NAVIGATING LIQUIDITY BY HARNESING THE TIDES OF SENTIMENT
ENHANCING EQUITY TRADING STRATEGIES AND TRADE EXECUTION USING SENTIMENT AND ILLIQUIDITY

BY JÜRGEN KRÜGER, MICHEL VAN TOL AND CARL WELLS
The Knock-On Effect of Sentiment on Liquidity

Liquidity is one of the great enigmas of the financial markets. The performance of many of the financial innovations of the past few decades, from derivatives to hedge fund strategies, are crucially dependent on market liquidity. Transacting on a financial exchange involves impacting the market to a degree, the depth of the impact being dependent on how liquid the market is over the period of time that the transaction takes place. An edge in understanding the relationship between liquidity and market impact, both at the individual trade level and at the level of the entire market, is important in achieving superior investment performance. This is particularly true for levered investment strategies and products where even small changes in liquidity can significantly affect performance.

Some academics have made significant progress in coming to grips with the ephemeral nature of liquidity, while many simply assume it away. We aim to show that using news sentiment information in conjunction with measures of illiquidity significantly improves the performance of a set of base trading strategies. We conducted two studies to illustrate the value of bringing these elements together. The first improves on a simple volume-slicing execution algorithm, and the second on a medium-term momentum strategy, which can be seen as a simple proxy for a discretionary investment approach.

TRNA Sentiment and “Big Data”

Over the past 15 years, most investment news has moved online. As a result, bulk news flow can be accessed and analysed relatively cheaply. The sheer volume of available, unstructured data, must be processed algorithmically to access timely and meaningful investment information. Thomson Reuters News Analytics (TRNA) is a cutting edge News analytics feed, which applies complex linguistic analysis to news items from numerous sources in real-time. Each news item is given company-specific ratings of relevance, sentiment, novelty and volume, together with an analysis of the headline. In this study we use TRNA sentiment data to improve on the performance of our base strategies.

Improving Trade Execution with Sentiment

Is there a relationship between news sentiment, as it relates to a specific stock, and short-term illiquidity that can be exploited to enhance trade execution? To investigate this question, we started with a simple volume-slicing base strategy and then sought to improve on it by taking illiquidity and news sentiment into account.

Our approach was straightforward in that for a particular stock, we generated 1000 random order entry times, split between buys and sells (our sample spans the year 2014). We require that there is stock specific news in the one day period after the order entry time, which allows us to adjust execution based on news sentiment flow. For each order, we assumed an order size of 5% of the average daily volume (ADV) traded in that stock over the preceding 20 days. We simulated market impact by adding the bid-ask spread to each buy order (and subtract it from each sell order).
We then consider three alternative approaches to executing the order in the market:

1. **Simple volume-slicing execution**: This is our base execution strategy. At the end of each minute, we observe the volume traded over the preceding minute and seek to execute 5% of that volume over the next minute using a market order.

2. **Iliquidity-enhanced volume-slicing execution**: We take the same approach as the base strategy except that we also compute the closing bid-ask spread at the end of the last bar and compare it to the spread over previous bars (during the execution of the order). We then scale the slice accordingly, becoming more aggressive when spreads are thin and less aggressive when they widen: if the spread is currently equal to or higher than 75% of the preceding spreads, we scale the 5% slice to 1.25% i.e. \((1 - 0.75) \times 5\%\). Subsequently, the execution algorithm is aggressive when spreads are thin and passive when they widen.

3. **Sentiment and illiquidity-enhanced volume-slicing execution**: We now add another dimension to the execution algorithm by introducing sentiment to the mix. Starting with (2) above, we add an ‘aggression multiplier’, and scale each slice again, based on the stock’s relevance-weighted sentiment over a certain time period before the end of the bar. We consider trailing sentiment windows ranging from 1 minute to 8 hours. The multiplier we settled on was 5, such that, when we wanted to be aggressive we could be targeting up to 25% of the previous bar’s traded volume instead of the 5% used in the base strategy. If the order is a buy and sentiment is positive, we become more aggressive, whereas if sentiment is negative, we become less aggressive. Similarly, if the order is a sell and sentiment is negative, we become more aggressive, whilst if sentiment is positive, we become less aggressive.

Conditioning the size of each slice on illiquidity improved an average execution by 3.42 bps i.e. a better execution price was achieved. Adding sentiment to the mix, as in (3) above, improved performance significantly to between 3.8 and 10.85 bps. The largest improvements relate to sentiment windows of 4 hours or more, suggesting that the process by which news is incorporated into a stock’s price may take several hours on average. These results are significant and will have a marked effect on the performance of any equity fund. An interesting observation is the asymmetric nature of the gains, which are primarily driven by the improved execution of sell orders. Indeed we only saw an improvement for buy orders over longer sentiment window lengths.

Given that our sample only spans 2014, one could question whether the bias towards improvements in sell orders is systematic or whether it will change during different states of the market. It may well be that the improvements are more evenly spread across buys and sells in a market that is trading sideways or that there is a bias towards the buys during a market sell-off. These are questions for future research.

<table>
<thead>
<tr>
<th>Iliquidity + Sentiment Window Length</th>
<th>8 Hours</th>
<th>4 Hours</th>
<th>2 Hours</th>
<th>1 Hour</th>
<th>30 Minutes</th>
<th>15 Minutes</th>
<th>5 Minutes</th>
<th>1 Minute</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy Order Hit Rate</td>
<td>46.86%</td>
<td>47.24%</td>
<td>49.33%</td>
<td>47.13%</td>
<td>44.86%</td>
<td>46.77%</td>
<td>45.07%</td>
<td>45.21%</td>
</tr>
<tr>
<td>Sell Order Hit Rate</td>
<td>54.69%</td>
<td>52.45%</td>
<td>51.92%</td>
<td>53.42%</td>
<td>51.54%</td>
<td>51.90%</td>
<td>54.42%</td>
<td>52.10%</td>
</tr>
<tr>
<td>Overall Hit Rate</td>
<td>50.94%</td>
<td>50.82%</td>
<td>50.60%</td>
<td>50.98%</td>
<td>49.53%</td>
<td>49.77%</td>
<td>51.08%</td>
<td>50.24%</td>
</tr>
<tr>
<td>Buy Order Price Improvement (bps)</td>
<td>-2.46</td>
<td>5.44</td>
<td>2.83</td>
<td>-3.29</td>
<td>-7.03</td>
<td>-4.68</td>
<td>-5.44</td>
<td>-4.65</td>
</tr>
<tr>
<td>Average Improvement in Executed Price (bps)</td>
<td>3.42</td>
<td>10.85</td>
<td>8.55</td>
<td>5.33</td>
<td>3.89</td>
<td>5.19</td>
<td>3.8</td>
<td>4.59</td>
</tr>
</tbody>
</table>
Below is a set of charts, which show a single base execution against the illiquidity and sentiment conditioned execution of a buy order in Apple (AAPL). The top left chart shows the stock price over the duration of the execution. The top right chart shows relevance-weighted sentiment aggregated over a trailing 4 hour window. Since we are buying during a period of negative sentiment (initially) we do so relatively passively, hence the order fills slowly. As sentiment switches to being positive around minute 300, we execute and fill the order aggressively. The bottom right chart shows the average price attained for the conditional and base executions. The illiquidity and sentiment conditioned execution outperforms the base execution by 23.51 bps.
Sentiment and Illiquidity

In theory, if markets are efficient, an investor will want to be compensated for taking the risk of holding an illiquid asset. Using data for the S&P1500 since January 2006 we find empirical evidence in support of this expectation. In our analysis, we use Amihud’s approach to measuring liquidity, or more specifically, illiquidity, from his seminal paper, ‘Illiquidity and stock returns: cross-section and time-series effects’ (2002). In the figure below, the green line, we evaluate the performance of a simple decile long/short portfolio (long illiquid/short liquid stocks based on Amihud’s illiquidity beta estimates) with daily rebalancing. As expected we observe an upward drift during ‘normal’ periods to reflect the illiquidity risk premium, as well as the realisation of the risk as of the beginning of 2008 as the ‘great recession’ starts to materialise. The correlation between these observations and our personal, practical experience during that period gives credibility to Amihud’s methodology.

The question which then arises is whether there was any indication of the impending ‘liquidity event’ that would have allowed market participants sufficient time to avoid being left ‘holding the hot potato’. Unsurprisingly, we turn to sentiment, or more specifically, aggregate sentiment for this signal. The orange line in the same chart is aggregate sentiment and appears to flag disruptions in the illiquidity premium. Casual observation of the co-movement between the illiquidity risk premium and aggregate sentiment suggests that sentiment (roughly) leads the illiquidity risk premium (as well as the equity market in general).

---

2 Relevance-weighted by news item then equally-weighted across the S&P1500.
3 The TRNA sentiment data used in this study was filtered on the source of the story to Reuters news sources, whether the news item was an article and whether it was an automatically generated stock exchange message reporting an imbalance of share purchase.
Improving the Performance of a Discretionary Strategy

We compute aggregate sentiment and average illiquidity\(^4\) except we enhance the signals by focusing on that subset of the S&P1500 universe\(^5\) with positive Amihud illiquidity beta estimates. In doing so, we tilt these measures into those stocks that have a defendable fundamental relationship between illiquidity and return: our new sentiment measure (green line) is shown in the figure below.

The base strategy is a simple long/short six-month momentum strategy where we compute the momentum of each stock at the end of every trading day, and then look to add a long or a short position to the portfolio during the course of the following day if the price breaks out of a pre-set level (the 10 stocks with highest or lowest momentum are candidates for inclusion in the portfolio). If a position is established, an initial stop is attached to the position which is updated at the end of each day that the position is in the portfolio. A position is closed when the price of the stock goes through the stop loss level. Stop levels are based on the short-term volatility of the stock when the position is established\(^6\). Throughout we’ve assumed a transaction cost of 10bps. Performance of this base strategy is shown in the figure below – the blue line.

Next we look to use average illiquidity as a timing signal. Our approach is very simple: stop adding positions to the portfolio and tighten the stops when average illiquidity is at a 52 week high. The performance of this conditional strategy is shown as the green line in the same chart. As the statistics in the table below show, both drawdown duration and portfolio volatility are substantially reduced.

Finally, we use aggregate sentiment as a timing signal in a similar fashion. As can be seen (orange line), the duration of the maximum drawdown period was substantially reduced from 172 days to 82 days. Annualised returns and Sharpe ratios also improved by exiting the market in anticipation of volatility (which subsequently materialised). While the approach we have taken is simple we have illustrated that using illiquidity and sentiment as timing factors can substantially improve the performance of a momentum-based strategy (and the discretionary strategy that it proxies for). Our aim is to illustrate the value of the information content of sentiment (and illiquidity) without weaving it into a complex model.

---

\(^4\) Computed by taking the average of each stock’s absolute return divided by its dollar volume across the S&P1500 on a given day.

\(^5\) Similar to the approach we took to aggregating sentiment for a previous paper (https://forms.thomsonreuters.com/mmarket).

\(^6\) We seek a price confirmation signal prior to establishing a position and therefore use an entry trigger price that is set equal to the previous day’s close price. The initial stop is set at 5 times the Average True Range (standard definition and parameters) away from the entry price which is updated at the end of every day that the stock is in the portfolio. The stop is updated when the price has moved more than 10 times the ATR away from the prevailing stop.
### Fund Performance

<table>
<thead>
<tr>
<th></th>
<th>MOMENTUM</th>
<th>MOMENTUM + ILLIQUIDITY</th>
<th>MOMENTUM + ILLIQUIDITY + SENTIMENT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ann. Ret</td>
<td>16.44%</td>
<td>20.30%</td>
<td>24.65%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.57</td>
<td>0.96</td>
<td>1.03</td>
</tr>
<tr>
<td>Max Drawdown</td>
<td>-56.05%</td>
<td>-24.05%</td>
<td>-35.60%</td>
</tr>
<tr>
<td>Max Drawdown Duration</td>
<td>172</td>
<td>144</td>
<td>82</td>
</tr>
</tbody>
</table>
Conclusion

The research questions that we addressed in this note suggest that TRNA sentiment data can easily be used to improve on a set of baseline strategies. We found that it added to performance at both the aggregate level, by providing downside protection during periods of market turbulence, and at a very granular level when modulating the level of aggression in an execution algorithm. We deliberately opted to avoid complex models that might have obscured the message we are hoping to convey, which is that news sentiment data contains significant price sensitive information. Our findings have also raised a number of interesting questions: Is there structure in the delay between the publication of a news item and subsequent price movement? By differentiating between the sources of news items we might be able to improve the conditional execution algorithm further. Indeed, this may also be the case if we differentiate between scheduled and unscheduled news items. Furthermore, there are some questions regarding the sensitivity of the outperformance of the conditioned execution algorithm, both in terms of magnitude, and symmetry, given different states of the market. Finally, when conditioning a discretionary strategy on illiquidity and sentiment we have been aggressive in terms of exiting and entering the market. A more subtle approach may be warranted whereby the gross exposure of a fund is guided by sentiment and illiquidity so as to improve its risk-adjusted performance. These findings are relevant for the entire investment community, from execution brokers and market makers, through to equity fund managers and asset managers.