Regularity of Constrained BSDEs 2nd Young Researchers Meeting on BSDEs, Numerics and Finance

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Joint work with Bruno Bouchard and Romuald Elie

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Introduction

Given a forward process

$$
X^{t,x} = x + \int_t^{\cdot} b_s \left(X_s^{t,x} \right) ds + \int_t^{\cdot} \sigma_s \left(X_s^{t,x} \right) dW_s.
$$

We are interested in the minimal solution of the constrained BSDE

$$
\mathcal{Y}^{t,x} \ge g\left(X_T^{t,x}\right) + \int_{\cdot}^T f_s\left(X_s^{t,x},\mathcal{Y}_s^{t,x},\mathcal{Z}_s^{t,x}\right) ds - \int_{\cdot}^T \mathcal{Z}_s^{t,x} dW_s
$$

with

$$
\mathcal{Z}^{t,x} \sigma^{-1}\left(X^{t,x}\right) \in K \quad dt \otimes d\mathbb{P}\text{-a.e.}
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with K convex set of support function $\delta(u):=\sup\{k^\top u\;;\;k\in K\}.$

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with K convex set of support function $\delta(u):=\sup\{k^\top u\;;\;k\in K\}.$

More precisely, we are interested in the regularity of

$$
(t,x)\in[0,T]\times\mathbb{R}^d\longmapsto\mathcal{Y}^{t,x}_t.
$$

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- ▶ Numerical Schemes;
- \blacktriangleright A priori regularity for PPDEs.

Super–Replication in Differential Games (1)

\triangleright We want to extend

$$
v(t,x,p) := \inf \left\{ y:\ \exists \ \nu \text{ s.t. } \mathbb{E}\left[\Psi\left(X^{t,x,\nu,\alpha}_T, Y^{t,x,y,\nu,\alpha}_T\right)\right] \ge p \ \forall \ \alpha \right\}
$$

to

$$
\inf \left\{ y:\ \exists\ " \nu \in K" \text{ s.t. } \mathbb{E}\left[\Psi\left(X^{t,x,\nu,\alpha}_T, Y^{t,x,y,\nu,\alpha}_T\right)\right] \geq p \ \forall \ \alpha\right\}.
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to

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$$

- \triangleright Difficulty to establish DPP;
- \triangleright In Bouchard, M. & Nutz, done by covering \oplus continuity;
- \blacktriangleright This does not allow to consider the Super-Replication :

$$
v(t,x):=\inf\left\{y:\ \exists\ " \nu\in K\text{'' s.t.}\ Y^{t,x,y,\nu,\alpha}_T\ge g\left(X^{t,x,\nu,\alpha}_T\right)\ \forall\ \alpha\right\}
$$

where $\Psi(x, y) := \mathbf{1}_{\{y \geq g(x)\}}$ and $p = 1$.

Super–Replication in Differential Games (2)

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The point [\(1\)](#page-0-0) need to have continuity for an object of this type

$$
(t,x)\longmapsto \sup_{\alpha} \mathcal{Y}^{t,x,\alpha}_t.
$$

Regularity for Solution of PPDE

F Singular Control Problem :

$$
v^{\varepsilon}(t,\omega,x):=\sup_{L}\mathbb{E}\left[U\left(X^{t,\omega,x,L,\varepsilon}_T\right)\right]
$$

$$
X^{t,\omega,x,L,\varepsilon} = x + \int_t^{\cdot} b_s^{t,\omega} (X_s) \, ds + \int_t^{\cdot} \sigma_s^{t,\omega} (X_s) \, dW_s + \int_t^{\cdot} f(\varepsilon) dL_s;
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$$

- \blacktriangleright Family of non-dominated measure indexed by L which is not-bounded ;
- \triangleright BUT "PPDE of quasi-variational" type;
- ► No-Trade Region : the optimal control $L \equiv 0$;
- ► Need for regularity of $(t, \omega, x) \longmapsto v^{\varepsilon}(t, \omega, x)$;
- ► Done by showing that $\mathcal{Y}^{t,\omega,x,\varepsilon} = v^{\varepsilon}(t,\omega,x)$.

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Dual Formulation $(\zeta := (t, x))$

Equivalent families of Measure

For each predictable bounded process ν we introduce

$$
\frac{d\mathbb{P}^{t,x,\nu}}{d\mathbb{P}} = e^{-\frac{1}{2}\int_{\tau}^{T}|\sigma^{-1}(X_s^{t,x})\nu_s|^2ds + \int_{\tau}^{T}\sigma^{-1}(X_s^{t,x})\nu_s dW_s}
$$

$$
W^{t,x,\nu} := W - \int_{\tau}^{\tau\vee\cdot} \sigma^{-1}(X_s^{t,x})\nu_s ds
$$

so that

$$
X^{t,x} = x + \int_t \left[b\left(X_s^{t,x}\right) + \nu_s \right] ds + \int_t^\cdot \sigma\left(X_s^{t,x}\right) dW_s^{t,x,\nu}.
$$

Dual Formulation The family of standard BSDEs

Let $(\bar{Y}^{t,x,\nu},\bar{Z}^{t,x,\nu})$ be the unique $\mathbf{S}^2(\mathbb{P}^{t,x,\nu})\times\mathbf{H}^2(\mathbb{P}^{t,x,\nu})$ -solution of

$$
\bar{Y}^{\zeta,\nu}=g\left(X_T^{\zeta}\right)+\int_{\cdot}^{T}\left[f\left(X_s^{\zeta},\bar{Y}_s^{\zeta,\nu},\bar{Z}_s^{\zeta,\nu}\right)-\delta(\nu_s)\right]ds-\int_{\cdot}^{T}\bar{Z}_s^{\zeta,\nu}dW_s^{\zeta,\nu}.
$$

Then

$$
\mathcal{Y}_{\theta}^{t,x} := \operatorname*{ess\,sup}_{\nu \in \mathcal{U}} \bar{Y}_{\theta}^{t,x,\nu}
$$
\n
$$
= \operatorname*{ess\,sup}_{\nu \in \mathcal{U}} \mathbb{E}_{\theta}^{\mathbb{P}^{t,x,\nu}} \left[g\left(X_T^{t,x}\right) + \int_{\theta}^T \left(f_s\left(X_s^{t,x}, \bar{Y}_s^{t,x,\nu}, \bar{Z}_s^{t,x,\nu}\right) - \delta(\nu_s)\right) ds \right]
$$

is the minimal solution of the previous constrained BSDE. (see Cvitanic, Karatzas and Soner for the case of a convex driver)

Dual Formulation

 Y is the minimal solution of the constrained BSDE

We have

$$
\bar{Y}^{\zeta,\nu} = g\left(X_T^{\zeta}\right) + \int_{\cdot}^{T} \left[f\left(X_s^{\zeta}, \bar{Y}_s^{\zeta,\nu}, \bar{Z}_s^{\zeta,\nu}\right) - \delta(\nu_s) + \bar{Z}_s^{\zeta,\nu}\sigma^{-1}(X_s^{t,x})\nu_s \right] ds
$$

$$
- \int_{\cdot}^{T} \bar{Z}_s^{\zeta,\nu} dW_s
$$

and the following characterization of K :

$$
z \in K \quad \Longrightarrow \quad \min\{\delta(u) - z \cdot u, u \in \mathbb{R}^d, |u| = 1\} \ge 0. \tag{3.1}
$$

1. The minimality comes from standard comparison and by (3.1) :

$$
f(X, y, z) + z\sigma^{-1}(X)\nu - \delta(\nu) \le f(X, y, z) \quad \text{whenever} \quad z \in K.
$$

2. V solution of the constrained BSDE comes from non-linear Doob-Meyer decomposition, the fact that ν lives in a cone, δ positively-homogeneous and [\(3.1\)](#page-0-0).

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Main difficulties when considering $\left|\mathcal{Y}^{t,x}_t-\mathcal{Y}^{t',x'}_{t'}\right|$ $\begin{bmatrix} t',x'\ t' \end{bmatrix}$ $\overline{}$ $\overline{}$

$$
\mathcal{Y}_{t}^{t,x} = \operatorname*{ess\,sup}_{\nu \in \mathcal{U}} \mathbb{E}_{t}^{\mathbb{P}^{t,x,\nu}} \left[g\left(X_{T}^{t,x}\right) + \int_{t}^{T} \left(f_s\left(X_s^{t,x}, \bar{Y}_s^{t,x,\nu}, \bar{Z}_s^{t,x,\nu}\right) - \delta(\nu_s)\right) ds\right]
$$

.

 \triangleright Different probabilities, conditional expectations (Strong Formulation);

Each ν is bounded, but all ν 's are not uniformly bounded (face-lift).

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The deterministic case

We have

$$
\underset{\nu \in \mathcal{U}}{\operatorname{ess\,sup}} \,\bar{Y}_{\theta}^{\zeta,\nu} = \underset{\nu \in \mathcal{U}}{\operatorname{ess\,sup}} \,\hat{Y}_{\theta}^{\zeta,\nu} \tag{5.1}
$$

with

$$
\bar{Y}^{\zeta,\nu} = g\left(X_T^{\zeta}\right) + \int_{\cdot}^{T} \left[f\left(X_s^{\zeta}, \bar{Y}_s^{\zeta,\nu}, \bar{Z}_s^{\zeta,\nu}\right) - \delta(\nu_s) \right] ds - \int_{\cdot}^{T} \bar{Z}_s^{\zeta,\nu} dW_s^{\zeta,\nu},
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\n
$$
\hat{Y}^{\zeta,\nu} = g\left(\hat{X}_T^{\zeta,\nu}\right) + \int_{\cdot}^{T} \left[f_s\left(\hat{X}_s^{\zeta,\nu}, \hat{Y}_s^{\zeta,\nu}, \hat{Z}_s^{\zeta,\nu}\right) - \delta(\nu_s) \right] ds - \int_{\cdot}^{T} \hat{Z}_s^{\zeta,\nu} dW_s.
$$

and

$$
X^{\zeta} = x + \int_{t}^{x} \left[b\left(X_{s}^{\zeta}\right) + \nu_{s} \right] ds + \int_{t}^{x} \sigma\left(X_{s}^{\zeta}\right) dW_{s}^{\zeta, \nu},
$$

$$
\hat{X}^{\zeta, \nu} = x + \int_{t}^{x} \left[b\left(\hat{X}_{s}^{\zeta, \nu}\right) + \nu_{s} \right] ds + \int_{t}^{x} \sigma\left(\hat{X}_{s}^{\zeta, \nu}\right) dW_{s}.
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This is done by :

1. The supremums in (5.1) may be taken among piecewise constant ν ;

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This is done by :

- 1. The supremums in (5.1) may be taken among piecewise constant ν ;
- 2. Then for each $\nu \in \mathcal{U}_{nc}$, find $\bar{\nu} \in \mathcal{U}_{nc}$ such that

$$
\bar{Y}_{\tau}^{\zeta,\nu} = \hat{Y}_{\tau}^{\zeta,\bar{\nu}}.
$$

With an Adverse Control

We have

ess sup
$$
\overline{Y}_{\theta}^{\zeta,\nu,\alpha}
$$
 = ess sup $\hat{Y}_{\theta}^{\zeta,\nu,\alpha}$ (5.2)
\n $\mu,\alpha\in\mathcal{U}\times\mathcal{A}$

With an Adverse Control

We have

$$
\underset{(\nu,\alpha)\in\mathcal{U}\times\mathcal{A}}{\text{ess sup }} \bar{Y}_{\theta}^{\zeta,\nu,\alpha} = \underset{(\nu,\alpha)\in\mathcal{U}\times\mathcal{A}}{\text{ess sup }} \hat{Y}_{\theta}^{\zeta,\nu,\alpha} \tag{5.2}
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$$

When the coefficients depend on ω

We have

$$
\underset{\nu \in \mathcal{U}}{\operatorname{ess\,sup}} \, \bar{Y}_{\theta}^{\zeta,\nu} = \underset{\nu \in \mathcal{U}}{\operatorname{ess\,sup}} \, \hat{Y}_{\theta}^{\zeta,\nu} \tag{5.3}
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In this case, even the definition of the strong formulation is not that clear

1. We added a delay on the dependence in ω ;

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- 1. We added a delay on the dependence in ω ;
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Definition of the Face–Lift

$$
\hat{g}(x) := \sup_{y} \{ g(x+y) - \delta(y) \}.
$$

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$$

1. One wants to hedge a digicall of strike K ;

 $(y) + y - \delta(y)$.

$$
\hat{g}(x) := \sup_{y} \{ g(x
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- 1. One wants to hedge a digicall of strike K ;
- 2. Under the delta constraint that $\Delta \in [0,1]$.

 $\hat{g}(x):=\sup$ \overline{y} ${g(x + y) - \delta(y)}.$

1. One wants to hedge a digicall of strike K ;

2. Under the delta constraint that $\Delta \in [0,1]$. In this case :

$$
\delta: u \in \mathbb{R} \longmapsto \begin{cases} u & \text{if } u \geq 0; \\ 0 & \text{if } u \leq 0. \end{cases}
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$$

And then :

$$
\hat{g}: x \in \mathbb{R}_{+} \longmapsto \begin{cases} 0 & \text{if } x \in [0, K-1]; \\ x + (1-K) & \text{if } x \in [K-1, K]; \\ 1 & \text{if } x \geq K. \end{cases}
$$

Let

Super-Replication price of digiCall with $\Delta \in [0,1]$:

$$
\operatorname*{ess\,sup}_{\nu}\mathbb{E}^{\mathbb{P}^{\zeta,\nu}}\left[g\left(X_T^{\zeta}\right)-\int_\tau^T \delta(\nu_s)ds\right].
$$

is the Super-Replication price of a callSpread with no constraints :

$$
\operatorname*{ess\,sup}_{\nu}\mathbb{E}^{\mathbb{P}^{\zeta,\nu}}\left[g\left(X_T^{\zeta}\right)-\int_\tau^T \delta(\nu_s)ds\right]=\mathbb{E}^{\mathbb{Q}}\left[\hat{g}\left(X_T^{\zeta}\right)\right].
$$

In the constrained BSDE case

We have

$$
\mathcal{Y}^{\zeta}_{\theta} = \operatorname*{ess\,sup}_{\nu \in \mathcal{U}} \mathbb{E}\left[\hat{g}\left(\hat{X}^{\zeta,\nu}_T\right) + \int_{\cdot}^T \left[f\left(\hat{X}^{\zeta,\nu}_s, \tilde{Y}^{\zeta,\nu}_s, \tilde{Z}^{\zeta,\nu}_s\right) - \delta(\nu_s)\right] ds\right]
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$$

In fact, one has the face-lift

$$
\mathcal{Y}^{t,x}_t \ge \underset{u \in L_{\infty}}{\mathrm{ess \, sup}} \left\{ \mathcal{Y}^{t,x+u}_t - \delta(u) \right\}.
$$

In the constrained BSDE case

We have

$$
\mathcal{Y}_{\theta}^{\zeta} = \underset{\nu \in \mathcal{U}}{\mathrm{ess}\sup} \, \mathbb{E}\left[\hat{g}\left(\hat{X}_{T}^{\zeta,\nu}\right) + \int_{\cdot}^{T}\left[f\left(\hat{X}_{s}^{\zeta,\nu}, \tilde{Y}_{s}^{\zeta,\nu}, \tilde{Z}_{s}^{\zeta,\nu}\right) - \delta(\nu_{s})\right] ds\right]
$$

Said differently

$$
v(t, x) = \hat{v}(t, x) := \sup_{y} \{ v(t, x + y) - \delta(y) \}.
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\hat{g}(x) := \sup_{y} \{ \hat{g}(x + y) - \delta(y) \} = \hat{g}(x).
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The $\delta(\nu)$ will kill the ν in $\hat X_T^{\zeta,\nu}.$

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The Stability Result

Finally we have

$$
\left|\mathcal{Y}^{t,x}_t - \mathbb{E}_t\left[\mathcal{Y}^{t',x'}_{t'}\right]\right| \leq C\left(|t'-t|^{1/2} + |x-x'|\right)
$$

and we split this stability into

- 1. Stability in space ;
- 2. Stability in time.

Stability in Space

► Easy with standard estimates when \hat{g} is Lipschitz–continuous :

$$
\left|\mathcal{Y}^{t,x}_t-\mathcal{Y}^{t,x'}_t\right| \leq \underset{\nu\in\mathcal{U}}{\mathrm{ess}\sup}\left|\bar{Y}^{t,x,\nu}_t-\bar{Y}^{t,x',\nu}_t\right|.
$$

 \triangleright We split in 2 inequalities

$$
\cdots \leq \mathcal{Y}^{t,x}_t - \mathbb{E}_t \left[\mathcal{Y}^{t',x'}_{t'} \right] \leq \cdots
$$

and use the DPP

$$
\mathcal{Y}^{t,x}_t = \operatorname*{ess\,sup}_{\nu \in \mathcal{U}} \mathcal{E}^{t,x,\nu}_{t,\theta} \left[\mathcal{Y}^{t,x}_\theta \right].
$$

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$$
-C\left(\left|t'-t\right|^{1/2}+\left|x-x'\right|\right)\leq \mathcal{Y}_t^{t,x}-\mathbb{E}_t\left[\mathcal{Y}_{t'}^{t',x'}\right]
$$

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\mathcal{Y}^{\theta,\bar{X}^{t,x}_{\theta}} - \int_t^{\theta} \delta(\nu_s ds) \leq \mathcal{Y}^{\theta,\bar{X}^{t,x}_{\theta}} - \delta\left(\int_t^{\theta} \nu_s ds\right) \leq \mathcal{Y}^{\theta,\bar{X}^{t,x}_{\theta} - \int_t^{\theta} \nu_s ds}
$$

since $\delta(\int_t^\theta \nu_s ds) \leq \int_t^\theta \delta(\nu_s ds)$ and $\int_t^\theta \nu_s ds \in \mathcal{U}$.

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$$

 \blacktriangleright And then

$$
\mathcal{Y}^{t,x} \mathbf{1}_{[0,T)} + \hat{g}(X^{t,x}_T)\mathbf{1}_{\{T\}}.
$$