

On Some Discontinuous Control Problems

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¹(joint work with Oana-Silvia Serea (CMAP))

$$\begin{cases} dX_s^{t,x,u} = b(s, X_s^{t,x,u}, u_s) ds \{ + \sigma(s, X_s^{t,x,u}, u_s) dW_s \}, & t \leq s \leq T, \\ X_t^{t,x,u} = x \in \mathbb{R}^N, \end{cases}$$

h semicontinuous,

$$V(t, x) = \inf \mathbb{E} [h(X_T^{t,x,u})],$$

Plan

- Deterministic framework
- Stochastic framework
- References

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- $$\begin{cases} dx_t^{t_0, x_0, u} = b(t, x_t^{t_0, x_0, u}, u_t) dt, & t_0 \leq t \leq T, \\ x_{t_0}^{t_0, x_0, u} = x_0 \in \mathbb{R}^N, \end{cases} \quad (1)$$

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- $(0, 0) \in cl(R(T, t_0)(0, 0))$ and $(0, 0) \notin R(T, t_0)(0, 0) \implies$

$$\inf_{u \in U} h\left(x_T^{t_0, 0, 0, u(\cdot)}, y_T^{t_0, 0, 0, u(\cdot)}\right) = 1 \neq V(t_0, 0, 0).$$



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$$\begin{cases} \partial_t V(t, x) + \min_{u \in U} \langle \partial_x V(t, x), f(t, x, u) \rangle = 0, \\ \text{if } t \in (0, T), x \in \mathbb{R}^N, \end{cases} \quad (\text{HJ Mayer})$$

Main Result

Theorem

- (a) h l.s.c., V is the smallest l.s.c. supersolution of (HJ Mayer) s.t. $V(T, \cdot) \geq h(\cdot)$.

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- (b) h u.s.c., V is the largest u.s.c. subsolution of (HJ Mayer) s.t. $V(T, \cdot) \leq h(\cdot)$.
- (c) h is bounded,

$$V = \inf \left\{ \begin{array}{l} \varphi : \varphi \text{ l.s.c. subsolution of (HJ Mayer) s.t.} \\ \varphi(T, \cdot) \geq h(\cdot) \end{array} \right\} \text{ and}$$

$$V = \sup \left\{ \begin{array}{l} \varphi : \varphi \text{ u.s.c. subsolution of (HJ Mayer) s.t.} \\ \varphi(T, \cdot) \leq h(\cdot) \end{array} \right\}.$$

Idea of the proof of (a)

Lemma

If φ is a l.s.c. supersolution of (HJ Mayer), s.t. $\varphi(T, \cdot) \geq h(\cdot)$, then

$$\varphi(t_0, x_0) \geq \inf \{ \varphi(T, x) : x \in cl(R(T, t_0) x_0) \},$$

$$\forall (t_0, x_0) \in (0, T) \times \mathbb{R}^N.$$

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- $h_n(x) = \inf_{y \in \mathbb{R}^N} (h(y) + n|y - x|)$,
- $V^n(t_0, x_0) = \inf_{u \in \mathcal{U}} h_n(x_T^{t_0, x_0, u})$, $W = \sup_n V^n$

Idea of the proof of (b)

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$$\varphi(t_0, x_0) \leq \varphi(T, x),$$

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- sup-convolution

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- Define $h_\varepsilon : \mathbb{R}^N \rightarrow \mathbb{R}$ l.s.c.

$$h_\varepsilon(x) = \begin{cases} h(x_\varepsilon), & \text{if } x = x_\varepsilon, \\ \sup_x h(x), & \text{otherwise.} \end{cases}$$

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- Value function

$$V_\varepsilon(t, x) = \inf \{h_\varepsilon(y) : y \in cl(R(T, t)x)\},$$

satisfies: $V_\varepsilon(t_0, x_0) = h(x_\varepsilon) \leq V(t_0, x_0) + \varepsilon$

Idea of the proof of (c) 2

- Define $g : \mathbb{R}^N \rightarrow \mathbb{R}$ u.s.c.

$$g(x) = \begin{cases} V(t_0, x_0), & \text{if } x \in cl(R(T, t_0) x_0), \\ \inf_{y \in \mathbb{R}^N} h(y), & \text{otherwise.} \end{cases}$$

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- Consider V_g

$$V_g(t, x) = \inf \{g(y) : y \in cl(R(T, t)x)\},$$

- $V_g(T, \cdot) \leq g(\cdot) \leq h(\cdot)$ and
 $V_g(t_0, x_0) = V(t_0, x_0)$

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Main assumptions

- $b : \mathbb{R} \times \mathbb{R}^N \times U \longrightarrow \mathbb{R}^N, \sigma : \mathbb{R} \times \mathbb{R}^N \times U \longrightarrow \mathbb{R}^{N \times d}$

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- (i) b, σ bounded, uniformly continuous
- (ii) $\exists c > 0$ s.t.
 $|b(t, x, u) - b(t, y, u)| + |\sigma(t, x, u) - \sigma(t, y, u)| \leq c|x - y|$
 and
 $|b(t, x, u) - b(s, x, u)| + |\sigma(t, x, u) - \sigma(s, x, u)| \leq$
 $c|t - s|^{\frac{\delta_0}{2}},$
 $\forall (t, s, x, y, u) \in [0, T]^2 \times \mathbb{R}^{2N} \times U.$

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$$\begin{cases} -\partial_t V_h(t, x) + H(x, DV_h(t, x), D^2 V_h(t, x)) = 0, \\ \text{for all } (t, x) \in (0, T) \times \mathbb{R}^N, & \text{(HJB)} \\ V_h(T, \cdot) = h(\cdot) \text{ on } \mathbb{R}^N, \end{cases}$$
- $H(t, x, p, A) = \sup_{u \in \mathcal{U}} \left\{ -\frac{1}{2} \text{Tr}(\sigma \sigma^*(t, x, u) A) - \langle b(t, x, u), p \rangle \right\},$

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- $(t, x) \in [0, T) \times \mathbb{R}^N$, $u \in \mathcal{U}$,
- $\gamma_{t,x,u}(A \times B \times C \times D) = \frac{1}{T-t} \mathbb{E} \left[\int_t^T \mathbf{1}_{A \times B \times C}((s, X_s^{t,x,u}, u_s)) ds \right] \mathbb{P}(X_T^{t,x,u} \in D)$,

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- $\int_{[t,T] \times \mathbb{R}^N \times U \times \mathbb{R}^N} (|y|^2 + |z|^2) \gamma_{t,x,u}(ds, dy, dv, dz) \leq C_0 (|x|^2 + 1)$.

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- $\gamma_{t,x,u} \in \mathcal{P}([t, T] \times \mathbb{R}^N \times U \times \mathbb{R}^N) : \forall \phi \in C_b^{1,2}([0, T] \times \mathbb{R}^N)$,

$$\int_{[t,T] \times \mathbb{R}^N \times U \times \mathbb{R}^N} \left[\begin{array}{l} (T-t) \mathcal{L}^v \phi(s, y) \\ + \phi(t, x) - \phi(T, z) \end{array} \right] \gamma(ds, dy, dv, dz) = 0$$
 (Itô's formula).

(Finite horizon) Occupational measures 2

- $$J_h(t, x, u) = \mathbb{E} [h(X_T^{t,x,u})] = \int_{\mathbb{R}^N} h(z) \gamma_{t,x,u}([t, T] \times \mathbb{R}^N \times U, dz).$$

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- $\Theta(t, x) = \left\{ \begin{array}{l} \gamma \in \mathcal{P}([t, T] \times \mathbb{R}^N \times U \times \mathbb{R}^N) : \forall \phi \in C_b^{1,2}([0, T] \times \mathbb{R}^N), \\ \int_{[t,T] \times \mathbb{R}^N \times U \times \mathbb{R}^N} \begin{bmatrix} (T-t) \mathcal{L}^v \phi(s, y) \\ + \phi(t, x) - \phi(T, z) \end{bmatrix} \gamma(ds, dy, dv, dz) = 0, \\ \int_{[t,T] \times \mathbb{R}^N \times U \times \mathbb{R}^N} (|y|^2 + |z|^2) \gamma(ds, dy, dv, dz) \leq C_0 (|x|^2 + 1) \end{array} \right.$

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- $\Theta(t, x) = \left\{ \begin{array}{l} \gamma \in \mathcal{P}([t, T] \times \mathbb{R}^N \times U \times \mathbb{R}^N) : \forall \phi \in C_b^{1,2}([0, T] \times \mathbb{R}^N), \\ \int_{[t,T] \times \mathbb{R}^N \times U \times \mathbb{R}^N} \begin{bmatrix} (T-t) \mathcal{L}^v \phi(s, y) \\ + \phi(t, x) - \phi(T, z) \end{bmatrix} \gamma(ds, dy, dv, dz) = 0, \\ \int_{[t,T] \times \mathbb{R}^N \times U \times \mathbb{R}^N} (|y|^2 + |z|^2) \gamma(ds, dy, dv, dz) \leq C_0 (|x|^2 + 1) \end{array} \right.$
- $\mathcal{L}^v \phi(s, y) = \frac{1}{2} \text{Tr} [(\sigma \sigma^*)(s, y, v) D^2 \phi(s, y)] + \langle b(s, y, v), D\phi(s, y) \rangle + \partial_t \phi(s, y)$,

Linearized formulation

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- dual formulation:

$$\eta^*(t, x) = \sup_{(t, x) \in [0, T) \times \mathbb{R}^N} \left\{ \begin{array}{l} \eta \in \mathbb{R} : \exists \phi \in C_b^{1,2}([0, T] \times \mathbb{R}^N) \text{ s.t.} \\ \forall (s, y, v, z) \in [t, T] \times \mathbb{R}^N \times V \times \mathbb{R}^N, \\ \eta \leq (T - t) \mathcal{L}^v \phi(s, y) + h(z) - \phi(T, z) + \phi(t, x), \end{array} \right\},$$

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$$(t, x) \in [0, T) \times \mathbb{R}^N.$$

- In infinite horizon (discounted) setting : Buckdahn, G., Quincampoix (preprint)

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$$\sup \left\{ \begin{array}{l} \eta \in \mathbb{R} : \exists \phi \in C_b^{1,2}([0, T] \times \mathbb{R}^N) \text{ s.t.} \\ \forall (s, y, v, z) \in [t, T] \times \mathbb{R}^N \times V \times \mathbb{R}^N, \\ \eta \leq (T - t) \mathcal{L}^v \phi(s, y) + h(z) - \phi(T, z) + \phi(t, x), \end{array} \right\},$$

$$(t, x) \in [0, T) \times \mathbb{R}^N.$$

- In infinite horizon (discounted) setting : Buckdahn, G., Quincampoix (preprint)

Theorem

h Lipschitz, bounded $\implies V_h(t, x) = h^*(t, x) = \eta^*(t, x),$
 $\forall (t, x) \in [0, T) \times \mathbb{R}^N.$

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- approximate V_h by smooth subsolutions V^ε ;
 $V^\varepsilon(t, x) - C\varepsilon \leq \eta^*(t, x)$ then $\varepsilon \rightarrow 0$ to get
 $\eta^*(t, x) \geq V_h(t, x)$

Lower semicontinuous case

- $$V_h(t, x) = \inf_{\gamma \in \Theta(t, x)} \int_{\mathbb{R}^N} h(z) \gamma([t, T], \mathbb{R}^N, U, dz),$$

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Theorem

V_h is the smallest lower semicontinuous viscosity supersolution and

$$V_h(t, x) = \eta^*(t, x),$$

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 $m \rightarrow \infty$, $n \rightarrow \infty$.

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V_h is the largest upper semicontinuous viscosity subsolution of (HJB).

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pass $n \rightarrow \infty.$

What about the dual formulation? 1

- $$\begin{cases} dX_s^{t,x} = 0, \text{ for } 0 \leq t \leq s \leq T = 1, \\ X_t^{t,x} = x \in \mathbb{R}. \end{cases}, h(\cdot) = \mathbf{1}_{\{0\}}(\cdot).$$

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- $z = \varepsilon, \varepsilon \rightarrow 0$ to get $\eta^*(\frac{1}{2}, 0) \leq 0 < V_h(\frac{1}{2}, 0)$.

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- $m \rightarrow \infty, n \rightarrow \infty$.

Weak control formulation. L.s.c. case

- $V_h^w(t, x) = \inf_{\pi \in \mathcal{U}^w} \mathbb{E}^\pi [h(X_T^{t,x,u})]$
- $\{\sigma\sigma^*(t, x, u), b(t, x, u) : u \in U\}$ is convex.

Proposition

If convexity and h is l.s.c., then $V_h(t, x) = V_h^w(t, x)$.

- **Idea of the proof:** use inf-convolution,
- $V^n(t, x) = \inf_{\pi \in \mathcal{U}^w} \mathbb{E}^\pi [h_n(X_T^{t,x,u})] = \int_{\tilde{\mathcal{X}}} h_n(y_T) R^n(dydq)$,
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- $V^m(t, x) \geq \int_{\tilde{\mathcal{X}}} h_n(y_T) R^m(dydq)$ if $m \geq n$;
- $m \rightarrow \infty, n \rightarrow \infty$.
- use l.s.c. of h and convexity to get $V_h(t, x) \geq V_h^w(t, x)$

L.s.c., nonconvex case 1

- \mathbb{R}^2 , $U = \{-1, 1\}$, $T = 1$

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- $h : \mathbb{R}^2 \longrightarrow \mathbb{R}, h(x, y) = \begin{cases} 1, & \text{if } (x, y) \neq (0, 0), \\ 0, & \text{if } (x, y) = (0, 0). \end{cases}$

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- Thus,

$$\inf_{u \in \mathcal{U}} h(x_1^{t_0, 0, 0, u(\cdot)}, y_1^{t_0, 0, 0, u(\cdot)}) = 1 > 0 = V_h^w(t_0, 0, 0),$$

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Thank you !