Algorithmic Trading (AT) and High-Frequency Trading (HFT) methodologies have become increasingly significant components of the order stream in many capital and commodity markets. The equity markets were the first to embrace AT methods on a large-scale but these practices migrated quickly to futures, interest rate, FX, commodities and any other markets that utilize electronic trading platforms.

In the process, many opinions and concerns have surfaced regarding the impact of AT and HFT practices on market dynamics. Some analysts argue that AT serves to enhance liquidity, which in turn mitigates untoward price volatility. Others have suggested that AT practices may exacerbate price volatility and lead to reduced liquidity, particularly in times of market stress.

Our objective is to assess the degree to which AT is correlated with market liquidity and volatility in the context of several flagship CME Group products including E-mini S&P 500, EuroFX, Eurodollar, 10-Year Treasury and Crude Oil futures.

Defining Algorithmic Trading – An algorithm simply refers to any pre-defined step-by-step process used to accomplish a task. We might broadly define the concept of a "trade algorithm" as any automated order execution methodology. Once the system is developed and deployed, the intervention of the human hand is not required to operate these systems although, of course, it is desirable closely to monitor the operation and performance of such systems to establish prudent credit controls.

The objective of such deployment may simply be to achieve more favorable fills. For example, volume-weighted average price (VWAP) methodologies were perhaps one of the first applications of AT systems.

But the term has expanded in recent years to refer to automated systems deployed for any purpose. Thus, one may implement a technical trading system on a completely automated basis. This may include references to empirical data or to objectively defined charting patterns or even to models that rely upon a weighted battery of fundamental indicators.

Or, a market maker may use automation to populate the market with quotes as a function of dynamic market conditions. This may be particularly useful in the context of options where there may be a huge number of different option series that one may re-price on a real-time basis with the use of mathematical option pricing models.

We might distinguish AT and HFT by suggesting that HFT represents a subset of AT. Specification of an empirical definition of "high-frequency" is arbitrary and ultimately a function of the technological state of the art which is of course dynamic over time. But it is noteworthy that some AT techniques, including the first applications of AT techniques such as the VWAP order entry, are intended to fragment orders into smaller bits and pieces in an attempt to minimize market impact.

Review of the Literature – The literature generally supports the notion that electronic trading contributes to market efficiencies by bolstering liquidity and thereby contributes to the price discovery function served by futures markets. Frino and McKenzie (2002) found that "the move to screen trading strengthens the simultaneity of price discovery in the cash and futures markets and lessens the existence of a lead-lag relationship."[1] Grunbickler, Schwartz and Longstaff (1994) concluded that their "results are consistent with the hypothesis that screen trading accelerates the price discovery process."[2]

But these studies do not directly address the impact of AT on market dynamics. In fact, the literature is rather scant in this regard due to the difficulty in obtaining data regarding the volume and messaging traffic associated with AT methodologies.

Hendershott, Jones, and Menkveld (2007) worked around the data constraint by referencing the volume of electronic message traffic (entry of orders) on the New York Stock Exchange (NYSE) as a proxy for algorithmic trading. They concluded that "algorithmic trading does causally improve liquidity and enhances the informativeness of quotes and prices." [3]

[1] Frino, Alex and McKenzie, Michael D., The Impact of Screen Trading on the Link Between Stock Index and Stock Index Futures Prices: Evidence from UK Markets. EFMA 2002 London Meetings.

[2] Grünbichler, Andreas; Schwartz, Eduardo S. and Longstaff, Francis A., Electronic Screen Trading and the Transmission of Information: An Empirical Examination. JOURNAL OF FINANCIAL INTERMEDIATION Vol 3 No 2, 1994.

[3] Hendershott, Terrence, Jones, Charles M. and Menkveld, Albert J., Does Algorithmic Trading Improve Liquidity? (February 5, 2009). WFA 2008 Paper.

More recently, Deutsche Bourse made data regarding AT on its markets available for academic purposes, prompting several new publications. Using that Deutsche Bourse data, Hendershott and Riordan (2009) determined that algorithmic traders "contribute more to the efficient price by placing more efficient quotes and … demanding liquidity to move the prices towards the efficient price." [4] Riordan and Storkenmaier (2009) found evidence that algorithmic traders are "using the increase in … [Deutsche Bourse electronic trading] … system speed to process information faster, thereby increasing liquidity and the informativeness of prices." [5]

Castura, Litzenberger and Gorelick (2010) approached the problem by studying bid/ask spreads in manually traded vs. automated equity markets. They concluded that "U.S. equity markets appear to have become more efficient with tighter spreads and greater liquidity over the past several years." [6]

Study Design - How are algorithmic trading methodologies affecting activity in CME Group markets? Examination of this activity is facilitated by CME Globex policy that requires Automated Trading Systems (ATS) to declare themselves as such. For purposes of this policy, we define an ATS as a system that automates the generation and routing of orders to Globex.

CME began requiring members utilizing ATS systems to register as such in 2006; NYMEX and COMEX began registration in Q4 2009. A trader who primarily enters orders manually but also uses automated spreading activity is not considered an ATS and is not required to register as such.

Accordingly, we can monitor the volume of executed orders emanating from ATSs vs. the entirety of orders. Similarly, we can monitor the volume of message traffic, *i.e.,* orders that might or might not ultimately be filled.

[4] Hendershott, Terrence and Riordan, Ryan, Algorithmic Trading and Information (September 2009). NET Institute Working Paper No. 09-08.
[5] Riordan, Ryan and Storkenmaier, Andreas, Exchange System Innovation and Algorithmic Liquidity Supply (July 27, 2009).
[6] Castura, Jeff; Litzenberger, Robert and Gorelick, Richard, Market Efficiency and Microstructure Evolution in U.S. Equity Markets: A High-Frequency Perspective, (April 22, 2010).

CME Group Rule 576 requires that each order entered into the CME Globex electronic trading system include the submission of an operator ID, also referred to as the "Tag 50 ID" or "User ID." These IDs are unique to the party who entered the order. For orders entered manually, the Tag 50 ID must be unique to the individual entering the order into CME Globex. For orders entered by an automated trading system ("ATS"), the Tag 50 ID must be unique to the person, or the identified team of persons on the same shift, who are responsible for the operation of the ATS. All Tag 50 IDs must be unique at the level of the clearing member firm. See Market Regulation Advisory Notice RA0915-5, "Operator ID ('Tag 50') Required on All CME Globex Orders," available online at www.cmegroup.com/rulebook/files/CME_Group_RA0915-5.pdf

Based upon this information, it is possible to determine the proportion of AT relative to total volume traded in any particular market. It is further possible to identify the proportion of message traffic, *i.e.,* entered orders, that may be traced back to algorithmic traders. Note that message traffic typically far exceeds volume despite the fact that any particular message may represent an order for multiple contracts.

Note that the proportion of volume and message traffic from algorithmic traders varies quite a bit from one market to the next. The proportion of AT is generally highest in CME currency futures such as EuroFX, followed by stock index futures such as the E-mini S&P 500. Interest rate markets including Eurodollar and 10-Year Treasury note futures are close behind with commodities such as crude oil displaying the least amount of AT activity.

Exhibit 1: Algorithmic Activity
(1st Qtr 2010)

	% from AT	
	Volume	**Message Traffic**
E-mini S&P 500 Futures	51.66%	69.93%
EuroFX Futures	69.32%	83.41%
Eurodollar Futures	51.29%	64.46%
10-Yr T-Note Futures	49.88%	68.33%
Crude Oil Futures	35.34%	71.24%

Our study plan deploys an ordinary least squares (OLS) regression analysis to determine any link between the proportion of AT activity and liquidity as well as volatility. In particular, we are interested in the slope of the beta coefficient generated by such analysis as well as the R-squared (R^2) and the t-statistic associated with that coefficient.

In order to measure liquidity, we examined two variables including the market width and market depth. Market width is expressed as the average bid-ask spread for a given size order during the course of a single day. This represents a classic measure of liquidity and is displayed in terms of dollars per contract. *E.g.,* the average bid-ask spread for E-mini S&P 500 futures might have been $16.00 during regular trading hours (RTH) throughout the course of a particular day, noting that the minimum tick size is 0.25 index points which equates to $12.50. Market depth is quoted in terms of contracts shown at the "top-of-the-book," *i.e.,* at the best bid-ask spread in the market. *E.g.,* there may be 1,000 contracts bid at the highest available bid; and, 1,200 contracts shown at the lowest available offer. Thus, we quote the average or 1,100 contracts.

In order to measure volatility, we reference the high-low range for any particular day. We display this information in dollars per contract. *E.g.,* if the high-low range for E-mini S&P 500 futures was 10.00 index points during the course of a particular day, then this range may be represented as $500.00 (= contract multiplier of $50 x 10.00 index points).

Our study called for us to apply the OLS analysis to find the relationship between our 2 measures of liquidity (market width and market depth) and one measure of volatility with our 2 measures of AT including the proportion of volume traced to AT and the proportion of message traffic traced to AT. We applied this analysis between May 1, 2008 and May 28, 2010 with nearby E-mini S&P 500 futures; nearby EuroFX futures; 5th month Eurodollar futures; nearby 10-year Treasury note futures; and, nearby crude oil futures.

The number of data points available was not consistent across all these analyses to the extent that there were various missing data points in the Exchange database. Further, we culled any apparent erroneous data points from our sample.

E-mini S&P 500 Results – In order to illustrate the results obtained from our OLS analysis, we provide a series of scatter diagrams in the context of our analysis of E-mini S&P 500 futures. Exhibit 2 depicts the relationship between the percentage or proportion of daily volume attributed to algorithmic traders vs. the average bid/ask spread or market width during regular trading hours (RTH). The graphic further illustrates the results of our OLS analysis, the R-squared associated with such analysis along with the trendline.

Exhibit 2: E-mini S&P 500 Algo Volume & Market Width

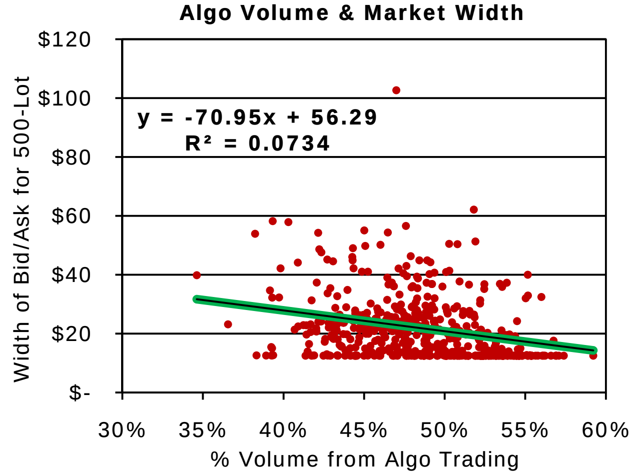
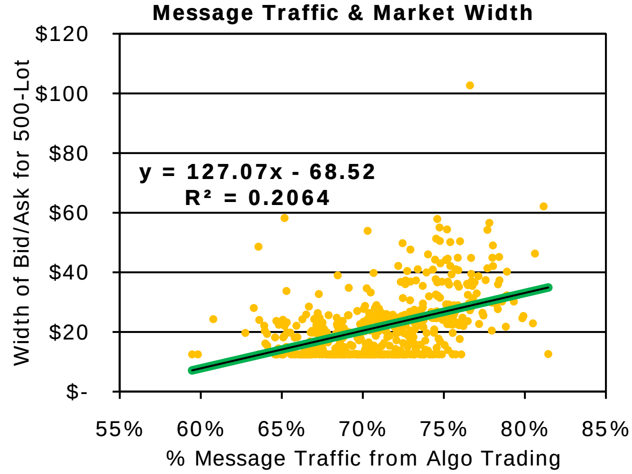


Exhibit 2 suggests that market width has generally decreased as a function of the proportion of AT in the marketplace. The beta coefficient or slope of the trendline is shown at -70.95. Note that we are quoting algo trading as a percentage amount and the width of the bid/ask spread in dollars per contract.

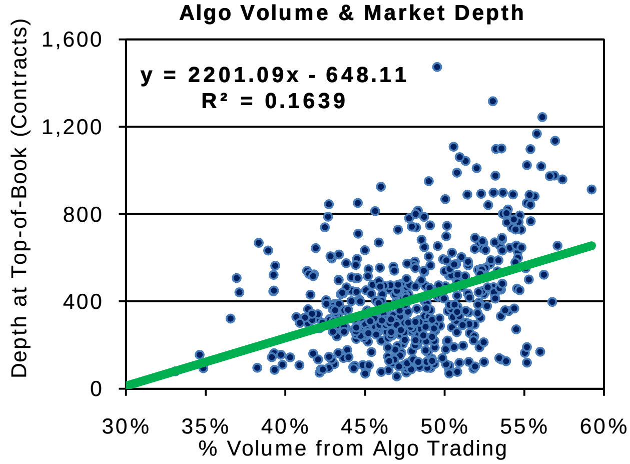
Exhibit 3: E-mini S&P 500 Algo Message Traffic & Market Width



Thus, a 1% (or 0.01) increase in the proportion of algorithmic trading might generally have been accompanied by a $0.7095 reduction in the bid/ask spread. The significance of that reduction might be appreciated when one considers that E-mini S&P 500 futures have traded on average 2.3 million contracts per day in 2010 through May. Thus, a cost reduction of \$0.7095 might represent savings of \$1.6 million a day or over \$400 million annually.

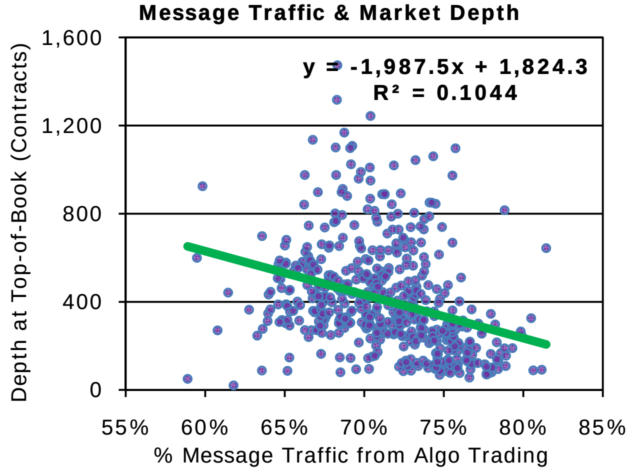
However, we note that the proportion of message traffic emanating from algorithmic sources is correlated with an increase in the width of the bid/ask spread as suggested in Exhibit 3.

Exhibit 4: E-mini S&P 500 Algo Volume & Market Depth



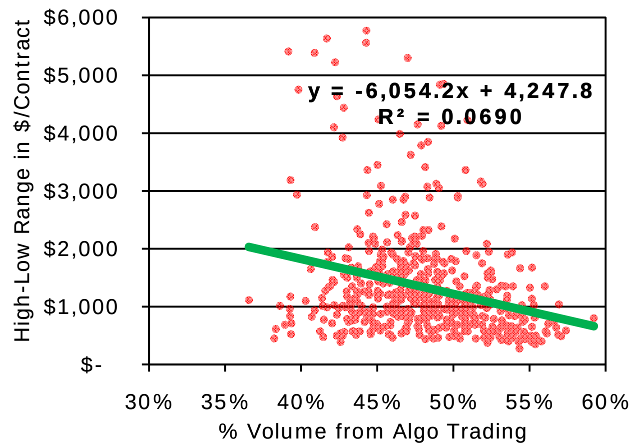
We might similarly depict the relationships between the proportion of algorithmic volume and algorithmic message traffic on market depth. As illustrated in Exhibit 4, we find that as the proportion of algorithmic volume increases, this is accompanied by enhanced depth of book. However, the depth of book was diminished as algorithmic message traffic increases over our sample period as illustrated in Exhibit 5.

Exhibit 5: E-mini S&P 500 Algo Message Traffic & Market Depth



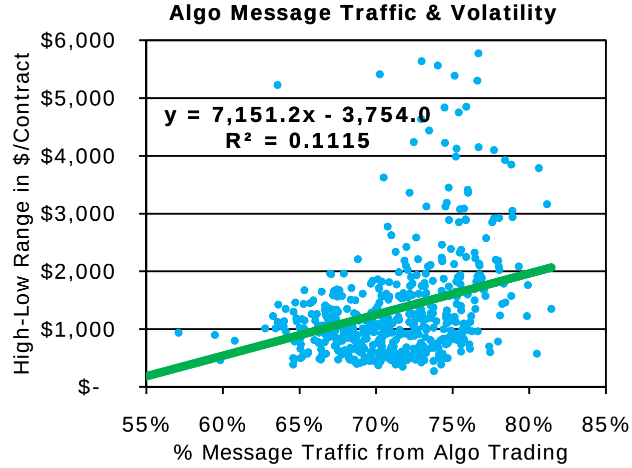
Exhibits 6 and 7 illustrate the historic relationship between the proportion of algorithmic volume and message traffic on volatility as measured by the high-low range. We find that while algorithmic volume is associated with reduced volatility, algorithmic message traffic was associated with generally increased volatility.

Exhibit 6: E-mini S&P 500 Algo Volume & Volatility



While the relationships achieved the threshold of statistical significance as suggested by the t-statistics, we caution that this does not necessarily imply a causal relationship. Rather, other relationships may be implicit.

Exhibit 7: E-mini S&P 500 Algo Message Traffic & Volatility



E.g., It is plausible that the proportion of algorithmic related message traffic increases as a function of market volatility noting that automated systems may be best postured to adapt to a "fast market" environment. In other words, volatility may be triggering increases in AT order flow rather than the reverse. Further, increased volatility tends to detract from liquidity in the sense that market makers react to increased volatility by showing wider bid/ask spreads and reducing the scale of their activity thereby diminishing the depth of the book.

EuroFX Results **–** Exhibit 8 summarizes the results of our study by providing the T-statistic for all relationships. As a general rule, the threshold of statistical significance may be found when the absolute value of the t-statistic exceeds 2.0.

The proportion of AT volume in EuroFX futures was insignificantly associated with greater liquidity (decreased bid/ask spread and more market depth) but greater volatility. However, the proportion of AT message traffic in EuroFX futures was significantly associated with reduced liquidity and greater volatility.

Again, however, we may question whether increased AT message traffic causes these effects or whether algorithmic traders are best equipped to "chase volatility" vis-à-vis so-called "point-and-click" traders. We further note the fact that increased volatility tends to be associated with reduced liquidity as traders respond by becoming more conservative in their trading practices.

It is further noteworthy that the proportion of AT activity in EuroFX is much higher than in any other market studied. Some 69.32% of volume and 83.41% of message traffic recorded in EuroFX futures during the 1st calendar quarter of 2010 is traced to algorithmic sources. It is plausible that as AT activity becomes dominant that the character of a market is altered and fluctuations in the proportion of AT activity become a non-factor.

Other Markets – The proportion of AT activity in terms of volume or message traffic was significantly associated with increased liquidity (diminished market width and increased market depth) and reduced volatility in the context of Eurodollar, 10-Year Treasury note and crude oil futures. While the R-squared associated with each of these OLS analyses was sufficiently modest to suggest that AT explains only a small proportion of the observed effects, the T-statistics are significant by any standard in each case studied.

Exhibit 8: Summary Results

	T-Stats		
	% AT Volume	**% AT Message Traffic**	**Comment**
E-mini S&P 500 Futures			
Width	-6.30	11.46	Mixed Results
Depth	10.07	-7.79	Mixed Results
Volatility	-6.29	8.08	Mixed Results
EuroFX Futures			
Width	-1.59	9.74	AT traffic correlated with wider bid/ask
Depth	1.33	-13.82	AT traffic correlated with reduced depth
Volatility	0.24	4.84	AT traffic correlated with increased volatility
Eurodollar Futures			
Width	-13.48	-4.10	AT volume and message traffic correlated with narrow bid/ask
Depth	16.64	9.65	AT volume and message traffic correlated with increased depth
Volatility	-13.29	-7.05	AT volume and message traffic correlated with reduced volatility
10-Yr T-Note Futures			
Width	-8.53	-13.62	AT volume and message traffic correlated with narrow bid/ask
Depth	8.66	9.68	AT volume and message traffic correlated with increased depth
Volatility	-3.13	-5.87	AT volume and message traffic correlated with reduced volatility
Crude Oil Futures			
Width	-15.00	-10.84	AT volume and message traffic correlated with narrow bid/ask
Depth	13.92	7.19	AT volume and message traffic correlated with increased depth
Volatility	-6.63	-6.53	AT volume and message traffic correlated with reduced volatility

It may further be noteworthy that the general proportion of AT activity in Eurodollars, 10-Year T-notes and crude oil is generally less than that observed in EuroFX and E-mini S&P 500 futures. Thus, to the extent that AT activity is beneficial, these markets may have more benefits yet to accrue.

Conclusion – Algorithmic or automated trading systems have become increasingly commonplace within CME Group markets. Thus, we are interested in determining the extent of such activity and the effect it may apply upon liquidity and volatility. Our results suggest that, on balance, increased proportions of AT sourced volume and message traffic tend to be associated with enhanced liquidity and reduced volatility.

However, these results are uneven across different markets. In particular, the results tend to be most positive in markets where the proportion of AT activity is relatively low including Eurodollar, 10-Year T-note and crude oil futures. Mixed results are observed in markets which enjoy higher current levels of AT activity including E-mini S&P 500 and EuroFX futures.

It is tempting, but perhaps unwarranted to attribute causal relationships. Certainly other factors are at work in this regard including the possibility that algorithmic traders are best equipped to respond in the context of "fast" markets exhibiting high volatility. We further note that high volatility tends to cause market makers to become less aggressive, showing wider bid/ask spreads and reducing the size of their standing orders. The complexity of these intertwined relationships likely detracts from our ability to draw unimpeachable conclusions.

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OLS Analysis: Market Width, Depth & Volatility as Function of % of Volume from Algorithmic Trading
(May 2, 2008 – May 28, 2010)

	Intercept	Beta	T-Stat	R-Squared	Sample Size
E-mini S&P 500 Futures (Nearby Month)					
Market Width (500-Lot)	56.29	-70.95	-6.30	0.0734	502
Market Depth (Top-of-Book)	-648.1	2,201.1	10.07	0.1639	513
Volatility (Daily High-Low Range)	4,247.8	-6,054.2	-6.29	0.0708	522
EuroFX Futures (Nearby Month)					
Market Width (25-Lot)	41.69	-24.17	-1.59	0.0053	479
Market Depth (Top-of-Book)	11.67	13.43	1.33	0.0037	483
Volatility (Daily High-Low Range)	1,079.0	197.5	0.24	0.0001	494
Eurodollar Futures (5th Month)					
Market Width (500-Lot)	73.16	-121.43	-13.48	0.2709	491
Market Depth (Top-of-Book)	-6,327.0	17,733.8	16.64	0.3522	511
Volatility (Daily High-Low Range)	881.8	-1,418.7	-13.29	0.2545	519
10-Year Treasury Note Futures (Nearby Month)					
Market Width (500-Lot)	72.99	-93.62	-8.53	0.1327	477
Market Depth (Top-of-Book)	-341.5	1,612.4	8.66	0.1310	500
Volatility (Daily High-Low Range)	1,105.6	-1,010.3	-3.13	0.0186	520
Crude Oil Futures (Nearby Month)					
Market Width (25-Lot)	136.3	-271.5	-15.00	0.3125	497
Market Depth (Top-of-Book)	-4.08	31.48	13.92	0.2734	517
Volatility (Daily High-Low Range)	7,960.5	-13,949	-6.63	0.0778	523

OLS Analysis: Market Width, Depth & Volatility as Function of % of Message Traffic from Algorithmic Trading
(May 2, 2008 – May 28, 2010)

	Intercept	Beta	T-Stat	R-Squared	Sample Size
E-mini S&P 500 Futures (Nearby Month)					
Market Width (500-Lot)	-68.52	127.07	11.46	0.2064	502
Market Depth (Top-of-Book)	1,824.3	-1,987.5	-7.79	0.1062	513
Volatility (Daily High-Low Range)	-3,754.0	7,151.2	8.08	0.1115	522
EuroFX Futures (Nearby Month)					
Market Width (25-Lot)	-108.4	150.6	9.74	0.1641	479
Market Depth (Top-of-Book)	137.7	-132.1	-13.82	0.2842	483
Volatility (Daily High-Low Range)	-2,447.6	4,163.8	4.84	0.0454	494
Eurodollar Futures (5th Month)					
Market Width (500-Lot)	38.66	-34.54	-4.10	0.0333	491
Market Depth (Top-of-Book)	-4,014.0	9,801.4	9.65	0.1547	511
Volatility (Daily High-Low Range)	657.5	-714.3	-7.05	0.0877	519
10-Year Treasury Note Futures (Nearby Month)					
Market Width (500-Lot)	132.6	-158.6	-13.62	0.2809	477
Market Depth (Top-of-Book)	-785.0	1,849.1	9.68	0.1585	500
Volatility (Daily High-Low Range)	1,873.6	-1,906.6	-5.87	0.0624	520
Crude Oil Futures (Nearby Month)					
Market Width (25-Lot)	146.6	-140.3	-10.84	0.1917	497
Market Depth (Top-of-Book)	-2.14	11.80	7.19	0.0913	517
Volatility (Daily High-Low Range)	9,686.1	-8,901.2	-6.53	0.0756	523