Optimal Technical Trading Rules and Risk Control in Managing Stock Portfolios

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Overview

• Basic premise of Program Trading
• Entry/exit of trades using Technical Indicators
• Objective criteria, cycle lengths, decision rules
• Hedge Fund style management - stochastic programming model
• Risk expressions: portfolio insurance, drawdown control, over-betting
• Forecasting and scenarios - extreme outcomes

• MiSOFT software
Introduction: Program Trading (PT)

- PT tries to exploit market inefficiencies
- PT is over 40% of market volume on certain days
- Identification of edges with high probability is key
- PT applies simultaneous trading of a portfolio
- Risk control via hedging is important.

hedge against likelihood of a declining market via Leverage, short sales ➔ Hedge Fund style

- Growth in PT is due to: trading in diversified portfolios, institutions trading larger equity fractions, technology
Components for Success of PT

1. Mathematical models quantifying edges
2. Optimization models of risk control and bet-sizing
3. Algorithmic trading components: Lot sizing of trades to minimize market impact
4. Data feeds and technology backbones

In this talk, I will focus on the first two components only.
Why models?

• Everyone is looking for edges, but edges exist in short term mostly
  → sudden market pullbacks
  → short term reaction to news
  → increases in volatility

• Reversion to mean effect can be expected, so must find and quantify these opportunities!

• Edges have short durations: few days, $T$

• Determine $T$ dynamically using mathematical models
• Technical Indicators (TA) are valuable tools for edge identification

• We use optimized models of decision criteria that involve TA tools for Trade signal generation

• TA tools must employ dynamic parameter selection for changes in investor psychology

• Similarly, risk of established market positions exist!
  → Market risk
  → Sector risk
  → Corporate risk

  Need models for risk control
Risk control models

➢ Portfolio risk models
  • Shorting strategies
  • Beta-neutral, volatility neutral
  • Drawdown control, catastrophic risk control

➢ Sector risk control
  • Sector allocation model
  • Control sector over-exposure
  • Explicit sector correlations

➢ Corporate risk control
  • Firm selections on a quarterly basis
  • Fundamental Analysis (FA) optimization models
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Schematic of a Fund Management system

1. Stock selection
2. Signal generator
3. Estimations
4. Scenarios
5. Risk control
6. Fast Solution

DATA

Fundamental Analysis

Market data

(MiSOFT)

Simulator
My recent work in this area:

4. “Mahalanobis-Squared Distance Based Outcomes Generation for Portfolio Optimization”, 2006
8. ….
Optimization Model for Equity Trading (OMLET)

1. Quarterly stock/sector selection based on DEA-based Fundamental Analysis – Optimized Relative Financial Strength metric (RFS)
2. Short-term stock selection based on Technical Indicator analysis of momentum and trend under Optimized Cyclic Parameter Selection (CPS)
3. Trade size optimizer using stochastic programming-based risk optimization model (MiSOFT ©).
DEA-model of Relative Financial Strength (RFS)

Central premise is the concept of market efficiency on a Quarterly basis.

Efficient Market Hypothesis (EMH)

Stock prices fully reflect all publicly-available information, but the future expectations of market price are determined by the perceived business strength of the firm.

Eugene Fama (1960s)

Period Length: EMH is applied on a 3-monthly basis
Supply/Demand Market Competition → Financial Statements → Relative Business Strength → EMH → Stock Market Return → Productivity and Efficiency

Data Envelopment Analysis (DEA)
## Financial Parameters

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<thead>
<tr>
<th>P1</th>
<th>Return on Equity</th>
<th>Profitability</th>
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<td>P2</td>
<td>Return on Assets</td>
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<td>P3</td>
<td>Net Profit Margin</td>
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<td>P4</td>
<td>Earnings Per Share</td>
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<td>Receivables Turnover</td>
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<td>P8</td>
<td>Current Ratio</td>
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<td>P9</td>
<td>Quick Ratio</td>
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<td>P10</td>
<td>Debt to Equity Ratio</td>
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<td>Solvency ratio-I</td>
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<td>P14</td>
<td>Price to Earnings Ratio</td>
<td>Valuation</td>
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<td>P15</td>
<td>Price to Book Ratio</td>
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<td>P16</td>
<td>Revenue Growth Rate</td>
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<td>P17</td>
<td>Net Income Growth Rate</td>
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<tr>
<td>P18</td>
<td>Earnings per Share Growth Rate</td>
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</tr>
</tbody>
</table>

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Determine $x^*$ that maximizes sector correlation
Fundamental Analysis DEA Optimization

\[ \eta_k(x) = \text{Maximize} \quad \sum_{i=1}^{n} (x_{n+i} \xi_{ik}) v_i \]

Subject to \[ \sum_{i=1}^{n} (x_i \xi_{ik}) u_i \leq 1 \]

\[-M \sum_{i=1}^{n} (x_i \xi_{ik}) u_i + \sum_{i=1}^{n} (x_{n+i} \xi_{ik}) v_i \leq 0 \]

\[- \sum_{i=1}^{n} (x_i \xi_{ij}) u_i + \sum_{i=1}^{n} (x_{n+i} \xi_{ij}) v_i \leq 0, \forall j, j \neq k \]

\[ u_i, v_i \geq 0, \quad i = 1, \ldots, n \]
## Case Study of the U.S. Market Sectors

**DATA PERIOD:** beg 1997 – end 2004

<table>
<thead>
<tr>
<th>Sector</th>
<th>Count</th>
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<tbody>
<tr>
<td>Technology</td>
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<tr>
<td>Health Care</td>
<td>107</td>
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<tr>
<td>Basic Materials</td>
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<td>Energy</td>
<td>49</td>
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<td>Industrial Goods</td>
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<tr>
<td>Consumer Discretionary</td>
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<td>Financial</td>
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<tr>
<td>Utilities</td>
<td>62</td>
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827 firms

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## Optimal Sector Selections

<table>
<thead>
<tr>
<th>Sector</th>
<th>Max. Corr</th>
<th>Selected?</th>
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<td>Technology</td>
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<td>Health Care</td>
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<td>Financials</td>
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<td>Utilities</td>
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<td>Consumer Discret.</td>
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<td>Consumer Staple</td>
<td>0.268</td>
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<tr>
<td>Basic Materials</td>
<td>0.169</td>
<td>Yes</td>
</tr>
<tr>
<td>Industrial Goods</td>
<td>0.210</td>
<td>Yes</td>
</tr>
</tbody>
</table>
**Stock Selections** Quarter 1 of 2005

$RFS^* = -0.45$

89 stocks
When to trade? – Daily Signal  Generation

♦ Market inefficiency and profiting from it via technical indicator analysis

♦ Empirical studies indicate a variety of seasonal and temporal irregularities in stock prices (January Effect, Weekend Effect, etc)

♦ Market inefficiency: in short term, stock prices may not react instantly to new information, so profitable opportunities are not removed instantaneously!

♦ Mis-pricing could persist for some periods of time. Lamont and Thaler (2003)
3 Technical Indicators for daily analysis

- Trend-following
  - **MACD** (moving average convergence divergence)

- Overbought/oversold strength
  - **RSI** (Relative Strength Index)
    - Compares the magnitude of recent gains to recent

- Momentum
  - **OBV** (on balance volume)
    - Relates volume to price change
• MACD shows the relationship between two moving averages of prices.

\[
MACD_t = \text{Price}^{MA}_t (l_2) - \text{Price}^{MA}_t (l_1)
\]

\[
\text{SIGNAL}_t = MACD_t - \text{Price}^{MA}_t (l_3)
\]

where \( l_1 > l_2 > l_3 \) are fixed time lengths (days).

• OBV is used to detect momentum, it shows whether this volume is flowing in or out of a given stock.

• OBV line can be used as confirmation of a price trend.

\[
OBV_t = \begin{cases} 
OBV_{t-1} + V_t, & \text{if } P_t - P_{t-1} \geq \tau \\
OBV_{t-1} - V_t, & \text{if } P_t - P_{t-1} \leq -\tau \\
OBV_{t-1}, & \text{if } -\tau < P_t - P_{t-1} < \tau 
\end{cases}
\]
Rules for Trading Signals

There are three kinds of trading decisions: **Buy, Sell, and Neutral signals.**

Define the indicator’s value of ticker $i$ on day $j = I_{i,j}$

On day $j$, if $I_{i,j} < \rho_1$ and $I_{i,j} > \rho_2$ (where $\rho_1 < \rho_2$)

“Buy” decision is made if the $I$ value increases with a significant rate, $\rho_3$ ($> 0$)

$$ICR_{i,j} = \frac{I_{i,j} - I_{i,j-1}}{|I_{i,j-1}| + 1}$$

“Sell” decisions are made similarly.
**DECISION RULES**

**BUY**

if \( I_{i,j} < \rho_1 \), \( I_{i,j} > \rho_2 \) and \( ICR_{i,j} > \rho_3 \)

**SELL**

if \( I_{i,j} > \rho_4 \), \( I_{i,j} < \rho_5 \) and \( ICR_{i,j} > \rho_6 \)

where \( \rho_1 < \rho_2 \), \( \rho_4 > \rho_5 \) and \( \rho_3, \rho_6 > 0 \).

Otherwise, the signal generates a **NEUTRAL** trade.

**Example:**

\( \rho_1 = -0.4 \quad \rho_2 = -0.2 \)
\( \rho_4 = +0.4 \quad \rho_5 = +0.2 \)
\( \rho_3 = \rho_6 = 0.15 \)
A strategy involves choosing a set of indicators $I$ and a value vector $\rho \rightarrow S(I, \rho)$

- Under $S(I,\rho)$, accumulate all trades over all $N$ stocks and over all $T$ days (of historical data)

- RoR for each trade is calculated, when positive it is a SUCCESS, when negative, it is a FAILURE.

- Evaluate the Probability of Success ($P_S$) over the $T$ days and $N$ tickers

- Evaluate the overall RoR ($R$) over the $T$ days and $N$ stocks

- Signal Optimization Model: \[
\text{MAXIMIZE} \quad \omega_1 R + \omega_2 P_S \\
\text{s.t.} \quad \rho_1 < \rho_2, \rho_4 > \rho_5, \rho_3, \rho_6 > 0.
\]
MACD optimization
RoR and Probability of Success
Typically, parameters of indicators are fixed. This assumes fixed investor perceptions.

Above Optimization Model is dynamically updated based on cyclic changes of perceptions.

Investor perceptions may remain unchanged only for a certain period of time. So there may be a certain cyclic pattern (such as monthly, quarterly, semi-annually or annually)

In a certain time of application, the appropriate optimal parameter set $\rho^*$ must be used.
Trade size optimization: Portfolio Trading

• Consider future when creating positions that tradeoff current costs with future returns?
  ⇒ multi-period/multistage modeling

• Trades need to respond to developing trends quicker?
  ⇒ forecast model based on trendiness/congestion

• Separate the ‘need to trade’ from ‘size the trade’ based on market barometers?
  ⇒ signal generating model for trading

• Need to track market barometers? Or stay neutral?
  ⇒ dollar-neutral, volatility-neutral, beta-neutral
Multiperiod Portfolio Rebalancing

Scenario-1

Returns vector of $N$ securities

$\mathbf{r}^t$

$t^{t-1}$

Day 1

Day 2

Day 4

Day 8

Day 15

$\mathbf{x}^{[h_{t-1}]}$, $\mathbf{C}^{[h_{t-1}]}$

$[h_t]$

rebalanced positions:

$\mathbf{x}^{[h_t]}$, $\mathbf{C}^{[h_t]}$

Observe price: $\mathbf{P}^{[h_t]}$
1. For the next period of trading, **Return Model** is:

   \[
   \mathbf{r}^t \sim \mathcal{D}(\mu^t(h_{t-1}), V^t(h_{t-1}))
   \]

   \[\text{Vector of rate of returns : } \mathbf{r}^t \sim \mathcal{D}(\mu^t(h_{t-1}), V^t(h_{t-1}))\]

2. Portfolio random return ($) after re-balancing:

   \[
   \xi_t(r^t, X^t) = \sum_{j=1}^{N} \left[ P_{j}^{t-1} r_{j}^t X_{j}^t - f_{j}^t(y_{j}^t) \right]
   \]

   \[\text{Loss Function } = \text{ Slippage } + \text{ other costs}\]

   \[= f_j( y_j )\]

3. Budget:

   \[P^t \left( X^t - X^{t-1} \right) + f(y^t) + C^t = B_t + (1 + \kappa_{t-1})C^{t-1}\]

4. Leverage constraints

5. Limiting positions, avoiding excessive short sales, …
Market Impact (Slippage)

\[ S_j(y_j) := y_j \left( \alpha_{0j} + \alpha_{1j} \frac{P_j y_j}{V_j} \right) \]

→ \( y \): trade size
→ \( P \): trade price
→ \( V \): expected daily volume
→ \( S \): slippage loss of trade
→ \( \alpha_0 \): fixed cost of slippage
→ \( \alpha_1 \): scaling factor

Also see: Keim/Madhavan (99), Loeb (83), Torre/Ferrari (99)
One aspect of Risk control involves shaping the above distribution appropriately!

• Direct tradeoff between *shape* parameters

• Control of *positions* through market strategies

\[
\xi_t(r^t, X^t) \sim \mathcal{S}(\bar{\xi}_t(X^t), \sigma_t^2(X^t))
\]
Leverage, shortsales control etc. may control risk to some extent.

But, here we refer to Risk that is tied to description of uncertainty (forecast parameters/scenarios etc)

**Static Risk Control (SRC)**
1. Conditional mean RoR: $\mu[h_t]$
2. Conditional StdDev: $\sigma[h_t]$
3. Var-Cov matrix: $\Sigma[h_t]$

**Dynamic Risk Control (DRC)**
1. Need a sample of outcomes at $[h_t]$ 
2. Outcomes may be nested to form a *scenario tree*

*Forecastsed parameters*
 SRC type-I: Benchmark Target Risk

- Benchmark (stochastic) target – S&P500 index
- Index RoR random variable: $R^{[h_t]}$
- Target return: $\tau^{[h_t]} (x^{[h_t]}) = P^{[h_{t-1}]} x^{[h_t]} R^{[h_t]}$
- penalty: $E_{x^{[h_t]}} \left\{ \left[ P^{[h_t]} D(r^{[h_t]}) x^{[h_t]} - \tau^{[h_t]} (x^{[h_t]}) \right]^2 \mid h_t \right\}$
- Upper bound on penalty:
  $$R_T^{[h_t]} (x^{[h_t]}) := \left[ \sigma_P^{[h_t]} (x^{[h_t]}) \right]^2 + \left[ P^{[h_t]} D(\mu^{[h_t]}) x^{[h_t]} - \mu_R^{[h_t]} P^{[h_t]} x^{[h_t]} \right]^2$$
  $$+ \left[ \sigma_R^{[h_t]} (P^{[h_t]} D(\beta^{[h_t]}) x^{[h_t]} - P^{[h_t]} x^{[h_t]}) \right]^2$$
  $$= \left[ \text{inherent risk due to security correlations} \right] + \left[ \text{risk due to not tracking benchmark mean return} \right] + \left[ \text{risk due to portfolio beta not being 1.0} \right]$$

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**SRC type-I**: tracking objective terms

\[
\text{maximize } G^{[h_t]}(\mu^{[h_t]}, x^{[h_t]}) - \lambda^t \mathcal{R}_{\mathcal{T}}^{[h_t]}(x^{[h_t]})
\]

- Portfolio expected net return at \([h_t]\)
- (static) tracking risk aversion coefficient
- Tracking risk penalty at \([h_t]\)

**Proposition**: If “stochastic target=portfolio mean”, then

*tracking risk=portfolio variance, i.e., Markowitz mean-variance tradeoff*
**Integrated Risk**

**SRC type-II: Catastrophic risk (Cat Risk)**

- Future direction of price is opposite to the sign of established position – *long positions fall in price, short positions rise in price*
- Portfolio variance or tracking risk cannot counter **Cat Risk** effect
- Cat Risk = anticipated total dollar wealth loss in the event stock returns move against each portfolio position by *one StdDev*.

\[
R_C^{[h_t]}(x^{[h_t]}) := \sum_{j=1}^{N} P_j^{[h_t]} \sigma_j^{[h_t]} |x_j^{[h_t]}|
\]

**Proposition:** The portfolio standard deviation is a lower bound on the catastrophic risk, i.e., \( R_C^{[h_t]}(x^{[h_t]}) \geq \sigma_P^{[h_t]}(x^{[h_t]}) \)

Mean-variance models can grossly *underestimate* Cat Risk, leading to severe portfolio losses in practice!!

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Standard Mean-Variance model

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**SRC type-III: Degree of Neutrality (DON)**

- Hedging strategies that balance investments among carefully chosen long/short positions
- Buffers the portfolio from severe market swings (*Nicholas, 2000, Jacobs/Levy, 2004*)
- Control market correlation risk to immunize against market “moves” → lose some “good” days, but avoid “bad” days
- Estimate parameters w.r.t. S&P500: 
  \[
  \beta_j^{[h_t]} := \frac{Cov(r_j^{[h_t]}, R^{[h_t]})}{Var(R^{[h_t]})}
  \]
- To control portfolio beta at: \( \gamma_0 \pm \gamma_1 \)

\[
(\gamma_0 - \gamma_1)w^{[h_t-1]} \leq P^{[h_t]} D(\beta^{[h_t]}) x^{[h_t]} \leq (\gamma_0 + \gamma_1)w^{[h_t-1]}
\]

Wealth trajectory up to \([h_t]\)

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Integrated Risk: Dynamic Risk Control

- Scenario samples are generated, and nested, according to conditional information ⇒ Scenario Tree
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DRC type-I: Drawdown risk control

- Portfolio Drawdown $\Rightarrow$ drop in portfolio value w.r.t. to a previously achieved maximum:
- Previous maximum may be defined over past $\hat{t}$ days:
  \[
  w_{\max}^{[h_t]} := \max_{\tau=t-\hat{t}, \ldots, t-1} w^{[h_\tau]}
  \]
- Under a certain market return vector: $r^{[h_t]}$, portfolio relative drawdown is measured by:
  \[
  \max \left\{ 0, \frac{w_{\max}^{[h_t]} - w^{[h_t]} (r^{[h_t]}, x^{[h_t]})}{w_{\max}^{[h_t]}} \right\}
  \]
- Small relative drawdown is PREFERRED
  Need portfolio growth with low DD $\rightarrow$ high RTD ratio
**DRC type-I: Drawdown risk control**

- wealth at $t_0 \rightarrow $109,020
- maximum % drawdown occurs at $t \rightarrow 12.35\%$
- At year end $T$, portfolio annual RoR $\rightarrow +11.78\%$
- Reward-to-Drawdown (RTD) ratio is $11.78/12.35 = 0.95$
- fund managers strive for RTD of greater than $2.0$!
• Existing work inadequate: lognormal assumptions (Grosmann and Zhou, 1993), Conditional DaR (Checkhlov, 2003), etc.

• Our approach: “Acceptable drawdown level (ADL)” for a fund: Losing more than a fraction $\pi$ (say 10%) from previous maximum $\rightarrow$ Penalize drawdown beyond the ADL

$$\begin{align*}
w^{[h_t]}(r^{[h_t]}, x^{[h_t]}) + q^{[h_t]}(r^{[h_t]}, x^{[h_t]}) \geq (1 - \pi) w^{[h_t]}_{\max} \\
q^{[h_t]}(r^{[h_t]}, x^{[h_t]}) \geq 0
\end{align*}$$

Need to track portfolio: $w^{[h_t]}_{\max} - w^{[h_\tau]} \geq 0$, $\forall \tau = 1, \ldots, t - 1$

Drawdown penalty:

$$
R^{[h_t]}_{D, \pi}(x^{[h_t]}) := E_t^{[h_t]} [q^{[h_t]}(r^{[h_t]}, x^{[h_t]})]^2
$$

$$\begin{align*}
\text{maximize} & \quad G^{[h_t]}(\mu^{[h_t]}, x^{[h_t]}) - \lambda^t_D R^{[h_t]}_{D, \pi}(x^{[h_t]}) \\
\text{(dynamic) drawdown risk aversion coefficient}
\end{align*}$$
Multistage Stoch Prog model

initial $x^0$ → $x^1$ → Period 1 → $x^2$ → Period 2

Trade-size, Wealth/Budget, Slippage, leverage, positions limits, SRC-I, SRC-II, SRC-III, DRC-I, DRC-II

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Basic idea is that mean estimation must be a highly adaptive process
As volatility/trend emerges in the time series, some anticipatory updating must be incorporated.
Motivation

Biggest dilemma in a financial crystal-ball is determining if prices are trending or are in a trading-range!

* **trending** periods $\Rightarrow$ *Quick response* with little smoothing
* **congestion** periods $\Rightarrow$ *Stability* with smoother forecasts
  (otherwise multiple conflicting trades)
* Need to adjust forecasts by the *trendiness* of prices

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Use VHF-based Volatility Estimator to Adjust the Moving Average Forecasting Process

**Calculation:**

**Input:** Current period ($t$), Period Length ($n$), Offset period ($\tau$)

- HCP $\iff$ Highest Closing Price over $n$-periods prior to $t$
- LCP $\iff$ Lowest Closing Price over $n$-periods prior to $t$
- $\Delta$ $\iff$ sum of absolute variation of Prices from period to period over $n$-periods prior to $t$

\[
VHF_t(n) = \frac{(HCP-LCP)}{\Delta}
\]

*VHF was introduced by Adam White, Futures Magazine, 1991*
Volatility Ratio (\( \phi \))

Volatility Ratio \( \phi_t \) (at time \( t \) using \( \tau \) offset-periods) is:

\[
\phi_t = \frac{VHF_t(n)}{VHF_{t-\tau}(n)}
\]

**Interpretation:**

1. Higher the ratio of VHFs, the higher the degree of *trending* (give more weight to recent prices)
2. Falling ratio of VHFs indicates that prices may be entering a *congestion* phase.
3. False signals are likely, so watch out!

\[\Rightarrow \text{Mean Forecast} = F(\phi,\ldots,\ldots)\]
Example: using $n = 28$ and $\tau = 12$ days
Challenges!

◆ stock returns have heavy tails
◆ with frequent trading, representation of central tendencies… not sufficient
◆ look at historical returns and understand Outliers, sample them by probability in to the scenario trees
◆ ⇒ Use distance-metric on multivariate historical return vectors, then sample outcomes, based on distance-bands

(Edirisinghe/Patterson, “Mahalanobis-metric based sampling”, 2005)
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Case Study

Standard & Poor 100 stocks
For the period: Jan 02, 1996 to Aug 16, 2002

- Begin investment from Oct 15, 1996 (initial data for parameter estimation)
- S&P100 (using SPY/SPDR Trust-ETF) Statistics:
  - Annualized Rate of Return (AROR) = + 5.78%
  - Annualized Std. Dev (AStD) = 35.94%
  - Maximum Drawdown (maxDD) = 47.94%
  - Sharpe ratio (AShR) = 0.049
  - ARTD ratio = 0.121

Riskfree: 4%
MODEL ROLLED OVER DAILY!

3 model types:

<table>
<thead>
<tr>
<th>T (stages)</th>
<th>Period Structure</th>
<th>L</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>1 day</td>
<td>1 day</td>
</tr>
<tr>
<td>2</td>
<td>1 day → 4 days</td>
<td>5 days</td>
</tr>
<tr>
<td>3</td>
<td>1 day → 4 days → 5 days</td>
<td>10 days</td>
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1450 model roll overs

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## Single stage models

**Comparison of Static Risk Control (SRC)**

Apply only one risk type at a time – **PURE mode**

<table>
<thead>
<tr>
<th></th>
<th>Pure Markowitz risk metric $[\sigma_P(.)]^2$</th>
<th>Pure Tracking risk metric $\mathcal{R}_T(.)$</th>
<th>Pure Cat Risk metric $\mathcal{R}_C(.)$</th>
</tr>
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<tr>
<td></td>
<td>Pure Markowitz risk metric $[\sigma_P(.)]^2$</td>
<td>Pure Tracking risk metric $\mathcal{R}_T(.)$</td>
<td>Pure Cat Risk metric $\mathcal{R}_C(.)$</td>
</tr>
<tr>
<td></td>
<td>2.99% 4.08% 8.85% 15.37% 21.78% 48.99%</td>
<td>17.54% 22.94% 34.94% 60.93% 99.31% 248.78%</td>
<td>17.77% 40.94% 70.93% 104.25% 140.17% 215.44%</td>
</tr>
<tr>
<td></td>
<td>13.89% 20.15% 42.24% 59.95% 86.61% 154.81%</td>
<td>15.23% 19.26% 26.14% 40.53% 57.33% 102.19%</td>
<td>14.60% 28.70% 42.68% 56.14% 69.43% 95.26%</td>
</tr>
<tr>
<td></td>
<td>28.01% 37.27% 54.32% 59.06% 67.64% 72.75%</td>
<td>19.17% 20.93% 26.27% 31.22% 35.04% 42.41%</td>
<td>9.89% 16.86% 20.88% 23.16% 26.53% 31.59%</td>
</tr>
<tr>
<td></td>
<td>-0.036 0.002 0.089 0.193 0.263 0.619</td>
<td>0.706 0.905 1.178 1.824 2.720 5.771</td>
<td>1.392 2.191 3.205 4.329 5.132 6.694</td>
</tr>
</tbody>
</table>

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RTD of 2.0 with the least maxDD=17%
Pure CATrisk model
Integrated (mixed) mode

Tracking Risk control
+
Cat Risk Control

RTD = 4.9, maxDD = 23%

CATrisk = 6% per day

ARoR = 118%, AShR = 2.59

RTD of 2.0 with the least maxDD = 6%

CATrisk = 1% per day

ARoR = 16%

ASHR = 1.44
Two-stage models
Markowitz Vs. SRC/DRC

SRC/DRC: CatRisk=2% per day, ADL=10%, with 225 scenarios

CatRisk controls StdDev of the portfolio well!
Effect of Cat Risk: Integrated Risk Two-stage Model

---

**Portfolio StdDev**

- CatRisk=3%
- CatRisk=5%
- CatRisk=10%

**Beta**

- CatRisk=3%
- CatRisk=5%
- CatRisk=10%
Effect of Slippage Costs
1-stage Vs. 2-stage Models

Return-to-Drawdown
Vs
Maximum Drawdown

Increased TC

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Another measure of importance is:

\[
\text{Drawdown Duration to Drawdown Recovery (DDDR) ratio} \left\{ \frac{t - t_0}{t_1 - t} \right\}
\]
Drawdown-Duration to Drawdown- Recovery (DDDR) ratios

Effect of Multistage SP modeling

RDDR > 1.0 is desired in fund management!

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More Computations

Chosen from S&P-100 and Nasdaq-100 base
for a total of 177 stocks

Test period: up to Aug 08, 2003

- 1124 days of return data from 1999
- SPY as a proxy for market (S&P500 index)
- Market Index Statistics for the period in 2003:
  - Annualized Rate of Return (AROR) = 15.57%
  - Annualized Std. Deviation (ASD) = 18.76%
  - Annualized Sharpe ratio (ASharpe) = 0.8296
Initial Budget = 1 million$ (on Jan 01, 2003)
Models run at Close of day, Trades executed next day using “price within bounds rule”
Simple parameter estimators

- 2-period model for each trading day with 1-day and 5-day consecutive periods.
- Solved using *Multistage BSD algorithm*
- 2nd stage nodal parameters are re-estimated conditional on the 1st period outcome
- Catastrophic risk varied from $8,000 to $32,000 per period.
- $20 \times 10 = 200$ scenarios in the two stage SP model

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Models are exactly the same except for the scenarios → about the same CPU time for solution

Each column involves 152 stochastic programs (× 2)
MSG

Cat risk = $8,000

Normal
MSG

Cat risk = $16,000

Normal
Cat risk = $24,000
Normal sample is too small!!

Increase scenario sample to $100 \times 20 = 2000$ for Normal SG, at the expense of CPU time

<table>
<thead>
<tr>
<th>CAT RISK per period</th>
<th>$8,000$</th>
<th>$16,000$</th>
<th>$24,000$</th>
<th>$32,000$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>100x20=2,000 scenarios</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annualized Rate of Return</td>
<td>$17.73%$</td>
<td>$24.31%$</td>
<td>$29.72%$</td>
<td>$22.74%$</td>
</tr>
<tr>
<td>Annualized Sharpe Ratio</td>
<td>$2.02$</td>
<td>$1.59$</td>
<td>$1.40$</td>
<td>$0.91$</td>
</tr>
<tr>
<td>Maximum Draw down</td>
<td>$2.38%$</td>
<td>$4.43%$</td>
<td>$6.08%$</td>
<td>$10.30%$</td>
</tr>
<tr>
<td>Portfolio BETA</td>
<td>$0.29$</td>
<td>$0.52$</td>
<td>$0.70$</td>
<td>$0.80$</td>
</tr>
</tbody>
</table>
What if we used **MSG** with **Cat risk= $ 32,000**

until Sep 11, 2003

<table>
<thead>
<tr>
<th></th>
<th>MODEL</th>
<th>INDEX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annualized Rate of Return</td>
<td>217.33%</td>
<td>20.78%</td>
</tr>
<tr>
<td>Annualized Sharpe Ratio</td>
<td>4.31</td>
<td>1.16</td>
</tr>
<tr>
<td>Maximum Draw down</td>
<td>13.42%</td>
<td>**</td>
</tr>
<tr>
<td>Portfolio BETA</td>
<td>0.59</td>
<td>1.00</td>
</tr>
</tbody>
</table>

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Welcome to **MiSOFT** version 3.6

*(Multistage interactive Stochastic Optimizer for Financial Trading)*

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