

Trading and Investment As A Science

Technical Analysis: A Scientific Perspective

Haksun Li
haksun.li@numericalmethod.com
www.numericalmethod.com

Speaker Profile



- Dr. Haksun Li
- CEO, Numerical Method Inc.
- (Ex-)Adjunct Professors, Industry Fellow, Advisor, Consultant with the National University of Singapore, Nanyang Technological University, Fudan University, the Hong Kong University of Science and Technology.
- Quantitative Trader/Analyst, BNPP, UBS
- PhD, Computer Sci, University of Michigan Ann Arbor
- M.S., Financial Mathematics, University of Chicago
- B.S., Mathematics, University of Chicago

Numerical Method Incorporation Limited

- A consulting firm in mathematical modeling, esp. algorithmic trading and quantitative investment.
- Products:
  - SuanShu: a modern math or numerical library
  - AlgoQuant: a financial technology for quantitative trading
- Customers:
  - brokerage houses and funds
  - multinational corporations
  - very high net worth individuals
  - gambling groups
  - academic institutions

References

- Emmanual Acar, Stephen Satchell. Chapters 4, 5 & 6, Advanced Trading Rules, Second Edition. Butterworth-Heinemann; 2nd edition. June 19, 2002.
- Algorithmic Trading: Hidden Markov Models on Foreign Exchange Data. Patrik Idvall, Conny Jonsson. University essay from Linköpings universitet/Matematiska institutionen; Linköpings universitet/Matematiska institutionen. 2008.
- A tutorial on hidden Markov models and selected applications in speech recognition. Rabiner, L.R. Proceedings of the IEEE, vol 77 Issue 2, Feb 1989.

What is Quantitative Trading?

Quantitative Trading?

- Quantitative trading is the buying and selling of assets following the instructions computed from a set of **mathematical** models.
- The differentiation from other trading approaches or the emphasis is on **how** a strategy is generated and not on what strategy is created.
- It applies (rigorous) mathematics in all steps during trading strategy construction from the start to the end.

NM Quantitative Trading Research Process

1. Translate a vague trading intuition (hypothesis) into a concrete mathematical model.
2. Translate the mathematical symbols and equations into a computer program.
3. Strategy evaluation.
4. Live execution for making money.

Step 1 - Modeling

- Where does a trading idea come from?
  - Ex-colleagues
  - Hearsays
  - Newspapers, books
  - NOW TV, e.g., Moving Average Crossover (MA)
- A quantitative trading strategy is a math function, f, that at any given time, t, takes as inputs any information that the strategy cares and that is available, F_t, and gives as output the position to take, $f(t,F_t)$.

Step 2 - Coding

- The computer code enables analysis of the strategy.
  - Most study of a strategy cannot be done analytically.
  - We must resort to simulation.
- The same piece of code used for research and investigation should go straight into the production for live trading.
  - Eliminate the possibility of research-to-IT translation errors.

Step 3 - Analysis

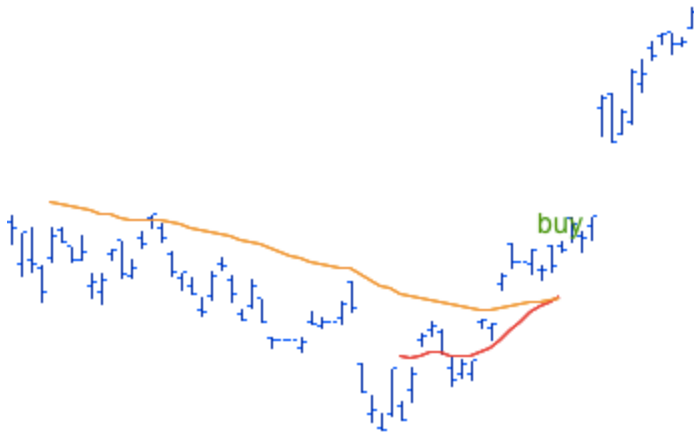
- Compute the properties of a trading strategy.
  - the P&L distribution
  - the holding time distribution
  - the stop-loss
  - the maximal drawdown
  - http://www.numericalmethod.com/trac/numericalmethod/browser/algoquant/core/src/main/java/com/numericalmethod/algoquant/execution/performance

Step 4 - Trading

- Put in capitals incrementally.
- Install safety measures.
- Monitor the performance.
- Regime change detection.

Moving Average Crossover as a TA

- A popular TA signal: Moving Average Crossover.
  - A crossover occurs when a faster moving average (i.e. a shorter period moving average) crosses above/below a slower moving average (i.e. a longer period moving average); then you buy/sell.
- In most TA book, it is then illustrated with an example of applying the strategy to a stock for a period of time to show the profits.



Technical Analysis is Not Quantitative Trading

- TA books merely describes the mechanics of strategies but seldom/never prove them.
- Appealing to common sense is not a mathematical proof.
- Conditional probabilities of outcomes are never computed. (Lo, Mamaysky, & Wang, 2000)
- Application of TA is more of an art (is it?) than a science.
  - How do you choose the parameters?

The Quantitative Trading Research Process

Moving Average Crossover as a Quantitative Trading Strategy

- There are many mathematical justifications to Moving Average Crossover.
  - weighted Sum of lags of a time series
  - Kuo, 2002
- Whether a strategy is quantitative or not depends not on the strategy itself but
  - entirely on the process to construct it;
  - or, whether there is a scientific justification to prove it.

Step 1

- Two moving averages: slower (n) and faster (m).
- Monitor the crossovers.
- $B_t = \left(\frac{1}{m}\sum_{j=0}^{m-1} P_{t-j}\right) - \left(\frac{1}{n}\sum_{j=0}^{n-1} P_{t-j}\right), n > m$
- Long when $B_t \geq 0$.
- Short when $B_t < 0$.



How to Choose n and m?

- It is an art, not a science (so far).
- They should be related to the length of market cycles.
- Different assets have different n and m.
- Popular choices:
  - (250, 5)
  - (250 , 20)
  - (20 , 5)
  - (20 , 1)
  - (250 , 1)



Two Simplifications

- Reduce the two dimensional problem to a one dimensional problem.
- Replace arithmetic averages with geometric averages.
  - This is so that we can work with log returns rather than prices.

AMA(n , 1)

- $B_t \geq 0$ iff $P_t \geq \left(\frac{1}{n}\sum_{j=0}^{n-1} P_{t-j}\right)$
- $B_t < 0$ iff $P_t < \left(\frac{1}{n}\sum_{j=0}^{n-1} P_{t-j}\right)$



GMA(n , 1)

- $B_t \geq 0$ iff $P_t \geq \left(\prod_{j=0}^{n-1} P_{t-j}\right)^{\frac{1}{n}}$
  - $R_t \geq -\sum_{j=1}^{n-2} \frac{n-(j+1)}{n-1} R_{t-j}$ (by taking log)
- $B_t < 0$ iff $P_t < \left(\prod_{j=0}^{n-1} P_{t-j}\right)^{\frac{1}{n}}$
  - $R_t < -\sum_{j=1}^{n-2} \frac{n-(j+1)}{n-1} R_{t-j}$ (by taking log)



What is n?

- $n = 2$
- $n = \infty$





Acar Framework

- Acar (1993): to investigate the probability distribution of realized returns from a trading rule, we need
  - the explicit specification of the trading rule
  - the underlying stochastic process for asset returns
  - the particular return concept involved



Empirical Properties of Financial Time Series

- Asymmetry
- Fat tails

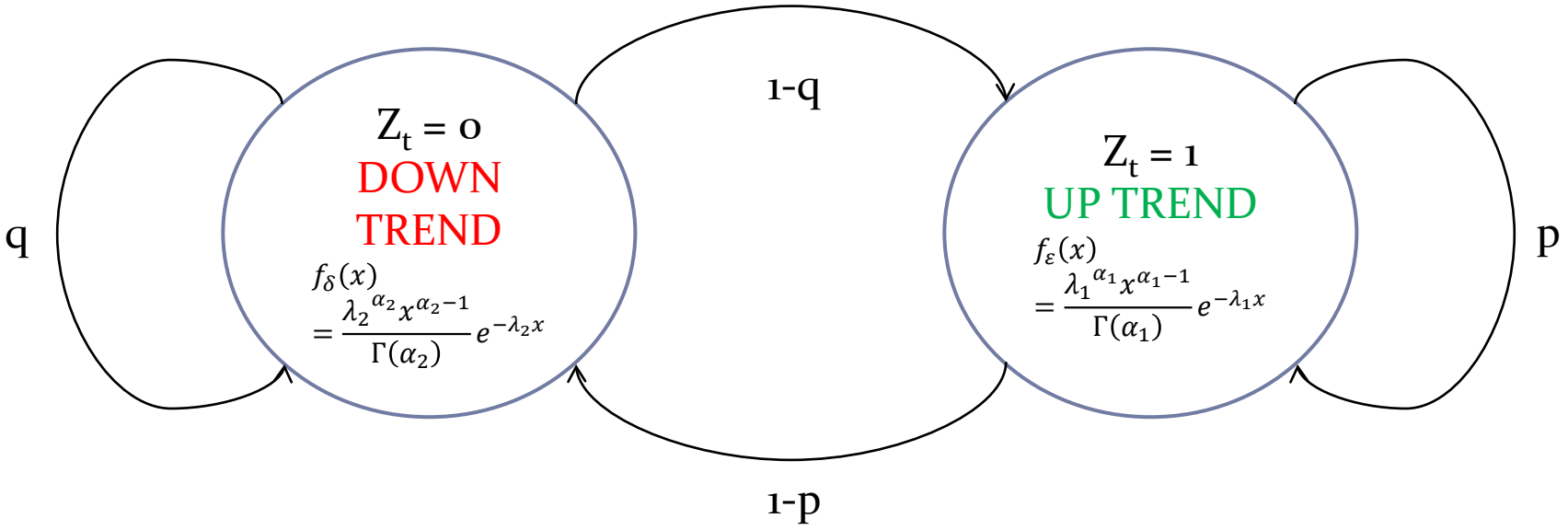


Knight-Satchell-Tran Intuition

- Stock returns staying going up (down) depends on
  - the realizations of positive (negative) shocks
  - the persistence of these shocks
- Shocks are modeled by gamma processes.
- Persistence is modeled by a Markov switching process.



Knight-Satchell-Tran Z_t

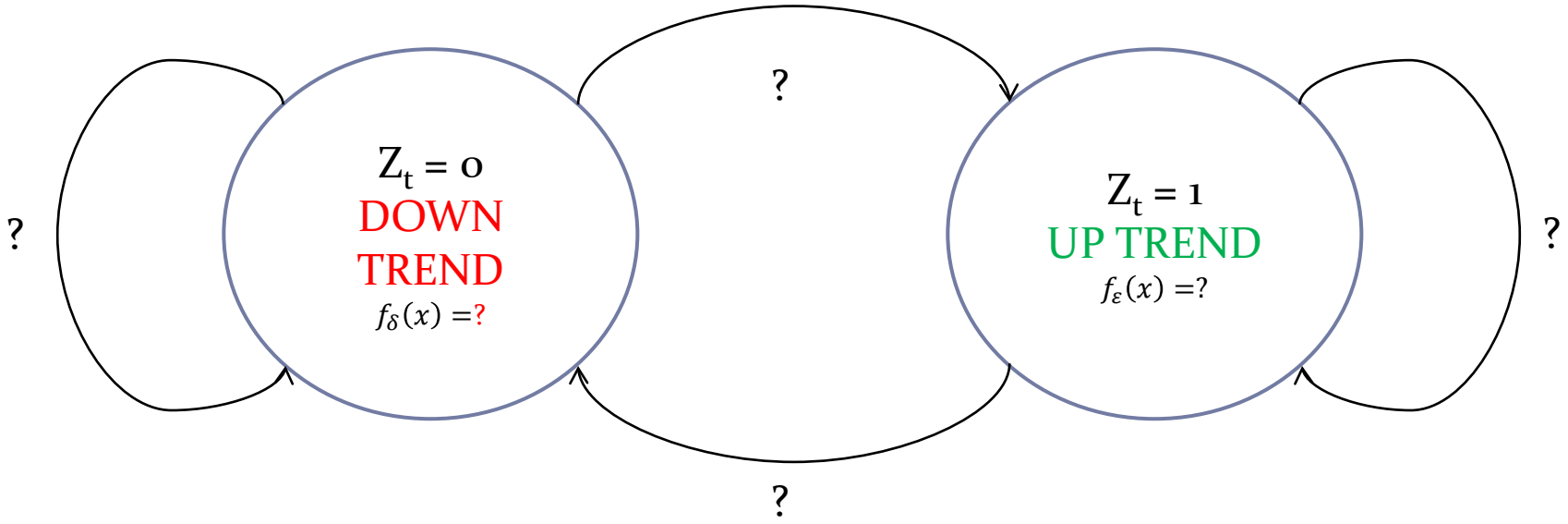


Knight-Satchell-Tran Process

- $R_t = \mu_l + Z_t\varepsilon_t - (1 - Z_t)\delta_t$
  - μ_l: long term mean of returns, e.g., o
  - ε_t, δ_t: positive and negative shocks, non-negative, i.i.d
- $f_\varepsilon(x) = \frac{{\lambda_1}^{\alpha_1} x^{\alpha_1 - 1}}{\Gamma(\alpha_1)} e^{-\lambda_1 x}$
- $f_\delta(x) = \frac{{\lambda_2}^{\alpha_2} x^{\alpha_2 - 1}}{\Gamma(\alpha_2)} e^{-\lambda_2 x}$



Estimation of Parameters



Markov Property

- Given the current information available at time $(t-1)$, the history, e.g., path, is irrelevant.
- $P(q_t|q_{t-1},\cdots,q_1) = P(q_t|q_{t-1})$
- Consistent with the weak form of the efficient market hypothesis.

Hidden Markov Chain

- Only observations are observable (duh).
- World states may not be known (hidden).
  - We want to model the hidden states as a Markov Chain.
- Two assumptions:
  - Markov property
  - $P(\omega_t|q_{t-1},\cdots,q_1,\omega_{t-1},\cdots,\omega_1) = P(\omega_t|q_t)$

Problems

- Likelihood
  - Given the parameters, λ, and an observation sequence, Ω, compute $P(\Omega|\lambda)$.
- Decoding
  - Given the parameters, λ, and an observation sequence, Ω, determine the best hidden sequence Q.
- Learning
  - Given an observation sequence, Ω, and HMM structure, learn λ.

Learning as a Maximization Problem

- Our objective is to find λ that maximizes $P(\Omega|\lambda)$.
- For any given λ, we can compute $P(\Omega|\lambda)$.
- Then solve a maximization problem.
- Algorithms:
  - Nelder-Mead
  - Baum-Welch (E-M algorithm)

Stationary State

- $\Pi = \frac{1-q}{2-p-q}$
- $R_t = \mu_l + \varepsilon_t \geq \mu_l$, with probability Π
- $R_t = \mu_l - \delta_t < \mu_l$, with probability $1 - \Pi$



Step 3

- Assume the long term mean is 0, $\mu_l = 0$.
- When $n = 2$,
  - $(B_t \geq 0) \equiv (R_t \geq 0) \equiv (Z_t = 1)$
  - $(B_t < 0) \equiv (R_t < 0) \equiv (Z_t = 0)$



GMA(2, 1) – Naïve MA Trading Rule

- Buy when the asset return in the present period is positive.
- Sell when the asset return in the present period is negative.



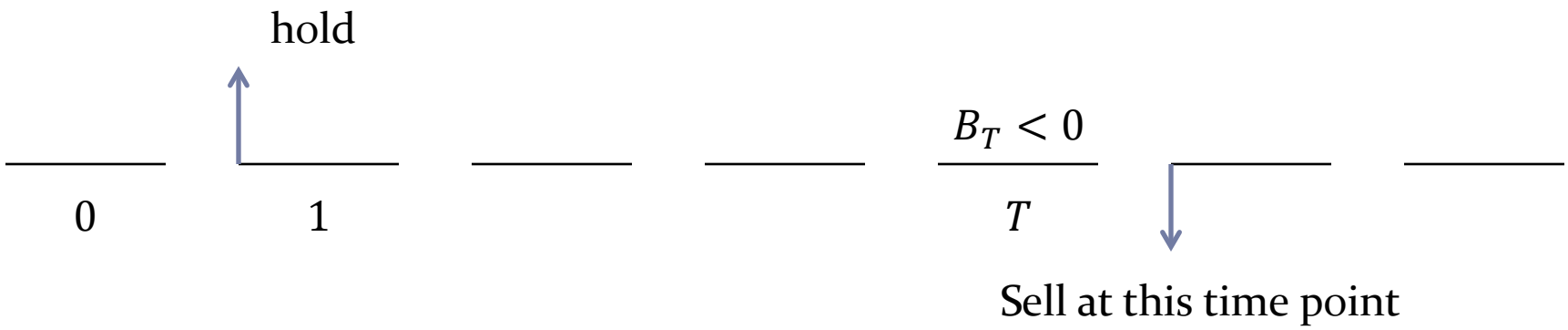
Naïve MA Conditions

- The expected value of the positive shocks to asset return >> the expected value of negative shocks.
- The positive shocks persistency >> that of negative shocks.



T Period Returns

- $RR_T = \sum_{t=1}^{T} R_t \times I_{\{B_{t-1} \geq 0\}}$



Holding Time Distribution

- $P(N = T)$
- $= P(B_T < 0, B_{T-1} \geq 0, \dots, B_1 \geq 0, B_0 \geq 0)$
- $= P(Z_T = 0, Z_{T-1} = 1, \dots, Z_1 = 1, Z_0 = 1)$
- $= P(Z_T = 0, Z_{T-1} = 1, \dots, Z_1 = 1 | Z_0 = 1) P(Z_0 = 1)$
- $= \begin{cases} \Pi p^{T-1}(1-p), & \mathrm{T} \geq 1 \\ 1 - \Pi, & \mathrm{T} = 0 \end{cases}$



Conditional Returns Distribution (1)

- $\Phi_{RR_T|N=T}(s) = \mathrm{E}\left[e^{\left\{i\left[\sum_{t=1}^{T} R_t \times I_{\{B_{t-1}\geq 0\}}\right]s\right\}} | N = T\right]$
- $= \mathrm{E}\left[e^{\left\{i\left[\sum_{t=1}^{T} R_t \times I_{\{B_{t-1}\geq 0\}}\right]s\right\}} | B_T < 0, B_{T-1} \geq 0, \ldots, B_0 \geq 0\right]$
- $= \mathrm{E}\left[e^{\{i[\sum_{t=1}^{T} R_t]s\}} | Z_T = 0, Z_{T-1} = 1, \ldots, Z_1 = 1\right]$
- $= \mathrm{E}\left[e^{\{i[\varepsilon_1 + \cdots + \varepsilon_{T-1} - \delta_T]s\}}\right]$
- $= \begin{cases} \Phi_\varepsilon{}^{T-1}(s)\Phi_\delta(-s), & \mathrm{T} \geq 1 \\ \Phi_\delta(-s), & \mathrm{T} = 0 \end{cases}$



Unconditional Returns Distribution (2)

- $\Phi_{RR_T}(s) =$
  $\sum_{T=0}^{\infty} \mathrm{E}\left[e^{\left\{i\left[\sum_{t=1}^{T} R_t \times I_{\{B_{t-1} \geq 0\}}\right]s\right\}} | N = T\right] P(N = T)$
- $=$
  $\sum_{T=1}^{\infty} \Pi p^{T-1}(1-p)\Phi_{\varepsilon}{}^{T-1}(s)\Phi_{\delta}(-s) + (1-\Pi)\Phi_{\delta}(-s)$
- $= (1-\Pi)\Phi_{\delta}(-s) + \Pi(1-p)\frac{\Phi_{\delta}(-s)}{1-p\Phi_{\varepsilon}(s)}$



Long-Only Returns Distribution

- $\Phi_{RR_T}(s|R_0 \geq 0) = \frac{(1-p)\Phi_\delta(-s)}{1-p\Phi_\varepsilon(s)}$
- Proof: make $P(Z_0 = 1) = \Pi = 1$



Expected Returns

- $\mathrm{E}(RR_T) = -i\Phi_{RR_T}{}'(0)$
- $= \frac{1}{1-p}\{\Pi p\mu_\varepsilon - (1-p)\mu_\delta\}$
- When is the expected return positive?
  - $\mu_\varepsilon \geq \frac{1-p}{\Pi p}\mu_\delta$, shock impact
  - $\mu_\varepsilon \gg \mu_\delta$, shock impact
  - $\Pi p \geq 1-p$, if $\mu_\varepsilon \approx \mu_\delta$, persistence



GMA(∞,1) Rule

- $P_t \geq \left(\prod_{j=0}^{n-1} P_{t-j}\right)^{\frac{1}{n}}$
- $\ln P_t \geq \frac{1}{n}\sum_{j=0}^{n-1} \ln P_{t-j}$
- $\ln P_t \geq \mu_1$



GMA(∞,1) Expected Returns

- $\Phi_{RR_T}(s) =$
  $(1 - \Pi)q[\Phi_\delta(s) + \Phi_\delta(-s)] +$
  $[1 - p(1 - \Pi)][\Phi_\varepsilon(s) + \Phi_\varepsilon(-s)]$
- $\mathrm{E}(RR_T) = -[1 - p(1 - \Pi)][\mu_\varepsilon + \mu_\delta]$



MA Using the Whole History

- An investor will always expect to lose money using GMA(∞,1)!
- An investor loses the least amount of money when the return process is a random walk.



Optimal MA Parameters

- So, what are the optimal n and m?



A Mathematical Analysis of Linear Technical Indicators

Linear Technical Indicators

- As we shall see, a number of linear technical indicators, including the Moving Average Crossover, are really the "same" *generalized* indicator using different parameters.



The Generalized Linear Trading Rule

- A linear predictor of weighted lagged returns
  - $F_t = \delta + \sum_{j=0}^{t} d_j X_{t-j}$
- The trading rule
  - Long: $B_t = 1$, iff, $F_t > 0$
  - Short: $B_t = -1$, iff, $F_t < 0$
- (Unrealized) rule returns
  - $R_t = B_{t-1} X_t$
    - $R_t = -X_t$ if $B_{t-1} = -1$
    - $R_t = +X_t$ if $B_{t-1} = +1$



Buy And Hold

- $B_t = 1$



Predictor Properties

- Linear
- Autoregressive
- Gaussian, assuming X_t is Gaussian
- If the underlying returns process is linear, F_t yields the best forecasts in the mean squared error sense.



Returns Variance

- $\mathrm{Var}(R_t) = \mathrm{E}\left(R_t{}^2\right) - (\mathrm{E}(R_t))^2$
- $= \mathrm{E}\left(B_{t-1}{}^2 X_t{}^2\right) - (\mathrm{E}(R_t))^2$
- $= \mathrm{E}\left(X_t{}^2\right) - (\mathrm{E}(R_t))^2$
- $= \sigma^2 + \mu^2 - (\mathrm{E}(R_t))^2$



Maximization Objective

- Variance of returns is inversely proportional to expected returns.
- The more profitable the trading rule is, the less risky this will be if risk is measured by volatility of the portfolio.
- Maximizing returns will also maximize returns per unit of risk.



Expected Returns

- $\mathrm{E}(R_t) = \mathrm{E}(B_{t-1}X_t)$
- $= \mathrm{E}(B_{t-1}(\mu + \sigma N))$
- $= \sigma\,\mathrm{E}(B_{t-1}N) + \mu\,\mathrm{E}(B_{t-1})$
- $\mathrm{E}(B_{t-1}) = 1 \times \mathrm{P}(F_{t-1} > 0) + -1 \times \mathrm{P}(F_{t-1} < 0)$
- $= \mathrm{P}(F_{t-1} > 0) - \mathrm{P}(F_{t-1} < 0)$
- $= 1 - 2 \times \mathrm{P}(F_{t-1} < 0)$
- $= 1 - 2 \times \Phi\left(-\frac{\mu_F}{\sigma_F}\right)$



Truncated Bivariate Moments

- Johnston and Kotz, 1972, p.116
- $\mathrm{E}(B_{t-1}N) = \iint_{F_t>0} N - \iint_{F_t<0} N$
- $= \sqrt{\frac{2}{\pi}}\rho e^{-\frac{{\mu_F}^2}{2{\sigma_F}^2}}$
- Correlation:
  - $\rho = \mathrm{Corr}(X_t, F_{t-1})$



Expected Returns As a Weighted Sum

- $\mathrm{E}(R_t) = \sigma\,\mathrm{E}(B_{t-1}N) + \mu\,\mathrm{E}(B_{t-1})$
- $= \sigma\sqrt{\frac{2}{\pi}}\rho e^{-\frac{{\mu_F}^2}{2{\sigma_F}^2}} + \mu\left(1 - 2 \times \Phi\left(-\frac{\mu_F}{\sigma_F}\right)\right)$

a term for volatility

a term for drift



Praetz model, 1976

- Returns as a random walk with drift.
- $\mathrm{E}(R_t) = \mu(1 - 2f)$, f the frequency of short positions
- $\mathrm{Var}(R_t) = \sigma^2$



Comparison with Praetz model

- Random walk implies $\rho = \mathrm{Corr}(X_t, F_{t-1}) = 0$.
- $\mathrm{E}(R_t) = \mu\left(1 - 2 \times \Phi\left(-\frac{\mu_F}{\sigma_F}\right)\right)$
- $\mathrm{Var}(R_t) = \sigma^2 + \mu^2 - \left\{\mu\left(1 - 2 \times \Phi\left(-\frac{\mu_F}{\sigma_F}\right)\right)\right\}^2$
- $= \sigma^2 + 4\mu^2\,\Phi\left(-\frac{\mu_F}{\sigma_F}\right)\left(1 - \Phi\left(-\frac{\mu_F}{\sigma_F}\right)\right)$

the probability of being short

increased variance



Biased Forecast

- A biased (Gaussian) forecast may be suboptimal.
- Assume underlying mean $\mu = 0$.
- Assume forecast mean $\mu_F \neq 0$.
- $\mathrm{E}(R_t) = \sigma\sqrt{\frac{2}{\pi}}\rho e^{-\frac{{\mu_F}^2}{2{\sigma_F}^2}} \leq \sigma\sqrt{\frac{2}{\pi}}\rho$



Maximizing Returns

- Maximizing the correlation between forecast and one-ahead return.
- First order condition:
  - $\frac{\mu_F}{\sigma_F} = \frac{\mu}{\sigma\rho}$



First Order Condition

- Let $\mathrm{x} = \frac{\mu_F}{\sigma_F}$
- $\mathrm{E}(R_t) = \sigma\sqrt{\frac{2}{\pi}}\rho e^{-\frac{x^2}{2}} + \mu(1 - 2 \times \Phi(-x))$
- $\frac{d\ \mathrm{E}(R_t)}{dx} = 0$
  - $\sigma\sqrt{\frac{2}{\pi}}\rho(-x)e^{-\frac{x}{2}} + \mu\sqrt{\frac{2}{\pi}}e^{-\frac{x^2}{2}} = 0$
  - $x = \frac{\mu_F}{\sigma_F} = \frac{\mu}{\sigma\rho}$



Fitting vs. Prediction

- If X_t process is Gaussian, no linear trading rule obtained from a finite history of X_t can generate expected returns over and above F_t.
- Minimizing mean squared error ≠ maximizing P&L.
- In general, the relationship between MSE and P&L is highly non-linear (Acar 1993).



Technical Analysis

- Use a finite set of historical prices.
- Aim to maximize profit rather than to minimize mean squared error.
- Claim to be able to capture complex non-linearity.
- Certain rules are ill-defined.



Technical Linear Indicators

- For any technical indicator that generates signals from a finite linear combination of past prices
  - Sell: $B_t = -1$ iff $\sum_{j=0}^{m-1} a_j P_{t-j} < 0$
- There exists an (**almost**) equivalent AR rule.
  - Sell: $\widetilde{B_t} = -1$ iff $\delta + \sum_{j=0}^{m-2} d_j X_{t-j} < 0$
  - $X_t = \ln \frac{P_t}{P_{t-1}}$
  - $\delta = \sum_{j=0}^{m-1} a_j$, $d_j = -\sum_{i=j}^{m-2} a_i$



Conversion Assumption

- $1 - \frac{P_{t-j}}{P_t} \approx \ln \frac{P_t}{P_{t-j}}$
- Monte Carlo simulation:
  - 97% accurate
  - 3% error.



Example Linear Technical Indicators

- Simple order
- Simple MA
- Weighted MA
- Exponential MA
- Momentum
- Double orders
- Double MA

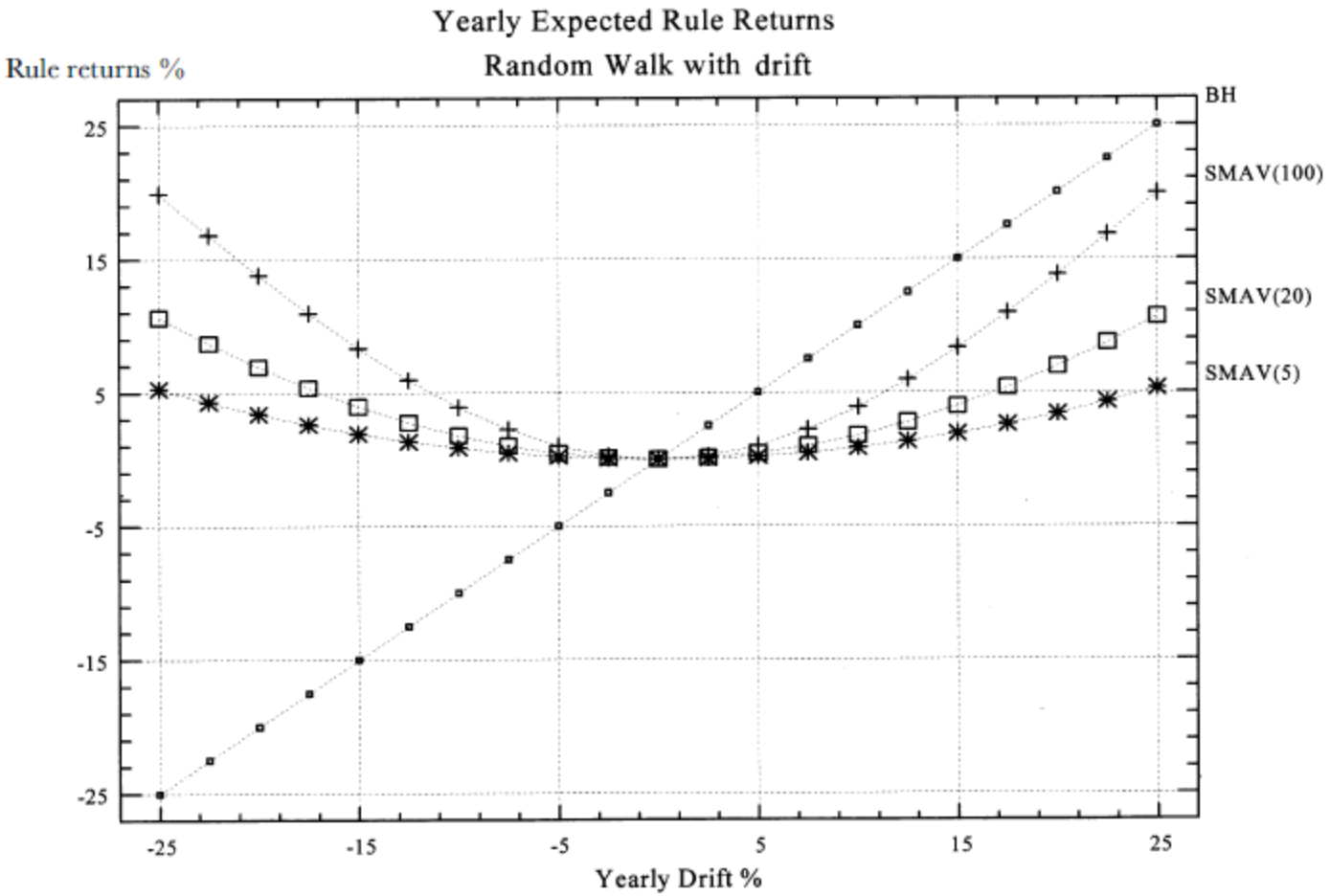


Returns: Random Walk With Drift

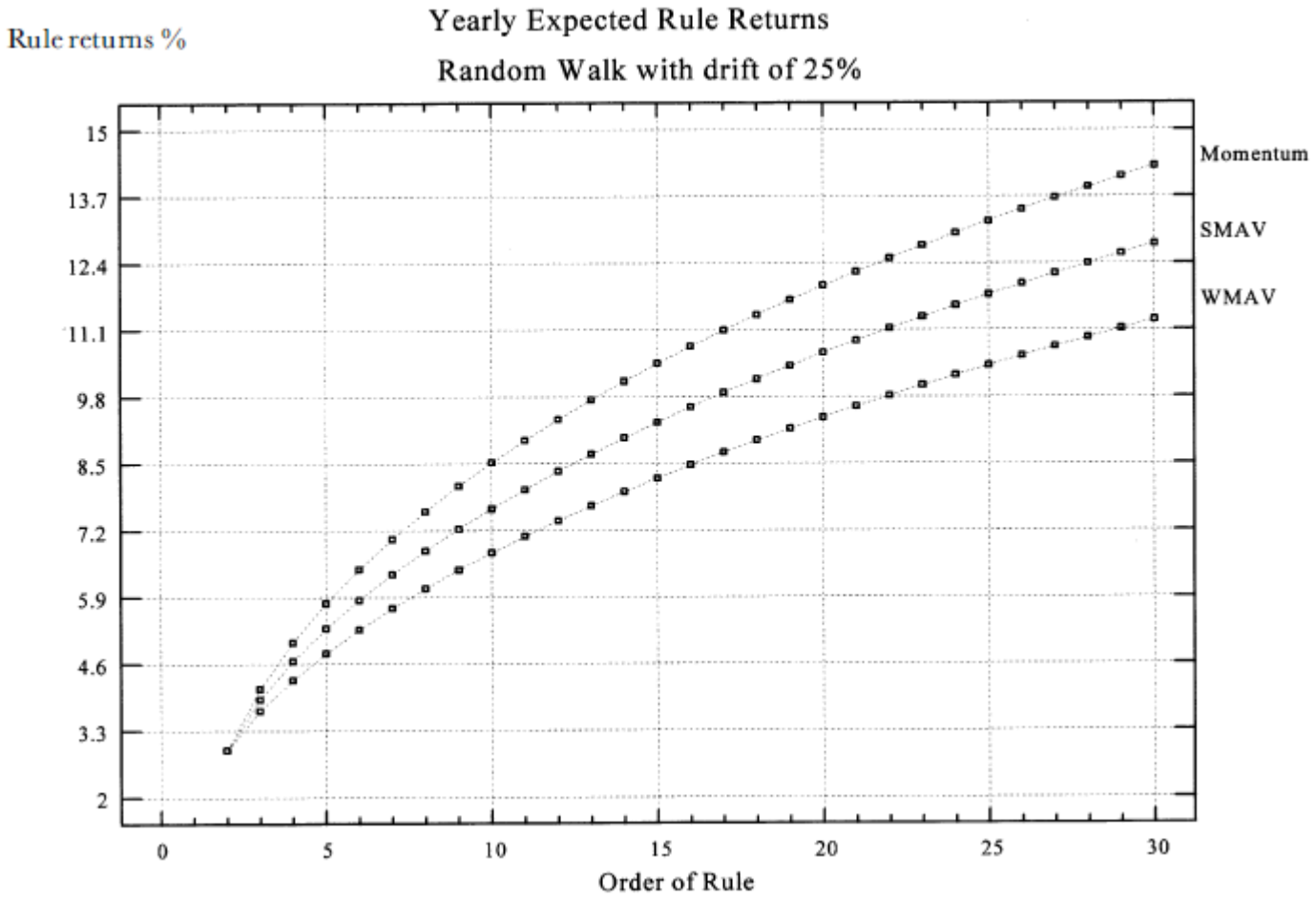
- $X_t = \mu + \varepsilon_t$
  - The bigger the order, the better.
  - Momentum > SMAV > WMAV
- How to estimate the *future* drift?
  - Crystal ball?
  - Delphic oracle?



Results


Yearly Expected Rule Returns
Random Walk with drift
Rule returns %
BH
SMAV(100)
SMAV(20)
SMAV(5)
25
15
5
-5
-15
-25
-25
-15
-5
5
15
25
Yearly Drift %

Results

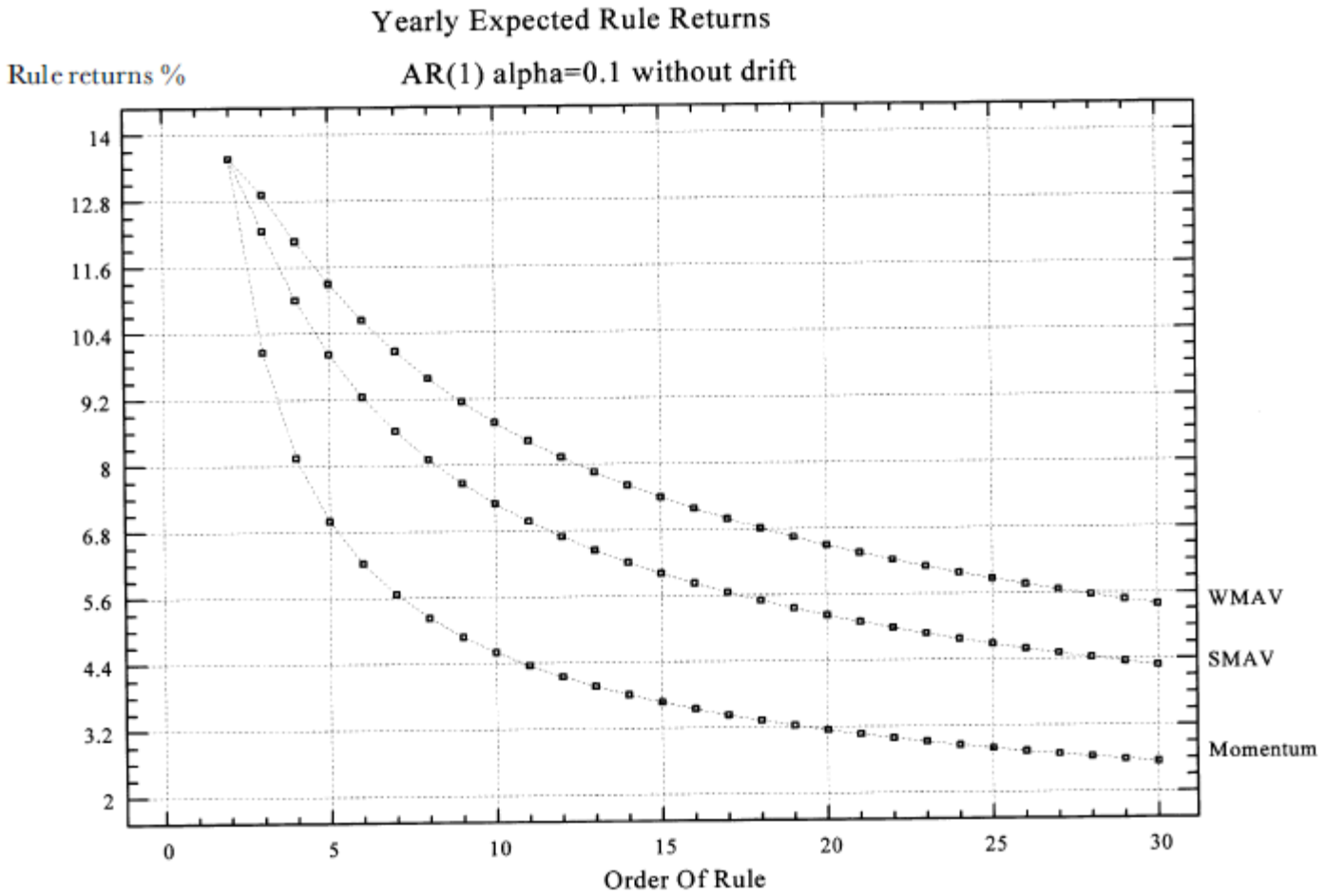

Yearly Expected Rule Returns
Random Walk with drift of 25%
Rule returns %
15
13.7
12.4
11.1
9.8
8.5
7.2
5.9
4.6
3.3
2
0
5
10
15
20
25
30
Order of Rule
Momentum
SMAV
WMAV

Returns: AR(1)

- $X_t = \alpha X_{t-1} + \varepsilon_t$
  - Auto-correlation is required to be profitable.
  - The smaller the order, the better. (quicker response)



Results


Yearly Expected Rule Returns
AR(1) alpha=0.1 without drift
Rule returns %
14
12.8
11.6
10.4
9.2
8
6.8
5.6
4.4
3.2
2
0
5
10
15
20
25
30
Order Of Rule
WMAV
SMAV
Momentum

ARMA(1, 1)

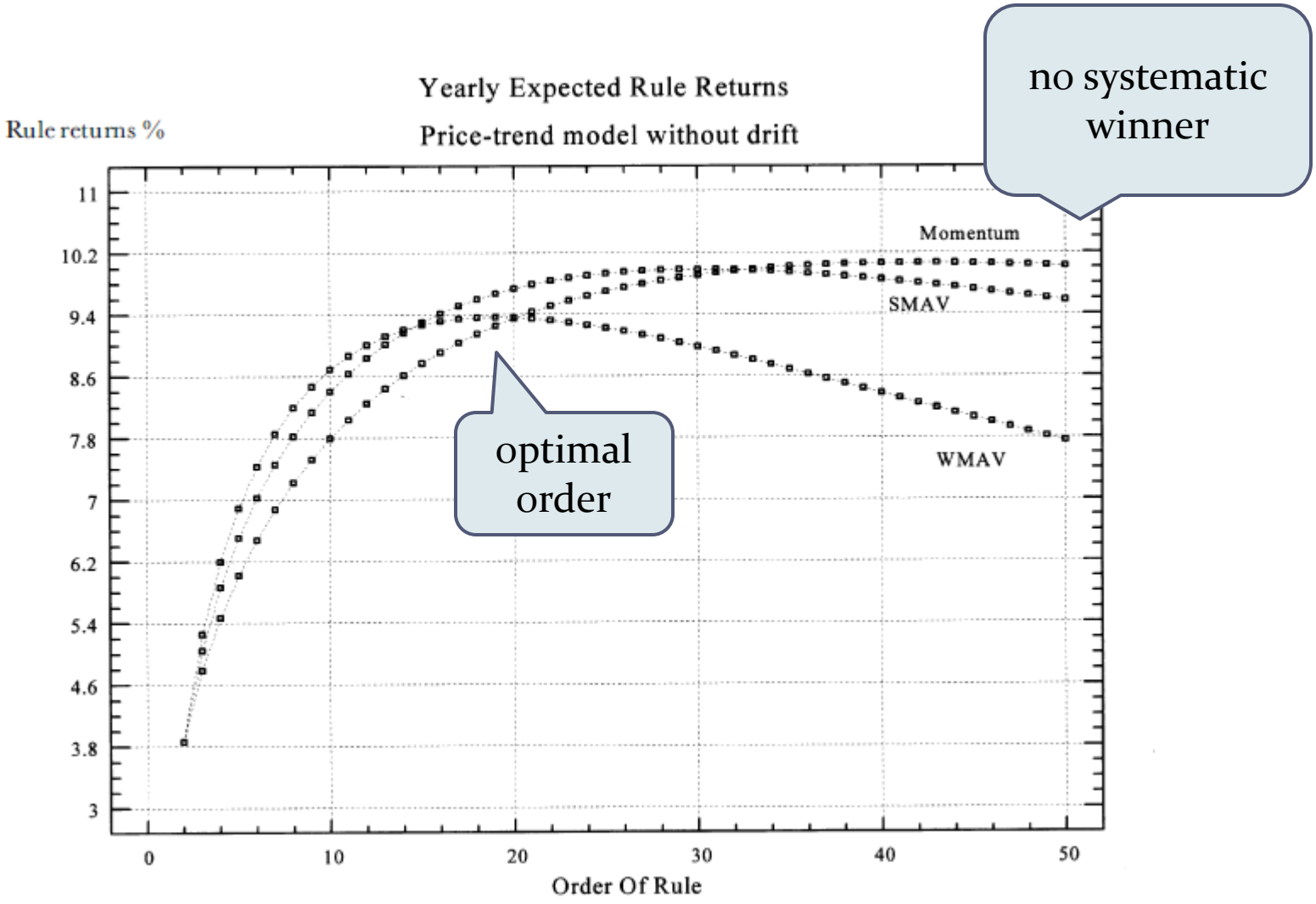
AR

MA

- $(X_t - \mu) - p(X_{t-1} - \mu) = \varepsilon_t - q\varepsilon_{t-1}$
- Prices tend to move in one direction (trend) for a period of time and then change in a random and unpredictable fashion.
  - Mean duration of trends: $m_d = \frac{1}{(1-p)}$
- Information has impacts on the returns in different days (lags).
  - Returns correlation: $\rho_h = Ap^h$



Results

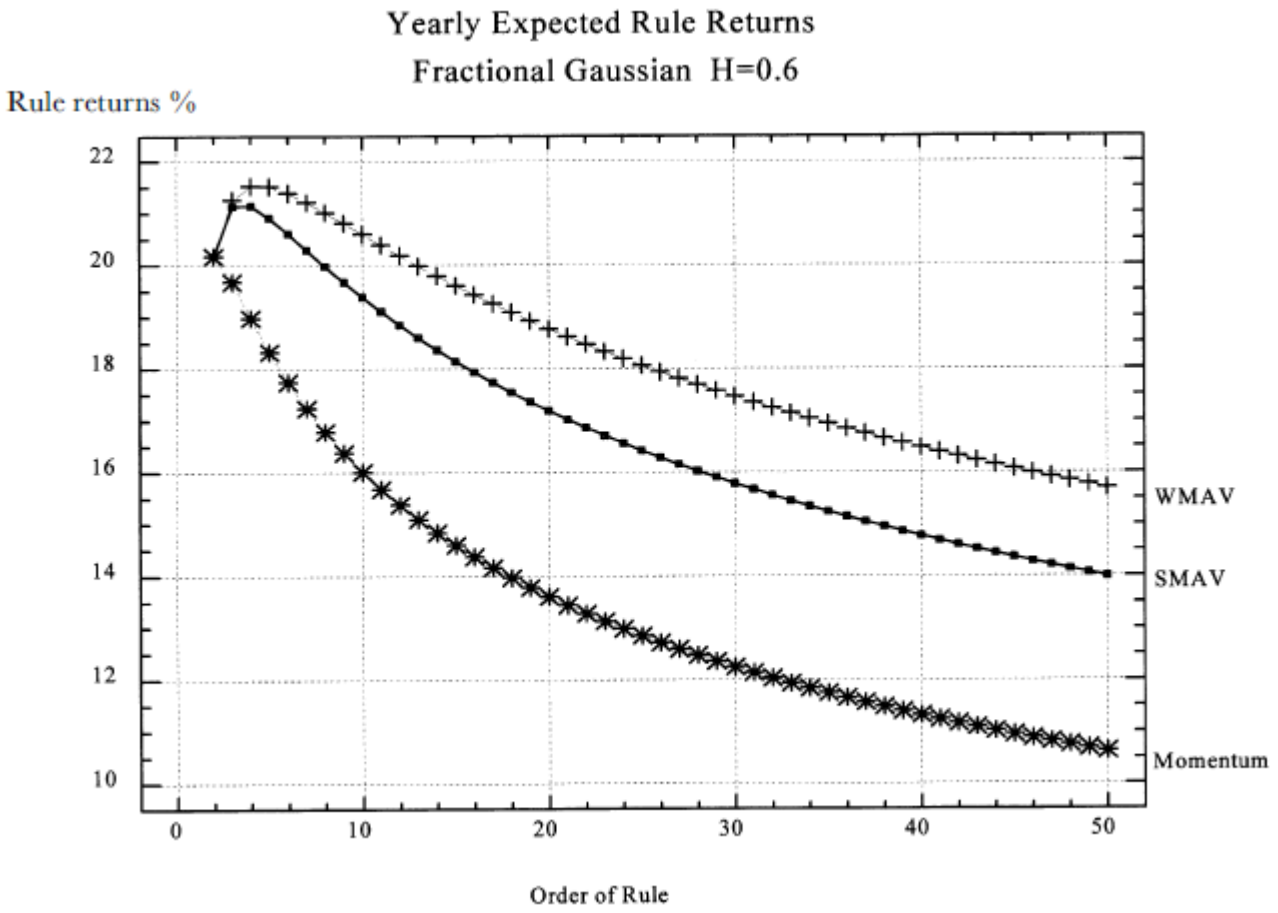

Yearly Expected Rule Returns
Price-trend model without drift
Rule returns %
11
10.2
9.4
8.6
7.8
7
6.2
5.4
4.6
3.8
3
0
10
20
30
40
50
Order Of Rule
Momentum
SMAV
WMAV
optimal order
no systematic winner

ARIMA(0, d, 0)

- $\nabla^d (X_t - \mu) = e_t$
- Irregular, erratic, aperiodic cycles.



Results


Yearly Expected Rule Returns
Fractional Gaussian H=0.6
Rule returns %
22
20
18
16
14
12
10
0
10
20
30
40
50
Order of Rule
WMAV
SMAV
Momentum

ARCH(p)

- $X_t = \mu + \left\{ \sqrt{\alpha_0 + \sum_{i=1}^{p} \alpha_i (X_{t-i} - \mu)^2} \right\} \varepsilon_t$
- $X_t - \mu$ are the residuals
- When $\mu = 0$, $\mathrm{E}(R_t) = 0$.

residual coefficients as a function of lagged squared residuals



AR(2) + GARCH(1,1)

- $X_t = a + b_1 X_{t-1} + b_2 X_{t-2} + \varepsilon_t$
- $\varepsilon_t = \sqrt{h_t} z_t$
- $h_t = \alpha_0 + \alpha_1 {\varepsilon_{t-1}}^2 + \beta h_{t-1}$

AR(2)

GARCH(1,1)

innovations

ARCH(1): lagged squared residuals

lagged variance



Results

- The presence of conditional heteroskedasticity will not drastically affect returns generated by linear rules.
- The presence of conditional heteroskedasticity, if unrelated to serial dependencies, may be neither a source of profits nor losses for linear rules.



Playing Trend Following Strategies

- Trend following model requires positive (negative) autocorrelation to be profitable.
  - What do you do when there is zero autocorrelation?
- Trend following models are profitable when there are drifts.
  - How to estimate drifts?
- It seems quicker response rules tend to work better.
- Weights should be given to the more recent data.



Conclusions

The Essential Skills

- Financial intuitions, market understanding, creativity.
- Mathematics.
- Computer programming.

An Emerging Field

- It is a financial industry where mathematics and computer science meet.
- It is an arms race to build
  - more reliable and faster execution platforms (computer sciences);
  - more comprehensive and accurate prediction models (mathematics).
- Structured products seem to be an evening industry after the financial crisis. Could quantitative trading be another gold mine?