SYSTEMATIC

~~ALGORITHMIC~~ TRADING. MTH9894

Lecture 5
Agency Execution Algorithms

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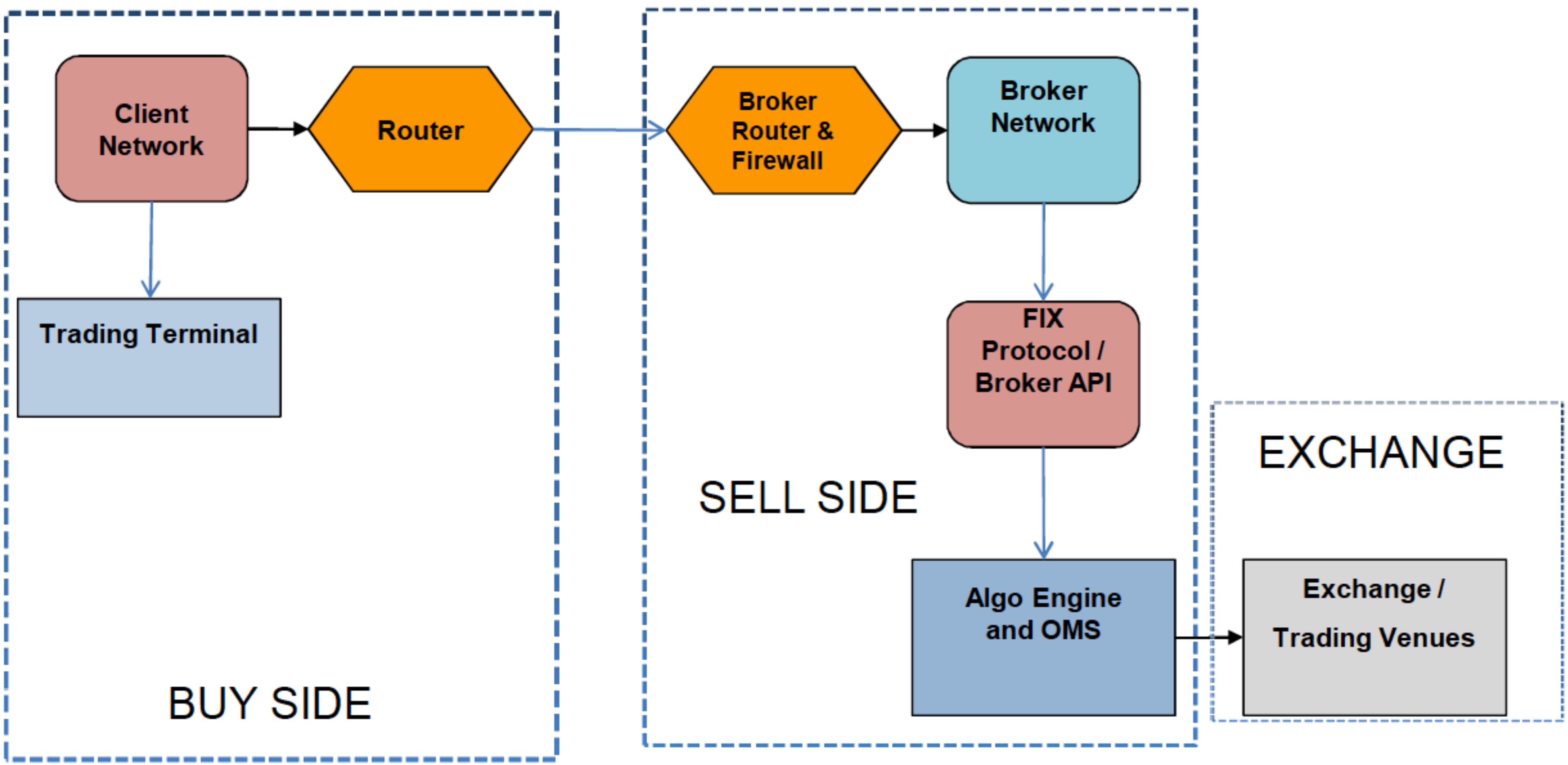
Typical Platform Setup



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TRADING TECHNOLOGY

OMS, EMS, Market Data, Reference Data, Connectivity, Pre-Trade Analytics (Compliance), Post-Trade Analytics (TCA & BestEx)

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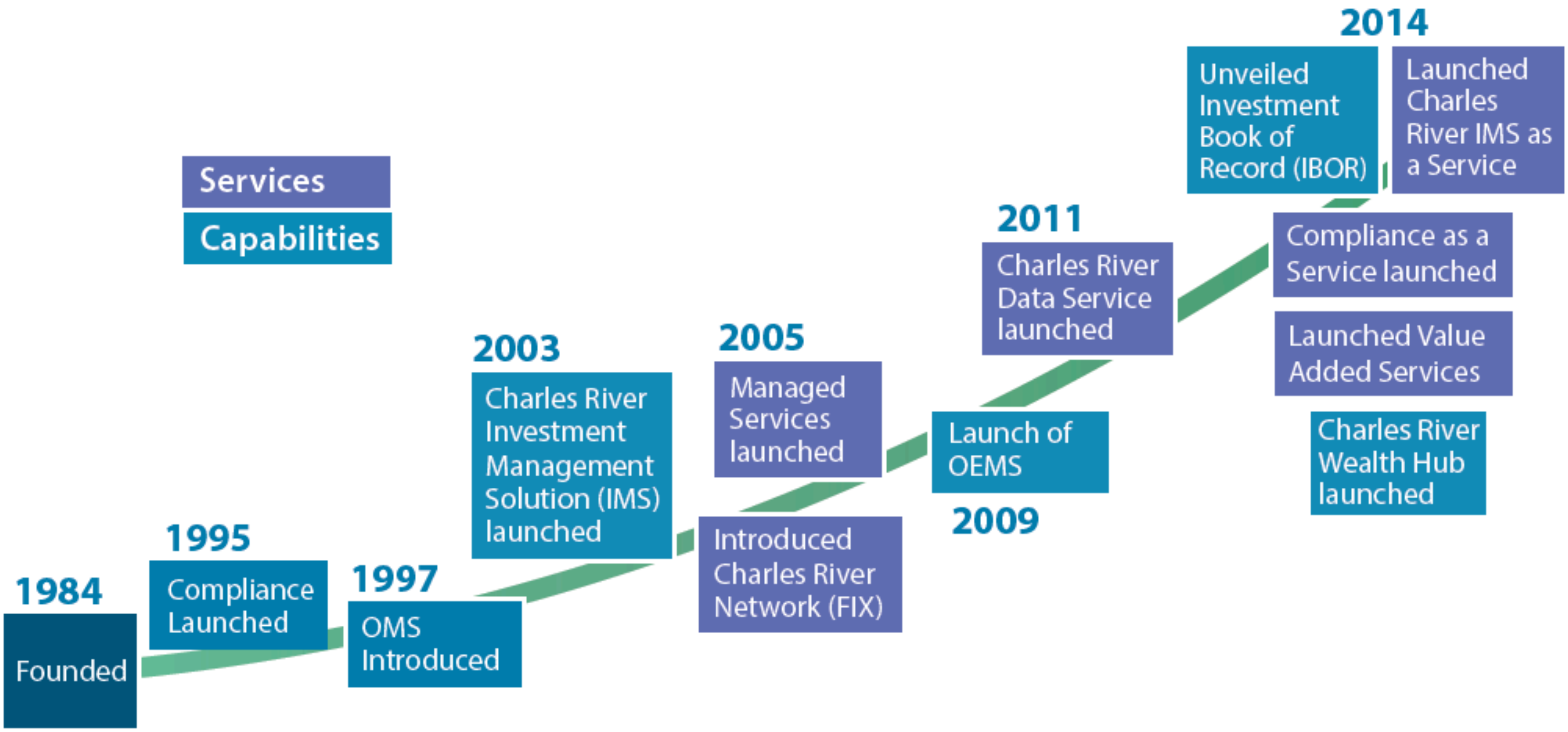
ORDER MANAGEMENT (CRD) -HTTP://WWW.CRD.COM/ASSETS/PDFS/CHARLES_RIVER_IMS_OVERVIEW_BROCHURE_WEB_US.PDF



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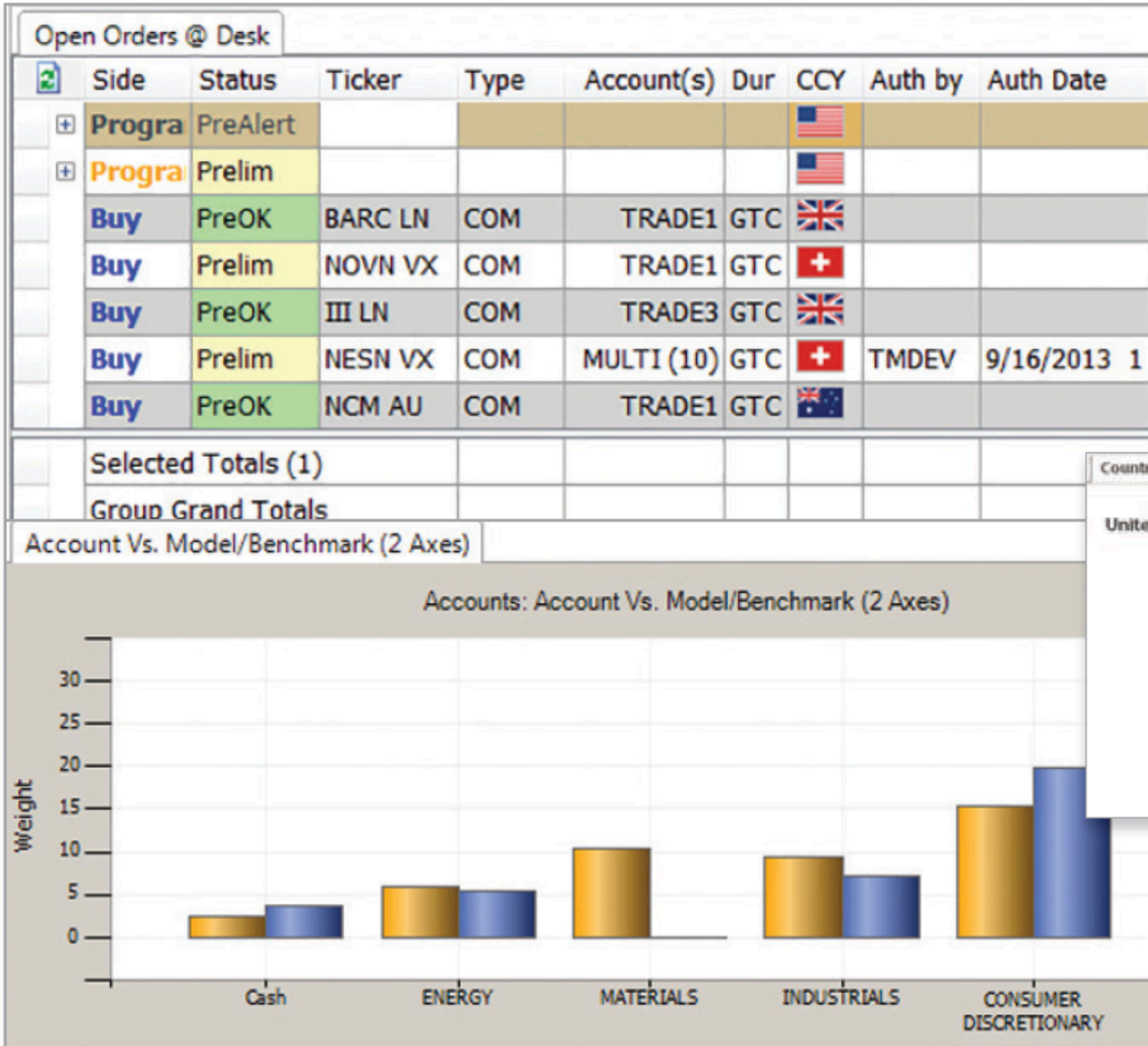
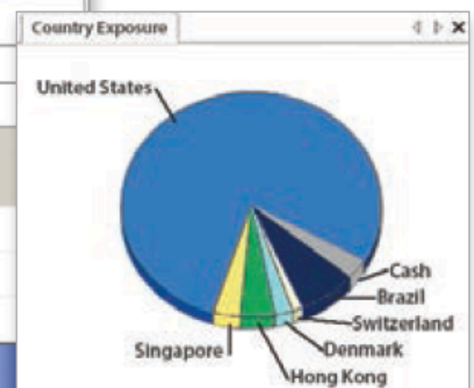
OMS – Order Management http://www.tradersmagazine.com/gallery/traders-oms-feature-chart-113232-1.html





Flexible tools enable portfolio managers to classify their holdings and implement investment decisions for one or many portfolios, align positions with benchmarks or models, and monitor the status of orders across the trading desk.

Comprehensive multi-currency and FX support help portfolio managers manage currency exposure across multinational portfolios.

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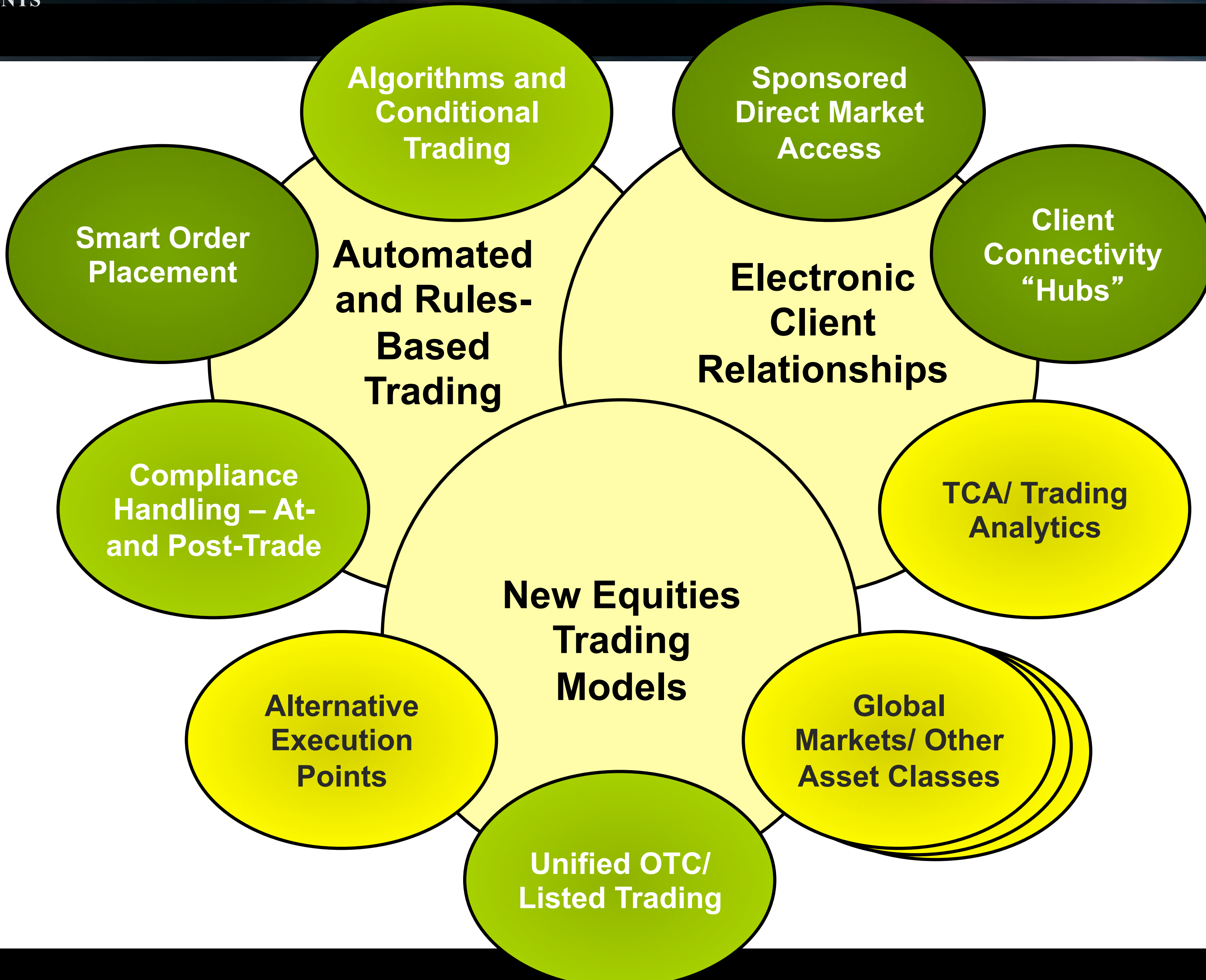
Components



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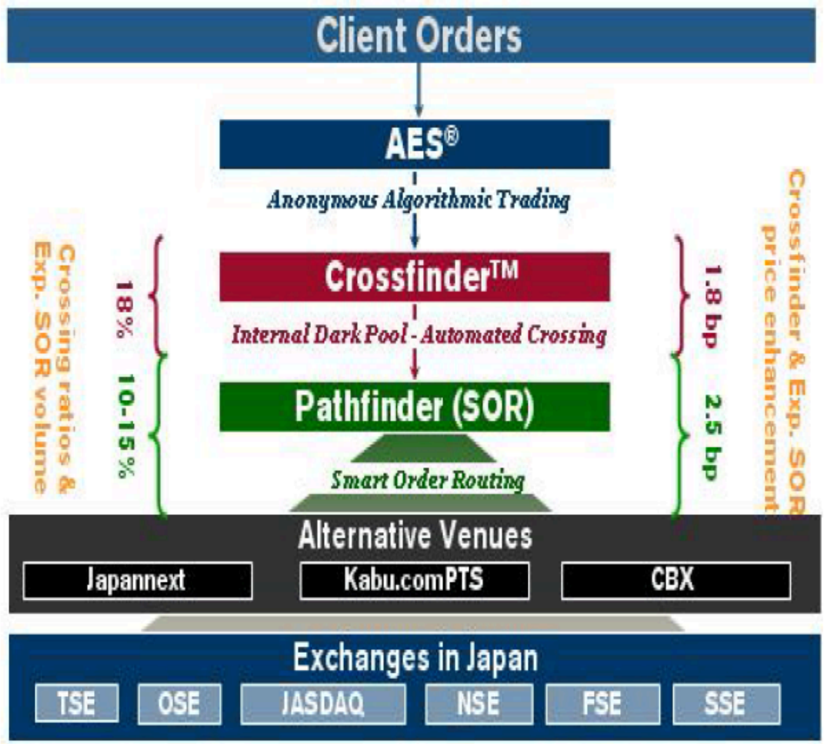
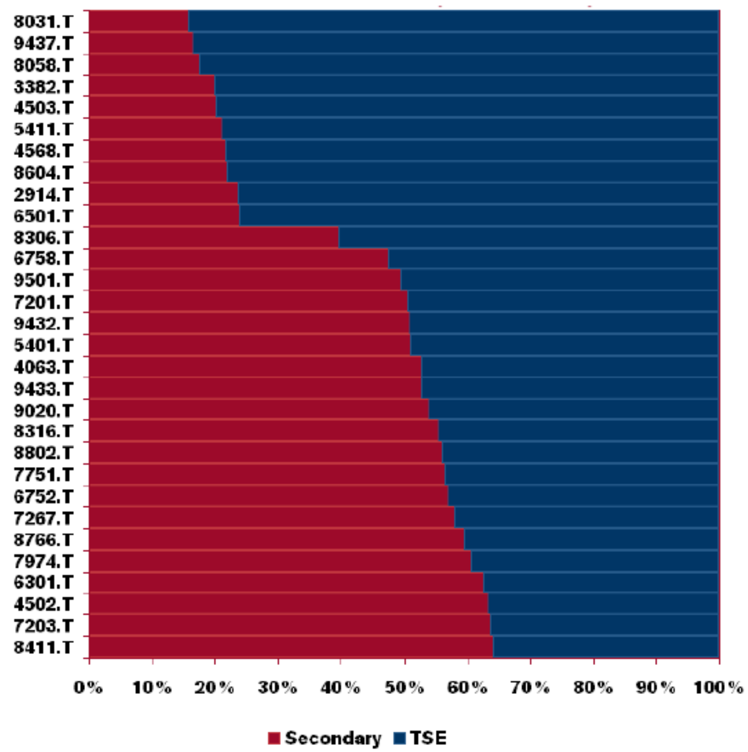
EMS (EMSX) – ORDER ENTRY TOOL

Smart Order Routing

Pathfinder - The Frontier of Execution Technology



WHERE IS THE BEST PRICE? (TOPIX CORE 30)



PATHFINDER SOR

- Price enhancements of 3 bp for TOPIX 500

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TYPICAL ALGO SUITE: HTTPS://EQUITY.NATIXIS.COM/NETIS/ACCUEIL/DOCUMENTS/ALGORITHMIC_TRADING.PDF

http://www.blr.natixis.com/

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1. **Market impact modeling (Transaction Cost Modeling)**
   A. Model estimation principles similar to multi-factor modeling in alpha research
   B. Markets have memory so static impact models are not adequate
   C. Example: Nomura METRIC model

2. **Liquidity, volume profile and volatility prediction**
   A. PCA decomposition of volume into systematic and idiosyncratic components
   B. Estimating volatility using non-stationary and non-synchronous tick data
   C. Example: Nomura Volume Prediction and Volatility Prediction Models

3. **Optimal trade scheduling**
   A. Non-linear optimisation techniques similar to multi-period portfolio construction
   B. Example: Nomura PortfolioIS Algorithm

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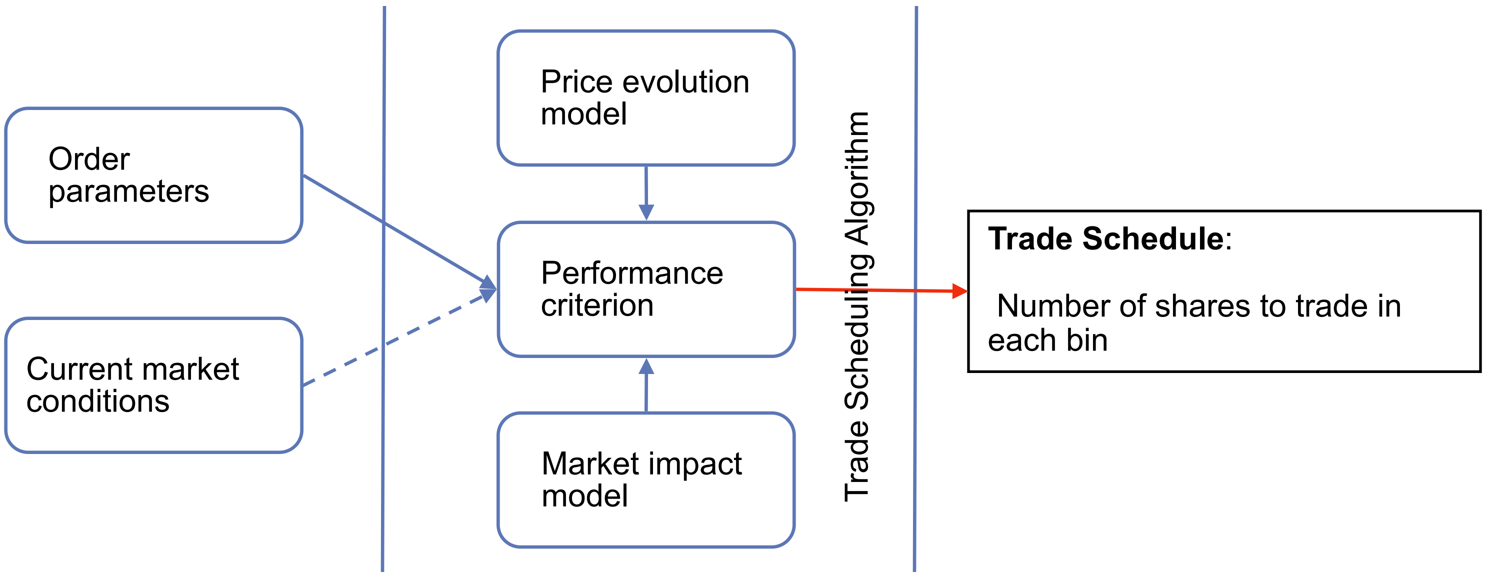
Trade Scheduling Algorithms are typically formulated as optimization problems



A. Price evolution model: Random walk, Short-term momentum, Mean-reversion
B. Market impact model: Instantaneous, with Memory
C. Performance criteria – deviation from a target benchmark
D. Trade as quickly as possible to reduce opportunity cost without causing market impact

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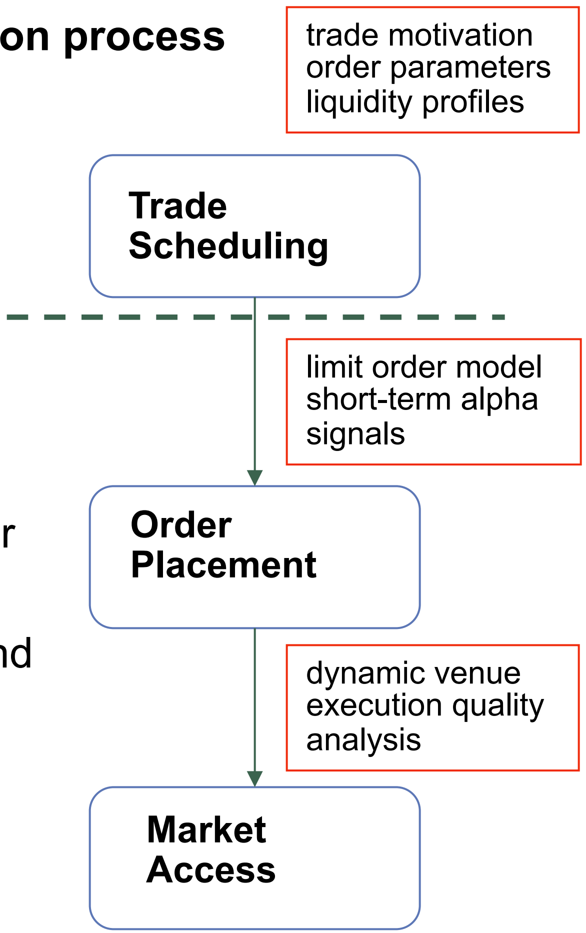
Execution algorithms implement a systematic trade implementation process

A. process vast amount of real-time market data

B. make simultaneous trading decisions at different time scales



Execution algorithms can be decomposed into three modules

- Trade scheduling algorithm slices the original institutional size order into a sequence of smaller trades (minutely horizon decisions)
- Order placement algorithm decides type and timing of trades to send to the market (secondly horizon decisions)
- Market access algorithm decides which destination to route each order (millisecond horizon decisions)

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A. Static Trade Scheduling Algorithms
   a) optimisation to compute trade schedule is performed initially
   b) computed trade schedule is kept constant throughout trading interval (e.g., VWAP, TWAP)

B. Dynamic Trade Scheduling Algorithms
   a) trade schedule is re-optimized at the beginning of each bin
   b) optimisation criterion is fixed but depends on market conditions (e.g., Participation, Dynamic VWAP)

C. Adaptive Trade Scheduling Algorithms
   a) trade schedule is re-optimized at the beginning of each bin
   b) optimisation criterion changes in response to market condition (e.g., Aggressive/Passive In The Money)

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A. Can combine risk, liquidity prediction and cost models to run mean-variance minimization of the objective function (for a given set of positions **X**(t)):

$$METRIC(t;\mathbf{X}(t)) + \lambda\hat{\mathbf{X}}(t).\boldsymbol{\sigma}(t).\hat{\mathbf{X}}(t)^T$$

B. Computed trade schedule is kept constant throughout trading interval (e.g., VWAP, TWAP) (i.e. pick appropriate discretisation)

Liquidity Prediction

A. Focus on volume, but same methodology is applied to volatility and spread
B. Profile shows a characteristic and persistent U shape
C. Suggest:

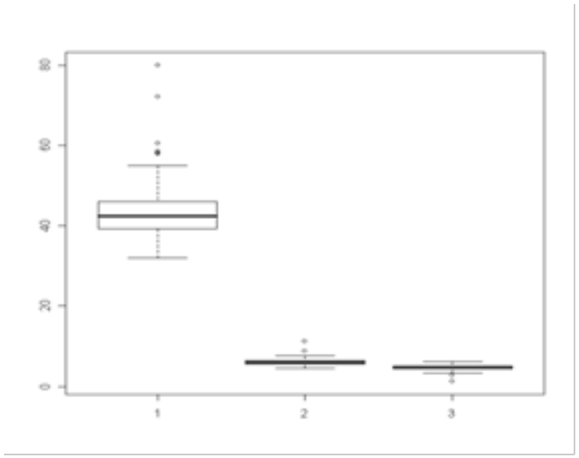
   Stock Profile = “Market Profile” + Stock Specific Deviation

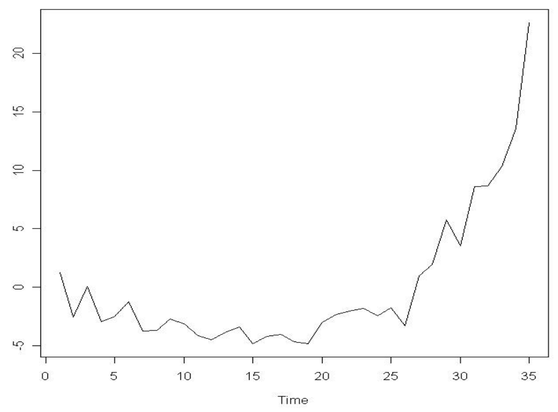
D. Given a list of stocks i=1, …., N and intraday time bins t=1, … , 35 can define a matrix of profiles for any given day $X_{i,t}$ and hence a correlation matrix can be defined

$$\begin{array}{ccc} & \text{Stocks : } i = 1,\ldots,I \longrightarrow & \\ X^j = & \begin{pmatrix} x^j_{11} & \cdot & \cdot & x^j_{1I} \\ \cdot & \cdot & & \cdot \\ \cdot & & \cdot & \cdot \\ \cdot & & & \cdot \\ x^j_{T1} & \cdot & \cdot & x^j_{TI} \end{pmatrix} & \begin{array}{l} \downarrow \ \text{Time bin} \\ t = 1,\ldots,T = 35 \end{array} \end{array}$$

Liquidity Prediction

A. First examine the eigenvalues: first mode is largest and explains more than 40% of the variance, magnitude of first three eigenvalues are much larger than the others





Eigenvalues of the correlation matrix of ***X***

Liquidity Prediction: Stock Specific

A. The following is observed for the profile after discounting the market profile for each stock:
   a) Null hypothesis of stochastic non-stationarity is rejected using Augmented Dickey Fuller Test (ADF)
   b) Box-Jenkins (noting ACF and partial ACFs decay exponentially) suggests that ARMA(1,1) is optimal; describing next bin in terms of the current one and the deviation of the previous bin:

$$Y_t = \sum_{i=1}^{p} a_i Y_{t-i} + \sum_{i=1}^{p} b_i \varepsilon_{t-i} + \varepsilon_t$$

   c) Important to note that $a_1 > 0, b_1 < 0$: mean reversion effect

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T-Cost & Market Microstructure Trends

- ❑ Ongoing exodus from active to passive and to ETFs:
  - ❑ Less funds turnover: less daily volume, volume shifts to 3pm-4pm window
- ❑ Brokers scaled down risk books (Volcker rule, part of Dodd-Frank)
  - ❑ Principal trading becomes more expensive
- ❑ Pressure from regulators: MIFID II, investigations into broker practices
  - ❑ Risk & cost for liquidity <u>providers</u> (HTF and statarb) is rising
  - ❑ High-turnover strategies may no longer be profitable

Trading costs for <u>liquidity takers</u> per $ traded are rising
Sophisticated hedge funds and assets managers invest into smarter trading: smaller, more passive orders, opportunistic trading

US is still the most liquid market

Stock Annualized Turnover: $Traded / $ Market Cap, %

Region	Average	$Mcap Wgt	10th pct	25th pct	Median	75th pct	90th pct	Dispersion
US	217	174	59	98	157	257	428	7.3
UK	137	137	34	60	115	181	264	7.8
EU	121	137	19	39	83	162	261	13.7
JP	130	102	27	48	80	135	230	8.5
FE	40	35	8	15	30	50	75	9.4
OC	87	79	20	41	68	110	172	8.6
CA	120	92	34	58	94	149	217	6.4
EM	92	37	15	27	55	109	188	12.5

ALGORITMIC TRADING – T-Cost Modeling

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A. The dependence of execution cost on many descriptive variables is quite intuitive and is easily verified:

a) Large orders are relatively expensive to trade.

b) Stocks with high volume tend to be cheaper to trade

c) Stocks with higher bid-ask spreads tend to be more expensive to trade

d) Volatile stocks tend to be more expensive to trade than stocks that stay in tight trading ranges

e) Similar stocks in different countries and on different exchanges within a country may be more or less expensive, depending on exchange structure and data reporting conventions.

T-Cost Modeling: Theoretical foundations

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T-Cost: the cost of removing liquidity.

Measured as the difference between average execution price & the price at order arrival.

- Spread cost (a.k.a. “instantaneous impact)
  - 25-50% of average bid-ask spread.
  - A measure of our micro execution skills which only affects child orders individually and then dissipates immediately.
  - When removing liquidity, more fills come from crossing spread (trading at far touch vs. near touch)

- Temporary impact
  - : Caused by temporary imbalances between supply and demand caused by our trades which lead to temporary price movement from equilibrium. Transient impact induced price will reverse after our trade and decay to 0 at the end.
  - Compensation to liquidity providers for taking on risk of being adversely selected by more informed order flow. Dissipates shortly after the trade is done.

- Permanent impact
  - Information from the order flow is reflected into prices (if there are more buyers than sellers, stock price must be attractive and therefore it should appreciate)
  - Permanent impact induced price will not mean reverse and stay at the end price level after trading. Therefore, we can capture permanent impact if and only if we wait long enough.

T-Cost Modeling: Theoretical foundations

- No-arbitrage argument
  - There should be no way to make money in the round-trip trade by executing legs faster or slower or splitting legs into multiple segments.
  - Early conclusion (2004): permanent impact must be linear in size
  - Later conclusion (2015) – there is a class of admissible functional forms (brokers didn't pay much attention to this result)
- Cost increases with volatility
  - Empirical observation
  - Intuition: liquidity providers (1) charge more for risk (2) they tend to make more money in volatile markets
- Executing same order size with higher urgency costs more
  - Empirical observation
  - Intuition: higher urgency is easier to detect. High-urgency orders must be associated with new information (alpha) or upcoming events. Thus, liquidity providers "fade", fearing adverse selection

T-Cost: Model Construction

$$E(C) \sim \alpha \cdot Spread + f(\sigma) \cdot Size^{\delta} POV^{\gamma} + \chi(\sigma) \cdot Size$$

Nomura Model :

$$E(\mathrm{Tcost}) = a_1 \Delta + a_2 \sigma^{2\gamma} Size^{\gamma} POV^{\rho-\gamma} + a_3 \sigma^2 Size$$

Bloomberg Model:

$$E(\mathrm{Tcost}) = a_1 \Delta + a_2 \sigma \cdot Size^{\beta_1} POV^{\beta_2-\beta_1} + a_3 \sigma \cdot Size^{\rho}$$

JPM Model:

$$E(\mathrm{Tcost}) = a_1 \Delta + a_2 \omega \cdot \sigma \cdot Size^{\beta} \frac{2POV}{1+POV} + a_2 (1-\omega) \cdot \sigma \cdot Size^{\beta}$$

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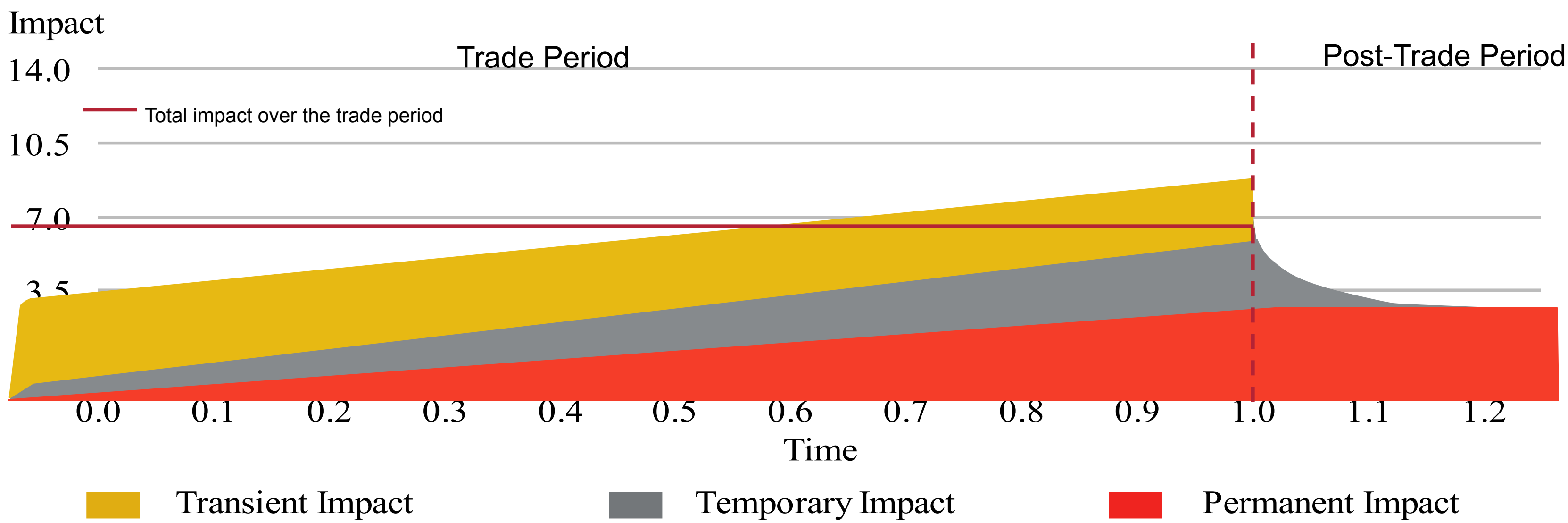

$$METRIC = \alpha \cdot S + \beta \cdot v^{\delta} \cdot \left(\sigma \sqrt{T}\right)^{\varphi} + \gamma \cdot v \cdot \left(\sigma \sqrt{T}\right)^{2}$$

$$METRIC2 = \alpha \cdot S + \beta \cdot v^{\delta} \cdot \sigma \left(\sqrt{T}\right)^{\varphi} + \gamma \cdot v \cdot \sigma \left(\sqrt{T}\right)^{2}$$

Where S is the average bid-ask spread, σ is the volatility, v is the trade rate and T is the trade duration

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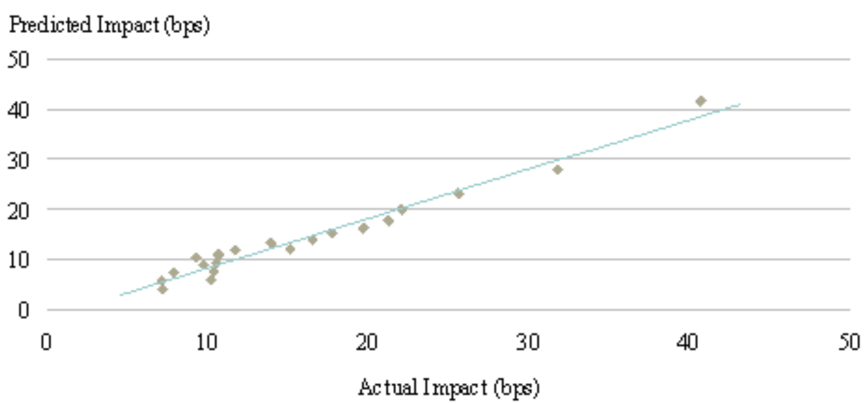
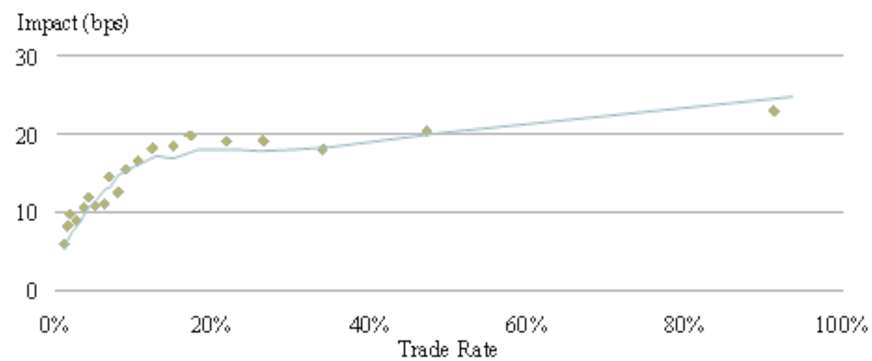
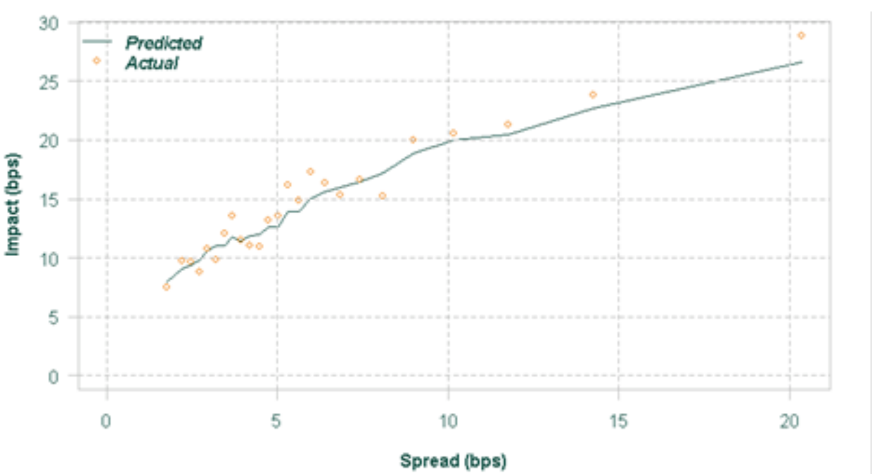
Out of Sample Performance



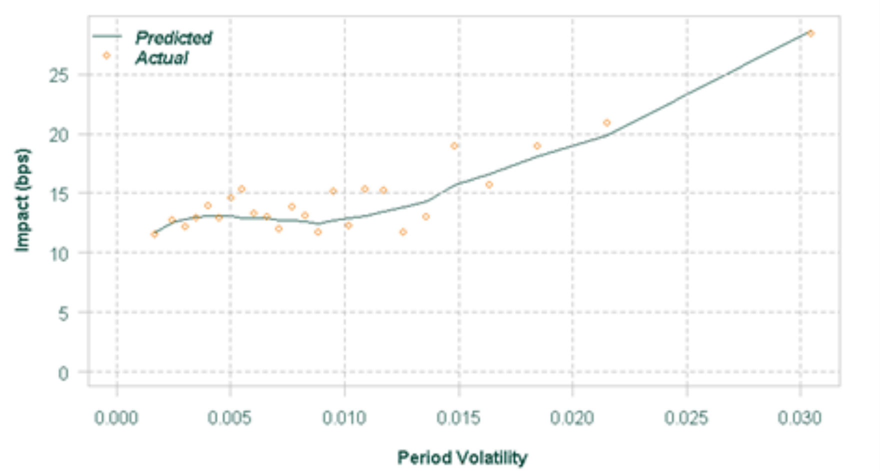
Performance versus Trade Rate



Performance versus Bid-Ask Spread



Performance versus Period Volatility



T-Cost: Typical Cost (R1000, 1Q 2017)

Size, %MDV\Prate, %	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%
1%	4.4	5.3	5.9	6.5	7.0	7.5	8.0	8.4	8.9	9.3
2%		6.6	7.4	8.1	8.7	9.3	9.9	10.4	10.9	11.4
3%			8.6	9.4	10.1	10.8	11.4	12.0	12.5	13.1
4%				10.7	11.4	12.1	12.8	13.4	14.0	14.6
5%					12.6	13.4	14.1	14.7	15.4	16.0

MDV: medium daily volume

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REFERENCES:

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