How Does a Stock Trade?

Stock-Specific Peer Group Analysis and its Application to Portfolio Liquidity

All data in this paper are sourced from ITG Inc.

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ABSTRACT

We introduce an activity-based approach to trading performance comparisons, in which the common denominator is an individual security. The framework facilitates answers to three questions. Is there valuable information in peer trading comparisons if one analyzes performance on a stock-by-stock basis? Aggregated comparisons across institutions and brokers disguise important differences in the effectiveness of trading process. How does a stock trade? An answer lies in the characterization of single-stock profiles. The approach exploits institutional trading activity, combining such information with market data, and repurposing old tools with the goal of reducing institutional trading cost. How does one characterize the liquidity profile of a portfolio? The answer relies on observed liquidity, as evidenced by institutional trading activity. The solution depends on building the portfolio profile up from individual securities, and yields not only the implementation costs of liquidation, for example, but also the horizon over which this may be accomplished.
Comparative studies are a staple of transaction cost analytics. Sometimes called “peer group” analysis, the goal is simple: to provide relative rankings of buy-side firms, brokers, and traders with respect to trading performance. In the process, strengths and weaknesses are uncovered and become susceptible to improvement as part of the overall investment process.

Peer group comparisons require the standardization of a vast amount of market and trading data, as well as decisions with respect to conceptual underpinnings. For example, does one focus on the difference between value and growth investing? On the size and nature of the institutions being compared?

Our philosophy always has been, you are what you trade. In that way of thinking, peer methodology is an activity-based system. Orders that share similar characteristics, such as market conditions, region, side, order size, and so forth, are assigned to distinct categories. The degree of differentiation across categories, such as trading in emerging as opposed to developed markets, is constrained only by the extent of data available. Comparisons are limited to trading within each activity category.

We extend that philosophy to its logical conclusion, the security itself, and introduce stock-specific peer group analytics. While activity-based metrics are most often ranking instruments, stock-specific peer group analytics addresses an additional and often-asked question, how does a stock trade?

The framework nests the ranking requirements of a peer group. We illustrate the idea through a ranking exercise across five brokers, trading large cap stocks generally, and several individual securities in particular. Grouping stocks together for comparison purposes hides large performance differences across brokers on a stock by stock basis. The actionable implication of the analysis is obvious: to the extent possible, given the overall broker relationship, institutions may hugely benefit from a routing mechanism whose mechanics are stock specific.

The value added by stock-specific transaction comparisons, relative to current use of peer group analytics in general, is in security trading profiles. This is our answer to the question, how does a stock trade? Others’ response typically relies on a combination of market data and technical analysis applied to them. In contrast, the decision support framework enabled by stock-specific peer group analytics is a marriage of market data to actual trading experience in a security. This in turn supports repurposing of old concepts, such as relative strength indexes, to the problem of minimizing trading cost in an institutional setting. The goal is actionable information on a pre-trade and trade-monitoring basis. We clarify some of the possibilities through a case study of an individual security, ranging from expected order sizes through momentum conditions and trading strategy selection.

We apply some early returns from this paradigm by examining the liquidity characteristics of portfolios, in the spirit of the 2017 Securities and Exchange Commission’s fund liquidity program. Stock-specific analysis permits the building of liquidity profiles for portfolios in general, and ETFs in particular. The interplay between stock-specific trading costs, observed as opposed to hypothetical trading horizons, and portfolio weights, produce cost and liquidation horizons for arbitrary slices of the overall portfolio on an aggregate basis.

The Case for Stock-Specific Trading Comparisons

The heart of an equities strategy is the selection of individual stocks. Despite the inherent and sometimes conflicting complications in portfolio trading, high touch facilitation, and automated trading strategies, investment decisions are implemented stock by stock.

The single stock may be the common denominator when it comes time to execute an order, but data limitations and trading desk orientation guide analysis into a diagram like that of Exhibit 1.
Exhibit 1
Comparative Trading Performance by Attribute

The box related to the security is represented by the characteristics of the stock, not the stock itself. If the stock is Biogen (BIIB), for example, the relevant data points include large cap and US-listed. Not all large cap US stocks have the same liquidity characteristics, however, and BIIB may look different from both its large cap category and other securities within that category. This is illustrated by a comparison of trading cost distributions in Exhibit 2.¹

Exhibit 2
Trading Cost Distributions for Large Cap Orders of $50,000 to $150,000 in Value

Relative to its large cap universe, BIIB exhibits a low-peaked distribution of outcomes with very fat tails. While median transaction costs for BIIB are almost the same as for AAPL and AMZN, for example, the probability of a poor trading outcome is much higher. Such probabilities, as well as average costs across broad categories differ, shown in Exhibit 3.

¹ All data, unless explicitly noted otherwise, is full-year 2016, taken from the ITG’s Global Peer™ database.
² Unfavorable momentum as exhibited by the stock-side adjusted difference between the order strike price and PWP15 less than -100
The probability of a loss greater than 25 bps in BIIB is three times larger than that for AAPL in markets characterized by unfavorable market momentum.\(^2\) Other differences are smaller, but economically significant. These phenomena are not limited to US stocks. Exhibit 4 contains an application to Australian securities, as a counterpoint.

\(^2\) Unfavorable momentum as exhibited by the stock-side adjusted difference between the order strike price and PWP15 less than -100 bps.
TLS, for example, has a unique distribution of performance outcomes, relative to both the Australian large cap universe and other large cap securities individually. Like BIIB in the US, MQG trading performance is erratic, at best, and not well represented by the universe. These observations change the workflow of Exhibit 1 into that of Exhibit 5.

Exhibit 5
Comparative Trading Performance by Security

Source: ITG

Rankings
The value added by stock-specific comparisons, relative to current use of peer group analysis, is in security trading profiles. The framework nests any ranking requirements of the peer group, however. The difference relative to Exhibit 1 is that ranking is by stock, by entity. For example, comparisons might be across brokers trading the same stock, controlling for all the usual market and order attributes.
Exhibit 6
Selected Broker Rankings by Security

<table>
<thead>
<tr>
<th></th>
<th>Raw IS Rank</th>
<th>Performance Rank</th>
<th>AAPL</th>
<th>AMZN</th>
<th>ADS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brk 1</td>
<td>61</td>
<td>65</td>
<td>84</td>
<td>61</td>
<td>39</td>
</tr>
<tr>
<td>Brk 2</td>
<td>43</td>
<td>39</td>
<td>20</td>
<td>44</td>
<td>27</td>
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<tr>
<td>Brk 3</td>
<td>84</td>
<td>79</td>
<td>81</td>
<td>34</td>
<td>17</td>
</tr>
<tr>
<td>Brk 4</td>
<td>66</td>
<td>66</td>
<td>55</td>
<td>38</td>
<td>23</td>
</tr>
<tr>
<td>Brk 5</td>
<td>50</td>
<td>42</td>
<td>61</td>
<td>60</td>
<td>33</td>
</tr>
</tbody>
</table>

Source: ITG

The cells in Exhibit 6 contain percentile rankings of trading costs for five brokers, the lower the better. Order sizes are in the 0-5% MDV range, and market conditions, including momentum, are neutral.

Broker 1’s performance deteriorates sharply when trading AAPL, while its costs for ADS improve by 40 percent relative to its average for large cap stocks. Similarly, Broker 5’s ranking is propped up largely based on trades in ADS.

Some differences can be breath-taking. Broker 3’s performance, for example, is heavily weighted towards how it does in AAPL, while relative AMZN and ADS costs are extremely low. This sort of observation highlights areas for improvement by security, as opposed to, say, by order size. If Broker 3 could replicate Broker 2’s track record in AAPL, the former would be a star overall, on a relative basis.

A single metric such as average trading cost cannot tell the entire story behind institutional or broker performance. Certainty of outcome, such as illustrated in Exhibit 3, is a factor. In this case, grouping the data into the typical large cap bucket, and controlling for size and market conditions as in Exhibit 6, yields the distribution of performance below, contrasted with that for AMZN alone.
Exhibit 7
Broker Performance in Large Cap Securities

Broker 2 is best-performing for large cap stocks in Exhibit 6, and that level of performance is also the most consistent. The distribution is highly peaked, and exhibits smaller tails than the remainder, implying lower probabilities of poor outcomes. These characteristics carry over to trading in AMZN, although Broker 5, despite poorer averages, also looks very good for this stock.

In contrast, consider Broker 1, a decent performer in terms of raw ranking. Certainty of outcome is terrible for this entity when trading in AMZN. Not only is the distribution flat relative to others, it is centered on a median loss. Tails of performance are larger than the rest, implying large probabilities of bad outcomes. A similar set of observations can be made for Broker 4, although it is ranked second at the 38th percentile, based on activity-based ranking alone.
Single Stock Profiles

Our data are rich enough to generate stock-specific comparisons for 500 US and 500 global securities. These stocks account for roughly 70% of institutional trading activity, and the majority of trading cost. Metrics include decile distributions of trading costs across side, size, horizons, market conditions, and quarterly trends. Trade horizon, in particular, plays an important role in the analysis of portfolio liquidity to follow. We illustrate some of the possibilities using a single security.

ADS is a US stock, classified as Business Services. Market capitalization is $14.6 billion, and average daily volume is 653,571 shares. The daily volume profile, measured at 15 minute intervals, is stable across month, year, and five-year periods.

Exhibit 8 suggests that ADS is nevertheless a difficult stock to trade. Broker 3, for example, maintains a reasonable average cost, but the distribution of cost outcomes appears to be the result of throwing darts at the problem. Broker 4 not only exhibits an average loss, but also has large (and lumpy) negative tails; the latter also is true for Broker 1. Only Broker 5 appears to have good overall performance.

Exhibit 8
ADS Cost Distribution by Broker

Yet, ADS deviations from the stock-specific peer group are remarkably stable over years, illustrated in Exhibit 9. Cells in the exhibit contain the percentage deviations relative to the US large cap universe over the last five years.

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3 All data comes from ITG’s Global Peer™ database.
4 “Cost@fav” (cost@unfav) is cost during periods in which the SPY is rising for a sell (falling), conversely for buys.
Exhibit 9

ADS Deviations from Peer Group

<table>
<thead>
<tr>
<th>Description</th>
<th>1 Year</th>
<th>2 Years</th>
<th>5 Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>ORDER VALUE</td>
<td>-6%</td>
<td>-3%</td>
<td>0%</td>
</tr>
<tr>
<td>VOLATILITY</td>
<td>16%</td>
<td>13%</td>
<td>18%</td>
</tr>
<tr>
<td>SPREAD</td>
<td>47%</td>
<td>47%</td>
<td>45%</td>
</tr>
<tr>
<td>COST @ FAV MARKET</td>
<td>-4%</td>
<td>-4%</td>
<td>-4%</td>
</tr>
<tr>
<td>COST @ UNFAV MARKET</td>
<td>4%</td>
<td>6%</td>
<td>4%</td>
</tr>
</tbody>
</table>

Source: ITG

There is a trend towards smaller order sizes. Volatility and spread are stable over a five-year period, however. A trader can chart cost relative to upticks and downticks in the SPY fairly accurately and with some confidence that the relationships are stable. Costs relative to the market are a fraction of the magnitude of movements in return; the beta for this stock is 1.63.

Where instability exists or a trend is evident, it may be worth looking at other patterns for current use. The distribution of order value, for example, is given in tabular form, in Exhibit 10.

Exhibit 10

ADS Order Distribution and Deviations from Peer Group

<table>
<thead>
<tr>
<th>ORDER VALUE</th>
<th>10th</th>
<th>20th</th>
<th>30th</th>
<th>40th</th>
<th>50th</th>
<th>60th</th>
<th>70th</th>
<th>80th</th>
<th>90th</th>
<th>1 Year</th>
<th>2 Years</th>
<th>5 Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ref</td>
<td>453</td>
<td>1,197</td>
<td>2,653</td>
<td>5,360</td>
<td>10,578</td>
<td>21,545</td>
<td>46,962</td>
<td>117,346</td>
<td>430,321</td>
<td>48</td>
<td>48</td>
<td>50</td>
</tr>
<tr>
<td>All</td>
<td>691</td>
<td>1,121</td>
<td>2,072</td>
<td>3,742</td>
<td>7,448</td>
<td>16,336</td>
<td>39,071</td>
<td>101,900</td>
<td>362,425</td>
<td>44</td>
<td>47</td>
<td>50</td>
</tr>
<tr>
<td>1 Day</td>
<td>670</td>
<td>1,091</td>
<td>2,017</td>
<td>3,493</td>
<td>6,801</td>
<td>14,532</td>
<td>32,902</td>
<td>88,771</td>
<td>320,688</td>
<td>44</td>
<td>48</td>
<td>50</td>
</tr>
<tr>
<td>Q1</td>
<td>632</td>
<td>1,073</td>
<td>1,821</td>
<td>3,192</td>
<td>6,282</td>
<td>14,147</td>
<td>34,394</td>
<td>99,532</td>
<td>381,850</td>
<td>44</td>
<td>47</td>
<td>50</td>
</tr>
<tr>
<td>Sell</td>
<td>606</td>
<td>1,054</td>
<td>1,914</td>
<td>3,490</td>
<td>7,563</td>
<td>17,310</td>
<td>40,767</td>
<td>104,091</td>
<td>357,416</td>
<td>44</td>
<td>47</td>
<td>50</td>
</tr>
</tbody>
</table>

Source: ITG

The table echoes the declining order size relative to the five-year order history of 500 US large cap stocks traded actively by institutional investors during 2016. It also gives some idea as to what a “large order” is likely to be. The real use of such information is in its application to trading performance by size.

Trading cost may be calculated for any given decile of order size, as in Exhibit 11.

The horizontal axis is the decile distribution. Cells in the columns 1 year, 2 years, and 5 years are percentiles relative to the order history of the top 500 stocks traded actively by institutional investors in 2016. Constancy across those rows indicates stability over time. The ‘Ref’ values are for the same stocks, in 2016. ‘All’ designates the full sample of trading data for the stock, ‘1 day’ signifies day orders, and Q1 is for 2016.
Exhibit 11
Trading Cost Distribution for the 80\textsuperscript{th} Percentile of Order Size

Source: ITG

<table>
<thead>
<tr>
<th>COST - ORDER</th>
<th>10\textsuperscript{th}</th>
<th>20\textsuperscript{th}</th>
<th>30\textsuperscript{th}</th>
<th>40\textsuperscript{th}</th>
<th>50\textsuperscript{th}</th>
<th>60\textsuperscript{th}</th>
<th>70\textsuperscript{th}</th>
<th>80\textsuperscript{th}</th>
<th>90\textsuperscript{th}</th>
<th>1 Year</th>
<th>2 Years</th>
<th>5 Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ref</td>
<td>(45)</td>
<td>(16)</td>
<td>(5)</td>
<td>(0)</td>
<td>1</td>
<td>4</td>
<td>10</td>
<td>22</td>
<td>53</td>
<td>49</td>
<td>49</td>
<td>50</td>
</tr>
<tr>
<td>80th</td>
<td>(86)</td>
<td>(32)</td>
<td>(14)</td>
<td>(4)</td>
<td>1</td>
<td>8</td>
<td>19</td>
<td>37</td>
<td>79</td>
<td>50</td>
<td>53</td>
<td>52</td>
</tr>
</tbody>
</table>

Source: ITG

Costs relative to the large cap universe (Ref) are stable over time. There is, however, a much wider cost distribution than the reference group. This is further illustrated in Exhibit 12.
Exhibit 12
Stock-Specific Cost Distribution for ADS

Source: ITG

<table>
<thead>
<tr>
<th>TRADING COST</th>
<th>10th</th>
<th>20th</th>
<th>30th</th>
<th>40th</th>
<th>50th</th>
<th>60th</th>
<th>70th</th>
<th>80th</th>
<th>90th</th>
<th>1 Year</th>
<th>2 Years</th>
<th>5 Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ref</td>
<td>(45)</td>
<td>(16)</td>
<td>(5)</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>10</td>
<td>22</td>
<td>53</td>
<td>49</td>
<td>49</td>
<td>50</td>
</tr>
<tr>
<td>All</td>
<td>(58)</td>
<td>(21)</td>
<td>(7)</td>
<td>0</td>
<td>2</td>
<td>8</td>
<td>16</td>
<td>31</td>
<td>69</td>
<td>52</td>
<td>52</td>
<td>52</td>
</tr>
<tr>
<td>Day 1</td>
<td>(58)</td>
<td>(21)</td>
<td>(7)</td>
<td>0</td>
<td>2</td>
<td>8</td>
<td>16</td>
<td>30</td>
<td>67</td>
<td>52</td>
<td>52</td>
<td>52</td>
</tr>
<tr>
<td>Q1</td>
<td>(82)</td>
<td>(30)</td>
<td>(10)</td>
<td>0</td>
<td>3</td>
<td>11</td>
<td>22</td>
<td>42</td>
<td>89</td>
<td>53</td>
<td>53</td>
<td>52</td>
</tr>
<tr>
<td>Sell</td>
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<td>(22)</td>
<td>(7)</td>
<td>0</td>
<td>1</td>
<td>7</td>
<td>14</td>
<td>27</td>
<td>59</td>
<td>50</td>
<td>51</td>
<td>51</td>
</tr>
</tbody>
</table>

Source: ITG

It is a rule-of-thumb that increased volatility leads to higher trading costs. The stock-specific view yields two additional pieces of information in that respect, shown in Exhibit 13, in which the columns contain the decile cost distribution for each decile of volatility.
**Exhibit 13**

**Universe Volatility and the Distribution of Trading Cost for ADS**

<table>
<thead>
<tr>
<th>COST - VOLA</th>
<th>10th</th>
<th>20th</th>
<th>30th</th>
<th>40th</th>
<th>50th</th>
<th>60th</th>
<th>70th</th>
<th>80th</th>
<th>90th</th>
<th>1 Year</th>
<th>2 Years</th>
<th>5 Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ref</td>
<td>(45)</td>
<td>(16)</td>
<td>(5)</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>10</td>
<td>22</td>
<td>53</td>
<td>49</td>
<td>49</td>
<td>50</td>
</tr>
<tr>
<td>40th</td>
<td>(40)</td>
<td>(16)</td>
<td>(5)</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>10</td>
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<td>52</td>
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<td>50th</td>
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<td>(7)</td>
<td>(1)</td>
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<td>5</td>
<td>13</td>
<td>25</td>
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<td>60th</td>
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</tr>
<tr>
<td>80th</td>
<td>(62)</td>
<td>(25)</td>
<td>(9)</td>
<td>0</td>
<td>3</td>
<td>9</td>
<td>18</td>
<td>33</td>
<td>70</td>
<td>54</td>
<td>53</td>
<td>53</td>
</tr>
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<td>38</td>
<td>94</td>
<td>53</td>
<td>54</td>
<td>54</td>
</tr>
</tbody>
</table>

Source: ITG

Not only do average costs increase with volatility, the distribution of performance outcomes widens. In other words, certainty decreases, but that decrease can be quantified and acted upon. The probabilities of performance by every volatility decile are stable year to year, and over as much as a five year period. There should be no surprises based on trading history.

Surprises come in the form of momentum. Difficult to forecast at best, the tracking of stock-specific momentum can lead to costly outcomes. The next exhibit illustrates a case of selling against sharp changes in momentum.
The order size here is in the range of the 80th percentile, based on Exhibit 10. The probability of an outcome worse than 37 bps is only 20%, which holds true even in a high volatility environment (Exhibits 11 and 13). The execution cost 91 bps, however, due to timing decisions relative to stock-specific momentum.

While stock-specific momentum may be difficult, traders often have an intuitive feel for market-wide movements. Besides, this security has a high beta relative to the broad market. Yet, the second order for this trade was released just as the SPY began to fall, along with ADS. That order was closed too soon, based on market momentum; in fact, it was not even completed.

It is possible to gain some insight into the effects of momentum on the trade, however, illustrated in Exhibit 15.\(^6\)

\(^6\) The rows contain the decile distribution of cost for each of five deciles of the extent of unfavorable market momentum.
Exhibit 15

Intra-day Market Moves and Changes in Trading Cost

<table>
<thead>
<tr>
<th>Unfavorable</th>
<th>10th</th>
<th>20th</th>
<th>30th</th>
<th>40th</th>
<th>50th</th>
<th>60th</th>
<th>70th</th>
<th>80th</th>
<th>90th</th>
<th>1 Year</th>
<th>2 Years</th>
<th>5 Years</th>
</tr>
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<tbody>
<tr>
<td>Ref</td>
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<td>(16)</td>
<td>(5)</td>
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<td>4</td>
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<td>57</td>
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<td>27</td>
<td>62</td>
<td>55</td>
<td>54</td>
<td>55</td>
</tr>
</tbody>
</table>

Source: ITG

Unfavorable market moves are based on minute-by-minute price changes in the SPY. The table is an example of a relative strength index (RSI), applied to trading cost. A high market momentum environment is something to steer away from, in the case of this particular stock; sometimes being out of the market is a good thing. In an unfavorable broad market, a sell order of ADS is expected to cost between 82 and 152 bps, in line with the example of Exhibit 14. These relationships are stable across time periods as long as five years.

Order-based peer group costs often are used to identify tradeoffs in trading strategy, as part of the pre-trade toolkit. This exercise can be refined to the level of the stock, as in Exhibit 16.

Exhibit 16

Three Trading Strategies and Associated Cost for ADS

Source: ITG

The strategies illustrated are applied to a sell order ranging between 47,000 and 117,000 shares of ADS, to be traded over a single day horizon. Interval VWAP, also known as order VWAP, is the middle ground in this example, in terms of cost relative to risk. Full-day VWAP would deliver performance results similar to throwing darts at the problem. A price-weighted-participation strategy at a 15% participation rate, returns consistent results, with a wide range of zero cost for the order.
Single-Stock Profiles Applied to Portfolios

The Securities and Exchange Commission has voted to adopt new rules affecting the management of liquidity risk in mutual fund portfolios. The rules are set to take effect in late 2018 for most fund managers. The regulations impose restrictions on what assets funds may hold, and in what quantities.

Liquidity risk is defined as the risk that a fund could not meet requests to redeem shares without material dilution of remaining investors’ interests. The mandated approach is granular. In particular, a fund is required to determine a minimum percentage of assets, which must be invested in highly liquid instruments. A fund also is prohibited from buying additional illiquid securities, if more than fifteen percent of its existing net assets are determined to be illiquid.

Liquidity cannot be judged by legacy measures such as market capitalization. For example, “highly liquid investments” are those capable of conversion into cash within three business days, without materially moving the market, which essentially means liquidation in a single trading day.

The framework provides quantitative information useful in judging the liquidity characteristics of a portfolio. We illustrate this using ETFs. The advantage of using ETFs lies in the known composition of the weights in any given portfolio. In practice, active portfolio weights are known to the fund, and can be employed in the same fashion as the ETF weightings. Exhibit 17 illustrates the basic idea for the Australian OZF ETF.

Exhibit 17
Australian Financial Sector

The left panel contains the holding percentages by leading stocks in the index, and the number of days it would take to liquidate the portfolio, stock by stock. The horizons are calculated from trading experience in the stocks, as represented in the stock-specific peer database, not from a model. As such, the calculations are strategy-independent. We had called out the difficulty in trading MQG, for example, in Exhibit 4. Its disproportionate size in the portfolio, and

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7 Managers with less than $1 billion under management are given until mid-2019 to comply. See Securities and Exchange Commission [2017], accessible through www.sec.gov.
relatively high average trading costs of almost 60 bps, are represented by one of the longest times to liquidate.

Trading cost, interpreted as the price of liquidity, is the best metric for a concept no one has been able to define effectively. In a portfolio setting, however, cost is not enough for the obvious reason: the cost of liquidity in a portfolio depends on the portfolio weights. An example of this is BTT. Average trading costs for this stock are around 100 bps, much higher than, say, MQG. The probability of losing more than 50 bps in cost is over 35%. On the other hand, trading experience translated into time-to-liquidate, yields a horizon of three days, 25% lower than for MQG.

The combination of cost, portfolio weighting, and observed trading horizons yields the chart for the ETF as a portfolio on the right side of Exhibit 17. Cost and days-to-completion are graphed for dollar-based slices of the portfolio to be liquidated. Portfolio weights by stock are applied to each slice, which in turn yields required order sizes. The order sizes are used to compute cost and horizon, stock by stock, and then aggregated to the portfolio level.

The exercise is useful for relatively small portfolios, with potentially undesirable liquidity characteristics which have been difficult to quantify. Exhibit 18 contains such an example.

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**Exhibit 18**

Taiwan’s ITWN

This is a case in which a single stock dominates the portfolio, and for which the small weightings for others could suggest a lack of liquidity problems. A stock such as 1301 costs 99 bps on average to trade, but represents a tiny fraction of the portfolio, for example.

Dismissing small weightings is a mistake. Security 1301 requires almost seven days to liquidate, based on realized trading experience. The right-hand panel of Exhibit 18 illustrates an alternative to calculating dollar slices of a basket, rather relying on the percentage of the portfolio to be sold. This is a question of taste, not substance. Stock-specific weights are applied to the overall portfolio percentage, order sizes are determined, and a combination of total cost and trading horizon is built up from the constituents.
Concluding Remarks

The big question in big-data analytics is, what is the question? We pose three questions here.

Is there valuable information in activity-based peer trading comparisons if one analyzes performance on a stock-by-stock basis? The answer is, yes. Aggregated comparisons across institutions and brokers disguise important differences in the effectiveness of trading process and performance.

How does a stock trade? Our answer lies in the characterization of single-stock profiles, a "blue book" of trading experience. Previous attempts rely on a combination of public market data and various technical trading techniques. Our approach exploits institutional trading activity on a stock-by-stock basis, combining such information with market data in such a way as to produce actionable insights and repurposing old tools with the goal of reducing institutional trading cost.

How does one characterize the liquidity profile of a portfolio? The answer relies on observed liquidity, as evidenced by institutional trading activity. The solution depends on building the portfolio profile up from individual securities, and yields not only the implementation costs of liquidation, for example, but also the horizon over which this may be accomplished. The general approach here opens the door to large-scale evaluation of global ETF liquidity, a topic worthy of pursuing further.