Impact of Automated Orders in Futures Markets

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The staff of the Market Intelligence Branch in the Division of Market Oversight ("DMO") conducted research on the entering of orders manually and automatically in commodity futures markets in the United States to determine how technological change is affecting futures trading. DMO staff used internal CFTC transactional data for thirty futures contracts during the period January 2013 – December 2018, and examined what effects, if any, the manual and automated order placement mechanisms had on these markets.

The research produced the following findings:

1. The percentage of automatically placed orders has increased for all commodity futures markets;

2. Automated orders have a smaller number of contracts per transaction than manual orders and their resting times are shorter than the resting times of orders placed manually;

3. Automated orders are almost always limit orders; and

4. Although the level of automation increased steadily each year, historical volatility of end-of-day prices did not exhibit the same trend.[1]

Automated and Manual Order Entry

Automated and manual order entry refers to how an order is entered on the order entry message. Automated order entry refers to orders that are generated and/or routed without human intervention. This includes any order generated by a computer system as well as orders that are routed using functionality that manages order submission through automated means (i.e., an execution algorithm). Manual order entry refers to orders that are submitted to CME Globex by an individual directly entering the order into a front-end system, typically via keyboard, mouse, or touch screen, and which is routed in its entirety to the matching engine at the time of submission.

Type of order entry is a self-identified tag, which market participants submit themselves. This tag is required only by the Chicago Mercantile Exchange (CME), as documented in CME (2012). Therefore, DMO staff analysis is limited to CME contract markets.

Level of Automation in Futures and Options Markets

DMO staff began the analysis by reviewing daily transactions in 30 futures contract markets. Staff classified the markets into eight commodity groups including: Currencies, Equities, Financials, Energies, Metals, Grain, Oilseeds, and Livestock.

Figure 1
Commodity Groups and Corresponding Commodity Contracts

Currencies
Brazilian Real Futures
British Pound Futures
Euro FX Futures
Mexican Peso Futures

Equities
E-mini NASDAQ 100 Futures
E-mini S&P 500 Futures
NIKKEI 225 ($) Stock Futures

Financials
10-YR Note Futures
30-YR Bond Futures
Eurodollar Futures
Federal Fund Futures

Energies
Natural Gas Henry Hub Futures
NYMEX Crude Oil Futures
NYMEX Heating Oil Futures
NYMEX NY Harbor Gas (RBOB) Futures

Metals
COMEX Copper Futures
COMEX Gold Futures
COMEX Silver Futures
NYMEX Palladium Futures
NYMEX Platinum Futures

Grains
Corn Futures
KC Wheat Futures
Rough Rice Futures
Wheat Futures

Oilseeds
Soybean Futures
Soybean Meal Futures
Soybean Oil Futures

Livestock
Feeder Cattle Futures
Lean Hog Futures
Live Cattle Futures

Figure 1 is a list of futures contracts that DMO staff assigned to the eight commodity groups. Staff included the most actively traded futures contracts within each commodity group.

Within each DMO-assigned commodity group, staff calculated the total number of outright and spread order transactions that were entered on CME Globex, which originated from either manual inputs or an automated trading system (ATS). Then, staff aggregated the individual markets' total number of consummated transactions for every year.

Figure 2
Share of Automated Futures and Options Transactions

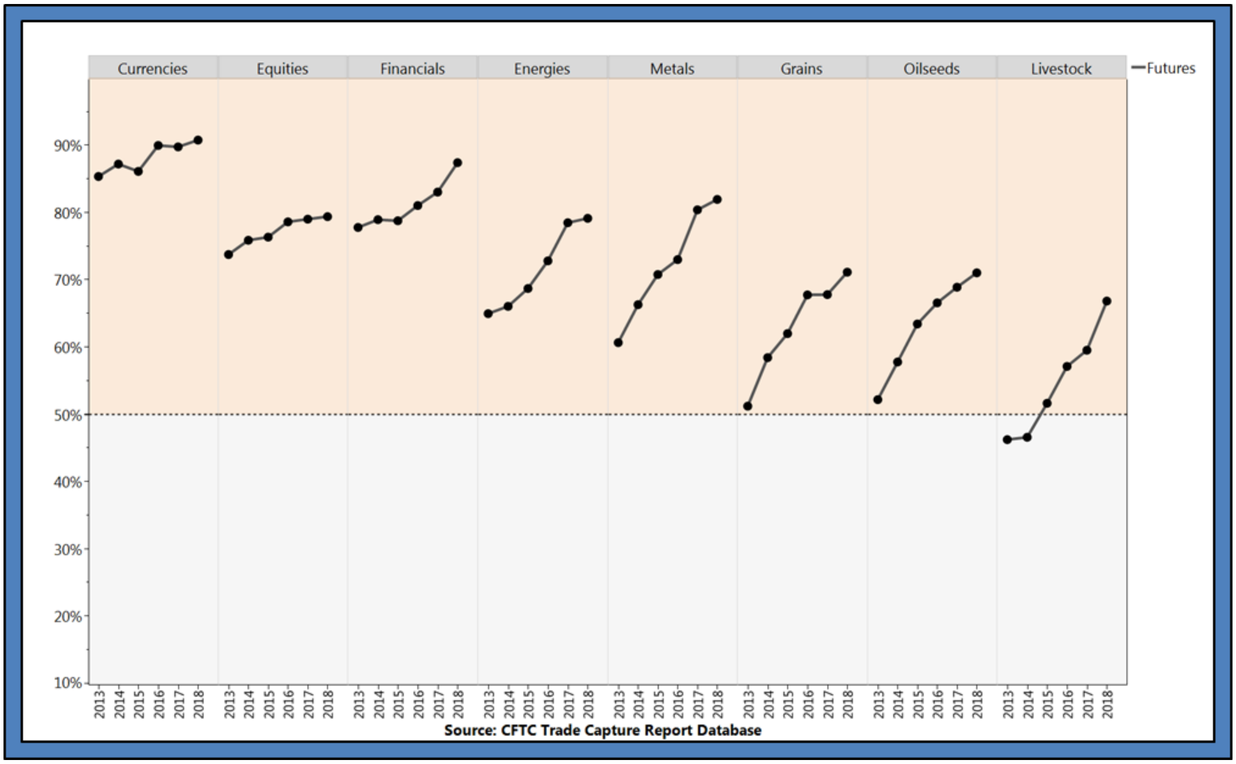

Figure 2 shows the share of ATS orders entered in futures markets. Overall, across all the commodity groups, the share of ATS orders[2] increased from 2013 to 2018. On average, the share of ATS orders in Currencies, Equities, and Financials increased 7%. The average percentage increase was 19% for Energy, Metals, Gains, Oilseeds, and Livestock.

Throughout the study period, the share of ATS orders was generally higher for financial products (i.e., Currencies, Equities, and Financials) than for physical commodities. After conducting interviews with market participants who trade futures and underlying cash products, DMO staff determined that a possible explanation for the higher level of automation in the financial products is the large transactional volume and low basis risk between the futures contracts and the underlying cash markets. Furthermore, the lower share of automation in the physical commodities may be attributed to the usually higher basis risk associated with delivery specifications in the cash markets and, in some cases, slight differences in the futures contracts to the actual cash market.

Resting Time

DMO staff reviewed the time period during which limit orders were exposed to the market before being filled. The time between when an order is entered and the time when it is consummated is known as order resting time. DMO staff considers resting time to be a measure of the speed of trading.

Figure 3
Median Resting Time of Limit Orders

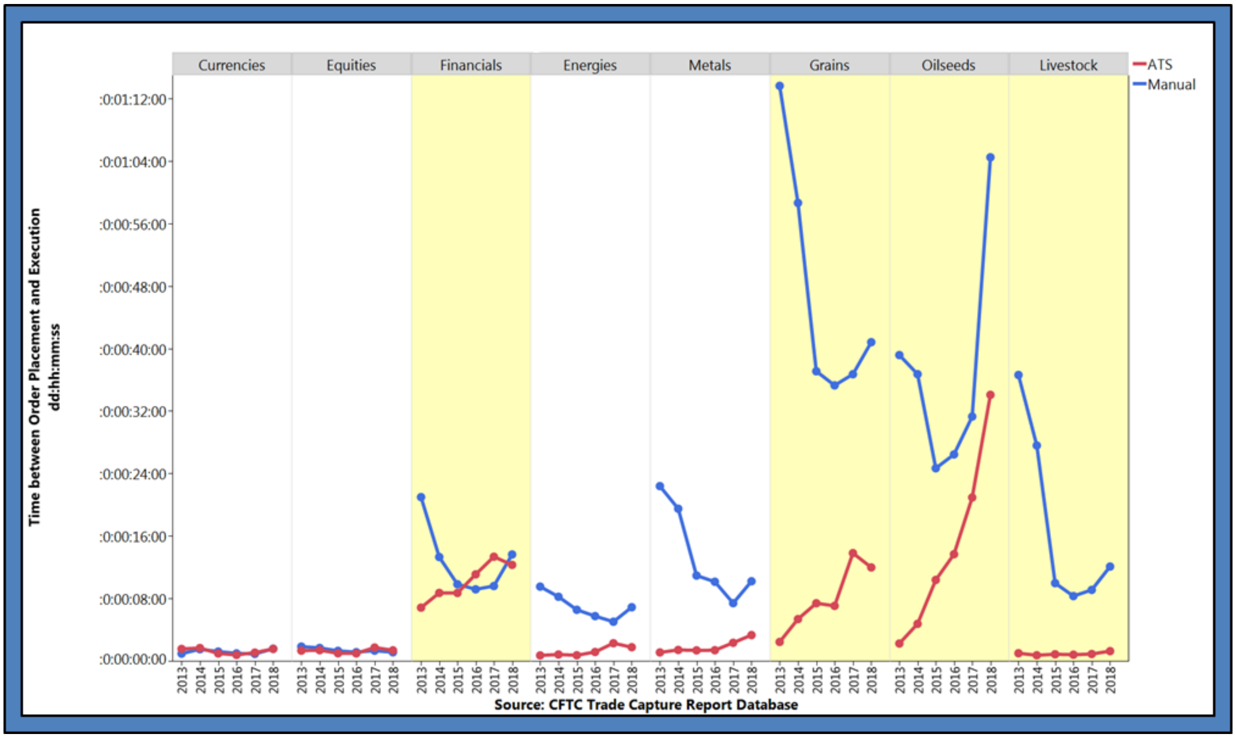

Figure 3 depicts median resting times for limit orders over the period from 2013 to 2018. The red lines show the ATS orders and the blue lines show the manual orders. DMO staff calculated the median resting time within each commodity group by using the individual contract markets' resting times, ordering them in value, and then finding the median for the entire group. In the groups with the white background, for all or most of the contract markets included in those groups, the exchange uses a first-in, first-out (FIFO) algorithm to match buy and sell orders; whereas for some of the contracts in the groups shaded in yellow, the matching algorithm prioritizes using order size.

The graph above shows that manual orders were exposed to the market for a slightly longer time than ATS orders. Based on interviews conducted with market participants, DMO staff determined that one contributing factor for these longer resting times may be that, in general, manual limit orders tend to be placed away from the market. The graph also shows that some commodity groups had shorter ATS order resting times than others. Based on the aforementioned interviews, DMO staff discovered that one explanation for the shorter resting times may be the significant high frequency trading activity in these commodity groups.

Transaction Size

DMO staff examined the average number of contracts per transaction during the period from 2013 to 2018. To calculate the average number of contracts within each commodity group, staff divided the total number of contracts by the total number of transactions and trading days for every year.

Figure 4
Average Number of Contracts Per Transaction

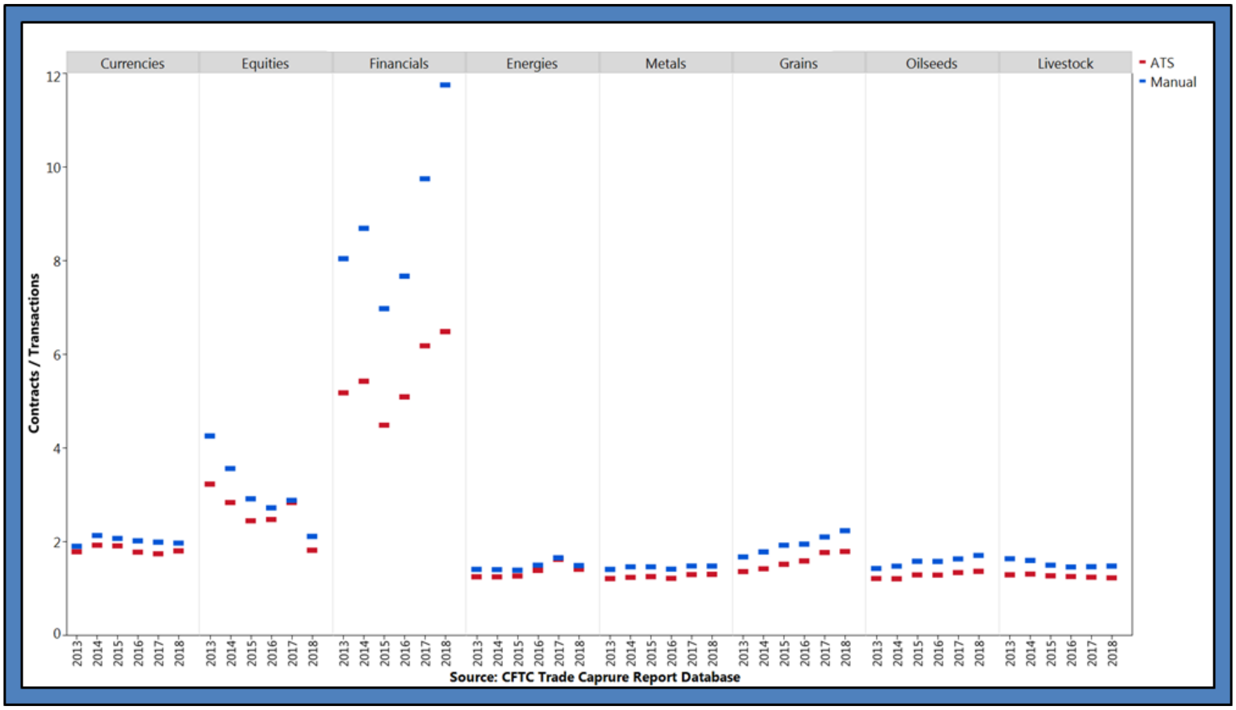

Figure 4 depicts, on average, the number of contracts that were consummated in every ATS order (in red) and manual order (in blue). Across all commodity groups, contract sizes per transaction for ATS orders were slightly smaller than for manual orders. Both groups had an average transaction size between 1 and 2 contracts. However, contract sizes per transaction in the Equities and Financials groups tended to be larger. After examining the market participants listed in the CFTC trade capture report database, DMO staff determined that there were considerable numbers of big institutional traders in the Equities and Financials groups who generally consummated more contracts per transaction.

Types of Orders

DMO staff examined the order type composition of automatically and manually entered orders. Staff categorized the order types simply based on whether they were limit, market, or stop orders. Limit orders define the maximum purchase price for buying and the minimum sale price for selling an instrument. Market orders get executed immediately at the current market price. Stop-loss orders do not immediately go on the book – they must be "triggered" at the price level submitted with the order.

Figure 5
Futures Order Type Breakdown

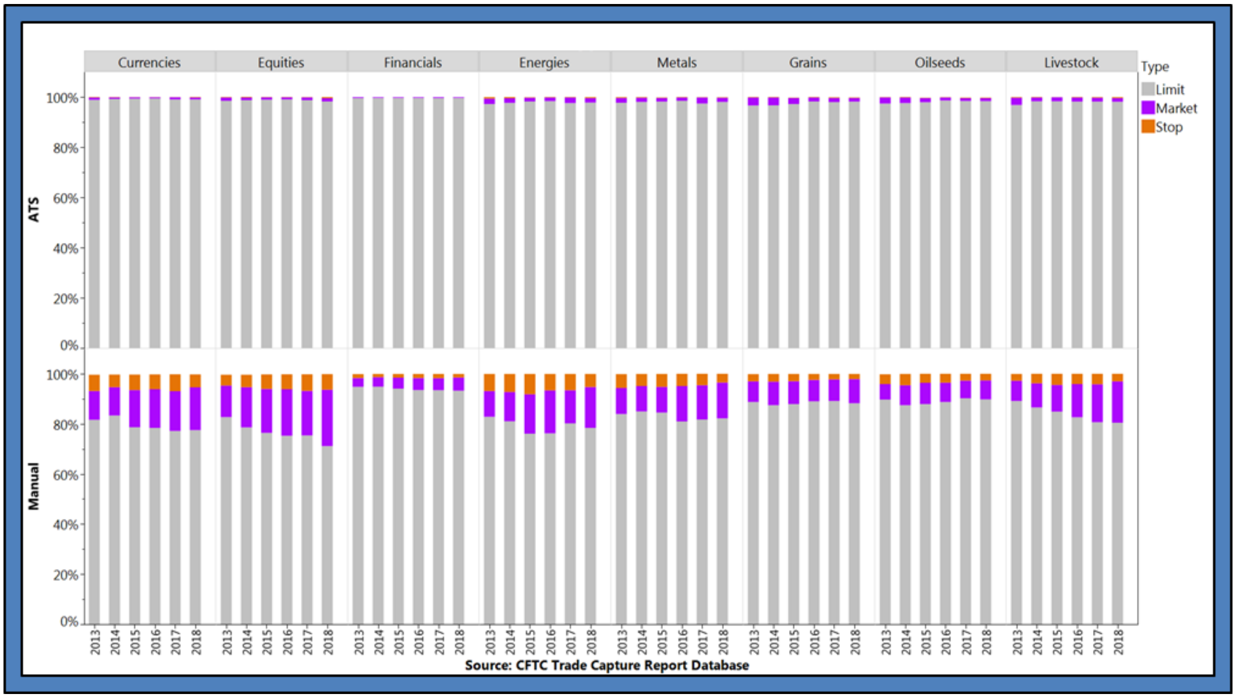

Figure 5 breaks down the order composition for ATS orders (top panel) and manual orders (bottom panel). The different order types are marked as follows: limit in grey, market in purple, and stop in orange. Staff calculated the order type percentage breakdowns in each commodity group based on the total traded volumes of the individual contract markets within the group. As the graph shows, ATS orders were almost exclusively limit orders. Manual orders were stop-loss orders 4% and market orders 11% of the time.

Based on interviews that DMO staff conducted with market participants who enter orders both manually or automatically, staff identified that a main reason for this difference is the ability of automated traders to replicate the functionality of stop-loss and market orders by relying on their speed in reading prices and placing limit orders instead. The implication of this finding is that market events, in terms of excessive price movements, cannot be explained solely by investigating stop-loss orders that were entered during the event. To reflect this, the CME's velocity halt logic includes both stop-loss and limit orders (CME, 2019).

Price Moves and Historical Volatility

DMO staff quantified the overall movement of commodity prices in two ways. First, staff counted the average number of daily price moves (up or down movements) in all contract markets within each commodity group. Second, staff calculated the standard deviation of a 252-day window of one-day, natural logarithm price returns. The aforementioned price returns were derived from the end-of-day settlement prices and were normalized to an annual volatility measure. Staff first calculated this historical price volatility for the individual contract markets. Then, staff averaged these numbers within each commodity group to arrive at a common volatility representation for every year. This depiction of volatility is considered to be driven by market fundamentals because it involves the change in prices over long periods of time, in this case over years.

Intra-day volatility, using pricing data within each trading date, from open to close, was not analyzed in this study.

Figure 6
Average Number of Daily Price Moves and Price Volatility

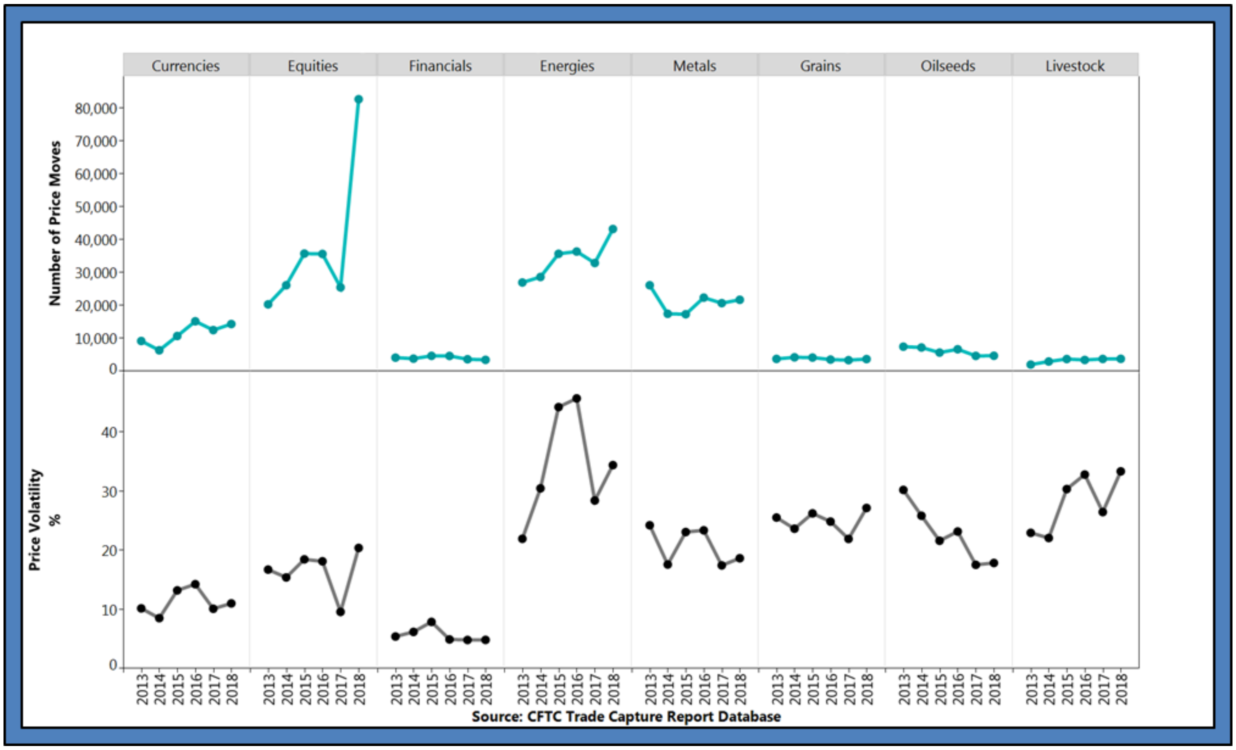

Figure 6 depicts the average number of daily price moves in the top panel, and the historical price volatility in the bottom panel of the graph. Based on this yearly depiction of the two price measurements, DMO staff concluded that for most of the commodity groups, when historical end-of-day volatility increased or decreased so did the number of daily price moves.

To further investigate the relationship between the two price measurements, DMO staff performed a correlation analysis, depicted in Figure 7 on the next page. Staff showed the degree and pattern of the relationships between the paired variables as a scatterplot. The numbers within the individual blocks represent the correlation coefficients. Most of the coefficients are above 0.5, meaning that there is moderate to high positive correlation between the two price measurements. This observation suggests that, in general, the fundamentals-driven historical volatility is not disconnected from trading activity that drives the number of up or down price ticks each day.

Figure 7
Correlation between Historical Volatility and Price Moves

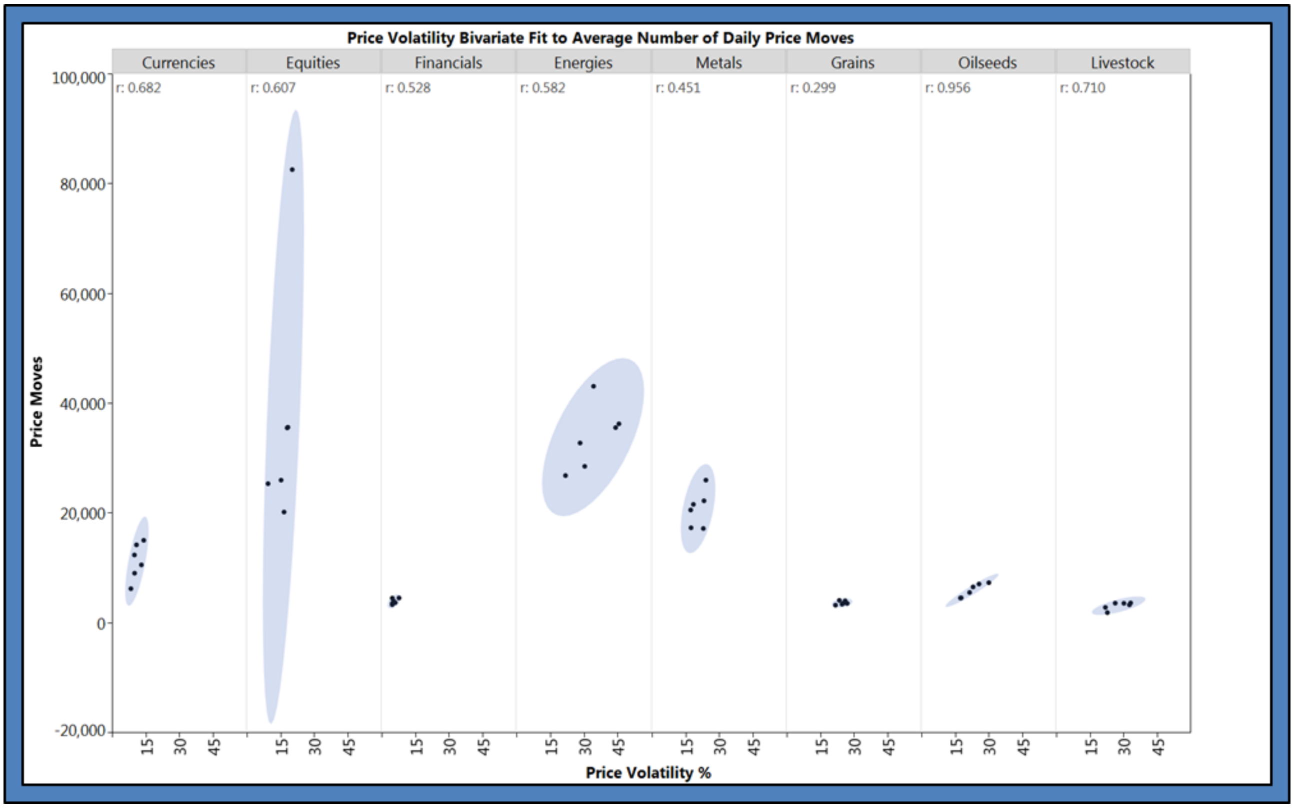

Figure 8
Correlation between Historical Volatility and Share of Automated Orders

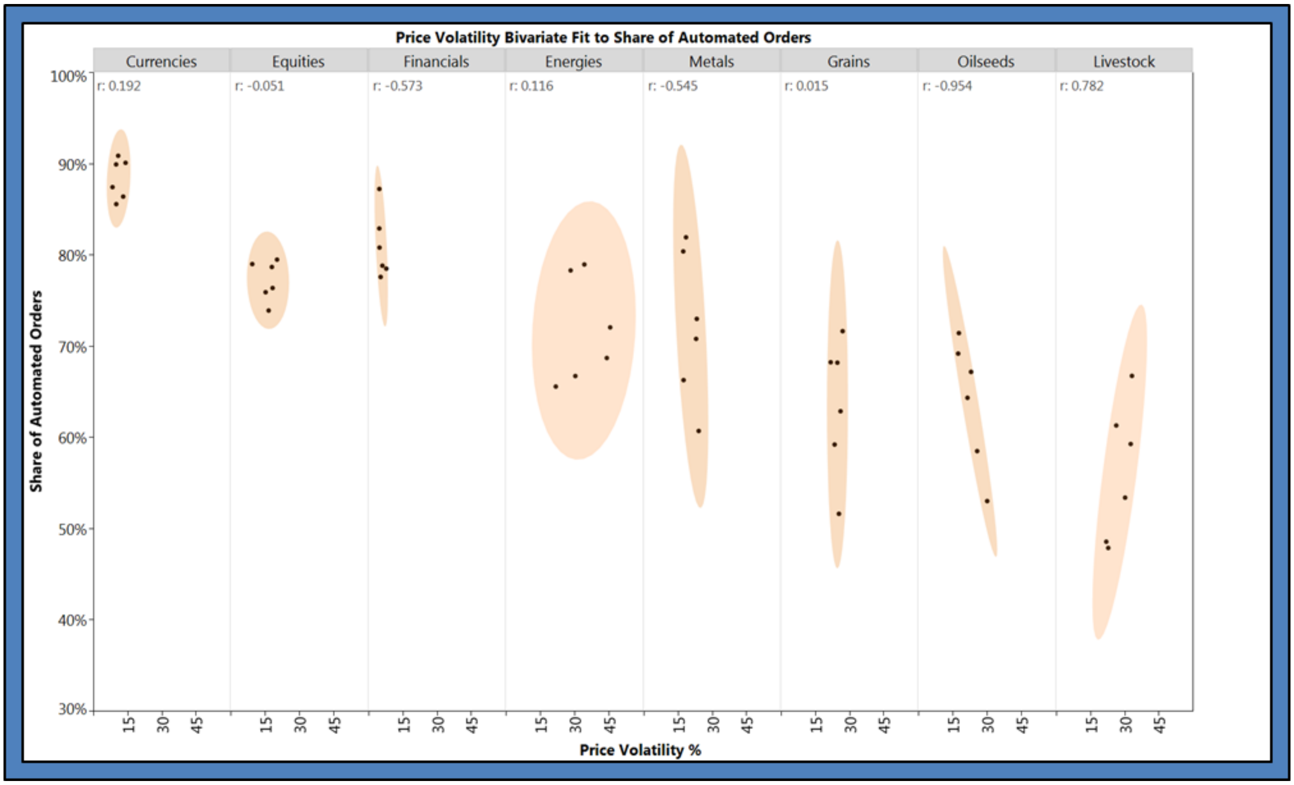

Figure 8 above shows a correlation analysis between historical end-of-day price volatility and share of automated orders. The numbers within the individual blocks represent the correlation coefficients. The majority of the correlation coefficients between these two variables are either around 0.1, which implies no relationship, or negative numbers, which implies a negative linear relationship.

As discussed at the beginning of this report, the level of automated trading in futures markets has been increasing steadily over the period from 2013 to 2018. The aforementioned price analysis shows that historical end-of-day price volatility has not been equally increasing year-over-year. However, this does not imply that automated trading has not affected short term market events or intra-day price volatility which was not part of this study.

Price Volatility and Transactional Volume

DMO staff also examined the volume traded, total number of transactions, and historical price volatility over the study period.

Figure 9
Total Futures Volume, Number of Transactions and Price Volatility

Figure 9 superimposes the total volume traded (in blue), the total number of transactions (in red), and the historical price volatility (in black) for every commodity group. Based on this analysis, the graph shows that generally as historical volatility goes up, so does the trading volume and number of transactions. For example, the notable decrease in historical volatility from 2015 to 2016 and its subsequent increase in 2017, in the Equities commodity group, are similarly reflected in the changes in volumes for the same years.

Conclusions and Takeaways

This research examined the effects that manually and automatically entered orders had on futures markets over a period of six years. DMO staff observed that automation has increased consistently over the study period. Furthermore, automatically submitted orders had a smaller number of contracts per transaction and were exposed to the market for shorter periods of time compared to manually entered orders. DMO staff also observed that historical end-of-day price volatility was positively correlated with the average number of daily price changes. Lastly, although DMO staff did not analyze intra-day price volatility movements, staff did not find a systematic rise in end-of-day historical price volatility as the share of automation increased across all futures markets.

Endnotes

1 End-of-day volatility is defined in this report as the statistical volatility calculated as a standard deviation of the natural logarithm of the end-of-day settlement price returns over a period of one year.

2 The analysis was based on the number of transactions regardless of the number of underlying contracts in each transaction.

References

CME, 2012, Chicago Mercantile Exchange Regulation Advisory Notice, "Manual/Automated Trading Indicator (FIX Tag 1028)," Rule 536.B., September 20. Accessed via website: https://www.cmegroup.com/rulebook/files/cme-group-Rule-536-B-Tag1028.pdf on June 13, 2019.

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Author Biographies

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Ms. Elitza Voeva-Kolev is a market analyst with the Market Intelligence Branch of the Division of Market Oversight at the Commodity Futures Trading Commission (CFTC). Prior to joining the CFTC, Ms. Voeva-Kolev was a surveillance analyst at the Federal Energy Regulatory Commission where she developed statistical methodologies for market models and surveillance screens, as well as assisted law enforcement officials in technical areas involving trading activities. Ms. Voeva-Kolev holds a Bachelor of Science degree in Civil Engineering from Rose-Hulman Institute of Technology and a Masters of Industrial and Systems Engineering degree from the University of Florida.

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Mr. Rahul Varma is the Associate Director, Division of Market Oversight, at the Commodity Futures Trading Commission. He has been an Associate Director at the CFTC since May 2013. From 2013 through 2016, Mr. Varma was in Market Surveillance with responsibility for Energy, Metals, Agricultural, and Softs markets. Since 2017, Mr. Varma has been in the newly formed Market Intelligence Branch of DMO.