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by

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Paper presented at the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management
St. Louis, Missouri, April 24-25, 2017.

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The rise of large/institutional traders in agricultural commodities calls for research on the analysis of market impact of trading. We aim to uncover the pattern and duration of market impact of trading in corn, soybeans and wheat during the period of 2008- 2015. Using the CME intraday electronic trade and quote data, we find support for square-root temporary impact of trading volume that lasts 10 minutes for corn and wheat, 16 minutes for soybeans. We also find evidence for post-trade permanent impact with a decaying effect in the form of -1/2 power of time. The permanent impact lasts 8 minutes for corn and wheat, 6 minutes for soybeans.

Keywords: Market Impact, Temporary Impact, Permanent Impact, USDA Reports

Introduction

The advent of automated trading and increasing percentage of large traders in the grain futures markets highlight the need for understanding intraday impact of trades. We propose to study the price impact of trades in the electronic corn, soybeans and wheat futures markets. Automated trading has gained substantial ground since the introduction of Globex electronic trading platform for grain futures in 2006. Automated trading was involved in 68.7%, 57.7% and 64.4% of corn, soybeans and wheat futures trading according to CFTC (Haynes and Roberts, 2015). Meanwhile, financialization of commodities, including agricultural commodities, has led to a rising percentage of large traders. Irwin and Sanders (2012) report that open interests held by the reporting, often large/institutional traders have increased to account for about 90% in grain futures. As a result, understanding market impact of trades is crucial to market participants as large orders and order splitting become an important aspect of the current electronic market.

Trade impact is an important dimension of liquidity that is key to market efficiency, asset pricing and corporate finance. Likely due to the lack of trade and quote data for agricultural commodity futures, there is limited research in the intraday market behavior and even less in the market impact of trades. The notable exceptions on intraday market behavior are Wang et al. (2014) on the bid-ask spread of corn futures and Lehecka et al. (2014) on the impact of USDA reports on intraday price changes. The former analyzed the quoted bid-ask spread using a regression model, while the latter compared intraday return and volume changes before and after the arrival of new information. More directly related to the issue of trade impact, Marshall et al. (2011) tried to find the best low-frequency proxy at daily interval that match intraday metrics of market impact. Hasbrouck (2004) analyzed the impact of trading volume of pork belly (along with financial futures) on unobserved efficient price using floor trading data. Therefore, none of the above research models the nature (transient or permanent) and shape (convex or concave) of price impact of trades in the electronic grain futures markets.

We try to fill the gap by modelling the trade impact on prices in the electronic grain futures markets. Our focus is on actual trade prices, instead of the efficient price. We contribute to the literature by (a) explicitly modeling the shape of trade impact over time; (b) allowing for both transient impact (due to order processing and inventory risk) and permanent impact (due to asymmetric information). We will employ trade and quote data for corn, soybeans and wheat from 2008 to 2015 obtained from the CME Group. Our regression analyses show evidence for both significant square-root effect and a time decaying effect of trading in the form of power function across all three commodities.

The rest of the paper is organized as follows. We first review the literature on market impact in equity and commodity markets. We describe the data and methodology employed for our regression analysis. We analyze the regression results before we conclude in the last section.

Literature Review

Market microstructure research on grain markets started gaining popularity in recent years. Two eminent examples are the bid-ask spread analysis of corn futures by Wang et al. (2014), and the description of volatility and volume of corn futures by Lehecka et al. (2014). The former found that grain stock reports, but not WASDE reports, have significant impact on the bid-ask spread. The latter found that market activity, reflected in return volatility and volume, is strong at market open and persists for 10 minutes.

More directly related to the issue of trade impact in commodity markets, Marshall et al. (2011) compared the low-frequency (daily interval) performance of proxies to intraday liquidity measures (bid-ask spread and price impact) in commodities. Their main purpose was to find the best low-frequency proxy that match intraday metrics. Another related research is Hasbrouck's (2004) study on pork belly futures using trade data from the *floor trading*. Hasbrouck (2004) focused on the trade impact on the *unobservable efficient price*, and inferred bid/ask levels and buy/sell directions from estimated efficient prices and transaction costs using Bayesian filtering techniques.

The literature on trade impact in equity markets is relatively extensive. Bouchard et al. (2004) and Almgren et al. (2005) and the references therein documented evidence for square root (or more generally power function) impact of trading volume on stock prices. Bacry et al. (2014), using proprietary trading data, found that there is a convex time decay after a meta (large) order ends, in addition to the square root impact of trading volume.

To the best of our knowledge, there is paucity of research on trade impact in commodity futures markets. We intend to fill the gap in the literature by analyzing the trade impact of corn, soybeans and wheat using intraday electronic trading data.

Data and Methodology

Data Summary

We obtain from the CME (Chicago Mercantile Exchange) Group the Trade and Quote data for corn, soybeans, and wheat futures from January 2008 to May 2015. We retain only the nearby futures contract for our empirical analysis. The CME intraday data is stamped to second.

Table 1 summarizes trade price and volume for the three commodities at 2-minute interval. Three variables are reported in the table: last trade price, first-order price difference and volume with Lee-Ready buy/sell signs (+1 for buy and -1 for sell). Average prices for corn, soybeans and wheat during the sample period are \$5.20/bushel, \$12.33/bushel, and \$6.56/bushel, respectively. The ADF test for three commodities (not reported) shows that the first-order price difference is stationary. Three commodities exhibit only mild degree of non-normality in futures prices. Figures 1-3 show the price and volume trend for corn, soybeans and wheat, respectively. The common feature of three commodity prices is mean-reversion. Although not visually evident, commodity prices have a slight downward trend during the sample period, which is consistent with the average negative (sell) trading volume as reported in Table 1. The three figures also show that trading volumes at the 2-min interval before 2012 are larger than after 2012, an evidence of fragmentation over time.

In addition, we include dummy variables to control the effect of official grain reports and seasonality at various frequencies. Specifically, WASDE and Grain Stock report dates obtained from the USDA are used to evaluate market impact surrounding heavy public information flow. We also control the effects of market open and close, day of the week, contract rolling dates as used in Wang et al. (2014), and contract expiration month.

Table 1: Summary Statistics for Corn, Soybeans and Wheat (2008-2015)

Commodity	Variable	N	Mean	Std. Dev.	Min.	Med.	Max.	Skew.	Kurt.
Corn	Price	205169	5.20	1.45	2.90	4.88	8.34	0.35	-1.31
	PDiff	205168	-7.2E-06	0.01	-1.72	0.00	0.42	-20.74	3259.75
	Volm*	205169	-1.02	9.64	-136.01	-1.73	100.70	-0.13	5.75
Soybeans	Price	172282	12.33	2.17	7.78	12.79	17.90	-0.04	-1.12
	PDiff	172281	-2.0E-05	0.02	-1.85	0.00	0.70	-12.16	892.81
	Volm*	172282	-0.79	4.13	-29.72	-1.41	27.62	0.21	0.50
Wheat	Price	168571	6.56	1.36	4.25	6.45	13.35	0.72	0.37
	PDiff	168570	-2.5E-05	0.02	-1.12	0.00	1.86	7.44	960.14
	Volm*	168571	-1.15	3.75	-28.12	-1.73	20.95	0.16	0.10

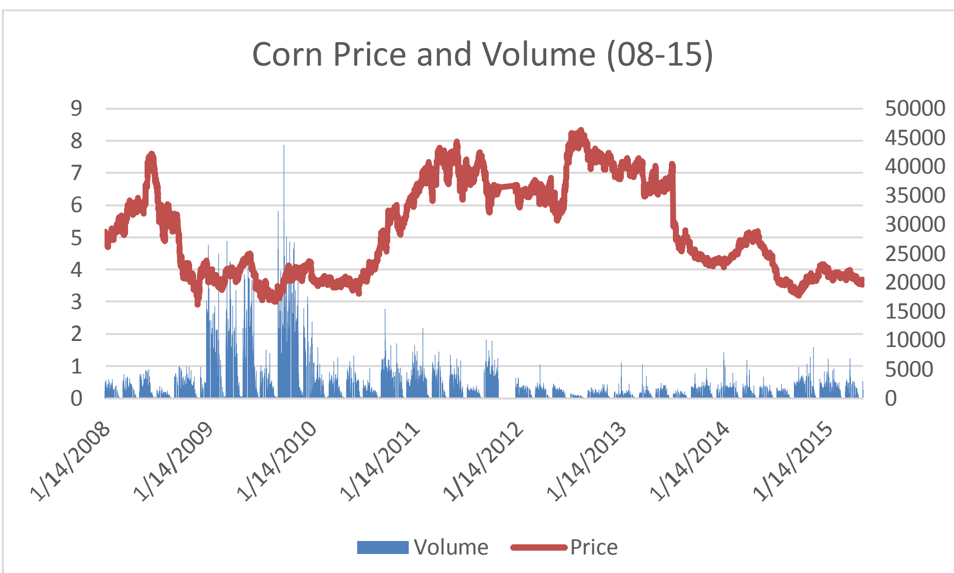

Figure 1: Corn Price and Volume (2008-2015)

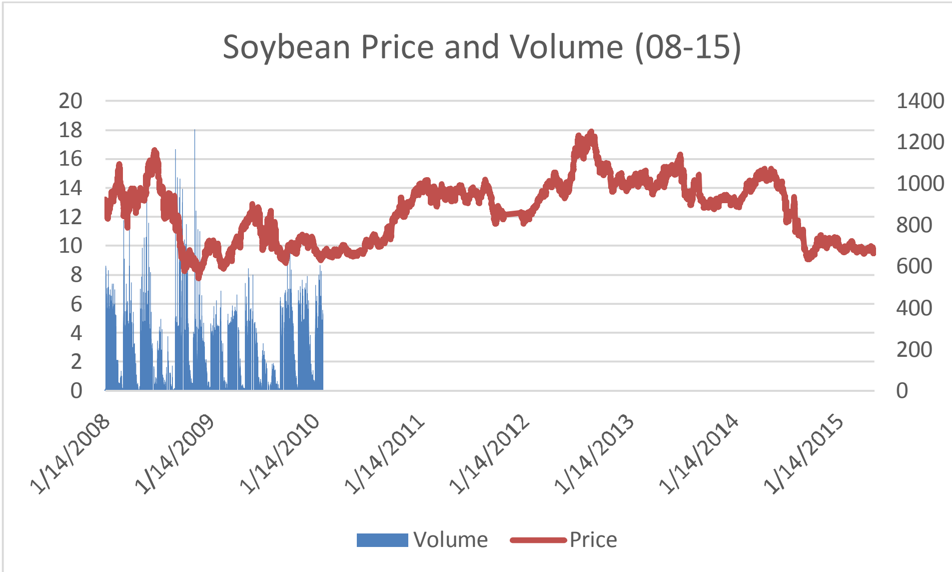

Figure 2: Soybean Price and Volume (2008-2015)

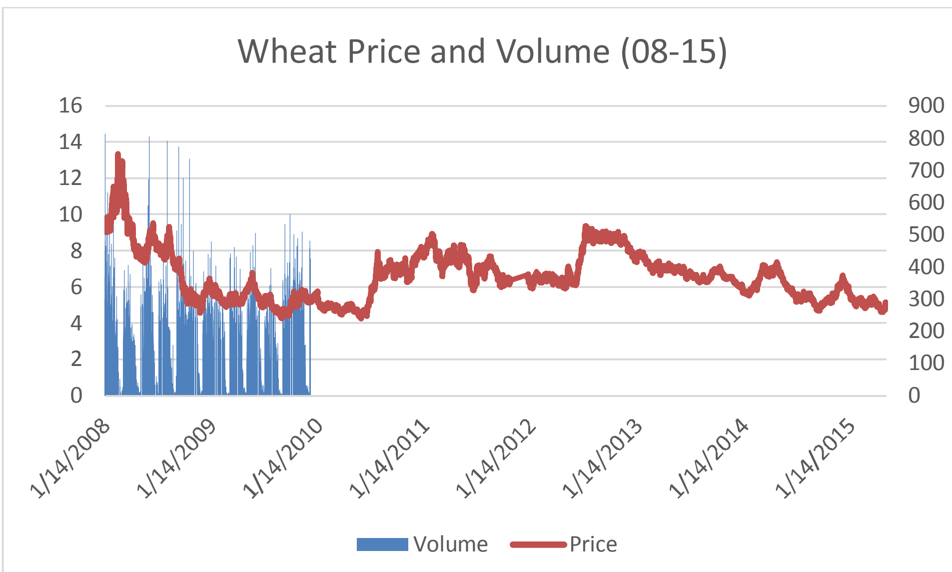

Figure 3: Wheat Price and Volume (2008-2015)

Regression Model

Based on Bouchaud et al. (2004), Almgren et al. (2005) and Bacry et al. (2014) findings in stock trading, we propose Hypotheses 1 and 2:

H1: There is a square-root effect of trading volume on commodity price.

H2: There is a convex decaying effect of trading volume on commodity price.

We hypothesize that USDA reporting induces trading activities and leads to significant market impact, as with Wang et al. (2014):

H3: There is significant market impact on the USDA reporting days.

Lastly, we conjecture that market impact tends to be more at the open and close time than other time of a day due to the U-shaped seasonality of intraday volatility (H4.1), more on the days of contract rolling than regular trading days (H4.2), no significant difference across days of week (H4.3), and contract months of year (H4.4).

H4: There is significant seasonality in market impact at open & close and contract rolling days, but not significant seasonality across days of week, and contract months of year.

We employ Equation (1) below to test the hypotheses above. In the regression, we also identify how long the impact of a trade lasts for each commodity, i.e. the number of lags I and leads L in the equation.

$$\Delta P_t = \beta_0 + \sum_{i=1}^{p} \beta_i \Delta P_{t-i} + \sum_{i=0}^{I} \gamma_i \sqrt{|V_{t-i} D_{t-i}|}\, D_{t-i} + \sum_{i=0}^{L} \lambda_i \frac{1}{\sqrt{t+i}} V_{t+i} D_{t+i} + \sum \alpha X_t + \epsilon_t \quad (1)$$

where P_t is the trade price and ΔP_t or *PDiff* hereafter is price impact at 2-min interval; V_t is volume; D_t is the Lee-Ready buy/sell indicator using quotes and trades as opposed to Hasbrouck's Bayesian inference using only trade data; X_t are dummy variables, including USDA WASDE and grain stock reports, market open (*open*) and close (*close*), day of the week (*Tue-Fri*), contract rolling dates (*ROLL*), contract expiration month (H, K, N, Q, U, X, Z representing March, May, July, August, September, November, December). β_i measures the time dimension of liquidity, or "resilience" of price impact. $\sqrt{|V_{t-i} D_{t-i}|}\, D_{t-i}$ or *Volume$_i$* hereafter, is a measure of signed square-root volume before a large trade ends. $\frac{1}{\sqrt{t+i}} V_{t+i} D_{t+i}$ or *T$_i$_lead* hereafter, measures the time-day effect of trade volume after a large trade ends. The coefficients γ and λ capture transient (convex) impact of *I* lags and post-trade permanent (concave) impact of *L* leads respectively. The concave impact as represented by the reciprocal of square root function is motivated by recent findings in the quantitative finance literature (Toth et al., 2011 and Bacry et al. 2015). We will also consider more general power and exponential functions for the concave impact.

Results

We elect to estimate the model using data at the 2-minute interval in consideration of the trade-off between fineness of time interval and computational burden. We report regression estimates for corn, soybeans and wheat in Table 2. Common to three commodities, two lagged price differences are statistically significant at least at the 0.10 level. Price impact itself shows resiliency for about 4 minutes. In the following, we reproduce the four hypotheses proposed previously and report empirical evidence for or against them based on Table 2.

Table 2: Regression Estimates for Corn, Soybeans and Wheat

	Corn			Soybeans			Wheat		
Variable	**Estimate**	**Std. Error**	**P val**	**Estimate**	**Std. Error**	**P val**	**Estimate**	**Std. Error**	**P val**
β_0	3.11e-04	5.87e-05	<.01	6.36e-04	1.42E-04	<.01	3.71e-04	1.07e-04	<.01
PDiff1	-2.70e-02	2.21e-03	<.01	-1.36e-02	2.41e-03	<.01	-3.04e-02	2.44e-03	<.01
PDiff2	3.85e-03	2.21e-03	0.08	-2.11e-02	2.41e-03	<.01	-2.32e-02	2.44e-03	<.01
Volm0	1.26e-04	3.68e-06	<.01	2.96e-04	1.82e-05	<.01	2.67e-04	1.54e-05	<.01
Volm1	2.11e-04	2.49e-06	<.01	8.19e-04	1.37e-05	<.01	2.09e-04	1.21e-05	<.01
Volm2	-2.30e-05	2.53e-06	<.01	-5.50e-05	1.38e-05	<.01	-4.90e-05	1.21e-05	<.01

Volm3	-2.30e-05	2.52e-06	<.01	-5.30e-05	1.38e-05	<.01	-2.10e-05	1.20e-05	0.08
Volm4	-6.44e-06	2.48e-06	0.01	-4.30e-05	1.37e-05	<.01	-1.10e-05	1.20e-05	0.37
Volm5	-8.33e-06	2.46e-06	<.01	-4.10e-05	1.37e-05	<.01	-3.80e-05	1.19e-05	<.01
Volm6	-	-	-	-3.00e-05	1.37e-05	0.03	-	-	-
Volm7	-	-	-	-2.60e-05	1.37e-05	0.06	-	-	-
Volm8	-	-	-	-4.60e-05	1.36e-05	<.01	-	-	-
T0_lead	-4.30e-04	9.14e-05	<.01	2.33e-03	9.29e-04	0.01	2.89e-03	8.09e-04	<.01
T1_lead	-1.42e-04	5.00e-05	<.01	-4.36e-03	6.98e-04	<.01	4.20e-03	6.72e-04	<.01
T2_lead	-4.55e-06	5.00e-05	0.93	-4.36e-03	6.97e-04	<.01	7.74e-04	6.72e-04	0.25
T3_lead	-4.40e-05	5.00e-05	0.38	-1.81e-03	6.93e-04	0.01	-2.29e-03	6.76e-04	<.01
T4_lead	1.14e-04	4.97e-05	0.02	-	-	-	-1.95e-03	6.65e-04	<.01
Open	1.53e-06	1.71e-07	<.01	9.21e-07	3.91e-06	0.81	-2.40e-05	3.55e-06	<.01
Close	-1.14e-07	2.38e-07	0.63	-3.57e-06	4.45e-06	0.42	-1.60e-07	4.25e-06	0.97
ROLL	6.00e-05	8.29e-05	0.47	4.43e-04	1.97e-04	0.02	7.01e-05	1.44e-04	0.63
WASDE	8.27e-05	1.32e-04	0.53	2.26e-04	3.12e-04	0.47	-4.87e-04	2.51e-04	0.05
Stock	-4.56e-04	1.90e-04	0.02	-6.11e-04	4.38e-04	0.16	-9.68e-04	3.26e-04	<.01
H	-	-	-	-3.16e-04	2.09e-04	0.13	-	-	-
K	-1.66e-04	9.64e-05	0.09	-2.92e-04	2.22e-04	0.19	9.63e-05	1.86e-04	0.61
N	-1.84e-04	9.39e-05	0.05	-7.55e-04	2.15e-04	<.01	4.76e-04	1.75e-04	0.01
Q	-	-	-	-7.73e-04	2.28e-04	<.01	-	-	-
U	-2.45e-04	9.90e-05	0.01	-1.15e-03	2.36e-04	<.01	-7.90e-05	1.85e-04	0.67
X	-	-	-	-4.26e-04	2.27e-04	0.06	-	-	-
Z	1.66e-05	9.80e-05	0.87	-	-	-	9.34e-05	1.95e-04	0.63
Tue	-1.70e-05	7.61e-05	0.83	1.76e-04	1.75e-04	0.31	-3.80e-05	1.36e-04	0.78
Wed	1.45e-05	7.66e-05	0.85	2.42e-04	1.76e-04	0.17	4.15e-05	1.37e-04	0.76
Thu	-1.70e-05	7.70e-05	0.83	2.60e-04	1.76e-04	0.14	-9.58e-06	1.38e-04	0.94
Fri	1.48e-05	7.75e-05	0.85	1.45e-04	1.78e-04	0.41	3.51e-05	1.39e-04	0.80

H1: There is a square-root effect of trading volume on commodity price.
Square-root of trade volume show up to 10 minutes (5 lags) of impact for corn and wheat, 16 minutes (8 lags) of impact for soybeans. The results for corn are consistent with Lehecka et al.'s (2014) findings, using different methods of analysis. The square-root impact for soybeans is longer than that for corn and wheat, indicating that soybean traders either reacts slower to market imbalance or use smaller orders than their counterparties in corn and wheat markets. We can accept H1 that trading volume has a square-root effect on commodity price.

H2: There is a convex decaying effect of trading volume on commodity price.
The time-decay effect, after the large trade ends, is significant up to 8 minutes (4 leads) for corn and wheat, and up to 6 minutes (3 leads) for soybeans. Unlike the pre-trade transient/temporary impact, the post-trade permanent impact lasts longer for corn and wheat than for wheat. Again, we can confirm the time-decay effect, in the form of the -½ power of time, exists for three commodities. In total, the combined (temporary and permanent) market impact is between 18 minutes to 22 minutes.

H3: There is significant market impact on the USDA reporting days.

WASDE reports have significant market impact for wheat, but no significant impact for corn and soybeans. Grain stock reports have significant market impact for corn and wheat, but only marginal significance (p-value=0.16) for soybeans. The corn results are consistent with Wang et al.'s (2014) analysis of the bid-ask spread.

H4: There is significant seasonality in market impact at open & close and contract rolling days, but not significant seasonality across days of week, and contract months of year.

H4.1: The coefficient for market open dummy variable is statistically significant for corn and wheat at the 0.01 level, but not for soybeans. In all three cases, the coefficient for market close dummy variable is not statistically significant. We can conclude that traders tend to trade more actively at the open than at the close, at least in the corn and wheat market. This might be due to (1) more news arrival, such as USDA reports, at the beginning of the day; and (2) the notion of market close for futures markets is largely symbolic in the CME Globex electronic trading system.

H4.2: The coefficient for ROLL is not significant for corn and wheat, but significant for soybeans. The corn results differ from the findings from Wang et al.'s (2014) bid-ask spread analysis.

H4.3: The coefficient for weekday dummy is not statistically significant for all three commodities, confirming the hypothesis of no significant difference across days of week. Our results contrast what is found for the bid-ask spread in the corn market by Wang et al. (2014), who report statistical significance for Tuesday, Thursday and Friday.

H4.4: The coefficient for the month of July is significantly different from that of the month of March for corn and wheat, which share the same series of contract months. There is no consistent conclusion between corn and wheat for other contract months. For soybeans, the distant (nearby) contract months, relative to January, (don't) have significant market impact. This is an evidence for equal trading across contract months by traders.

Conclusions

The rise of large/institutional traders in agricultural commodities calls for research on the analysis of market impact of trading. There is lack of research in trade impact analysis in agricultural commodity markets. We aim to uncover the pattern and duration of market impact of trading in corn, soybeans and wheat during the period of 2008- 2015. Using the CME intraday electronic trade and quote data, we find support for square-root temporary impact of trading volume that lasts 10 minutes for corn and wheat, 16 minutes for soybeans. We also find evidence for post-trade permanent impact with a decaying effect in the form of -1/2 power of time. The permanent impact lasts 8 minutes for corn and wheat, 6 minutes for soybeans. There is mixed evidence for the market impact of USDA reports, namely WASDE and Grain Stock reports. Grain stock reports tend to be more impactful. The impact of contract rolling and contract months is inconclusive across commodities, although we find no significant difference in market impact across weekdays.

Our current research is limited by the nature of public data in which traders can not be identified and the full trace of trades is not directly available. Future research using proprietary data can further refine our research results.

References

Almgren, R., C. Thum, E. Hauptmann, and H. Li (2005). Equity market impact, *Risk*, July 2005, 56-62.

Bacry, E., A. Iuga, M. Lasnier, and C. Lehalle (2015). Market Impacts and the Life Cycle of Investors Orders. *Market Microstructure and Liquidity*, 1(2),1-46.

Bouchaud, J.-P., Gefen, Y., Potters, M. and M. Wyart. (2004). Fluctuations and response in financial markets: the subtle nature of 'random' price changes. *Quantitative Finance*, 4, 176–190.

Hasbrouck, J. (2004). Liquidity in the Futures Pits: Inferring Market Dynamics from Incomplete Data. *Journal of Financial and Quantitative Analysis*, 39(2), 305-326.

Haynes, R. and J.S. Roberts (2015). Automated Trading in Futures Markets. Office of Chief Economist, CFTC White Paper.

Lehecka, G.V., X. Wang, and P. Garcia (2014). Gone in Ten Minutes: Intraday Evidence of Announcement Effects in the Electronic Corn Futures Market. *Applied Economic Perspectives and Policy* 36(3), 504–526.

Marshall, B., N.H. Nguyen, and N. Visaltanachoti (2012). Commodity Liquidity Measurement and Transaction Costs. *Review of Financial Studies* 25(2), 599-638.

Irwin, S.H. and D.W. Sanders (2012). Financialization and Structural Change in Commodity Futures Markets. *Journal of Agricultural and Applied Economics*, 44(3), 371-396.

Toth, B., Lemperiere, Y., Deremble, C., de Lataillade, J., Kockelkoren, J., and Bouchaud,J. (2011). Anomalous price impact and critical nature liquidity in financial markets. Physics Review X 1(2), 1-11.

Wang, X., P. Garcia, and S.H. Irwin (2014). "The Behavior of Bid-Ask Spreads in the Electronically-Traded Corn Futures Market." *American Journal of Agricultural Economics* 96, 557–77.