

Technical Analysis Compared to Mathematical Models under Misspecification

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Outline

- 1 Introduction
- 2 Our Model
- 3 Optimal Portfolio Allocation
 - Mathematical Results
 - Numerical Results
- 4 Comparisons of Strategies

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Motivation

Technical Analysis

- avoids model specification and calibration problems

Mathematical Models

- theoretically better
- liable to miscalibration

Framework

Bond $dS_t^0 = S_t^0 r dt,$

Stock $dS_t = \mu(t) S_t dt + \sigma S_t dB_t,$

- B standard Brownian motion,
- $\mu(t) \in \{\mu_1, \mu_2\}$ independent of B ,
- $\pi_t \in \{0, 1\}$ proportion of the wealth invested in the stock
- terminal time T

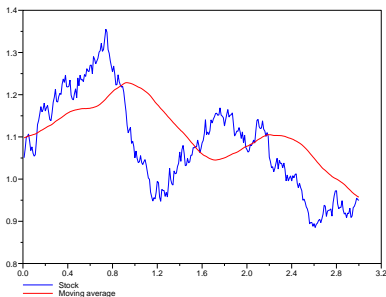
Technical Analyst Strategy

Technical analyst: moving average strategy

$$M_t^\delta = \frac{1}{\delta} \int_{t-\delta}^t S_u du$$

If $S_t > M_t^\delta$ buy

If $S_t < M_t^\delta$ sell



$$\begin{aligned} \mu_1 &= -0.2, \mu_2 = 0.2, \\ \sigma &= 0.15, \delta = 0.8. \end{aligned}$$

Previous work

BLANCHET, DIOP, GIBSON, KAMINSKI, TALAY, TANRÉ (2005)

One change of drift:

- $\mu(t) = \mu_1$ if $t < \tau$

- $\mu(t) = \mu_2$ if $t \geq \tau$

with $\mathbb{P}(\tau > t) = e^{-\lambda t}$

Optimal strategy: detect τ .

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Our Model

- Several changes of drift

(ξ_{2n+1}) iid $\text{Exp}(\lambda_1)$, (ξ_{2n}) iid $\text{Exp}(\lambda_2)$

$\tau_0 = 0$, $\tau_n = \xi_1 + \dots + \xi_n$

$$\mu(t) = \begin{cases} \mu_1 & \text{if } \tau_{2n} \leq t < \tau_{2n+1} \\ \mu_2 & \text{if } \tau_{2n+1} \leq t < \tau_{2n+2} \end{cases}$$

- Transaction costs

- g_{01} buying cost
- g_{10} selling cost

Admissible Strategies

$\pi_t \in \{0, 1\}$ proportion of the wealth invested in the stock

$$\mathcal{F}_t^S = \sigma(\mathbf{S}_u, u \leq t) \neq \mathcal{F}_t^B = \sigma(\mathbf{B}_u, u \leq t)$$

We want π_t measurable w.r.t. \mathcal{F}_t^S

\implies change of framework

Filtering Theory

Optional projection: $F_t = \mathbb{P}(\mu(t) = \mu_1 \mid \mathcal{F}_t^S)$

$$\bar{B}_t = \frac{1}{\sigma} \left(\log \frac{S_t}{S_0} - \int_0^t (\mu_1 F_s + \mu_2(1 - F_s) - \frac{\sigma^2}{2}) ds \right)$$

Proposition (Martinez, Rubenthaler, Tanré 2005)

- \bar{B} is a (\mathcal{F}^S) Brownian Motion
- $\mathcal{F}^S = \mathcal{F}^{\bar{B}}$

$$\frac{dS_t}{S_t} = (\mu_1 F_t + \mu_2(1 - F_t)) dt + \sigma d\bar{B}_t$$

Theorem (KURTZ, OCONE 1988)

New Framework

W_t^π : Wealth process with strategy π

$$\begin{aligned} \frac{dW_t^\pi}{W_{t^-}^\pi} &= \pi_t \frac{dS_t}{S_t} + (1 - \pi_t) \frac{dS_t^0}{S_t^0} \\ &\quad - g_{01} \delta(\Delta\pi_t = 1) - g_{10} \delta(\Delta\pi_t = -1) \\ &= (\pi_t(\mu_1 F_t + \mu_2(1 - F_t)) + (1 - \pi_t)r) dt + \pi_t \sigma d\bar{B}_t \\ &\quad - g_{01} \delta(\Delta\pi_t = 1) - g_{10} \delta(\Delta\pi_t = -1) \end{aligned}$$

$$dF_t = (-\lambda_1 F_t + \lambda_2(1 - F_t)) dt + \frac{\mu_1 - \mu_2}{\sigma} F_t(1 - F_t) d\bar{B}_t,$$

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Value Functions

Utility: $U(x) = x^\alpha$, $\alpha \in]0, 1[$

Value functions:

$$V^0(t, x, f) = \sup_{\pi} \mathbb{E}[U(W_T^\pi) \mid \pi_{t-} = 0, W_{t-}^\pi = x, F_t = f]$$

$$V^1(t, x, f) = \sup_{\pi} \mathbb{E}[U(W_T^\pi) \mid \pi_{t-} = 1, W_{t-}^\pi = x, F_t = f]$$

Properties of V

Proposition (Continuity)

For all $i \in \{0; 1\}$, $0 \leq t \leq \hat{t} \leq T$, $x, \hat{x} > 0$, $0 \leq f, \hat{f} \leq 1$:

$$\begin{aligned} & |V^i(\hat{t}, \hat{x}, \hat{f}) - V^i(t, x, f)| \\ & \leq C(1 + x^{\alpha-1} + \hat{x}^{\alpha-1})(|\hat{x} - x| + x(|\hat{f} - f| + |\hat{t} - t|^{1/2})) \end{aligned}$$

Theorem (Dynamic Programming Principle)

For all $0 \leq s \leq t \leq T$ and x, f, i :

$$V^i(s, x, f) = \sup_{\pi} \mathbb{E}[V^{\pi_{t-}}(t, W_t^{s,x,f,\pi}, F_t^{s,f})]$$

Hamilton Jacobi Bellman Equations

\mathcal{V}_α : set of continuous functions φ on $[0; T] \times [0; +\infty[\times [0; 1]$ satisfying $\varphi(t, 0, f) = 0$ and

$$\sup_{[0; T] \times [0; +\infty[\times [0; 1]^2} \frac{|\varphi(t, \mathbf{x}, f) - \varphi(t, \hat{\mathbf{x}}, \hat{f})|}{(1 + \mathbf{x}^{\alpha-1} + \hat{\mathbf{x}}^{\alpha-1})(|\mathbf{x} - \hat{\mathbf{x}}| + \mathbf{x}|f - \hat{f}|)} < \infty.$$

Theorem

(V^0, V^1) is the unique viscosity solution of

$$\begin{cases} \min \left\{ -\frac{\partial \varphi^0}{\partial t} - \mathcal{L}^0 \varphi^0; \varphi^0(t, \mathbf{x}, f) - \varphi^1(t, \mathbf{x}(1 - g_{01}), f) \right\} = 0 \\ \min \left\{ -\frac{\partial \varphi^1}{\partial t} - \mathcal{L}^1 \varphi^1; \varphi^1(t, \mathbf{x}, f) - \varphi^0(t, \mathbf{x}(1 - g_{10}), f) \right\} = 0 \end{cases}$$

in $\mathcal{V}_\alpha \times \mathcal{V}_\alpha$ such that $V^0(T, \mathbf{x}, f) = V^1(T, \mathbf{x}, f) = U(\mathbf{x}) = \mathbf{x}^\alpha$

Discretization Scheme

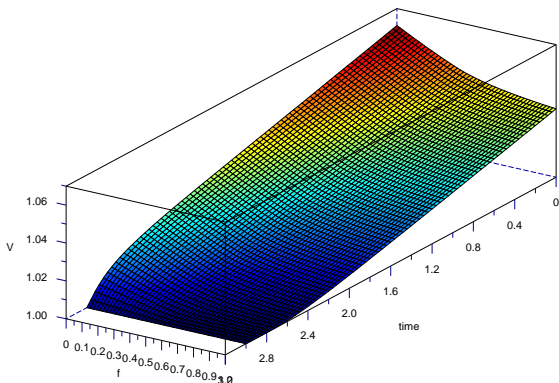
Dependence on x :

$$\begin{aligned} V^i(t, x, f) &= \sup_{\pi} \mathbb{E}[U(W_T^{\pi}) \mid \pi_{t-} = 0, W_{t-}^{\pi} = x, F_t = f] \\ &= x^{\alpha} V^i(t, 1, f) \end{aligned}$$

- First step: compute $\overline{V}^0(t, \cdot)$ and $\overline{V}^1(t, \cdot)$ that solve HJB equation from $\hat{V}^0(t + dt, \cdot)$ and $\hat{V}^1(t + dt, \cdot)$
- Second step: comparison
 - if $\overline{V}^0(t, f) \geq (1 - g_{01})^{\alpha} \overline{V}^1(t, f)$, take $\hat{V}^0(t, f) = \overline{V}^0(t, f)$
 otherwise take $\hat{V}^0(t, f) = (1 - g_{01})^{\alpha} \overline{V}^1(t, f)$
 - if $\overline{V}^1(t, f) \geq (1 - g_{10})^{\alpha} \overline{V}^0(t, f)$, take $\hat{V}^1(t, f) = \overline{V}^1(t, f)$
 otherwise take $\hat{V}^1(t, f) = (1 - g_{10})^{\alpha} \overline{V}^0(t, f)$

Value Function V^0

Parameters: $T = 3$, $\mu_2 = -\mu_1 = 0.2$, $\lambda_1 = \lambda_2 = 2$, $\sigma = 0.15$,
 $g_{01} = g_{10} = 0.001$

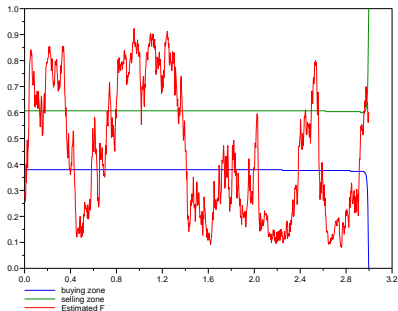


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An efficient strategy

- Compute \hat{V}^0 and \hat{V}^1
- Estimate \hat{F}_t from the stock
- Compare $\hat{V}^0(t, \hat{F}_t)$ and $\hat{V}^1(t, \hat{F}_t)$:
 - buy if $\hat{V}^0(t, \hat{F}_t) = (1 - g_{01})^\alpha \hat{V}^1(t, \hat{F}_t)$
 - sell if $\hat{V}^1(t, \hat{F}_t) = (1 - g_{10})^\alpha \hat{V}^0(t, \hat{F}_t)$



$$\mu_1 = -0.2, \mu_2 = 0.2,$$

$$\sigma = 0.15, \lambda_1 = 2,$$

$$\lambda_2 = 2, T = 3$$

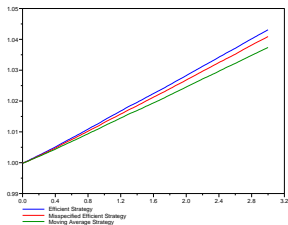
Efficient Strategy vs Value Function

100000 Monte Carlo simulations of the efficient strategy

F_0	0	0.1	0.2	0.3	0.4	0.5
Computed V^0	1.061	1.057	1.053	1.049	1.045	1.043
Efficient strategy	1.061	1.057	1.052	1.049	1.045	1.043

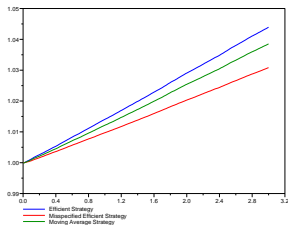
F_0	0.6	0.7	0.8	0.9	1
Computed V^0	1.041	1.039	1.038	1.037	1.036
Efficient strategy	1.040	1.039	1.038	1.037	1.036

Misspecified Strategy vs Moving Average



Misspecified parameters:

$$\mu_1 = -1.8, \mu_2 = 1.8, \sigma = 0.15, \\ \lambda_1 = 4, \lambda_2 = 4$$



Misspecified parameters:

$$\mu_1 = -1.8, \mu_2 = 1.8, \sigma = 0.25, \\ \lambda_1 = 4, \lambda_2 = 4$$

Real parameters: $\mu_1 = -0.2, \mu_2 = 0.2, \sigma = 0.15, \lambda_1 = 2,$
 $\lambda_2 = 2, T = 3, \delta = 0.8, 100000$ Monte Carlo simulations