Trading Activity and Price Behavior in Chinese Agricultural Futures Markets

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Abstract: Using a comprehensive sample of China's agricultural futures from 2010 to 2015, we investigate the relation between trading activities and futures markets liquidity, returns and volatilities. We find that contemporaneous order imbalances are positively related to returns. Order imbalance caused by price pressure lasts more than one day indicating difficulty in absorbing excess buy and sell orders. We also find that lagged order imbalance can predict current returns and that the effect of order imbalance on liquidity is limited. These results are consistent with the explanation that speculative trading not liquidity hinders the Chinese agricultural futures markets to accommodate excess order imbalance.

Keywords: agricultural futures, order imbalance, market returns, liquidity.

1. Introduction

Agricultural futures markets play a significant and important role in the production, circulation and consumption of agricultural commodities in the world. According to the latest investigation of FIA (Futures Industry Association), China has already been the largest market in the global agriculture futures markets. The dramatic emergence of these markets in China comes as no surprise because governments at all levels in China have always set food security one of the most important policy goals and Chinese leaders hope to nurture domestic futures markets to influence the often volatile prices. Foreign investors start to participate more in the Chinese markets due to loosening regulation. Therefore understanding of the Chinese agricultural futures markets is of great interest to regulators, practitioners and researchers alike.

We measure trading activity mainly by order imbalance in addition to trading volume. Trading volume is frequently split into small orders by investors, and volume alone could not represent the direction of trade. In contrast order imbalance could better reflect trading activity, it overcomes the inherent weaknesses of volume. A large body of literature studies the relationship between order imbalance and stock market returns. In the early phase most studies analyze order imbalances around specific events over short time horizon. Blume et al. (1989) demonstrate that there is a strong relation between order imbalance and stock price movements at both the time series and cross-section level when using data surrounding the October 1987 crash; Lee (1992) examines the volume reaction with order imbalance around earnings announcements. Lauterbach and Ben-Zion (1993) also analyze order imbalance within small stock markets surrounding the October 1987 crash. Sias (1997) investigates the relationship between order imbalance and closed-end fund share prices or discounts; Chan and Fong (2000) explain the volatility-volume relationship with order imbalance for a sample of NYSE and NASDAQ stocks. They demonstrate that the largest return impact comes from the order imbalance for NASDAQ stocks using data for an approximately six-month period. Hasbrouck and Seppi (2001), and Brown et al. (1997) analyze order imbalances for thirty and twenty stocks over one and two years respectively. Chordia et al. (2002, 2004) study order imbalance using the Institute for the Study of Security Markets (ISSM) data covering the period from 1988 to 1992 as well as from the Trades Automated Quotations database (TAQ) data covering the years 1993 to 1998. Fung (2007) demonstrates that the arbitrage spread is positively related to the aggregate order imbalance in the underlying index stocks, as well as that a negative order imbalance has a stronger impact than a positive order imbalance. Fung and Yu (2007) examine the impact of stock market order imbalance on the lead-lag relationship between index futures and cash index prices. Cao, Hansch, and Wang (2009) find that order imbalances are significantly related to future short-term returns when using data from the Australian Stock Exchange. Chen et al. (2014) examine order imbalances as a proxy for the influence of informed volatility trading.

There is extensive study on the effect of order imbalance on returns in various financial markets that are well developed. We conduct a similar study of the Chinese futures markets in nine agriculture futures contracts in two Chinese future markets, the Dalian Commodity Exchange (DCE) and Zhengzhou Commodity Exchange (ZCE) covering the period from 2010 to 2015. The availability of high-frequency data allows us to examine a wide variety of issues in Chinese agriculture markets. A critical factor for many of these studies is the ability to determine trade direction. Who is buying and who is selling are important elements in determining the information content of trades, the order imbalance and inventory accumulation of liquidity providers, the price impact of large trades, the effective spread, as well as many other related questions. The commonly available high frequency databases do not provide information on trade direction. Empirical researchers consequentially rely on trade direction algorithms in order to classify trades as either buyer- or seller-motivated. Most studies use one of three trade classification algorithms: the quote rule, the tick rule, and the Lee-Ready (1991) rule. The quote rule classifies a transaction as a buy if the associated trade price is above the midpoint of the best bid and the best ask price. It is classified as a sell if the trade price is below the midpoint quote, and trades executed at the midpoint are not classified. The tick rule classification is based on price movements relative to previous trades. If the transaction is above (below) the previous price, then it is a buy (sell). If there is no price change but the previous tick change was up (down), then the trade is classified as a buy (sell). The Lee-Ready procedure is essentially a combination of these two rules: first, trades are classified according to the quote rule (above or below the mid-point), and then the mid-point transaction is classified using the tick rule. Lee and Radahakrishna (1996) use the TORQ database in order to report an overall 93% agreement between the actual order and Lee-Ready algorithmic inferences. Odders-White (1999) reports a success rate of 85% for the Lee-Ready algorithm when using the same data source but a different selection criterion.

Our study focuses on the daily time-series relation between order imbalances and agriculture futures returns. Our empirical results find that contemporaneous order imbalances are positively related to returns. Yet order imbalance caused by price pressure on a given day persists without sufficient investors taking the opposite side. This hinders absorption of price induced buying/selling pressure. We also find lagged order imbalances have a positive predictive relation to current day returns and that the effect of order imbalance on contemporaneous liquidity is moderate and very little on the subsequent liquidity, measured as quoted spread. These results are consistent with the explanation that speculative trading not liquidity makes the Chinese agricultural futures markets less able to absorb order imbalance. Finally, we examine the impact of the order imbalance on return volatilities.

This paper is organized as follows. Section 2 introduces the background of Chinese futures institutions. Section 3 describes the data. Section 4 discusses the relation between order imbalance and returns. Section 5 discusses the relation between market volatility and order imbalances. Section 6 concludes.

2. Institutional Background

Chinese agriculture futures markets have experienced an unprecedented ascendancy. China inaugurated the first true futures exchange- Zhengzhou Commodity Exchange (ZCE) in 1993. The success of ZCE spawned numerous imitators and soon Chinese futures were booming. Last year the three most active agricultural futures in the world by contract volume were Chinese - ZCE Rapeseed meal, DCE Soy meal and ZCE White sugar contracts - which traded over 303 million, 204 million and 97 million respectively. There are currently three futures exchanges in China: the Zhengzhou Commodity Exchange (ZCE), the Dalian Commodity Exchange (DCE), and the Shanghai Futures Exchange (SFE). Both the ZCE and DCE trade in agricultural commodity futures, primarily wheat in the ZCE and soybean in the DCE; the SFE specializes in trading metals. According to the United States Futures Industry Association (FIA) the SHFE, DCE, and ZCE ranked ninths, tenth, and twelfth respectively in global leading derivative exchanges by number of contracts traded and cleared during 2015.

Table 1 show the global top 20 agriculture futures and options contracts; eight contracts are from China among the top 10. Obviously China is already the biggest market in the global agriculture futures markets. Both the ZCE and DCE have fully functional electronic systems including trading, delivery, clearing, risk control, news release, member services, etc. The Exchanges' Automatic Matching System process reports buying and selling orders on the principles of price priority focused on time. When the buying price is higher than or equal to the selling price then the orders are automatically matched and the transaction is complete. The matched transaction price is equal to the middle price between the buying, selling, and final transaction prices. Transactions become valid as soon as the order to buy and the order to sell are matched by the computing system. The Trading Reporting System sends this information back to the member's computer network terminal, and the member promptly reports the transaction completion to the customer. If an order has been only partially filled then the remaining order portion will remain in the Exchange's main system in price competition.

Both the ZCE and DCE utilize various futures trading systems such as margin requirement, daily price-limit, mark-to-the-market, physical delivery, etc. Both markets also adopt a membership system. At the end of 2013 the ZCE included 203 members. Among the total futures company members (162) account for 80% and non-futures companies (41) account for 20%. By the end of 2014 the DCE listed 170 member companies and 193 designated delivery warehouses.

3. Data

Since near month futures contracts are usually the most actively traded we use these data for our study. However, in order to avoid thin markets and expiration effects we roll over to the next nearest contract when it becomes the most active. The sample period is from January 1, 2010 to March 30, 2015, including 1269 trading days. The trading day is divided into five-minute intervals (including 57105 intervals). Our proprietary data provide both the bid and ask quotes, the transaction price, the trade volume, and a buy/sell indicator. The buy/sell indicator specifies the direction of the reporting party. If the seller reported the trade then the trade would be called a sale regardless of the price at which it occurred. This indicator accordingly tells us the buyer and the seller involved in the transaction, but not the trade direction per se.

Each transaction is designated as either buyer- or seller-initiated according to the Lee and Ready (1991) algorithm. We use the quote rule in order to classify trades as a buy if the transaction price is above the mid-point or as a sell if they occur below the mid-point. Trades executed at the mid-point cannot be classified using the quote rule. We instead use the tick rule and classify trades using the price movement prior to the trade. If the transaction price is above the previous price then the trade is classified as a buy, and if it is below the previous price then it is a sell. If there is no price change but the previous tick change was up (down) then the trade is a buy (sell).

Transaction data are respectively included or excluded according to the following criteria:

A trade is excluded if it is out of sequence, recorded before the open or after the closing time, or has special settlement conditions (since it may be subject to distinct liquidity considerations);

Quotes established before the opening of the market or after the close are excluded;

Negative bid–ask spreads are discarded;

Following Lee and Ready (1991), any quote less than five seconds prior to the trade is ignored and the first quote at least five seconds prior to the trade is retained.

In this paper, each transaction is designated as either buyer- or seller-initiated according to the Lee and Ready (1991) algorithm. For each day interval we compute the following:

$NOIB_{it}$: the number of buyer-initiated trades less the number of seller-initiated trades during day t for agriculture future i;

$VOIB_{it}$: the buyer-initiated volume purchased less the seller-initiated volume sold during day t for agriculture future i;

$SOIB_{it}$: the buyer-initiated sales less the seller-initiated sales during day t for agriculture future i.

We also computed the following measures of trading activity and liquidity:

SPR_{it}: the quoted bid-ask spread averaged across all trades during day t for agriculture future i;

$VOLAT_{it}$: the realized volatility during day t for agriculture future i;

$NTAQ_{it}$: the total number of transactions during day t for agriculture future i;

$DEPTH_{it}$: represents depth averaged across all trades during day t for agriculture future i;

$RETURN_{it}$: the return on agricultural futures during day t for agriculture future i.

Panel A of Table 2 presents descriptive statistics for market-wide order imbalance measures along with other measures of liquidity and trading activity used in this study.

4. Order Imbalances and Returns in Chinese Agricultural Futures Markets

Order imbalance could be caused by many factors on a given day. Large price movements are commonly associated with large contemporaneous order imbalance. A resilient market absorbs the excess buying or selling pressure rather quickly so we do not observe large imbalance subsequently. Accordingly, the current imbalance should have little predictive power on future market returns. We investigate whether the Chinese agricultural futures markets function in such a fashion.

4.1. What Drives Order Imbalance?

In this section we explores whether or not order imbalance can be predicted using past market returns after controlling for weekly regularities and past lagged order imbalance values, as well as whether or not a seasonality effect exists in the China agriculture futures market. We regress the daily order imbalance in the number of transactions (NOIB) on day-of-the-week dummies and variables designed to capture past up-market and down market moves, as well as on past values of order imbalance.

We report the time-series regression described in Table 3. Panel A of Table 3 shows that order imbalances are highly predictable in most agriculture futures markets except for soybean oil and rapeseed. In contrast to findings in Chordia et al. (2002) on the NYSE, traders in the Chinese agricultural futures markets tend to chase short-term momentum in returns in that they sell after the market declines and buy after the market advances. This is especially significant in the soybean meal, white sugar, and cotton futures markets. This behavior often reverses itself within the first five days. Panel A of Table 3 also reveals that there appears to be a weak Wednesday or Thursday regularity in order imbalance.[1] We scaled the dependent variable OIBNUM by the total number of transactions (see Panel B of Table 3) in order to ascertain whether or not the above results are driven by trading activity. There remains strong evidence of a different pattern in investor trading.

Order imbalances are more predictable than futures returns. Hence, how order imbalances respond to past market moves explains whether the returns are close to a random walk. The returns are less predictable if order imbalance caused by price pressure on a given day is corrected by some investors taking the opposite side of the market the next day. In particular, the inventory argument suggests that after an event that causes a large inventory imbalance on one side of the market, dealers/brokers elicit trading on the other side of the market. If traders are net sellers after market rises and vice versa, it indicates that temporary price pressures are promptly countervailed and markets are resilient absorbing large imbalances. Our results suggest that after a market decline, soybean, corn and wheat futures markets recover faster than the rest by trader taking net long positions within the subsequent five days. On the other side, after a market advance soybean and corn futures markets have more net sell orders to countervail the upward price pressure. Interestingly trading in these agriculture commodities is more dominant in CBOT than others.

Overall, we do not find the Chinese futures markets can absorb price pressure promptly. There may be two explanations for this. First the liquidity can dry up after large order imbalance taking markets a longer period to absorb the imbalance. Second the traders in the Chinese markets speculate on the short-term price movements in that they buy after a market advance with a large buying pressure and vice versa. We next investigate these two potential explanations.

4.2. Order Imbalance and Changes in Liquidity

[1] Gibbons and Hess (1981) document the weekly regularities in order imbalance. Chordia et al. (2001) document weekly regularities in market liquidity caused by order imbalance. Chordia et al. (2002) also demonstrate that there is no significant seasonality in order imbalance after controlling for the overall level of trading activity.

We average agriculture futures quoted spreads over all daily transactions in order to measure the relationship between liquidity and order imbalance. The daily percentage change in the quoted spread is regressed on: (1) the contemporaneous daily change in the absolute order imbalance between the number of buyer- and seller-initiated trades, (2) the simultaneous daily percentage change in the number of transactions, (3) concurrent return, (4) concurrent market volatility (measured as the absolute return on agriculture futures), and (5) simultaneous realized market volatility.

The controls (2) to (5) are intended to account for aggregate trading activity and market movements. Order imbalance itself could be associated with greater trading activity as well as with large market movements; however, our aim is to untangle the incremental effect if any of order imbalance on liquidity above and beyond its association with trading and price moves.

Our results from Panel A, Table 4 indicates that that higher spreads occur when orders are more unbalanced in either direction for soybean meal, palm oil, and rapeseed futures. The change in the number of transactions has a separate and very significant positive impact on spreads in most agriculture futures on the Dalian Commodity Exchange (DCE). An explanation for this is that the inside limit orders are picked off during periods of increased trading volume, widening the difference between posted bid and ask quotes. However, this effect is only negatively significant for rapeseed futures on the Zhengzhou Commodity Exchange (ZCE), similar to corn futures on the DCE.

We also measure market volatility using the absolute value of the contemporaneous market return since it is negatively associated with changes in spreads. This is consist with the notion that market returns are negatively associated with changes in spreads and the effect is highly positive in most agriculture futures on the DCE (except corn futures) reported in Panel A of Table 4. Additionally there is a positive relationship between market volatility and quoted spread on corn and wheat futures.

We explore the predictability of liquidity using the next day’s percentage change in the quoted spread, reporting our results in Panel B of Table 4. Order imbalance appears to have no forecasting ability for all agriculture futures types after controlling for a one-day lagged percentage change in the quoted spread. Neither the number of trades (except soybean, white sugar, and cotton futures) nor the market returns (except soybean meal, corn, white sugar, and wheat futures) can predict future changes in liquidity. The predictive power of realized volatility is still significant for wheat futures after controlling for the market return.

In Panel C of Table 4 we further test the role of market moves. We use separate variables for up and down market moves in this regression instead of the return and its absolute value. Liquidity persistently follows previous market moves; a down market predicts low liquidity (higher spreads) the next day. However, an up market cannot predict liquidity. Table 4 also shows that an increase in transactions is associated with a spread increase on the same day for most agriculture futures (except corn) for the DCE; this effect is reversed in corn futures. We further find that transaction change has a negative effect associated with the contemporaneous spread in rapeseed and corn futures.

Overall, we find that the effect of order imbalance on contemporaneous liquidity is moderate and very little on the subsequent liquidity.

4.3. The Impact of Order Imbalance on Returns

We next examine how contemporaneous and lagged order imbalance impacts returns in the Chinese futures markets. To account for differential impact of excess buy and excess sell orders, we split order imbalance into positive and negative parts. We expect the contemporaneous imbalance is positively correlated with the returns - net buy orders during positive return days and net sell order during negative return days. Including contemporaneous imbalance in the regression, the effect of lagged order imbalance on returns is less obvious. If the market is resilient and previous day's imbalance is promptly reversed, the lagged imbalance can be negatively associated with returns. In terms predicting returns, we expect lagged imbalance has little predicative power if excess buying/selling pressure is promptly absorbed, which is the case with the presence of reversal in imbalance. However, the presence of short term speculators who buy/sell when markets face excess buying/selling pressure might mitigate the effect of lagged imbalance on returns.

Panel A of Table 5 shows that contemporaneous order imbalance (as measured by NOIB) is significantly positively associated with market returns except for soybean meal futures; the positive coefficients imply that excess buy (sell) orders drive up (down) prices. In general, lagged excess buy/sell orders have a negative but insignificant effect on return after controlling for the contemporaneous order imbalance. The few exceptions are soybean, palm oil, and rapeseed oil futures in lagged excess buy orders. The explanatory power is good for daily returns with an adjusted R^2 of 5%- 14%. Panel B of Table 5 includes additional controls, lagged negative and positive market returns. Lagged positive returns are negatively with wheat futures market returns while lagged negative returns are positive. Lagged positive returns are negatively significant with soybean meal futures market returns and lagged negative returns are negatively significant with cotton futures market returns, both positive and negative returns exhibit discontinuation after controlling for order imbalances in other agriculture futures markets.

We test whether or not lagged order imbalance can predict returns in Panel D of Table 5. Our results show that lagged order imbalance is highly significant except for the soymeal futures. This provides a rationale for the short term speculators to chase the previous day's large price movement and buying/selling pressure. In so doing, this trading behavior would make it more difficult for the markets to offset existing imbalance after a large price movement. Overall our results are consistent with the explanation that speculative trading not liquidity makes the Chinese agricultural futures markets less able to absorb order imbalance.

5. Volatility, Volume, and Imbalance

Extensive literature (Karpoff, 1987; Schwert, 1989; Gallant et al., 1992; Daigler and Wiley, 1999; Chan and Fong, 2000) provides evidence that there is a positively relationship between volatility and trading volume. In this section we investigate the roles of order imbalance (buyer- versus seller-initiated trades) in affecting volatilities for Chinese agriculture futures.

The first regression reported in Panel A of Table 6 regresses the absolute value of the contemporaneous agriculture futures returns on volume, the positive and negative portions of order imbalance, the average quoted spread, and the lagged absolute market returns. We include the quoted spread in order to control for any liquidity effect on volatility, while the lagged absolute return is included to account for the persistence in volatility. Order imbalance is significant for the soybean, soybean oil, wheat, and rapeseed oil futures markets. The effect is asymmetric where excess sell orders have greater influence than excess buy orders. Both the volume and quoted spreads are also significant, excluding the spread on the white sugar futures market. Notice that the lagged absolute wheat and rapeseed futures market returns have positive coefficients. In Panel B of Table 6 we use the same variable in order to predict volatility on the following day. Here order imbalance disappears as a significant explanatory factor.

We also calculate the realized volatility for these nine agriculture futures and repeat the same exercise in Table 7. Panel A of Table 7 demonstrates that excess buy orders have a significantly negative influence on realized volatility in the Zhengzhou Commodity Exchange (ZCE), while excess sell orders are not significant. This effect only exists for the soybean meal and corn futures markets in the DCE. The same variables are also used to predict the realized volatility on the following day; the results reported in Panel B of Table 7 show that order imbalance on soybean oil, corn, cotton, and wheat futures market have a significant influence on the realized volatility.

Panel A of Table 8 reports the relation of realized volatility and share volume. It shows that there is a positive relationship between realized volatility and trading volume in most agriculture futures on the Dalian Commodity Exchange (DCE) excluding corn futures, while this effect is reversed for all agriculture futures on the Zhengzhou Commodity Exchange (ZCE) and Corn futures.

In order to examine whether share volume or number of trades better explains the realized volatility we investigate the relation between realized volatility and number of transactions in Panel B of Table 8. We find that trade volume explains the realized volatility better than number of transaction. In Panel A including trade volume the average adjust R^2 is 0.29, while in Panel B using the number of trades the average adjust R^2 is 0.27. This finding is inconsistent with Jones et al. (1994), and Chan et al. (2000) who find that the volatility-volume relation is primarily driven by the number of trades rather than by the total volume. In both the DCE and ZCE trade volume and the number of transactions have a similar influence on realized volatility.

Panels C and D of Table 8 report the roles of order imbalance in explaining the volatility-volume relation; trade volume is used in Panel C and number of transactions is used in Panel D. The realized volatility-volume relation becomes much weaker on the Zhengzhou Commodity Exchange (ZCE) after controlling for the impact of order imbalance, which is consistent with Chan and Fong's (2000) finding that the volatility-volume relation becomes weaker after controlling for order imbalance. However, the realized volatility-volume relation is still significant for the DCE, indicating that order imbalance does not influence its positive volatility-volume relation.

6. Conclusion

Agriculture involves a supply chain that takes food from the farmer to the consumer. Advanced economies use sophisticated technology at each stage, however, the story is different for the poorer countries and regions and sophisticated risk management tools are also absent. China, a country home to over 1.6 billion people, became interested in developing sophisticated financial markets and institutions starting from the 1980s. Futures trading on agricultural commodities began in China in 1993. The first few years saw new exchanges mushroomed and speculative behavior ballooned. Since then the Chinese authorities closed more than forty of these exchanges. The Dalian Commodity Exchange, the Shanghai Futures Exchange, the Zhengzhou Commodity Exchange, and the China Financial Futures Exchange are the remaining. All four show up in the list of top thirty derivatives exchanges in the world.

An October 12, 2009, article in the Wall Street Journal titled “China Targets Commodity Prices by Stepping Into Futures Markets” reported that China develops their commodities exchanges as “major players in setting world prices for metal, energy and farm commodities” to be less susceptible to exchange prices elsewhere. As futures traders joke that “China is second only to the weather in driving some commodity prices—but less predictable," Chinese futures prices have begun affecting global prices for many key commodities even with restrictions on foreign participation in Chinese exchanges and the government's role as both a player and a policy maker in the markets.

Against this backdrop, we conduct an analysis on the microstructure of the Chinese agricultural futures markets. Our results suggest that these markets are still not resilient against large market price movements and speculative behavior might be the reason. We also find these markets are liquid facing excessive buying/selling pressure. Policy implication of our results is that the current proposal to open these markets to foreign investors can help curb the speculative behavior and make the markets more resilient to supply/demand shocks.

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Table 1 Top 20 Agriculture Futures and Options Contracts

Rank	Contract	Exchange	Contract Size	Jan-Dec 2013 Volume	Jan-Dec 2014 Volume	Annual % change
1	Rapeseed Meal Futures	ZCE	10 tonnes	160,100,378	303,515,966	89.60%
2	Soy Meal Futures	DCE	10 tonnes	265,357,592	204,988,746	-22.70%
3	White Sugar Futures	ZCE	10 tonnes	69,794,046	97,726,662	40.00%
4	Rubber Futures	SHFE	10 tonnes	72,438,058	88,631,586	22.40%
5	Palm Oil Futures	DCE	10 tonnes	82,495,230	79,996,388	-3.00%
6	Corn Futures	CBOT	5000 bushels	64,322,600	69,437,304	8.00%
7	Soy Oil Futures	DCE	10 tonnes	96,334,673	64,082,631	-33.50%
8	Soybean Futures	CBOT	5000 bushels	46,721,081	49,169,361	5.20%
9	Egg Futures*	DCE	5 tonnes	1,951,323	35,188,187	1703.30%
10	Cotton No. 1 Futures	ZCE	5 tonnes	7,452,748	31,782,665	326.50%
11	Wheat Futures	CBOT	5000 bushels	24,993,158	31,722,024	26.90%
12	Sugar #11 Futures	ICE Futures U.S.	112,000 pounds	29,813,680	29,396,597	-1.40%
13	No.1 Soybean Futures	DCE	10 tonnes	10,993,500	27,197,413	147.40%
14	Soybean Oil Futures	CBOT	50,000 pounds	23,805,912	23,769,391	-0.20%
15	Corn Options	CBOT	5000 bushels	23,534,308	21,246,732	-9.70%
16	Soybean Meal Futures	CBOT	100 short tons	20,237,181	20,637,382	2.00%
17	Soybean Options	CBOT	5000 bushels	14,760,704	17,916,675	21.40%
18	Rapeseed Oil Futures	ZCE	5 tonnes	11,853,858	13,897,650	17.20%
19	Live Cattle Futures	CME	40,000 pounds	12,463,043	13,599,292	9.10%
20	Lean Hogs Futures	CME	40,000 pounds	11,277,038	10,656,944	-5.50%

*Began trading in November 2013 (Data from FIA 2015: 2014 FIA Annual Global Futures and Options Volume)

Table 2 Market-wide order imbalance: summary statistics and correlations.

We provide descriptive statistics for the average daily order imbalance measures from the DCE (Dalian Commodity Exchange) and ZCE (Zhengzhou Commodity Exchange); this includes nine futures types belonging to the agriculture category over the period from 2010 to 2015 inclusive (11421 observations). We sign trades using the Lee and Ready (1991) algorithm. NOIB, VOIB, and SOIB measure order imbalance in the number of transactions, shares, and turnovers respectively. VOL, NUMTRANS, and QSPR are the volume, number of transactions, and the average daily quoted spread respectively. The variables DQSPR and DOIBNUM denote the daily percentages and daily first differences in QSPR and OIBNUM respectively. Ret is the daily return on average.

Panel A：Summery Statistic

Agriculture Futures	Variable	Mean	Median	Std.
Soybean Futures	NOIB	15.82821	13	487.8402
	VOIB	656.5831	576	12798.91
	SOIB	2856607	2442448	5.80×10^{7}
	ABS_NOIB	359.2136	285	330.3069
	ABS_VOIB	8520.044	5428	9570.528
	ABS_SOIB	3.81×10^{7}	2.39×10^{7}	4.38×10^{7}
	SPR	1.013201	1.105002	142.0246
	VOLAT	0.000194	0.000164	0.00016
	NTAQ	12882.25	12916	5217.711
	VOL	183399.9	125870	198802
Soybean Meal Futures	NOIB	-115.173	-110	1156.42
	VOIB	2907.316	998	58888.78
	SOIB	9171516	2882988	2.00×10^{8}
	ABS_NOIB	757.937	587	880.7162
	ABS_VOIB	41749.57	29502	41616.66
	ABS_SOIB	1.38×10^{8}	9.52×10^{7}	1.45×10^{8}
	SPR	-1.94263	1.013292	181.0092
	VOLAT	0.000592	0.000582	0.000173
	NTAQ	22216.16	22481	2745.836
	VOL	1114292	930256	821022.8
Corn Futures	NOIB	-140.42	-119	725.0786
	VOIB	376.8857	434	22500.56
	SOIB	861108	974104	5.25×10^{7}
	ABS_NOIB	537.5359	395	506.2604
	ABS_VOIB	14751.45	9490	16989.43
	ABS_SOIB	3.41×10^{7}	2.19×10^{7}	3.98×10^{7}
	SPR	0.000357	0.000293	0.000266
	VOLAT	0.386226	1.013106	26.72403
	NTAQ	10175.33	9913	5599.034
	VOL	151492.4	95948	191118
Palm Oil Futures	NOIB	31.27344	43	735.5068
	VOIB	3758.109	2104	22618.24
	SOIB	2.27×10^{7}	1.58×10^{7}	1.44×10^{8}
	ABS_NOIB	494.4003	385	545.2748
	ABS_VOIB	15153.58	9392	17201.95
	ABS_SOIB	1.01×10^{8}	6.92×10^{7}	1.06×10^{8}
	SPR	4.406267	2.098301	369.6693
	VOLAT	0.000412	0.000383	0.00022
	NTAQ	19017	19401	3374.248

	VOL	335673.1	286794	204436.6
Soybean Oil Futures	NOIB	91.88337	71	712.273
	VOIB	2975.641	2446	25870.15
	SOIB	2.18×10^{7}	1.97×10^{7}	2.11×10^{8}
	ABS_NOIB	524.3641	434	490.5176
	ABS_VOIB	18746.05	13608	18067.51
	ABS_SOIB	1.51×10^{8}	1.11×10^{8}	1.48×10^{8}
	SPR	1.975827	2.062822	399.9937
	VOLAT	0.000335	0.000317	0.000121
	NTAQ	20558.12	21129	3032.947
	VOL	520253.4	458764	278028.5
White Sugar Futures	NOIB	-95.4523	-122	659.6492
	VOIB	2830.059	3536	43381.69
	SOIB	1.22×10^{7}	1.85×10^{7}	2.39×10^{8}
	ABS_NOIB	417.621	313	519.3367
	ABS_VOIB	30219.95	21478	31241.33
	ABS_SOIB	1.67×10^{8}	1.19×10^{8}	1.72×10^{8}
	SPR	0.000425	0.000276	0.004996
	VOLAT	0.050462	1.031919	229.6046
	NTAQ	21279.16	22437	3412.663
	VOL	992536.1	795442	690849.9
Cotton No.1 Futures	NOIB	-20.2585	-32	634.3106
	VOIB	686.2396	744	22345.52
	SOIB	8802078	1.33×10^{7}	5.05×10^{8}
	ABS_NOIB	383.357	266	505.6503
	ABS_VOIB	13107.94	6648	18106.35
	ABS_SOIB	2.75×10^{8}	1.23×10^{8}	4.23×10^{8}
	SPR	0.000564	0.000221	0.009449
	VOLAT	-2.53979	5.238141	1225.99
	NTAQ	12674.34	11924	7438.701
	VOL	367437.7	125178	551699.4
Wheat Futures	NOIB	36.14894	-1	376.8826
	VOIB	1001.319	240	8045.787
	SOIB	2565895	582694	2.09×10^{7}
	ABS_NOIB	246.7683	157	287.0638
	ABS_VOIB	4152.449	1676	6962.879
	ABS_SOIB	1.08×10^{7}	4500198	1.80×10^{7}
	SPR	0.000157	9.17×10^{-5}	0.000176
	VOLAT	1.353402	1.076687	2.623531
	NTAQ	5121.727	3470	4747.582
	VOL	56456.25	17878	106229.4
Rapeseed Oil Futures	NOIB	30.39716	41	381.7886
	VOIB	885.3838	520	5733.797
	SOIB	6692050	4514308	4.66E+07
	ABS_NOIB	278.3483	213	262.9608
	ABS_VOIB	3547.231	2160	4590.008
	ABS_SOIB	2.94×10^{7}	1.83×10^{7}	3.68×10^{7}
	SPR	0.000162	0.000122	0.000179

	VOLAT	2.735029	2.299234	120.7995
	NTAQ	8840.165	8401	3826.991
	VOL	62194.82	41242	63905.39
Total	NOIB	-18.4191	-18	693.0601
	VOIB	1786.393	650	29450.18
	SOIB	9735342	2759248	2.18×10^8
	ABS_NOIB	444.3939	317	532.1356
	ABS_VOIB	16660.92	7952	24349.42
	ABS_SOIB	1.05×10^8	4.38×10^7	1.91×10^8
	SPR	0.607792	0.000514	197.3091
	VOLAT	0.220762	1.009831	417.6652
	NTAQ	14751.58	15934	7434.35
	VOL	420415	209156	565999.7

Panel B：Correlation

	NOIB	VOIB	SOIB	SPREAD	VOLAT	NTAQ
VOIB	-0.332					
SOIB	-0.2845	0.7619				
SPREAD	-0.2675	0.0897	0.0622			
VOLAT	-0.1799	0.0708	0.194	0		
NTAQ	-0.0213	0.0332	0.0174	0.014	-0.0103	
VOLUME	-0.0746	0.0187	-0.0006	0.006	-0.0068	0.6999

Table 3 What causes agriculture futures markets order imbalance?

Measures of daily order imbalance are regressed on day-of-the-week dummies as well as past positive and negative parts for each agriculture futures' returns. R_{it} denotes the agriculture future returns on day t. We applied the Cochrane/Orcutt procedure in order to adjust for first-order serial dependence in the residuals. Data are from the years 2010 to 2015 inclusive (11421 observations, t-statistics are in parentheses).

Panel A: Dependent variables are the daily order imbalance measured in number of transactions, $NOIB_{it}$, on trading day t.

	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton No.1 Futures	Wheat Futures	Rapeseed Oil Futures
Monday	9.616	-26.31	28.05	-26.72	2.737	-86.62	-28.13	15.81	-17.53
	(0.22)	(-0.26)	(0.45)	(-0.42)	(0.04)	(-1.49)	(-0.49)	(0.48)	(-0.51)
Tuesday	-35.32	-78.07	78.69	-9.996	62.46	-67.34	-29.38	10.10	-3.350
	(-0.82)	(-0.77)	(1.25)	(-0.16)	(0.96)	(-1.17)	(-0.52)	(0.31)	(-0.10)
Wednesday	-35.51	-164.9*	44.93	-105.7*	104.1*	14.92	-47.54	-27.81	-45.18
	(-0.83)	(-1.83)	(0.72)	(-1.65)	(1.65)	(0.26)	(-0.84)	(-0.85)	(-1.32)
Thursday	-84.35**	-124.5	-99.91*	-92.16	29.86	-95.20*	-39.30	-36.38	-5.489
	(-1.98)	(-1.24)	(-1.65)	(-1.45)	(0.46)	(-1.66)	(-0.69)	(-1.12)	(-0.16)
Min(0, R_{it-1})	7836.7**	17085.0**	7134.2	13647.1*	3051.0	11295.6***	13270.2***	-4161.4	3472.9
	(2.13)	(2.11)	(1.55)	(1.81)	(0.75)	(3.09)	(3.99)	(-1.17)	(1.28)
Min(0, R_{it-2})	-5170.0	-4895.7	5149.7	8342.8	2570.3	-5963.0*	1730.0	1559.5	3771.3
	(-1.42)	(-0.61)	(1.13)	(1.11)	(0.64)	(-1.66)	(0.52)	(0.44)	(1.40)
Min(0, R_{it-3})	-3395.5	24908.8***	2161.2	-5081.0	-1287.2	-456.9	2039.2	2120.9	-2758.2
	(-0.94)	(3.11)	(0.48)	(-0.68)	(-0.32)	(-0.13)	(0.60)	(0.59)	(-1.02)
Min(0, R_{it-4})	-2878.9	2150.6	-2197.2	-2244.7	-7356.9*	2501.4	1350.9	-13916.4***	-1543.6
	(-0.79)	(0.27)	(-0.49)	(-0.30)	(-1.86)	(0.70)	(0.40)	(-3.88)	(-0.58)
Min(0, R_{it-5})	-487.4	-6374.3	2988.8	-11823.9	5077.2	4965.7	-4986.6	-9090.1***	222.8
	(-0.13)	(-0.79)	(0.66)	(-1.59)	(1.28)	(1.37)	(-1.46)	(-2.56)	(0.08)
Max(0, R_{it-1})	4986.1	12424.2*	6948.0	10796.8	14278.4***	6713.6**	9325.3***	10902.1***	4061.3
	(1.39)	(1.65)	(1.35)	(1.41)	(3.19)	(1.82)	(2.75)	(3.27)	(1.34)
Max(0, R_{it-2})	4350.5	13616.7*	1886.4	-9400.5	-733.8	2603.3	-3029.4	-554.7	-2327.6
	(1.21)	(1.81)	(0.37)	(-1.22)	(-0.16)	(0.71)	(-0.89)	(-0.16)	(-0.77)
Max(0, R_{it-3})	-7366.4**	-11914.5	2625.5	6684.5	-531.0	3926.0	4292.0	-6624.7**	856.2
	(-2.08)	(-1.58)	(0.51)	(0.86)	(-0.12)	(1.07)	(1.27)	(-2.01)	(0.28)
Max(0, R_{it-4})	1326.2	-10697.5	445.6	1386.4	6825.5	8550.1***	-3047.0	2343.6	662.2
	(0.37)	(-1.42)	(0.09)	(0.18)	(1.53)	(2.34)	(-0.92)	(0.71)	(0.22)
Max(0, R_{it-5})	-3811.5	1854.4	-4101.1	-15383.0**	-8637.2**	-6664.8*	7049.1**	-1000.9	-4227.3
	(-1.07)	(0.25)	(-0.80)	(-1.99)	(-1.93)	(-1.81)	(2.16)	(-0.30)	(-1.41)
$Noibi_{t-1}$	0.0553*	0.0825***	0.0897***	0.129***	0.0797***	0.0897***	0.0571	0.135***	0.0561*
	(1.80)	(2.88)	(3.06)	(4.39)	(2.71)	(3.06)	(1.89)	(4.35)	(1.80)
$Noibi_{t-2}$	0.103***	0.0919***	0.104***	0.0637**	0.0822***	0.0704***	0.00358	0.0609**	0.0394
	(3.33)	(3.20)	(3.53)	(2.14)	(2.80)	(2.40)	(0.12)	(1.95)	(1.25)
$Noibi_{t-3}$	0.0704**	0.0864***	0.0582**	0.0280	0.0187	0.0323	0.00336	0.0986***	0.0570*

	(2.28)	(3.02)	(1.98)	(0.94)	(0.63)	(1.09)	(0.11)	(3.21)	(1.82)
$Noibi_{t-4}$	0.0627**	0.0460	0.0678**	0.0344	0.0581**	0.00733	-0.0377	0.0648**	0.0421
	(2.03)	(1.61)	(2.31)	(1.16)	(1.97)	(0.25)	(-1.25)	(2.10)	(1.34)
$Noibi_{t-5}$	0.0839***	0.0386	0.0133	0.0163	0.0217	0.0597*	0.0651**	0.0703**	0.0618**
	(2.74)	(1.36)	(0.46)	(0.56)	(0.74)	(2.10)	(2.19)	(2.30)	(1.98)
Cons	29.84	76.37	76.57	-42.24	-44.23	-40.49	-0.913	-27.30	46.91
	(0.75)	(0.75)	(1.24)	(-0.73)	(-0.68)	(-0.71)	(-0.02)	(-0.94)	(1.48)
N	1264	1264	1264	1264	1264	1231	1231	1204	1236
Durbin-Watson	2.01	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Adj. R^2	0.043	0.047	0.044	0.036	0.030	0.041	0.034	0.083	0.013

Panel B: Dependent variables are the daily order imbalance measured in $NOIB_{it}/Ntaq_{it}$ on trading day t, where $Noib_{it}$ is the daily order imbalance measured in number of transactions, Ntaq is total number of transactions. They are regressed on day-of-the-week dummies and past positive and negative parts of each agriculture futures' returns. R_{it} denotes the agriculture future returns on day t. Data are from 2010-2015 inclusive (11421 observations, t-statistics in parentheses).

	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton No.1 Futures	Wheat Futures	Rapeseed Oil Futures
Monday	-0.0576	-0.127	-0.00541	-0.140	0.0258	-0.105*	-0.0856	0.0464	-0.154
	(-0.69)	(-1.50)	(-0.07)	(-1.26)	(0.35)	(-1.77)	(-0.92)	(0.40)	(-1.69)
Tuesday	-0.0974	-0.104	0.0907	-0.0641	0.0609	-0.0467	-0.0460	0.0808	-0.0415
	(-1.17)	(-1.23)	(1.23)	(-0.58)	(0.83)	(-0.80)	(-0.50)	(0.69)	(-0.46)
Wednesday	-0.110	-0.196**	0.0394	-0.281***	0.0875	-0.00387	0.0543	-0.108	-0.126
	(-1.32)	(-2.31)	(0.53)	(-2.55)	(1.19)	(-0.07)	(0.59)	(-0.93)	(-1.40)
Thursday	-0.225***	-0.108	-0.139**	-0.249**	-0.00906	-0.0788	-0.145	-0.139	-0.0541
	(-2.72)	(-1.28)	(-1.90)	(-2.27)	(-0.12)	(-1.34)	(-1.57)	(-1.20)	(-0.60)
Min(0, R_{it-1})	15.37**	11.99	8.726	21.61*	-0.717	13.25***	14.25***	-8.762	-1.609
	(2.19)	(1.77)	(1.61)	(1.67)	(-0.16)	(3.57)	(2.66)	(-0.68)	(-0.23)
Min(0, R_{it-2})	-7.786	-5.907	4.314	9.835	3.184	-2.231	4.552	-0.684	4.543
	(-1.12)	(-0.88)	(0.81)	(0.76)	(0.71)	(-0.60)	(0.85)	(-0.05)	(0.65)
Min(0, R_{it-3})	-4.892	8.413	4.808	-17.52	0.106	-2.270	-0.765	-3.184	-5.698
	(-0.71)	(1.26)	(0.91)	(-1.35)	(0.02)	(-0.62)	(-0.14)	(-0.25)	(-0.81)
Min(0, R_{it-4})	-7.092	2.755	4.190	-6.151	-4.961	3.572	-4.772	-38.44***	-0.790
	(-1.03)	(0.41)	(0.79)	(-0.48)	(-1.11)	(0.97)	(-0.87)	(-2.99)	(-0.11)
Min(0, R_{it-5})	1.099	0.00296	5.974	7.822	1.671	1.935	-1.744	-17.61	6.872
	(0.16)	(0.00)	(1.13)	(0.62)	(0.38)	(0.52)	(-0.32)	(-1.42)	(1.00)
Max(0, R_{t-1})	8.616	13.01**	5.949	30.49**	18.05***	8.321**	6.097	17.32	3.266
	(1.23)	(2.05)	(0.98)	(2.29)	(3.55)	(2.24)	(1.12)	(1.45)	(0.41)
Max(0, R_{it-2})	5.349	11.62*	5.162	-12.01	-0.0286	2.801	-8.257	6.352	-5.561
	(0.76)	(1.83)	(0.86)	(-0.90)	(-0.01)	(0.76)	(-1.52)	(0.53)	(-0.70)
Max(0, R_{it-3})	-9.974	-7.212	7.906	11.98	1.123	2.848	4.687	1.269	0.892
	(-1.44)	(-1.14)	(1.31)	(0.89)	(0.22)	(0.78)	(0.87)	(0.11)	(0.11)
Max(0, R_{it-4})	-0.593	-6.143	-3.851	4.936	9.352*	-0.455	4.525	3.527	-0.184
	(-0.09)	(-0.97)	(-0.64)	(0.37)	(1.84)	(-0.12)	(0.85)	(0.30)	(-0.02)
Max(0, R_{it-5})	1.465	-4.354	-3.268	-23.17*	-7.312	-1.501	3.843	-1.341	-10.88
	(0.21)	(-0.69)	(-0.54)	(-1.76)	(-1.44)	(-0.41)	(0.74)	(-0.11)	(-1.43)
$Noib_{it-1}$	0.0623**	0.102***	0.0671***	0.0582*	0.0648***	0.0919***	0.0762**	0.123**	0.0933**
	(2.03)	(4.55)	(3.06)	(1.72)	(2.85)	(4.54)	(2.25)	(2.16)	(2.29)
$Noib_{it-2}$	0.0963***	0.0837***	0.0714***	0.0233	0.0644***	0.0666***	0.0642*	0.0448	0.0589
	(3.11)	(3.72)	(3.23)	(0.69)	(2.83)	(3.27)	(1.89)	(0.78)	(1.44)
$Noib_{it-3}$	0.0673**	0.0552***	0.0312	0.0196	0.0299	0.0395**	-0.0322	0.0382	0.0678*
	(2.18)	(2.45)	(1.42)	(0.58)	(1.31)	(1.93)	(-0.95)	(0.67)	(1.66)
$Noib_{it-4}$	0.0902***	0.0525**	0.0569***	0.00275	0.0635***	0.0242	0.0327	0.0598	0.0276
	(2.92)	(2.34)	(2.60)	(0.08)	(2.80)	(1.19)	(0.97)	(1.05)	(0.67)

Cons	0.0711	0.0583	0.137	-0.108	-0.0675	-0.0450	-0.0358	-0.207*	0.168*
	(0.92)	(0.68)	(1.90)	(-1.08)	(-0.91)	(-0.77)	(-0.49)	(-2.00)	(2.02)
N	1264	1264	1264	1264	1264	1231	1231	1204	1236
Durbin-Watson	2.02	2.00	2.01	2.01	2.00	2.00	2.01	2.01	2.00
Adj. R^2	0.035	0.057	0.044	0.013	0.036	0.057	0.016	0.015	0.003

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4 Changes in market liquidity, contemporaneous changes in order imbalance, number of transactions, and market up/ down moves

Our dependent variables are the contemporaneous and next-day's daily percentage changes in the quoted spread for nine agriculture futures types in the Dalian Commodity Exchange (DCE) and Zhengzhou Commodity Exchange (ZCE). Explanatory variables include the daily first difference in the absolute value of the value-weighted order imbalance as measured in the number of shares (NOIB), the daily percentage change in the number of transactions, the agriculture futures return if it is positive (and zero otherwise (Max(0,Ret_{it}))), and the S&P500 return if it is negative (and zero otherwise (Min(0,Ret_{it}))). We applied Cochrane/Orcutt procedure in order to correct for first-order serial dependence in the residuals. The data are for January 2010 to March 2015 inclusive (11421 observations, t-statistics are in parentheses).

Panel A: Dependent Variable: Percentage change in quoted spread (contemporaneous)

	DCE					ZCE			
	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Palm Oil Futures	Corn Futures	White Sugar Futures	Cotton No.1 Futures	Wheat Futures	Rapeseed Oil Futures
Explanatory variable	Coefficient $\times 10^{-3}$ (t-statistic)				Coefficient $\times 10^{-9}$ (t-statistic)	Coefficient $\times 10^{-9}$ (t-statistic)			
$\lvert NOIB_{it}\rvert - \lvert NOIB_{it-1}\rvert$	0. 280	0.409***	1.03	2.66***	0.0145	0.497	-2.74	0.749	1.67**
	(1.14)	(3.31)	(1.23)	(3.29)	(0.68)	(0.06)	(-0.12)	(0.42)	(1.91)
% change in $NTAQ_{it}$	0. 584***	2.52***	9.19***	6.96***	-0.0565***	-2.23	19.1	-1.07	-1.33***
	(3.13)	(6.75)	(5.39)	(5.59)	(-2.62)	(-0.15)	(1.28)	(-1.40)	(-2.75)
Ret_{it}	-0.523***	-0.403**	-0.844	-1.24*	-0.184	6.88	45.1***	1.77	-2.03***
	(-2.34)	(-2.22)	(-0.88)	(-1.71)	(-0.46)	(1.04)	(2.99)	(1.09)	(-3.32)
Abs_Ret_{it}	-0.704***	-0.412**	-2.73***	-1.91***	0.114	-2.94	-3.11**	-0.411	-1.31**
	(-3.18)*	(-2.27)	(-2.88)	(-2.63)	(0.28)	(-0.46)	(-2.10)	(-0.25)	(-2.15)
$Volatility_{it}$	1.758	-0.146	6.831	-0.357	24.7***	15.5	35.50	90.0***	-0.651
	(1.17)	(-0.15)	(0.72)	(-0.09)	(7.65)	(0.30)	(0.43)	(27.11)	(-0.17)
Cons	-0.301	0.449	-2.050	1.350	3.52	2.06	-49.5	-84.8***	19.3**
	(-0.49)	(0.65)	(-0.49)	(0.61)	(0.91)	(0.03)	(-0.24)	(-18.09)	(1.98)
N	1267	1267	1267	1267	1267	1253	1253	1242	1255
Adj. R^2	0.018	0.049	0.028	0.038	0.048	-0.003	0.009	0.372	0.017

Panel B: Dependent Variable: Percentage change in quoted spread (next day)

Explanatory variable	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Palm Oil Futures	Corn Futures	White Sugar Futures	Cotton No.1 Futures	Wheat Futures	Rapeseed Oil Futures
	Coefficient × 10^{-3} (t-statistic)				Coefficient × 10^{-9} (t-statistic)				
$\lvert NOIB_{it}\rvert - \lvert NOIB_{it-1}\rvert$	0.188	-0.0429	0.0226	0.902	0.165	0.782	34	-0.158	-0.263
	(0.77)	(-0.34)	(0.03)	(1.10)	(0.88)	(0.09)	(1.52)	(-0.09)	(-0.03)
% change in $NTAQ_{it}$	-0.341	-1.94***	-6.74***	-5.70***	1.66***	-1.47	-10.6	2.48***	1.61***
	(-1.80)	(-5.09)	(-3.93)	(-4.53)	(8.79)	(-0.10)	(-0.71)	(3.10)	(3.30)
Ret_{it}	-0.664***	-0.339	-2.36***	-1.62**	0.22	-3.26	-32.2**	0.0554	-1.29**
	(-2.95)	(-1.81)	(-2.45)	(-2.19)	(0.62)	(-0.49)	(-2.12)	(0.03)	(-2.09)
Abs_Ret_{it}	0.0614	0.0860	-0.578	-0.0361	0.402	-0.372	5.38	1.63	0.292
	(0.28)	(0.46)	(-0.61)	(-0.05)	(1.15)	(-0.06)	(0.36)	(0.97)	(0.48)
$Volatility_{it}$	3.888**	1.335	25.93***	6.443	-3.03	-2.62	1.25	80***	-3.45
	(2.56)	(1.20)	(2.59)	(1.49)	(-1.05)	(-0.05)	(0.02)	(18.47)	(-0.89)
Lagged dependent Variable	-9.164	14.44	11.75	27.01	0.506***	-415	797	0.0594**	0.104***
(one day)	(-1.15)	(0.59)	(0.15)	(0.38)	(20.60)	(-0.01)	(0.28)	(2.02)	(3.61)
Cons	-0. 284	-1.21	-11.2	-4.62	19.8***	24.1	38.2	-73.5***	24.4***
	(-0.29)	(-0.72)	(-1.08)	(-0.53)	(5.88)	(0.38)	(0.18)	(-13.48)	(2.49)
N	1267	1267	1267	1267	1267	1246	1246	1230	1249
Adj. R^2	0.014	0.024	0.025	0.021	0.277	-0.005	0.002	0.337	0.018

Panel C: Dependent Variable: Percentage change in quoted spread (next day)

Explanatory variable	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Palm Oil Futures	Corn Futures	White Sugar Futures	Cotton No.1 Futures	Wheat Futures	Rapeseed Oil Futures
	Coefficient (t-statistic)				Coefficient × 10^{-8} (t-statistic)				
$\lvert NOIB_{it}\rvert - \lvert NOIB_{it-1}\rvert$	0.00616	-0.00297	-0.0123	0.0553	0.877	6.36	210	-1.44	-2.09
	(0.39)	(-0.37)	(-0.23)	(1.05)	(0.73)	(0.12)	(1.53)	(-0.11)	(-0.38)
% change in $NTAQ_{it}$	-0.0199	-0.128***	-0.460***	-0.376***	11.2***	-12.6	-50.3	17.0**	11.8***
	(-1.63)	(-5.24)	(-4.21)	(-4.68)	(9.23)	(-0.13)	(-0.53)	(2.92)	(3.75)
$Max(0,Ret_{it})$	0.00305	-0.00587	0.0318	-0.0139	8.87***	-22.9	35.2	-8.84	8.68
	(0.19)	(-0.45)	(0.43)	(-0.25)	(3.49)	(-0.52)	(0.37)	(-0.71)	(1.94)
$Min(0,Ret_{it})$	-0.0612***	-0.0241*	-0.233***	-0.120***	-7.17***	-1.63	-293***	2.27	-16.8***
	(-3.82)	(-1.72)	(-3.55)	(-2.39)	(-2.76)	(-0.04)	(-3.04)	(0.17)	(-4.06)
Lagged dependent Variable	-0.0190	0.00454	-0.00698	0.00902	136000***	-81.6	388	117000***	25500***
(one day)	(-0.77)	(0.07)	(-0.03)	(0.05)	(17.19)	(-0.01)	(0.05)	(14.95)	(2.93)
Cons	0.0291	0.00977	-0.0587	0.00976	109***	150**	50.8	154***	89.3***
	(0.54)	(0.14)	(-0.11)	(0.02)	(20.35)	(2.03)	(0.32)	(11.30)	(15.02)
N	1267	1267	1267	1267	1267	1253	1253	1242	1255
Adj. R^2	0.014	0.024	0.024	0.021	0.284	-0.004	0.006	0.153	0.027

Table 5 Returns on the nine agriculture futures types contemporaneous and lagged order imbalances, and lagged returns

The dependent variable is the daily return on the agriculture futures in the Dalian Commodity Exchange (DCE) and Zhengzhou Commodity Exchange (ZCE), denoted R_{it}. Explanatory variables include contemporaneous and lagged positive as well as negative daily order imbalances measured in the number of trades along with the lagged positive and negative index returns. These data cover the period from January 2010 to March 2015 inclusive (11421 observations, t-statistics are in parentheses)

Panel A: Dependent variable: R_{it}

	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton No.1 Futures	Wheat Futures	Rapeseed Oil Futures
Excess buy orders,	0.471***	0.0566	0.307***	0.266***	0.285***	0.359***	0.431***	0.451***	0.716***
Max(0, $NOIB_{it}$)	(5.60)	(0.49)	(3.13)	(4.09)	(2.47)	(2.70)	(3.34)	(6.20)	(8.14)
Excess sell orders,	0.408***	0.103	0.266***	0.251***	0.440***	-0.0467	0.607***	0.455***	0.436***
-|Min(0, $NOIB_{it}$)|	(5.12)	(1.02)	(2.81)	(4.66)	(4.05)	(-0.45)	(5.40)	(6.66)	(5.02)
Excess buy orders,	-0.229***	-0.171	-0.118	-0.0382	-0.287**	-0.0793	-0.0196	-0.0691	-0.297***
Max(0, $NOIB_{it-1}$)	(-2.73)	(-1.47)	(-1.21)	(-0.59)	(-2.49)	(-0.60)	(-0.15)	(-0.95)	(-3.38)
Excess sell orders,	-0.0846	-0.0437	-0.143	-0.0565	0.130	-0.117	-0.198	-0.0763	0.0759
-|Min(0, $NOIB_{it-1}$)|	(-1.06)	(-0.43)	(-1.51)	(-1.05)	(1.20)	(-1.12)	(-1.76)	(-1.12)	(0.88)
Cons	0.0261	0.110	-0.0995	0.0401	0.118	-0.124	0.0318	-0.0471	-0.0459
	(0.40)	(0.94)	(-1.11)	(0.78)	(1.14)	(-1.29)	(0.37)	(-1.31)	(-0.79)
N	1268	1268	1268	1268	1268	1261	1261	1255	1262
Adj. R^2	0.109	0.006	0.049	0.091	0.054	0.007	0.073	0.118	0.144

Panel B: Dependent variable: R_{it}

	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton No.1 Futures	Wheat Futures	Rapeseed Oil Futures
Excess buy orders,	0.472***	0.0717	0.309**	0.268***	0.287***	0.368***	0.435***	0.483***	0.722***
Max(0, $NOIB_{it}$)	(5.60)	(0.62)	(3.15)	(4.13)	(2.48)	(2.75)	(3.37)	(6.56)	(8.16)
Excess sell orders,	0.411***	0.101	0.262***	0.258***	0.439***	-0.0524	0.642***	0.445***	0.428***
-|Min(0, $NOIB_{it}$)|	(5.14)	(1.00)	(2.76)	(4.77)	(4.04)	(-0.50)	(5.67)	(6.47)	(4.90)
Excess buy orders,	-0.214*	-0.173	-0.122	-0.0219	-0.288***	-0.0650	0.002	-0.0405	-0.323***
Max(0, $NOIB_{it-1}$)	(-2.50)	(-1.50)	(-1.23)	(-0.34)	(-2.50)	(-0.49)	(0.02)	(-0.54)	(-3.53)
Excess sell orders,	-0.0835	-0.0443	-0.149	-0.0447	0.128	-0.122	-0.149	-0.116	0.0551
-|Min(0, $NOIB_{it-1}$)|	(-1.03)	(-0.44)	(-1.57)	(-0.82)	(1.17)	(-1.17)	(-1.30)	(-1.62)	(0.62)
Lagged positive return,	-5.317	-18.13***	-0.0298	-8.678	-2.207	4.014	2.428	-16.26***	4.960
Max(0, R_{it-1})	(-0.84)	(-2.75)	(-0.00)	(-1.38)	(-0.32)	(0.61)	(0.41)	(-2.67)	(0.74)
Lagged negative return,	0.158	-1.315	4.564	-5.647	2.804	-5.732	-18.02***	15.07**	6.519
Min(0, R_{it-1})	(0.03)	(-0.19)	(0.74)	(-0.92)	(0.46)	(-0.85)	(-2.99)	(2.31)	(1.12)
Cons	0.0363	0.157	-0.0881	0.0489	0.134	-0.167	-0.0100	-0.0125	-0.0409
	(0.54)	(1.30)	(-0.94)	(0.93)	(1.23)	(-1.60)	(-0.11)	(-0.33)	(-0.67)
N	1268	1268	1268	1268	1268	1254	1254	1243	1256
Adj. R^2	0.108	0.012	0.048	0.092	0.053	0.006	0.078	0.123	0.145

Panel C: Dependent variable: R_{it+1}

	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton No.1 Futures	Wheat Futures	Rapeseed Oil Futures
Excess buy orders,	0.452***	0.0611	0.270***	0.275***	0.299***	0.343***	0.443***	0.475***	-0.298***
Max(0, $NOIB_{it}$)	(5.34)	(0.53)	(4.20)	(2.38)	(3.03)	(2.57)	(3.49)	(6.82)	(-3.02)
Excess sell orders,	0.405***	0.0817	0.254***	0.436***	0.241***	-0.0591	0.624***	0.440***	0.117
-|Min(0, $NOIB_{it}$)|	(5.04)	(0.81)	(4.73)	(4.01)	(2.54)	(-0.56)	(5.60)	(6.60)	(1.24)
Lagged positive return,	-10.07	-16.90***	-10.46	-3.196	-3.080	3.724	1.728	-17.57***	0.0395
Max(0, R_{it})	(-1.62)	(-2.56)	(-1.70)	(-0.46)	(-0.44)	(0.56)	(0.30)	(-2.95)	(1.19)
Lagged negative return,	-3.910	-3.544	-7.050	1.469	2.223	-5.935	-20.12***	10.91	0.0213
Min(0, R_{it})	(-0.64)	(-0.51)	(-1.17)	(0.24)	(0.36)	(-0.88)	(-3.42)	(1.75)	(0.71)
Cons	0.0022	0.107	0.0612	-0.0080	-0.0892	-0.128	0.0272	-0.0017	0.0545
	(0.04)	(1.20)	(1.42)	(-0.10)	(-1.21)	(-1.55)	(0.36)	(-0.05)	(1.01)
N	1268	1268	1268	1268	1268	1254	1254	1243	1256
Adj. R^2	0.099	0.007	0.092	0.049	0.039	0.004	0.078	0.121	0.136

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6 Absolute returns on the agriculture futures markets, order imbalance, volume, and liquidity.

The dependent variable is the absolute value for the daily return on nine agriculture futures types on the Dalian Commodity Exchange (DCE) and Zhengzhou Commodity Exchange (ZCE), denoted as R_{it}. Explanatory variables include contemporaneous and lagged positive and negative daily order imbalances measured in the number of trades, volume, quoted spreads, and one-day lagged absolute returns. These data cover the period from January 2010 to March 2015 inclusive (11421 observations, t-statistics are in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Dependent Variable: | R_{it} |

	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton No.1 Futures	Wheat Futures	Rapeseed Oil Futures
Excess buy orders,	0.100***	-0.0287	0.0573	0.0280	-0.0743	-0.0028	-0.0051	0.0629	0.149***
Max(0, $NOIB_{it-1}$)	(2.57)	(-0.67)	(1.51)	(1.03)	(-1.54)	(-0.05)	(-0.09)	(1.63)	(3.22)
Excess sell orders,	0.0715***	0.0287	0.0449**	0.0004	-0.0046	-0.0192	0.0380	0.100***	0.0827***
|Min(0, $NOIB_{it-1}$)|	(3.45)	(1.21)	(1.97)	(0.03)	(-0.17)	(-0.75)	(1.32)	(5.16)	(3.47)
$Volume_{it}$	0.492***	0.160***	0.336***	0.221***	0.262***	0.457***	0.565***	0.442***	0.660***
	(10.83)	(4.55)	(11.23)	(9.53)	(8.34)	(12.12)	(19.98)	(10.98)	(9.55)
$Spread_{it}$	0.187***	-0.281***	-0.347***	648.6***	-0.500***	2.944	5.030***	26.61***	236.8***
	(2.81)	(-2.49)	(-2.83)	(11.46)	(-3.58)	(0.88)	(3.48)	(2.44)	(6.58)
Abs_Ret_{it-1}	0.0121	0.0272	-0.0246	-0.0253	0.0057	-0.0321	0.0109	0.0599***	0.0463**
	(0.54)	(1.22)	(-1.11)	(-1.29)	(0.24)	(-1.27)	(0.36)	(2.67)	(1.99)
Cons	-0.149	0.668***	0.843***	-0.198***	1.686***	-0.108	0.235***	0.258***	0.254***
	(-0.93)	(3.46)	(2.75)	(-4.30)	(5.05)	(-1.12)	(4.72)	(9.49)	(6.61)
N	1268	1268	1268	1268	1268	1254	1254	1243	1256
Adj. R^2	0.175	0.056	0.135	0.256	0.079	0.104	0.320	0.168	0.140

Panel B: Dependent Variable: | R_{it+1} |

	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton No.1 Futures	Wheat Futures	Rapeseed Oil Futures
Excess buy orders,	-0.0521	-0.0203	-0.0204	0.00757	0.00320	-0.0554	-0.0384	0.121**	-0.0663
Max(0, $NOIB_{it-1}$)	(-0.88)	(-0.33)	(-0.36)	(0.18)	(0.05)	(-0.66)	(-0.46)	(2.09)	(-0.96)
Excess sell orders,	-0.0675**	0.0175	0.0138	-0.00868	0.0126	-0.00603	0.0429	0.0324	0.0446
|Min(0, $NOIB_{it-1}$)|	(-2.14)	(0.52)	(0.41)	(-0.41)	(0.32)	(-0.16)	(1.00)	(1.10)	(1.25)
$Volume_{it}$	0.243***	0.0461	0.248***	0.171***	0.0930**	0.300***	0.602***	0.211***	0.381***
	(3.41)	(0.92)	(5.39)	(4.61)	(1.99)	(5.25)	(13.93)	(3.42)	(3.64)
$Spread_{it}$	14.45	-674.1***	37.08	530810.4***	-86.03	-3855.8	-736.7	-28874.0	31099.6
	(0.12)	(-3.37)	(0.16)	(4.64)	(-0.34)	(-0.64)	(-0.28)	(-1.42)	(0.46)
Abs_Ret_{it}	0.0987**	0.0535	0.00201	0.0172	0.0337	0.00645	0.144***	0.179***	0.146***
	(2.32)	(1.33)	(0.05)	(0.39)	(0.82)	(0.16)	(3.43)	(4.22)	(3.46)
Cons	0.728***	1.528***	0.501	0.175***	1.209***	0.573***	0.432***	0.527***	0.725***
	(3.03)	(5.56)	(1.10)	(2.41)	(2.46)	(4.06)	(6.15)	(13.79)	(13.55)
N	1269	1269	1269	1269	1269	1255	1255	1244	1257
Adj. R^2	0.039	0.021	0.027	0.068	0.002	0.022	0.234	0.054	0.030

Table 7 Realized Volatility on the agriculture futures markets, order imbalance, volume and liquidity

The dependent variable is the daily realized volatility on 9 kinds of agriculture futures in Dalian Commodity Exchange (DCE) and Zhengzhou Commodity Exchange (ZCE), denoted $Volatility_{it}$. Explanatory variables include contemporaneous and lagged positive and negative daily order imbalances measured in number of trades, volume, quoted spreads and one day lagged volatility. Data cover January 2010-March 2015 inclusive (11421 observations, t-statistics in parentheses).

Panel A: Dependent Variable: $Volatility_{it}$

	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton No.1 Futures	Wheat Futures	Rapeseed Oil Futures
Excess buy orders,	-0.000393	-0.00190**	-0.000141	-1.764***	0.00100	-6.465***	-11.65***	-2.635**	-3.652***
Max(0, $NOIB_{it-1}$)	(-0.40)	(-2.03)	(-0.28)	(-2.97)	(0.85)	(-5.06)	(-6.15)	(-2.14)	(-2.95)
Excess sell orders,	-0.000348	-0.000175	0.000473	-0.507*	0.00157**	-0.525	-0.568	-1.043	-0.270
|Min(0, $NOIB_{it-1}$)|	(-0.66)	(-0.34)	(1.58)	(-1.73)	(2.34)	(-0.92)	(-0.59)	(-1.67)	(-0.42)
$Volume_{it}$	0.0120***	0.00712***	0.00665***	-2.954***	0.0206***	-0.810	-2.831***	-4.104**	-15.02***
	(10.40)	(9.04)	(16.17)	(-5.97)	(23.76)	(-0.98)	(-3.48)	(-3.27)	(-8.09)
$Spread_{it}$	12.46***	-26.44***	-0.250	14983049.2***	13.12***	-7913.0	1315.2	5160102.2***	997760.7
	(5.98)	(-8.42)	(-0.12)	(9.89)	(3.10)	(-0.09)	(0.02)	(9.90)	(0.83)
$Volatility_{it-1}$	6.212**	60.75***	52.54***	19.27***	16.90***	14.17***	-3.349	93.63***	1.286
	(2.00)	(26.39)	(21.18)	(6.31)	(6.21)	(4.64)	(-1.06)	(58.73)	(0.41)
Cons	0.0142***	0.0445***	0.0140**	105.2***	-0.00268	123.7***	299.3***	25.11***	285.4***
	(3.42)	(9.83)	(3.29)	(28.11)	(-0.33)	(28.91)	(36.68)	(11.05)	(35.17)
N	1268	1268	1268	1268	1268	1261	1261	1255	1262
Adj. R^2	0.099	0.611	0.504	0.122	0.450	0.038	0.044	0.859	0.069

Panel B: Dependent Variable: $Volatility_{it+1}$

	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton No.1 Futures	Wheat Futures	Rapeseed Oil Futures
Excess buy orders,	0.00000481	0.00000443	0.00000925**	-0.0171***	0.00000437	-0.00190	0.00934	-0.0340***	0.00512
Max(0, $NOIB_{it-1}$)	(0.54)	(0.48)	(1.93)	(-3.15)	(0.37)	(-0.17)	(0.54)	(-3.01)	(0.46)
Excess sell orders,	-0.00000568	0.00000425	0.00000579**	-0.00764***	0.00000539	-0.000558	0.0186**	-0.0144***	0.00735
|Min(0, $NOIB_{it-1}$)|	(-1.19)	(0.84)	(2.01)	(-2.86)	(0.80)	(-0.11)	(2.17)	(-2.51)	(1.28)
$Volume_{it}$	0.0000507***	0.0000164**	0.00000115	-0.00751	0.000115***	-0.000623	-0.0375***	0.00867	-0.116***
	(4.69)	(2.05)	(0.27)	(-1.64)	(11.40)	(-0.08)	(-5.19)	(0.75)	(-6.92)
$Spread_{it}$	0.0186	-0.0248	-0.154***	21739.0	-0.102***	-32.87	8.113	7137.3	10719.7
	(0.97)	(-0.78)	(-8.01)	(1.51)	(-2.38)	(-0.04)	(0.02)	(1.44)	(1.00)
$Volatility_{it}$	0.000525**	0.00598***	0.00495***	0.00171***	0.00163***	0.00115***	-0.000234	0.00796***	0.000205
	(2.06)	(26.90)	(21.39)	(6.71)	(5.83)	(4.68)	(-0.93)	(59.20)	(0.81)
Cons	0.000302***	0.000201***	0.000457***	0.966***	0.000453***	1.054***	2.595***	0.147***	2.470***
	(8.24)	(4.40)	(11.49)	(28.50)	(5.52)	(26.59)	(34.72)	(6.85)	(33.56)
N	1268	1268	1268	1268	1268	1261	1261	1255	1262
Adj. R^2	0.049	0.519	0.420	0.057	0.284	0.014	0.019	0.848	0.040

Table 8 Realized volatility in the agriculture futures markets, volume, number of transactions, and order imbalance

The dependent variable is the daily realized volatility for nine agriculture futures types on the Dalian Commodity Exchange (DCE) and Zhengzhou Commodity Exchange (ZCE), denoted as $Volatility_{it}$. Explanatory variables include the contemporaneous share volume and number of trades for agriculture future i on day t and one-day lagged volatility; Monday is a dummy variable equal to 1 for Mondays, and 0 otherwise. These data cover the period from January 2010 to March 2015 inclusive (11421 observations, t-statistics in the parentheses).

Panel A: Dependent Variable: $Volatility_{it}$

	DCE					ZCE			
	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton Futures	Wheat Futures	Rapeseed Oil Futures
Monday	0.0001	0.000003	0.00082	-0.392	0.00047	1.691	-2.483	0.147	-1.115
	(0.10)	(0.00)	(1.41)	(-0.64)	(0.36)	(1.38)	(-1.27)	(0.14)	(-0.98)
$Volatility_{it-1}$	6.301**	65.66***	52.63***	24.38***	16.87***	14.59***	-2.824	103.3***	1.486
	(2.00)	(28.63)	(21.42)	(7.80)	(6.16)	(4.74)	(-0.88)	(79.20)	(0.47)
$Volume_{it}$	0.0063***	0.0105***	0.0067***	-0.921**	0.0201***	-0.470	-2.954***	-3.678***	-16.08***
	(9.24)	(14.88)	(17.34)	(-2.10)	(23.95)	(-0.57)	(-3.61)	(-3.19)	(-8.94)
Cons	0.0370***	0.0085***	0.0136***	106.5***	0.0236***	119.8***	294.4***	14.27***	284.4***
	(28.95)	(4.93)	(13.07)	(28.29)	(16.65)	(28.47)	(35.77)	(7.40)	(35.13)
N	1268	1268	1268	1268	1268	1268	1268	1268	1268
adj. R^2	0.074	0.588	0.504	0.049	0.444	0.017	0.009	0.848	0.063

Panel B: Dependent Variable: $Volatility_{it}$

	DCE					ZCE			
	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton Futures	Wheat Futures	Rapeseed Oil Futures
Monday	0.000321	0.00172**	0.00115*	-0.419	0.00126	1.685	-2.471	0.147	-1.239
	(0.30)	(1.99)	(1.89)	(-0.69)	(0.87)	(1.37)	(-1.25)	(0.14)	(-1.07)
$Volatility_{it-1}$	9.225***	45.01***	62.31***	23.31***	33.71***	14.55***	-1.687	102.0***	4.097
	(2.92)	(20.71)	(25.51)	(7.43)	(12.00)	(4.73)	(-0.53)	(73.35)	(1.28)
$Ntaq_{it}$	0.00413***	0.0322***	0.00747***	-1.145***	0.0212***	0.800	-1.145	-3.052***	-5.573***
	(6.82)	(27.85)	(12.20)	(-3.54)	(15.60)	(0.76)	(-1.46)	(-4.09)	(-6.10)
Cons	0.0412***	0.0143***	0.0160***	106.5***	0.0289***	118.0***	288.5***	11.30***	269.4***
	(30.84)	(11.14)	(14.85)	(28.58)	(18.93)	(30.73)	(35.77)	(6.41)	(33.97)
N	1268	1268	1268	1268	1268	1268	1268	1268	1268
adj. R^2	0.047	0.700	0.450	0.055	0.322	0.017	0.001	0.849	0.032

Panel C: Dependent Variable: Volatility$_{it}$

	DCE					ZCE			
	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton Futures	Wheat Futures	Rapeseed Oil Futures
Monday	0.000119	-0.0000252	0.000796	-0.390	0.000498	1.502	-2.752	0.158	-1.199
	(0.11)	(-0.02)	(1.38)	(-0.64)	(0.38)	(1.23)	(-1.42)	(0.15)	(-1.05)
Volatility$_{it-1}$	6.381**	65.50***	52.60***	24.28***	16.95***	14.12***	-3.556	103.3***	1.221
	(2.02)	(28.58)	(21.44)	(7.77)	(6.20)	(4.62)	(-1.13)	(79.12)	(0.39)
Volume$_{it}$	0.00626***	0.0103***	0.00666***	-0.928**	0.0201***	-0.756	-3.191***	-3.572***	-15.78***
	(9.26)	(14.60)	(17.38)	(-2.12)	(23.94)	(-0.92)	(-3.95)	(-3.03)	(-8.78)
Noib$_{it}$	-0.000314	-0.000632**	-0.000460**	-0.304	-0.00103**	-2.232***	-4.811***	-0.250	-1.636***
	(-0.71)	(-1.95)	(-2.23)	(-1.37)	(-2.14)	(-4.41)	(-5.73)	(-0.40)	(-2.78)
Cons	0.0370***	0.00888***	0.0137***	106.5***	0.0237***	120.6***	296.4***	14.23***	285.2***
	(28.92)	(5.12)	(13.17)	(28.31)	(16.74)	(28.84)	(36.43)	(7.37)	(35.30)
N	1268	1268	1268	1268	1268	1268	1268	1268	1268
adj. R^2	0.074	0.589	0.505	0.050	0.445	0.031	0.033	0.848	0.068

Panel D: Dependent Variable: Volatility$_{it}$

	DCE					ZCE			
	Soybean Futures	Soybean Meal Futures	Soybean Oil Futures	Corn Futures	Palm Oil Futures	White Sugar Futures	Cotton Futures	Wheat Futures	Rapeseed Oil Futures
Monday	0.000345	0.00172**	0.00113*	-0.417	0.00130	1.486	-2.736	0.150	-1.330
	(0.33)	(1.98)	(1.86)	(-0.68)	(0.90)	(1.22)	(-1.40)	(0.14)	(-1.15)
Volatility$_{it-1}$	9.312***	45.01***	62.30***	23.19***	33.69***	14.12***	-2.365	102.0***	3.730
	(2.95)	(20.70)	(25.53)	(7.39)	(12.02)	(4.62)	(-0.75)	(73.03)	(1.17)
Ntaq$_{it}$	0.00417***	0.0322***	0.00746***	-1.163***	0.0213***	0.311	-1.340*	-3.035***	-5.481***
	(6.87)	(27.52)	(12.20)	(-3.59)	(15.70)	(0.30)	(-1.73)	(-3.94)	(-6.01)
Noib$_{it}$	-0.000388	-0.0000429	-0.000435**	-0.328	-0.00144***	-2.179***	-4.706***	-0.0561	-1.824***
	(-0.86)	(-0.15)	(-2.01)	(-1.48)	(-2.70)	(-4.29)	(-5.58)	(-0.09)	(-3.06)
Cons	0.0412***	0.0143***	0.0160***	106.6***	0.0290***	118.6***	290.0***	11.31***	270.6***
	(30.84)	(11.10)	(14.94)	(28.61)	(19.05)	(31.06)	(36.36)	(6.40)	(34.19)
N	1268	1268	1268	1268	1268	1268	1268	1268	1268
adj. R^2	0.046	0.700	0.452	0.056	0.325	0.031	0.024	0.849	0.039

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$