae.fr

Lunteren, January 24-26, 2005

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1. INTRODUCTION : THE BLACK-SCHOLES MODEL

1. The financial market : $(\Omega, \mathcal{F}, \mathbb{F}, \mathbb{P})$, W Brownian motion valued in \mathbb{R}^1

- 1 non-risky asset $S^0 \equiv 1$ (change of numéraire)
- 1 risky asset S : $dS_t = S_t [\mu dt + \sigma dW_t]$
- Contingent claim : $g(S_T)$, where $g : \mathbb{R}_+ \longrightarrow \mathbb{R}$ l.s.c. and bounded from below (not necessarily continuous)

Main problem Valuation of the option $g(S_T)$

1. INTRODUCTION, Continued

2. Superhedging : under the self-financing condition, *wealth process*

$$X_t^{x,\theta} := x + \int_0^t \theta_u (\mu du + \sigma dW_u)$$

$\theta \in \mathcal{A}$: set of *admissible strategies*

$$\int_0^T |\theta_u|^2 du < \infty \text{ and } X^{x,\theta} \text{ bounded from below}$$

• Super-replication problem

$$v_0 := \inf \left\{ x : X_T^{x,\theta} \geq g(S_T) \text{ a.s. for some } \theta \in \mathcal{A} \right\}$$

\implies Reduction : Change of measure \implies assume $\mu = 0$ wlog

1. INTRODUCTION, Continued

3. Explicit solution in complete market :

$$v_t = V(t, S_t) := \mathbb{E}[g(S_T)|S_t]$$

PDE characterization

$$-\mathcal{L}V := -\frac{\partial V}{\partial t} - \frac{1}{2} \sigma^2 s^2 \frac{\partial^2 V}{\partial s^2} = 0 \quad \text{and} \quad V(T, s) = g(s)$$

\implies *Differentiate w.r.t. σ :*

$$-\frac{\partial V_\sigma}{\partial t} - \frac{1}{2} \sigma^2 s^2 \frac{\partial^2 V_\sigma}{\partial s^2} = \sigma s^2 V_{ss} \quad \text{and} \quad V_\sigma(T, s) = 0$$

1. INTRODUCTION, Continued

4. Greeks

- $\Delta_t := \frac{\partial V}{\partial s}(t, S_t) : \text{Hedging portfolio}$
- $\Gamma_t := \frac{\partial^2 V}{\partial s^2}(t, S_t) : \text{variation of the hedging portfolio}$
- $\text{Vega}_t := \frac{\partial V}{\partial \sigma}(t, S_t) : \text{sensitivity to volatility}$
- *Classical connection between Γ and Vega*

$$\text{Vega}_t = \mathbb{E} \left[\int_t^T \sigma S_u^2 \Gamma_u du \middle| S_t \right]$$

2. SUPER-REPLICATION UNDER PORTFOLIO CONSTRAINTS : Formulation

$K = [\ell, u] \ni 0$ (K closed convex subset of $\mathbb{R}^d \ni 0$)

- *Set of admissible portfolios*

$$\mathcal{A}_K := \{\theta \in \mathcal{A} : \theta \text{ valued in } K\}$$

- *Super-replication problem*

$$V(t, s) := \inf \left\{ x : X_T^{x, \theta} \geq g(S_T^{t, s}) \text{ for some } \theta \in \mathcal{A}_K \right\}$$

2. PORTFOLIO CONSTRAINTS : Main result

Face-lifting : introduce Support function of K : $\delta(y) := \sup_{x \in K} x \cdot y$

Face-lifting operator : $\hat{g}(s) := \sup_{y \in \mathbb{R}^n} g(se^y) - \delta(y)$

1. **Theorem** <Broadie, Cvitanić and Soner 98> $V(t, s) = \mathbb{E}_{t,s} [\hat{g}(S_T)]$
i.e. The problem of hedging $g(S_T)$ under constraints is solved by the classical Black-Scholes hedging of $\hat{g}(S_T)$

2. **Local volatility model** $\sigma(t, s) \implies$ Free boundary problem

$$\min \left\{ -V_t - \frac{1}{2} \sigma(t, s)^2 s^2 V_{ss}, sV_s - \ell, u - sV_s \right\} = 0 \quad \text{and} \quad V(T, \cdot) = \hat{g}$$

2. PORTFOLIO CONSTRAINTS : Duality

<Cvitanic and Karatzas 93, Föllmer-Kramkov 95>

$$V(t, s) = \sup_{\nu \in \mathcal{D}} \mathbb{E}_{t,s}^{P^\nu} \left[e^{-\int_t^T \delta(\nu_u) du} g(S_T) \right]$$

where $\mathcal{D} = \{ \text{predictable bounded processes valued in } \tilde{K} \}$ and

$$P^\nu \sim P, \quad \left\{ S_t e^{-\int_0^t \delta(\nu_u) du} \right\} \text{ is } P^\nu \text{ supermartingale}$$

i.e. *penalization of the drift* of price processes

\implies Standard stochastic control problem...

3. HEDGING UNDER GAMMA CONSTRAINTS

Recall the Black-Scholes model, *optimal* wealth process $X_t^* := V(t, S_t)$

By Itô's lemma, twice

$$\begin{aligned} X_t^* &= X_0^* + \int_0^t \mathcal{L}V(u, S_u)du + \int_0^t \Delta_u^* dS_u \\ &= V(0, S_0) + \int_0^t \Delta_u^* dS_u \end{aligned}$$

and

$$\Delta_t^* = V_s(0, S_0) + \int_0^t \mathcal{L}V_s(u, S_u)du + \int_0^t \Gamma_u^* dS_u$$

3. GAMMA CONSTRAINTS : Motivation

Goal : Hedge under constraints on the gamma of the portfolio Γ_t

\implies Control on the portfolio re-balancement

$$\Delta_{t+dt} - \Delta_t = V_s(t + dt, S_{t+dt}) - V_s(t, S_t)$$

\implies Controlling the Vega risk

$$\text{Vega}_t = E \left[\int_t^T \sigma S_u^2 \Gamma_u du \middle| S_t \right]$$

- large investor problem
- transaction costs
- The digital option example

3. GAMMA CONSTRAINTS : Model formulation

- *Non-risky asset S^0 normalized to 1*

- *Risky asset S : $dS_t = S_t \sigma dW_t$*

- *European option $g(S_T)$,*

$$g : \mathbb{R}_+ \longrightarrow \mathbb{R} \text{ l.s.c. and } -C \leq g(s) \leq C(1 + s)$$

- *Wealth process $X_t = x + \int_0^t Y_u dS_u = x + \int_0^t Y_u \sigma S_u dW_u$*

- *Portfolio process $Y_t = y + \int_0^t \alpha_u du + \int_0^t \Gamma_u dS_u$*

3. GAMMA CONSTRAINTS : Problem formulation

- *Admissible portfolio* : $\nu = (y, \alpha, \Gamma) \in \mathcal{G}$ if

$y \in \mathbb{R}$, α , γ bounded predictable processes,

$$\text{and } -\underline{\Gamma} \leq \Gamma_u S_u^2 \leq \bar{\Gamma}$$

- *Super-replication problem*

$$V(t, s) := \inf \left\{ x : X_T^{t,x,\nu} \geq g(S_T^{t,s}) \text{ for some } \nu \in \mathcal{G} \right\}$$

where

$$X_T^{t,x,\nu} = x + \int_t^T Y_u^{t,\nu} dS_u \quad \text{and} \quad Y_u^{t,\nu} = y + \int_t^u \alpha_u du + \int_t^u \Gamma_u dS_u$$

3. GAMMA CONSTRAINTS : First intuitions

We formally expect that V solves the free boundary problem

$$F(V_t, s^2 V_{ss}) := \min \left\{ -V_t - \frac{1}{2} \sigma^2 s^2 V_{ss}, \bar{\Gamma} - s^2 V_{ss}, \underline{\Gamma} + s^2 V_{ss} \right\} = 0$$

- Correct if $\underline{\Gamma} = +\infty$ <Soner-Touzi 2000>
- Can not be true if $\underline{\Gamma} > +\infty$: F is not elliptic
- Example : $g(s) := s \wedge 1$, $\underline{\Gamma} = 0$, $\bar{\Gamma} = \infty$. Then $V = g$ (*is not convex!*)

\implies Hedging by *buy-and-hold* strategies

\implies if **jumps** are allowed in the Y process, then non-uniqueness of hedging strategy...

3. GAMMA CONSTRAINTS : Warnings (1)

Lemma For all predictable W -integrable cadlag process ϕ , and all $\varepsilon > 0$:

$$\sup_{0 \leq t \leq 1} \left| \int_0^t \phi_r dW_r - \int_0^t \phi_r^\varepsilon dW_r \right| \leq \varepsilon$$

→ for some predictable step process ϕ^ε <Levental-Skorohod AAP95>

→ for some absolutely continuous predictable process $\phi_t^\varepsilon = \phi_0^\varepsilon + \int_0^t \alpha_r dr$, $\int_0^1 |\alpha_r| dr < \infty$ a.s. <Bank-Baum 04>

3. GAMMA CONSTRAINTS : Warnings (2)

\implies Usual *control relaxation* in stochastic control problems *does not hold here* :

- Allow for arbitrary jumps in $Y \implies V = \text{BS price}$

- Allow for arbitrary absolutely continuous $\int_0^t \alpha_u du \implies V = \text{BS price}$

(with $\gamma = 0$ in both cases)

- $V > \text{BS price}$, in general, for *bounded α* and *bounded number of jumps*

3. GAMMA CONSTRAINTS : The dynamic programming PDE

Theorem 3 V is the unique viscosity solution of

$$(DPE) \quad \hat{F}(V_t, s^2 V_{ss}) = 0 \quad \text{and} \quad V(T-, \cdot) = \hat{g}$$

with $|V - \hat{g}|_\infty < \infty$, where $\hat{F}(p, A) := \sup_{\beta \geq 0} F(p, A + \beta)$ is the *elliptic envelope of F* , and

$$\hat{g}(s) := h^{\text{conc}}(s) - \bar{\Gamma} \ln s, \quad h(s) := g(s) + \bar{\Gamma} \ln s$$

- If $\bar{\Gamma} = +\infty \implies$ No Face-lifting !!
- For $\underline{\Gamma} = +\infty : \hat{F} = F$ (Agree with intuition)
- Example : $g(s) := s \wedge 1$, $\underline{\Gamma} = 0$, $\bar{\Gamma} = \infty$, we find $V = g$

Sketch of proof of the super-solution property

For simplicity, assume V smooth and

$$V(t, s) := \underline{\min} \left\{ x : X_T^{t,x,\nu} \geq g(S_T^{t,s}) \text{ for some } \nu \in \mathcal{G} \right\}$$

Then, with $\hat{x} := V(t, s) \implies X_T^{t,\hat{x},\hat{\nu}} \geq g(S_T^{t,s})$ for some $\hat{\nu} \in \mathcal{G}$

- *Geometric Dynamic programming* (trivial inequality) :

$$X_{\theta_h}^{t,\hat{x},\hat{\nu}} \geq V(\theta_h, S_{\theta_h}^{t,s})$$

- Apply *Itô's lemma* twice :

$$\begin{aligned} 0 &\leq V(t, s) - V(\theta_h, S_{\theta_h}^{t,s}) + \int_t^{\theta_h} Y_u^{t,\hat{y}} dS_u \\ &= - \int_t^{\theta_h} \mathcal{L}V(u, S_u^{t,s}) du + \int_t^{\theta_h} \left(c + \int_t^u a_v dv + \int_t^u b_v dS_v \right) dS_u \end{aligned}$$

where $c := y - V_s(t, s)$, $a_u := \alpha_u - \mathcal{L}V_s(u, S_u)$, $b_u := \gamma_u - V_{ss}(u, S_u)$

Sketch of proof of the super-solution property, continued

- Compare orders of the different terms

$$0 \leq - \int_t^{\theta_h} \mathcal{L}V(u, S_u^{t,s}) du + \int_t^{\theta_h} \left(c + \int_t^u a_v dv + \int_t^u b_v dS_v \right) dS_u$$

$\implies c = y - V_s(t, s) = 0$, and forget the term $\int \int dt dW_t$

- Analysis of the term $\int \int b_u dW_u dW_v$ requires fine results on the *local path behavior of double stochastic integrals*

\longrightarrow Intuition : if $b_u \equiv \beta$ constant, then

$$0 \leq - \int_t^{\theta_h} \mathcal{L}V(u, S_u^{t,s}) du + \frac{\beta}{2} \left((S_{\theta_h} - s)^2 - \int_t^{\theta_h} \sigma^2 S_u^2 du \right)$$

Divide by h and send h to zero :

$$\limsup \implies \beta \geq 0 \quad \text{and} \quad \liminf \implies 0 \leq -\mathcal{L}V(t, s) - \frac{1}{2} \beta \sigma^2 s^2$$

3. GAMMA CONSTRAINTS : Main result

Theorem *The function v has the stochastic representation*

$$V(t, s) = \sup_{\theta \in \mathcal{T}_t^T} \mathbb{E}_{t,s} \left[\hat{g}(S_\theta) - \frac{1}{2} \Gamma \sigma^2(T - \theta) \right]$$

where \mathcal{T}_t^T is the collection of all \mathbb{F} -stopping times with values in $[t, T]$.

\implies Upper bound on gamma \implies *Face-lifting*

\implies Lower bound on gamma \implies *American option/optimal stopping*

- For general local volatility models $\sigma(t, s)$:

Treatment of both bounds does not separate, in general

3. GAMMA CONSTRAINTS : Hedging strategy

- Pass from g to \hat{g} , and *forget about upper bound $\bar{\Gamma}$*
- For simplicity, consider the case $\underline{\Gamma} = 0$
- *smoothfit holds, i.e. V is C^1*
- *Buy-and-hold \equiv "keep going along the tangent"*

\implies Hedge by **succession** of

Standard *Black-Scholes* and *buy-and-hold* strategy

3. GAMMA CONSTRAINTS : Duality

$$V(t, s) = \sup_{\mathcal{X} \times \mathcal{Y}} \mathbb{E}_{t,s} \left[g \left(\hat{S}_T^{\mathcal{X}, \mathcal{Y}} \right) - \frac{1}{2} \sigma^2 \int_t^T \left(\underline{\Gamma} x_r + \overline{\Gamma} y_r \right) dr \right]$$

where

$$d\hat{S}_r^{\mathcal{X}, \mathcal{Y}} = \hat{S}_r^{\mathcal{X}, \mathcal{Y}} \sigma \sqrt{1 - x_r + y_r} dW_r$$

and

$$\mathcal{X} = \{ \text{predictable processes with values in } [0, 1] \}$$

$$\mathcal{Y} = \{ \text{predictable processes with values in } \mathbb{R}_+ \}$$

\implies Dual problem by *penalizing the volatility!*

4. BACKWARD SDE's AND SEMI-LINEAR PDE's

Consider the Backward Stochastic Differential Equation :

$$Y_t = g(X_T) + \int_t^T f(X_r, Y_r, Z_r) dr - \int_t^T Z_r \cdot \sigma(X_r) dW_r$$

where X_t is defined by the (forward) SDE

$$dX_t = \sigma(X_t) dW_t$$

Then $Y_t = V(t, X_t)$, and V satisfies the *semi-linear PDE*

$$-\frac{\partial V}{\partial t} - \frac{1}{2} \text{Tr} \left[\sigma \sigma^T(x) D^2 V(t, x) \right] - f(x, V(t, x), DV(t, x)) = 0$$

(Easy application of Itô's lemma)

4. BSDE's AND SEMI-LINEAR PDE's :

Stochastic representation

- Any semi-linear PDE has a representation in terms of a BSDE
- Consider a stochastic control problem with *no control* on volatility.
Then, the associated HJB equation is *semi-linear* :

$$-V_t(t, x) - \frac{1}{2} \text{Tr} \left[\sigma \sigma^*(x) D^2 V(t, x) \right] - \sup_{u \in U} b(x, u) \cdot DV(t, x) = 0$$

So any stochastic control problem with *no control* on volatility has a representation in terms of a Backward SDE

4. BSDE's AND SEMI-LINEAR PDE's : Numerical issue

Numerical solution of a semi-linear PDE by *simulating* the associated backward sde by means of Monte Carlo methods

Start from Euler discretization : $Y_{t_n}^\pi = g(X_{t_n}^\pi)$ is given, and

$$Y_{t_{i+1}}^\pi - Y_{t_i}^\pi = -f(X_{t_i}^\pi, Y_{t_i}^\pi, Z_{t_i}^\pi) \Delta t_i + Z_{t_i}^\pi \cdot \sigma(X_{t_i}^\pi) \Delta W_{t_{i+1}}$$

\implies Discrete-time approximation :

$$Y_{t_n}^\pi = g(X_{t_n}^\pi)$$

4. BSDE's AND SEMI-LINEAR PDE's : Numerical issue

Numerical solution of a semi-linear PDE by *simulating* the associated backward sde by means of Monte Carlo methods

Start from Euler discretization : $Y_{t_n}^\pi = g(X_{t_n}^\pi)$ is given, and

$$\mathbb{E}_i^\pi [Y_{t_{i+1}}^\pi - Y_{t_i}^\pi = -f(X_{t_i}^\pi, Y_{t_i}^\pi, Z_{t_i}^\pi) \Delta t_i + Z_{t_i}^\pi \cdot \sigma(X_{t_i}^\pi) \Delta W_{t_{i+1}}]$$

\implies Discrete-time approximation :

$$Y_{t_n}^\pi = g(X_{t_n}^\pi)$$

$$Y_{t_i}^\pi = \mathbb{E}_i^\pi [Y_{t_{i+1}}^\pi] + f(X_{t_i}^\pi, Y_{t_i}^\pi, Z_{t_i}^\pi) \Delta t_i \quad 0 \leq i \leq n-1 ,$$

4. BSDE's AND SEMI-LINEAR PDE's : Numerical issue

Numerical solution of a semi-linear PDE by *simulating* the associated backward sde by means of Monte Carlo methods

Start from Euler discretization : $Y_{t_n}^\pi = g(X_{t_n}^\pi)$ is given, and

$$\mathbb{E}_i^\pi [\Delta W_{t_{i+1}} \quad Y_{t_{i+1}}^\pi - Y_{t_i}^\pi] = -f(X_{t_i}^\pi, Y_{t_i}^\pi, Z_{t_i}^\pi) \Delta t_i + Z_{t_i}^\pi \cdot \sigma(X_{t_i}^\pi) \Delta W_{t_{i+1}}$$

\implies Discrete-time approximation :

$$Y_{t_n}^\pi = g(X_{t_n}^\pi)$$

$$Y_{t_i}^\pi = \mathbb{E}_i^\pi [Y_{t_{i+1}}^\pi] + f(X_{t_i}^\pi, Y_{t_i}^\pi, Z_{t_i}^\pi) \Delta t_i \quad 0 \leq i \leq n-1$$

$$Z_{t_i}^\pi = \frac{1}{\sigma(X_{t_i}^\pi) \Delta t_i} \mathbb{E}_i^\pi [Y_{t_{i+1}}^\pi \Delta W_{t_{i+1}}]$$

4. BSDE's AND SEMI-LINEAR PDE's : Numerical issue

Numerical solution of a semi-linear PDE by simulating the associated backward sde by means of Monte Carlo methods

Start from Euler discretization : $Y_{t_n}^\pi = g(X_{t_n}^\pi)$ is given, and

$$\mathbb{E}_i^\pi[\Delta W_{t_{i+1}} \quad Y_{t_{i+1}}^\pi - Y_{t_i}^\pi] = -f(X_{t_i}^\pi, Y_{t_i}^\pi, Z_{t_i}^\pi) \Delta t_i + Z_{t_i}^\pi \cdot \sigma(X_{t_i}^\pi) \Delta W_{t_{i+1}}$$

\implies Discrete-time approximation :

$$Y_{t_n}^\pi = g(X_{t_n}^\pi)$$

$$Y_{t_i}^\pi = \mathbb{E}_i^\pi [Y_{t_{i+1}}^\pi] + f(X_{t_i}^\pi, Y_{t_i}^\pi, Z_{t_i}^\pi) \Delta t_i \quad 0 \leq i \leq n - 1$$

$$Z_{t_i}^\pi = \frac{1}{\sigma(X_{t_i}^\pi) \Delta t_i} \mathbb{E}_i^\pi [Y_{t_{i+1}}^\pi \Delta W_{t_i}]$$

\equiv Pricing of Bermudan options [Bally-Pagès 01, Bouchard-Touzi 04]

5. SECOND ORDER BSDE's and FULLY NONLINEAR PDE's

Let $f(x, y, z, \gamma) + \frac{1}{2} \text{Tr}[\sigma \sigma^T(x) \gamma]$ non-decreasing in γ

Consider the 2nd order BSDE :

$$dX_t = \sigma(X_t) dW_t$$

$$(2\text{BSDE}) \quad dY_t = -f(X_t, Y_t, Z_t, \Gamma_t) dt + Z_t \cdot \sigma(X_t) dW_t, \quad Y_T = g(X_T)$$

$$dZ_t = \alpha_t dt + \Gamma_t dW_t$$

A solution of (2BSDE) is

a process (Y, Z, α, Γ) with values in $\mathbb{R} \times \mathbb{R}^n \times \mathbb{R}^n \times \mathcal{S}^n$

Question : existence ? uniqueness ?

5. 2nd ORDER BSDE's : Main result

$$\text{Set } \mathcal{L}v(t, x) := \frac{\partial v}{\partial t}(t, x) + \frac{1}{2} \text{Tr} \left[\sigma \sigma^T(x) D^2 v(t, x) \right]$$

Theorem Assume that there is a *unique smooth* solution v of the *fully-nonlinear PDE*

$$-\mathcal{L}v(t, x) - f \left(x, v(t, x), Dv(t, x), D^2v(t, x) \right) = 0, \quad v(T, x) = g(x).$$

Then

$$Y_t := v(t, X_t), \quad Z_t := Dv(t, X_t), \quad \alpha_t := \mathcal{L}Dv(t, X_t), \quad \Gamma_t := D^2v(t, X_t)$$

is the unique solution of (2BSDE)

<Cheridito, Soner, Touzi and Victoir 05>

5. 2nd ORDER BSDE's : Numerical implication

- Any fully nonlinear PDE has a representation in terms of a 2BSDE
- In particular, any stochastic control problem has a representation in terms of a Backward SDE (the associated HJB equation is a fully nonlinear PDE)

⇒ Numerical solution by Monte Carlo methods (future project)

$$Y_{t_n}^\pi = g(X_{t_n}^\pi) ,$$

$$Y_{t_{i-1}}^\pi = \mathbb{E}_{i-1}^\pi [Y_{t_i}^\pi] + f(X_{t_{i-1}}^\pi, Y_{t_{i-1}}^\pi, Z_{t_{i-1}}^\pi, \Gamma_{t_{i-1}}^\pi) \Delta t_i , \quad 1 \leq i \leq n ,$$

$$Z_{t_{i-1}}^\pi = \frac{1}{\sigma(X_{t_{i-1}}^\pi) \Delta t_i} \mathbb{E}_{i-1}^\pi [Y_{t_i}^\pi \Delta W_{t_i}]$$

$$\Gamma_{t_{i-1}}^\pi = \frac{1}{\sigma(X_{t_{i-1}}^\pi) \Delta t_i} \mathbb{E}_{i-1}^\pi [Z_{t_i}^\pi \Delta W_{t_i}]$$

Sketch of the proof :

Existence of solution for (2BSDE)

1. (Easy part) Let v be the unique solution of

$$-\mathcal{L}v(t, x) - f(x, v(t, x), Dv(t, x), D^2v(t, x)) = 0, \quad v(T, x) = g(x).$$

Then

$$Y_t = v(t, X_t), \quad Z_t = Dv(t, X_t)$$

$$z = Dv(t, x), \quad \alpha_t = \mathcal{L}Dv(t, X_t), \quad \Gamma_t = D^2v(t, X_t)$$

is a solution of (2BSDE)

Sketch of the proof :

Uniqueness of solution for (2BSDE)

2. Given a control $\nu := (z, \alpha, \Gamma)$, define the controlled process

$$dY_t^\nu = -f(X_t, Y_t^\nu, Z_t, \Gamma_t) dt + Z_t \cdot \sigma(X_t) dW_t$$

$$dZ_t = \alpha_t dt + \Gamma_t \cdot \sigma(X_t) dW_t$$

together with the "super-hedging" problems (Seller / Buyer)

$$V(t, x) := \inf \{y : Y_T^\nu \geq g(X_T) \text{ a.s. for some } \nu \in \mathcal{G}\}$$

$$U(t, x) := -\inf \{y : Y_T^\nu \geq -g(X_T) \text{ a.s. for some } \nu \in \mathcal{G}\}$$

- Any solution of (2BSDE) satisfies $V(t, X_t) \leq Y_t \leq U(t, X_t)$
- V and U are both solution of the fully nonlinear PDE $\implies U = V$