Nomura Securities International, Inc. Equity Quantitative Analytics

Timing is Money:
The Value of Execution Scheduling

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**Liquid Markets Analytics** 

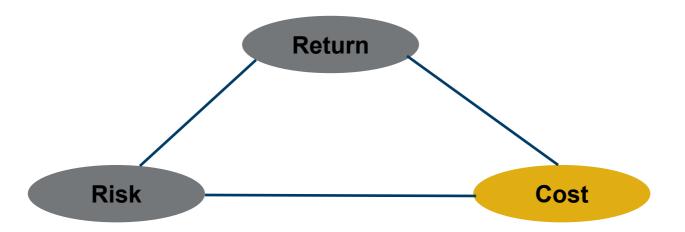
# **NOMURA**

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### The Troika of Quantitative Investment

- Primary focus of the quant community
- Factor models to exploit behavioural biases in security valuation
- Represent systematization of the stock selection process



- Focus on loss preservation and efficient capital allocation
- Estimated using fundamental/statistical factor models
- Generally purview of third-party vendors but recently an area of internal focus

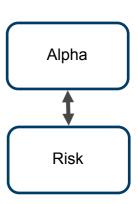
- Measures shortfall due to the implementation process
- Depends critically on the execution style and strategy (front-loaded, passive, backloaded, etc)
- Usually receives the least focus by quants

# Trade Implementation as a Scientific Process

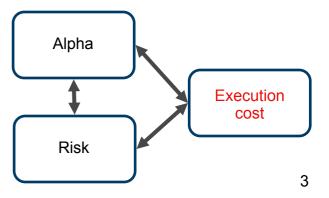
- Market impact modeling
  - Model estimation principles similar to multi-factor modeling in alpha research
  - Markets have memory so static impact models are not adequate
  - Example: Nomura METRIC model
- Liquidity, volume profile and volatility prediction
  - PCA decomposition of volume into systematic and idiosyncratic components
  - Estimating volatility using non-stationary and non-synchronous tick data
  - Example: Nomura Volume Prediction and Volatility Prediction Models
- Optimal trade scheduling
  - Non-linear optimization techniques similar to multi-period portfolio construction
  - Example: Nomura Portfolio Target Strike Algorithm

## Including Execution Costs in the Investment Process

- Traditional portfolio construction paradigm
  - Construct optimal portfolio by balancing alpha and risk
  - Well-understood problem since the 70s
  - Transaction costs estimates used for post-facto filtering (pre-trade)
  - Sub-optimal since transaction costs are not included "upstream"



- Modern portfolio construction paradigm:
  - Construct optimal portfolio by balancing alpha, risk and execution cost
  - Complex problem since transaction costs depend on both the alpha and the trading process
  - Allows optimal allocation of capital across different tradable opportunities

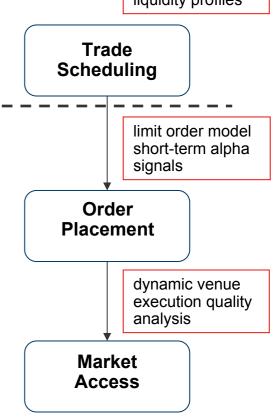


## **Execution Algorithms Systematize Implementation**

- Execution algorithms implement a systematic trade implementation process
  - Process vast amount of real-time market data
  - Make simultaneous trading decisions at different time scales

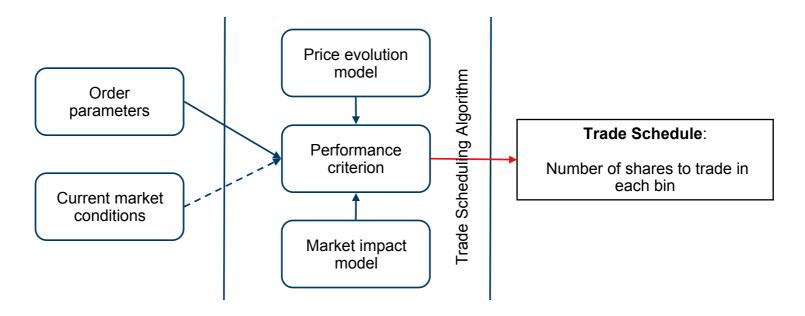
trade motivation order parameters liquidity profiles

- 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)



## **Construction of Trade Scheduling Algorithms**

Trade Scheduling Algorithms are typically formulated as optimization problems



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

# **Examples of Trade Scheduling Algorithms**

- Static Trade Scheduling Algorithms
  - Optimization to compute trade schedule is performed initially
  - Computed trade schedule is kept constant throughout trading interval (e.g., VWAP, TWAP)

### Dynamic Trade Scheduling Algorithms

- Trade schedule is re-optimized at the beginning of each bin
- Optimization criterion is fixed but depends on market conditions (e.g., Participation, Dynamic VWAP)

### Adaptive Trade Scheduling Algorithms

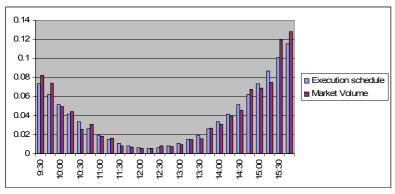
- Trade schedule is re-optimized at the beginning of each bin
- Optimization criterion changes in response to market condition (e.g., Aggressive/Passive In The Money

## **Measuring Performance of Execution Algorithms**

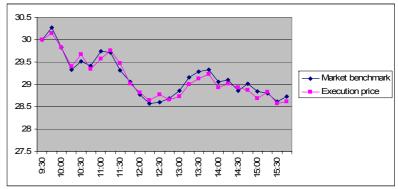
- Execution cost is measured as the difference between execution price and the benchmark
  - estimated pre-trade
  - measured post-trade

ExecutionCost = ExecPrice-BenchmarkPrice

= OrderPlacementCost+ TradeSchedulingCost





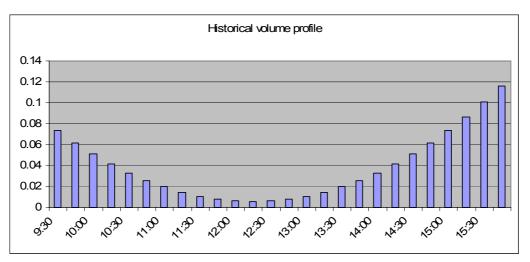


Source: Nomura Securities International, Inc.

- There is no universal execution benchmark
  - Arrival price: used by quant funds
  - Close price: used by index and mutual funds
  - VWAP price: used as execution benchmark large multi-day trades (e.g., buyback)

### **VWAP**

- Trade proportionally to the historical volume profile
  - Reduces standard deviation of the trade scheduling cost
  - Reduces mean of the order placement cost
  - Performs well when price evolves as a random walk and price and volume are uncorrelated

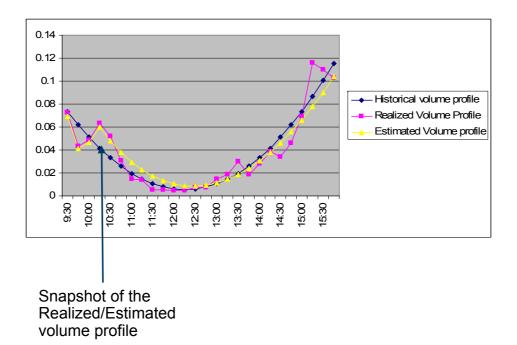


Source: Nomura Securities International. Inc.

- Exchange specific historical volume profiles
- Stock specific historical volume profile

# **Dynamic VWAP**

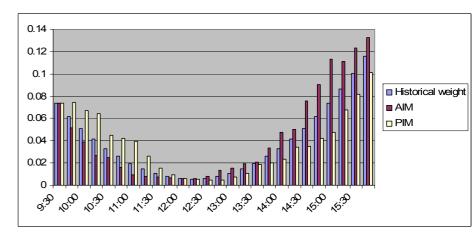
- Trade proportionally to the estimated volume profile
  - Volume profile is estimated in each bin based on the volume profile prior to this bin
  - Attempts to reduce standard deviation of the trade scheduling cost and improve mean of the order placement cost



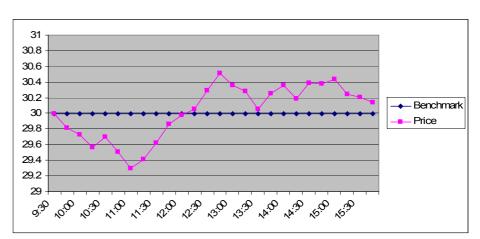
Source: Nomura Securities International, Inc.

# **Aggressive/Passive in the Money**

- Trade depending on the price evolution
  - Attempts to reduce the mean scheduling cost at the expense of standard deviation
- Passive-in-the-Money (PIM): performs well when price exhibits momentum
  - Accelerate if the price moves unfavorably
  - Decelerate if the price moves favorably
- Aggressive-in-the-Money (AIM): performs well when price exhibits mean-reversion
  - Decelerate if the price moves favorably
  - Decelerate if the price moves unfavorably



Source: Nomura Securities International, Inc.

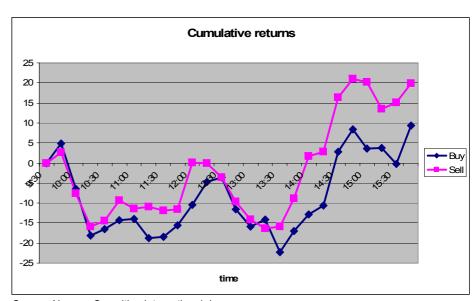


Source: Nomura Securities International, Inc.

### **Simulation Framework**

- Goals
  - Compare performance of different trade scheduling algorithms
  - Infer properties of recent markets
- Data set consists of actual orders received by Nomura's PT desk
  - Full day orders from Jan to May 2009 (approx. 15,000)
- Individual bin execution price is assumed to occur at local VWAP

- Price movement during the day
  - 10 bps for buy orders
  - 20 bps for sell orders
  - Price "trends" between 2pm and close



Source: Nomura Securities International, Inc.

### **VWAP Results**

	Sell		Buy		Total	
	mean (bps)	std (bps)	mean (bps)	std (bps)	mean (bps)	std (bps)
Exchange historical profile	-2.8	28.2	2.7	23.7	0.2	26.0
Stock historical profile	-0.4	27.2	0.8	22.8	0.3	25.2
Dynamic VWAP	-2.1	24.5	1.5	23.1	-0.2	23.8

Source: Nomura Securities International, Inc.

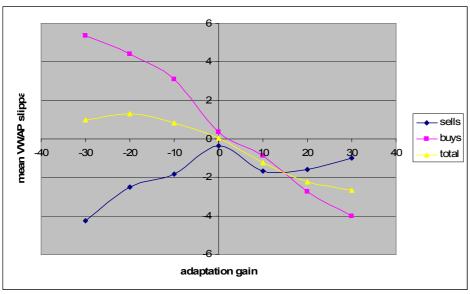
#### Stock historical profiles outperform exchange specific profiles

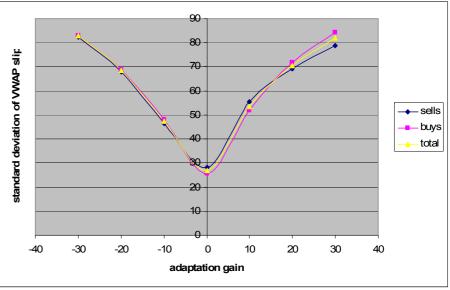
- Improves overall performance
- Reduces magnitude of the mean trade scheduling costs as a function of the trading direction
- Reduces standard deviation of the trade scheduling cost

#### Dynamic VWAP

- Reduces standard deviation of the trade scheduling cost
- Degrades overall mean trade scheduling cost
- Improves mean trade scheduling cost for buys and degrades it for sells

### **PIM/AIM Results**





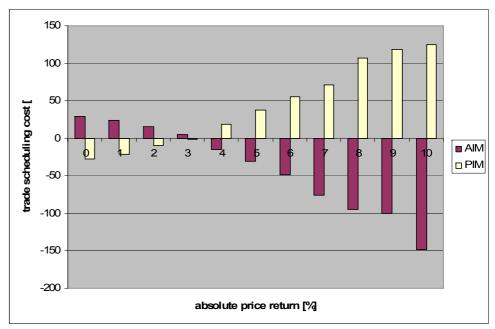
Source: Nomura Securities International, Inc.

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- PIM dramatically improves mean cost for sell trades
  - Price predominantly evolves as a momentum process
- Adaptation does not materially improve mean cost for buy trades
  - Price predominantly evolves as a random-walk
- Adaptation increases standard deviation of the trade scheduling cost
  - Stronger the adaptation, the larger standard deviation

# **Dynamic PIM/AIM Results**

- Detecting market regime
  - Large price move indicates momentum
  - Small price move indicates mean-reversion
- Estimating the market regime dramatically reduces cost
- Can market regime be estimated?



Source: Nomura Securities International, Inc.

	Sell		Buy		Total	
	mean (bps)	std (bps)	mean (bps)	std (bps)	mean (bps)	std (bps)
Dynamic AIM/PIM	0.1	58.8	-0.2	54.6	-0.1	56.6

Source: Nomura Securities International, Inc.

### Conclusion

- Execution cost is an important determinant of investment performance
  - Execution cost can be modeled and controlled using scientific methods
  - Can be decomposed into order placement and trade scheduling components
- Trade scheduling algorithm fundamentally impacts trade implementation
  - Knowledge of current market regime can significantly reduce the execution cost
  - Novel algorithms for market regime detection and liquidity estimation are needed
  - Timing is money!

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