Algorithmic Trading: A Buy-side Perspective

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Agenda

I. Algorithmic trading primer

- Market structure and “low touch” trading

II. User’s guide to algorithmic trading

- Conceptual framework for a quantitative investor

III. What lies ahead?

- Algorithms as dynamic limit orders

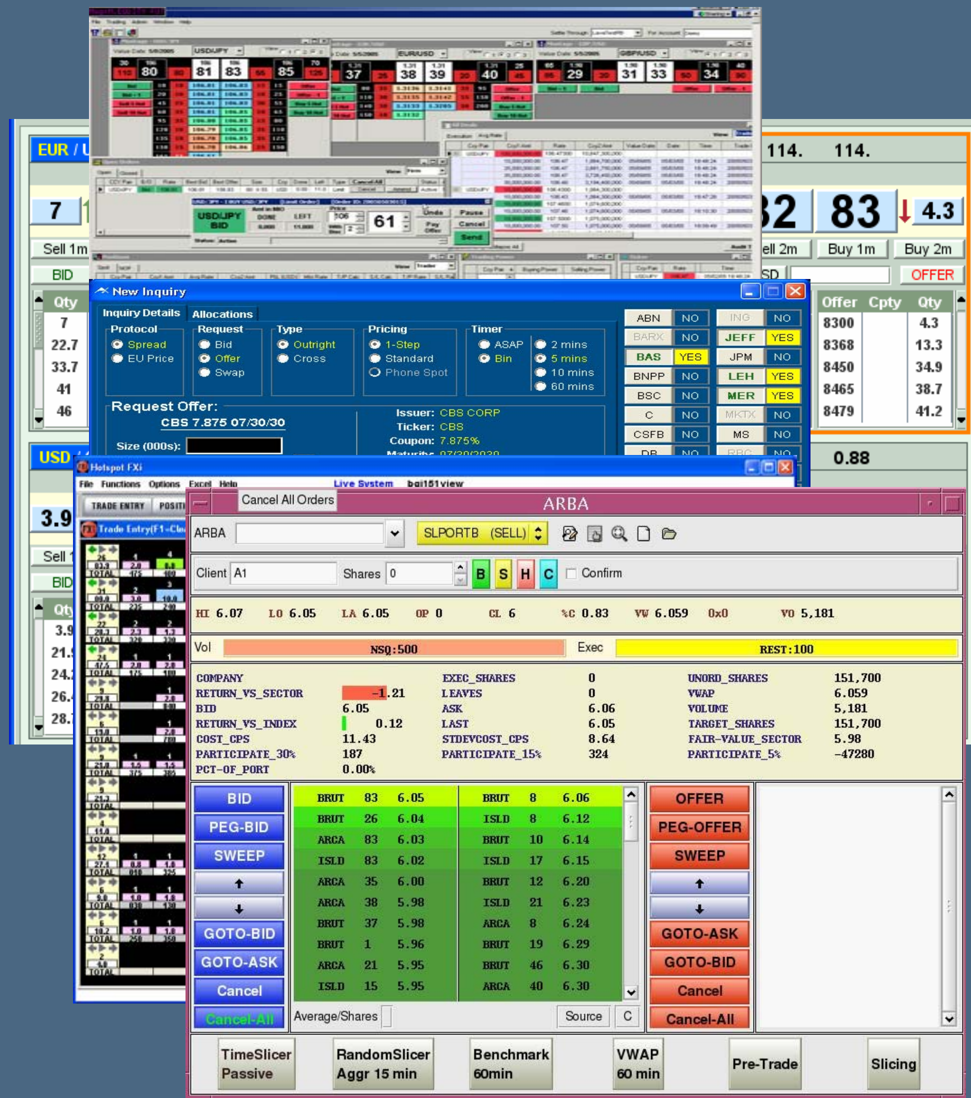
I. Algorithmic trading primer

Technology and competition drive market structure changes

- Faster markets, more real time information
- Cross-product and cross-border consolidation reduces trading costs, but fragments liquidity

Shift towards electronic trading venues across asset classes

- Global trend in equities, derivatives; increasing adoption in FX and fixed income
- Scalable, anonymous, transparent, and efficient



Growth of “low touch” trading

Automation begets automation

- Trend to electronic markets accompanied by rapid growth in (“low touch”) trading - Direct Market Access (DMA) and algorithms – relative to traditional “high touch” brokerage
- Origins in simple automated trading by proprietary trading desks
- Variety of trading tactics offer control, low cost, and flexibility

1980s	1990s	Present	Future?
Program trading	**Automated trading**	**Intelligent execution**	**Expert systems**
• Inter-listed Arb	• Rule-based	• Integrated modules	• Adaptive learning
• Index Arb	• Event driven	• Risk control	• Global, multi-asset
• Semi-manual	• Long/Short	• List orientation	

Anatomy of an algorithm

Key elements

- Select execution profile for *parent* order and level of aggression
- *Child* order placement logic
  1. Micro limit order management (queue, price, cancel & correct)
  2. Choice variables include start/end time, risk aversion, tolerance etc.
- Smart routing/Smart posting
  - Access multiple liquidity pools; venue specific protocols
  - Blend into the flow…
    1. Avoid detection (see Prix, Loistl, and Huetl, 2007)
    2. Avoid gaming, including in "dark pools"

Drivers of algorithmic trading

Increased buy-side use reflects many factors:

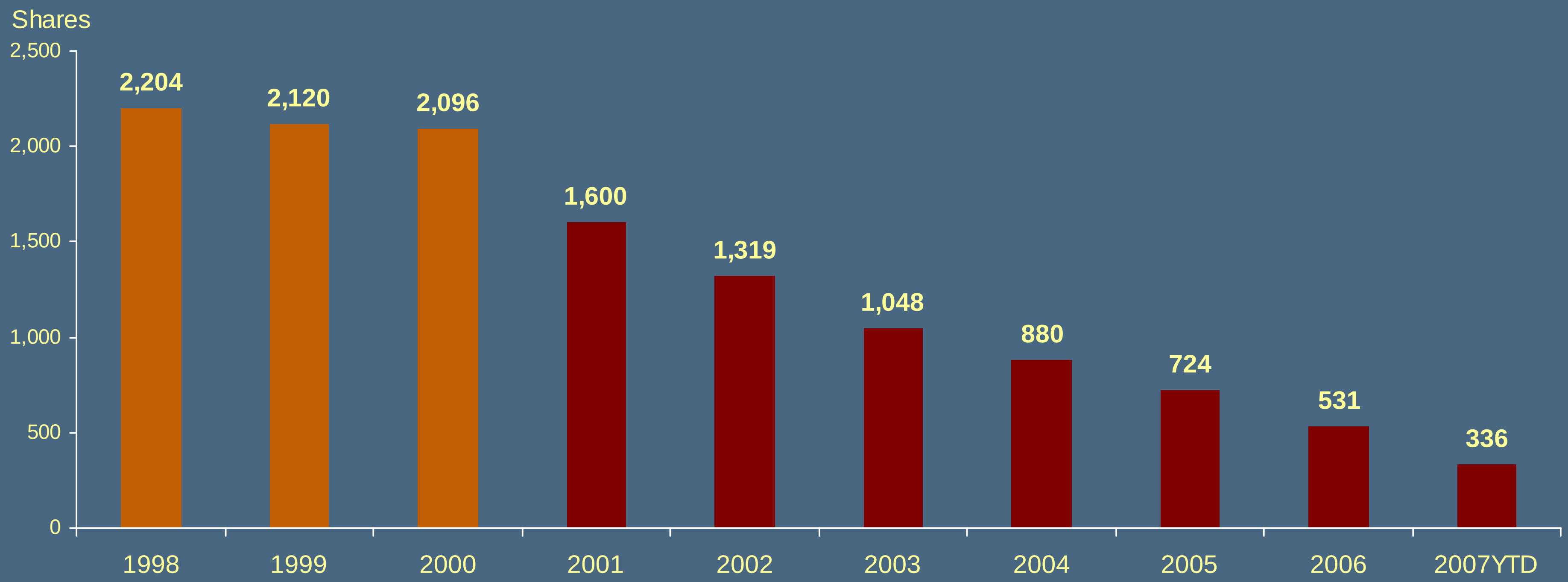
- Automation helps scale the trading desk
- Traders become "macro-managers"
- Anonymity and low cost
- Controlled crossing
- Explicit selection of aggression, execution profile
- Increased adoption of algorithms drives order size down, further reinforcing use of low touch trading

Market efficiency implications

- Edelen and Kadlec (2007) argue that use of VWAP benchmarks causes a divergence in incentives between portfolio manager and traders and results in price-adjustment delays

Average trade size on the NYSE

Algorithmic use has steadily increased and estimates show algorithmic trading at 15% of volume traded in US equity markets in 2007*



Source: Goldman Sachs, based on NYSE reported statistics

* Greenwich Associates 2007 Survey of pure algorithmic flow, excluding direct market access.

II. User's guide to algorithmic trading

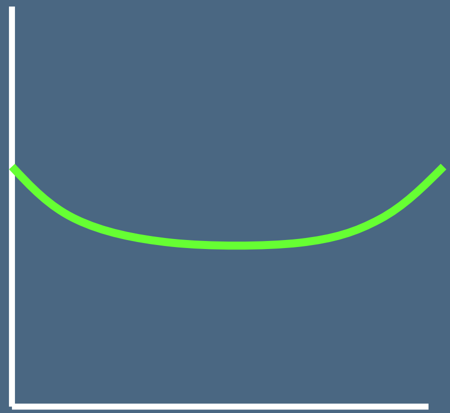
- Execution profiles vary in aggression
- The tactic's name is a proxy for execution profile, not necessarily the target or benchmark price
- Given trade list $\Delta \boldsymbol{h}_t$ select appropriate tactic $\sum_{k=1}^{T} s(\Delta t_k) = \Delta h_t$

TWAP

$$s(\Delta t_k) = \Delta h_t / T$$

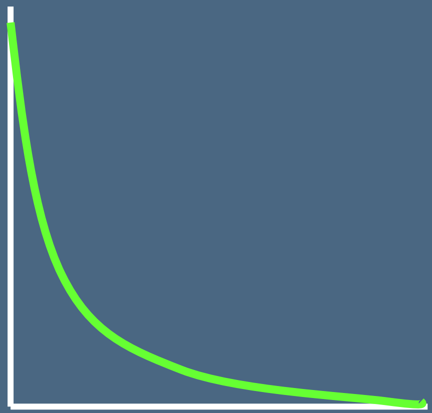
VWAP

$$s(\Delta t_k) = \Delta h_t E[\frac{V(\Delta t_k)}{V(T)}]$$



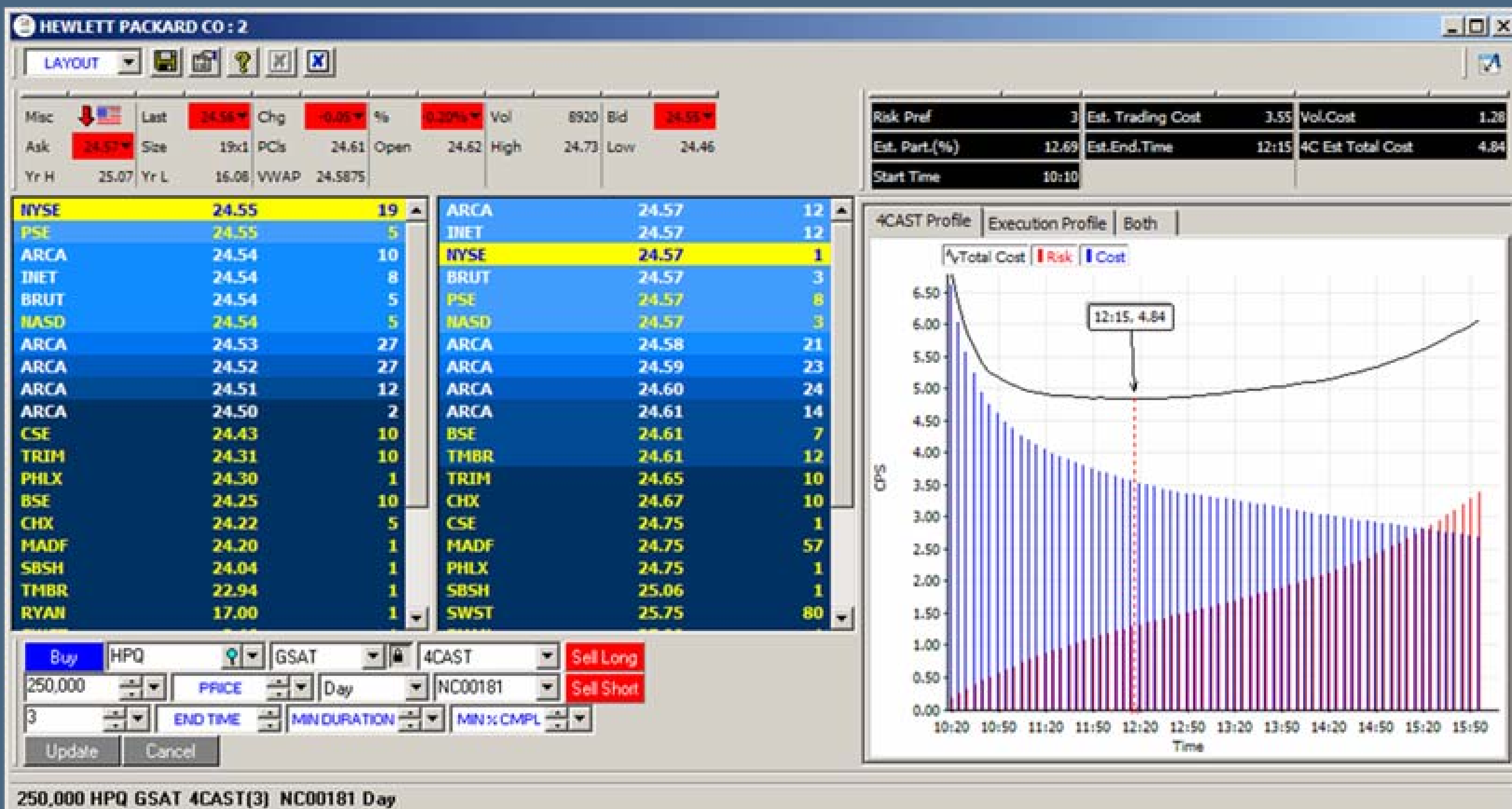
IS

$$Min_{\{S(\Delta t)\}} = E[C] + \lambda Var[C]$$



Implementation shortfall

- Implementation shortfall (IS) algorithms trade-off risk against market impact (See Almgren & Chriss, 2000; Engle & Ferstenberg, 2006, Kissell & Malamut, 2006, and contrast with Bertsimas & Lo, 1998, and Hora, 2007)
- Separability of portfolio and trading problems under certain assumptions



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Quantitative manager's challenge

Two basic questions

1. How do traders select among tactics?
   - Quantitative considerations including liquidity, risk, strategy type, calendar effects (time of day, expiration dates, earnings release, etc.)
   - Qualitative considerations including urgency, motivation, preferences, etc.
2. How do we evaluate an algorithm's performance?
   - Systematic analysis of execution data
   - Cannot examine costs of execution without understanding choice of tactics

Analytic framework

- Conceptual framework illustrated using 101,000 recent order-level execution data from an anonymous buy-side firm
  - Compare use of multiple broker algorithms (9 brokers) vs. multiple clients for a single broker
  - Map algorithm name (37 algorithms represented) to tactic type
  - Measure execution costs through *implementation shortfall* (Treynor, 1981; Perold, 1988) at order level (tactic as profile vs. benchmark)
  - For trade i (where $i = 1,\ldots, N$) we have (with f being the fill rate):

$$C_i = comm_i + sign_i \left[f_i . \ln\left(\frac{p_i^{exec}}{p_i^{strike}}\right) + (1 - f_i). \ln\left(\frac{p_i^{close}}{p_i^{strike}}\right) \right]$$

  - Model costs as a function of a vector $\mathbf{x}_i$ (representing stock characteristics such as market capitalization, price, market etc.), interactions of broker identity and order size, and trade tactic, y_i

$$C_i = \mathbf{x}_i' \beta + \delta y_i + \varepsilon_i$$

Choice of tactics

- Distinguish between “active” (i.e., front-loaded, aggressive) trading tactics ($y_i = 1$) and passive (TWAP/VWAP, passive participation) strategies ($y_i = 0$)
- Factors driving selection:
  1. Liquidity: Market impact costs for a front-loaded profile are greater in less liquid stocks (measured by proxies like market capitalization, exchange listing, etc.)
  2. Information leakage: Less likelihood of revelation of trade intentions for orders that are quickly executed (Sofianos, 2006)
  3. Risk: More aggressive trading can reduce trade list risk (However, trade lists might be small relative to holdings)
  4. Urgency: Prefer more rapid execution for urgent orders (Note: these are not necessarily highest alpha orders – urgency can be driven by binding constraints, hedging transactions, etc.)

Model of choice

Consider selection equation

- For trade i (where i = 1,…, N) the utility associated with the use of active and passive tactics, respectively, is a function of a $k\times1$ vector of state variables $\mathbf{z}_i$ and (unobserved) terms capturing urgency, θ_i

$$U_i^A = \mathbf{z}_i{}'\gamma^A + \theta_i^A \qquad U_i^P = \mathbf{z}_i{}'\gamma^P + \theta_i^P$$

- Observe use of active tactic (y_i = 1) only if : $U_i^A > U_i^P$

$$\Pr[y_i = 1 \,|\, \mathbf{z}_i] = \Pr[U_i^A > U_i^P \,|\, \mathbf{z}_i] = \Pr[\mathbf{z}_i{}'(\gamma^A - \gamma^P) + (\theta_i^A - \theta_i^P) > 0 \,|\, \mathbf{z}_i]$$

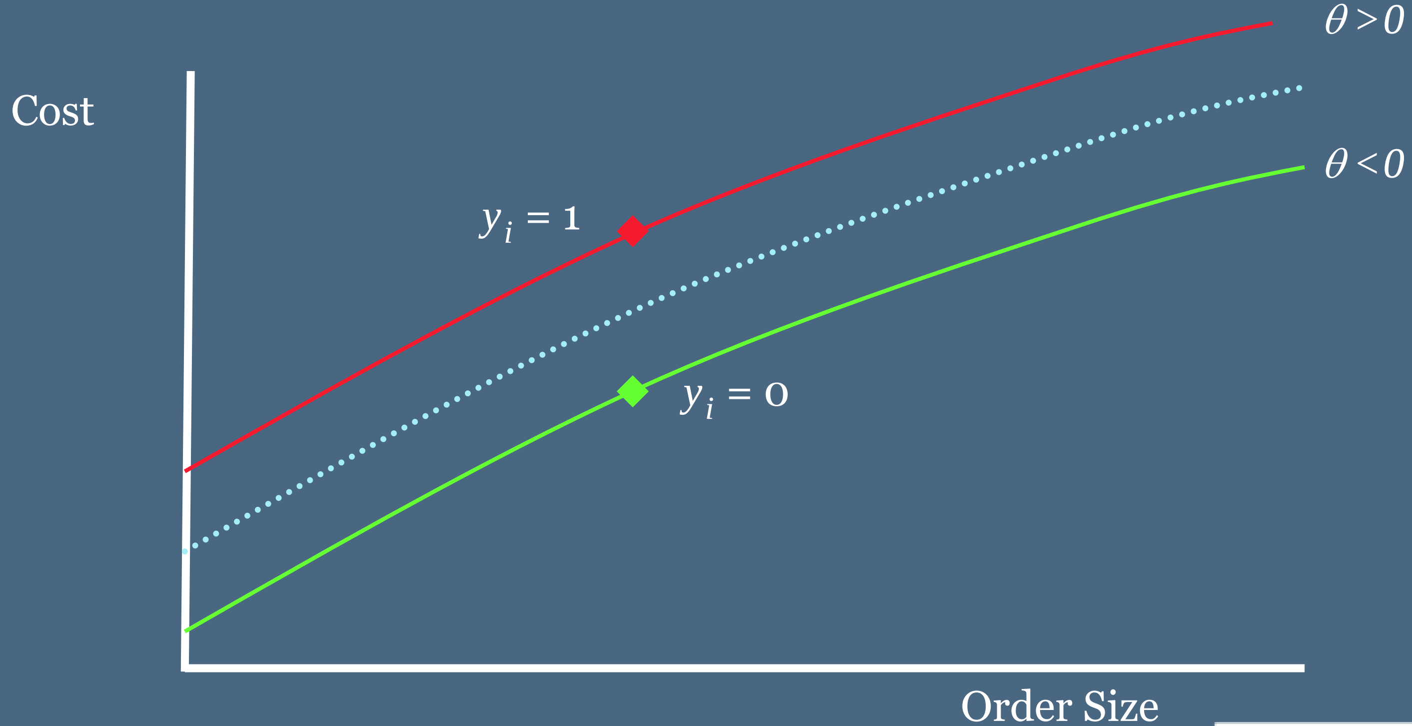
- Then

$$\Pr[y_i = 1 \,|\, \mathbf{z}_i] = \Phi[\mathbf{z}_i{}'\gamma + \theta_i > 0 \,|\, \mathbf{z}_i]$$

- Normalize variance of error term to be 1; error term is assumed normally distributed.

Possible bias

- Traders select tactic based on (unobserved) qualitative factors that also affect cost
- Example:
  - A trader selects passive strategies for orders marked “not urgent” by the portfolio manager
  - Lack of urgency is associated with greater likelihood of crossing (less same direction order flow), and hence below average costs irrespective of particular tactic selected



Conditional means

- Using properties of the normal distribution

$$E[C_i \mid y_i = 1, \mathbf{x}_i, \mathbf{z}_i] = \mathbf{x}_i'\beta + \delta + \rho\sigma_\varepsilon \left(\frac{\phi(\mathbf{z}_i'\gamma)}{\Phi(\mathbf{z}_i'\gamma)} \right)$$

- Regression equation follows directly
  - Estimate first-stage probit model and inverse Mill's ratio
  - Dependent variable is *Active* (use of front-loading profile; results generalize when active includes opportunistic tactics with aggressive user settings, etc.)
  - Regressions are value-weighted and include selectivity measure and controls

What can we learn from the selection process?

Binomial Regression model (Link = Probit)

$$E[y_i = 1 \mid \mathbf{z}_i] = \Phi[\mathbf{z}_i'\gamma + \theta_i > 0 \mid \mathbf{z}_i]$$

Control variables for ***Z***:

- *Broker* indicator variables
- *Volatility* (previous day's high/low range as a percent of opening price)
- *Exchange-listing* (NYSE/AMEX) indicator variable
- *Market Capitalization* (square-root transformed)
- *Order Size* (relative to Average Daily Volume; square-root transformed) and trade value

Interpreting the results:

- Broker indicator variables capture preferred choices controlling for stock specific and exchange factors
- Active strategies are preferred in smaller capitalization, volatile stocks that are not exchange-listed
- Prefer active strategies for higher liquidity demands (consistent with information leakage hypothesis) and smaller trade values

Cost model

Estimates

- Broker indicator variables interacted with *Order Size* (relative to Average Daily Volume and square-root transformed) show differential price response to order flow
- Costs increase with volatility and order size variable
- Costs decrease with market capitalization
- Strong economic and statistical significance of selectivity variable indicates endogenous choice
- Correcting for selectivity and other factors, aggression increases costs*
- Robust to alternative definitions of "active"

Extensions

- Consider second and higher moments
- Comparison by tactic benchmark
- Develop approach for multinomial choice in variables relating to aggression (ordinal rank)
- Use survival models for trade duration

* Note: this is likely to be quite different for a high-frequency trader

III. What lies ahead?

Continued expansion of algorithmic trading across asset classes and regions

Greater complexity (adaptive learning, etc.)

More fundamental shifts:

There has long been a separation between portfolio management and trading

- Quantitative managers determine optimal holdings using mean-variance optimization (inputs are alpha, risk, and cost)
- Trade lists (changes in holdings) are handled by trading desk (selection of tactic)
- Reflects the path of development of algorithmic trading and original technical limitations

Today's computational technology allows us to directly "solve" for the right trading strategy as a function of underlying signals

- In this view, the algorithm is a *dynamic* limit order
- Implementation requires a quantitative process
- Several subtleties in implementation (e.g., distinguish permanent and temporary components, analysis at signal level)

Trade list construction

Portfolio management and trading

- Mean-variance utility function (L/S)
- $\boldsymbol{h_t}$ is a $N\times 1$ vector of desired holdings, Ω is a $N\times N$ variance matrix, and Γ is a $N\times N$ matrix of market impact coefficients
- Solve

$$\max_h u\left(h_t; h_{t-1}\right) = h_t'\alpha_t - \lambda h_t'\Omega h_t - \eta\left(h_t - h_{t-1}\right)'\Gamma\left(h_t - h_{t-1}\right)$$

- Rebalance interval is Δt
- Optimal trade list satisfies:

$$\Delta h_t = \Lambda^{-1}(\alpha_t + 2\eta\Gamma h_{t-1}) - h_{t-1}$$
$$\Lambda = 2(\lambda\Omega + \eta\Gamma)$$

- Date t prices and market conditions do not affect solution (See also Hora, 2007)
- Tactics do not enter optimization

Generalized approach

Model optimal holdings as a function of state variables, tactics

- Computationally intensive, but feasible given the technology now available
- Model α as function of price insensitive signals and "fundamental" signals, weighted by transfer coefficient:

$$\alpha_t(p_t, y_t) = \tau(y_t) \sum w_j s_{j,t}(p_t)$$

- Model predicted market impact as a function of current state variables

$$\Gamma_{i,t} = \Gamma_i(\mathbf{x}_t; y_t)$$

- Then, given state and conditional upon choice of tactic, we compute utility maximizing solution over choice of holdings and aggressiveness
- Make explicit the link between choice of tactic and signal set
- Allow for dynamic price response versus setting limit prices (typically not optimal except under special assumptions for the evolution of prices)
- Similarity to continuous rebalancing, but with less turnover

Example

Consider special case

- Both Ω and Γ are diagonal so order *i* at date *t* is

$$\Delta h_{i,t} = (2\lambda\sigma_i^2 + 2\eta\Gamma_i)^{-1}(\alpha_i + 2\eta\Gamma_i h_{i,t-1}) - h_{i,t-1}$$

- Model α as function of price insensitive signals and "fundamental" signals so that:

$$\alpha_i(p_i) = \sum_j w_{i,j} s_{i,j}(p_i)$$

- Model predicted market impact as a function of current state variables

$$\Gamma_{i,t} = \Gamma_i(\mathbf{x}_t)$$

$$\Delta h_{i,t}(p_i) = (2\lambda\sigma_i^2 + 2\eta\Gamma_i(\mathbf{x}_t))^{-1}(\alpha_i(p_i) + 2\eta\Gamma_i(\mathbf{x}_t)h_{i,t-1}) - h_{i,t-1}$$

Example (Continued)

- Consider canonical "fundamental" signal, ratio of earnings to "long-run" price e_t

$$s_1 = k(e_i - \overline{e}) / \sigma_e$$

$$\alpha_i = w_1 k(E / \overline{p}_i) + w_2 s_2$$

- Note that price enters through alpha and let π denote the permanent price impact component ($0<\pi \leq 1$)
- The sensitivity of prices to flow (Γ parameter) is assumed for simplicity to be constant (Don't double count!), i.e., we've already conditioned on strategy and alpha capture
- Trade list sensitivity to prices

$$\frac{d\Delta h_{i,t}}{dp_i} = -(2\lambda\sigma_i^2 + 2\eta\Gamma_i)^{-1} w_1 k(E / \overline{p}_i)^2 \pi$$

Conclusions

Algorithmic trading continues to evolve

- More complex, robust tactics
- Buy-side needs to answer fundamental questions that must be jointly addressed, in the context of alpha generation
- As technology evolves, algorithms will evolve into dynamic limit orders
- Requires us to specify explicitly the link between current market state (prices, volumes, news, etc.) and the determinants of the trade list – alpha, risk, and expected cost

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