

Multi-Person Game Options in Discrete and Continuous Time

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Outline

- 1 Two-Person Game Options
- 2 Equilibria of Multi-Player Stopping Games
- 3 Multi-Player Single-Period Games
- 4 Multi-Player Stochastic Stopping Games
- 5 Continuous-Time Multi-Person Stopping Games

This talk is based to the following working papers:

-  **Guo, I. and Rutkowski, M.:**
A zero-sum multi-player game. *Demonstratio Mathematica* 45 (2012), 415–433.
 -  **Guo, I.:**
Unilaterally competitive multi-player stopping games. Working paper, University of Sydney, 2011.
 -  **Guo, I. and Rutkowski, M.:**
Multi-person game options. Working paper, University of Sydney, 2012.
 -  **Nie, T. and Rutkowski, M.:**
Multi-dimensional reflected BSDEs for multi-person stopping games. Working paper, 2013.
- ... and several related papers by other authors, for instance,
-  **Karatzas, I. and Li, Q.:**
BSDE approach to non-zero-sum stochastic differential games of control and stopping. Working paper, 2011.

Our main goals are:

- 1 to examine equilibria for certain multi-player stochastic games,
- 2 to find explicit algorithm for finding the value process for a class of multi-player stopping games,
- 3 to examine the multi-dimensional reflected backward stochastic difference equation for the value process of the multi-player stopping game,
- 4 to find arbitrage prices and super-hedging strategies for a multi-person game option in discrete time,
- 5 to propose an extension to the continuous-time setup via multi-dimensional reflected backward stochastic differential equation.

REMINDER: TWO-PERSON GAME OPTIONS

Two-Person Zero-Sum Game Options

Definition

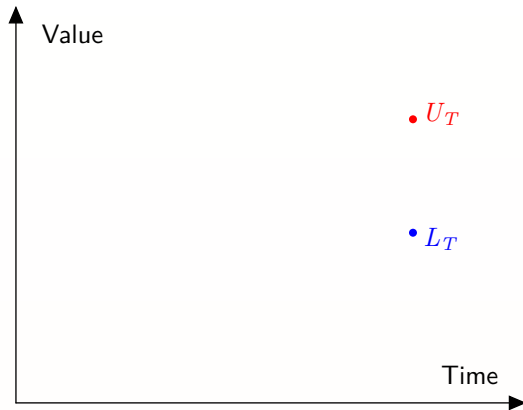
A *game option* is a contract where each party has the right to exercise at any time before expiry T according to the following rules:

- The holder can *exercise* the option at any time $t < T$ for the payoff L_t .
- The issuer can *cancel* the option at any time $t < T$ for the cancellation fee of U_t .
- If the option is not exercised then it expires at time T and the terminal payoff for the holder equals ξ .
- The assumption that $L_t \leq U_t$ for every t will ensure that the outcome of the contract is always well defined.

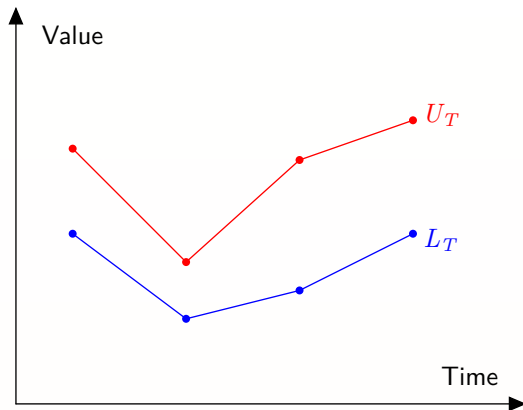
We denote by Y_t the *arbitrage price* of the game option at time t .

The game option is closely related to the zero-sum Dynkin (stopping) game.

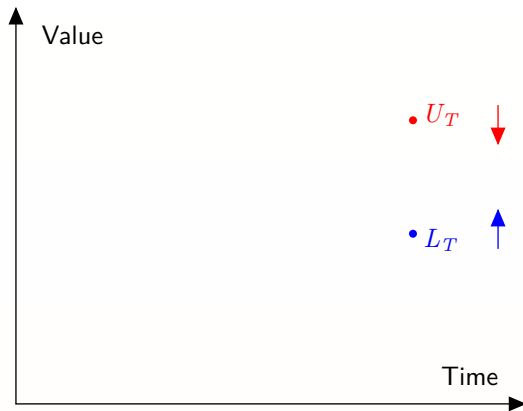
Valuation Scheme for the Game Option



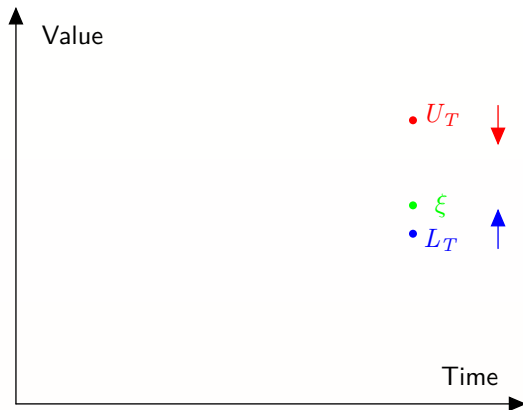
Valuation Scheme for the Game Option



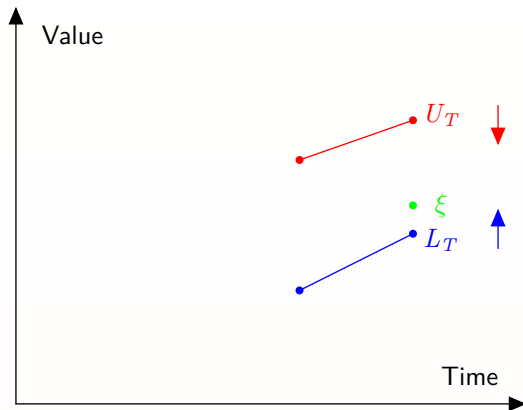
Valuation Scheme for the Game Option



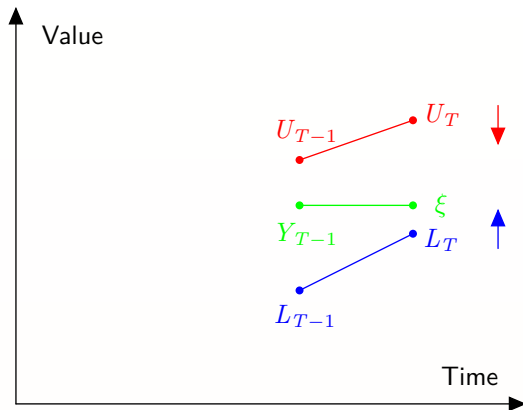
Valuation Scheme for the Game Option



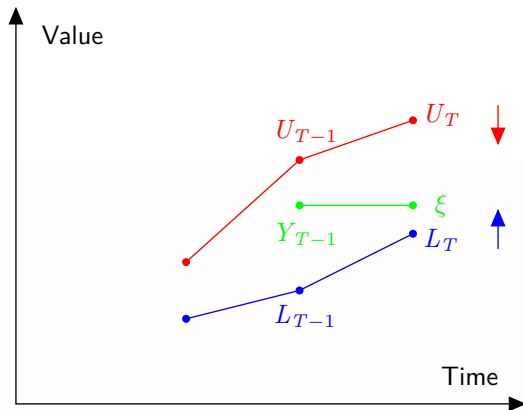
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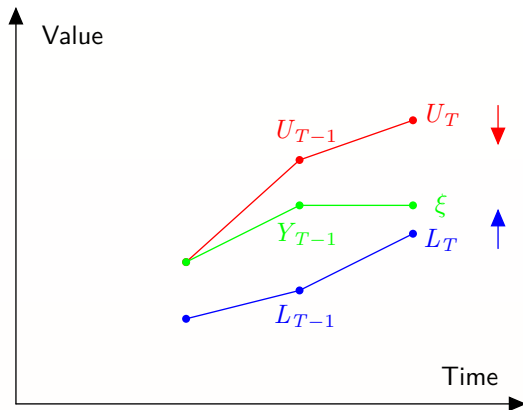
Valuation Scheme for the Game Option



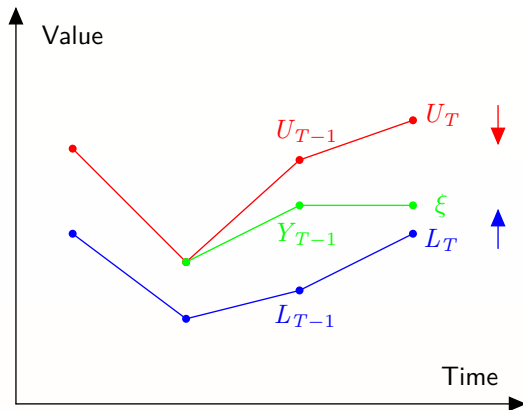
Valuation Scheme for the Game Option



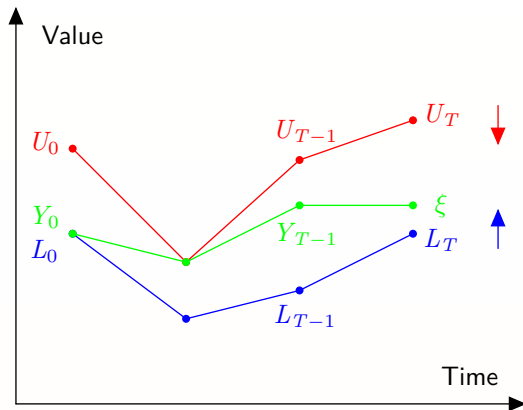
Valuation Scheme for the Game Option



Valuation Scheme for the Game Option



Valuation Scheme for the Game Option



Value Process via Reflected BSDE

Consider a complete and arbitrage-free market model with the unique martingale measure \mathbb{P}^* for the discounted prices S . We denote $\Delta Y_{t+1} = Y_{t+1} - Y_t$.

Definition

A *solution* to the reflected BSDE (L, U, ξ, S) is a quadruplet (Y, Z, K^1, K^2) of processes that satisfy for $t = 0, 1, \dots, T$

$$Y_t + \sum_{u=t}^{T-1} Z_u \cdot \Delta S_{u+1} - (K_T^1 - K_t^1) + (K_T^2 - K_t^2) = \xi$$

$$L_t \leq Y_t \leq U_t$$

$$\sum_{t=0}^{T-1} \mathbb{1}_{\{Y_t > L_t\}} \Delta K_{t+1}^1 = 0$$

$$\sum_{t=0}^{T-1} \mathbb{1}_{\{Y_t < U_t\}} \Delta K_{t+1}^2 = 0$$

where K^1 and K^2 are \mathbb{F} -predictable and non-decreasing processes.

Value Process via Projection

Proposition

The unique solution to reflected BSDE (L, U, ξ, S) equals $Y_T = \xi$ and

$$Y_t = \min \left(U_t, \max \left(L_t, \mathbb{E}_{\mathbb{P}^*} (Y_{t+1} | \mathcal{F}_t) \right) \right).$$

for $t = 0, 1, \dots, T - 1$. Equivalently, $Y_T = \xi$ and for $t = 0, \dots, T - 1$

$$Y_t = \pi_{[L_t, U_t]} \left(\mathbb{E}_{\mathbb{P}^*} (Y_{t+1} | \mathcal{F}_t) \right).$$

The arbitrage price process of the zero-sum two-person game option equals Y .
The rational exercise time for the buyer equals

$$\tau_1 = \min \{ t \in \{0, \dots, T - 1\} \mid \Delta K_{t+1}^1 > 0 \}$$

and the rational exercise time for the seller equals

$$\tau_2 = \min \{ t \in \{0, \dots, T - 1\} \mid \Delta K_{t+1}^2 > 0 \}.$$

EQUILIBRIA OF MULTI-PLAYER STOPPING GAMES

Equilibria of Multi-Player Stopping Games

Consider an m -person stochastic stopping game in which the goal of each player is to maximise his expected payoff. Let $s = (s^1, \dots, s^m)$ be an m -tuple of exercise times. The expected payoff of the k th player is denoted by $J_k(s^1, \dots, s^m)$ or $J_k(s^k, s^{-k})$ where $s^{-k} = (s^1, \dots, s^{k-1}, s^{k+1}, \dots, s^m)$.

Definition

A family (τ^1, \dots, τ^m) of stopping times is said to be a *Nash equilibrium* if

$$J_k(\tau^k, \tau^{-k}) \geq J_k(s_k, \tau^{-k}), \quad \forall s^k.$$

A family (τ^1, \dots, τ^m) of stopping times is called an *optimal equilibrium* when it is a Nash equilibrium and

$$J_k(\tau^k, s^{-k}) \geq J_k(\tau^k, \tau^{-k}), \quad \forall s^{-k}.$$

For zero-sum stopping games any Nash equilibrium is also an optimal equilibrium.

Maximin and Minimax Values

Definition

The *lower value* (or *maximin value*) V_k^l for player k is defined by

$$V_k^l = \sup_{s^k} \inf_{s^{-k}} J_k(s^k, s^{-k}).$$

A *maximin strategy* is any s^k such that $J_k(s^k, s^{-k}) \geq V_k^l$ for all s^{-k} .

Definition

The *upper value* (or *minimax value*) V_k^u for player k is defined by

$$V_k^u = \inf_{s^{-k}} \sup_{s^k} J_k(s^k, s^{-k}).$$

A *minimax strategy* is any s^{-k} such that $J_k(s^k, s^{-k}) \leq V_k^u$ for all s^k .

Value of the Game

Lemma

In any m -person stochastic stopping game the following holds:

- 1 if (τ^1, \dots, τ^m) is an optimal equilibrium then it is an optimal strategy, in the sense that

$$\inf_{s^{-k}} J_k(\tau^k, s^{-k}) = J_k(\tau^k, \tau^{-k}) = \sup_{s^k} J_k(s^k, \tau^{-k}),$$

- 2 the inequality $V_k^u \geq V_k^l$ is valid,
- 3 If (τ^1, \dots, τ^m) is an optimal equilibrium then $V_k^u = V_k^l = J_k(\tau^k, \tau^{-k})$.

Definition

If $V_k^l = V_k^u$ then $V_k^* := V_k^l = V_k^u$ is called the *value* of the game for player k . The *value* of the game is the vector (V_1^*, \dots, V_m^*) , provided that it is well defined.

Weakly Unilaterally Competitive Games

Definition (Kats and Thisse (1992))

An m -player game is said to be *weakly unilaterally competitive* (WUC) if for every $k, l = 1, \dots, m$, $k \neq l$ and all s^k, \hat{s}^k, s^{-k} the following implications hold

$$J_k(s^k, s^{-k}) > J_k(\hat{s}^k, s^{-k}) \Rightarrow J_l(s^k, s^{-k}) \leq J_l(\hat{s}^k, s^{-k})$$

$$J_k(s^k, s^{-k}) = J_k(\hat{s}^k, s^{-k}) \Rightarrow J_l(s^k, s^{-k}) = J_l(\hat{s}^k, s^{-k}).$$

Proposition (Kats and Thisse (1992), De Wolf (1999))

If (τ^1, \dots, τ^m) is a Nash equilibrium for a WUC game then is also an optimal equilibrium and:

- ① $\min_{s^{-k}} J_k(\tau^k, s^{-k}) = J_k(\tau^k, \tau^{-k})$ for every $k = 1, \dots, m$,
- ② the equality $J_k(\tau^k, \tau^{-k}) = V_k^u = V_k^l$ is valid and for every player the strategies τ^k and τ^{-k} are maximin and minimax strategies, respectively,
- ③ (s^k, τ^{-k}) is an optimal equilibrium if and only if s^k is a maximin strategy.

MULTI-PLAYER SINGLE-PERIOD GAMES

Deterministic Single-Period WUC Game

We first focus on the single-period game where exercise is only allowed at $t = 0$.

- Players: $\mathcal{M} = \{1, 2, \dots, m\}$.
- Exercise payoff: $\mathbf{x} = (x_1, \dots, x_m)$ where x_k is the amount received by player k if he exercises at time 0.
- Terminal payoff: $\mathbf{p} = (p_1, \dots, p_m)$ where p_k is the amount received by player k if no player exercises at time 0.
- $\sum_{k \in \mathcal{M}} p_k = c$.
- $\sum_{k \in \mathcal{M}} x_k \leq c$.
- c is the total value of the contract.

Redistribution of losses:

- In the two player case, when one player exercises, the payoff, or 'burden' of this action is paid entirely by the other player.
- In the multi-player case, when someone exercises, this 'burden' should be split among non-exercising players according to some predetermined rule.

Strategies and Exercise

- The *strategy* $s^k \in \mathcal{S}^k = \{0, 1\}$ of player k specifies if he will exercise at $t = 0$.
- Then any $s = (s^1, \dots, s^m) \in \{0, 1\}^m$ is a *strategy set*.
- Given a strategy set s , the *exercise set* $\mathcal{E}(s)$ is the set of players who exercised at time 0.

Definition

For a strategy set s , the *modified payoff* $\mathbf{v}(s) = (v_1(s), \dots, v_m(s))$ is the actual payoff received by the players if a strategy set s is carried out. We set

$$v_k(s) = \begin{cases} x_k & k \in \mathcal{E}(s), \\ p_k - w_k(s) \sum_{j \in \mathcal{E}(s)} (x_j - p_j) & k \in \mathcal{M} \setminus \mathcal{E}(s). \end{cases}$$

This means that

- exercising players receive their exercise payoffs,
- non-exercising payoffs receive their terminal payoffs diminished by their allocated 'burdens'.

Weights of Strategy Sets

- This is a *constant-sum game*: $\sum_{k \in \mathcal{M}} v_k(s) = \sum_{k \in \mathcal{M}} p_k = c$, except when all players exercise.
- Weights are used to determine how the burden of exercising is split between the non-exercising players. They depend on strategy sets.
- For any strategy set s , $w_k(s)$ is defined for all non-exercising players, that is, for all $k \in \mathcal{M} \setminus \mathcal{E}(s)$.
- We assume $w_k(\mathcal{E}) \neq 0$ for any non-empty subset $\mathcal{E} \subset \mathcal{M}$, $\mathcal{E} \neq \mathcal{M}$ and $k \notin \mathcal{E}$.

Proposition

The game \mathcal{G} is WUC for all choices x and p if and only if the weights can be written in the following form:

$$w_k(\mathcal{E}) = \frac{\alpha_k}{1 - \sum_{i \in \mathcal{E}} \alpha_i}$$

where $\alpha_k > 0$ and $\sum_{i \neq k} \alpha_i < 1$ for all k .

Vector Space and Projection

Definition

The modified payoff $v(s^*)$ corresponding to an optimal equilibrium s^* is called the *value* of the game.

The value $v^* = v(s^*)$ is unique. We will now address the following question: how to express the value v^* in terms of vectors v and x ?

Proposition

If $\sum_{k \in \mathcal{M}} x_k = c$ then the unique value satisfies $v^ = x$. Moreover, the strategy set $s^* = (0, \dots, 0)$ is an optimal equilibrium.*

We endow the space \mathbb{R}^m with the norm $\|\cdot\|$ generated by the inner product

$$\langle \mathbf{y}, \mathbf{z} \rangle = \sum_{k=1}^m \left(\frac{y_k z_k}{\alpha_k} \right).$$

Hyperplanes and Modified Payoffs

For any vector \mathbf{p} and any closed convex set \mathbb{K} in \mathbb{R}^m , there exists a unique projection $\pi_{\mathbb{K}}(\mathbf{p})$ of \mathbf{p} onto \mathbb{K} such that: $\pi_{\mathbb{K}}(\mathbf{p}) \in \mathbb{K}$ and

$$\|\pi_{\mathbb{K}}(\mathbf{p}) - \mathbf{p}\| \leq \|\mathbf{q} - \mathbf{p}\| \quad \forall \mathbf{q} \in \mathbb{K}.$$

For any proper subset $\mathcal{E} \subset \mathcal{M}$, we define the hyperplane

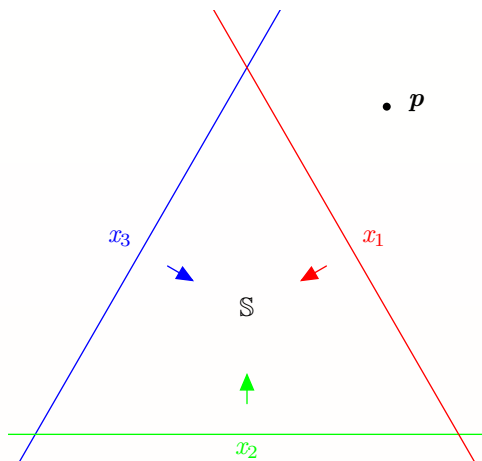
$$\mathcal{H}_{\mathcal{E}} = \left\{ \mathbf{y} \in \mathbb{R}^m : y_i = x_i \text{ for all } i \in \mathcal{E} \text{ and } \sum_{k=1}^m y_k = c \right\}.$$

Lemma

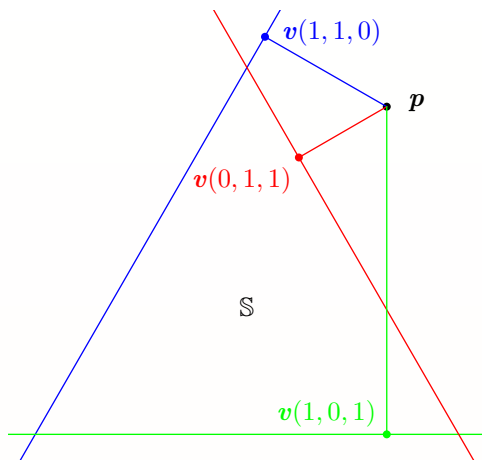
Let s be any strategy set such that $\mathcal{E}(s)$ is a proper subset of \mathcal{M} . Then the vector $\mathbf{v}(s)$ of modified payoffs equals

$$\mathbf{v}(s) = \pi_{\mathcal{H}_{\mathcal{E}(s)}}(\mathbf{p}).$$

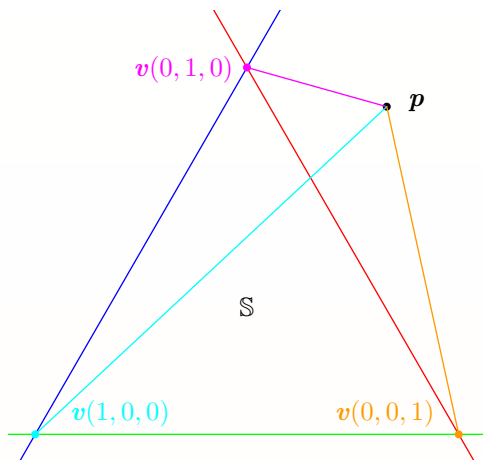
Modified Payoff as Projection: Suboptimal



Modified Payoff as Projection: Suboptimal



Modified Payoff as Projection: Suboptimal



Existence and Uniqueness of the Value

Consider the simplex \mathbb{S} given by

$$\mathbb{S} = \left\{ \mathbf{y} \in \mathbb{R}^m : y_k \geq x_k, 1 \leq k \leq m \text{ and } \sum_{k=1}^m y_k = c \right\}.$$

Proposition

Assume that $\sum_{k=1}^m x_k < c$. Then:

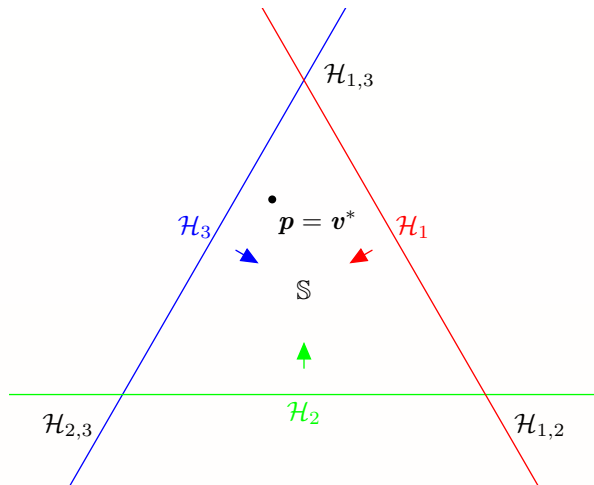
- 1 a strategy set s^* is an optimal equilibrium for the game if and only if the set of exercising players $\mathcal{E}(s^*)$ is such that

$$\pi_{\mathcal{H}_{\mathcal{E}(s^*)}}(\mathbf{p}) = \pi_{\mathbb{S}}(\mathbf{p}), \quad (*)$$

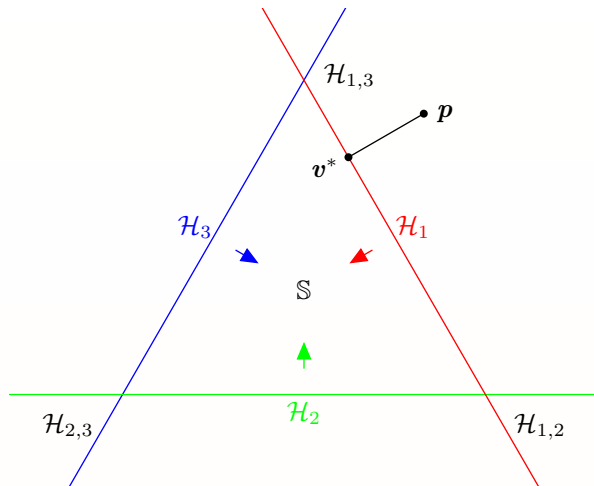
- 2 a strategy set s^* satisfying (*) always exists and the unique value of the game equals

$$\mathbf{v}^* = \mathbf{v}(s^*) = (v_1(s^*), \dots, v_m(s^*)) = \pi_{\mathbb{S}}(\mathbf{p}).$$

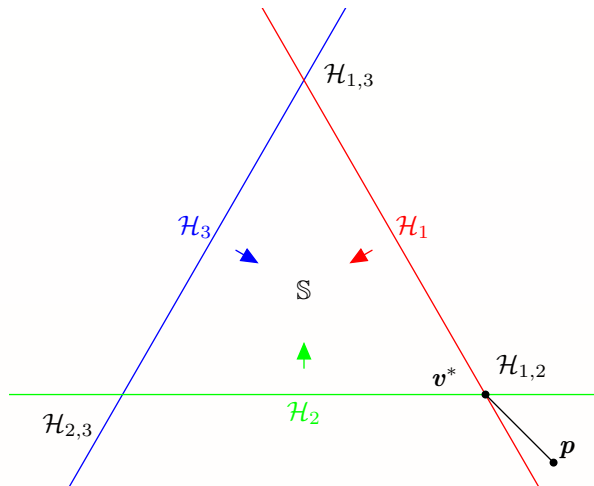
Value of the Game: Optimal Equilibrium



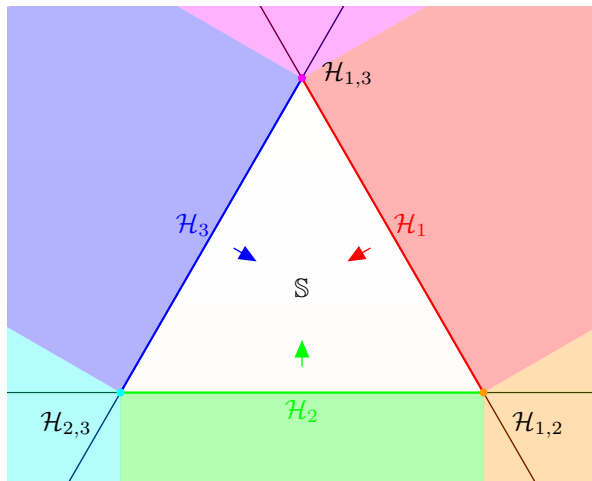
Value of the Game: Optimal Equilibrium



Value of the Game: Optimal Equilibrium



Value of the Game: Optimal Equilibrium



Multi-Period Zero-Sum Extension

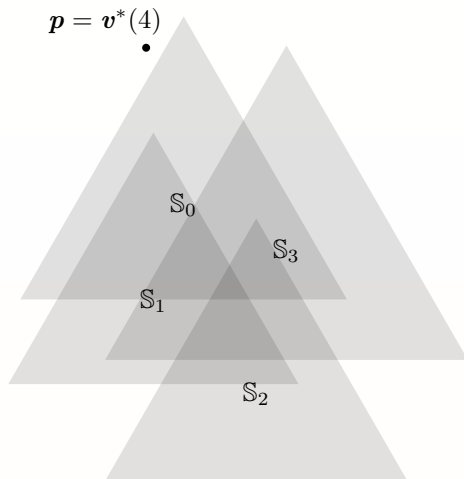
One possible formulation is the *compound game* approach: for $t = T$ we set $V^*(T) = X_T$. For each $t = 0, \dots, T - 1$, we consider the game with modified payoffs:

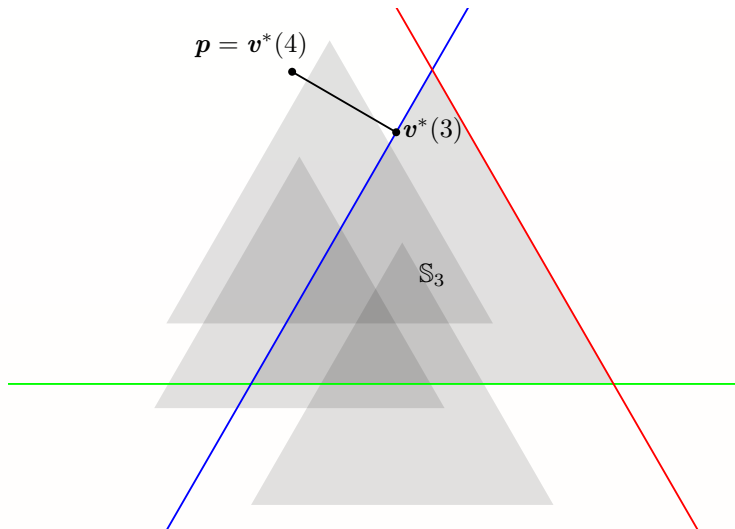
$$V_k(t) = \begin{cases} X_k(t), & k \in \mathcal{E}_t, \\ V_k^*(t+1) - w_k(\mathcal{E}_t) \sum_{j \in \mathcal{E}_t} (X_j(t) - V_j^*(t+1)), & k \notin \mathcal{E}_t. \end{cases}$$

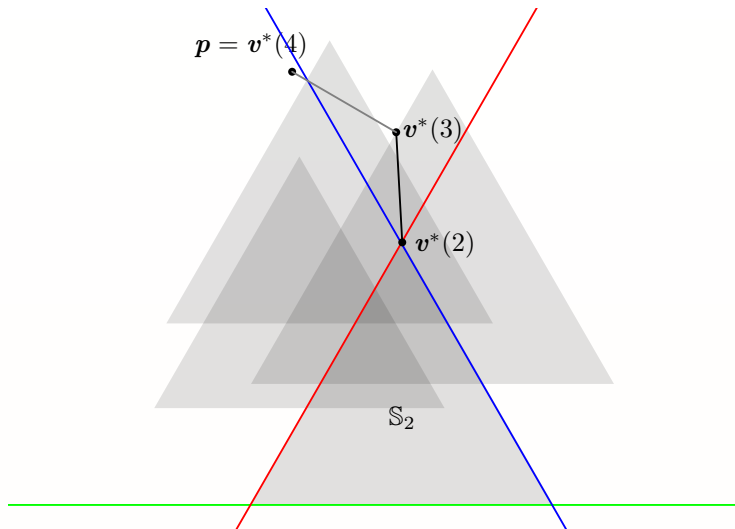
According to this specification of a multi-period game at each time t player k can either

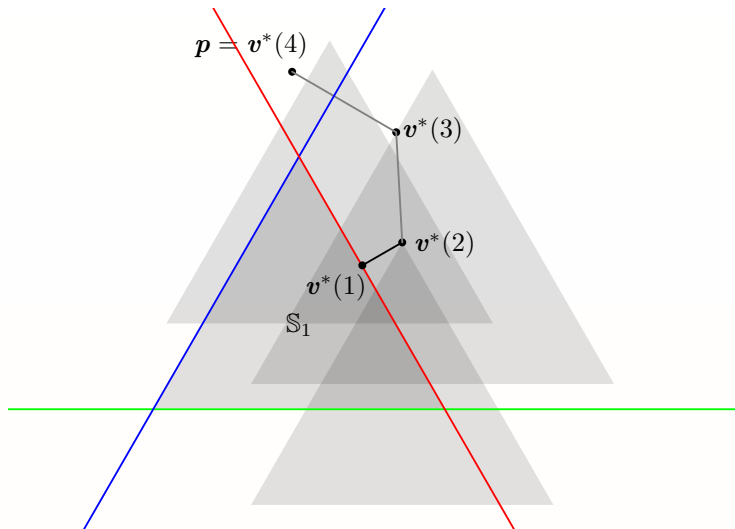
- stop (or exercise) the game for $X_{k,t}$ or
- receive a suitably adjusted amount based on the value of the subgame starting at time $t + 1$.

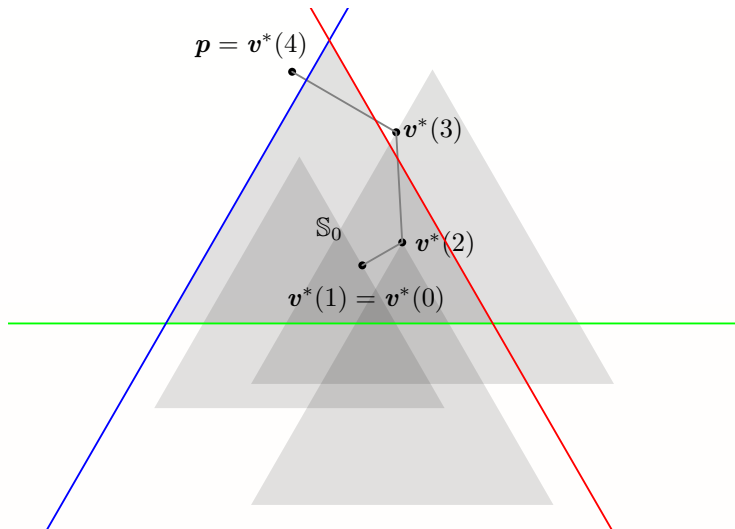
Let us first assume that the multi-period game happens to be a zero-sum game at each stage. Then it can be solved using the method developed for the single-period game.

Multi-Period Zero-Sum Extension: $T = 4$ 

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Multi-Period Zero-Sum Extension: $T = 4$ 

Non-Zero-Sum Multi-Period Stopping Game

The assumption that the game is zero-sum has essential drawbacks:

- It is not suitable to impose this condition in the multi-period stochastic case,
- One has to decide how the game is settled when everyone decides to exercise prematurely.

To overcome this difficulty, we propose to introduce a *dummy* player $m + 1$ who

- does not have the right to exercise the game,
- covers a possible shortfall when all other players decide to exercise simultaneously.

Then the non-zero-sum game can be solved using similar techniques as for the zero-sum case.

MULTI-PLAYER STOCHASTIC STOPPING GAMES

Multi-Player Stochastic Stopping Game

The following building blocks are used to construct the multi-period stochastic stopping game:

- The set $\mathcal{M} = \{1, 2, \dots, m\}$ of players.
- The probability space $(\Omega, \mathbb{F}, \mathbb{P})$ with the filtration $\mathbb{F} = (\mathcal{F}_t)_{t=0}^T$ representing the information flow available to all players.
- The class \mathcal{S}_t of all \mathbb{F} -stopping times taking values in $\{t, \dots, T\}$.
- The \mathbb{F} -adapted *exercise payoff* $X_t = (X_t^1, \dots, X_t^m)$ for $t = 0, 1, \dots, T$.
- The random subsets $\mathcal{E}_t \subset \mathcal{M}$ of exercising players.
- For every $k \in \mathcal{M}$ and every non-empty subset $\mathcal{E} \subset \mathcal{M}$ such that $k \notin \mathcal{E}$ the real-valued, \mathbb{F} -adapted *non-exercise payoff* process

$$\tilde{X}_t^k = \tilde{X}_t^k(\mathcal{E}), \quad t = 0, 1, \dots, T - 1.$$

- The random variable \tilde{X}_t^k is the payoff received by player k when all players from \mathcal{E} exercise at t assuming that the game was not yet stopped.

Multi-Player Stochastic Stopping Game

The m -player stochastic stopping game $\mathcal{G} = (\mathcal{G}_0, \dots, \mathcal{G}_T)$ is defined recursively:

- All players are assumed to exercise at time T . The game \mathcal{G}_T is trivial with the value $V_T^* = X_T$.
- Assuming that the games $\mathcal{G}_{t+1}, \dots, \mathcal{G}_T$ were already defined, the game \mathcal{G}_t is specified as follows.
- The game starts at time t and each player can exercise at any time in the interval $[t, T]$. The game stops as soon as anyone exercises.
- The strategy s_t^k of player k is a stopping time from the space \mathcal{S}_t , so that the strategy profile $s_t = (s_t^1, \dots, s_t^m) \in \mathcal{S}_t^m$.
- Let $\widehat{s}_t = s_t^1 \wedge \dots \wedge s_t^m \in \mathcal{S}_t$. The exercise set

$$\mathcal{E}(s_t) = \{i \in \mathcal{M} : s_t^i = \widehat{s}_t\}$$

is the \mathcal{F}_T -measurable random set of earliest exercising players.

Multi-Player Stochastic Stopping Game

- For each strategy profile s_t , the *expected payoff* at time t

$$V_t(s_t) = (V_t^1(s_t), \dots, V_t^m(s_t))$$

is defined by

$$V_t^k(s_t) = \mathbb{E}_{\mathbb{P}}(X_{s_t}^k \mathbf{1}_{\{k \in \mathcal{E}(s_t)\}} + \tilde{X}_{s_t}^k \mathbf{1}_{\{k \notin \mathcal{E}(s_t)\}} \mid \mathcal{F}_t).$$

In general, the non-exercise payoffs are given by

$$\tilde{X}_{s_t}^k = g_{\mathcal{E}(s_t)}^k(X_{s_t}, V_{s_{t+1}}^*, \hat{s}_t) \mathbf{1}_{\{\hat{s}_t < T\}}$$

for a family of functions $g_{\mathcal{E}}^k : \mathbb{R}^{2m} \times [0, T] \rightarrow \mathbb{R}$ where we denote by $V_u^* = (V_u^{1*}, \dots, V_u^{m*})$ the value of the game \mathcal{G}_u for $u = t + 1, \dots, T$.

Multi-Player Stochastic Stopping Game

- To summarize, for any strategy profile s_t

$$\begin{aligned}
 V_t^k(s_t) &= \mathbb{E}_{\mathbb{P}} \left(\sum_{u=t}^T X_u^k \mathbb{1}_{\{k \in \mathcal{E}_u(s_t)\}} \mathbb{1}_{\{\widehat{s}_t = u\}} \mid \mathcal{F}_t \right) \\
 &+ \mathbb{E}_{\mathbb{P}} \left(\sum_{u=t}^{T-1} \widetilde{X}_u^k(\mathcal{E}_u(s_t)) \mathbb{1}_{\{k \notin \mathcal{E}_u(s_t)\}} \mathbb{1}_{\{\widehat{s}_t = u\}} \mid \mathcal{F}_t \right).
 \end{aligned}$$

where

$$\mathcal{E}_u(s_t) = \{i \in \mathcal{M} : s_t^i = \widehat{s}_t = u\}$$

is the \mathcal{F}_u -measurable random subset of earliest exercising players who decide to exercise at time u .

Candidate for the Value Process

- We will now search for the candidate for the value process of the game.
- Let $U = (U^1, \dots, U^m)$ be an arbitrary \mathbb{F} -adapted, \mathbb{R}^m -valued process such that $U_T = X_T$.
- We define the family $\tau_t = (\tau_t^1, \dots, \tau_t^m) \in \mathcal{S}_t^m$ of stopping times

$$\tau_t^k := \inf \{u \geq t : U_u^k = X_u^k\}.$$

- Let $\mathcal{E}(\tau_t)$ stand for the following random set

$$\mathcal{E}(\tau_t) := \{k \in \mathcal{M} : U_t^k = X_t^k\} = \{k \in \mathcal{M} : \tau_t^k = t\} = \{i \in \mathcal{M} : \tau_t^i = \widehat{\tau}_t\}$$

where $\widehat{\tau}_t := \tau_t^1 \wedge \dots \wedge \tau_t^m$. We write

$$\widehat{\tau}_t^{-k} := \tau_t^1 \wedge \dots \wedge \tau_t^{k-1} \wedge \tau_t^{k+1} \wedge \dots \wedge \tau_t^m.$$

- For brevity, we denote $P_t = \mathbb{E}_{\mathbb{P}}(U_{t+1} \mid \mathcal{F}_t)$.

Value Process: Sufficient Conditions

Proposition

Let $U = (U^1, \dots, U^m)$ be an arbitrary \mathbb{F} -adapted, \mathbb{R}^m -valued process such that $U_T = X_T$. Assume that for all $k \in \mathcal{M}$ and $t = 0, 1, \dots, T - 1$,

- ① $U_t^k \geq X_t^k$,
- ② $U_t^k \leq P_t^k$ on the event $\{\tau_t^k > t\}$,
- ③ $U_t^k \geq P_t^k$ on the event $\{\widehat{\tau}_t^{-k} > t\}$,
- ④ $U_t^k \geq \widetilde{X}_t^k$ on the event $\{\widehat{\tau}_t^{-k} = t < s_t^k\}$ for every $s_t^k \in \mathcal{S}_t$,
- ⑤ $U_t^k \leq \widetilde{X}_t^k$ on the event $\{\widehat{s}_t^{-k} = t < \tau_t^k\}$ for every $s_t^{-k} \in \mathcal{S}_t^{m-1}$.

Then, for every $k \in \mathcal{M}$, $t = 0, 1, \dots, T - 1$, and s_t^1, \dots, s_t^m in \mathcal{S}_t ,

$$\mathbb{E}_{\mathbb{P}}(Z^k(s_t^k, \tau_t^{-k}) | \mathcal{F}_t) \leq U_t^k \leq \mathbb{E}_{\mathbb{P}}(Z^k(\tau_t^k, s_t^{-k}) | \mathcal{F}_t)$$

and thus

$$\mathbb{E}_{\mathbb{P}}(Z^k(s_t^k, \tau_t^{-k}) | \mathcal{F}_t) \leq \mathbb{E}_{\mathbb{P}}(Z^k(\tau_t^k, \tau_t^{-k}) | \mathcal{F}_t) \leq \mathbb{E}_{\mathbb{P}}(Z^k(\tau_t^k, s_t^{-k}) | \mathcal{F}_t).$$

Value Process: Sufficient Conditions

Proposition

Consequently:

- ① The process U is the value process of the m -player stopping game, that is, for all $k \in \mathcal{M}$ and $t = 0, 1, \dots, T$,

$$\begin{aligned} U_t^k &= \inf_{s_t^{-k} \in \mathcal{S}_t^{m-1}} \sup_{s_t^k \in \mathcal{S}_t} \mathbb{E}_{\mathbb{P}}(Z^k(s_t^k, s_t^{-k}) | \mathcal{F}_t) \\ &= \mathbb{E}_{\mathbb{P}}(Z^k(\tau_t^k, \tau_t^{-k}) | \mathcal{F}_t) \\ &= \sup_{s_t^k \in \mathcal{S}_t} \inf_{s_t^{-k} \in \mathcal{S}_t^{m-1}} \mathbb{E}_{\mathbb{P}}(Z^k(s_t^k, s_t^{-k}) | \mathcal{F}_t) = V_t^{k*}. \end{aligned}$$

- ② For every $t = 0, 1, \dots, T$, the family $\tau_t = (\tau_t^1, \dots, \tau_t^m) \in \mathcal{S}_t^m$ is an optimal equilibrium for the game \mathcal{G}_t .
- ③ For all $t = 0, 1, \dots, T - 1$, the stopped process $(\widehat{U}_u^{\tau_t})_{u=t}^T$ is an \mathbb{F} -martingale.

Affine Stopping Games

Definition

The m -player stochastic stopping game $\mathcal{G} = (\mathcal{G}_0, \dots, \mathcal{G}_T)$ is said to be *affine* whenever:

- 1 For any $\mathcal{E} \subset \mathcal{M}$, we are given the set of *weights*

$$w_k(\mathcal{E}) = \frac{\alpha_k}{1 - \sum_{i \in \mathcal{E}} \alpha_i}$$

for $k \in \mathcal{M} \setminus \mathcal{E}$ where $\alpha_i > 0$ and $\sum_{i \in \mathcal{M}} \alpha_i < 1$.

- 2 The non-exercise payoff on the event $\{\hat{s}_t < T\}$ is given by

$$\tilde{X}_{s_t}^k = V_{s_{t+1}}^{k*} - w_k(\mathcal{E}(s_t)) \sum_{i \in \mathcal{E}(s_t)} (X_{s_t}^i - V_{s_{t+1}}^{i*})$$

where $V_u^* = (V_u^{1*}, \dots, V_u^{m*})$ is the value of the game \mathcal{G}_u .

Expected Payoff as Projection

Given the vector $\alpha = (\alpha_1, \dots, \alpha_m)$, we endow \mathbb{R}^m with the inner product $\langle \cdot, \cdot \rangle_\alpha$

$$\langle x, y \rangle_\alpha = \sum_{i=1}^m \frac{x_i y_i}{\alpha_i} + \frac{(\sum_{i=1}^m x_i)(\sum_{i=1}^m y_i)}{1 - \sum_{i=1}^m \alpha_i}.$$

Proposition

The expected payoff $V_t(s_t) = (V_t^1(s_t), \dots, V_t^m(s_t))$ can be represented as follows

$$V_t(s_t) = \mathbb{E}_{\mathbb{P}} \left(\mathbb{1}_{\{\widehat{s}_t < T\}} \pi_{\mathcal{H}_{\mathcal{E}(s_t)}} (V_{s_t+1}^*) + \mathbb{1}_{\{\widehat{s}_t = T\}} X_T \mid \mathcal{F}_t \right)$$

where $\mathcal{H}_{\mathcal{E}(s_t)}$ is the \mathcal{F}_{s_t} -measurable random hyperplane

$$\mathcal{H}_{\mathcal{E}(s_t)} := \left\{ y \in \mathbb{R}^m : y_i = X_{s_t}^i, \forall i \in \mathcal{E}(s_t) \right\}.$$

Value Process via Projection

Definition

Let the \mathbb{F} -adapted payoff processes be given. The \mathbb{F} -adapted, \mathbb{R}^m -valued process $U = (U^1, \dots, U^m)$ is defined by setting $U_T := X_T$ and for $t = 0, 1, \dots, T - 1$

$$U_t := \pi_{\mathbb{O}(X_t)} (\mathbb{E}_{\mathbb{P}}(U_{t+1} \mid \mathcal{F}_t))$$

where $\mathbb{O}(X_t)$ is the \mathcal{F}_t -measurable orthant

$$\mathbb{O}(X_t(\omega)) := \left\{ y \in \mathbb{R}^m : y_i \geq X_t^i(\omega), \forall i \in \mathcal{M} \right\}.$$

We define the strategy set $\tau_t = (\tau_t^1, \dots, \tau_t^m) \in \mathcal{S}_t^m$ by setting

$$\tau_t^k := \inf \{ u \geq t : U_u^k = X_u^k \}.$$

Value Process via Projection

Lemma

Recall that we set $U_T = X_T$

$$U_t = \pi_{\mathbb{O}(X_t)}(\mathbb{E}_{\mathbb{P}}(U_{t+1} \mid \mathcal{F}_t)), \quad t = 0, 1, \dots, T-1,$$

and

$$\tau_t^k := \inf \{u \geq t : U_u^k = X_u^k\}.$$

Then for every $k \in \mathcal{M}$ and $t = 0, 1, \dots, T-1$:

- ① $U_t^k \geq X_t^k$; moreover, $U_t^k = P_t^k$ on the event $\{\widehat{\tau}_t > t\}$,
- ② $U_t^k \leq P_t^k$ on the event $\{\tau_t^k > t\}$,
- ③ $U_t^k \geq P_t^k$ on the event $\{\widehat{\tau}_t^{-k} > t\}$,
- ④ $U_t^k \geq \widetilde{X}_t^k$ on the event $\{\widehat{\tau}_t^{-k} = t < s_t^k\}$ for every $s_t^k \in \mathcal{S}_t$,
- ⑤ $U_t^k \leq \widetilde{X}_t^k$ on the event $\{\widehat{s}_t^{-k} = t < \tau_t^k\}$ for every $s_t^{-k} \in \mathcal{S}_t^{m-1}$.

Value Process via Projection

The main result for the affine stopping game is the following corollary.

Corollary

Consider the m -person affine stopping game $\mathcal{G} = (\mathcal{G}_0, \dots, \mathcal{G}_T)$ with the vector of powers $\alpha = (\alpha_1, \dots, \alpha_m)$ such that $\sum_{i=1}^m \alpha_i < 1$. The game is solvable with the value process V^* given by the recursive formula: $V_T^* = X_T$ and

$$V_t^* := \pi_{\mathbb{O}(X_t)} \left(\mathbb{E}_{\mathbb{P}} \left(V_{t+1}^* \mid \mathcal{F}_t \right) \right) = \pi_{\mathbb{O}(X_t)} (P_t).$$

The sequence of optimal equilibria (τ_0, \dots, τ_T) is given by

$$\tau_t^k := \inf \{ u \geq t : V_u^{k*} = X_u^k \}.$$

Value Process via Reflected BSDE

Assume that $\sum_{i=1}^m \alpha_i < 1$. Recall that we endowed \mathbb{R}^m with the following inner product

$$\langle y, z \rangle = \sum_{i=1}^m \left(\frac{y_i z_i}{\alpha_i} \right) + \frac{(\sum_{i=1}^m y_i)(\sum_{i=1}^m z_i)}{1 - \sum_{i=1}^m \alpha_i} =: y^T D z.$$

It can be shown that $\widehat{D} := D^{-1}$ equals

$$\widehat{D} = \begin{pmatrix} \alpha_1 - \alpha_1^2 & -\alpha_1 \alpha_2 & \dots & -\alpha_1 \alpha_m \\ -\alpha_2 \alpha_1 & \alpha_2 - \alpha_2^2 & \dots & -\alpha_2 \alpha_m \\ \vdots & \vdots & \ddots & \vdots \\ -\alpha_m \alpha_1 & -\alpha_m \alpha_2 & \dots & \alpha_m - \alpha_m^2 \end{pmatrix}.$$

The matrix \widehat{D} will be used to derive the reflected BSDE.

Affine Variational Inequality

Lemma

A vector $v^* = \Pi_{\mathbb{O}(x)}(p)$ if there exists a vector μ^* such that (v^*, μ^*) is a solution to the following affine variational inequality (AVI)

$$\begin{aligned} v^* - \widehat{D}\mu^* &= p, \\ v^* &\geq x, \quad \mu^* \geq 0, \\ \langle v^* - x, \mu^* \rangle &= 0, \end{aligned}$$

or, more explicitly, for all $i = 1, \dots, m$,

$$\begin{aligned} v_i^* &= p_i + \sum_{j=1}^m \widehat{D}_{ij} \mu_j^*, \\ v_i^* &\geq x_i, \quad \mu_i^* \geq 0, \quad (v_i^* - x_i) \mu_i^* = 0, \end{aligned}$$

where $\widehat{D}_i = (\widehat{D}_{i1}, \dots, \widehat{D}_{im})$ is the i th row of the matrix \widehat{D} .

Value Process via Reflected Backward Equation

Corollary

Assume that the pair (v^*, μ^*) solves the AVI. Then (v^*, μ^*) solves the following reflected backward equation (RBE)

$$v_i^* + \alpha_i \sum_{l=1, l \neq i}^m \alpha_l \mu_l^* \mathbf{1}_{\{v_l^* = x_l\}} - \alpha_i (1 - \alpha_i) \mu_i^* \mathbf{1}_{\{v_i^* = x_i\}} = p_i,$$

$$v_i^* - x_i \geq 0, \quad \mu_i^* \geq 0,$$

or, equivalently,

$$v_i^* + \alpha_i \sum_{l=1, l \neq i}^m \alpha_l \mu_l^* - \alpha_i (1 - \alpha_i) \mu_i^* = p_i,$$

$$v_i^* - x_i \geq 0, \quad \mu_i^* \geq 0, \quad (v_i^* - x_i) \mu_i^* = 0.$$

Classes of Players

We can identify three classes of players:

- 1 Players for whom it is optimal to exercise since their continuation payoff is strictly below their exercise payoff: $p_i < x_i = v_i^*$ and $\mu_i^* \geq x_i - p_i > 0$,
- 2 Players who are forced to exercise: $p_i \geq x_i = v_i^*$ and $\mu_i^* > 0$,
- 3 Players who do not exercise: $p_i \geq x_i$ and $\mu_i^* = 0$.

To simplify the reflected backward equation, we denote $k^l := \alpha_l \mu_l^*$.

Then we obtain the following equation for vectors $v = (v_1, \dots, v_m)^T \in \mathbb{R}^m$ and $k = (k_1, \dots, k_m)^T \in \mathbb{R}_+^m$

$$v_i + \alpha_i \sum_{l=1, l \neq i}^m k_l \mathbb{1}_{\{v_l = x_l\}} - (1 - \alpha_i) k_i \mathbb{1}_{\{v_i = x_i\}} = p_i,$$

$$v_i \geq x_i, \quad k_i \geq 0.$$

CONTINUOUS-TIME MULTI-PERSON STOPPING GAMES

Continuous-Time Multi-Person Stopping Game

The continuous-time multi-person stopping game is given by its terminal value ξ , the exercise payoffs X^i and the redistribution rule $(\alpha^1, \dots, \alpha^m)$ upon stopping. The randomness is introduced via the Brownian motion $B = (B^1, \dots, B^d)$.

Definition

The m -dimensional RBSDE corresponding to the *continuous-time multi-person stopping game* reads: for all $t \in [0, T]$,

$$\left\{ \begin{array}{l} Y_t^i = \xi^i - \sum_{j \neq i, j=1}^m r_{i,j} (K_T^j - K_t^j) - (K_T^i - K_t^i) - \int_t^T \sum_{l=1}^d Z_s^{i,l} dB_s^l, \\ Y_t^i \geq X_t^i, \\ \int_0^t \mathbf{1}_{\{Y_s^i > X_s^i\}} dK_s^i = 0, \quad 1 \leq i \leq m, \end{array} \right.$$

where $r_{i,j} = \frac{\alpha_j}{1 - \alpha_j}$ for $i \neq j$, and $\alpha_i > 0$ are such that $\sum_{i=1}^m \alpha_i < 1$.

Multi-Reflected BSDE

In general, we consider the following multi-reflected BSDE (ξ, X, f, R)

$$\begin{cases} Y_t^i = \xi^i + \int_t^T f_i(s, Y_s) ds + \sum_{j \neq i, j=1}^m \int_t^T r_{i,j}(s, Y_s) dK_s^j + K_T^i - K_t^i \\ \quad - \int_t^T \sum_{l=1}^d Z_s^{i,l} dB_s^l, \\ Y_t^i \geq X_t^i \quad \text{and} \quad K_t^i = \int_0^t \mathbf{1}_{\{Y_s^i = X_s^i\}} dK_s^i, \quad 1 \leq i \leq m. \end{cases}$$

where

- $\xi = (\xi_1, \dots, \xi_m)$ is an \mathcal{F}_T -measurable bounded random variable such that $\xi_i \geq X_T^i$, for each $1 \leq i \leq m$,
- the process $X = (X^1, \dots, X^m)$ is a continuous semimartingale,
- the map $f = (f_1, \dots, f_m) : \Omega \times [0, T] \times \mathbb{R}^m \rightarrow \mathbb{R}^m$ and the map $R = (r_{i,j})_{1 \leq i, j \leq m} : \Omega \times [0, T] \times \mathbb{R}^m \rightarrow \mathbb{M}_m(\mathbb{R})$ are both bounded measurable functions,
- $\mathbb{M}_m(\mathbb{R})$ denotes the class of $m \times m$ matrices with real entries.

Solution to Multi-Reflected BSDE

Definition

A pair (Y, K) of \mathbb{F} -progressively measurable and continuous processes is a *solution* to RBSDE (ξ, X, f, R) if there exists an \mathbb{F} -progressively measurable, square-integrable process $Z_t = (Z_t^{i,j})_{1 \leq i, j \leq m}$ such that:

- the following equality is satisfied, for all $1 \leq i \leq m$ and $0 \leq t \leq T$,

$$Y_t^i = \xi^i + \int_t^T f_i(s, Y_s) ds + \sum_{j \neq i, j=1}^m \int_t^T r_{i,j}(s, Y_s) dK_s^j + K_T^i - K_t^i - \int_t^T \sum_{l=1}^d Z_s^{i,l} dB_s^l,$$

- the inequality $Y_t^i \geq X_t^i$ holds for all $1 \leq i \leq m$ and $t \in [0, T]$,
- for every $1 \leq i \leq m$, the process K^i is continuous, non-decreasing, with $K_0^i = 0$ and $K_t^i = \int_0^t \mathbb{1}_{\{Y_s^i = X_s^i\}} dK_s^i$.

Assumptions

- (H₁) The \mathbb{R}^m -valued random variable ξ is \mathcal{F}_T -measurable and bounded.
- (H₂) For $1 \leq i \leq m$, the mapping $y \mapsto f_i(\omega, t, y) : \mathbb{R}^m \rightarrow \mathbb{R}$ is Lipschitz continuous, uniformly with respect to (ω, t) and $f_i(\cdot, \cdot, y)$ is an \mathbb{F} -predictable process bounded by β_i for all fixed $y \in \mathbb{R}^m$.
- (H₃) For $i \neq j$, the map $y \mapsto r_{i,j}(\omega, t, y) : \mathbb{R}^m \rightarrow \mathbb{R}$ is Lipschitz-continuous, uniformly with respect to (ω, t) and $r_{i,j}(\cdot, \cdot, y)$ is an \mathbb{F} -predictable process.
- (H₄) For $i \neq j$, there exists a constant $\lambda_{i,j} \geq 0$ such that $|r_{i,j}(\omega, t, y)| \leq \lambda_{i,j}$ for all (ω, t, y) . Setting $\Lambda = (\lambda_{i,j})_{1 \leq i, j \leq m}$ with $\lambda_{i,i} = 0$, we assume that the spectral radius $\rho(\Lambda) < 1$.
- (H₅) For $1 \leq i \leq m$, the process X^i satisfies

$$X_t^i = X_0^i + \int_0^t G_s^i ds + \int_0^t \sum_{l=1}^d H_s^{i,l} dB_s^l,$$

where G^i and $H^{i,l}$ are processes such that there exists a constant $L_i \geq 0$ such that $|G_t^i| \leq L_i$ for all (ω, t) , and $\int_0^T |H_s^{i,l}|^2 ds < \infty$. Finally, $\xi_i \geq X_T^i$ for $1 \leq i \leq m$.

Alternative Assumption

The following alternative assumption, weaker than (H_4) , will be sufficient:

(H'_4) For $i \neq j$, there exists a constant $\lambda_{i,j} \geq 0$ such that for all (ω, t, y)

$$|r_{i,j}(\omega, t, y)| \leq \lambda_{i,j}.$$

We set $\Lambda = (\lambda_{i,j})_{1 \leq i,j \leq d}$ with $\lambda_{i,i} = 0$ and we assume that $(I - \Lambda)^{-1}$ is a matrix with nonnegative entries. Moreover, there are constants $a_j > 0$, $1 \leq j \leq d$ and $0 < \delta < 1$ such that

$$\sum_{i \neq j, i=1}^m a_i |r_{i,j}(\omega, t, y)| \leq \sum_{i \neq j, i=1}^m a_i \lambda_{i,j} \leq \delta$$

for all $1 \leq j \leq d$ and $(\omega, t, y) \in \Omega \times [0, T] \times \mathbb{R}^m$.

An analysis of the proof of the main result in Ramasubramanian (2002) shows that if we replace (H_4) by the weaker condition (H'_4) then the assertion of the theorem is still valid.

Space of Solutions

Using the vector (a_1, \dots, a_m) in assumption (H'_4) , we introduce the space \mathcal{H}_X associated with the semimartingale X as the space of all \mathbb{F} -progressively measurable processes (Y, K) such that:

- the inequality $Y_t^i \geq X_t^i$ holds for all $1 \leq i \leq d$ and $t \in [0, T]$,
- for all $1 \leq i \leq m$, the process K^i is nondecreasing with $K_0^i = 0$,
- $\mathbb{E}_{\mathbb{P}} \left(\sum_{i=1}^m \int_0^T e^{\theta t} a_i |Y_t^i| dt \right) < \infty$,
- $\mathbb{E}_{\mathbb{P}} \left(\sum_{i=1}^m \int_0^T e^{\theta t} a_i \|K^i\|_{[t, T]} dt \right) < \infty$,

where θ is a constant and $\|K^i\|_{[t, T]}$ denotes the total variation of the process K^i over $[t, T]$, that is, $\|K^i\|_{[t, T]} = \int_t^T |dK_s^i|$. If we define the metric on \mathcal{H}_X

$$d((Y, K), (\hat{Y}, \hat{K})) := \mathbb{E}_{\mathbb{P}} \left(\sum_{i=1}^m \int_0^T e^{\theta t} a_i |Y_t^i - \hat{Y}_t^i| dt \right) \\ + \mathbb{E}_{\mathbb{P}} \left(\sum_{i=1}^m \int_0^T e^{\theta t} a_i \|K^i - \hat{K}^i\|_{[t, T]} dt \right)$$

then (\mathcal{H}_X, d) is a complete metric space.

Theorem of Ramasubramanian (2002)

Theorem (Ramasubramanian (2002))

Let the assumptions (H_1) – (H_4) hold. If $\xi_i \geq 0$ for $1 \leq i \leq m$ then there exists a unique solution $(Y, K) \in \mathcal{H}_0$ to the RBSDE $(\xi, 0, f, R)$

$$\left\{ \begin{array}{l} Y_t^i = \xi_i + \int_t^T f_i(s, Y_s) ds + \sum_{j \neq i, j=1}^m \int_t^T r_{i,j}(s, Y_s) dK_s^j + K_T^i - K_t^i \\ \quad - \int_t^T \sum_{l=1}^d Z_s^{i,l} dB_s^l, \\ Y_t^i \geq 0, \quad 1 \leq i \leq m. \end{array} \right.$$

Moreover,

$$0 \leq dK_t^i \leq ((I - \Lambda)^{-1} \beta)_i dt$$

for all $t \in [0, T]$ and $1 \leq i \leq m$, where $\beta = (\beta_1, \dots, \beta_m)$ satisfies (H_3) .

Multi-Reflected BSDE for Affine Stopping Game

Recall that the Multi-Reflected BSDE corresponding to the continuous-time affine stopping game reads: for all $t \in [0, T]$

$$\left\{ \begin{array}{l} Y_t^i = \xi_i - \sum_{j \neq i, j=1}^m r_{i,j} (K_T^j - K_t^j) - (K_T^i - K_t^i) - \int_t^T \sum_{l=1}^d Z_s^{i,l} dB_s^l, \\ Y_t^i \geq X_t^i, \\ \int_0^t \mathbb{1}_{\{Y_s^i > X_s^i\}} dK_s^i = 0, \quad 1 \leq i \leq m, \end{array} \right.$$

where $r_{i,j} = \frac{\alpha_i}{1-\alpha_j}$ for $i \neq j$, and $\alpha_i > 0$, $\sum_{i=1}^m \alpha_i < 1$. According to assumption (H_4') , we can set $\lambda_{i,j} = r_{i,j}$, for $i \neq j$, $1 \leq i, j \leq m$ and $\lambda_{i,i} = 0$. This means that

$$\Lambda = \begin{pmatrix} 0 & \frac{\alpha_1}{1-\alpha_2} & \cdots & \frac{\alpha_1}{1-\alpha_m} \\ \frac{\alpha_2}{1-\alpha_1} & 0 & \cdots & \frac{\alpha_2}{1-\alpha_m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\alpha_m}{1-\alpha_1} & \frac{\alpha_m}{1-\alpha_2} & \cdots & 0 \end{pmatrix}.$$

Value Process for Continuous-Time Multi-Person Game

Lemma

Assume that $\alpha_i > 0$ and $\sum_{i=1}^m \alpha_i < 1$. Then Λ satisfies condition (H'_4) .

The following result shows that the continuous-time multi-person stopping game has the unique value process.







Theorem

Under assumptions (H_1) and (H_5) , the Multi-Reflected BSDE associated with the multi-person game has a unique solution $(Y, K) \in \mathcal{H}_X$. Moreover,

$$0 \leq dK_t^i \leq ((I - \Lambda)^{-1} L)_i dt$$

for all $i = 1, \dots, m$ and $t \in [0, T]$, where $L = (L_1, \dots, L_m)$.

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