GLOBAL VOLATILITY SUMMIT

September 2020 Newsletter

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The Global Volatility Summit ("GVS") brings together volatility and tail hedge managers, institutional investors, thought-provoking speakers, and other industry experts to discuss the volatility markets and the roles volatility strategies can play in institutional investment portfolios. The GVS aims to keep investors updated on the volatility markets throughout the year, and educated on innovations within the space.

Quantitative Brokers has provided the latest piece in the GVS newsletter series.

Cheers,
Global Volatility Summit

11th Annual Global Volatility Summit

We are excited to announce the first ever Virtual Global Volatility Summit taking place from September 21 to September 23. Virtual GVS consists of though-provoking panel discussions with managers and investors around the globe as well as a timely keynote from Demetri Sevastopulo (Washington Bureau Chief, Financial Times).

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VOLATILITY, MULTIDIMENSIONAL REGIMES AND EXECUTION PERFORMANCE

SHANKAR NARAYANAN
MARCH 23, 2020

EXECUTIVE SUMMARY

- Regimes are states of good and bad execution performance.
- Volatility is an important factor for execution performance but not sufficient by itself to identify regimes.
- Regimes are persistent for several hours, days or even weeks and deterministic in advance using our signal framework.
- Market microstructure variables such as quote size, real time volatility, liquidity, and quote spread, etc play a significant role in the regime identification process.
- During rough times or bad regimes, it is better to use an optimal combination of algos such as a schedule along with arrival price algorithm.

INTRODUCTION AND MOTIVATION

As we write this article, the U.S. Treasury yields have dropped to historical lows and the VIX has crossed 85. In addition, as shown in our recent white paper (Narayanan, March 2020), quote size of the most traded E-mini S&P 500 is lowest in at least eight years. Volatility is not new to the markets and we have witnessed it several times during the course of the last several years after a calm regime of low VIX periods. Clearly, there has been a shift in the macro conditions. As such volatility is a critical input to the concept of regimes, which are typically thought of as changes in macro sentiment. There are some academic papers which focus on regimes and portfolio construction.

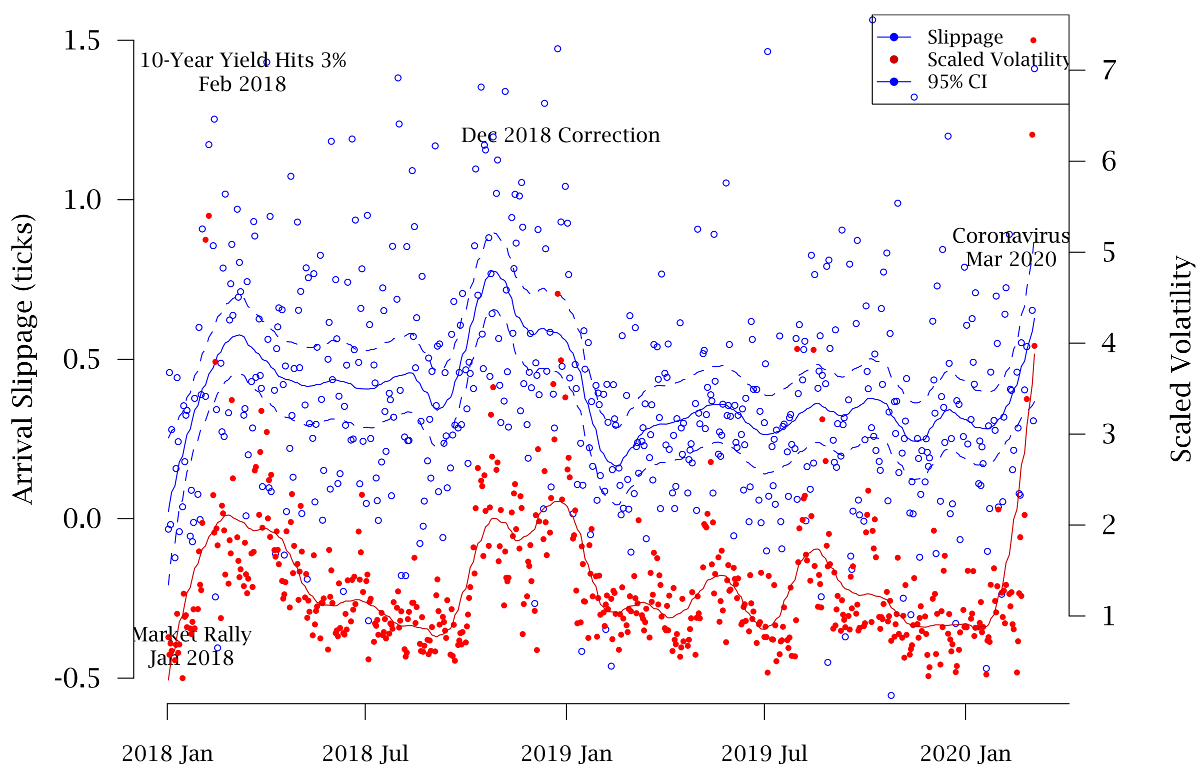
In this research, we discuss different market microstructure variables in addition to volatility and as to how the execution cost varies with them. We define regimes for execution as states of the market microstructure and the impact on slippage. We use empirical methods to determine regimes and their impact on the execution performance. To that effect, this paper also shares some of the findings of Capponi and Cont (2019), who find that volatility and trade duration are the main determinants of the amplitude of price variations during trading execution. We can speak only in reference to QB's algos, however, the problem is fairly generic. There are certain regimes where particular algos tend to be optimal in minimizing the cost of execution. Another important takeaway of this research is that regimes are persistent as market microstructure is persistent and so regimes can be known well in advance such as a few hours, days or even weeks ahead. Given the knowledge of regimes ahead of time, a trader has an opportunity to make intelligent choices to improve execution performance. The underlying study enables us to customize algos based on the regimes and the client's need.

In the seminal paper by Almgren and Chriss (2000), total cost of trading is modeled as the weighted summation of market impact and timing risk. If we recall, volatility is the key input to the total cost and the trade-off between the two components is based on the risk aversion parameter of the trader. Separately, there is a relationship between the cost of trading, the quote size and the bid-ask spread, which changes during volatile periods as well, in turn impacting the total cost of trading.

$$\texttt{Total Cost} = \texttt{Market Impact}(\sigma, \texttt{bid-ask spread}, \alpha) + \lambda * \texttt{Timing Risk}(\sigma, \alpha) \quad (1)$$

In the above equation, α is the participation rate and σ is the volatility. It can be clearly seen that changes in volatility, bid-ask spread or other market microstructure variables such as quote size will impact the total cost of trading. Furthermore, the risk aversion parameter can vary under different circumstances and thus aid in modifying the algo behavior. Figure 1 shows the average daily slippage of the E-mini S&P 500 futures from

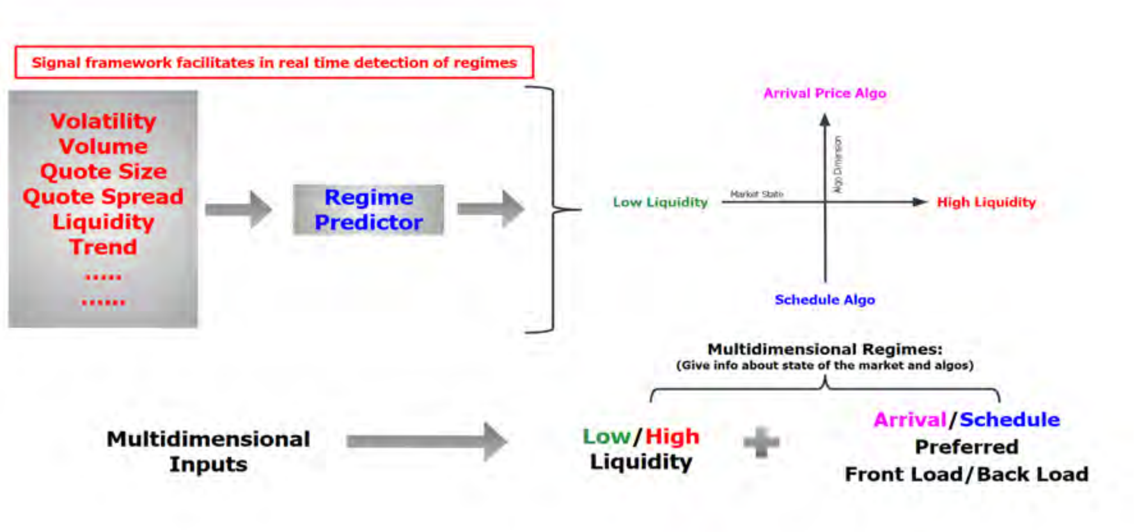
FIGURE 1
E-mini S&P 500 Futures. Shows how arrival price slippage changes across different regimes. Right hand side shows scaled volatility.



January 2018 until March 2020. Also, shown is the scaled volatility on the right side of the plot. It can be seen that the slippage increases with the rise in volatility and drops accordingly. The Figure also illustrates the different regimes such as the rise of the 10-Year yield in February 2018 and the market correction of December 2018 followed by the FOMC meeting and the more recent market correction of March 2020 on account of the Coronavirus. While the Figure illustrates the relationship with volatility on an aggregate basis, the rest of the research focuses on the intraday dynamics of market microstructure variables used for the determination of regimes. Our signal framework facilitates real time detection of regimes, which is crucial as regimes can change intraday or during the course of an order. The below figure gives a high-level summary of the same.

FIGURE 2 The regime identifier takes multidimensional inputs and spits out both regime and the recommendation of the algo.

Multidimensional Regimes



IDENTIFICATION

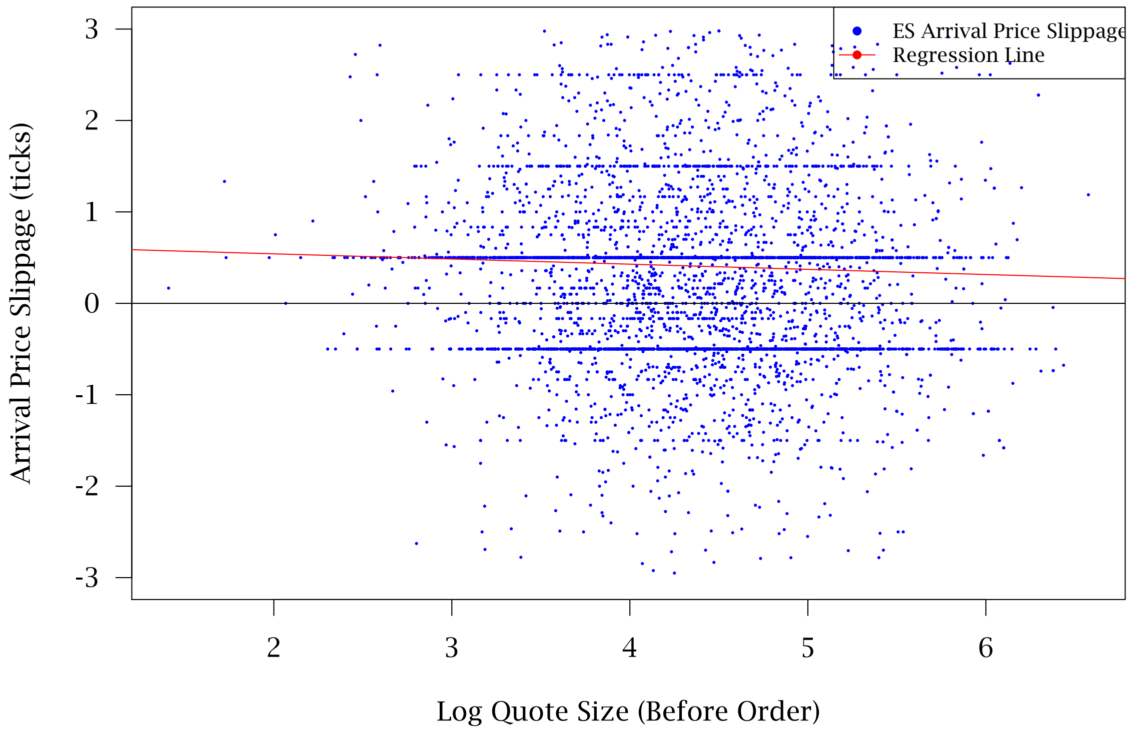
Identifying the regimes in advance is necessary to minimize the cost of trading. However, the variables need to be carefully chosen. For this purpose, we first show the relationship of some variables with slippage.

Figures 3 and 4 show the relationship of the arrival price slippage of E-mini S&P 500 futures with volatility and quote size determined before the order. In the Figures, each dot is a parent order. As can be seen, there is a positive relationship with volatility and negative relationship with quote size. However, volatility by itself is not sufficient for the identification of the regimes for all the instruments and therefore regimes tend to be multidimensional in its input. Similarly, the output of the regime is not simply to know if the regime is good, normal or bad but also to take decisive actions so as to be able to minimize the total cost of trading. Hence, the research has multidimensional inputs and multidimensional outputs.

For identification, we use several measures of volatility and proxies for liquidity such as quote size, Kyle's lambda and Amihud liquidity. In addition, we also look at the square root of the sum of the squared mid points at 1-minute intervals as a measure of volatility. Furthermore, we have trend in both a longer and shorter-term window. Some of these are variables are listed below:

FIGURE 3 Shows how arrival price slippage changes across different regimes of Quote Size. Essentially, there is a negative correlation. Each dot on this plot is a parent order and slippage is measured in ticks from arrival price.

E-mini S&P 500 Futures: Arrival Price Algo vs. Log Quote Size



$$\Delta P_t = \alpha + \delta \mathtt{OFI}_t + \varepsilon_t$$
$$\mathtt{OFI} = \frac{\mathtt{Buy\ Volume} - \mathtt{Sell\ Volume}}{\mathtt{Total\ Volume}} \tag{2}$$
$$\mathtt{liquidity} \propto 1/\delta$$

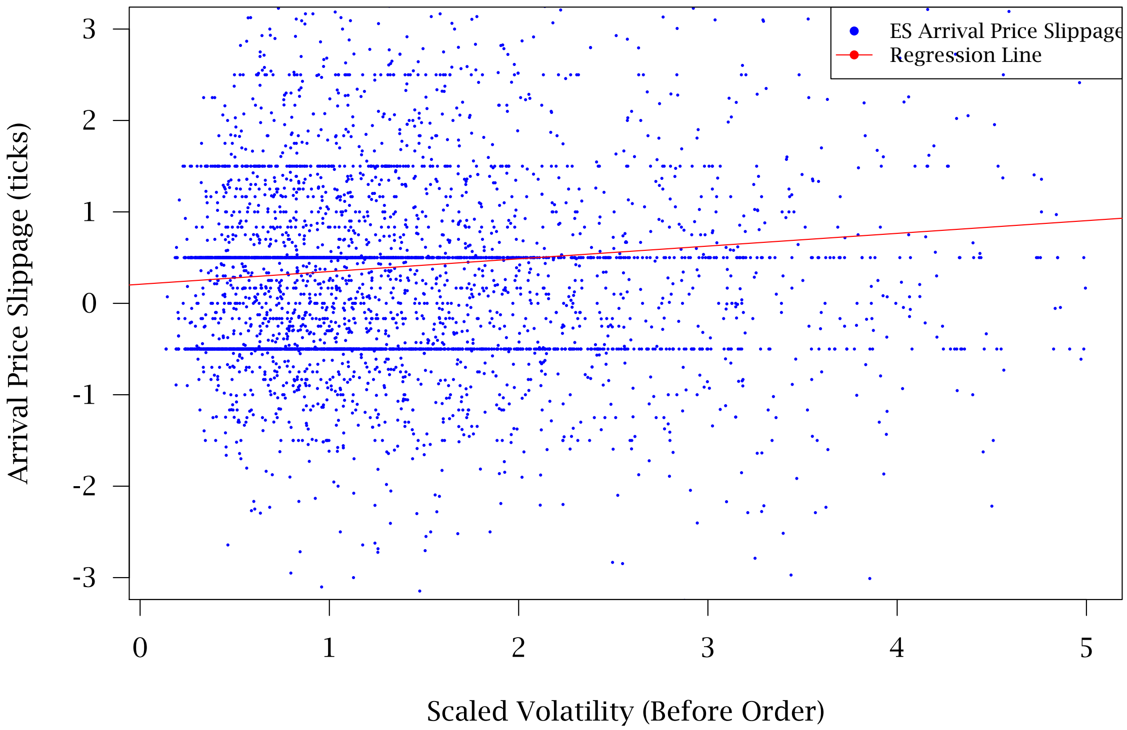
$$\sigma_k = \sqrt{\sum_{t=0}^{k} (Mid_{t+1} - Mid_t)^2} \tag{3}$$

$$\mathtt{Effective\ Bid\text{-}Ask\ Spread} \propto 2 * \sqrt{max(0, -Cov(P_t, P_{t-1}))} \tag{4}$$

In the equations above, liquidity is the inverse of the slope $1/\delta$, where ΔP_t is the mid-price change and $\mathtt{OFI}_t$ is the signed trade imbalance as defined above in each one minute bin. For robustness, we also looked into different interval bins such as 5 minutes and 15 minutes and found a similar pattern. Also, volatility in k minutes is defined by σ_k, each t is a trade event. In the equation 3 above, we compute a measure of effective bid-ask spread, which is useful for the large tick assets that tend to have several trades whereas the actual observed bid-ask spread is always the minimum price increment. Noteworthy to mention that these variables are measured at least 5 minutes prior to the start of the order and in some cases are in a longer window.

FIGURE 4 Shows how arrival price slippage changes with volatility before the order. There is a mild positive correlation. Each dot on this plot is a parent order and slippage is measured in ticks from arrival price.

E-mini S&P 500 Futures: Arrival Price Algo vs. Volatility



In the example of E-mini S&P 500 futures, we find that both quote size and volatility impact slippage. The next step is to verify if both are equally important. So, in the next subsection, we show the average arrival price slippage of two of our algos broken down by two of the most important and carefully chosen variables for some of the instruments.

BI-VARIATE SORTS

Figures 5 shows the average arrival price slippage by volatility and quote size for E-mini S&P 500 futures by breaking the same into 3x3 sorts. Note that not all the groups have same observations. It is clear that both quote size and volatility are important. One can see that within each quote size group, there is meaningful variation across different volatility groups and similarly within each volatility group, there is variation in slippage across different quote size groups. The average arrival price slippage is the lowest (highest) when the volatility is lowest (highest) and quote size is highest (lowest). The difference is statistically significant.

Figure 6 shows arrival price slippage of schedule based algo divided into 3 quote size groups and 2 volatility groups. The variation across different quote size groups is insignificant whereas volatility still tends to be important. The sub groups of quote size during high volatile periods are not statistically significant from each other. It is interesting to see that the arrival price slippage of a schedule based algo on an average can be negative during low quote size and low volatility periods, whereas for an arrival price algo (as shown in Figure 5), the arrival price slippage is on an average positive during such regimes.

FIGURE 5

Heat map shows arrival price slippage. Figure shows how slippage changes across different groups of Quote Size vs. Volatility. The height and color of the bar imply the same. Each group has unequal number of observations. It can be seen that quote size and volatility are both important. And the algo is sub-optimal during low quote size periods.

E-mini S&P 500 Futures: Arrival Price Algo (Quote Size vs. Volatility)

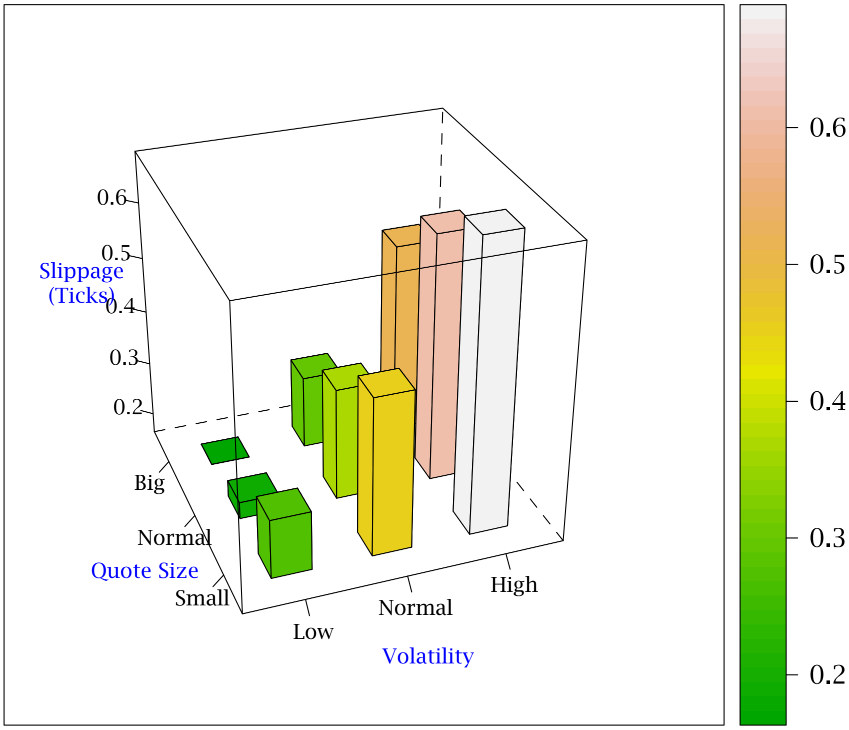


Figure 7 further shows the 3-dimensional plot of the E-mini S&P 500 futures execution performance from the arrival price. The red plane is the bi-variate regression and shows the slope of the two variables. The three red dots show the average slippage in three regimes of volatility. The slippage is highest when volatility is high. It can be seen from the scatter plot with the bi-variate regression plane that the sensitivity of slippage to quote size is low whereas there is still a positive slope to volatility. This aspect of the schedule based algo is found to be useful in navigating through time periods when the quote sizes are especially low.

Figure 8 shows that a price trend before the order in metals plays a significant role in addition to volatility. In this case, the trend variable is measured before the start of the order. Consequently, trend can be a regime. Figures 9 and 10 compare the arrival price and scheduled based algo for Eurodollar futures. When quote sizes are low, the execution performance tends to be somewhat sub-optimal when using an arrival price algo. However, our schedule based algo has on an average negative arrival price slippage during the same regimes of low quote size.

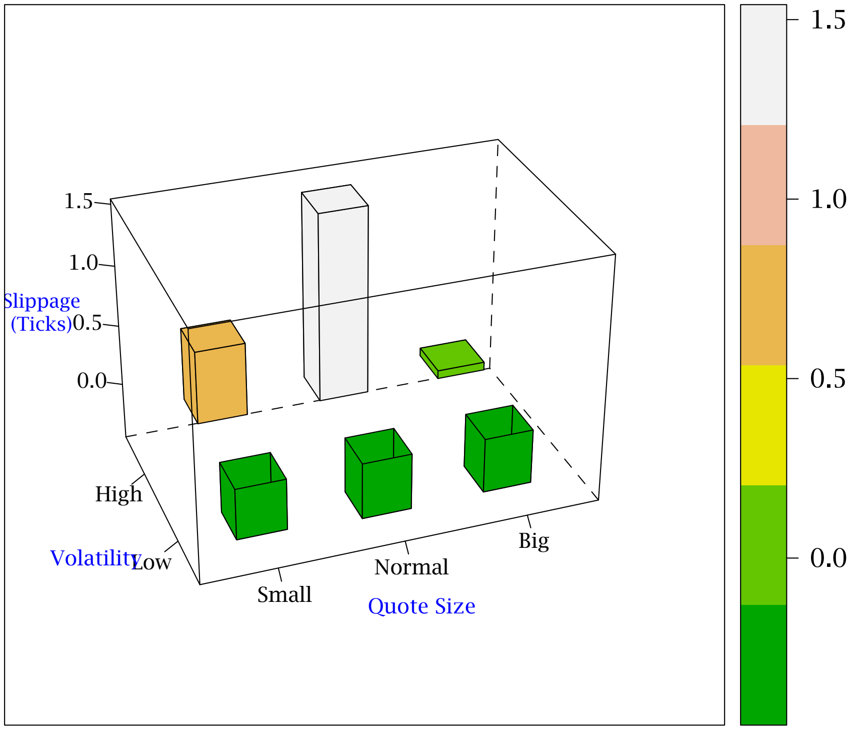
The next sub-section shows a multivariate set up to incorporate many of these variables to identify regimes. This is accomplished in our framework using the k-means algorithm.

K-MEANS AND REGIMES

Given that we have several variables that tend to impact the slippage for a given instrument, we use a simple unsupervised k-means clustering to determine different

FIGURE 6 Heat map shows arrival price slippage. Each group has unequal number of observations. It can be seen that quote size is less important and high volatile periods tend to have higher slippage. However, the arrival price slippage during low quote size and low volatility periods can be negative; unlike an arrival price algo as shown in Figure 5.

E-mini S&P 500 Futures: Schedule Based Algo (Quote Size vs. Volatility)



groups of regimes based on the market microstructure variables around the order time. We then analyze the slippage of different groups. Figures 11 and 12 show two of the important features of the clustering and how the slippage varies across different groups for E-mini S&P 500 for arrival price and schedule based algo respectively. In can be seen again that quote size and volatility are both important for arrival price algo where as only volatility is dominant for the schedule based algo. This is aids in customization of the algo for optimal performance.

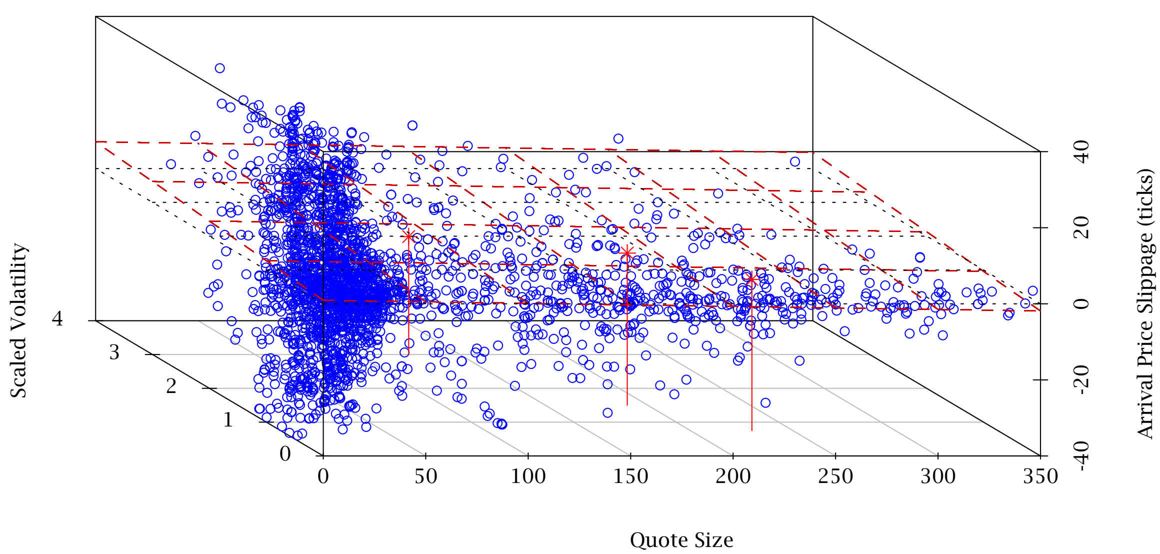
The above Figures are for the sake of illustration. For the sake of conciseness, we show results of only two factors and also omit the k-means Figures for rest of the instruments.

SUMMARY AND RECOMMENDATION

The previous sections highlight some of the details of the identification of regimes based on multidimensional inputs measured before the start of the order. During these regimes, we look at the arrival price slippage of two of our flagship algos - one without any hard schedule and the other with a predetermined schedule. We show that having a schedule during rough times is helpful for even an arrival price algo. Consequently, working the order through a predetermined optimal time is desirable during low quote size regimes for E-mini S&P 500 futures (as shown in Figures 5-7) and this pattern is similar for instruments with similar market microstructure. In general, large tick assets such as E-mini S&P 500 and Eurodollar futures (see Figures 9 and 10) benefit by having an optimal participation rate or schedule combined with our arrival price logic during rough regimes.

FIGURE 7
Figure shows arrival price slippage of schedule based algo. Each dot on this plot is a parent order and slippage is measured in ticks. It can be seen that the slope to quote size is almost zero where as there is still a positive slope to the volatility.

E-mini S&P 500 Futures: Schedule Based Algo (Quote Size vs. Volatility)



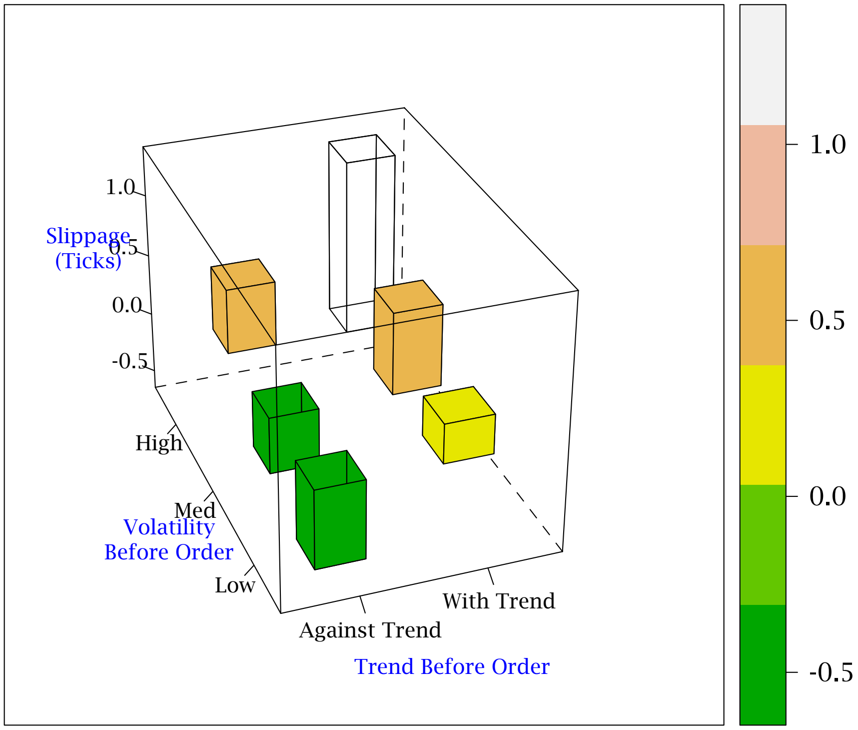
Similarly, and as shown in the Figure 8, trends play a dominant role in metals and several small tick assets. Given the knowledge of trend, volatility and other market microstructure variables, we can improve slippage to arrival price by the use of a schedule and either front load or back load depending on the trend and side of the trade. This has to be combined with our arrival price algo's optimal order placement logic as well.

However, one size does not fit all and so it is important to adapt. This is also desirable since during volatile periods, targeting one benchmark is difficult but using a combination of benchmarks and algo behaviors tend to minimize the risk of execution performance. This is similar to the concept of a portfolio diversification. Furthermore, switching entirely to a schedule based algorithm is not recommended either as it might result in high dispersion around the arrival price benchmark, especially during normal or good regimes. Therefore, our recommendation is a combination of algo behavior customized to the instrument, regimes and to the client's need. In a manner, it takes us back to our equation (1), which gives us a formulation to compute an optimal rate given alpha (trend), volatility and risk aversion coefficient of the client so as to minimize the total cost of trading. However, there is a key input of risk aversion which is specific to instrument, regime and the client's need. Hence, the output is different for different cases.

Given our signal framework, we can detect regimes or change in regimes during the course of the order as well and take a pre-determined action. Before we conclude this research article, it is also noteworthy to mention that our arrival price algo is optimized for various market conditions and it will be a continuous process to improve the same.

FIGURE 8
Heat map shows arrival price slippage. Figure shows average by different groups of trend and volatility. In this figure, the trend is broken into two groups based on trade direction being same/opposite to that of price direction. The slippage is higher when trading in the same direction as trend. Volatility is still important and price direction is measured before the start of the order.

Metals: Arrival Price Slippage (Volatility vs. Trend)



Nevertheless, we will encounter certain unchartered territories with high volatility or unfavorable market microstructure. Identifying these regimes in advance and taking an intuitive and optimal action is QB's answer to improving execution performance in an era of constantly changing and at times tumultuous market conditions.

References

[1] Narayanan S., "Quote Size vs. Liquidity of E-mini S&P 500 Futures from 2012-2020", *QB White Paper*, March 2020.

[2] Capponi F. and Cont R., "Trade Duration, Volatility And Market Impact", *April 2019*

[3] Almgren R. and Chriss N. (2000), "Optimal Execution of Portfolio Transactions", *Journal of Risk* Volume 3, Number 2 (Winter 2000), Pages 5–39.

FIGURE 9 Heat map shows arrival price slippage. Figure shows how slippage changes across different regimes of Liquidity and Quote Size for an arrival price algo. During low quote size and low liquidity periods, the algo is sub-optimal. A schedule helps during these regimes as shown the Figure below

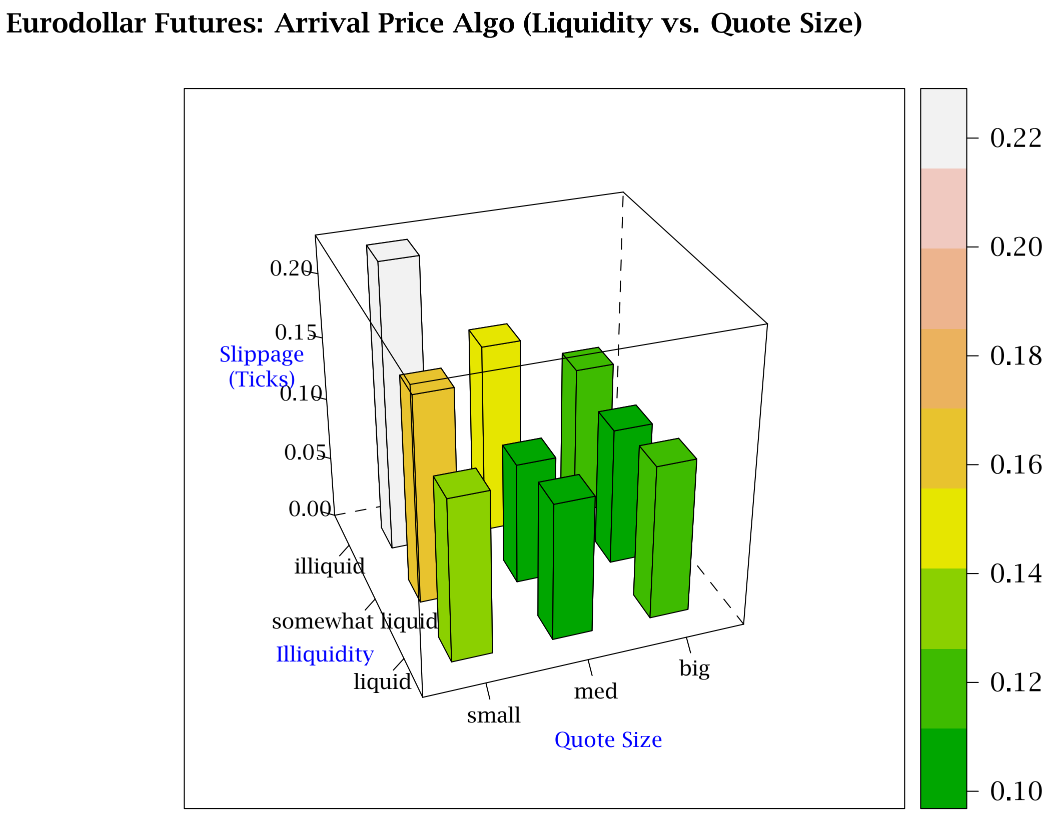


FIGURE 10 Heat map shows arrival price slippage. Figure shows how slippage changes across different regimes of Liquidity and Quote Size. As can be seen that during low quote size regimes, there is a possibility for a schedule based algo to have negative slippage.

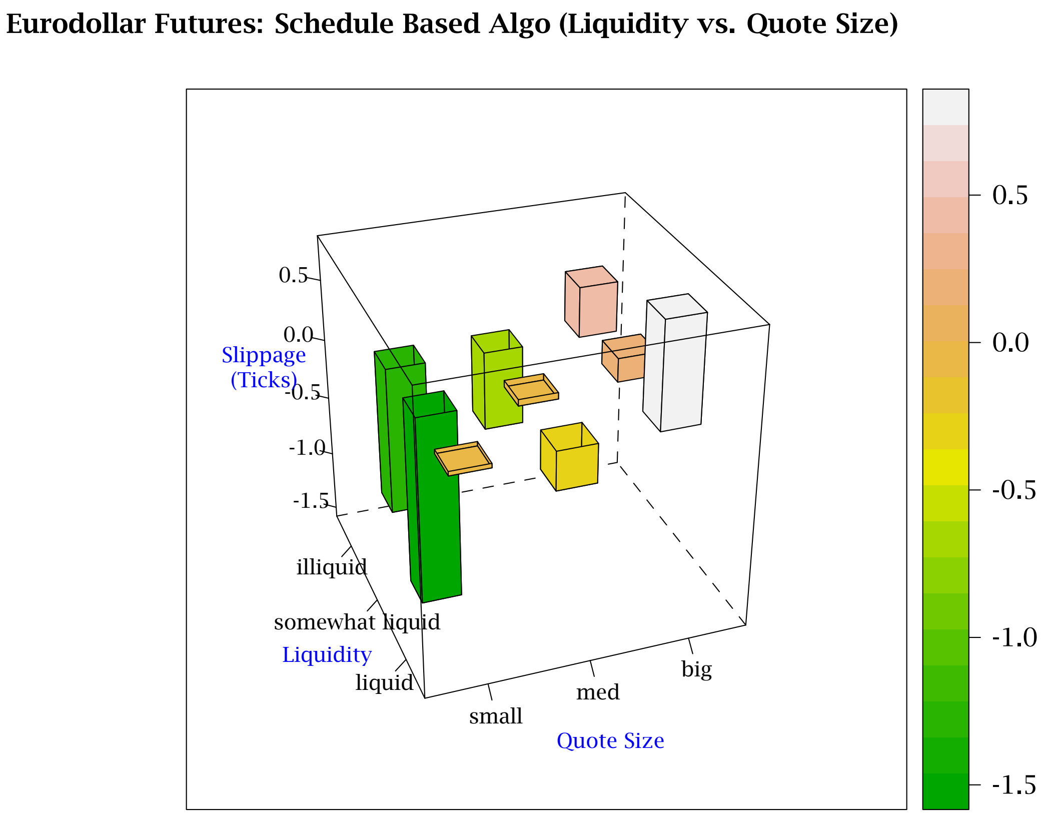


FIGURE 11
Regimes with two factors and heat map shows arrival price slippage. Good regimes have large quote size and low volatility. Bad regimes have low quote size and high volatility. Each dot is a parent order. It can be seen that slippage is lowest in low volatility and high quote size regimes

E-mini S&P 500 Futures: Arrival Price Algo, Quote Size vs. Volatility

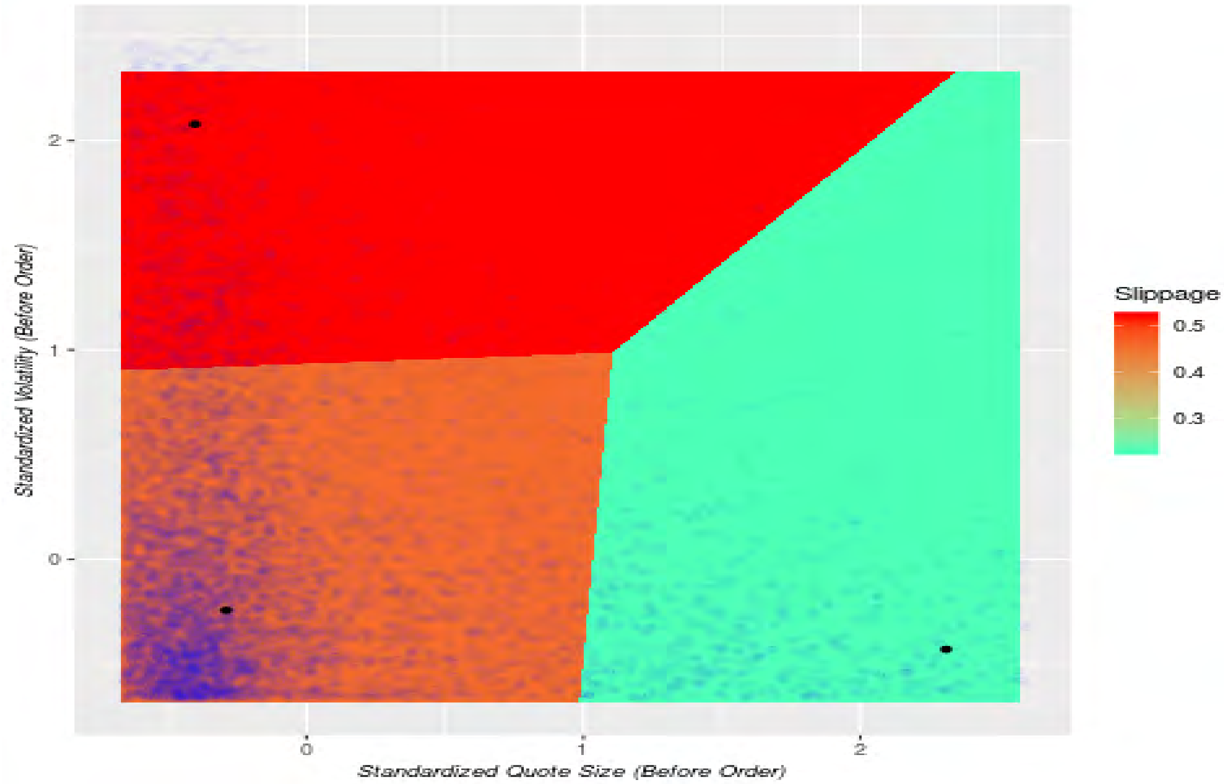


FIGURE 12
Regimes with two factors and heat map shows arrival price slippage. The centroids are the same as used for the arrival price algo (shown above). Each dot is a parent order. It can be seen that slippage is invariant to quote size. Slippage is highest when volatility is high. The arrival price slippage on an average is negative during low volatile periods, an improvement to arrival price algo (Figure 11).

E-mini S&P 500 Futures: Schedule Based Algo, Quote Size vs. Volatility