Execution strategies
Why is it so hard to optimize?

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Q Group Seminar
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Overview

- Big change over past decade: buy-side traders now choose from a wide spectrum of execution choices
  - This was not always the case
  - Ten years ago few execution choices and buy-side traders would delegate most of these choices to high-touch executing brokers
- Expected short-term alpha is perhaps the most important determinant of the appropriate execution strategy\(^1\)
- We have a large data set of buy-side trader executions across the whole spectrum of execution choices
- What is the empirical evidence: do traders optimize across execution choices?
- We find no evidence traders optimize executions based on expected ST-alpha

Why?
- ST-alpha is difficult to forecast?
- Sub-optimal flow of information between PMs and traders
- Transition period: traders are still learning
- The offering is too complicated, traders cannot easily choose

What are the implications?
- Cannot properly evaluate execution strategies & algorithms if traders do not optimize their usage of strategies & algorithms
- Should not design execution strategies & algorithms that require unrealistic information, e.g. dynamic algorithms
- Traders should be modest in their execution choices; should not fine-tune too much

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Wide spectrum of execution choices

Increasingly, buy-side traders make most of these execution choices

The buy-side choices

1. Full service
   - High-touch commissions > 12 bps
     - Capital request
     - Agency
     - Market
     - Aggressive
     - Passive

   - DMA algo trading
     - VWAP
     - Shortfall
     - Participation, etc.

   - DMA other

2. Low-touch commissions < 3 bps
   - Broker-sponsored (e.g. REDIPlus)
   - ECNs (e.g. BATS)
   - Crossing networks (e.g. Sigma X)

Portfolio trading

4. Full service
   - Agency
   - Capital request

5. DMA algo trading
   - Shortfall
   - Participation, etc.

6. DMA other
   - Broker-sponsored

How should buy-side traders choose?

How do buy-side traders choose?
How should buy-side traders choose: the Cube framework

- Choice of execution strategy depends on order difficulty
- Order difficulty depends on
  - Order size
  - Stock liquidity
  - Trade urgency

Hypothesis: for difficult orders buy-side traders should choose high-touch; for easy orders should choose low-touch

- Trade urgency has 2 components:
  - Short-term (ST) alpha
  - Execution risk

1. For details see Goldman Sachs, Street Smart report, Issue 22
The trading cost measure: execution shortfall

- Definition of execution shortfall (buy orders)
  - Execution price minus price when trader received the order (strike price)
  - Includes opportunity cost of slow execution

Hypothetical example

Order to buy 100,000 shares XYZ

Average execution price: 60 bps
Strike price: 0 bps
Execution shortfall
Execution horizon
Trade urgency: ST-alpha

- Definition of ST-alpha (buy orders)
  - Price increase over execution horizon, aside from impact of trade itself

Hypothesis: higher expected ST-alpha means higher trading urgency; traders should choose higher execution aggressiveness

The two components of shortfall
  - Liquidity impact
  - ST-alpha loss
  Very different trading implications

Trader objective:
Minimize shortfall = minimize liquidity impact + ST-alpha loss
Minimize impact: execute slow
Minimize ST-alpha loss: execute fast

Order to buy 100,000 shares XYZ

Hypothetical example
Trade urgency: volatility and execution risk

- Pure execution risk
  - Price equally likely to go up or down
  - Risk increases with time to completion
  - Risk depends on stock volatility

Hypothesis: assuming risk aversion, higher execution risk means higher trading urgency; traders should choose higher execution aggressiveness.

Order to buy 100,000 shares XYZ

Hypothetical example
Objective function for trader to minimize:

$$(I + \lambda v^e + \Phi a^e)$$

### The fundamental execution optimization

- Choose execution aggressiveness to minimize impact plus execution risk plus expected ST-alpha
- Higher volatility, higher execution risk, higher execution aggressiveness
- Higher expected ST-alpha, higher execution aggressiveness

**Implications**

- Higher volatility, higher execution risk, higher execution aggressiveness
- Higher expected ST-alpha, higher execution aggressiveness

**Order to buy 100,000 shares XYZ**

**Execution start time 9:30**

**Optimum end time 10:45**

**Expected impact ($I^e$)**

**Execution risk ($\pm v^e$)**

**Expected ST-alpha ($a^e$)**

**Trader risk aversion**

**Intra-day execution horizon**

**Hypothetical example**
How do buy-side traders choose? Overview

Some intriguing evidence on suboptimal execution optimization

- Effect of recent market turmoil on execution choices
  - No shift from low-touch to high touch
  - No attempt to reduce execution risk: are traders risk neutral?
- Choice between high-touch and low-touch
  - Some evidence of differentiation
  - Comparisons of short-term price dynamics
- Choice between passive and aggressive algorithms
  - “VWAP or Shortfall Algorithms” paper¹
  - Just as likely to get it wrong as right
- Within an algorithm choice of aggressiveness level
  - Shortfall (4Cast) algorithm risk preference settings
  - Just as likely to get it wrong as right
- Choice of aggressiveness level across all execution strategies
  - Regressions of participation rate on possible determinants
  - Again, just as likely to get it wrong as right

Effect of recent market turmoil on execution choices¹

Benchmark period: Jul 02 – Jul 25 1.0 %
Market turmoil period: Jul 26 – Aug 17 2.3 %

S&P 500 Daily Volatility²

July 26
Moved from low volatility to high volatility on Thursday, July 26

Mean

<table>
<thead>
<tr>
<th>Day</th>
<th>Benchmark period</th>
<th>Market turmoil period</th>
</tr>
</thead>
<tbody>
<tr>
<td>7/2</td>
<td>1.0</td>
<td>3.5</td>
</tr>
<tr>
<td>7/3</td>
<td>0.5</td>
<td>2.0</td>
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<td>7/4</td>
<td>0.8</td>
<td>2.3</td>
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<td>7/5</td>
<td>0.4</td>
<td>1.6</td>
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<td>0.9</td>
<td>1.0</td>
</tr>
<tr>
<td>7/7</td>
<td>0.7</td>
<td>0.9</td>
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<tr>
<td>7/8</td>
<td>0.6</td>
<td>1.4</td>
</tr>
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<td>7/9</td>
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<tr>
<td>7/15</td>
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<tr>
<td>7/17</td>
<td>0.6</td>
<td>0.9</td>
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</tr>
<tr>
<td>8/17</td>
<td>3.3</td>
<td>2.7</td>
</tr>
</tbody>
</table>

Hypothesis: market turmoil increased order difficulty so we should see a shift to high-touch
We see no such shift in our data!
Also, within high-touch we see little shift towards higher aggressiveness to offset the increased execution risk

2. Daily high minus daily low as % of average high plus low.
More on the recent market turmoil: choice of algorithms

Hypothesis: market turmoil increased execution risk so we should see a shift to more aggressive algorithms.

We see no such shift in our data!

Little change in average order characteristics across the various GSAT algorithms.

The participation rate actually decreased slightly!

$ value executed

<table>
<thead>
<tr>
<th>Algorithmic trading (US GSAT)</th>
<th>Order size</th>
<th>Arrival strike time</th>
<th>Part. rate</th>
<th>Expected shortfall (bps)</th>
<th>Actual shortfall (bps)</th>
<th>Alpha-to-close (bps)</th>
<th>Exec. half life</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark</td>
<td>119,105</td>
<td>11:13</td>
<td>10%</td>
<td>12</td>
<td>14</td>
<td>15</td>
<td>105 min</td>
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<tr>
<td>Market turmoil</td>
<td>171,025</td>
<td>11:30</td>
<td>9%</td>
<td>14</td>
<td>25</td>
<td>23</td>
<td>90 min</td>
</tr>
</tbody>
</table>

Choice between high-touch and low-touch

- Evidence of some order flow segmentation between high-touch and low-touch
- ST-alpha higher for high-touch

In constructing the short-term price dynamic we exclude orders with clustering (same client, symbol, side) T to T+5
Choice between passive and aggressive algorithms

- VWAP is a passive algorithm, Shortfall (4Cast) is a more aggressive algorithm
- What is the evidence on how buy-side traders choose?

### Sub-optimal choice between VWAP and 4Cast

<table>
<thead>
<tr>
<th></th>
<th>Expected Shortfall</th>
<th>Part. Rate</th>
<th>Actual Shortfall</th>
<th>ST-alpha</th>
<th>Execution Half-life</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong># Orders</strong></td>
<td></td>
<td>Two Hours</td>
<td>Actual Horizon</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VWAP algorithm</td>
<td>28,022</td>
<td>12 bps</td>
<td>12 bps</td>
<td>10%</td>
<td>12 bps (1.0)</td>
</tr>
<tr>
<td>4Cast algorithm</td>
<td>5,033</td>
<td>11 bps</td>
<td>14 bps</td>
<td>22%</td>
<td>15 bps (1.2)</td>
</tr>
</tbody>
</table>

- a. Standard errors in brackets below the estimates.
- b. From Goldman Sachs expected shortfall model assuming the execution starts at order arrival and ends two hours later or to the close, whichever comes first. $ value-weighted.
- c. $ value filled as % of total $ value executed in the market over the execution horizon. If numerator exceeds denominator we add numerator to denominator.
- d. For buys: volume-weighted execution price minus strike price as percent of strike price. For sells: Strike price minus volume-weighted execution price as percent of strike price.
- e. Alpha-to-same-day-close. For buys: same-day official close minus strike price as % of strike price. For sells: strike price minus same-day official close as % of strike price.
- f. $ value-weighted (in case of multiple executions) time to execution in minutes.

**Hypothesis:** Orders with higher ST-alpha should go to the more aggressive 4Cast algorithm

**Our data shows this is not the case!**

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A simple empirical model of optimal execution aggressiveness

- The model
  \[ \pi^* = F(\ X^e, \ ve, \ a^e) \]
  - Where
    \[ \pi^* = \text{optimally chosen execution aggressiveness} \]
    \[ ve = \text{expected volatility} \]
    \[ a^e = \text{expected ST-alpha} \]
    \[ X^e = \text{other factors determining execution aggressiveness} \]

- Using a linear approximation for illustration purposes:
  \[ \pi^* = b_1 X^e + b_2 ve + b_3 a^e + u \]

- Our main hypothesis:
  \[ b_2 > 0, \ b_3 > 0 \]

- To empirically test the model, we measure:
  - \( \pi^* \) by the actual intra-day participation rate \( P^a \)
  - \( ve \) by the previous 21 days median volatility
  - \( a^e \) by the actual T+5 price return (perfect foresight)
  - \( X^e \) other factors include: stock capitalization, quoted spreads, listing venue, limit order

- Unobservable factors that could explain chosen aggressiveness
  - Forced liquidations
  - Holding constraints, etc.
  - By definition, we cannot control for these unobservable factors

- In our analysis we focus on intra-day executions

Examples of execution aggressiveness
- Choose short execution horizon
- Choose high participation rate
- Request capital
- Choose must-fill market orders

All else equal, optimizing traders should execute more aggressively for higher expected volatility and ST-alpha
The actual intra-day participation rate

- Definition of actual intra-day participation (part) rate
  - \( P^a = \frac{Q^a}{EV^a} \)
- Where
  - \( Q^a = \) actual quantity executed
  - \( EV^a = \) actual consolidated market volume in stock over execution horizon
- The part rate is a natural measure of order aggressiveness
- But: must deal with several measurement issues
  - Correlation between part rate and order size as % of day’s volume (DV)
  - Ceilings on part rate
  - Ideally we need the intended part rate but we only have the actual part rate
  - Bi-modal distribution of part rate: small-order fast executions
  - In certain pathological cases, part rate can exceed 100% (we exclude them)
- We examine each of these issues in turn

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By definition: \( EV \leq DV \)
The intra-day part rate can never be less than order size as % of day's volume

\[ P^a = \frac{Q^a}{EV^a} \geq \frac{Q^a}{DV^a} \]

Because

\[ EV^a \leq DV^a \]

Also ceilings on part rate

- Part rate cannot exceed 100%\(^1\)
- Trading rules: e.g. do not exceed 25% of day’s volume

**Solution 1: A two-step approach**

- **Step one**
  - Regress part rate on order size as % of day’s volume: \( \frac{Q^a}{EV^a} \) on \( \frac{Q^a}{DV^a} \)
  - Non-linear to take account of ceilings
  - Call the residual the excess part rate (EP)

- **Step two**
  - Regress EP on the factors that may explain the choice of high aggressiveness

**Solution 2**

- One-step, but add order size as % of day’s volume as an additional explanatory variable

**Solution 3**

- One-step, but use the difference between part rate and order size as % of day’s volume as the dependent variable

It does not make much difference which solution we use!

We report results for Solution 2.
The evidence in our data on the part rate

Order size to day’s volume ($Q^a / DV^a$)

Order size to execution-horizon volume ($Q^a / EV^a$)

100%

Relatively few orders above 50%

50%

45°
Intended and actual part rates

- Traders optimize their *intended* part rate ($P^e$), based on information available pre-trade
  - $P^e = G(X^e, v^e, a^e)$
- But what we observe is the actual part rate $P^a$
- Reasons why actual part rate may differ from intended part rate:
  - Actual execution-horizon volume ($EV^a$) different than expected ($EV^e$)
  - Actual executed order size ($Q^a$) different than intended ($Q^e$)
    - Cancelled market orders
    - Limit orders that do not fully execute
- We control for these factors by including in our regressions:
  - Volume surprises ($EV^a/EV^e$)
    - We measure expected volume as the prior 21 trading days median
  - Fill rates ($Q^a/Q^e$)
    - Where we measure intended order size by the order size submitted
  - Limit order dummy

Hypothesis: positive volume surprise ($EV^a > EV^e$) lowers actual part rate
Hypothesis: low fill rate lowers actual part rate
ST-alpha again

- Back to our model....
  - \( P^e = G( X^e, y^e, a^e) \)
- We cannot observe \( a^e \)
- We use actual ST-alpha (\( a^a \)) through T+5 close (see diagram below)
  - T+5 to allow for reversal to play through
- Implications of using actual (perfect foresight) ST-alpha
  - Cannot distinguish between inability to optimize or inability to forecast ST-alpha
- Complication: multi-day executions - impact may stretch over several days
  - We drop orders that “cluster” T through T+5
    - Same-trader, same-symbol, same-side within the 5-day window
Small orders with fast executions

- Another issue with the part rate:
  - It has a bi-modal distribution as a function of order size
- Small orders that execute fast may have a very high part rate but it is not aggressiveness
  - The liquidity is there just take it
  - 100 shares of MSFT executing instantaneously may have a 100% part rate
- Our model applies to relatively large orders where there is a credible time-impact trade-off
  - What length execution time provides a credible time-impact trade-off?

Solution: Drop orders with fast executions
- Sensitivity analysis using different cut-offs
Summary of main estimated aggressiveness model

- Dependent variable
  - \( \log \left( \frac{P_a}{1-P_a} \right) \)
  - Where \( P_a \) is the actual part. rate \( \left( \frac{Q_a}{EV_a} \right) \)

The 9 explanatory variables

<table>
<thead>
<tr>
<th></th>
<th>Relation to part. rate</th>
<th>Detail</th>
<th>Notation</th>
<th>Functional form</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Size as % of DV</td>
<td>POSITIVE (+)</td>
<td>Executed order size as % of same day’s volume</td>
<td>( \frac{Q_a}{DV_a} )</td>
</tr>
<tr>
<td>2</td>
<td>Volume surprise</td>
<td>NEGATIVE (-)</td>
<td>Expected day’s volume divided by actual day’s volume</td>
<td>( \frac{DV^e}{DV_a} )</td>
</tr>
<tr>
<td>3</td>
<td>Fill rate</td>
<td>NEGATIVE (-)</td>
<td>Actual quantity executed divided by intended quantity</td>
<td>( \frac{Q_a}{Q^e} )</td>
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<td>4</td>
<td>Market cap</td>
<td>Stock market capitalization</td>
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<td>Log</td>
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<tr>
<td>5</td>
<td>Spread</td>
<td>21-day median daily average bid-ask spread (in bps)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Listing venue</td>
<td>NYSE=1, NASDAQ=0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Limit order</td>
<td>NEGATIVE (-)</td>
<td>Limit=1, Market=0</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Volatility</td>
<td>POSITIVE (+)</td>
<td>21-day median % day’s high price minus low price</td>
<td>( v^e )</td>
</tr>
<tr>
<td>9</td>
<td>ST-alpha</td>
<td>POSITIVE (+)</td>
<td>Percent price return from order arrival to T+5 close (in bps)</td>
<td>( a^a )</td>
</tr>
</tbody>
</table>

- Main results are not sensitive to the regression functional form
Sample description

- US equity trading, Goldman Sachs client orders
- June 06 to June 07 (13 months)
  - High-touch single-stock (US Shares) orders
  - Low-touch GSAT Direct orders (GSAT=Goldman Sachs Algorithmic Trading)
  - Low-touch GSAT REDIPlus orders (Feb to Jun 07)
- We aggregate intra-day same orders
  - Same-trader, same-symbol, same-side<sup>1</sup>
- We do extensive filtering, e.g.
  - Only stocks with US country of origin
  - Only common stocks
  - Regular settlement
  - Intra-day executions (09:30 – 15:55)
  - Execution half-life > 1 min
  - Drop odd lots
  - Drop if exec. quantity > exec. horizon volume
  - Drop outliers, e.g. 5-day return > 20%, shortfall > 1000 bps
  - Drop orders with missing information
- We also exclude multi-day T to T+5 orders
  - Same-trader, same-symbol, same-side<sup>1</sup>
- Final sample: ~300,000 orders

<table>
<thead>
<tr>
<th></th>
<th>High-touch single-stock</th>
<th>Low-touch algo (GSAT)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial</td>
<td>1,400,000</td>
<td>1,600,000</td>
<td>3,000,000</td>
</tr>
<tr>
<td>After aggregation</td>
<td>300,000</td>
<td>700,000</td>
<td>1,000,000</td>
</tr>
<tr>
<td>After filtering</td>
<td>170,000</td>
<td>530,000</td>
<td>700,000</td>
</tr>
<tr>
<td>Excl. multi-day</td>
<td>70,000</td>
<td>230,000</td>
<td>~300,000</td>
</tr>
</tbody>
</table>

1. The order after aggregation assumes strike time at first order's arrival and end time at last order's last execution.
Part rate regressions: results and sensitivity analysis

Summary statistics: the t-values

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Execution half-life:</th>
<th>Half-life &gt;15 &amp; order size (%DV):</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>&gt;1 min</td>
<td>&gt;5 min</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Intercept</td>
<td>-21.5</td>
<td>18.3</td>
</tr>
<tr>
<td>Size as % of DV (+)</td>
<td>426.1</td>
<td>649.8</td>
</tr>
<tr>
<td>Volume surprise (-)</td>
<td>1.9</td>
<td>-7.6</td>
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<tr>
<td>Fill rate ( -)</td>
<td>-35.3</td>
<td>-43.2</td>
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<tr>
<td>Market cap</td>
<td>39.8</td>
<td>23.3</td>
</tr>
<tr>
<td>Spread</td>
<td>23.8</td>
<td>9.1</td>
</tr>
<tr>
<td>Listing venue</td>
<td>16.5</td>
<td>9.1</td>
</tr>
<tr>
<td>Limit order ( -)</td>
<td>-4.7</td>
<td>-11.2</td>
</tr>
<tr>
<td>Volatility (+)</td>
<td>10.5</td>
<td>9.6</td>
</tr>
<tr>
<td>ST-alpha (+)</td>
<td>-0.8</td>
<td>-1.8</td>
</tr>
<tr>
<td>Sample size</td>
<td>302,290</td>
<td>245,410</td>
</tr>
<tr>
<td>R-square</td>
<td>41%</td>
<td>67%</td>
</tr>
</tbody>
</table>

- No evidence of ST-alpha optimization
  - In all specifications!
  - ST-alpha is never positive & significant
  - A robust result
- Volume surprise, fill rates, limit orders: significant and with predicted sign
  - Most of the time!
- Volatility: mixed evidence
- Tried many other specifications (market orders only, algo only, high-touch only, etc.), similar results!
The two-step approach

Step one
- Regress part rate on order size as % of day’s volume (Q\(^a\) / EV\(^a\) on Q\(^a\) / DV\(^a\))
- Call the residual the excess part rate (EP)

Step two
- Regress EP on the factors that may explain choice of high aggressiveness

### The t-values

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Half-life &gt;15 min</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Step one: part rate on size as % DV</strong></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>140.5</td>
</tr>
<tr>
<td>Size as % of DV (+)</td>
<td>900.5</td>
</tr>
<tr>
<td>R-square</td>
<td>80%</td>
</tr>
<tr>
<td><strong>Step two: excess part rate</strong></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-10.3</td>
</tr>
<tr>
<td>Volume surprise (-)</td>
<td>-9.2</td>
</tr>
<tr>
<td>Fill rate</td>
<td>-40.5</td>
</tr>
<tr>
<td>Market cap</td>
<td>9.9</td>
</tr>
<tr>
<td>Spread</td>
<td>7.1</td>
</tr>
<tr>
<td>Listing venue</td>
<td>0.8</td>
</tr>
<tr>
<td>Limit order (-)</td>
<td>-6.8</td>
</tr>
<tr>
<td>Volatility ( +)</td>
<td>-0.4</td>
</tr>
<tr>
<td>ST-alpha</td>
<td>-0.6</td>
</tr>
<tr>
<td>R-square</td>
<td>1%</td>
</tr>
</tbody>
</table>

Most explanatory power in first step

Consistent with our one-step regression results:
- Most explanatory power is in the first step regressing the part rate on order size as % of day’s volume
- In the second step, little explanatory power in explaining the excess part rate

Little explanatory power in explaining the excess part rate
Liquidity impact and reversal

- An interesting decomposition of ST-alpha
  - Liquidity impact ($I^a$)
  - Reversal ($R^a$)
- Where
  - $a^a = I^a + R^a$
- We also ran regressions on the impact and reversal decomposition
  - $P^a = b_1 X^e + b_2 v^e + b_4 I^a + b_5 R^a$
  - Hypothesis: $b_4 > 0$, $b_5 < 0$

The t-values

<table>
<thead>
<tr>
<th></th>
<th>Hypothesis</th>
<th>Half-life &gt;15 min</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>Intercept</td>
<td>36.6</td>
<td>36.5</td>
</tr>
<tr>
<td>Size as % of DV (+)</td>
<td>817.9</td>
<td>813.4</td>
</tr>
<tr>
<td>Volume surprise (-)</td>
<td>-10.0</td>
<td>-9.8</td>
</tr>
<tr>
<td>Fill rate (-)</td>
<td>-40.9</td>
<td>-40.9</td>
</tr>
<tr>
<td>Market cap</td>
<td>11.3</td>
<td>11.1</td>
</tr>
<tr>
<td>Spread</td>
<td>6.5</td>
<td>6.5</td>
</tr>
<tr>
<td>Listing venue</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>Limit order (-)</td>
<td>-8.1</td>
<td>-7.6</td>
</tr>
<tr>
<td>Volatility (+)</td>
<td>0.0</td>
<td>-0.2</td>
</tr>
<tr>
<td>ST-alpha (+)</td>
<td>-0.8</td>
<td></td>
</tr>
<tr>
<td>Liquidity impact (+)</td>
<td>5.6</td>
<td></td>
</tr>
<tr>
<td>Reversal (-)</td>
<td>-2.2</td>
<td></td>
</tr>
<tr>
<td>R-square</td>
<td>80%</td>
<td>80%</td>
</tr>
</tbody>
</table>

High part rate drives up price but price then reverses

Buy order

10:00

Order arrives at Goldman Sachs

Execution completes

12:30

$I^a$ (impact)

T+5 close

$R^a$ (reversal)

$a^a$
Evidence on algo choice: choosing aggressiveness settings

- A different dependent variable in our regressions
  - No longer part rate
  - Our results are not sensitive to the use of part rate as our aggressiveness indicator

<table>
<thead>
<tr>
<th>The 4Cast probit z-values</th>
<th>All 4Cast orders</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-18.9</td>
</tr>
<tr>
<td>Size as % of DV</td>
<td>14.2</td>
</tr>
<tr>
<td>Volume surprise</td>
<td>4.8</td>
</tr>
<tr>
<td>Fill rate</td>
<td>-3.9</td>
</tr>
<tr>
<td>Market cap</td>
<td>25.6</td>
</tr>
<tr>
<td>Spread</td>
<td>3.2</td>
</tr>
<tr>
<td>Listing venue</td>
<td>11.1</td>
</tr>
<tr>
<td>Limit order</td>
<td>59.7</td>
</tr>
<tr>
<td><strong>Volatility</strong></td>
<td>-0.6</td>
</tr>
<tr>
<td><strong>ST-alpha</strong></td>
<td>-2.5</td>
</tr>
<tr>
<td>Sample size</td>
<td>25,977</td>
</tr>
</tbody>
</table>

- We already discussed the evidence on the choice between passive and aggressive algorithms
  - No evidence traders optimize

- How about within an algorithm?
  - Do traders optimize in the choice of aggressiveness settings?

- Focus on the Goldman Sachs 4Cast algorithm
- Ten aggressiveness settings
  - 1 (least aggressive) to 10 (most aggressive)
  - Divided them into two groups:
    - 1 – 4 Aggressive dummy variable=0
    - 5 – 10 Aggressive dummy variable=1

- We estimated a multifactor probit model to explain the [0,1] aggressiveness choice

- Main findings:
  - Volatility does not explain the choice
  - ST-alpha does not explain the choice

- No evidence traders optimize the 4Cast algorithm's aggressiveness settings
  - In terms of volatility
  - In terms of ST-alpha
Why is it so hard to optimize? Focus on evidence on ST-alpha

- Shortfall Surprises paper¹: ST-alpha main reason why actual shortfall differs from expected shortfall
  - Expected ST-alpha by far the most important factor in predicting shortfall
  - Expected ST-alpha by far the most important factor in choosing the right execution strategy and managing shortfall
- But our data suggests no correlation between actual ST-alpha and choice of execution strategy
- Why?
  - Possibility one: traders do not optimize
    - A transition period, they are still learning
    - The offering is too complicated, traders cannot easily choose
  - Possibility two: traders cannot easily predict ST-alpha
- We prefer the 2nd possibility
- The question then becomes: why is it so hard to predict ST-alpha?
- At least four reasons
  - Organizational failure: suboptimal communication between portfolio managers and traders
  - ST-alpha is intrinsically hard to predict: exactly how alpha signal gets incorporated in price
  - ST-alpha is intrinsically hard to predict: short-term order flow considerations
  - If can predict ST-alpha should be trading on that!


The sell-side should simplify its offering, e.g. streamline algorithms
The investment & execution process

The investment process
- Idea generation
- Stock selection
- Portfolio construction
- Maximize PM alpha

The execution process
- Minimize alpha loss over the execution horizon

Execution process enhances investment process

PM alpha: months to years

Investment horizon

Execution horizon

ST alpha: hours to days

Trade execution

Strategic

Tactical

Organizational failure

Idea generation
Stock selection
Portfolio construction
The ideal organizational structure

- Complete integration of idea generation, stock selection, portfolio construction & execution
- Ideas are balanced with expected trading costs
- Dialog exists among idea generation, portfolio construction & execution

In reality, sub-optimal information flow across three stages in the process

Estimating ST alpha
- PM input: investment strategy
- Trader input: “feel for the market”
- Data analysis: the “science” part
Challenges in estimating ST-alpha

- Extracting ST-alpha from PM-alpha
  - Not trivial, even with perfect communication!

- Distinguishing between momentum and reversal (permanent and transitory price moves)

- What determines ST-alpha?
  - Short-term order-flow dynamics more than long-term PM-alpha signals
  - Traders "feel for the market" is important
    - But for traders to have a good “feel for the market” must have central view of order flow
    - NYSE specialists & floor brokers used to, but nobody has any more!
  - Traders that are good in predicting ST-alpha will quickly move to other opportunities!

- 3% excess return one month out

Why a straight line?!
How fast does the PM-alpha signal get incorporated in the price?
Also depends on execution strategy!

During execution, price accelerates away from trader
How should trader react?
Execute faster? May be causing it!
Or slow down and wait for reversal?

Order flow concentration
NYSE specialists & floor brokers
Sell-side traders
Buy-side traders
Choice of execution strategy is shifting away from center of order flow