QUANTITATIVE ANALYSIS OF DUAL MOVING AVERAGE INDICATORS IN AUTOMATED TRADING SYSTEMS

Doug Service

May 21, 2016

CFRM Program Applied Mathematics University of Washington

OUTLINE

- 1. Introduction
- 2. Assumptions
- 3. Continuous Time Model
- 4. Strategy Definition
- 5. Evaluation Criteria
- 6. Example
- 7. Strategy Analysis
 - Exponentially Filtered Logarithm of Asset Price
 - **Difference Indicator**
 - **Transient Behavior**
 - Steady State
 - Log Return
- 8. Summary

INTRODUCTION



Dual Moving Average Technical Trading Strategy [Jaekle and Tomasini(2009)]

Long position - fast MA above slow MA

Short position - fast MA below slow MA

INTRODUCTION

Luxor dual moving average trading strategy

Luxor historically analyzed via inferential statistics

- Discrete time setting
- Historical data [Jaekle and Tomasini(2009)]
- Bootstrapped resampled [Efron(1979)]) [William Brock(1992)]

to determine

- Expected returns
- Draw down
- Select strategy parameters etc.

Our goal

Assume price dynamics are controlled by a stochastic differential equation (SDE) and derive the Luxor closed form expected log returns in a continuous time setting

- Inspired by work in options pricing [Black and Scholes(1973), Merton(1973)]
- Gain analytical tractability by using the natural logarithm of the price
- Build frame work for analyzing trading strategies

©Doug Service 2016 @🖲 🕲 🎯

ASSUMPTIONS

To gain analytical tractability we assume a frictionless market

- 1. Difference between the bid and ask price is infinitesimal
- 2. Transaction costs are zero
- 3. Transaction execution is instantaneous
- 4. Buy (sell) transactions fully execute at the current ask (bid) price
- 5. Market contains a single risky asset with price S_t

CONTINUOUS TIME MODEL

Price Dynamics

- Let $\left(\Omega,\mathcal{F},\left\{\mathcal{F}_{t}\right\}_{t\geq0},\mathbb{P}\right)$ be a complete filtered probability space
- Dynamics of S_t under \mathbb{P} is controlled by the SDE

 $dS_t = \mu S_t dt + \sigma S_t dW_t$ $\mu, \sigma \in \mathbb{R}$ constant

- W_t is one dimensional Brownian motion whose history up to time t contained in the filtration $\{\mathcal{F}_t\}_{t>0}$
- For each $\omega \in \Omega$ there exits a function

 $W_t(\omega) : \mathbb{R}_+ \times \Omega \to \mathbb{R}_+$ (the samples)

• $W_0(\omega) = 0$, disjoint increments of $W_t(\omega)$ are independent, increments $W_{\Delta t}(\omega)$ are normally distributed with mean zero and variance Δt , and $W_t(\omega)$ is continuous on [0, t].

SDE Solution

Let

$$f(s) = \ln s, \quad f'(s) = \frac{1}{s}, \quad f''(s) = -\frac{1}{s^2}$$
$$(dt)^2 = 0, \quad (dt)(dW_t) = 0, \quad (dW_t)^2 = dt \quad ([W, W]_t = t)$$

Apply Itô's formula [Shreve(2004)] to $d \ln S_t$ where $dS_t = \mu S_t dt + \sigma S_t dW_t$

$$df(S_t) = f'(S_t) dS_t + \frac{1}{2} f''(S_t) (dS_t)^2$$

$$d \ln S_t = \frac{1}{S_t} dS_t + \frac{1}{2} \left(-\frac{1}{S_t^2} \right) (dS_t)^2$$

$$= \frac{1}{S_t} \left(\mu S_t dt + \sigma S_t dW_t \right) + \frac{1}{2} \left(-\frac{1}{S_t^2} \right) \left(\sigma^2 S_t^2 dt \right)$$

$$= \left(\mu - \frac{\sigma^2}{2} \right) dt + \sigma dW_t$$
(1)

SDE Solution

Integrate equation 1 from 0 to t and apply exponential function to both sides

$$\int_{0}^{t} d\ln S_{t} = \int_{0}^{t} \left(\mu - \frac{\sigma^{2}}{2}\right) du + \int_{0}^{t} \sigma dW_{u}$$
$$\ln S_{t} = \ln S_{0} + \left(\mu - \frac{\sigma^{2}}{2}\right) t + \sigma W_{t}$$
$$S_{t} = S_{0} e^{\left(\mu - \frac{\sigma^{2}}{2}\right) t + \sigma W_{t}}$$
(2)

The solution S_t is known as geometric Brownian motion.

J

Model

Dividing both sides of the SDE by S_t , it can be rewritten as

$$\frac{dS_t}{S_t} = \mu dt + \sigma dW_t \tag{3}$$

In essence, the instantaneous return is a constant term plus a volatility term

• If we knew that either $\mu >> \frac{\sigma^2}{2}$ or $\mu << \frac{\sigma^2}{2}$ and the SDE model is accurate, investing would be easy; thus, we assume $|\mu - \frac{\sigma^2}{2}|$ is not large and μ is not easy to determine for a given asset over a short time frame

Exponentially Filtered Stochastic Process

An exponentially filtered stochastic process $\Upsilon_t[X_t; \tau]$ where $\tau > 0$ is a convolution of the exponential kernel function $\frac{1}{\tau}e^{-\frac{1}{\tau}t}$ with the stochastic process X_t .

$$\Upsilon_t[X_t;\tau] = \int_0^t \frac{1}{\tau} e^{-\frac{1}{\tau}(t-u)} X_u du \tag{4}$$

Note:

- $\Upsilon_t[X_t; \tau]$ is a path dependent time series operator
- $\Upsilon_t[X_t; \tau]$ is $\{\mathcal{F}_t\}_{t>0}$ measurable can calculate $\Upsilon_t[X_t; \tau]$ given filtration at time t
- Lower limit is usually defined as $-\infty$; however, we work with processes on [0, *T*] and assume a steady state is reached in finite time at $t > t_{ss}$

STRATEGY DEFINITION

Strategy Components [Peterson(2015)]

- Filters select instruments
- · Indicators quantitative values derived from market data
- · Signals respond to interactions between filters, market data, and indicators
- Rules make path dependent actionable decisions when signals fire

Formulate Luxor as a set of equations following this model

Difference Indicator

The difference indicator $\Psi_t : \mathbb{R} \to \mathbb{R}$ is the difference of two exponential filters applied to a stochastic process X_t where $0 < \tau_1 < \tau_2$.

$$\Psi_t[X_t;\tau_1,\tau_2] = \Upsilon_t[X_t;\tau_1] - \Upsilon_t[X_t;\tau_2]$$

- Use natural logarithm of the asset price $X_t = \ln S_t$ to gain analytical tractability
- $\Psi_t[X_t; \tau_1, \tau_2]$ known as moving average convergence divergence (MACD) oscillator in technical analysis.

Position Indicator

The position indicator $\varrho_t : \mathbb{R} \to \{-1, 0, 1\}$ is the composition of the signum function with the difference indicator and indicates potential long or short position opportunities.

$$\varrho_{t} = (\operatorname{sgn} \circ \Psi)_{t} = \operatorname{sgn} (\Psi_{t}) = \begin{cases} 1 & \Psi_{t} \ge 0 & \operatorname{long} \\ 0 & \Psi_{t} = 0 & \operatorname{previous} \\ -1 & \Psi_{t} < 0 & \operatorname{short} \end{cases}$$
(5)

Position Entry/Exit Signals

Position indicator transitions

- + (-1 \rightarrow +1) or (-1 \rightarrow 0 \rightarrow +1) exit any short position and enter a long position
- + (1 \rightarrow -1) or (1 \rightarrow 0 \rightarrow -1) exit any long position and enter short position

Initial entry/final exit occur on first position indicator entry/exit signal after steady state is reached at t $>t_{\rm SS}$

Rules

Always act on position indicator signals (identity function)

- Gain analytical tractability
- Efficient implementation uses rules to define
 - · When and how to enter or exit the market
 - Determine position size
 - Manage risk

EVALUATION CRITERIA

Luxor Log Return

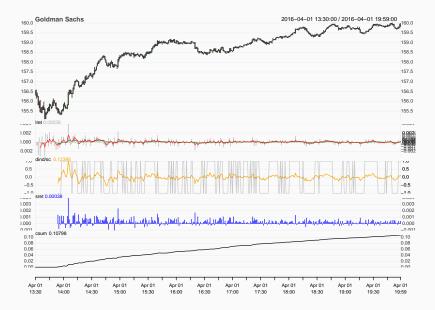
The log return r_t of the Luxor strategy on [0, t] is given by the integral of the position indicator ρ with respect to the change of the logarithm of the asset price.

$$r_t = \int_0^t \varrho_u d\ln S_u \tag{6}$$

Assumes equal size positions in the asset

EXAMPLE

EXAMPLE



STRATEGY ANALYSIS

Construct the exponentially filtered logarithm of the asset price $\Upsilon_t[\ln S_t, \tau]$ by substituting the logarithm of the SDE solution S_t from equation 2 for X_t in the filter definition in equation 4.

$$\begin{split} \Upsilon_t[\ln S_t,\tau] &= \int_0^t \frac{1}{\tau} e^{-\frac{1}{\tau}(t-u)} \left[\ln S_0 + \left(\mu - \frac{\sigma^2}{2}\right) u + \sigma W_u \right] du \\ &= \frac{e^{-\frac{1}{\tau}t}}{\tau} \left[\ln S_0 \int_0^t e^{\frac{1}{\tau}u} du + \left(\mu - \frac{\sigma^2}{2}\right) \int_0^t u \, e^{\frac{1}{\tau}u} du + \sigma \int_0^t e^{\frac{1}{\tau}u} W_u du \right] \end{split}$$
(7)

First two integrals in $\Upsilon_t[\ln S_t, \tau]$ are deterministic Riemann integrals wrt time and have explicit solutions. The last integral is a stochastic Riemann integral of Brownian motion wrt time.

First integral in $\Upsilon_t[\ln S_t, \tau]$, equation is solved using the fundamental theorem of calculus.

$$\int_{0}^{t} e^{\frac{1}{\tau}u} du = \tau \left[e^{\frac{1}{\tau}u} \right]_{0}^{t}$$
$$= \tau \left(e^{\frac{1}{\tau}t} - 1 \right)$$
(8)

The second integral requires in addition to the fundamental theorem of calculus integration by parts where $\int x dy = xy - \int y dx$. Let x = u which implies dx = du, and let

(

$$dy = e^{\frac{1}{\tau}u} du$$
$$y = \int e^{\frac{1}{\tau}u} du$$
$$= \tau e^{\frac{1}{\tau}u}$$
(9)

Using the results from equation 9 to complete the integration by parts solves the second integral in $\Upsilon_t[\ln S_t, \tau]$ from equation 7.

$$\int_{0}^{t} u e^{\frac{1}{\tau}u} du = \tau \left[u e^{\frac{1}{\tau}u} \right]_{0}^{t} - \int_{0}^{t} \tau e^{\frac{1}{\tau}u} du$$
$$= \tau t e^{\frac{1}{\tau}t} - \tau^{2} \left[e^{\frac{1}{\tau}u} \right]_{0}^{t}$$
$$= \tau \left[t e^{\frac{1}{\tau}t} - \tau \left(e^{\frac{1}{\tau}t} - 1 \right) \right]$$
(10)

Inserting the results of equations 8 and 10 into $\Upsilon_t[\ln S_t, \tau]$, equation 7, results in an equation with two deterministic terms and a stochastic term which is a Riemann integral of scaled Brownian motion wrt time.

$$\begin{split} \Upsilon_{t}[\ln S_{t},\tau] &= \frac{e^{-\frac{1}{\tau}t}}{\tau} \left[\tau \ln S_{0} \left(e^{\frac{1}{\tau}t} - 1 \right) \right. \\ &+ \tau \left(\mu - \frac{\sigma^{2}}{2} \right) \left[t e^{\frac{1}{\tau}t} - \tau \left(e^{\frac{1}{\tau}t} - 1 \right) \right] + \sigma \int_{0}^{t} e^{\frac{1}{\tau}u} W_{u} du \\ &= \ln S_{0} \left(1 - e^{-\frac{1}{\tau}t} \right) \\ &+ \left(\mu - \frac{\sigma^{2}}{2} \right) \left[t - \tau \left(1 - e^{-\frac{1}{\tau}t} \right) \right] + \frac{\sigma e^{-\frac{1}{\tau}t}}{\tau} \int_{0}^{t} e^{\frac{1}{\tau}u} W_{u} du \quad (11) \end{split}$$

Difference Indicator

Let $0 < \tau_1 < \tau_2$, the difference indicator $\Psi_t[\ln S_t, \tau_1, \tau_2]$ is formed from the difference of two versions of Υ with different values of τ applied to $\ln S_t$.

$$\begin{split} \Psi_{t}[\ln S_{t},\tau_{1},\tau_{2}] &= \Upsilon_{t}[\ln S_{t},\tau_{1}] - \Upsilon_{t}[\ln S_{t},\tau_{2}] \\ &= \ln S_{0} \left(1 - e^{-\frac{1}{\tau_{1}}t}\right) + \left(\mu - \frac{\sigma^{2}}{2}\right) \left[t - \tau_{1} \left(1 - e^{-\frac{1}{\tau_{1}}t}\right)\right] + \frac{\sigma e^{-\frac{1}{\tau_{1}}t}}{\tau_{1}} \int_{0}^{t} e^{\frac{1}{\tau_{1}}u} W_{u} du \\ &- \ln S_{0} \left(1 - e^{-\frac{1}{\tau_{2}}t}\right) - \left(\mu - \frac{\sigma^{2}}{2}\right) \left[t - \tau_{2} \left(1 - e^{-\frac{1}{\tau_{2}}t}\right)\right] - \frac{\sigma e^{-\frac{1}{\tau_{2}}t}}{\tau_{2}} \int_{0}^{t} e^{\frac{1}{\tau_{2}}u} W_{u} du \\ &= \ln S_{0} \left(e^{-\frac{1}{\tau_{2}}t} - e^{-\frac{1}{\tau_{1}}t}\right) \\ &+ \left(\mu - \frac{\sigma^{2}}{2}\right) \left[\tau_{2} \left(1 - e^{-\frac{1}{\tau_{2}}t}\right) - \tau_{1} \left(1 - e^{-\frac{1}{\tau_{1}}t}\right)\right] \\ &+ \sigma \int_{0}^{t} \left(\frac{1}{\tau_{1}}e^{-\frac{1}{\tau_{1}}(t-u)} - \frac{1}{\tau_{2}}e^{-\frac{1}{\tau_{2}}(t-u)}\right) W_{u} du \end{split}$$
(12)

From this point forward $\Psi_t = \Psi_t[\ln S_t, \tau_1, \tau_2]$.

Convert to Itô Integral

When f_t is deterministic, the Itô product rule [Oksendal(2000)], reduces to

$$d(f_tW_t) = (df_t)W_t + f_tdW_t + (df_t)(dW_t)$$
$$= f'_tdtW_t + f_tdW_t$$

Rearranging terms and integrating both sides from 0 to t gives an integration by parts formula that converts a Riemann integral of Brownian motion wrt time to a scaled Brownian motion term and an Itô integral

$$f'_{t}W_{t}dt = d(f_{t}W_{t}) - f_{t}dW_{t}$$

$$\int_{o}^{t} f'_{u}W_{u}du = \int_{o}^{t} d(f_{u}W_{u}) - \int_{o}^{t} f_{u}dW_{u}$$

$$\int_{o}^{t} f'_{u}W_{u}du = [f_{u}W_{u}]_{o}^{t} - \int_{o}^{t} f_{u}dW_{u}$$
(13)

Convert to Itô Integral

Let

$$\frac{df_{u}}{du} = \sigma \left(\frac{1}{\tau_{1}} e^{-\frac{1}{\tau_{1}}(t-u)} - \frac{1}{\tau_{2}} e^{-\frac{1}{\tau_{2}}(t-u)} \right)
\int df_{u} = \sigma \int \left(\frac{1}{\tau_{1}} e^{-\frac{1}{\tau_{1}}(t-u)} - \frac{1}{\tau_{2}} e^{-\frac{1}{\tau_{2}}(t-u)} \right) du
f_{t} = \sigma \left(e^{-\frac{1}{\tau_{1}}(t-u)} - e^{-\frac{1}{\tau_{2}}(t-u)} \right)$$
(14)

Rearrange terms as in equation 13

$$\sigma \int_{0}^{t} \left(\frac{1}{\tau_{1}} e^{-\frac{1}{\tau_{1}}(t-u)} - \frac{1}{\tau_{2}} e^{-\frac{1}{\tau_{2}}(t-u)} \right) W_{u} du$$

$$= \sigma \left[\left(e^{-\frac{1}{\tau_{1}}(t-u)} - e^{-\frac{1}{\tau_{2}}(t-u)} \right) W_{u} \right]_{0}^{t} - \sigma \int_{0}^{t} \left(e^{-\frac{1}{\tau_{1}}(t-u)} - e^{-\frac{1}{\tau_{2}}(t-u)} \right) dW_{u}$$

$$= \sigma \int_{0}^{t} \left(e^{-\frac{1}{\tau_{2}}(t-u)} - e^{-\frac{1}{\tau_{1}}(t-u)} \right) dW_{u}$$
(15)

©Doug Service 2016 @ 🖲 🕲 🔘

R/Finance 2016

Itô Process

Substituting the results of the integration by parts into equation 12 converts Ψ_t to an 1tô process

$$\Psi_{t} = \ln S_{0} \left(e^{-\frac{1}{\tau_{2}}t} - e^{-\frac{1}{\tau_{1}}t} \right) + \left(\mu - \frac{\sigma^{2}}{2} \right) \left[\tau_{2} \left(1 - e^{-\frac{1}{\tau_{2}}t} \right) - \tau_{1} \left(1 - e^{-\frac{1}{\tau_{1}}t} \right) \right] + \sigma \int_{0}^{t} \left(e^{-\frac{1}{\tau_{2}}(t-u)} - e^{-\frac{1}{\tau_{1}}(t-u)} \right) dW_{u}$$
(16)

Transient Behavior

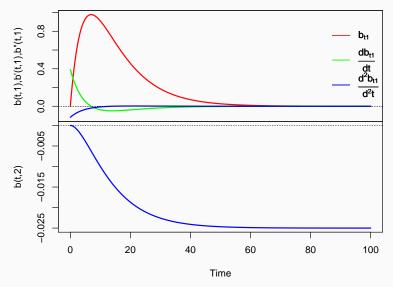
Define the first two terms of Ψ_t equation 16 as

$$b_{t,1} = \ln S_0 \left[e^{-\frac{1}{\tau_2}t} - e^{-\frac{1}{\tau_1}t} \right]$$
(17)

$$b_{t,2} = \left(\mu - \frac{\sigma^2}{2}\right) \left[\tau_2 \left(1 - e^{-\frac{1}{\tau_2}t}\right) - \tau_1 \left(1 - e^{-\frac{1}{\tau_1}t}\right)\right]$$
(18)

STRATEGY ANALYSIS: DIFFERENCE INDICATOR

Plot of $b_{t,1}$ and $b_{t,2}$ with $\mu = 0$, $\sigma = 0.1$, $\tau_1 = 5$, and $\tau_2 = 10$



R/Finance 2016

Steady State Assumptions

We assume that for $S_0 > 1$ and $0 < \tau_1 < \tau_2$ there exists a t_{ss} such that for all $t > t_{ss}$ the transient behavior of the deterministic terms $b_{t,1}$ and $b_{t,2}$ is insignificant to the analysis and can be ignored.

$$\lim_{t \to \infty} [b_{t,1} + b_{t,2}] = \lim_{t \to \infty} \left[\ln S_0 \left(e^{-\frac{1}{\tau_2} t} - e^{-\frac{1}{\tau_1} t} \right) + \left(\mu - \frac{\sigma^2}{2} \right) \left[\tau_2 \left(1 - e^{-\frac{1}{\tau_2} t} \right) - \tau_1 \left(1 - e^{-\frac{1}{\tau_1} t} \right) \right] \right] = \left(\mu - \frac{\sigma^2}{2} \right) (\tau_2 - \tau_1)$$
(19)

We assume that

$$\left| \lim_{t \to \infty} \left[b_{t,1} + b_{t,2} \right] - \left[b_{t,1} + b_{t,2} \right]_{t=t_{SS}} \right| < \delta$$
 (20)

for some sufficiently small δ .

Steady State Difference Indicator

$$\Psi_{t} = \left(\mu - \frac{\sigma^{2}}{2}\right)(\tau_{2} - \tau_{1}) + \sigma \int_{0}^{t} \left(e^{-\frac{1}{\tau_{2}}(t-u)} - e^{-\frac{1}{\tau_{1}}(t-u)}\right) dW_{u}$$
(21)

Expected Value and Variance of Ψ_t

Let M_t represent the Itô integral contained in the definition of Ψ_t in equation 21.

$$M_{t} = \sigma \int_{0}^{t} \left(e^{-\frac{1}{\tau_{2}}(t-u)} - e^{-\frac{1}{\tau_{1}}(t-u)} \right) dW_{u}$$

= $\int_{0}^{t} \Gamma_{(u;t)} dW_{u}$ where $\Gamma_{(u;t)} = \sigma \left(e^{-\frac{1}{\tau_{2}}(t-u)} - e^{-\frac{1}{\tau_{1}}(t-u)} \right)$ (22)

Since $\Gamma_{(u;t)}^2$ is square integrable, $\mathbb{E}\left[\int_0^t \Gamma_{(u;t)}^2 du\right] < \infty$, and for all $u \le t$, $\Gamma_{(u;t)}$ is \mathcal{F}_t adapted, the conditions of Theorem 4.3.1 [Shreve(2004)] are met and M_t is a martingale. This implies that given 0 < s < t

$$\mathbb{E}\left[M_t | \mathcal{F}_s\right] = M_s \tag{23}$$

 $\Gamma_{(o;o)=o}$ and $W_o = o$ implies that $M_o = o$ which combined with the martingale property expressed in equation 23 implies for all $t > o \mathbb{E}[M_t] = o$.

©Doug Service 2016 @🖲 🏵 🎯

Expected Value and Variance of Ψ_t

Theorem 4.3.1 [Shreve(2004)] also implies

$$\mathbb{E}\left[\Psi_{t}\right] = \mathbb{E}\left[\left(\mu - \frac{\sigma^{2}}{2}\right)(\tau_{2} - \tau_{1}) + \sigma \int_{0}^{t} \left(e^{-\frac{1}{\tau_{2}}(t-u)} - e^{-\frac{1}{\tau_{1}}(t-u)}\right) dW_{u}\right]$$
$$= \left(\mu - \frac{\sigma^{2}}{2}\right)(\tau_{2} - \tau_{1}) \tag{24}$$

Expected Value and Variance of Ψ_t

Only the Itô integral contributes to the variance of Ψ_t

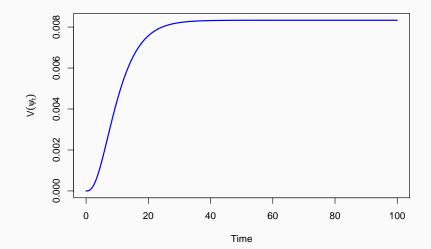
$$\begin{aligned} \mathbb{V} \left[\Psi_{t} \right] &= \mathbb{V} \left[M_{t} \right] \\ &= \mathbb{E} \left[(M_{t} - \mathbb{E} \left[M_{t} \right])^{2} \right] = \mathbb{E} \left[M_{t}^{2} \right] \\ &= \mathbb{E} \left[\int_{0}^{t} \Gamma_{(u;t)}^{2} \, du \right] \\ &= \mathbb{E} \left[\sigma^{2} \int_{0}^{t} \left(e^{-\frac{1}{\tau_{2}}(t-u)} - e^{-\frac{1}{\tau_{1}}(t-u)} \right)^{2} \, du \right] \\ &= \sigma^{2} \int_{0}^{t} \left(e^{-\frac{1}{\tau_{2}}(t-u)} - e^{-\frac{1}{\tau_{1}}(t-u)} \right)^{2} \, du \\ &= \sigma^{2} \int_{0}^{t} \left(e^{-\frac{2}{\tau_{2}}(t-u)} - 2e^{-\left(\frac{1}{\tau_{1}} + \frac{1}{\tau_{2}}\right)(t-u)} + e^{-\frac{2}{\tau_{1}}(t-u)} \right) \, du \\ &= \sigma^{2} \left(\left[\frac{\tau_{2}}{2} e^{-\frac{2}{\tau_{2}}(t-u)} \right]_{0}^{t} - \left[\frac{2}{\frac{1}{\tau_{1}} + \frac{1}{\tau_{2}}} e^{-\left(\frac{1}{\tau_{1}} + \frac{1}{\tau_{2}}\right)(t-u)} \right]_{0}^{t} + \left[\frac{\tau_{1}}{2} e^{-\frac{2}{\tau_{1}}(t-u)} \right]_{0}^{t} \right) \\ &= \sigma^{2} \left(\frac{\tau_{2}}{2} \left(1 - e^{-\frac{2}{\tau_{2}}t} \right) - \frac{2}{\frac{1}{\tau_{1}} + \frac{1}{\tau_{2}}} \left(1 - e^{-\left(\frac{1}{\tau_{1}} + \frac{1}{\tau_{2}}\right)t} \right) + \frac{\tau_{1}}{2} \left(1 - e^{-\frac{2}{\tau_{1}}t} \right) \right)$$
(25)

©Doug Service 2016 @ 🖲 🕲 🔘

R/Finance 2016

STRATEGY ANALYSIS: STEADY STATE

Variance of Ψ_t for parameter values $\sigma = 0.1$, $\tau_1 = 5$ and $\tau_2 = 10$



STRATEGY ANALYSIS: STEADY STATE

When t = 0 in equation 25, the variance of M_t is equal to zero which is expected since $W_0 = 0$. Consider the limit of equation 25 as t goes to infinity.

$$\lim_{t \to \infty} \mathbb{V}[M_t] = \lim_{t \to \infty} \left[\sigma^2 \left(\frac{\tau_2}{2} \left(1 - e^{-\frac{2}{\tau_2}t} \right) - \frac{2}{\frac{1}{\tau_1} + \frac{1}{\tau_2}} \left(1 - e^{-\left(\frac{1}{\tau_1} + \frac{1}{\tau_2}\right)t} \right) + \frac{\tau_1}{2} \left(1 - e^{-\frac{2}{\tau_1}t} \right) \right) \right] = \sigma^2 \left(\frac{\tau_2}{2} - \frac{2}{\frac{1}{\tau_1} + \frac{1}{\tau_2}} + \frac{\tau_1}{2} \right) = \frac{\sigma^2}{2} \left(\frac{(\tau_2 - \tau_1)^2}{\tau_1 + \tau_2} \right)$$
(26)

Since $o < \tau_1 < \tau_2$ the steady state variance of Ψ_t is always greater than zero which is expected as it should only be zero if the two exponentially filtered stochastic process have the same value of τ . We assume that

$$\lim_{t \to \infty} \mathbb{V}\left[M_{t}\right] - \mathbb{V}\left[M_{t}\right]|_{t=t_{ss}} < \delta$$
(27)

for some sufficiently small δ .

©Doug Service 2016 @ 🖲 🕲 🕲

R/Finance 2016

Distribution of Ψ_t

Since M_t is an Itô integral with respect to Brownian motion with a deterministic integrand $\Gamma_{(u;t)}$, by Theorem 4.4.9 [Shreve(2004)] for each t > 0, M_t is normally distributed with expected value zero and variance $\int_0^t \Gamma_{(u;t)}^2 du$. Thus, Ψ_t from equation 21 is normally distributed with the expected value u and variance s given by equations 24 and 26.

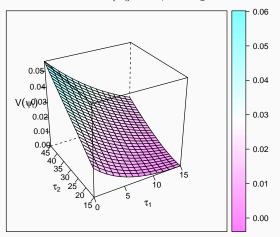
$$\Psi_{t} \sim \mathcal{N}\left(u, s^{2}\right)$$
$$\sim \mathcal{N}\left(\left(\mu - \frac{\sigma^{2}}{2}\right)\left(\tau_{2} - \tau_{1}\right), \frac{\sigma^{2}}{2}\left(\frac{\left(\tau_{2} - \tau_{1}\right)^{2}}{\tau_{1} + \tau_{2}}\right)\right)$$
(28)

Note that for $t > t_{ss}$ mean and variance are constant and not dependent on t, but on the constants μ , σ , τ_1 , and τ_2 .

STRATEGY ANALYSIS: STEADY STATE

$$\mathbb{V}\left[\Psi_{t}\right] = \frac{\sigma^{2}}{2} \left(\frac{(\tau_{2} - \tau_{1})^{2}}{\tau_{1} + \tau_{2}}\right)$$

Plot of V(Ψ_t) vs τ_1 and τ_2



Density of Ψ_t

Given that Ψ_t is normal with mean u and variance s^2 , $\Psi_t \sim \mathcal{N}(u, s)$, the cumulative distribution function (CDF) F_{Ψ} and probability density function (PDF) f_{Ψ} for Ψ_t are

$$F_{\Psi} = \Phi\left(\frac{\psi - u}{s}\right)$$
(29)
$$f_{\Psi} = \frac{d}{d} \frac{F_{\Psi}}{\psi} = \frac{1}{s} \phi\left(\frac{\psi - u}{s}\right)$$
(30)

where Φ is the standard normal CDF and ϕ is the standard normal PDF. Substitution of *u* and *s* from equation 28 into equation 30 gives the full density function for Ψ_t . Once the steady state regime is reached the density function has no dependence on *t*.

$$f_{\Psi} = \frac{1}{\sigma(\tau_2 - \tau_1)\sqrt{\frac{\pi}{(\tau_1 + \tau_2)}}} \exp\left[\frac{-\left(\psi - \left(\mu - \frac{\sigma^2}{2}\right)(\tau_2 - \tau_1)\right)^2}{\frac{\sigma^2(\tau_2 - \tau_1)^2}{(\tau_1 + \tau_2)}}\right]$$
(31)

Expected Value of ρ_t

The position indicator ρ_t from equation 5 is a function of the random variable Ψ_t whose distribution we have from equation 28; thus, we can calculate the expected value of the position indicator using Theorem 3.2.2 part (*ix*) [Itó(1984)].

$$\mathbb{E}\left[\varrho_{t}\right] = \int_{-\infty}^{\infty} \operatorname{sgn}\left(\psi\right) f_{\Psi}(\psi) \, d\psi$$
$$= \int_{-\infty}^{\infty} \operatorname{sgn}\left(\psi\right) \frac{1}{s} \phi\left(\frac{\psi - u}{s}\right) \, d\psi$$
$$= \int_{-\infty}^{0} (-1) \frac{1}{s} \phi\left(\frac{\psi - u}{s}\right) \, d\psi + \int_{0}^{\infty} (1) \frac{1}{s} \phi\left(\frac{\psi - u}{s}\right) \, d\psi$$
$$= \lim_{a \to \infty} \left[\Phi\left(\frac{\psi - u}{s}\right) \right]_{0}^{a} - \lim_{b \to -\infty} \left[\Phi\left(\frac{\psi - u}{s}\right) \right]_{b}^{0}$$
$$= \left[1 - \Phi\left(\frac{0 - u}{s}\right) \right] - \left[\Phi\left(\frac{0 - u}{s}\right) - 0 \right]$$

Expected Value of ρ_t Continued

$$\mathbb{E}\left[\varrho_{t}\right] = 1 - 2\Phi\left(-\frac{u}{s}\right)$$

$$= 1 - 2\Phi\left(-\frac{\left(\mu - \frac{\sigma^{2}}{2}\right)\left(\tau_{2} - \tau_{1}\right)}{\frac{\sigma^{2}}{2}\left(\frac{\left(\tau_{2} - \tau_{1}\right)^{2}}{\tau_{1} + \tau_{2}}\right)}\right)$$

$$= 1 - 2\Phi\left[-\frac{2}{\sigma^{2}}\left(\mu - \frac{\sigma^{2}}{2}\right)\frac{\tau_{1} + \tau_{2}}{\tau_{2} - \tau_{1}}\right]$$
(32)

Log Return Expected Value

We have now assembled the results needed to calculate the Luxor steady state expected log return r_t as given in definition 16.

$$\mathbb{E}[r_{t}] = \mathbb{E}\left[\int_{0}^{t} \varrho_{u} d(\ln Su)\right]$$

$$= \mathbb{E}\left[\int_{0}^{t} \varrho_{u} \left[\left(\mu - \frac{\sigma^{2}}{2}\right) du + \sigma dW_{u}\right]\right]$$

$$= \mathbb{E}\left[\left(\mu - \frac{\sigma^{2}}{2}\right)\int_{0}^{t} \varrho_{u} du + \sigma \int_{0}^{t} \varrho_{u} dW_{u}\right]$$

$$= \left(\mu - \frac{\sigma^{2}}{2}\right)\mathbb{E}\left[\int_{0}^{t} \varrho_{u} du\right] + \sigma \mathbb{E}\left[\int_{0}^{t} \varrho_{u} dW_{u}\right]$$
(33)

Log Return

The position indicator ϱ_t by definition is a random sequence of the elements in the set $\{-1, 0, 1\}$ which implies

$$\int_{0}^{t} \varrho_{u}^{2} \, du \leq t < \infty \tag{34}$$

thus ϱ_t^2 is square integrable on [o, t]. In addition, ϱ_t is \mathcal{F}_t adapted; therefore, the ltô integral inside the second expected value in equation 33 mets the conditions of Theorem 4.3.1 [Shreve(2004)] and the integral is a martingale with an initial and expected value of zero.

Define the function g such that

$$\xi = g(\rho) = \int_0^t \rho \, du \tag{35}$$

and define the random variable Ξ_t .

$$\Xi_t = g(\varrho_t) = \int_0^t \varrho_u \, du \tag{36}$$

Log Return

Since the last term in equation 33 is zero, the expected value of the log return is given by the first term.

$$\mathbb{E}[r_t] = \left(\mu - \frac{\sigma^2}{2}\right) \mathbb{E}\left[\int_0^t \varrho_u \, du\right]$$
$$= \left(\mu - \frac{\sigma^2}{2}\right) \mathbb{E}[\Xi_t]$$
$$= \left(\mu - \frac{\sigma^2}{2}\right) \int_{-\infty}^\infty \xi f_{\Xi_t}(\xi) \, d\xi$$

Substitute $\xi = g(\rho)$ and $f_{\Xi_t}(\xi) d\xi = f_{\varrho_t}(\rho) d\rho$

via Theorem 3.2.2 part (*ix*) in [Itó(1984)]

$$= \left(\mu - \frac{\sigma^2}{2}\right) \int_{-\infty}^{\infty} g(\rho) f_{\varrho_t}(\rho) d\rho$$
$$= \left(\mu - \frac{\sigma^2}{2}\right) \int_{-\infty}^{\infty} \left(\int_{0}^{t} \rho \, du\right) f_{\varrho_t}(\rho) d\rho \tag{37}$$

(38)

Log Return

Change the order of integration via Fubini's theorem

$$= \left(\mu - \frac{\sigma^2}{2}\right) \int_0^t \left(\int_{-\infty}^\infty \rho f_{\varrho_t}(\rho) \, d\rho\right) du$$
$$= \left(\mu - \frac{\sigma^2}{2}\right) \int_0^t \mathbb{E}\left[\varrho_u\right] \, du \tag{39}$$

Inserting the expected value of ρ from equation 32 into equation 39 and solving the integral gives the expected log return.

$$\mathbb{E}\left[r_{t}\right] = \left(\mu - \frac{\sigma^{2}}{2}\right) \int_{0}^{t} \left[1 - 2\Phi\left(-\frac{2}{\sigma^{2}}\left(\mu - \frac{\sigma^{2}}{2}\right)\frac{\tau_{1} + \tau_{2}}{\tau_{2} - \tau_{1}}\right)\right] du$$
$$= \left(\mu - \frac{\sigma^{2}}{2}\right) \left(1 - 2\Phi\left[-\frac{2}{\sigma^{2}}\left(\mu - \frac{\sigma^{2}}{2}\right)\frac{\tau_{1} + \tau_{2}}{\tau_{2} - \tau_{1}}\right]\right) t \tag{40}$$

Proposition:

Given the assumptions and model in sections 5 and 6, the expected steady state log return of the Luxor strategy is greater than or equal to zero.

$$\mathbb{E}\left[r_{t}\right] \geq 0 \tag{41}$$

Proof:

We proceed by determining the sign of each term in equation 40. t and σ^2 are positive by definition, and $\frac{\tau_1 + \tau_2}{\tau_2 - \tau_1} > 0$ since $0 < \tau_1 < \tau_2$. Let

$$C = -\frac{2}{\sigma^2} \left(\mu - \frac{\sigma^2}{2}\right) \frac{\tau_1 + \tau_2}{\tau_2 - \tau_1}$$
(42)

Thus the order relation between μ and $\frac{\sigma^2}{2}$ controls the sign of C.

Proof (Continued):

Table 1 gives the value of μ relative to $\frac{\sigma^2}{2}$ in the left column, the sign of each term that can take on a negative value in the center columns and the resulting expected log return $\mathbb{E}[r_t]$ in the right hand column.

μ	С	Φ	1 — 2Ф	$\left(\mu - \frac{\sigma^2}{2}\right)$	$\mathbb{E}[r_t]$
$> \frac{\sigma^2}{2}$	-	$< \frac{1}{2}$	+	+	+
$=\frac{\sigma^2}{2}$	0	$=\frac{1}{2}$	0	0	0
$<\frac{\sigma^2}{2}$	+	$> \frac{1}{2}$	-	-	+

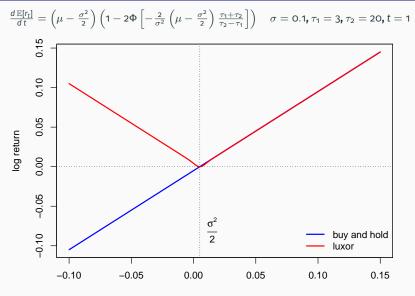
Table 1: Expected Log Return Relative to μ and σ

Comparing the far left hand column with the far right hand column in table 1, we see that for every $\mu \in \mathbb{R}$, $\sigma \in \mathbb{R}_{\geq 0}$, and $0 < \tau_1 < \tau_2$, the expected log return r_t is greater than or equal to zero.

©Doug Service 2016 @ 🖲 🕲 🎯

R/Finance 2016

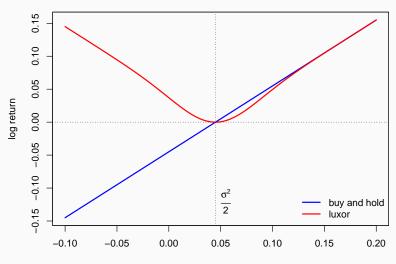
STRATEGY ANALYSIS: LOG RETURN



mu

STRATEGY ANALYSIS: LOG RETURN

$$\frac{d\mathbb{E}[r_t]}{dt} = \left(\mu - \frac{\sigma^2}{2}\right) \left(1 - 2\Phi\left[-\frac{2}{\sigma^2}\left(\mu - \frac{\sigma^2}{2}\right)\frac{\tau_1 + \tau_2}{\tau_2 - \tau_1}\right]\right) \quad \sigma = 0.3, \tau_1 = 3, \tau_2 = 20, t = 1$$



mu

SUMMARY

Results

Given the assumptions and model in sections 5 and 6, we

- Derived a closed form solution for the expected log returns of Luxor
- Demonstrated Luxor has a non negative expected value
- When $\mu > \frac{\sigma^2}{2}$ high volatility causes under performance compared to buy and hold

Issues

Issues we are currently addressing

- Simple SDE model does not capture features of stock prices that may be advantageous to strategies like Luxor
- More accurate price SDE models
- More realistic transaction and slippage models

Fischer Black and Myron Scholes. The pricing of options and corporate liabilities.

Journal of Political Ecomon, 1973.

B. Efron.

Bootstrap methods: Another look at the jackknife.

The Annals of Statistics, 7(1):1–26, Jan 1979.



Kiyosi Itó.

Introduction to Probability Theory.

Cambridge University Press, english edition, 1984. Originally published in Japanese 1978.



Urban Jaekle and Emilio Tomasini.

Trading Systems - A New Approach to System Development and Portfolio Optimization.

HarrimanHouse Ltd, 2009.



Robert C. Merton.

Theory of rational option pricing.

The Bell Journal of Economics and Mangement Science, 4(1):141–183, Spring 1973.

BIBLIOGRAPHY II



Bernt Oksendal.

Stochastic Differential Equations: An Introduction with Applications.

Springer-Verlag, 5th edition, 2000.



Brian G. Peterson.

Developing and backtesting systematic trading strategies.

June 2015.

URL https://r-forge.r-project.org/scm/viewvc.php/*checkout*/pkg/quantstrat/ sandbox/backtest_musings/strat_dev_process.pdf?root=blotter.



Steven E. Shreve.

Stochastic Calculus for Finance: Continous-Time Models, volume II of Springer Finance Textbook.

Springer, 2004.

Blake LeBaron William Brock, Josef Lakonishokk. **Simple technical trading rules and the stochastic properties of stock returns.** *The Journal of Finance*, 47(5):1731–1764, Dec 1992.