

Utility Maximization with Floor Constraint

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Oct. 26, 2013, Okinawa

Merton Problem

§1. Introduction

▷ Merton Prob.

▷ Floor/DD Const.

▷ Motivations

▷ RS Criterion

▷ Scale Invariance

▷ Plan

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

$$\sup_{(\pi, c)} \mathbb{E} \left[\int_0^T e^{-\rho t} U_1(c_t) dt + e^{-\rho T} U_2(X_T^{x, \pi, c}) \right],$$

where $X^{x, \pi, c}$ is the sol. to

$$dX_t = \sum_{i=1}^n \pi_t^i \frac{dS_t^i}{S_t^i} + \left(X_t - \sum_{i=1}^n \pi_t^i \right) \frac{dS_t^0}{S_t^0} - c_t dt,$$

$$X_0 = x \quad : \text{ budget constraint}$$

Here,

- x : initial wealth,
- $\pi := (\pi_t)_{t \in [0, T]}$: dynamic investment strategy,
- $c := (c_t)_{t \in [0, T]}$: consumption plan,
- $\rho (\geq 0)$: discount rate, U_1, U_2 : utility functions.

Floor/Drawdown Constraint

§1. Introduction

▷ Merton Prob.

▷ Floor/DD Const.

▷ Motivations

▷ RS Criterion

▷ Scale Invariance

▷ Plan

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

Merton Prob. subject to

■ floor constraint:

$$X_t^{x,\pi,c} \geq K_t \quad \text{for all } t \in [0, T],$$

◆ $(K_t)_{t \in [0, T]}$: floor process (given, adapted).

Floor/Drawdown Constraint

§1. Introduction

▷ Merton Prob.

▷ Floor/DD Const.

▷ Motivations

▷ RS Criterion

▷ Scale Invariance

▷ Plan

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

Merton Prob. subject to

■ floor constraint:

$$X_t^{x,\pi,c} \geq K_t \quad \text{for all } t \in [0, T],$$

◆ $(K_t)_{t \in [0, T]}$: floor process (given, adapted).

■ (generalized) drawdown constraint:

$$X_t \geq g(X_t, \bar{X}_t) \quad \text{for all } t \in [0, T],$$

where

◆ $\bar{X}_t := \sup_{s \in [0, t)} X_s,$

◆ $g(\cdot, \cdot) : \mathbb{R}_+^2 \rightarrow \mathbb{R}.$

Motivations

§1. Introduction

- ▷ Merton Prob.
- ▷ Floor/DD Const.

▷ Motivations

- ▷ RS Criterion
- ▷ Scale Invariance
- ▷ Plan

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

- Asset Management
 - ◆ portfolio insurance + optimization
 - ◆ protected drawdown-based performance + optimization

Motivations

§1. Introduction

- ▷ Merton Prob.
- ▷ Floor/DD Const.

▷ Motivations

- ▷ RS Criterion
- ▷ Scale Invariance
- ▷ Plan

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

- Asset Management
 - ◆ portfolio insurance + optimization
 - ◆ protected drawdown-based performance + optimization
- Mathematical
 - ◆ stochastic control with state constraint
 - e.g., Ishii and Loreti (2002): analysis of HJB eq. via viscosity approach
 - difficulty in constructing optimal control
 - ◆ El Karoui, Jeanblanc and Lacoste (2005), El Karoui and Meziou (2008): $U_1 \equiv 0$ (no consumption) + Complete market case.
 - probabilistic approach,
 - optimality from stochastic order relation.

Long-term risk-sensitive criterion

§1. Introduction

- ▷ Merton Prob.
- ▷ Floor/DD Const.
- ▷ Motivations

▷ RS Criterion

- ▷ Scale Invariance
- ▷ Plan

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

- Simplified long-term asymptotic criterion:

$$\sup_{\pi} \overline{\lim}_{T \rightarrow \infty} \frac{1}{T} \log \mathbb{E}U(X_T^{x,\pi}) \quad (\log x = -\log(-x) \text{ if } x < 0)$$

- Long-term risk-sensitive criterion:

$$\text{(RSPO)} \quad \sup_{\pi} \overline{\lim}_{T \rightarrow \infty} C_T^{x,\pi}, \quad C_T^{x,\pi} := \frac{1}{\gamma T} \log \mathbb{E}(X_T^{x,\pi})^{\gamma}.$$

Long-term risk-sensitive criterion

§1. Introduction

- ▷ Merton Prob.
- ▷ Floor/DD Const.
- ▷ Motivations
- ▷ RS Criterion
- ▷ Scale Invariance
- ▷ Plan

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

- Simplified long-term asymptotic criterion:

$$\sup_{\pi} \overline{\lim}_{T \rightarrow \infty} \frac{1}{T} \log \mathbb{E}U(X_T^{x,\pi}) \quad (\log x = -\log(-x) \text{ if } x < 0)$$

- Long-term risk-sensitive criterion:

$$\text{(RSPO)} \quad \sup_{\pi} \overline{\lim}_{T \rightarrow \infty} C_T^{x,\pi}, \quad C_T^{x,\pi} := \frac{1}{\gamma T} \log \mathbb{E}(X_T^{x,\pi})^{\gamma}.$$

“Risk-sensitized” modification of

$$\sup_{\pi} \overline{\lim}_{T \rightarrow \infty} \mathbb{E}G_T^{x,\pi}, \quad G_T^{x,\pi} := \frac{1}{T} \log X_T^{x,\pi},$$

recalling cumulant expansion:

$$C_T^{x,\pi} = \frac{1}{\gamma T} \log \mathbb{E}e^{\gamma T G_T^{x,\pi}} = \mathbb{E}G_T^{x,\pi} + \frac{\gamma}{2} \text{var}[\sqrt{T} G_T^{x,\pi}] + O(\gamma^2).$$

Scale Invariance

§1. Introduction

- ▷ Merton Prob.
- ▷ Floor/DD Const.
- ▷ Motivations
- ▷ RS Criterion

▷ Scale Invariance

- ▷ Plan

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

- The scale-invariant property,

$$\overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E}(xX)^\gamma = \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E}X^\gamma, \quad \forall x \in \mathbb{R}_{++},$$

$$\overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E}(NX)^\gamma = \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E}(X)^\gamma \quad \forall N(> 0): \text{bdd r.v.},$$

disregarding a bounded-factor.

- The translation-invariant property,

$$\overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E}e^{\gamma(\log x + \log X)} = \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E}e^{\gamma \log X} \quad \forall \log x \in \mathbb{R}.$$

§1. Introduction

- ▷ Merton Prob.
- ▷ Floor/DD Const.
- ▷ Motivations
- ▷ RS Criterion
- ▷ Scale Invariance

▷ Plan

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

§1 Introduction

§2 RSPO with floor constraint

- ◆ PI techniques + optimization

§3 RSPO with drawdown constraint

- ◆ Azéma-Yor technique works for *discounted* problem

§4 A dual approach to Merton problem with floor constraint

- ◆ To overcome RSPO's drawbacks..
- ◆ To treat consumption maximization via a systematic approach..

Risk-Sensitive Optimal Portfolio with Floor

§1. Introduction

§2. RSPO with Floor

▷ Problem

- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ Baseline Prob.
- ▷ BS Model
- ▷ Lin. Gauss Factor
- ▷ Wishart factor
- ▷ RSPO with Floor
- ▷ Key Observation
- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ OBPI
- ▷ DFP
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

$$\sup_{\pi} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} \left(X_T^{x, \pi} \right)^{\gamma} \quad \text{s.t.} \quad X_t^{x, \pi} \geq K_t \quad \text{for all } t \geq 0$$

- to reduce computational difficulties.
- to consider applications of other PI techniques.

RSPO: Review

§1. Introduction

§2. RSPO with Floor

▷ Problem

▷ RSPO: Review

▷ Market Model

▷ SF Investor

▷ Baseline Prob.

▷ BS Model

▷ Lin. Gauss Factor

▷ Wishart factor

▷ RSPO with Floor

▷ Key Observation

▷ CPPI (1)

▷ CPPI (2)

▷ OBPI

▷ DFP

▷ OBPI-G

▷ Example

§3. RSPO with DDC

§4. A Dual Approach

- Without Floor: Bielecki and Pliska (1999), Fleming and Sheu (2000, 2002), Kuroda and Nagai (2002), Nagai (2003), Davis and Lleo (2008), Hata and S (2013), etc.
- With Floor: S (2012), Cherny and Obloj (2013).
- Large Deviations Controls:
(Heuristics: Bielecki and Pliska, Stutzer).
Pham (2003a-b), Hata and S (2005, 2010), Hata, Nagai and Sheu (2010), Nagai (2012a-b), Knispel (2012), etc.

Market model

§1. Introduction

§2. RSPO with Floor

▷ Problem

▷ RSPO: Review

▷ Market Model

▷ SF Investor

▷ Baseline Prob.

▷ BS Model

▷ Lin. Gauss Factor

▷ Wishart factor

▷ RSPO with Floor

▷ Key Observation

▷ CPPI (1)

▷ CPPI (2)

▷ OBPI

▷ DFP

▷ OBPI-G

▷ Example

§3. RSPO with DDC

§4. A Dual Approach

- $S^0 := (S_t^0)_{t \geq 0}$: bank account process, nondecreasing adapted s.t. $S_0^0 \equiv 1$.
- $S := (S^1, \dots, S^n)^\top$: price process of n -risky assets,

$$dS_t^i = S_{t-}^i \left(dR_t^i + \frac{dS_t^0}{S_t^0} \right), \quad S_0^i \in \mathbb{R},$$

with the excess return, $R := (R^1, \dots, R^n)^\top$, a given n -dim. semimartingale s.t. $R_0 \equiv 0$.

$$S_t^i = S_0^i S_t^0 \mathcal{E}(R^i)_t, \quad \text{where}$$

$$\mathcal{E}(R^i)_t := \exp \left(R_t^i - \frac{1}{2} [R^i]_t^c \right) \prod_{s \leq t} (1 + \Delta R_s^i) e^{-\Delta R_s^i}.$$

Self-financing Investor

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model

▷ SF Investor

- ▷ Baseline Prob.
- ▷ BS Model
- ▷ Lin. Gauss Factor
- ▷ Wishart factor
- ▷ RSPO with Floor
- ▷ Key Observation
- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ OBPI
- ▷ DFP
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

$$dX_t^{x,\pi} = X_{t-}^{x,\pi} \left[\sum_{i=1}^n \pi_t^i \frac{dS_t^i}{S_{t-}^i} + \left(1 - \sum_{i=1}^n \pi_t^i \right) \frac{dS_t^0}{S_t^0} \right]$$
$$X_0^{x,\pi} = x.$$

- $x \in \mathbb{R}_{>0}$: initial wealth,
- $\pi := (\pi_t)_{t \geq 0}$, $\pi_t := (\pi_t^1, \dots, \pi_t^n)^\top$: dynamic investment policy.

$$dX_t^{x,\pi} = X_{t-}^{x,\pi} \left(\pi_t^\top dR_t + \frac{dS_t^0}{S_t^0} \right), \quad X_0^{x,\pi} = x,$$
$$X_t^{x,\pi} = x S_t^0 \mathcal{E} \left(\int_t \pi^\top dR \right).$$

Baseline Problem: RSPO without Floor.

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ **Baseline Prob.**
- ▷ BS Model
- ▷ Lin. Gauss Factor
- ▷ Wishart factor
- ▷ RSPO with Floor
- ▷ Key Observation
- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ OBPI
- ▷ DFP
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

First, consider

$$(RSPO) \quad \bar{\Gamma} := \sup_{\pi \in \mathcal{A}_0} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} \left(X_T^{x, \pi} \right)^\gamma$$

without floor, assuming

Hypothesis:

- (1) $\mathcal{A}_0 \ni 0$, and (predictably) convex,
- (2) (RSPO) has an x -independent sol., that is,
 $\exists \hat{\pi} \in \mathcal{A}_0$ so that $\hat{X} := X^{1, \hat{\pi}}$ satisfies

$$\begin{aligned} \bar{\Gamma} &:= \sup_{\pi \in \mathcal{A}_0} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} \left(X_T^{x, \pi} \right)^\gamma = \sup_{\pi \in \mathcal{A}_0} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} \left(X_T^{1, \pi} \right)^\gamma \\ &= \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} \left(\hat{X}_T \right)^\gamma. \end{aligned}$$

Ex. 1: Black-Scholes-type Model

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ Baseline Prob.

▷ BS Model

- ▷ Lin. Gauss Factor
- ▷ Wishart factor
- ▷ RSPO with Floor
- ▷ Key Observation
- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ OBPI
- ▷ DFP
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

$$S^0 \equiv 1,$$

$$dS_t = \text{diag}(S_t) (\mu dt + \sigma dw_t),$$

- w : n -dim. BM,
- $\mu \in \mathbb{R}^n$, $\sigma \in \mathbb{R}^{n \times n}$.
- S is a multi-dimensional GBM.
- $\mathcal{A} := \mathcal{L}_{2,n}$, where

$$\mathcal{L}_{2,n} := \left\{ (\pi_t)_{t \geq 0} \mid \begin{array}{l} n\text{-dim. prog. m'ble,} \\ \int_0^T |\pi_t|^2 dt < \infty \text{ for } \forall T > 0 \end{array} \right\}.$$

- $\hat{\pi}(\gamma) \equiv \frac{1}{1-\gamma} (\sigma \sigma^\top)^{-1} \mu.$

Ex. 2: Linear-Gaussian Factor Model

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ Baseline Prob.
- ▷ BS Model

▷ Lin. Gauss Factor

- ▷ Wishart factor
- ▷ RSPO with Floor
- ▷ Key Observation
- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ OBPI
- ▷ DFP
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

$$S^0 \equiv 1,$$

$$dS_t = \text{diag}(S_t) \{ \mu(Y_t) dt + \Sigma dW_t \},$$

$$dY_t = (b_0 + B_1 Y_t) dt + \Lambda dW_t, \quad Y_0 \in \mathbb{R}^m,$$

- W : $m + n$ -dim. BM.
- $\Sigma \in \mathbb{R}^{n \times (m+n)}$, $\Lambda \in \mathbb{R}^{m \times (m+n)}$, $b_0 \in \mathbb{R}^m$, $B_1 \in \mathbb{R}^{m \times m}$.
- $\mu(y) := m_0 + M_1 y$, $m_0 \in \mathbb{R}^n$, $M_1 \in \mathbb{R}^{n \times m}$.
- $\mathcal{A} := \mathcal{L}_{2,n}$.
- Long-term RSPO = LEQG with infinite horizon.
- $\hat{\pi}_t^{(\gamma)} := \frac{1}{1-\gamma} (\Sigma \Sigma^\top)^{-1} \left\{ \mu(Y_t) + \gamma (\Sigma \Lambda^\top) (\hat{q} + \hat{Q} Y_t) \right\}$.

Ex. 3: Wishart-Autoregressive Factor Model

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ Baseline Prob.
- ▷ BS Model
- ▷ Lin. Gauss Factor

▷ Wishart factor

- ▷ RSPO with Floor
- ▷ Key Observation
- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ OBPI
- ▷ DFP
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

$$S^0 \equiv 1,$$

$$dS_t = \text{diag}(S_t) \left\{ \mu(Y_t)dt + \Sigma \sqrt{Y_t} dw_t \right\},$$

$$dY_t = \left(LL^\top + KY_t + Y_t K^\top \right) dt + \sqrt{Y_t} dB_t \Lambda^\top + \Lambda dB_t^\top \sqrt{Y_t}.$$

- (B, z) is a $(d \times d + d)$ -dim. BM.
 $w_t := B_t \rho + \sqrt{1 - |\rho|^2} z_t$: d -dim. BM. $\rho \in \mathbb{R}^d$ s.t. $|\rho| \leq 1$.
- $Y_0 \in \mathbb{S}_{++}^d := \{M \in \mathbb{S}^d; M > 0\}$.
- $\Sigma \in \mathbb{R}^{n \times d}$, $L, K, \Lambda \in \mathbb{R}^{d \times d}$.
- $\mu(y) := (\Sigma y \Sigma^\top) \lambda$, $\lambda \in \mathbb{R}^n$.
- $\mathcal{A} := \{\pi \in \mathcal{L}_{2,n}; \text{bounded}\}$.
- $\hat{\pi}^{(\gamma)} := \frac{1}{1 - \gamma} (\Sigma \Sigma^\top)^{-1} \left(\lambda + 2\gamma \hat{Q} \Sigma \Lambda \rho \right)$.

Upgraded Problem: RSPO with Floor

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ Baseline Prob.
- ▷ BS Model
- ▷ Lin. Gauss Factor
- ▷ Wishart factor
- ▷ **RSPO with Floor**
- ▷ Key Observation
- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ OBPI
- ▷ DFP
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

Next, admitting Hypothesis, consider

$$\bar{\Gamma}^K := \sup_{\pi \in \mathcal{A}^K(x)} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} (X_T^{x,\pi})^\gamma$$

where

- $\mathcal{A}^K(x) := \{\pi \in \mathcal{A}_0; X_t^{x,\pi} \geq K_t \text{ for all } t \geq 0\}$,
- $K := (K_t)_{t \geq 0}$: given nonnegative adapted floor.

Key Observation

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ Baseline Prob.
- ▷ BS Model
- ▷ Lin. Gauss Factor
- ▷ Wishart factor
- ▷ RSPO with Floor

▷ Key Observation

- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ OBPI
- ▷ DFP
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

Find some $\check{\pi} \in \mathcal{A}^K(x)$ so that

$$\check{X} := X^{x, \check{\pi}} \geq \epsilon \hat{X} \quad \text{with some } \epsilon > 0.$$

Key Observation

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ Baseline Prob.
- ▷ BS Model
- ▷ Lin. Gauss Factor
- ▷ Wishart factor
- ▷ RSPO with Floor

▷ Key Observation

- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ OBPI
- ▷ DFP
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

Find some $\check{\pi} \in \mathcal{A}^K(x)$ so that

$$\check{X} := X^{x, \check{\pi}} \geq \epsilon \hat{X} \quad \text{with some } \epsilon > 0.$$

Then,

$$\overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} (\check{X}_T)^\gamma \geq \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} (\hat{X}_T)^\gamma =: \bar{\Gamma},$$

which implies

$$\bar{\Gamma}^K = \bar{\Gamma} = \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} (\check{X}_T)^\gamma,$$

the optimality of $\check{\pi} \in \mathcal{A}^K(x) (\subset \mathcal{A}_0)$ for RSPO with floor.

Generalized CPPI (1)

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ Baseline Prob.
- ▷ BS Model
- ▷ Lin. Gauss Factor
- ▷ Wishart factor
- ▷ RSPO with Floor
- ▷ Key Observation

▷ CPPI (1)

- ▷ CPPI (2)
- ▷ OBPI
- ▷ DFP
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

Let

- $\bar{K} := (\bar{K}_t)_{t \geq 0}$: superhedging of the floor $K := (K_t)_{t \geq 0}$,
- $x > \bar{K}_0$.

$$\begin{aligned}\hat{X}^{(\text{CPPI-1})} &:= (x - \bar{K}_0)\hat{X} + \bar{K} \\ &\geq (x - \bar{K}_0)\hat{X} + K\end{aligned}$$

is an RSOP with floor.

Generalized CPPI (2)

Let $x > K_0$ and K/S^0 be nonincreasing. $\hat{X}^{(\text{CPPI-2})}$, the sol. to SDE,

$$dY_t = (Y_{t-} - K_{t-}) \sum_{i=1}^n \hat{\pi}_t^i \frac{dS_t^i}{S_{t-}^i} + \left\{ \left(1 - \sum_{i=1}^n \hat{\pi}_t^i \right) (Y_{t-} - K_{t-}) + K_{t-} \right\} \frac{dS_t^0}{S_t^0},$$
$$Y_0 = x,$$

which has the expression,

$$\hat{X}_t^{(\text{CPPI-2})} = \left\{ (x - K_0) - \int_0^t \frac{S_u^0}{\hat{X}_u} d \left(\frac{K_u}{S_u^0} \right) \right\} \hat{X}_t + K_t$$
$$\geq (x - K_0) \hat{X}_t + K_t,$$

defines an RSOP with floor.

§1. Introduction

§2. RSPO with Floor

▷ Problem

▷ RSPO: Review

▷ Market Model

▷ SF Investor

▷ Baseline Prob.

▷ BS Model

▷ Lin. Gauss Factor

▷ Wishart factor

▷ RSPO with Floor

▷ Key Observation

▷ CPPI (1)

▷ CPPI (2)

▷ OBPI

▷ DFP

▷ OBPI-G

▷ Example

§3. RSPO with DDC

§4. A Dual Approach

American Perpetual OBPI

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ Baseline Prob.
- ▷ BS Model
- ▷ Lin. Gauss Factor
- ▷ Wishart factor
- ▷ RSPO with Floor
- ▷ Key Observation
- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ **OBPI**
- ▷ DFP
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

In a complete market, American perpetual:

$$\begin{aligned} V_{\text{OBPI}}(t, \lambda) &:= \sup_{t \leq \tau \leq \infty} \tilde{\mathbb{E}} \left[\frac{S_t^0}{S_\tau^0} \left(K_\tau \vee \lambda \hat{X}_t \right) \middle| \tilde{\mathcal{F}}_t \right] \\ &:= \sup_{t \leq \tau \leq \infty} \tilde{\mathbb{E}} \left[\frac{S_t^0}{S_\tau^0} \left(K_\tau - \lambda \hat{X}_t \right)^+ \middle| \tilde{\mathcal{F}}_t \right] + \lambda \hat{X}_t. \end{aligned}$$

Superhedging portfolio \check{X}^{OBPI} , which satisfies

$$\check{X}_t^{\text{OBPI}} \geq V_{\text{OBPI}} \left(t, \hat{\lambda}(x) \right) \geq K_t \vee \hat{\lambda}(x) \hat{X}_t$$

and $\check{X}_0^{\text{OBPI}} = x$, is an RSOP with floor.

Dynamic Fund Protection

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ Baseline Prob.
- ▷ BS Model
- ▷ Lin. Gauss Factor
- ▷ Wishart factor
- ▷ RSPO with Floor
- ▷ Key Observation
- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ OBPI
- ▷ **DFP**
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

Russian-type option (American lookback perpetual):

$$V_{\text{DFP}}(t, \lambda) := \sup_{t \leq \tau \leq \infty} \tilde{\mathbb{E}} \left[\frac{S_t^0}{S_\tau^0} \left\{ \lambda \vee \max_{s \in [0, \tau]} \left(\frac{K_s}{\hat{X}_s} \right) \right\} \hat{X}_\tau \mid \tilde{\mathcal{F}}_t \right].$$

Superhedging portfolio \check{X}^{DFP} , which satisfies

$$\check{X}_t^{\text{DFP}} \geq V_{\text{DFP}}(t, \hat{\lambda}(x)) \geq \hat{\lambda}(x) \hat{X}_t \vee K_t$$

and $\check{X}_0^{\text{DFP}} = x$, is an RSOP with floor.

Another OBPI with “Gittins-type” index

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ Baseline Prob.
- ▷ BS Model
- ▷ Lin. Gauss Factor
- ▷ Wishart factor
- ▷ RSPO with Floor
- ▷ Key Observation
- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ OBPI
- ▷ DFP
- ▷ **OBPI-G**
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

Apply EJM (2005) and EM (2006, 2008): Let

$$G_t := \sup_{u \in [0, t)} L_u, \quad L_t := \sup \left\{ \lambda \in \mathbb{R}_{>0}; V_{\text{OBPI}}(t, \lambda) = K_t \vee \lambda \hat{X}_t \right\}.$$

Then,

$$\check{X}_t^{\text{OBPI-G}} := V_{\text{OBPI}} \left(t, \hat{\lambda}(x) \vee G_t \right)$$

is an self-financing wealth process.

It defines an RSOP with floor, since

$$\begin{aligned} \check{X}_t^{\text{OBPI-G}} &\geq K_t \vee (\hat{\lambda}(x) \vee G_t) \hat{X}_t \\ &\geq K_t \vee \hat{\lambda}(x) \hat{X}_t \end{aligned}$$

and $\hat{X}_0^{\text{OBPI-G}} = x$.

Example: Constant market price of risk, uncorrelated interest rates, and GBM floor

§1. Introduction

§2. RSPO with Floor

- ▷ Problem
- ▷ RSPO: Review
- ▷ Market Model
- ▷ SF Investor
- ▷ Baseline Prob.
- ▷ BS Model
- ▷ Lin. Gauss Factor
- ▷ Wishart factor
- ▷ RSPO with Floor
- ▷ Key Observation
- ▷ CPPI (1)
- ▷ CPPI (2)
- ▷ OBPI
- ▷ DFP
- ▷ OBPI-G
- ▷ Example

§3. RSPO with DDC

§4. A Dual Approach

Explicit representations are obtained for OBPI/DFP-based methods in the following situation:

■ Market model:

$$\begin{aligned}dS_t^0 &= r_t S_t^0 dt, \\dS_t &= \text{diag}(S_t) (\mu_t dt + \sigma_t dw_t)\end{aligned}$$

on $(\Omega, \mathcal{F}, \mathbb{P}, (\mathcal{F}_t)_{t \geq 0})$ with n -dim. BM w , where

- ◆ σ : \mathcal{F}_t -adapted,
- ◆ $\mu_t = r_t \mathbf{1} + \sigma_t \theta$ with the constant market price of risk $\theta \in \mathbb{R}^n$,
- ◆ $r := (r_t)_{t \geq 0}$: independent of w .

■ Floor:

$$K_t = K_0 S_t^0 \times \text{GBM}(w_t).$$

Risk-Sensitive Optimal Portfolio with Drawdown Constraint

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

$$\sup_{\pi} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E}(X_T^{x,\pi})^\gamma$$

subject to

$$X_t^{x,\pi} \geq f \left(\sup_{s \in [0,t)} X_s^{x,\pi} \right) \quad \text{for all } t \geq 0.$$

■ $0 < f(x) < x.$

(Non-)Constant Constraint on Relative Drawdown

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ **RDD**

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

- Relative drawdown:

$$\text{RDD}_t := \frac{\bar{X}_t - X_t}{\bar{X}_t}, \quad \text{where} \quad \bar{X}_t := \sup_{s \in [0, t]} X_s,$$

a measure of “riskiness” of fund wealth.

- DD constraint:

$$X_t \geq f(\bar{X}_t) \quad \Leftrightarrow \quad \text{RDD}_t \leq 1 - \frac{f(\bar{X}_t)}{\bar{X}_t}.$$

- Example: $f(x) := x \sum_{i=1}^m \alpha_i 1_{[K_{i-1}, K_i)}(x)$ with $x_0 = K_0 < \dots < K_{m-1} < K_m = +\infty$ and $\alpha_i \in [0, 1)$ ($i \in \{1, \dots, m\}$). Piecewise const. constraint on RDD:

$$\text{RDD}_t \leq 1 - \alpha_i 1_{[K_{i-1}, K_i)}(\bar{X}_t) \quad \text{for all } t \geq 0.$$

From a Report by Credit Suisse on Hedge Fund Indexes

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

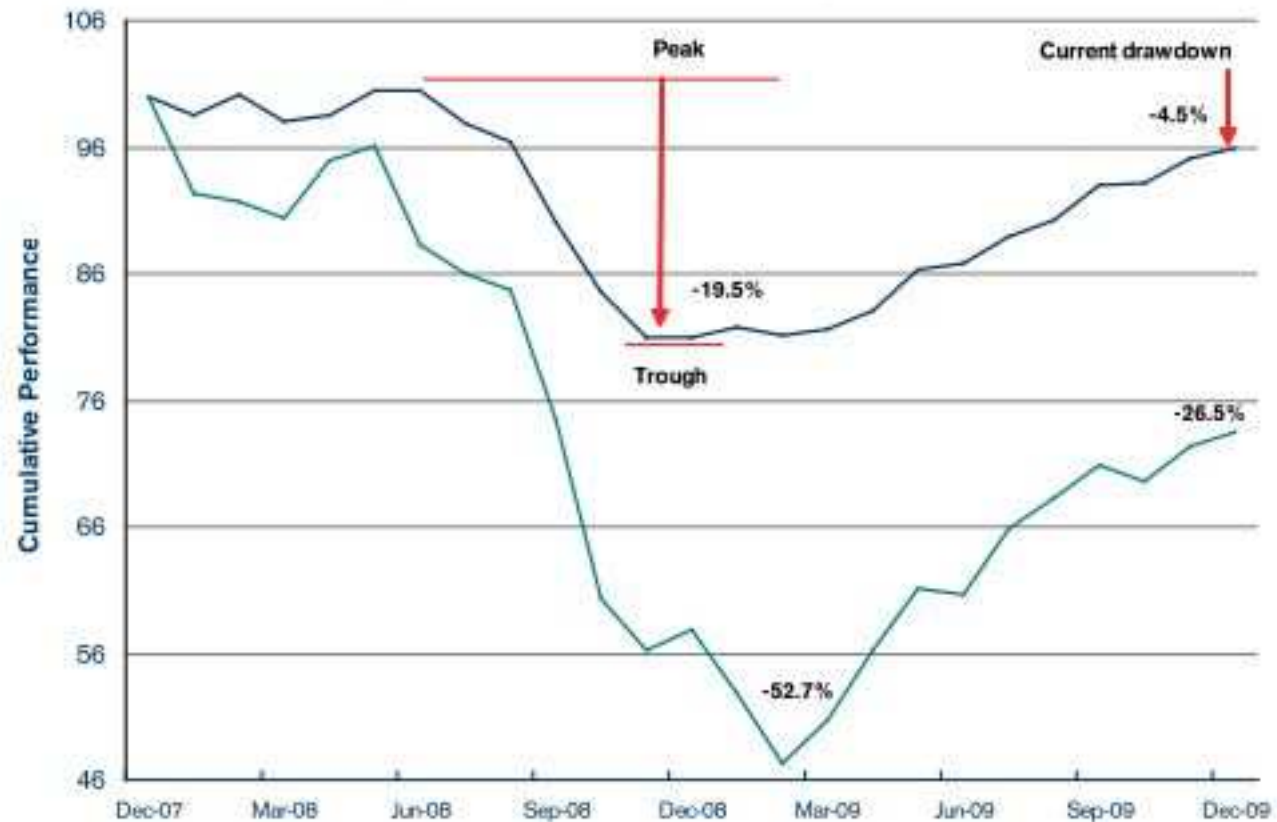
▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

Figure 3: Drawdown Analysis, Credit Suisse/Tremont Hedge Fund Index and MSCI World Index (data as of December 31, 2009)



Source: Credit Suisse / Tremont Hedge Fund Index, Bloomberg. Data based on a sample set of funds reflective of the Credit Suisse / Tremont Hedge Fund index as of December 31, 2009. Credit Suisse has not sought to independently verify information obtained from public and third party sources and makes no representations or warranties as to accuracy, completeness or reliability of such information.

Performance Comparisons

- §1. Introduction
- §2. RSPO with Floor
- §3. RSPO with DDC
 - ▷ Problem
 - ▷ RDD
 - ▷ Drawdown Analysis
 - ▷ Performances
 - ▷ CAL/STE/BUR
 - ▷ Lower-bdd Ratios
 - ▷ Related Works
 - ▷ RSPO
 - ▷ Baseline Prob.
 - ▷ Upgraded Prob.
 - ▷ DD equation
 - ▷ AY Process
 - ▷ Plotting AY
 - ▷ Result
 - ▷ Variant
- §4. A Dual Approach

Performance Comparison With Other Strategies

The tables below allows you to compare the key performance statistics of one Strategy with another, and can be sorted by column headings:

Strategy Name	Av Annual Return	Total Profit	Monthly CROR	Av Monthly Profit	Sharpe Ratio	Strike Rate Ratio	Profit Factor	Winning Months
Happy Days	45.3%	\$0	3.1%	\$0	1.66	1.57	3.29	73.1%
NASDAQ 100 Leveraged	67.2%	\$0	4.8%	\$0	1.46	2.05	6.12	76.5%
Russell 2000 Leveraged	29.6%	\$0	2.4%	\$0	1.01	1.48	1.94	58.1%
S&P 500 Leveraged	70.3%	\$0	4.6%	\$0	1.41	1.58	3.39	74.4%
S&P 500 Non-Leveraged	24.0%	\$0	2.1%	\$0	2.19	1.98	8.12	82.1%

Strategy Name	Maximum Drawdown	Longest Drawdown	Standard Deviation	Largest Monthly Gain	Largest Monthly Loss	Av % Return/Trade	Av Gain/Win Trade	Av Loss/Loss Trade
Happy Days	-6.1%	2.0	6.0%	25.5%	-6.2%	1.7%	3.1%	-2.9%
NASDAQ 100 Leveraged	-14.5%	3.0	12.8%	91.0%	-24.9%	10.2%	16.9%	-11.4%
Russell 2000 Leveraged	-27.2%	2.0	11.0%	30.4%	-16.1%	3.1%	13.0%	-6.4%
S&P 500 Leveraged	-26.4%	2.0	12.2%	44.2%	-26.4%	4.9%	13.0%	-8.5%
S&P 500 Non-Leveraged	-6.5%	2.0	2.8%	7.1%	-6.5%	3.2%	4.1%	-3.3%

Strategy Name	Maximum Con Wins	Maximum Con Losses	Drawdown Ratio	Av Drawdown Length	Av Wins/Year	Largest Win Trade	Largest Loss Trade	Number of Components
Happy Days	23	5	2.36	1.2	148.2	31.4%	-35.9%	5
NASDAQ 100 Leveraged	23	5	3.89	1.6	45.9	434.4%	-72.1%	5
Russell 2000 Leveraged	4	5	2.73	1.6	19.2	93.4%	-17.7%	4
S&P 500 Leveraged	7	4	3.59	1.3	30.6	92.2%	-123.0%	5
S&P 500 Non-Leveraged	23	4	3.00	1.2	48.6	22.1%	-13.8%	4

(http://www.pro-trading-profits.com/risk_reduction/compare.asp)

Drawdown-based Performance Measures

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

■ Calmar Ratio:

$$\text{CAL}_T := \frac{R_T}{\text{MDD}_T} := \frac{R_T}{\max_{t \in [0, T]} \text{DD}_t},$$

■ Sterling Ratio:

$$\text{STE}_T := \frac{R_T}{\text{ADD}_T} := \frac{R_T}{\frac{1}{T} \int_0^T \text{DD}_t dt},$$

■ Burke Ratio:

$$\text{BUR}_T := \frac{R_T}{\sqrt{\int_0^T \text{DD}_t^2 dt}},$$

where $(R_t)_{t \geq 0}$ is the cumulative (excess) return and

$$\text{DD}_t := \bar{R}_t - R_t, \quad \bar{R}_t := \bar{R}_0 \vee \max_{s \in [0, t]} R_s.$$

Lower-bounds of CAL/STE/BUR Ratios

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

■ Let $R_t := \frac{X_t - X_0}{X_0}$.

$$X_t \geq \frac{\beta}{1+\beta} \bar{X}_t + \frac{X_0}{1+\beta} \quad \forall t \geq 0$$

$$\Rightarrow \text{CAL}_T \geq \beta, \text{STE}_T \geq \beta, \text{BUR}_T \geq \frac{\beta}{\sqrt{T}}, \quad \forall T \geq 0.$$

■ Let $R_t := \log \frac{X_t}{X_0}$.

$$X_t \geq X_0^{\frac{1}{1+\beta}} \bar{X}_t^{\frac{\beta}{1+\beta}} \quad \forall t \geq 0$$

$$\Rightarrow \text{CAL}_T \geq \beta, \text{STE}_T \geq \beta, \text{BUR}_T \geq \frac{\beta}{\sqrt{T}}, \quad \forall T \geq 0.$$

Related Works

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

- ▷ Problem
- ▷ RDD
- ▷ Drawdown Analysis
- ▷ Performances
- ▷ CAL/STE/BUR
- ▷ Lower-bdd Ratios

▷ Related Works

- ▷ RSPO
- ▷ Baseline Prob.
- ▷ Upgraded Prob.
- ▷ DD equation
- ▷ AY Process
- ▷ Plotting AY
- ▷ Result
- ▷ Variant

§4. A Dual Approach

- $f(x) = \alpha x$ ($0 < \alpha < 1$):
 - ◆ Grossman and Zhou (1993), Cvitanic and Karatzas (1995), S (2006)
- Nonlinear f :
 - ◆ Cherney and Obloj (2013), S (2013).
- Consumption optimization with BS model under linear DD const:
 - ◆ Roche(2006), Rogers(2006), Elie and Touzi (2008), Elie (2008).

Long-term RSPO with Drawdown Constraint

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

- ▷ Problem
- ▷ RDD
- ▷ Drawdown Analysis
- ▷ Performances
- ▷ CAL/STE/BUR
- ▷ Lower-bdd Ratios
- ▷ Related Works

▷ RSPO

- ▷ Baseline Prob.
- ▷ Upgraded Prob.
- ▷ DD equation
- ▷ AY Process
- ▷ Plotting AY
- ▷ Result
- ▷ Variant

§4. A Dual Approach

$$\Gamma_\alpha(x, \gamma) := \sup_{\pi \in \mathcal{A}_\alpha(x)} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E}(X_T^{x, \pi})^\gamma,$$

where **discounted wealth** is governed by

$$\frac{dX_t^{x, \pi}}{X_t^{x, \pi}} = \sum_{i=1}^n \pi_t^i \frac{dS_t^i}{S_t^i}, \quad X_0^{x, \pi} = x,$$

with continuous S^i , and $\mathcal{A}_\alpha(x)$ is a suitable subset of

$$\left\{ \pi; X_t^{x, \pi} > f_\alpha \left(M_0 \vee \max_{s \in [0, t]} X_s^{x, \pi} \right) \text{ for all } t \geq 0 \right\}.$$

Long-term RSPO with Drawdown Constraint

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

$$\Gamma_\alpha(x, \gamma) := \sup_{\pi \in \mathcal{A}_\alpha(x)} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E}(X_T^{x, \pi})^\gamma,$$

where **discounted wealth** is governed by

$$\frac{dX_t^{x, \pi}}{X_t^{x, \pi}} = \sum_{i=1}^n \pi_t^i \frac{dS_t^i}{S_t^i}, \quad X_0^{x, \pi} = x,$$

with continuous S^i , and $\mathcal{A}_\alpha(x)$ is a suitable subset of

$$\left\{ \pi; X_t^{x, \pi} > f_\alpha \left(M_0 \vee \max_{s \in [0, t]} X_s^{x, \pi} \right) \text{ for all } t \geq 0 \right\}.$$

- $x \geq M_0$ with $\exists M_0 > 0$, the current running maximum,
- $f_\alpha : [M_0, \infty) \rightarrow \mathbb{R}_{>0}$ satisfies, with $\exists \alpha \in (0, 1)$ and $\exists \beta < 1$, $0 < \exists \delta < f_\alpha(x) < x$ for $\forall x \geq M_0$ and $f_\alpha(x) = \alpha x + O(x^\beta)$ as $x \rightarrow \infty$.

Baseline Standard Problem: RSPO without Floor.

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ **Baseline Prob.**

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

First, consider

$$(RSPO) \quad \Lambda(\gamma) := \sup_{\pi \in \mathcal{A}} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} (X_T^{x, \pi})^\gamma$$

without floor, where \mathcal{A} is (predictably) convex, $0 \in \mathcal{A}$.

Baseline Standard Problem: RSPO without Floor.

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ **Baseline Prob.**

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

First, consider

$$(RSPO) \quad \Lambda(\gamma) := \sup_{\pi \in \mathcal{A}} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} \left(X_T^{x, \pi} \right)^\gamma$$

without floor, where \mathcal{A} is (predictably) convex, $0 \in \mathcal{A}$.

Suppose (RSPO) has an x -independent sol., that is,

$\exists \hat{\pi}(\gamma) \in \mathcal{A}$ so that $\hat{X} := X^{1, \hat{\pi}(\gamma)}$ satisfies

$$\begin{aligned} \Lambda(\gamma) &:= \sup_{\pi \in \mathcal{A}} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} \left(X_T^{x, \pi} \right)^\gamma = \sup_{\pi \in \mathcal{A}} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} \left(X_T^{1, \pi} \right)^\gamma \\ &= \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E} \left(\hat{X}_T \right)^\gamma. \end{aligned}$$

Moreover, suppose $\Lambda(\cdot)$ is continuous on some interval.

Upgraded Problem: RSPO with GDD Constraint

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ **Upgraded Prob.**

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

Next, using the solution to Baseline problem (without floor), we construct a solution to

$$\Gamma_\alpha(x, \gamma) := \sup_{\pi \in \mathcal{A}_\alpha(x)} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\gamma T} \log \mathbb{E}(X_T^{x, \pi})^\gamma,$$

where $\mathcal{A}_\alpha(x)$ is a suitable subset of

$$\left\{ \pi; X_t^{x, \pi} > f_\alpha \left(\max_{s \in [0, t]} X_s^{x, \pi} \right) \text{ for all } t \geq 0 \right\}.$$

Drawdown Equation

For a given $X > 0$, consider SDE,

$$(DD) \quad \frac{dY_t}{Y_t - f_\alpha(\bar{Y}_t)} = \frac{dX_t}{X_t}, \quad \text{where} \quad \bar{Y}_t := \sup_{s \in [0, t]} Y_s.$$

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ **DD equation**

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

Drawdown Equation

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ **DD equation**

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

For a given $X > 0$, consider SDE,

$$(DD) \quad \frac{dY_t}{Y_t - f_\alpha(\bar{Y}_t)} = \frac{dX_t}{X_t}, \quad \text{where } \bar{Y}_t := \sup_{s \in [0, t]} Y_s.$$

The solution is the Azéma-Yor process, given by

$$(AY) \quad Y_t := U_\alpha(\bar{X}_t) - u_\alpha(\bar{X}_t) (\bar{X}_t - X_t) =: M^{U_\alpha}(X)_t,$$

where

■ $V_\alpha : [M_0, \infty) \rightarrow [v_0^*, \infty)$ by

$$V_\alpha(y) = v_0^* \exp \left\{ \int_{M_0}^y \frac{dx}{x - f_\alpha(x)} \right\}, \quad v_0^* \in \mathbb{R}_{>0}.$$

■ $U_\alpha := V_\alpha^{-1}$, $u_\alpha := U'_\alpha$.

Result by Carraro, El Karoui and Obłój (2010)

$$(1) \quad \bar{Y} = U_\alpha(\bar{X}), \quad \bar{X} = V_\alpha(\bar{Y}).$$

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ DD equation

▷ **AY Process**

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

Result by Carraro, El Karoui and Obłój (2010)

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

$$(1) \quad \bar{Y} = U_\alpha(\bar{X}), \quad \bar{X} = V_\alpha(\bar{Y}).$$

(2) Let $X \equiv X^{V_\alpha(x), \pi}$, and $Y \equiv M^{U_\alpha}(X)$. Then,
 $Y - f_\alpha(\bar{Y}) = u_\alpha(\bar{X})X > 0$. Moreover,

$$Y \equiv X^{x, \rho} \quad \text{with} \quad \rho_t := \left\{ 1 - \frac{f_\alpha(\bar{Y}_t)}{Y_t} \right\} \pi_t.$$

Result by Carraro, El Karoui and Obłój (2010)

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

$$(1) \quad \bar{Y} = U_\alpha(\bar{X}), \quad \bar{X} = V_\alpha(\bar{Y}).$$

(2) Let $X := X^{V_\alpha(x), \pi}$, and $Y := M^{U_\alpha}(X)$. Then, $Y - f_\alpha(\bar{Y}) = u_\alpha(\bar{X})X > 0$. Moreover,

$$Y \equiv X^{x, \rho} \quad \text{with} \quad \rho_t := \left\{ 1 - \frac{f_\alpha(\bar{Y}_t)}{Y_t} \right\} \pi_t.$$

(3) Let $Y := X^{x, \rho}$ with $\rho \in \mathcal{A}_\alpha(x)$, i.e., $Y - f_\alpha(\bar{Y}) > 0$. Then, Y solves (DD):

$$\frac{dY_t}{Y_t - f_\alpha(\bar{Y}_t)} = \frac{dX_t^{V_\alpha(x), \pi}}{X_t^{V_\alpha(x), \pi}}$$

with $\exists \pi$. Moreover, letting $v_\alpha := V'_\alpha$,

$$X_t^{V_\alpha(x), \pi} = V_\alpha(\bar{Y}_t) - v_\alpha(\bar{Y}_t) (\bar{Y}_t - Y_t).$$

Plotting Azéma-Yor processes: $f(x) := \alpha x$, i.e., $\text{RDD} < 1 - \alpha$.

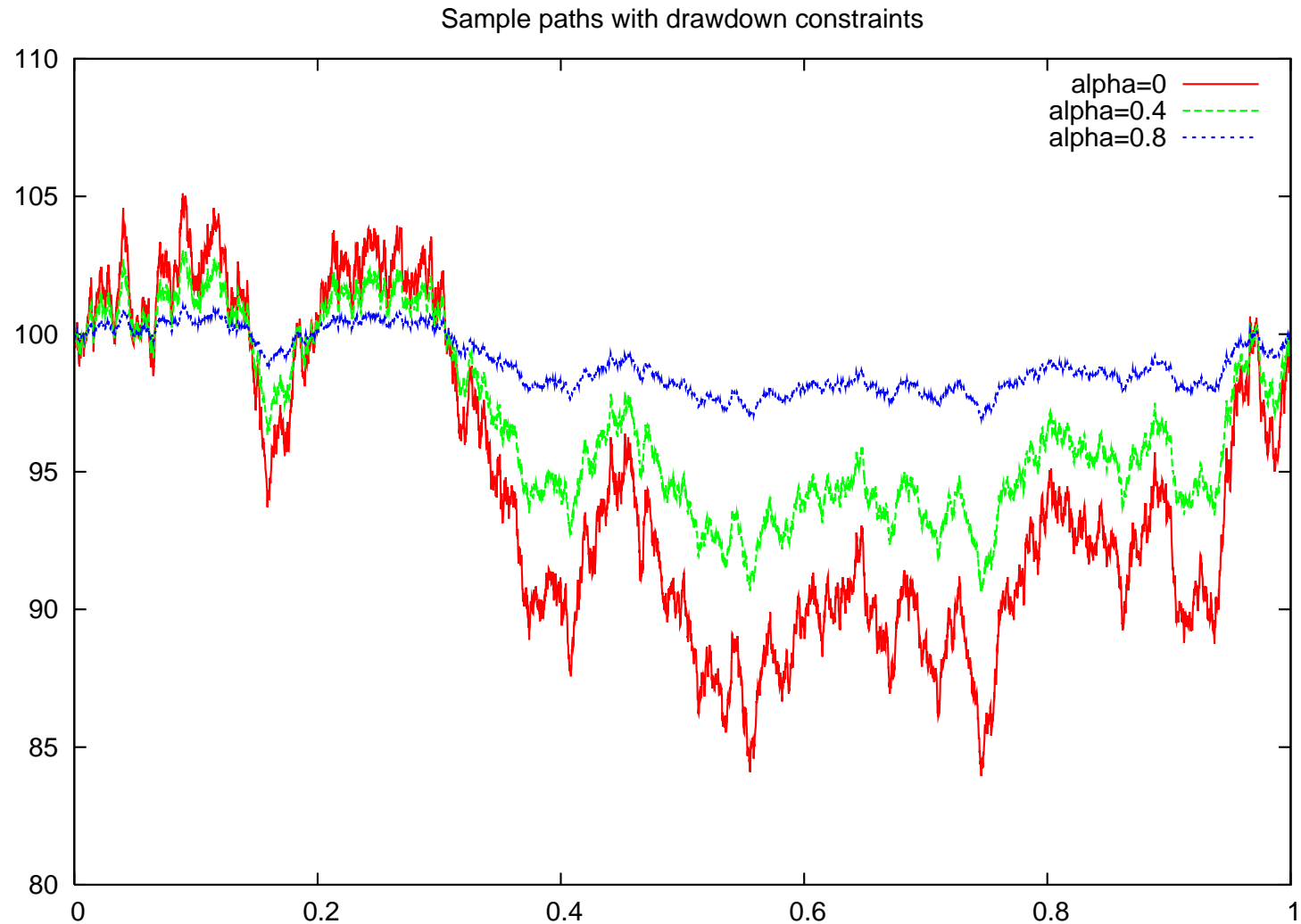
§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

- ▷ Problem
- ▷ RDD
- ▷ Drawdown Analysis
- ▷ Performances
- ▷ CAL/STE/BUR
- ▷ Lower-bdd Ratios
- ▷ Related Works
- ▷ RSPO
- ▷ Baseline Prob.
- ▷ Upgraded Prob.
- ▷ DD equation
- ▷ AY Process
- ▷ Plotting AY
- ▷ Result
- ▷ Variant

§4. A Dual Approach



Result on GDD Constrained Problem

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ **Result**

▷ Variant

§4. A Dual Approach

(1) $\Gamma_\alpha(x, \gamma) = (1 - \alpha)\Lambda((1 - \alpha)\gamma)$ for $\forall x \geq x_0$. Here,

$$\begin{aligned}\Lambda(\lambda) &:= \sup_{\pi} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\lambda T} \log \mathbb{E}(X_T^{x, \pi})^\lambda \\ &= \overline{\lim}_{T \rightarrow \infty} \frac{1}{\lambda T} \log \mathbb{E}(X_T^{x, \hat{\pi}(\lambda)})^\lambda,\end{aligned}$$

imposing *no DD-constraint*.

Result on GDD Constrained Problem

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

(1) $\Gamma_\alpha(x, \gamma) = (1 - \alpha)\Lambda((1 - \alpha)\gamma)$ for $\forall x \geq x_0$. Here,

$$\begin{aligned}\Lambda(\lambda) &:= \sup_{\pi} \overline{\lim}_{T \rightarrow \infty} \frac{1}{\lambda T} \log \mathbb{E}(X_T^{x, \pi})^\lambda \\ &= \overline{\lim}_{T \rightarrow \infty} \frac{1}{\lambda T} \log \mathbb{E}(X_T^{x, \hat{\pi}(\lambda)})^\lambda,\end{aligned}$$

imposing *no DD-constraint*.

(2) Let $\hat{X} := X^{V_\alpha(x), \hat{\pi}((1-\alpha)\gamma)}$. $\hat{Y} := M^{U_\alpha}(\hat{X})$ is optimal for GDD constrained problem. The associated optimal investment strategy is

$$\check{\pi}_t := \left\{ 1 - \frac{f_\alpha(\sup_{s \in [0, t]} \hat{Y}_s)}{\hat{Y}_t} \right\} \hat{\pi}_t^{((1-\alpha)\gamma)}.$$

Drawdown and Floor Constraints

Optimization under

$$X_t^{x,\pi} > K_t \text{ and } X_t^{x,\pi} > f_\alpha \left(\max_{s \in [0,t]} X_s^{x,\pi} \right) \text{ for } \forall t \geq 0,$$

where $(K_t)_{t \geq 0}$ is a given floor process and $f_\alpha(x) := \alpha x$.

Optimal strategy:

$$\tilde{\pi}_t := \left\{ 1 - \frac{\alpha \left(\max_{s \in [0,t]} \hat{Y}_s \right)}{\hat{Y}_t} \right\} \left\{ 1 - \frac{V_\alpha \left(\frac{1}{\alpha} K \right)}{M^{V_\alpha}(\hat{Y})_t} \right\} \hat{\pi}_t,$$

where $d\hat{Y}_t = \left\{ \hat{Y}_t - \alpha \left(\max_{s \in [0,t]} \hat{Y}_s \right) \right\} \frac{d\bar{X}_t}{\bar{X}_t}, \quad \hat{Y}_0 = x,$

$$d\bar{X}_t = \left\{ \bar{X}_t - V_\alpha \left(\frac{1}{\alpha} K \right) \right\} \sum_{i=1}^n \hat{\pi}_t^i \frac{dS_t^i}{S_t^i}, \quad \bar{X}_0 = V_\alpha(x)$$

with $\hat{\pi} := \hat{\pi}^{((1-\alpha)\gamma)}$ ($\hat{Y} := M^{U_\alpha}(\bar{X})$).

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

▷ Problem

▷ RDD

▷ Drawdown Analysis

▷ Performances

▷ CAL/STE/BUR

▷ Lower-bdd Ratios

▷ Related Works

▷ RSPO

▷ Baseline Prob.

▷ Upgraded Prob.

▷ DD equation

▷ AY Process

▷ Plotting AY

▷ Result

▷ Variant

§4. A Dual Approach

Markovian Model

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

$$dS_t^0 = rS_t dt, \quad S_0^0 = 1,$$

$$dS_t = \text{diag}(S_t) \{ \mu(Y_t) dt + \sigma(Y_t) dW(t) \}, \quad S_0 \in \mathbb{R}_{++}^n,$$

$$dY_t = b(Y_t) dt + a(Y_t) dW_t, \quad Y_0 \in \mathbb{R}^m,$$

where $W := (W^1, \dots, W^n)^\top$, $W^i := (W_t^i)_{t \geq 0}$: n -dim. BM, $r \in \mathbb{R}$,
 $\mu : \mathbb{R}^m \rightarrow \mathbb{R}^n$, $\sigma : \mathbb{R}^m \rightarrow \mathbb{R}^{n \times d}$ so that

$$\sigma \sigma^\top(\cdot) > 0,$$

$b : \mathbb{R}^m \rightarrow \mathbb{R}^m$, and $a : \mathbb{R}^m \rightarrow \mathbb{R}^{m \times n}$.

Self-financing Investor

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

$$dX_t = \sum_{i=1}^n \pi_t^i \frac{dS_t^i}{S_t^i} + \left(X_t - \sum_{i=1}^n \pi_t^i \right) \frac{dS_t^0}{S_t^0} - c_t dt,$$
$$X_0 = x \in \mathbb{R}_{++}.$$

(X, Y) satisfies

$$dX_t = \left\{ rX_t - c_t + \pi_t^\top \lambda(Y_t) \right\} dt + \pi_t^\top \sigma(Y_t) dW_t,$$

$$X_0 = x \in \mathbb{R}_{++},$$

$$dY_t = b(Y_t) dt + a(Y_t) dW_t,$$

$$Y_0 = y \in \mathbb{R}^m,$$

where, with $\mathbf{1} := (1, \dots, 1)^\top \in \mathbb{R}^n$,

$$\lambda(y) := \mu(y) - r\mathbf{1}.$$

Floor, Admissible Strategies, Utilities

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

- Floor $K := (K_t)_{t \geq 0}$

$$dK_t = K_t(r + \alpha)dt, \quad K_0 = k_0 \in \mathbb{R}_+,$$

($\alpha \geq 0$: absorbing barrier, $\alpha < 0$: reflecting barrier)

- Space of admissible strategies

$$\mathcal{A}_T^K(x) := \{(\pi, c) \mid c \geq 0, X_t^{x, \pi, c} \geq K(t) \text{ for all } t \in [0, T]\}.$$

- $U_1, U_2 : \mathbb{R}_{++} \rightarrow \mathbb{R}$ are utility functions so that, for $i = 1, 2$,

$$U_i \in C^2(\mathbb{R}_{++}), \quad U_i' > 0, \quad U_i'' < 0, \quad U_i'(0+) = +\infty, \quad U_i'(+\infty) = 0.$$

Primal HJB(1)

Associated with Merton problem with floor constraint, deduce the HJB equation,

$$-V_t = \sup_{(\pi, c) \in \mathbb{R}^n \times \mathbb{R}_{++}} H(x, y, \pi, c, V, V_x, V_y, V_{xx}, V_{xy}, V_{yy}),$$

$$(t, x, y) \in [0, T) \times [K(t), \infty) \times \mathbb{R}^m,$$

$$V(T, x, y) = U_2(x),$$

where we define

$$\begin{aligned} H(x, y, \pi, c, V_x, V_y, V_{xx}, V_{xy}, V_{yy}) \\ := -\rho V + U_1(c) + (rx - c + \pi^\top \lambda)V_x + b^\top V_y \\ + \frac{1}{2} \pi^\top \sigma \sigma^\top \pi V_{xx} + \pi^\top \sigma a^\top V_{xy} + \frac{1}{2} \text{tr} \left(a a^\top V_{yy} \right). \end{aligned}$$

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

Primal HJB(2)

Assuming that $V_{xx} < 0$, HJB is rewritten as

$$\begin{aligned} -V_t = & -\rho V + \tilde{U}_1(V_x) + rxV_x + b^\top V_y + \frac{1}{2} \text{tr} \left(aa^\top V_{yy} \right) \\ & - \frac{1}{2V_{xx}} \left(\lambda V_x + \sigma a^\top V_{xy} \right)^\top (\sigma \sigma^\top)^{-1} \left(\lambda V_x + \sigma a^\top V_{xy} \right), \\ & (t, x, y) \in [0, T) \times [K(t), \infty) \times \mathbb{R}^m, \end{aligned}$$

$$V(T, x, y) = U_2(x).$$

where

$$\tilde{U}_1(y) := \sup_{c>0} \{U_1(c) - cy\},$$

and the maximizers are given by

$$\begin{aligned} \bar{c} & := (U_1')^{-1}(V_x), \\ \bar{\pi} & := -\frac{1}{V_{xx}} (\sigma \sigma^\top)^{-1} \left(\lambda V_x + \sigma a^\top V_{xy} \right). \end{aligned}$$

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

Dual HJB (1)

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

Suppose $K = 0$. $\tilde{V}(t, z, y) := \sup_{x \in (0, \infty)} \{V(t, x, y) - xz\}$ satisfies

$$\begin{aligned} & \tilde{V}(t, z, y) \\ &= \mathbb{E} \left[\int_0^{T-t} e^{-\rho u} \tilde{U}_1(Z_u) du + e^{-\rho(T-t)} \tilde{U}_2(Z_{T-t}) \mid Z_0 = z, Y_0 = y \right], \end{aligned}$$

with

$$dY_t = b(Y_t)dt + a(Y_t)dW_t, \quad dZ_t = Z_t \left\{ (\rho - r)dt - \theta(Y_t)^\top dW_t \right\}$$

and $\theta := \sigma^{-1}(\mu - r\mathbf{1})$. So,

$$\begin{aligned} & \tilde{V}_t + (\mathbb{L} - \rho)\tilde{V} = 0, \quad \tilde{V}(T, z, y) = \tilde{U}_2(z), \\ & \mathbb{L} := b^\top \partial_y + (\rho - r)z\partial_z + \frac{1}{2}\text{tr}(aa^\top \partial_{yy}) - \theta^\top a^\top z\partial_{yz} + \frac{1}{2}|\theta|^2 z^2 \partial_{zz}. \end{aligned}$$

Dual HJB (2)

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

For the *constrained* Fenchel-Legendre transform:

$$\hat{V}(t, z, y) := \sup_{x \in (K(t), \infty)} \{V(t, x, y) - xz\},$$

we deduce the variational inequality,

$$\max \left\{ \hat{V}_t + (\mathbb{L} - \rho)\hat{V}, \hat{V} - \mathcal{K} \right\} = 0, \quad \hat{V}(T, z, y) = \hat{U}_2(T, z)$$

where

$$\mathcal{K}(t, z, y) := V(t, K(t), y) - K(t)z,$$

$$\hat{U}_2(T, z) := \sup_{x \geq K(T)} \{U_2(x) - zx\}.$$

Dual HJB (3)

The associated dual stochastic control problem is

$$\inf_{\eta \in \mathcal{B}_{T-t}} \mathbb{E} \left[\int_0^{T-t} e^{-\rho u} \tilde{U}_1 (Z_u^{z,\eta}) du + e^{-\rho(T-t)} \hat{U}_2 (T, Z_{T-t}^{z,\eta}) + \int_{[0, T-t)} e^{-\rho u} \mathcal{K} (t+u, Z_u^{z,\eta}, Y_u) d\eta_u \mid Y_0 = y \right],$$

where \mathcal{B}_T is the space of nondecreasing, LCRL, adapted processes on the time-interval $[0, T]$, starting from 0 at time 0, and

$$dZ_s^{z,\eta} = Z_s^{z,\eta} \left[(\rho - r) ds - \theta(Y(s))^\top dW_s \right] - d\eta_s,$$
$$Z_0^{z,\eta} = z.$$

Not described in “closed-forms”. They contain the solution V to the primal.

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ **Dual HJB (3)**

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

Equation for Differential of “Dual”

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

Compute the equation for $g : [0, T] \times \mathbb{R}_+ \times \mathbb{R}^m$, which satisfies

$$(i) \quad g := g(t, z, y) \geq K(t),$$

$$(ii) \quad V_x(t, g, y) - z = 0 \quad \text{if } g(t, z, y) > K(t).$$

We deduce that

$$\min \left\{ -g_t - (\hat{\mathbb{L}} - r)g + \tilde{U}'_1, g - K \right\} = 0,$$

where

$$\hat{\mathbb{L}} := (b - a\theta)^\top \partial_y + (|\theta|^2 + \rho - r)z \partial_z + \frac{1}{2} \text{tr}(aa^\top \partial_{yy}) - \theta^\top a^\top z \partial_{yz} + \frac{1}{2} |\theta|^2 z^2 \partial_{zz}.$$

Differential of Dual (2)

This is deduced from the optimal stopping problem associated with the differential of the dual stochastic control problem:

$$\sup_{t \leq \tau \leq T} \mathbb{E} \left[- \int_t^\tau e^{-\rho(s-t)} Z(s) \tilde{U}'_1(Z(s)) ds \right. \\ \left. + e^{-\rho(\tau-t)} Z(\tau) \left\{ K(\tau) 1_{\{\tau < T\}} - \hat{U}_{2z}(T, Z(T)) 1_{\{\tau = T\}} \right\} \middle| \mathcal{F}_t \right],$$

where $\hat{U}_{2z} := \partial_z \hat{U}_2$, or

$$Z(t) \times \sup_{t \leq \tau \leq T} \tilde{\mathbb{E}} \left[- \int_t^\tau e^{-r(s-t)} \tilde{U}'_1(Z(s)) ds \right. \\ \left. + e^{-r(\tau-t)} \left\{ K(\tau) 1_{\{\tau < T\}} - \hat{U}_{2z}(T, Z(T)) 1_{\{\tau = T\}} \right\} \middle| \mathcal{F}_t \right],$$

introducing a measure change.

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

Free Boundary Problem

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

$$-\hat{g}_t = (\hat{\mathbb{L}} - r)\hat{g} - \tilde{U}'_1 \quad \text{for } z < \beta(t, y),$$

$$\hat{g} > K \quad \text{for } z < \beta(t, y),$$

$$\hat{g}(t, z, y)|_{z=\beta(t,y)-} = K(t),$$

$$\hat{g} = K \quad \text{for } z > \beta(t, y),$$

$$-\hat{g}_t > (\hat{\mathbb{L}} - r)\hat{g} - \tilde{U}'_1 \quad \text{for } z > \beta(t, y),$$

$$\hat{g}(T, z, y) = -\hat{U}_{2z}(T, z)$$

with smooth-fit conditions:

$$g_z(t, z, y)|_{z=\beta(t,y)-} = 0, \quad g_y(t, z, y)|_{z=\beta(t,y)-} = 0,$$

assuming that, with some $\beta : [0, T] \times \mathbb{R}^m \rightarrow \mathbb{R}_+$,

$$\mathcal{C} = \{(t, z, y) \in [0, T] \times \mathbb{R}_+ \times \mathbb{R}^m; z < \beta(t, y)\},$$

$$\mathcal{D} = \{(t, z, y) \in [0, T] \times \mathbb{R}_+ \times \mathbb{R}^m; z \geq \beta(t, y)\}.$$

Constructing Optimal Strategy (1)

Suppose that the free-boundary problem has a nice solution:

- (i) The solution is $C^{1,2,2}$ in \mathcal{C} .
- (ii) The smooth-fit condition (4.8) is satisfied at the free-boundary.
- (iii) The free-boundary satisfies $\beta \in C^{1,2}([0, T] \times \mathbb{R}^m)$ (to apply Itô's calculus).

Recovering the primal value function V directly from g (differential of the dual) is not easy (\exists ambiguity of (t, y)). However, maximizers are written as

$$\begin{aligned}\bar{c}(t, x, y) &:= (U'_1)^{-1}(V_x(t, x, y)) = (U'_1)^{-1}(z), \\ \bar{\pi}(t, x, y) &:= - \left\{ (\sigma\sigma^\top)^{-1} \frac{\lambda V_x + \sigma a^\top V_{xy}}{V_{xx}} \right\} (t, x, y) \\ &= - z g_z(t, z, y) ((\sigma\sigma^\top)^{-1} \lambda)(y) + ((\sigma\sigma^\top)^{-1} \sigma a^\top)(y) g_y(t, z, y)\end{aligned}$$

with $z = h(t, x, y)$ ($h := g^{-1}$).

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ **Verification (1)**

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

Constructing Optimal Strategy (2)

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ **Verification (2)**

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

Let

$$dZ^{(z)}(s) = Z^{(z)}(s) \left\{ -\theta(Y(s))^{\top} dW(s) + (\rho - r)ds \right\},$$
$$Z^{(z)}(0) = z.$$

Define the process $\bar{Y} := (Y^0, Y)$ by the SDE with (non-sticky) reflection

$$dY^0(t) = dZ^{(z)}(t) - d\beta(t, Y(t)) - d\eta(t), \quad Y^0(0) = z - \beta(0, y),$$

$$dY(t) = b(Y(t))dt + a(Y(t))dW(t), \quad Y(0) = y \in \mathbb{R}^m.$$

Here, $Y^0 \leq 0$, and η is a continuous, adapted and non-decreasing process such that $\eta(0) = 0$ and that

$$\int_0^t 1_{\{Y^0(s)=0\}} d\eta(s) = \eta(t).$$

Constructing Optimal Strategy (3)

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ **Verification (3)**

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

Write

$$\bar{Z}^{(y,z)}(t) := Y^0(t) + \beta(t, Y^{(y)}(t)), \quad Y^{(y)}(t) := Y(t),$$

emphasizing the initial value $(\bar{Z}^{(y,z)}(0), Y^{(y)}(0)) = (z, y) \in \mathbb{R} \times \mathbb{R}^m$.

Note that the process \bar{Z} always stays below the free-boundary, i.e.,

$$\bar{Z}(t) \leq \beta(t, Y(t)), \quad \forall t \in [0, T],$$

and (non-stickily) reflects on the free-boundary. Define

$$\tilde{c}(z) := (U'_1)^{-1}(z),$$

$$\tilde{\pi}(t, z, y) := -z g_z(t, z, y) \left((\sigma \sigma^\top)^{-1} \lambda \right) (y) + \left((\sigma \sigma^\top)^{-1} \sigma a^\top \right) (y) g_y(t, z, y)$$

Constructing Optimal Strategy (4)

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

Define

$$\hat{\Xi}(t; y, z) := g \left(t, \bar{Z}^{(z,y)}(t), Y^{(y)}(t) \right).$$

Use Itô's formula to see that

$$\begin{aligned} d\hat{\Xi}(t) &= g_z(t, \bar{Z}(t), Y(t)) d\bar{Z}(t) + g_y(t, \bar{Z}(t), Y(t)) dY(t) \\ &\quad + g_t(t, \bar{Z}(t), Y(t)) dt + \frac{1}{2} g_{zz}(t, \bar{Z}(t), Y(t)) d\langle \bar{Z} \rangle(t) \\ &\quad + g_{zy}(t, \bar{Z}(t), Y(t)) d\langle \bar{Z}, Y \rangle(t) + \frac{1}{2} g_{yy}(t, \bar{Z}(t), Y(t)) d\langle Y \rangle(t) \\ &= \left(-z g_z \theta^\top + g_y^\top a \right) (t, \bar{Z}(t), Y(t)) \{ dW(t) + \theta(Y(t)) dt \} \\ &\quad - g_z(t, \bar{Z}(t), Y(t)) d\eta(t) + (\partial_t + \hat{\mathbb{L}})g(t, \bar{Z}(t), Y(t)) dt. \end{aligned}$$

Constructing Optimal Strategy (5)

Note the following:

- (i) $-z g_z \theta^\top + g_y^\top a = \tilde{\pi}^\top \sigma.$
- (ii) $g_z (t, \bar{Z}(t), Y(t)) d\eta(t) = 0$ a.e. (t, ω) by smooth-fit.
- (iii) $(t, \bar{Z}(t), Y(t)) \in \mathcal{C}$ for a.e. (t, ω) , hence, the drift $\hat{\mathbb{L}}g (t, \bar{Z}(t), Y(t)) dt$ is well-defined and we see that

$$(\partial_t + \hat{\mathbb{L}})g (t, \bar{Z}(t), Y(t)) dt = \{rg (t, \bar{Z}(t), Y(t)) - \tilde{c}(\bar{Z}(t))\} dt.$$

So,

$$d\hat{\Xi}(t) = \left\{ r\hat{\Xi}(t) - \tilde{c} + \tilde{\pi}^\top \lambda \right\} (t, \bar{Z}(t), Y(t)) dt + (\tilde{\pi}^\top \sigma) (t, \bar{Z}(t), Y(t)) dW$$

$$\hat{\Xi}(0) = g(0, z, y).$$

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

▷ Free Bdry Prob.

▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

Constructing Optimal Strategy (6)

§1. Introduction

§2. RSPO with Floor

§3. RSPO with DDC

§4. A Dual Approach

▷ Markovian Model

▷ SF Investor

▷ Floor etc.

▷ Primal HJB(1)

▷ Primal HJB(2)

▷ Dual HJB (1)

▷ Dual HJB (2)

▷ Dual HJB (3)

▷ Diff. of Dual (1)

▷ Diff. of Dual (2)

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▷ Verification (1)

▷ Verification (2)

▷ Verification (3)

▷ Verification (4)

▷ Verification (5)

▷ Verification (6)

Define the wealth process

$$\hat{X}(t) = \hat{\Xi}(t; h(0, x, y), y) = g\left(t, \bar{Z}^{(y, h(0, x, y))}(t), Y(t)\right),$$

which satisfies $\hat{X}(0) = x$. The associated portfolio investment strategy is

$$\hat{\pi}(t) := \tilde{\pi}\left(t, \hat{Z}(t), Y(t)\right), \quad \hat{c}(t) := \tilde{c}\left(\hat{Z}(t)\right),$$

where

$$\hat{Z}(t) := \bar{Z}^{(y, h(0, x, y))}(t).$$

Using

$$\hat{X}(t) = g(t, \hat{Z}(t), Y(t)), \quad \hat{Z}(t) = h(t, \hat{X}(t), Y(t)),$$

we verify that \hat{X} is the optimal wealth and can write down the feedback-form dynamics of (\hat{X}, Y) .