

Optimal Portfolio under Fractional Stochastic Environment

Jean-Pierre Fouque
Joint work with Ruimeng Hu

Department of Statistics and Applied Probability
University of California, Santa Barbara

Jim Gatheral's 60th Birthday Conference
NYU October 13-15, 2017

Portfolio Optimization: Merton's Problem

An investor manages her portfolio by investing in a riskless asset B_t and in a risky asset S_t (single asset for simplicity)

$$\begin{cases} dB_t = rB_t dt \\ dS_t = \mu S_t dt + \sigma S_t dW_t \end{cases}$$

- π_t – amount of wealth invested in the risky asset at time t
- X_t^π – the wealth process associated to the strategy π

$$\begin{aligned} dX_t^\pi &= \frac{\pi_t}{S_t} dS_t + \frac{X_t^\pi - \pi_t}{B_t} dB_t \quad (\text{self-financing}) \\ &= (rX_t^\pi + \pi_t(\mu - r)) dt + \pi_t \sigma dW_t \end{aligned}$$

Objective:

$$M(t, x; \lambda) := \sup_{\pi \in \mathcal{A}(x, t)} \mathbb{E}[U(X_T^\pi) | X_t^\pi = x], \quad \text{Sharpe ratio: } \lambda = \frac{\mu}{\sigma}$$

where $\mathcal{A}(x)$ contains all admissible π and $U(x)$ is a utility function on \mathbb{R}^+

Portfolio Optimization: Merton's Problem

An investor manages her portfolio by investing in a riskless asset B_t and in a risky asset S_t (single asset for simplicity)

$$\begin{cases} dB_t = rB_t dt \\ dS_t = \mu S_t dt + \sigma S_t dW_t \end{cases}$$

- π_t – amount of wealth invested in the risky asset at time t
- X_t^π – the wealth process associated to the strategy π

$$\begin{aligned} dX_t^\pi &= \frac{\pi_t}{S_t} dS_t + \frac{X_t^\pi - \pi_t}{B_t} dB_t \quad (\text{self-financing}) \\ &= (rX_t^\pi + \pi_t(\mu - r)) dt + \pi_t \sigma dW_t \end{aligned}$$

Objective:

$$M(t, x; \lambda) := \sup_{\pi \in \mathcal{A}(x, t)} \mathbb{E}[U(X_T^\pi) | X_t^\pi = x], \quad \text{Sharpe ratio: } \lambda = \frac{\mu}{\sigma}$$

where $\mathcal{A}(x)$ contains all admissible π and $U(x)$ is a utility function on \mathbb{R}^+

Stochastic Volatility

- In Merton's work, μ and σ are constant, complete market
- Empirical studies reveals that σ exhibits “random” variation
- Implied volatility skew or smile
- Stochastic volatility model: $\mu(Y_t), \sigma(Y_t) \rightarrow$ incomplete market
- Rough Fractional Stochastic volatility:
 - Gatheral, Jaisson and Rosenbaum '14 (“volatility is rough”)
 - Jaisson, Rosenbaum '16 (“from Hawkes processes to fractional diffusions”)
 - Omar, Masaaki and Rosenbaum '16 (“leveraged rough volatility”)

We study the Merton problem under slowly varying fractional stochastic environment:

Nonlinear + Non-Markovian \rightarrow HJB PDE not available

Stochastic Volatility

- In Merton's work, μ and σ are constant, complete market
- Empirical studies reveals that σ exhibits “random” variation
- Implied volatility skew or smile
- Stochastic volatility model: $\mu(Y_t), \sigma(Y_t) \rightarrow$ incomplete market
- Rough Fractional Stochastic volatility:
 - Gatheral, Jaisson and Rosenbaum '14 (“volatility is rough”)
 - Jaisson, Rosenbaum '16 (“from Hawkes processes to fractional diffusions”)
 - Omar, Masaaki and Rosenbaum '16 (“leveraged rough volatility”)

We study the Merton problem under **slowly varying fractional stochastic environment**:

Nonlinear + Non-Markovian \rightarrow HJB PDE not available

Related Literature

- Option Pricing + Markovian modeling:
Fouque, Papanicolaou, Sircar and Solna '11 (CUP)
- Portfolio Optimization + Markovian modeling:
Fouque, Sircar and Zariphopoulou '13 (MF)
Fouque and Hu '16 (SICON)
- Option Pricing + Non-Markovian modeling:
Garnier and Solna '15 (SIFIN), '16 (MF)
- Portfolio Optimization + Non-Markovian modeling:
Fouque and Hu arXiv:1703.06969 (slow factor)
Fouque and Hu arXiv:1706.03139 (fast factor)

A General Non-Markovian Model

Dynamics of the risky asset S_t

$$\begin{cases} dS_t = S_t [\mu(Y_t) dt + \sigma(Y_t) dW_t], \\ Y_t: \text{ a general stochastic process, } \mathcal{G}_t := \sigma \left\{ (W^Y)_{0 \leq u \leq t} \right\} \text{-adapted,} \end{cases}$$

with $d\langle W, W^Y \rangle_t = \rho dt$.

Dynamics of the wealth process X_t (assume $r = 0$ for simplicity):

$$dX_t^\pi = \pi_t \mu(Y_t) dt + \pi_t \sigma(Y_t) dW_t$$

Define the **value process** V_t by

$$V_t := \sup_{\pi \in \mathcal{A}_t} \mathbb{E} [U(X_T^\pi) | \mathcal{F}_t]$$

where $U(x)$ is of **power type** $U(x) = \frac{x^{1-\gamma}}{1-\gamma}$, $\gamma > 0$.

Proposition: Martingale Distortion Transformation¹

- The value process V_t is given by

$$V_t = \frac{X_t^{1-\gamma}}{1-\gamma} \left[\widetilde{\mathbb{E}} \left(e^{\frac{1-\gamma}{2q\gamma} \int_t^T \lambda^2(Y_s) ds} \middle| \mathcal{G}_t \right) \right]^q, \quad \lambda(y) = \frac{\mu(y)}{\sigma(y)}$$

where under $\widetilde{\mathbb{P}}$, $\widetilde{W}_t^Y := W_t^Y + \int_0^t a_s ds$ is a BM.

- The optimal strategy π^* is

$$\pi_t^* = \left[\frac{\lambda(Y_t)}{\gamma\sigma(Y_t)} + \frac{\rho q \xi_t}{\gamma\sigma(Y_t)} \right] X_t$$

where ξ_t is given by the martingale representation $dM_t = M_t \xi_t d\widetilde{W}_t^Y$ and M_t is

$$M_t = \widetilde{\mathbb{E}} \left[e^{\frac{1-\gamma}{2q\gamma} \int_0^T \lambda^2(Y_s) ds} \middle| \mathcal{G}_t \right]$$

¹Tehranchi '04: different utility function, proof and assumptions

Remarks

- only works for one factor models
- assumptions: integrability conditions of ξ_t , X_t^π and π_t
- $\gamma = 1 \rightarrow$ case of log utility, can be treated separately
- degenerate case $\lambda(y) = \lambda_0$, M_t is a constant martingale, $\xi_t = 0$

$$V_t = \frac{X_t^{1-\gamma}}{1-\gamma} e^{\frac{1-\gamma}{2\gamma} \lambda_0^2 (T-t)}, \quad \pi_t^* = \frac{\lambda_0}{\gamma \sigma(Y_t)} X_t.$$

- uncorrelated case $\rho = 0$, the problem is “linear” since $q = 1$

$$V_t = \frac{X_t^{1-\gamma}}{1-\gamma} \mathbb{E} \left[e^{\frac{1-\gamma}{2\gamma} \int_t^T \lambda^2(Y_s) ds} \middle| \mathcal{G}_t \right], \quad \pi_t^* = \frac{\lambda(Y_t)}{\gamma \sigma(Y_t)} X_t.$$

Sketch of Proof (Verification)

- V_t is a supermartingale for any admissible control π
- V_t is a true martingale following π^*
- π^* is admissible

Define $\alpha_t = \pi_t / X_t$, then

$$dV_t = V_t D_t(\alpha_t) dt + d\text{Martingale}$$

with the drift factor $D_t(\alpha_t)$

$$D_t(\alpha_t) := \alpha_t \mu - \frac{\gamma}{2} \alpha_t^2 \sigma^2 - \frac{\lambda^2}{2\gamma} + \frac{q}{1-\gamma} a_t \xi_t + \frac{q(q-1)}{2(1-\gamma)} \xi_t^2 + \rho q \alpha_t \sigma \xi_t$$

maximize $D_t \Rightarrow \alpha_t^*$ and $D_t(\alpha_t^*) = 0$ with the right choice of a_t and q :

$$a_t = -\rho \left(\frac{1-\gamma}{\gamma} \right) \lambda(Y_t), \quad q = \frac{\gamma}{\gamma + (1-\gamma)\rho^2}.$$

Sketch of Proof (Verification)

- V_t is a supermartingale for any admissible control π
- V_t is a true martingale following π^*
- π^* is admissible

Define $\alpha_t = \pi_t / X_t$, then

$$dV_t = V_t D_t(\alpha_t) dt + d\text{Martingale}$$

with the drift factor $D_t(\alpha_t)$

$$D_t(\alpha_t) := \alpha_t \mu - \frac{\gamma}{2} \alpha_t^2 \sigma^2 - \frac{\lambda^2}{2\gamma} + \frac{q}{1-\gamma} a_t \xi_t + \frac{q(q-1)}{2(1-\gamma)} \xi_t^2 + \rho q \alpha_t \sigma \xi_t$$

maximize $D_t \Rightarrow \alpha_t^*$ and $D_t(\alpha_t^*) = 0$ with the right choice of a_t and q :

$$a_t = -\rho \left(\frac{1-\gamma}{\gamma} \right) \lambda(Y_t), \quad q = \frac{\gamma}{\gamma + (1-\gamma)\rho^2}.$$

Sketch of Proof (Verification)

- V_t is a supermartingale for any admissible control π
- V_t is a true martingale following π^*
- π^* is admissible

Define $\alpha_t = \pi_t / X_t$, then

$$dV_t = V_t D_t(\alpha_t) dt + d \text{Martingale}$$

with the drift factor $D_t(\alpha_t)$

$$D_t(\alpha_t) := \alpha_t \mu - \frac{\gamma}{2} \alpha_t^2 \sigma^2 - \frac{\lambda^2}{2\gamma} + \frac{q}{1-\gamma} a_t \xi_t + \frac{q(q-1)}{2(1-\gamma)} \xi_t^2 + \rho q \alpha_t \sigma \xi_t$$

maximize $D_t \Rightarrow \alpha_t^*$ and $D_t(\alpha_t^*) = 0$ with the right choice of a_t and q :

$$a_t = -\rho \left(\frac{1-\gamma}{\gamma} \right) \lambda(Y_t), \quad q = \frac{\gamma}{\gamma + (1-\gamma)\rho^2}.$$

Relation to the Distortion Transformation ²

In the Markovian setup, Y_t is a diffusion process

$$dY_t = k(Y_t) dt + h(Y_t) dW_t^Y,$$

$V(t, x, y)$ solves a HJB equation and the distortion transformation is

$$V(t, x, y) = \frac{x^{1-\gamma}}{1-\gamma} \Psi(t, y)^q$$

where $\Psi(t, y)$ solves the linear PDE

$$\Psi_t + \left(\frac{1}{2} h^2(y) \partial_{yy} + k(y) \partial_y + \rho \frac{1-\gamma}{\gamma} \lambda(y) h(y) \partial_y \right) \Psi + \frac{1-\gamma}{2q\gamma} \lambda^2(y) \Psi = 0,$$

and has the probabilistic representation

$$\Psi(t, y) = \widetilde{\mathbb{E}} \left[e^{\frac{1-\gamma}{2q\gamma} \int_t^T \lambda^2(Y_s) ds} \middle| Y_t = y \right].$$

²Zariphopoulou '99 : Y_t is a diffusion process

Relation to the Distortion Transformation ²

In the Markovian setup, Y_t is a diffusion process

$$dY_t = k(Y_t) dt + h(Y_t) dW_t^Y,$$

$V(t, x, y)$ solves a HJB equation and the distortion transformation is

$$V(t, x, y) = \frac{x^{1-\gamma}}{1-\gamma} \Psi(t, y)^q$$

where $\Psi(t, y)$ solves the linear PDE

$$\Psi_t + \left(\frac{1}{2} h^2(y) \partial_{yy} + k(y) \partial_y + \rho \frac{1-\gamma}{\gamma} \lambda(y) h(y) \partial_y \right) \Psi + \frac{1-\gamma}{2q\gamma} \lambda^2(y) \Psi = 0,$$

and has the probabilistic representation

$$\Psi(t, y) = \widetilde{\mathbb{E}} \left[e^{\frac{1-\gamma}{2q\gamma} \int_t^T \lambda^2(Y_s) ds} \middle| Y_t = y \right].$$

²Zariphopoulou '99 : Y_t is a diffusion process

Multiple Assets Modeling

Consider the following model of $S_t^1, S_t^2, \dots, S_t^n$

$$dS_t^i = \mu^i(Y_t^i)S_t^i dt + \sum_{j=1}^k \sigma_{ij}(Y_t^i)S_t^i dW_t^j, \quad i = 1, 2, \dots, n.$$

Each S_t^i is driven by a stochastic factor Y_t^i , but all factors Y_t^i are adapted to the same single Brownian motion W_t^Y with the correlation structure:

$$d\langle W^i, W^j \rangle_t = 0, \quad d\langle W^i, W^Y \rangle_t = \rho dt, \quad \forall i, j = 1, 2, \dots, n.$$

Martingale Distortion Transformation with Multiple Assets

Then, the portfolio value V_t can be expressed as

$$V_t = \frac{X_t^{1-\gamma}}{1-\gamma} \left[\widetilde{\mathbb{E}} \left(e^{\frac{1-\gamma}{2q\gamma} \int_t^T \mu(\mathbf{Y}_s)^\dagger \Sigma(\mathbf{Y}_s)^{-1} \mu(\mathbf{Y}_s) ds} \middle| \mathcal{G}_t \right) \right]^q,$$

the constant q is chosen to be:

$$q = \frac{\gamma}{\gamma + (1-\gamma)\rho^2 \mathbb{1}_k^\dagger \sigma(\mathbf{Y}_t)^\dagger \Sigma^{-1}(\mathbf{Y}_t) \sigma(\mathbf{Y}_t) \mathbb{1}_k},$$

and $\mathbb{1}_k$ is a k -vector of ones. The optimal control π^* is given by

$$\pi_t^* = \left[\frac{\Sigma(\mathbf{Y}_t)^{-1} \mu(\mathbf{Y}_t)}{\gamma} + \frac{\rho q \xi_t \Sigma(\mathbf{Y}_t)^{-1} \sigma(\mathbf{Y}_t) \mathbb{1}_k}{\gamma} \right] X_t.$$

Fractional Processes

A fractional Brownian motion $W_t^{(H)}$, $H \in (0, 1)$

- a continuous Gaussian process
- zero mean
- $\mathbb{E} \left[W_t^{(H)} W_s^{(H)} \right] = \frac{\sigma_H^2}{2} (|t|^{2H} + |s|^{2H} - |t - s|^{2H})$
- $H < 1/2$: short-range correlation; $H > 1/2$: long-range correlation

A fractional Ornstein–Uhlenbeck process solves

$$dZ_t^H = -aZ_t^H dt + dW_t^{(H)}$$

- stationary solution $Z_t^H = \int_{-\infty}^t e^{-a(t-s)} dW_s^{(H)} = \int_{-\infty}^t \mathcal{K}(t-s) dW_s^Z$
- Gaussian process with zero mean and constant variance
- \mathcal{K} is non-negative, $\mathcal{K} \in L^2$

Fractional Processes

A fractional Brownian motion $W_t^{(H)}$, $H \in (0, 1)$

- a continuous Gaussian process
- zero mean
- $\mathbb{E} \left[W_t^{(H)} W_s^{(H)} \right] = \frac{\sigma_H^2}{2} (|t|^{2H} + |s|^{2H} - |t - s|^{2H})$
- $H < 1/2$: short-range correlation; $H > 1/2$: long-range correlation

A fractional Ornstein–Uhlenbeck process solves

$$dZ_t^H = -aZ_t^H dt + dW_t^{(H)}$$

- stationary solution $Z_t^H = \int_{-\infty}^t e^{-a(t-s)} dW_s^{(H)} = \int_{-\infty}^t \mathcal{K}(t-s) dW_s^Z$
- Gaussian process with zero mean and constant variance
- \mathcal{K} is non-negative, $\mathcal{K} \in L^2$

Fractional Processes

A fractional Brownian motion $W_t^{(H)}$, $H \in (0, 1)$

- a continuous Gaussian process
- zero mean
- $\mathbb{E} \left[W_t^{(H)} W_s^{(H)} \right] = \frac{\sigma_H^2}{2} (|t|^{2H} + |s|^{2H} - |t - s|^{2H})$
- $H < 1/2$: short-range correlation; $H > 1/2$: long-range correlation

A fractional Ornstein–Uhlenbeck process solves

$$dZ_t^H = -aZ_t^H dt + dW_t^{(H)}$$

- stationary solution $Z_t^H = \int_{-\infty}^t e^{-a(t-s)} dW_s^{(H)} = \int_{-\infty}^t \mathcal{K}(t-s) dW_s^Z$
- Gaussian process with zero mean and constant variance
- \mathcal{K} is non-negative, $\mathcal{K} \in L^2$

Merton Problem under Slowly Varying Fractional SV

Consider a rescaled stationary fOU process $Z_t^{\delta,H}$

$$\begin{cases} dS_t = S_t \left[\mu(Z_t^{\delta,H}) dt + \sigma(Z_t^{\delta,H}) dW_t \right], \\ Z_t^{\delta,H} = \int_{-\infty}^t \mathcal{K}^\delta(t-s) dW_s^Z, \quad \mathcal{K}^\delta(t) = \sqrt{\delta} \mathcal{K}(\delta t), \end{cases} \quad d\langle W, W^Z \rangle_t = \rho dt.$$

Our study gives, for all $H \in (0, 1)$:

- The value process $V_t^\delta := \text{ess sup}_{\pi \in \mathcal{A}_t^\delta} \mathbb{E}[U(X_T^\pi) | \mathcal{F}_t]$
- The corresponding optimal strategy π^*
- First order approximations to V_t^δ and π^*
- A practical strategy to generate this approximated value process

Apply the martingale distortion transformation with $Y_t = Z_t^{\delta,H}$

$$V_t^\delta = \frac{X_t^{1-\gamma}}{1-\gamma} \left[\widetilde{\mathbb{E}} \left(e^{\frac{1-\gamma}{2q\gamma} \int_t^T \lambda^2(Z_s^{\delta,H}) ds} \middle| \mathcal{G}_t \right) \right]^q,$$

Merton Problem under Slowly Varying Fractional SV

Consider a rescaled stationary fOU process $Z_t^{\delta,H}$

$$\begin{cases} dS_t = S_t \left[\mu(Z_t^{\delta,H}) dt + \sigma(Z_t^{\delta,H}) dW_t \right], \\ Z_t^{\delta,H} = \int_{-\infty}^t \mathcal{K}^\delta(t-s) dW_s^Z, \quad \mathcal{K}^\delta(t) = \sqrt{\delta} \mathcal{K}(\delta t), \end{cases} \quad d\langle W, W^Z \rangle_t = \rho dt.$$

Our study gives, for all $H \in (0, 1)$:

- The value process $V_t^\delta := \text{ess sup}_{\pi \in \mathcal{A}_t^\delta} \mathbb{E}[U(X_T^\pi) | \mathcal{F}_t]$
- The corresponding optimal strategy π^*
- First order approximations to V_t^δ and π^*
- A practical strategy to generate this approximated value process

Apply the martingale distortion transformation with $Y_t = Z_t^{\delta,H}$

$$V_t^\delta = \frac{X_t^{1-\gamma}}{1-\gamma} \left[\widetilde{\mathbb{E}} \left(e^{\frac{1-\gamma}{2q\gamma} \int_t^T \lambda^2(Z_s^{\delta,H}) ds} \middle| \mathcal{G}_t \right) \right]^q,$$

Merton Problem under Slowly Varying Fractional SV

Consider a rescaled stationary fOU process $Z_t^{\delta,H}$

$$\begin{cases} dS_t = S_t \left[\mu(Z_t^{\delta,H}) dt + \sigma(Z_t^{\delta,H}) dW_t \right], \\ Z_t^{\delta,H} = \int_{-\infty}^t \mathcal{K}^\delta(t-s) dW_s^Z, \quad \mathcal{K}^\delta(t) = \sqrt{\delta} \mathcal{K}(\delta t), \end{cases} \quad d\langle W, W^Z \rangle_t = \rho dt.$$

Our study gives, for all $H \in (0, 1)$:

- The value process $V_t^\delta := \text{ess sup}_{\pi \in \mathcal{A}_t^\delta} \mathbb{E}[U(X_T^\pi) | \mathcal{F}_t]$
- The corresponding optimal strategy π^*
- First order approximations to V_t^δ and π^*
- A practical strategy to generate this approximated value process

Apply the martingale distortion transformation with $Y_t = Z_t^{\delta,H}$

$$V_t^\delta = \frac{X_t^{1-\gamma}}{1-\gamma} \left[\widetilde{\mathbb{E}} \left(e^{\frac{1-\gamma}{2q\gamma} \int_t^T \lambda^2(Z_s^{\delta,H}) ds} \middle| \mathcal{G}_t \right) \right]^q,$$

Approximation to the Value Process

Theorem (Fouque-Hu '17)

For fixed $t \in [0, T)$, $X_t = x$ and the observed value $Z_0^{\delta, H}$, the value process V_t^δ takes the form

$$\begin{aligned} V_t^\delta &= \frac{X_t^{1-\gamma}}{1-\gamma} e^{\frac{1-\gamma}{2\gamma} \lambda^2(Z_0^{\delta, H})(T-t)} + \frac{X_t^{1-\gamma}}{\gamma} e^{\frac{1-\gamma}{2\gamma} \lambda^2(Z_0^{\delta, H})(T-t)} \lambda(Z_0^{\delta, H}) \lambda'(Z_0^{\delta, H}) \phi_t^\delta \\ &+ \delta^H \rho \frac{X_t^{1-\gamma}}{1-\gamma} e^{\frac{1-\gamma}{2\gamma} \lambda^2(Z_0^{\delta, H})(T-t)} \lambda^2(Z_0^{\delta, H}) \lambda'(Z_0^{\delta, H}) \left(\frac{1-\gamma}{\gamma} \right)^2 \frac{(T-t)^{H+\frac{3}{2}}}{\Gamma(H+\frac{5}{2})} \\ &+ \mathcal{O}(\delta^{2H}), \end{aligned}$$

where ϕ_t^δ is the random component of order δ^H

$$\phi_t^\delta = \mathbb{E} \left[\int_t^T \left(Z_s^{\delta, H} - Z_0^{\delta, H} \right) ds \middle| \mathcal{G}_t \right].$$

Approximation to the Optimal Strategy

Recall that

$$\pi_t^* = \left[\frac{\lambda(Z_t^{\delta,H})}{\gamma\sigma(Z_t^{\delta,H})} + \frac{\rho q \xi_t}{\gamma\sigma(Z_t^{\delta,H})} \right] X_t$$

and ξ_t is from the martingale rep. of $M_t = \widetilde{\mathbb{E}} \left[e^{\frac{1-\gamma}{2q\gamma} \int_0^T \lambda^2(Z_s^{\delta,H}) ds} \middle| \mathcal{G}_t \right]$.

Theorem (Fouque-Hu '17)

The optimal strategy π_t^ is approximated by*

$$\begin{aligned} \pi_t^* &= \left[\frac{\lambda(Z_t^{\delta,H})}{\gamma\sigma(Z_t^{\delta,H})} + \delta^H \frac{\rho(1-\gamma)}{\gamma^2\sigma(Z_t^{\delta,H})} \frac{(T-t)^{H+1/2}}{\Gamma(H+\frac{3}{2})} \lambda(Z_0^{\delta,H}) \lambda'(Z_0^{\delta,H}) \right] X_t \\ &\quad + \mathcal{O}(\delta^{2H}) \\ &:= \pi_t^{(0)} + \delta^H \pi_t^{(1)} + \mathcal{O}(\delta^{2H}). \end{aligned}$$

Approximation to the Optimal Strategy

Recall that

$$\pi_t^* = \left[\frac{\lambda(Z_t^{\delta,H})}{\gamma\sigma(Z_t^{\delta,H})} + \frac{\rho q \xi_t}{\gamma\sigma(Z_t^{\delta,H})} \right] X_t$$

and ξ_t is from the martingale rep. of $M_t = \widetilde{\mathbb{E}} \left[e^{\frac{1-\gamma}{2q\gamma} \int_0^T \lambda^2(Z_s^{\delta,H}) ds} \middle| \mathcal{G}_t \right]$.

Theorem (Fouque-Hu '17)

The optimal strategy π_t^ is approximated by*

$$\begin{aligned} \pi_t^* &= \left[\frac{\lambda(Z_t^{\delta,H})}{\gamma\sigma(Z_t^{\delta,H})} + \delta^H \frac{\rho(1-\gamma)}{\gamma^2\sigma(Z_t^{\delta,H})} \frac{(T-t)^{H+1/2}}{\Gamma(H+\frac{3}{2})} \lambda(Z_0^{\delta,H}) \lambda'(Z_0^{\delta,H}) \right] X_t \\ &\quad + \mathcal{O}(\delta^{2H}) \\ &:= \pi_t^{(0)} + \delta^H \pi_t^{(1)} + \mathcal{O}(\delta^{2H}). \end{aligned}$$

How Good is the Approximation?

Corollary

In the case of power utility $U(x) = \frac{x^{1-\gamma}}{1-\gamma}$, $\pi^{(0)} = \frac{\lambda(Z_t^{\delta,H})}{\gamma\sigma(Z_t^{\delta,H})} X_t$ generates the approximation of V_t^δ up to order δ^H (leading order + two correction terms of order δ^H), thus asymptotically optimal in \mathcal{A}_t^δ .

- $H = \frac{1}{2}$, $Z_t^{\delta,H}$ becomes the Markovian OU process, both approximation coincides with results in [Fouque Sircar Zariphopoulou '13]. The corollary recovers [Fouque -Hu '16].
- Sketch of proofs: Apply Taylor expansion to $\lambda(z)$ at the point $Z_0^{\delta,H}$, and then control the moments $Z_t^{\delta,H} - Z_0^{\delta,H}$.

How Good is the Approximation?

Corollary

In the case of power utility $U(x) = \frac{x^{1-\gamma}}{1-\gamma}$, $\pi^{(0)} = \frac{\lambda(Z_t^{\delta,H})}{\gamma\sigma(Z_t^{\delta,H})} X_t$ generates the approximation of V_t^δ up to order δ^H (leading order + two correction terms of order δ^H), thus asymptotically optimal in \mathcal{A}_t^δ .

- $H = \frac{1}{2}$, $Z_t^{\delta,H}$ becomes the Markovian OU process, both approximation coincides with results in [Fouque Sircar Zariphopoulou '13]. The corollary recovers [Fouque -Hu '16].
- Sketch of proofs: Apply Taylor expansion to $\lambda(z)$ at the point $Z_0^{\delta,H}$, and then control the moments $Z_t^{\delta,H} - Z_0^{\delta,H}$.

Merton Problem under General Utility

Martingale Distortion Transformation is not available

→ Start with a given strategy $\pi^{(0)}$

- A first order approximation to $V^{\pi^{(0)},\delta}$
obtained by epsilon-martingale decomposition³⁴
- Optimality of $\pi^{(0)}$ in a smaller class of controls of feedback form

Denote by $v^{(0)}(t, x, z)$ the value function at the Sharpe-ratio $\lambda(z)$, we define $\pi^{(0)}$ by

$$\pi^{(0)}(t, x, z) = -\frac{\lambda(z)}{\sigma(z)} \frac{v_x^{(0)}(t, x, z)}{v_{xx}^{(0)}(t, x, z)}$$

and the associated value process $V^{\pi^{(0)},\delta}$

$$V_t^{\pi^{(0)},\delta} := \mathbb{E} \left[U(X_T^{\pi^{(0)}}) | \mathcal{F}_t \right].$$

³Fouque Papanicolaou Sircar '01

⁴Garnier Solna '15

Merton Problem under General Utility

Martingale Distortion Transformation is not available

→ Start with a given strategy $\pi^{(0)}$

- A first order approximation to $V^{\pi^{(0)},\delta}$
obtained by epsilon-martingale decomposition³⁴
- Optimality of $\pi^{(0)}$ in a smaller class of controls of feedback form

Denote by $v^{(0)}(t, x, z)$ the value function at the Sharpe-ratio $\lambda(z)$, we define $\pi^{(0)}$ by

$$\pi^{(0)}(t, x, z) = -\frac{\lambda(z)}{\sigma(z)} \frac{v_x^{(0)}(t, x, z)}{v_{xx}^{(0)}(t, x, z)}$$

and the associated value process $V^{\pi^{(0)},\delta}$

$$V_t^{\pi^{(0)},\delta} := \mathbb{E} \left[U(X_T^{\pi^{(0)}}) | \mathcal{F}_t \right].$$

³Fouque Papanicolaou Sircar '01

⁴Garnier Solna '15

Merton Problem under General Utility

Martingale Distortion Transformation is not available

→ Start with a given strategy $\pi^{(0)}$

- A first order approximation to $V^{\pi^{(0)},\delta}$
obtained by epsilon-martingale decomposition³⁴
- Optimality of $\pi^{(0)}$ in a smaller class of controls of feedback form

Denote by $v^{(0)}(t, x, z)$ the value function at the Sharpe-ratio $\lambda(z)$, we define $\pi^{(0)}$ by

$$\pi^{(0)}(t, x, z) = -\frac{\lambda(z)}{\sigma(z)} \frac{v_x^{(0)}(t, x, z)}{v_{xx}^{(0)}(t, x, z)}$$

and the associated value process $V^{\pi^{(0)},\delta}$

$$V_t^{\pi^{(0)},\delta} := \mathbb{E} \left[U(X_T^{\pi^{(0)}}) | \mathcal{F}_t \right].$$

³Fouque Papanicolaou Sircar '01

⁴Garnier Solna '15

Merton Problem under General Utility

Martingale Distortion Transformation is not available

→ Start with a given strategy $\pi^{(0)}$

- A first order approximation to $V^{\pi^{(0)},\delta}$
obtained by epsilon-martingale decomposition³⁴
- Optimality of $\pi^{(0)}$ in a smaller class of controls of feedback form

Denote by $v^{(0)}(t, x, z)$ the value function at the Sharpe-ratio $\lambda(z)$, we define $\pi^{(0)}$ by

$$\pi^{(0)}(t, x, z) = -\frac{\lambda(z)}{\sigma(z)} \frac{v_x^{(0)}(t, x, z)}{v_{xx}^{(0)}(t, x, z)}$$

and the associated value process $V^{\pi^{(0)},\delta}$

$$V_t^{\pi^{(0)},\delta} := \mathbb{E} \left[U(X_T^{\pi^{(0)}}) | \mathcal{F}_t \right].$$

³Fouque Papanicolaou Sircar '01

⁴Garnier Solna '15

Epsilon-Martingale Decomposition

Find $Q_t^{\pi^{(0)},\delta}$ such that

- $Q_T^{\pi^{(0)},\delta} = V_T^{\pi^{(0)},\delta} = U(X_T^{\pi^{(0)}}),$
- $Q_t^{\pi^{(0)},\delta} = M_t^\delta + R_t^\delta$, where M_t^δ is a martingale and R_t^δ is of order δ^{2H} .

Then

$$\begin{aligned} V_t^{\pi^{(0)},\delta} &= \mathbb{E} \left[Q_T^{\pi^{(0)},\delta} | \mathcal{F}_t \right] = M_t^\delta + \mathbb{E} \left[R_T^\delta | \mathcal{F}_t \right] \\ &= Q_t^{\pi^{(0)},\delta} - R_t^\delta + \mathbb{E} \left[R_T^\delta | \mathcal{F}_t \right], \end{aligned}$$

and $Q_t^{\pi^{(0)},\delta}$ is an approximation to $V_t^{\pi^{(0)},\delta}$ with error of order $\mathcal{O}(\delta^{2H})$

Epsilon-Martingale Decomposition

Find $Q_t^{\pi^{(0)},\delta}$ such that

- $Q_T^{\pi^{(0)},\delta} = V_T^{\pi^{(0)},\delta} = U(X_T^{\pi^{(0)}}),$
- $Q_t^{\pi^{(0)},\delta} = M_t^\delta + R_t^\delta$, where M_t^δ is a martingale and R_t^δ is of order δ^{2H} .

Then

$$\begin{aligned} V_t^{\pi^{(0)},\delta} &= \mathbb{E} \left[Q_T^{\pi^{(0)},\delta} | \mathcal{F}_t \right] = M_t^\delta + \mathbb{E} \left[R_T^\delta | \mathcal{F}_t \right] \\ &= \textcolor{blue}{Q}_t^{\pi^{(0)},\delta} - \textcolor{red}{R}_t^\delta + \mathbb{E} \left[\textcolor{red}{R}_T^\delta | \mathcal{F}_t \right], \end{aligned}$$

and $Q_t^{\pi^{(0)},\delta}$ is an approximation to $V_t^{\pi^{(0)},\delta}$ with error of order $\mathcal{O}(\delta^{2H})$

Epsilon-Martingale Decomposition

Find $Q_t^{\pi^{(0)},\delta}$ such that

- $Q_T^{\pi^{(0)},\delta} = V_T^{\pi^{(0)},\delta} = U(X_T^{\pi^{(0)}}),$
- $Q_t^{\pi^{(0)},\delta} = M_t^\delta + R_t^\delta$, where M_t^δ is a martingale and R_t^δ is of order δ^{2H} .

Then

$$\begin{aligned} V_t^{\pi^{(0)},\delta} &= \mathbb{E} \left[Q_T^{\pi^{(0)},\delta} | \mathcal{F}_t \right] = M_t^\delta + \mathbb{E} \left[R_T^\delta | \mathcal{F}_t \right] \\ &= \textcolor{blue}{Q}_t^{\pi^{(0)},\delta} - \textcolor{red}{R}_t^\delta + \mathbb{E} \left[\textcolor{red}{R}_T^\delta | \mathcal{F}_t \right], \end{aligned}$$

and $Q_t^{\pi^{(0)},\delta}$ is an approximation to $V^{\pi^{(0)},\delta}$ with error of order $\mathcal{O}(\delta^{2H})$

First order approximation to $V^{\pi^{(0)},\delta}$

Proposition

For fixed $t \in [0, T)$, $X_t^{\pi^{(0)}} = x$, and the observed value $Z_0^{\delta,H}$, the \mathcal{F}_t -measurable value process $V_t^{\pi^{(0)},\delta}$ is of the form

$$V_t^{\pi^{(0)},\delta} = Q_t^{\pi^{(0)},\delta}(X_t^{\pi^{(0)}}, Z_0^{\delta,H}) + \mathcal{O}(\delta^{2H}),$$

where $Q_t^{\pi^{(0)},\delta}(x, z)$ is given by:

$$\begin{aligned} Q_t^{\pi^{(0)},\delta}(x, z) = & v^{(0)}(t, x, z) + \lambda(z)\lambda'(z)D_1v^{(0)}(t, x, z)\phi_t^\delta \\ & + \delta^H \rho \lambda^2(z)\lambda'(z)D_1^2v^{(0)}(t, x, z) \frac{(T-t)^{H+3/2}}{\Gamma(H + \frac{5}{2})}. \end{aligned}$$

- For power utility, $Q_t^{\pi^{(0)},\delta}$ coincides with the approximation of V_t^δ
- In the Markovian case $H = \frac{1}{2}$, recovers the results in [Fouque-Hu '16]

First order approximation to $V^{\pi^{(0)},\delta}$

Proposition

For fixed $t \in [0, T)$, $X_t^{\pi^{(0)}} = x$, and the observed value $Z_0^{\delta, H}$, the \mathcal{F}_t -measurable value process $V_t^{\pi^{(0)},\delta}$ is of the form

$$V_t^{\pi^{(0)},\delta} = Q_t^{\pi^{(0)},\delta}(X_t^{\pi^{(0)}}, Z_0^{\delta, H}) + \mathcal{O}(\delta^{2H}),$$

where $Q_t^{\pi^{(0)},\delta}(x, z)$ is given by:

$$\begin{aligned} Q_t^{\pi^{(0)},\delta}(x, z) = & v^{(0)}(t, x, z) + \lambda(z)\lambda'(z)D_1v^{(0)}(t, x, z)\phi_t^\delta \\ & + \delta^H \rho \lambda^2(z)\lambda'(z)D_1^2v^{(0)}(t, x, z) \frac{(T-t)^{H+3/2}}{\Gamma(H + \frac{5}{2})}. \end{aligned}$$

- For power utility, $Q_t^{\pi^{(0)},\delta}$ coincides with the approximation of V_t^δ
- In the Markovian case $H = \frac{1}{2}$, recovers the results in [Fouque-Hu '16]

Asymptotically Optimality of $\pi^{(0)}$

Theorem (Fouque-Hu '17)

The trading strategy $\pi^{(0)}(t, x, z) = -\frac{\lambda(z)}{\sigma(z)} \frac{v_x^{(0)}(t, x, z)}{v_{xx}^{(0)}(t, x, z)}$ is asymptotically optimal in the following class:

$$\tilde{\mathcal{A}}_t^\delta[\tilde{\pi}^0, \tilde{\pi}^1, \alpha] := \left\{ \pi = \tilde{\pi}^0 + \delta^\alpha \tilde{\pi}^1 : \pi \in \mathcal{A}_t^\delta, \alpha > 0, 0 < \delta \leq 1 \right\}.$$

The proof uses the nice properties of the **risk tolerance function**

$$R(t, x, z) = -\frac{v_x^{(0)}(t, x, z)}{v_{xx}^{(0)}(t, x, z)} \text{ and the operator } D_1 = R\partial_x$$

Merton Problem under Fast-Varying Fractional SV

Consider a ϵ -scaled stationary fOU process $Y_t^{\epsilon, H}$

$$Y_t^{\epsilon, H} = \epsilon^{-H} \int_{-\infty}^t e^{-\frac{a(t-s)}{\epsilon}} dW_s^{(H)} = \int_{-\infty}^t \mathcal{K}^\epsilon(t-s) dW_s^Y$$

together with the risky asset

$$dS_t = S_t \left[\mu(Y_t^{\epsilon, H}) dt + \sigma(Y_t^{\epsilon, H}) dW_t \right], \quad d\langle W, W^Y \rangle_t = \rho dt,$$

For power utilities, we obtain:

- The value process V_t^ϵ and the corresponding optimal strategy π^*
- First order approximations to V_t^ϵ and π^*
- A strategy $\pi^{(0)}$ to generate this approximated value process

Using singular perturbation , but only valid for $H \in (\frac{1}{2}, 1)$

Merton Problem under Fast-Varying Fractional SV

Consider a ϵ -scaled stationary fOU process $Y_t^{\epsilon, H}$

$$Y_t^{\epsilon, H} = \epsilon^{-H} \int_{-\infty}^t e^{-\frac{a(t-s)}{\epsilon}} dW_s^{(H)} = \int_{-\infty}^t \mathcal{K}^\epsilon(t-s) dW_s^Y$$

together with the risky asset

$$dS_t = S_t \left[\mu(Y_t^{\epsilon, H}) dt + \sigma(Y_t^{\epsilon, H}) dW_t \right], \quad d\langle W, W^Y \rangle_t = \rho dt,$$

For power utilities, we obtain:

- The value process V_t^ϵ and the corresponding optimal strategy π^*
- First order approximations to V_t^ϵ and π^*
- A strategy $\pi^{(0)}$ to generate this approximated value process

Using singular perturbation , but only valid for $H \in (\frac{1}{2}, 1)$

Merton Problem under Fast-Varying Fractional SV

Consider a ϵ -scaled stationary fOU process $Y_t^{\epsilon, H}$

$$Y_t^{\epsilon, H} = \epsilon^{-H} \int_{-\infty}^t e^{-\frac{a(t-s)}{\epsilon}} dW_s^{(H)} = \int_{-\infty}^t \mathcal{K}^\epsilon(t-s) dW_s^Y$$

together with the risky asset

$$dS_t = S_t \left[\mu(Y_t^{\epsilon, H}) dt + \sigma(Y_t^{\epsilon, H}) dW_t \right], \quad d\langle W, W^Y \rangle_t = \rho dt,$$

For power utilities, we obtain:

- The value process V_t^ϵ and the corresponding optimal strategy π^*
- First order approximations to V_t^ϵ and π^*
- A strategy $\pi^{(0)}$ to generate this approximated value process

Using singular perturbation , but only valid for $H \in (\frac{1}{2}, 1)$

Approximation to the Value Process V_t^ϵ

Theorem (Fouque-Hu '17)

For fixed $t \in [0, T)$, $X_t = x$ the value process V_t^ϵ takes the form

$$\begin{aligned} V_t^\epsilon &= \frac{X_t^{1-\gamma}}{1-\gamma} e^{\frac{1-\gamma}{2\gamma} \bar{\lambda}^2 (T-t)} + \frac{X_t^{1-\gamma}}{\gamma} e^{\frac{1-\gamma}{2\gamma} \bar{\lambda}^2 (T-t)} \phi_t^\epsilon \\ &+ \epsilon^{1-H} \rho \frac{X_t^{1-\gamma}}{1-\gamma} e^{\frac{1-\gamma}{2\gamma} \bar{\lambda}^2 (T-t)} \tilde{\lambda} \left(\frac{1-\gamma}{\gamma} \right)^2 \frac{\langle \lambda \lambda' \rangle (T-t)^{H+\frac{1}{2}}}{a \Gamma(H + \frac{3}{2})} \\ &+ o(\epsilon^{1-H}), \end{aligned}$$

where ϕ_t^ϵ is the random component of order ϵ^{1-H}

$$\phi_t^\epsilon = \mathbb{E} \left[\frac{1}{2} \int_t^T \left(\lambda^2(Y_s^{\epsilon, H}) - \bar{\lambda}^2 \right) ds \middle| \mathcal{G}_t \right].$$

Optimal Portfolio

Theorem (Fouque-Hu '17)

The optimal strategy π_t^* is approximated by

$$\pi_t^* = \left[\frac{\lambda(Y_t^{\epsilon,H})}{\gamma\sigma(Y_t^{\epsilon,H})} + \epsilon^{1-H} \frac{\rho(1-\gamma)}{\gamma^2\sigma(Y_t^{\epsilon,H})} \frac{\langle \lambda\lambda' \rangle (T-t)^{H-1/2}}{a\Gamma(H+\frac{1}{2})} \right] X_t + o(\epsilon^{1-H})$$

Corollary

In the case of power utility, $\pi^{(0)} = \frac{\lambda(Y_t^{\epsilon,H})}{\gamma\sigma(Y_t^{\epsilon,H})} X_t$ generates the approximation of V^ϵ up to order ϵ^{1-H} (leading order + two correction terms of order ϵ^{1-H}), thus asymptotically optimal in \mathcal{A}_t^ϵ .

Comparison with the Markovian Case

- The value function and the optimal strategy are derived in [FSZ '13]:

$$V^\epsilon(t, X_t) = \frac{X_t^{1-\gamma}}{1-\gamma} e^{\frac{1-\gamma}{2\gamma} \bar{\lambda}^2 (T-t)} \left[1 - \sqrt{\epsilon} \rho \left(\frac{1-\gamma}{\gamma} \right)^2 \frac{\langle \lambda \theta' \rangle}{2} (T-t) \right] + \mathcal{O}(\epsilon)$$

$$\pi^*(t, X_t, Y_t^{\epsilon, H}) = \left[\frac{\lambda(Y_t^{\epsilon, H})}{\gamma \sigma(Y_t^{\epsilon, H})} + \sqrt{\epsilon} \frac{\rho(1-\gamma)}{\gamma^2 \sigma(Y_t^{\epsilon, H})} \frac{\theta'(Y_t^{\epsilon, H})}{2} \right] X_t + \mathcal{O}(\epsilon)$$

- Formally let $H \downarrow \frac{1}{2}$ in our results:

$$V_t^\epsilon = \frac{X_t^{1-\gamma}}{1-\gamma} e^{\frac{1-\gamma}{2\gamma} \bar{\lambda}^2 (T-t)} \left[1 + \sqrt{\epsilon} \rho \left(\frac{1-\gamma}{\gamma} \right)^2 \frac{\tilde{\lambda} \langle \lambda \lambda' \rangle}{a} (T-t) \right] + o(\sqrt{\epsilon})$$

$$\pi_t^* = \left[\frac{\lambda(Y_t^{\epsilon, H})}{\gamma \sigma(Y_t^{\epsilon, H})} + \sqrt{\epsilon} \frac{\rho(1-\gamma)}{\gamma^2 \sigma(Y_t^{\epsilon, H})} \frac{\langle \lambda \lambda' \rangle}{a} \right] X_t + o(\sqrt{\epsilon})$$

Joyeux Anniversaire Jim!