Liquidity of the Chinese Agricultural Futures Market and Its Impact on Futures Price—Based on High-Frequency Data

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Abstract: This study examines the price impact of intraday trading activity and daily market liquidity of Chinese agricultural futures by analyzing continuous intraday 15-min and daily trading datasets, respectively. Corn and soybean, the necessity of the nation and people’s survival in China, are taken as case studies. Our main findings are threefold. Firstly, there is evidence of the presence of informed trading through persistent effects of trade size for both purchases and sales. The magnitude of effects and the seasonality of informed trading vary among varieties, which support the importance of night trading for price smoothing. Secondly, the impact of liquidity costs on returns does not permanently persist. For example, there appears a significant Friday effect with a linear negative relationship in the soybean market, while an exact opposite effect can be found in the corn market for Monday. Thirdly, while the results show no effect of holding position on asset returns in the corn market, the market size of soybean futures exerts a positive Thursday effect, which is prior to the Friday effect of transaction cost. A better understanding of liquidity costs and liquidity pricing is of great significance to a sustainable development of the agricultural commodity market in China.

Keywords: liquidity of commodity market; effective spread; informed trading; asset pricing model; China

1. Introduction

Futures markets play a critical role in hedging trading risks, driving the price discovery, and guiding sustainable agricultural production. Transaction costs and liquidity are important indicators for measuring the efficiency and maturity of futures markets. The Bank for International Settlements (BIS) gives a comprehensive definition of market liquidity, which enables market participants to trade quickly, without causing large fluctuations in the price of financial assets. Hence, liquidity costs could be considered as the transaction costs for the sake of assuring liquidity. In practice, however, futures markets may present new challenges for market participants and regulators, since information asymmetry is prevalent and may cause an imbalance between fundamental values and market prices. If futures markets possess good liquidity, multifaceted information can be reflected promptly along with transactions characterized by large trading volume and high market participation, which would be conducive to effectively reducing risks of prices high volatility. In such an environment, investigating how intraday trading activities and daily liquidity costs affect asset prices, which attribute the effects present when trading in different intervals, will yield meaningful implications for market participants.

The topic of the liquidity of commodity markets sparked the interest of academic literature. Many researchers were committed to verifying the effectiveness of liquidity proxies when high-frequency...
data were not available; however, the effectiveness of those measurements remains an open question [1–3]. Based on accurately measuring the liquidity index from high-frequency data, our objectives in this paper were to better understand the impact of intraday trades on futures price from information asymmetry perspectives, and to explore how daily liquidity affects asset pricing and its day-of-the-week effect. Obviously, the answers for the above outstanding issues contribute to providing guidance about futures trading efficiently and giving a further boost to the sustainability of the Chinese agricultural futures market.

A large body of literature, which pays more attention to the liquidity seasonality, refers to two terms: whether liquidity has any significant difference at different trading times within a day (intraday effect), and whether there is a significant difference in liquidity from Monday to Friday (weekday effect). Statistical tests were used in most relevant literature and showed that the liquidity level of an asset (expressed by the bid–ask spread) changes over time and looks generally U-shaped on a daily or weekly basis [4–6]. Some scholars also tried exploring other empirical studies to access the characteristic of liquidity. For example, Cenesizoglu and Grass [7] disentangled bid- and ask-side liquidity to better understand the determinants and commonalities of liquidity, and to explore whether the factors driving liquidity differ between bid- and ask-side. Obviously, exiting literature takes mainly the stock market and bond market as the research objects, and much less is known about the agricultural futures market. This paper contributes insight into the liquidity variation of agricultural commodities traded at futures markets in China. When separating day trading and night trading into individual sections, our results support previous findings about the U-shaped pattern of the intraday liquidity trend, whereby the liquidity is higher during the opening and closing periods than the middle of trading hours. Next, based on statistical analysis of the liquidity distribution, we empirically explore the intraday seasonality of informed trading in the Chinese agricultural market, taking corn and soybean as examples.

Informed trading was studied and documented early in market microstructure literature. Using the market microstructure model, Kyle [8], Admati and Pfleiderer [9], Foster and Vishwanathan [10], and Chan and Fong [11] considered uninformed traders as noise traders, and studied the trade strategies of informed traders. McGroarty et al. [12] pointed out that trade volumes could respond sensitively to information flows, and both of them are closely associated with informed trader activity. Schlag and Stoll [13], who used a basic regression approach to investigate volume–price impact, drew a conclusion that the effect of trade volume on the German DAX index is largely permanent, thus confirming the presence of information effects. Under similar model settings, Chang et al. [14], Ryu [15], and Webb [16] proved again that informed trading is prevalent in most futures markets, and found that it is mainly concentrated in the opening period. When being conscious of microstructure models being sensitive to model biases and requiring unrealistic assumptions, we follow Webb [16] and utilize regression models as alternatives for microstructure models to reduce estimation errors and noise. We use high-frequency records associated approximately with each trade from January to April in 2018 to analyze the price impact of trading volumes and attempt to figure out the presence or absence of informed trades and its seasonality. Our research supports the existing consensus that futures trades as carriers of information have significant explanatory power for the price movements of underlying assets. However, in terms of whether investors may prefer trading in a specific interval according to their trading motives and goals, the differences in the patterns of intraday trading make the findings in the soybean market not necessarily acceptable for the corn market. Simply stated from our findings, while the significant seasonality of price impact is not found in the soybean market, informed trading is concentrated in the opening and closing periods in the corn market. We think that the accessibility of night trading and the linkage extent with foreign markets are at the root of differences.

The other purpose of this paper was to investigate the heterogeneous performance of liquidity pricing and its variability in the futures market of China’s bulk agricultural products. In theory, liquidity is closely related to asset pricing; liquidity drives a wedge between the returns an investor might realize net of trading costs and the gross returns used in most asset pricing tests. Since the
relationship between liquidity costs and asset pricing was first proposed and explored by Amihud and Mendelsonian [17] from a micro perspective, it attracted wide attention in the financial world, especially in the stock market and bond market. According to their views, the return of assets is positively correlated with liquidity costs, which means that the higher liquidity costs are, the higher the return rate will be. Amihud [18] confirmed again his conclusion of the stronger illiquidity of the stocks market resulting in higher excess returns in the same period. However, Kadlec and McConnell [19] summarized that the increase in liquidity (decrease in bid–ask spread) would significantly increase the stock returns, inconsistent with the theory of Amihud. Empirically, different measurement methods or sample data may bring diverse results [20–25], even a few of which suspect the stable existence of the liquidity premium phenomenon, especially in some emerging markets [26]. Some researchers [27–30] empirically revealed seasonality characteristics of liquidity pricing as well. Liu and Jiang [31] devised an asset pricing model which also accounts for the economics of scale and the cyclical effect in the futures market, finding that liquidity cost should be included in the excess return and it has a cyclical effect on asset prices. Most empirical studies paid more attention to the generality of the liquidity effect rather than the heterogeneity among different commodities. To fill the gap, this study implements a complementary analysis of liquidity variation using high-frequency measures from January 2016 to December 2017. The results propose the view that the effects of liquidity on asset prices are statistically significant and economically important. However, they are less supportive of continuous liquidity premium effects, especially for the soybean market. That is, the influence of transaction cost on returns manifests a significant Friday effect with an apparent linear negative relationship in the soybean market. Additionally, although there appears to be a significant linear positive relationship in the corn market, the effect only occurs in Monday, since they often pay more for liquidity on Monday after acquiring private information during weekends in order to reduce delay cost and increase returns.

The rest of the paper is set out as follows: Section 2 describes the Chinese soybean and corn futures markets in detail and clarifies the reasons for selecting these markets as ideal settings for this study. Section 3 introduces the basic features of the dataset, including sample data and a liquidity benchmark. Section 4 details the empirical model employed in the study, with corresponding empirical findings. Section 5 discusses and explains the empirical results. Finally, Section 6 concludes and presents ideas for further work.

2. The Chinese Commodity Futures Market

Futures trading in China has a short but high-growth history. Since China accelerated the transformation from a centrally planned to a market-oriented economy, Chinese commodity markets developed dramatically. Next, we successively introduce Chinese agricultural spots and futures markets, and explain which representative setting soybean and corn markets provide for our research questions. Based on our brief introduction for the running procedure of the Chinese futures market, trading types and how to impact dynamic assets price are illustrated in the final sub-section.

2.1. Chinese Agricultural Market

Dalian Commodity Exchange (DCE) became one of the most successful and significant commodity futures exchanges in China. Its soybean and corn futures prices are the most important price signal for China’s farmers, market participants, and other users. The liquidity of both markets, as measured by effective spread, is continuously climbing, driven by the facts that spots trades grow simultaneously and futures investors increase accordingly.

Since 1994, China essentially unrestricted soybean imports, and the Chinese soybean market is of particular interest to other soybean-producing countries because of the current serious import dependence of soybean products. On average, China produces 14.2 million tons of soybeans, almost all of which are used in food, and oil-pressed soybeans are imported entirely, with annual imports reaching 97 million tons. According to customs data, China imported 95.55 million tons of soybeans in 2017, of which 32.86 million tons came from the United States, 50.93 million tons from Brazil, and 6.58
millon tons from Argentina. Unlike high self-sufficiency agricultural staple foods such as rice, wheat, and corn, soybean was removed from the category of “strategic” crops, and its price is prone to being influenced by the external market environment. Because of this, the soybean futures market is increasingly filled with hedgers who are interested in reducing risk and speculators who attempt to profit from price fluctuations.

Due to the food security strategy, farmers of corn were supported by the Chinese government for self-reliance. One of the major farm policies, called the temporary purchases and storage policy, was to purchase surplus grain from farmers at the targeted floor prices if the market prices fell below the floor prices, such that the price trend of corn was strongly dominated by policies. Stable market expectations and high reserve capacities of state warehouses greatly compressed investment space and effectively reduced speculation in the futures market. The government gradually canceled the temporary purchases and storage policy after 2016, and the corn market that used to be controlled by the Chinese government attracted more arbitragers; however, there are still fewer speculators entering the market due to narrow profit margins.

2.2. Chinese Commodity Futures Markets

In contrast to most quote-driven commodity futures markets, Chinese futures markets operate as a purely order-driven market, where all orders are transacted through the centralized limit order book and matched automatically by computers. To be specific, 8:55–8:59 a.m. of the trading day is the collective bidding period, and then opening prices are brokered and determined in the next minute. After that, the market enters the procedure of successive bidding, and all the incomplete price limit orders stay in the order book. If the new limit order is a purchase order, the transaction can be completed at the cost of optimal commission sale price when the entrusted purchase price is higher than the optimal commission sale price on the order book; otherwise, the order stays sequentially in the order book and waits for the new sell order that meets the transaction conditions. Similarly, if the new order is a sell order, the transaction goes with the parallel rules. Automated systems are increasingly applied to monitor the markets for trading opportunities and execute the trades as soon as trade criteria are met, since computers respond immediately to changing market conditions. In addition, China’s commodity futures market adopts a T + 0 trading mode, attracting most small and medium traders to participate in trading and holding positions. Combined with the margin system, trading boards, and daily debt-free system, they encourage investors to choose (or be forced to) leave the market to reduce losses or lock in profits after big price swings, thus working together to form a sustainable mechanism for China’s commodity futures market.

For most futures varieties, the agricultural trades in DCE start from 9:00 to 11:30 a.m., during which trades are closed for 15 min (i.e., from 10:00 to 10:15 a.m.), and from 1:30 to 3:30 p.m., almost synchronized with the underlying spots market. In addition to general trading hours, there is night trading from 9:00 to 11:30 p.m. for soybean products, nearly keeping in step with the Chicago Board of Trade (CBOT) bidding openly from 9:30 a.m. to 1:15 p.m. in the Central time zone. The trading time of Chinese futures contracts without night trading does not coincide with that of the CBOT, one of the main trading venues of international agricultural products futures. Overnight price change may occur. For example, asset price often changes from the close to the open. In particular, if great changes take place in the futures market due to an international bombshell, the domestic price cannot fluctuate in a timely manner, which will bring about price gaps at the opening of the next day. For some futures with night trading, the domestic price could be linked tightly to the external market; thus, investors adjust timely the position in light of the market quotation. That is, the greatest benefit of night trading is to reduce the risk of overnight positions, especially for the varieties which have a strong connection with international markets. Based on the discussion above, there appears great differentiation among different varieties in terms of policy environment and market mechanism. Therefore, translating the results of the soybean market to the corn market is not a straightforward exercise, and vice versa.
2.3. Informed Trading and Uninformed Trading

The movements of asset prices are mainly derived from information which is carried to markets by different investors, and asset prices appear to have various degrees of volatility in the process of responding to information. Market impact represents the movement in the asset price caused by a particular trade or order. In the financial market, price impacts can be divided into permanent impact caused by information effect, and temporal impact resulting from the depletion of the liquidity supply when executing big deals [16]. As shown in Figure 1, market impact occurs due to the information content (permanent) of the trade and the liquidity demand (temporary) of the trader, where the former can change the price balance and the latter does not prevent new prices from reverting in successive intervals. A permanent impact of informed trading on futures prices is irreversible, while the price change caused by a temporary impact would recover after large trading. Once the transaction is completed, the partial information of informed trading would be reflected in the prices. Following subsequent repeated exchanges, the market prices continuously reveal the information until they approach the real value. A trade price may become stable in that it no longer reflects all available information, whereas the order book may be updated at any time, even with no trading taking place.

Many investors consider transaction cost analysis as a decision-making tool and then select their trading algorithms, utilizing valuable opportunities to increase returns [32]. Algorithmic trading remains an essential ingredient to achieve the best execution and reduce transaction costs. Investors who are properly managing all phases of the trading activity can minimize (if not avoid completely) all potential costs, except for the risk of overnight holding position. Generally, informed traders usually utilize their advantages strategically to make profits by controlling trade volumes and trade immediacy in certain periods [10,11]. As such, informed traders have to submit their order as soon as they can in order to compete for price/time priority during the process of private information diffusing. However, they may unintentionally convey information to the market about their trading intentions and order size (information leakage) as well. As a consequence, uninformed traders, without superior information, could only estimate the value and liquidity of futures contracts according to transaction records, and utilize the statistical edge to further determine their optimal order. Thus, they would bear a huge loss to liquidate the futures contracts when informed trades predominate, and rational investors should avoid trading in those periods of time [33,34].

![Figure 1](image_url)

**Figure 1.** Permanent impact and temporary impact of trading volume on future price. When large trading is initiated by sellers, futures prices drop suddenly from Pa to Pb; after two units of time, the price recovers gradually to Pd via Pc.

Consequently, in order to measure the efficiency of Chinese agricultural futures markets more comprehensively and to guarantee sustainable trading for investors, more in-depth studies are needed to reach a definitive conclusion about the impacts of trading activities and market liquidity on asset prices, as well as the mechanism of these impacts.
3. Sample Data

This study examines real-time trade of Chinese soybean and corn futures from January 2016 to December 2017 on a daily basis, as well as 15-min data from January 2018 to April 2018. We get the data of individual contracts from the Dafuweng database, each of which includes the latest price, bid price, sell price, holding position, open position, trading volume, and the specific time of each transaction that is accurate within seconds. Then, we construct 15-min continuous series using order data of the most active contracts from January 2018 to April 2018, and daily continuous series using order data from January 2016 to December 2017. This paper selects the contract with the largest trading volume and the most active trading to analyze the continuous sequence. Not only could this method structuring continuous contracts get good representative indicators such as futures price, trading volume, and holding volume, but it should also overcome the discontinuity of price series and effectively avoid the price jump of the contract junction. In total, we used over 14,000,000 observations from 2016 and 2017, and 1,800,000 in 2018 (from January to April), among which about half were actually complete.

Liquidity is a very abstract concept, and we introduce its quantification below. The measurement of transaction cost we considered is spread, which is the cost of transacting at the best bid or ask quote. Based on high-frequency data, we used a well-established liquidity benchmark to measure the transaction costs: effective spread, provided by Bessembinder and Kaufman [31]. It is measured as two times the absolute value of the natural log of the trade price minus the natural log of the bid–ask midpoint prevailing at the time of the trade.

Effective Spread = \(2 \times |\ln (P_k) - \ln (M_k)|\), where \(P_k\) and \(M_k\) are the price of the \(k\)-th trade and the midpoint of the prevailing bid price \((B_k)\) and ask price \((A_k)\) at the time of the \(k\)-th trade, respectively. The 15-min and daily observations are correspondingly calculated as the average during intervals.

Table 1 presents the summary statistics of the sampled data of the soybean and corn futures from January to April in 2018, including the time-series mean, standard deviation, 25th percentile, 50th percentile, 75th percentile, and maximum values of the positive (buy) and negative (sell) amounts for futures trades during one-minute intervals. Table 1 shows that the corn futures have larger trading volume than the soybean futures. Upon comprehensively considering the trading frequency during this period, 390,000 times for corn futures and 566,000 times for soybean futures, we can see that small trades are dominant in the soybean futures market. We can further infer that the soybean market is highly speculative and filled with short-term trades. For soybean futures, the day-trading volume constitutes a larger portion of total trading volume than night trading, whether negative volume (NV) or positive volume (PV). Its higher standard deviation reflects the fact that day trading is more heterogeneous and has a wider variety of trading motives than night trading. Moreover, negative futures volume is slightly higher than the positive futures volume for both categories.

### Table 1. Summary statistics of the data.

| Varieties | Volume | Time | Mean  | SD   | Min   | 25th pct | 50th pct | 75th pct | Max   | Unit Root |
|-----------|--------|------|-------|------|-------|----------|----------|----------|-------|-----------|
| Soybean   | PV     | Day  | 279.3 | 311.4| 6.4   | 120.2    | 191.7    | 336.0    | 3671.6| I (0)     |
|           |        | Night| 184.1 | 190.4| 9.2   | 69.0     | 127.7    | 222.1    | 1160.8| I (0)     |
|           |        | Average| 240.2| 272.5| 6.4   | 90.8     | 160.9    | 294.5    | 3671.6| I (0)     |
|           | NV     | Day  | 304.5 | 361.4| 37.7  | 114.9    | 201.1    | 353.8    | 3245.6| I (0)     |
|           |        | Night| 203.3 | 222.8| 11.2  | 81.0     | 130.3    | 219.4    | 1340.8| I (0)     |
|           |        | Average| 262.9| 316.0| 11.2  | 100.7    | 167.9    | 315.3    | 3245.6| I (0)     |
| Corn      | PV     | Average| 802.6| 1153.2| 41.5  | 230.5    | 458.6    | 921.5    | 11,556.8| I (0)     |
|           | NV     | Average| 821.5| 1070.4| 42.8  | 253.9    | 487.3    | 944.8    | 9748.4| I (0)     |

Note: For the positive volume (PV) and the negative volume (NV) separately, trades of soybean and corn are presented. All values are measured over 5- or 15-min intervals from January to April in 2018 and then are standardized as 1-min values based on the algorithm, along with their percentiles (pct).
One of the main research questions of this study was whether informed trading is concentrated in a specific intraday time period, particularly the opening or closing period of each trading day. To obtain a broad outline of the intraday trading pattern, we measured the trading volumes, consisting of 5-min intervals for the opening (9:00–9:15 a.m. and 9:00–9:15 p.m.) and the closing (2:45–3:00 p.m. and 11:15–11:30 p.m.) periods and 15-min intervals for other periods. Soybean futures trade in two sections per day; the opening period includes 9:00–9:15 a.m. and 9:00–9:15 p.m., while the opening period for corn futures is only 9:00–9:15 a.m. Similarly, the closing period of soybean futures includes 2:15–3:00 p.m. and 11:15–11:00 p.m., while that of corn futures is only 2:15–3:00 p.m. To ensure a fair comparison among intervals which have different time lengths, we calculated the normalized futures trading volume—the average trading volume divided by the corresponding time length. Figure 2 presents the normalized trading volume (i.e., the trading volume divided by the length of the minute interval) in each intraday interval for soybean and corn.

![Graph showing normalized trading volume and transaction costs for soybean and corn futures.](image)

**Figure 2.** Normalized trade volume and transaction costs over intraday intervals from January to April in 2018. (a) The per-minute futures trading volume (both for the positive volume (PV) and the negative volume (NV)) and effective spread for soybean futures over 33 intraday trading intervals. (b) The per-minute futures trading volume and effective spread for corn futures over 19 intraday trading intervals.

As shown in Figure 2, effective spread, for both the day-trading section and night-trading section, exhibits a nearly U-shaped pattern. That is, the liquidity cost drops significantly after the opening and then remains relatively stable until trading hours approach the closing period, during which it obviously rises. The results are consistent with previous studies of Kyle [8], Ryu [15], and Mcinish and Wood [21] which agreed that severe information asymmetry should be responsible for the lack of liquidity during the phases of opening and closing. However, transaction costs of the soybean market are apparently lower than that of the corn market; thus, soybean futures with greater liquidity are more likely to attract speculators compared to corn futures, consistent with the discussion above.

Furthermore, intraday trading volumes of two varieties also follow the U-shaped variation pattern, which specifically shows that the trading volumes in the opening period are a bit higher than those in the closing period. One possible interpretation is that traders may prefer trading in opening periods to take full advantage of the information accumulating overnight, and trading in closing periods to reduce the risk of holding positions overnight. Higher liquidity may attract informed traders, and increase the proportion of informed trading during these periods. Nevertheless, night trading in the soybean market can not only balance all-day distribution of trading volumes, but also the response to information without delay and a lower share of informed trading in the opening and closing periods. Therefore, the soybean futures market may have a less significant opening or closing effect than the corn market, and the smoother slopes of trade volumes changing in the opening and closing periods can attest to that.

Figure 3 shows that corn futures have larger transaction costs than soybean futures, consistent with the findings in Figure 2. It is well known that the smaller trade size is, the more liquidity traders...
there will be; thus, the expectation of larger transaction costs following larger trade sizes appears to be reasonable in the corn market. However, this is not always the case for the soybean market. When trade size is relatively small, a negative relationship between trade size and transaction cost implies an economy of scale in trading; when the trade size grows to a certain degree, the expectation of a positive relationship between trade size and transaction costs will occur, that is, a larger trade size could bring a greater price response against the backdrop of lacking liquidity.

![Figure 3. Spread costs on the basis of trade size. This figure reports spread costs based on trade size, for which daily mean effective spreads were measured using transaction data from January 2016 to December 2017; the trade size ranged from 0 to 100,000 to 800,000 and above.](image)

4. Empirical Methodology

The above analysis characterized trading patterns in different sample intervals; next, we were interested to know whether transaction activities would converge to certain periods, and we explored the underlying reason and the possible influence on asset pricing. Based on structuring effective spread using high-frequency data, there are two key components included in this paper. The first one is the qualitative analysis of the impact of trading activities on price changes, considering unique trade behavior in the opening and closing periods. The second one is the quantification of the impact of liquidity costs on asset pricing and its seasonality in a week. For each part, we applied the empirical approach described below.

4.1. Model Introduction

4.1.1. Regression Framework of Price Movement on Trading Volume

We used a basic regression framework to analyze intraday trades and their effects. Assuming that traders can be divided into two categories—informed traders and uninformed (or liquidity) traders—we decomposed price changes caused by each trading activity into permanent and transitory portions related to informed trading and liquidity trading, respectively [15]. Bulleted lists suggest that investors may prefer trading in a specific interval depending on their information content and trading motives. Thus, it is possible that informed traders and uninformed traders exhibit quite different patterns during the trading periods, which may reflect the intraday seasonality of price impact. In this case, these processes can be described using the following regression equation:

\[
\Delta P_t = c + \sum_{i=1}^{2} \alpha_i \Delta P_{t-i} + \sum_{i=0}^{2} \beta_i PV_{t-i} + \sum_{i=0}^{2} \gamma_i PV_{t-i} + \sum_{i=1}^{1} \beta'_{i} OV_{t-i} + \sum_{i=0}^{1} \gamma'_{i} OV_{t-i} + \epsilon_t
\]

where \( c \) is an intercept term, \( \epsilon_t \) is an error term, and \( i \) and \( t \) represent the \( i \)-th time lag and the \( t \)-th per-minute time interval during each trading day, respectively; \( \Delta P_t \) and its lagged futures price changes, \( \Delta P_{t-i} \), denote changes in the futures prices during one-minute intervals. The remaining independent
variables, current and lagged positive volumes \((PV_{t-i})\), and negative volumes \((NV_{t-i})\), and interaction terms \((PV_{t-i}O_{t-i}, NV_{t-i}O_{t-i})\), capturing the impacts of trading volumes on price changes during the opening period (the first 15-min interval of trading parts) or the closing period (the last 15-min interval of trading parts), were all measured during one-minute intervals. Generally, \(PV\) is considered as the trading volume of the transaction initiated by buyers and \(NV\) is the trading volume when sellers are deemed as initiators of the transaction. \(O_{t}^x\) is a dummy variable, and it is equal to 1 if the \(t\)-th interval is included in the opening (+) or closing (−) periods, and is equal to 0 otherwise; the superscript \(x\) indicates the opening period (+) or closing period (−).

When a submitted order hits the limit order book and is, thus, transacted, the order exerts an impact on the futures price, causing the latter to change. If the order was submitted by an informed investor, the price impact becomes permanent, and the changed price would settle at a new equilibrium level. If the order was submitted by an uninformed trader, the price change is transitory, and the price would revert to its original (pre-trade) level. We inferred the information content of intraday futures trading by comparing the estimated coefficients of \(\beta\) and its lagged values in terms of the relative sizes and significance. When current \(\beta\) coefficients are statistically significant, if the lagged coefficients \((\beta_i, i = 1, 2)\) are not significant, we can infer that the trades can greatly impact prices and are initiated by informed investors; if the lagged coefficients have opposite signs, we can conclude that the trades exert temporary price effects and are regarded as uninformed or liquidity trading. We also examined whether informed trading distributes intensively in the opening or closing periods by estimating the \(\gamma\) coefficients. If the current and lagged \(\gamma\) coefficients are significant and their summations have positive (negative) values for the positive (negative) volume in a specific period, we can infer that informed trading is relatively concentrated in that period. If the summations of \(\gamma\) coefficients have inconsistent signs, we can interpret that uninformed trading prevails in that period.

4.1.2. Modified Model of Asset Pricing

Next, we turned to applications of effective spread in asset pricing specifications of commodity futures. In most risk premium models, the key of the analysis is to derive the relationship between various asset returns and market risks.

\[
R_w = \alpha + \beta F_w + \delta c_w + \epsilon
\]  

(2)

In Equation (2), two risk factors are considered. One is the market risk factor, namely \(F_w = R_{m,w} - R_{f,w}\), where \(R_{m,w}\) denotes the daily logarithmic return of the commodity index, and \(R_{f,w}\) is the Shibor overnight interest rate that expresses risk-free interest rate. The other is the characteristic risk factor, namely the transaction cost \((c_w)\) which is estimated by effective spread.

Here, we set the transaction cost as a characteristic risk factor and applied it to the asset pricing model. The approach in this study is an extended and modified model, not only combining the market scale and transaction cost with the rate of return, but also taking their weekly seasonality into account. The steps to achieve these are as threefold. Firstly, we took the transaction cost computed by effective spread into the model, and chose holding position as the indicator measuring market scale. Next, we structured a dummy variable which considers a certain weekday from Monday to Friday and aggregative remaining periods over the week. Lastly, we captured weekly seasonality of price impact using the interaction effect between the dummy variable and the transaction cost (and market size).

The transaction cost is denoted by \(c_w\) as in Equation (2), and the market size is replaced by the logarithmic mean value of the holding position denoted by \(MC_w\). Factors related to day-of-the-week effect can be processed as follows: \(WeekDum_{w,x}\) is an aggregative dummy variable, and the superscript \(x\) represents further subdivision from “Monday” to “Friday”. Taking “\(WeekDum_{w,Monday}\)” as an example, this variable is equal to 1 if the day is Monday, and is equal to 0 otherwise. \(WeekDum_{w,x}^x\), where \(x\) is successively substituted from Monday to Friday, is multiplied by the transaction cost \((c_w WeekDum_{w,x}^x)\) and holding position \((MC_w WeekDum_{w,x}^x)\) to analyze the seasonality effects of transaction cost and
market size, respectively, on asset pricing. Therefore, the modified futures asset pricing model, a model
used to analyze the role of transaction costs in futures pricing and their seasonality, is shown below.

\[
R_w = \delta_0 + \beta \gamma_w + \delta_{\text{Week}} \text{WeekDum}_w + \delta_{c \cdot \text{Week}} (c_w \cdot \text{WeekDum}_w) + \delta_{w \cdot \text{Week}} (w_w \cdot \text{WeekDum}_w) + \delta_{mc \cdot \text{Week}} (MC_w \cdot \text{WeekDum}_w) + \delta_{mc \cdot -\text{Week}} (MC_w \cdot (-\text{WeekDum}_w)) + \epsilon_w
\]

where the dependent variable is excess return \(R_w\), which is equal to the difference between the
daily return rate of futures contracts \(r_w\) and the risk-free rate \(r_f\). \(\delta c\) and \(\delta \text{Week}\) are coefficients of
daily return sensitive to transaction cost \(c_w\) and to dummy variable \(\text{WeekDum}_w\), respectively;
and significance levels of these coefficients play a decisive role in judging the existence of liquidity
pricing and intraweek effect. \(\delta_{c \cdot \text{Week}}\) and \(\delta_{c \cdot -\text{Week}}\) are coefficients of daily return sensitive to the
transaction cost which happens on a certain weekday “c” and in aggregative periods of remaining
weekdays which exclude “c”, respectively, collecting a basis for the intraweek seasonality
impact of transaction cost on assets pricing. Similarly, \(\delta_{mc \cdot \text{Week}}\) and \(\delta_{mc \cdot -\text{Week}}\) are coefficients of daily
return sensitive to the holding position of a certain weekday and non-given periods, and work together
to capture intraweek effect of market size. Within the bracket, the top and bottom expressions are
mutually exclusive (to avoid linear dependence).

Logarithmic value, the rate of return \(r_w\) calculated by the daily closing price of each contract,
holding position \(MC_w\) measured by daily holding position, and Shibor interest rate which is an
alternative variable for the risk-free rate \(r_f\), are all available from Wind database. The market risk
return \(r_m\) is replaced by the rate of the CSI commodity futures composite index from China Securities
Index Co., Ltd., which uses the index of holding volume to weigh the closing price of all contracts that
go public over one year. As mentioned above, the transaction costs \(c_w\) are expressed using the daily
liquidity benchmarks calculated as the average of the intraday effective spread observations.

4.2. Result Analysis

4.2.1. Impact of Trading Activity on Futures Price and Its Intraday Seasonality

Table 2 reports the estimation results of Equation (1) regarding intraday price impact of futures
trades for soybean and corn. Informed trading is prevalent in the futures market, due to the fact that
a significant portion of the price dispersion induced by both positive and negative futures trades
persists after its initial impact. For instance, after ruling out the possibilities on collinearity between
regressors, a net purchase (sale) of 1000 futures contracts instantly causes a price increase (decrease)
of 4.167 (4.504) points for soybean and of 0.210 (0.226) points for corn during a one-minute period.
Note that the price impact coefficients of \(\beta\) are absolute indices which are not only affected by the
degree of market liquidity, but also by the basic price itself. When there are larger differences in base
price, horizontal comparison on price impacts is of less significance. Lagged values of \(\beta\) indicate that
price impacts during the following two intraday intervals still exist, and even get stronger for the
corn market. The above can make sense from the perspective of information sources in soybean and
corn markets. For the former, the majority of traders with large-scale trading usually take the soybean
price of CBOT as a reference on price movement; thus, their superiority is just maintained for short
periods because public and market-wide information is easier to spread. By contrast, for the latter,
the superiority of private information is essentially longer-lived.

Table 2 also reports the price impacts of futures trades during the opening period and the closing
period. The estimated coefficients \(\gamma_{\text{open},0}\) and \(\gamma_{\text{open},1}\) capture the price impacts of intraday futures
trades in the opening period, and the estimated coefficients \(\gamma_{\text{close},0}\) and \(\gamma_{\text{close},1}\) capture the price
impacts in the closing period. As Table 2 shows below, it is obvious that both opening and closing
effects of trading activity in the soybean market are not significant; thus, uninformed and liquidity
trading are dominant in these periods. As for corn futures, the $\gamma_{close,0}$ coefficient of negative volume is significantly negative, and the following reversal captured by the coefficient $\gamma_{close,1}$ is insignificant, suggesting that futures trades have permanent price impacts during the opening period. The $\gamma_{close,0}$ coefficient of positive (negative) volume is significantly positive (negative), and the $\gamma_{close,1}$ coefficients have opposite signs. The result of a negative value ($-0.0000138$) of the close_sum for negative volume indicates that the futures market does not fully absorb the price changes. However, its small absolute value implies most price changes are explained by the temporary effect caused by liquidity trading, while only a small proportion of price change can be regarded as a permanent price impact owing to informed trading. Taken together, the opening effect of informed trades is more significant than the closing effect in the corn market, because most investors may submit orders aggressively to avoid overnight inventory-holding risk in the closing period, and price effects brought about by frequent trading behaviors are shorter than those in the opening period. Another possible explanation for weaker informed trading in the closing period is that informed traders may prefer to trade in periods with higher liquidity in order to exploit the liquidity and make the deal quickly; however, this also lowers the relative share of informed trading during these periods.

The intraday seasonality of soybean trading differs from the findings of corn trading, which may be attributed to the differences in trading regimes between the corn futures market and the soybean futures market. Considering that the Chinese futures market is highly affected by CBOT market shocks, as for the market of soybean products, the setting of the night market prolongs trading time and allows investors to use the public international information to adjust their position, which makes it reasonable to distribute price fluctuations in the time dimension. At the opening market for corn futures, informed traders adjust their investment strategy according to private information accumulated during non-trading periods overnight, and this leads to a relatively volatile reaction in price changes. Overall, we can interpret these findings in terms of the presence or absence of night trading related closely to the overseas market.

Furthermore, price effects are driven asymmetrically by the positive and negative volumes, characterized by the price reaction on negative information hitting the market being sharper than that on positive shocks. This conclusion is consistent with our general knowledge. Small and medium retail investors like to take long, because going short generally requires relative spots reserves. Once the bearish trend is formed, investors in parties will take the initiative or be forced to liquidate the positions, resulting in continued falling of futures prices.

Table 2. Price impact of trade volumes.

| Coefficients | Soybean Futures | Corn Futures |
|--------------|-----------------|--------------|
|              | PV              | NV           | PV          | NV           |
| $\beta_0$    | 0.004167 (8.668)| -0.00450 (10.510)| 0.00021 (7.848)| -0.00023 (8.764) |
| $\beta_1$    | -0.00028 (0.550)| 0.00038 (0.803)  | 8.86 $\times$ 10^{-5} (0.317)  | 2.48 $\times$ 10^{-5} (0.873)  |
| $\beta_2$    | -0.00023 (0.797) | 0.00029 (1.052)  | 4.18 $\times$ 10^{-5} (2.637)  | -5.84 $\times$ 10^{-5} (3.132) |
| $\gamma_{open,0}$ | -0.00056 (-0.937) | 0.00011 (0.206)  | 2.30 $\times$ 10^{-5} (0.753)  | -7.12 $\times$ 10^{-5} (-2.250) |
| $\gamma_{open,1}$ | -0.00050 (-0.830)| 0.00048 (0.919)  | -4.31 $\times$ 10^{-5} (-0.144) | 2.70 $\times$ 10^{-5} (0.864)  |
| $\gamma_{close,0}$ | -0.00061 (-0.931)| 0.00065 (1.040)  | 8.00 $\times$ 10^{-5} (1.783)  | -8.91 $\times$ 10^{-5} (-2.334) |
| $\gamma_{close,1}$ | -0.00211 (-3.189)| 0.00240 (3.767)  | -0.000114 (-2.427) | 7.53 $\times$ 10^{-5} (1.905)  |
| $\gamma_{sum}$ | 0.00365 | -0.003837 | 0.00026066 | -0.0002596 |
| $\gamma_{lags}$ | -0.0000517 | 0.000667 | 0.00005066 | -0.0000336 |
| $\gamma_{open_S}$ | -0.00106 | 0.000584 | 0.00001869 | -0.0000442 |
| $\gamma_{close_S}$ | -0.0002718 | 0.0003053 | -0.000034 | -0.0000138 |
| $\alpha_1$ | 0.084864 (2.021) | -0.206752 (3.949) | (-6.917) | (-6.917) |
| $\alpha_2$ | 0.068259 (1.660) | -0.301608 (-6.917) | (-6.917) | (-6.917) |
| $C$ | 0.080078 (1.332) | 0.010469 (0.655) | (6.917) | (6.917) |

Adjusted $R^2$ | 0.486 | 0.629 |
4.2.2. Role of Liquidity in Asset Pricing and Its Weekday Seasonality

The regression results for soybean futures are shown in Table 3. The results of the second column account for the risk factor including a constant term, showing that the price of market risk is 0.010 and the t value is 1.662, which rejects the null hypothesis that market risk has no influence on the return of soybean futures. The finding is consistent with the conclusion of general pricing models. In the third column, the coefficient of transaction cost is $-54.817$, which is not significant. One possible explanation for this finding is that the excess return may include the cost of obtaining liquidity, but has no universal significance. To further verify the existence of seasonal impacts of transaction costs on assets pricing, the fourth column to the eighth column introduce the virtual variables. From the results, the coefficient of transaction costs on Friday is $-246.170$ with $-2.018$ as the t-value, which is significantly negative; meanwhile, the coefficient of transaction costs on non-Friday is insignificant. Thus, we deduce that there appears an obvious periodicity of liquidity effects in the soybean market, and the distinct contribution of liquidity to return occurs on Friday. From the ninth column to the 13th column, considering the combined effect of transaction costs and market sizes, the coefficient of transaction costs on Friday is $-263.913$ with $-2.129$ as the t-value, not obviously different from the result of not taking the market size factor into account. However, the coefficient (0.007) of market size is insignificant because of the smaller t value (0.683) than 10% standard values (1.648) on Friday. According to the t-value, Thursday is the day on which the market size has a significant positive impact on futures return, with 0.021 influence coefficient. Consequently, the significant impact of liquidity costs on assets pricing remains on Friday as before, while the scale effect works on Thursday and is not synchronized with liquidity effect.

One needs to notice, in particular, that the negative sign of the significant coefficient in the soybean market counters the liquidity premium theory. Approaching the closing on Friday, the majority of uninformed traders who are afraid to take risks of holding positions over the weekends or to miss investment opportunities will trade contracts to follow the herd, which will improve the liquidity of the market to some extent. Meanwhile, some informed traders may fully take advantage of the high-liquidity market to trade reversely so as to maximize profits, and asset returns may increase subsequently due to the cost of ensuring the liquidity drop. This explains why there is a negative effect on Friday between asset returns and transaction cost in the soybean market. With the effective diffusion of private information, trading is generally active and relatively rational in the middle of the week. The Thursday effect of market size occurs due to the largest holding position before closing positions widely being on Friday. The larger market would bring about higher futures returns, that is, the scale advantage.

Table 4 reports the estimation results of corn futures. The result in the second column indicates that market risk also has a persistent influence on the return of corn futures, and the third column shows that the effect of transaction costs on corn futures return is not significant overall. The following verification on the seasonality effect of transaction costs in the fourth column to the eighth column displays that the coefficient of transaction costs on Monday is 100.311 with a t-value of 2.367, and the coefficient of transaction costs on non-Monday is insignificant. Thus, we deduce that there are positive effects of liquidity costs on futures returns on Monday. The ninth column to the 13th column indicate that the coefficient of transaction costs on Monday is 132.638 with 2.674 as the t-value, which becomes more significant after considering the market factor; however, the effect of market size is of no significance all the time.
Table 3. Regression results of soybean future.

| (1) | (2) | Week and Transaction Costs | Week and Holding Position |
|-----|-----|-----------------------------|---------------------------|
|     |     | Monday | Tuesday | Wednesday | Thursday | Friday | Monday | Tuesday | Wednesday | Thursday | Friday |
| $\delta_0$ | 0.015 | 0.014 | -0.002 | 0.008 | 0.017 | 0.003 | -0.102 | -0.025 | 0.004 | 0.017 | 0.001 |
| (1.287) | (1.086) | (0.879) | (2.049) | (0.443) | (-1.620) | (-1.793) | (0.275) | (1.753) | 0.111 |
| $\beta$ | 0.009 | 0.009 | 0.009 | 0.057 | 0.010 | 0.009 | 0.009 | 0.011 | 0.009 | 0.010 |
| (1.662) | (1.629) | (1.650) | (1.599) | (1.779) | (1.656) | (1.640) | (1.652) | (1.863) | (1.475) | 1.656 |
| $\delta_c$ | -54.817 | -51.089 | 3.969 | -61.040 ** | -13.974 | -63.082 | -77.823 | -60.454 | -79.455 | -33.312 |
| (-1.220) | (-1.166) | (0.114) | (-0.889) | (-2.035) | (-0.487) | (-1.315) | (-1.563) | (-1.208) | (-1.449) | (-0.698) |

Note: the value in brackets is the $t$-statistic; *, **, and *** indicate correlations that are statistically significant at the 10%, 5%, and 1% levels, respectively.
Table 4. Regression results of corn futures.

|       | (1)          |       | (2)          |       | Week and Transaction Costs |       | (1)          | (2)          | Week and Holding Position |
|-------|--------------|-------|--------------|-------|----------------------------|-------|--------------|--------------|----------------------------|
|       | Monday       | Tuesday | Wednesday    | Thursday | Friday                     | Monday| Tuesday | Wednesday | Thursday | Friday | Monday       | Tuesday | Wednesday | Thursday | Friday | Monday       | Tuesday | Wednesday | Thursday | Friday | Monday       | Tuesday | Wednesday | Thursday | Friday | Monday       | Tuesday | Wednesday | Thursday | Friday |
| $\delta_0$ | $-0.001$     | $-0.006$ | $0.009$      | $-0.017$ | $-0.005$                  | $-0.002$ | $0.037$ | $-0.018$ | $0.0023$ | $0.0046$ | $0.0050$     |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
|       | ($-0.968$)   | ($-0.4700$) | ($0.670$)   | ($-1.816$) | ($-0.564$)                  | ($-0.227$) | ($0.844$) | ($-1.330$) | ($0.165$) | ($0.464$) | ($0.508$)     |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| $\beta$ | $0.010$ *    | $0.010$ *  | $0.010$      | $0.010$   | $0.010$ *                  | $0.010$   | $0.010$ * | $0.010$ * | $0.010$ * | $0.010$ * | $0.010$ *     |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
|       | ($1.648$)    | ($1.647$)  | ($1.646$)    | ($1.649$) | ($1.620$)                  | ($1.688$) | ($1.644$) | ($1.650$) | ($1.647$) | ($1.677$) | ($1.653$)     |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| $\delta_c$ | $7.626$      |       | ($0.396$)    |       |                           |       |       |       |       |       |       |     |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| $\delta_{\text{Week}}$ | $-0.069$ ** | $0.031$ | $0.011$      | $0.004$   | $0.016$                    | $0.008$   | $-0.024$ | $0.0651$ | $0.0250$ | $0.0868$ |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
|       | ($-2.418$)   | ($1.131$)  | ($0.409$)    | ($0.147$) | ($0.578$)                  | ($0.083$) | ($-0.264$) | ($0.723$) | ($0.281$) | ($0.979$) |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| $\delta_{\text{Week}}$ | $100.311$ *** | $-26.241$ | $-12.188$    | $-7.137$  | $-22.218$                  | $132.638$ *** | $-43.641$ | $9.3780$ | $2.4525$ | $5.0923$ |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
|       | ($2.367$)    | ($-0.623$) | ($-0.283$)   | ($-0.164$) | ($-0.504$)                  | ($2.674$) | ($-0.874$) | ($0.181$) | ($0.047$) | ($0.096$) |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| $\delta_{\text{MC Week}}$ | $-16.115$ | $27.716$ *  | $7.656$      | $2.024$   | $0.658$                    | $-6.735$  | $26.818$ | $21.4300$ | $24.5699$ | $23.1365$ |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
|       | ($-0.750$)   | ($1.759$)  | ($0.485$)    | ($0.154$) | ($0.050$)                  | ($-0.263$) | ($1.078$) | ($0.865$) | ($0.991$) | ($0.939$) |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| $\delta_{\text{MC Week}}$ | $-0.002$   | $0.000$   | $-0.011$     | $-0.004$  | $-0.004$                  | $-0.677$  | ($0.068$) | ($-0.748$) | ($-1.079$) | ($-1.102$) |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |

Note: the value in brackets is the $t$-statistic; *, **, and *** indicate correlations that are statistically significant at the 10%, 5%, and 1% levels, respectively.
The influence of liquidity costs on return rates for corn has a significant positive Monday effect, which is different from the negative Friday effect for soybean. The lack of trading on Friday night prolongs the time for corn traders to gather and accumulate information from all directions. Once opening the trade on Monday, informed traders would devote themselves to making a deal. However, at the beginning of every week, uninformed traders are generally in a wait-and-see state which may contribute to a low-liquidity market, while there are relatively larger percentages of traders who are informed over the weekend and eager to trade on Monday. To finish transactions completely, they are willing to pay for liquidity, and the higher the profits they want to achieve are, the higher the price they need to pay for good liquidity will be. It also explains why transaction costs positively affect corn futures return on Monday.

5. Discussion

5.1. Price Impact of Intraday Trading Activity

Several conclusions can be drawn from the above analysis. Firstly, a substantial portion of the price impact of futures trades is persistent, providing evidence of the presence of informed trading in Chinese agricultural futures markets. Secondly, the price impact in the soybean market lasts a shorter time than that in the corn market, highlighting the significance of night trading for price smoothing. Thirdly, the dummy variables measuring informed trading behavior in specific intraday intervals successfully capture the permanent price impacts of trades in the corn market during the opening and closing periods, while there is no significant seasonality of informed trading in the soybean market. Obviously, price impacts of informed trading are widely different between the soybean market and the corn market, as well as its lasting time and seasonality. It extends, to some extent, the research of Chang et al. [14], Ryu [15], and Webb [16], all of whom measured the price impact of trades targeting a single market while neglecting the otherness among markets.

The soybean market with good liquidity can attract more speculators than the corn market, as evidenced by higher trading frequency and smaller trading size. In this case, a group of speculators could not make it possible to control the market price for a long period of time. On the other hand, in the corn market, informed traders occupy a larger proportion, and they manipulate the market by buying or selling a substantial proportion of contracts based on private information, which could bring about a longer impact on assets price, along with an opening and closing effect. There are two possible explanations for why the opening effect and the closing effect of informed trading happen in the corn futures market but not in the soybean futures market. One is the difference of trade rules between both markets. The night trade of soybean futures enables investors to obtain the information from simultaneous trading in the CBOT and to handle the futures contracts in time, which subsequently leads to the unremarkable seasonality of soybean intraday trading. By contrast, the trading time of the corn market is completely opposite between the DCE and the CBOT. Not only do corn investors tend to submit futures orders during the closing period to reduce the risk of holding an inventory overnight, but they also exploit and release accumulated information from the outside market by trading contracts in the opening of the next day. The other is the linkage with the international market. While the corn market weakly links the international market due to the lack of international trades, the ever-growing import demand in the soybean spots market reinforces the tie between domestic and foreign futures markets. Many sophisticated and professional soybean traders usually regard the foreign futures prices as benchmarks to adjust their investment strategy; thus, price changes of the soybean market in the opening and closing periods are more stationary than that of the corn market, where information superiority would be released intensively.

5.2. Price Impact of Daily Market Liquidity

Price impacts of liquidity costs and holding position do not persist all the time, presenting different directions and seasonality across both varieties. Specifically, in the soybean market, the apparent
negative effect of transaction cost on returns appears on Friday, and the scale effect of “the larger the market size, the higher the asset return” emerges on Thursday. Meanwhile, in the corn market, the influence of transaction cost on asset return manifests a significant Monday effect with a linear positive relationship, and there is no evidence of scale effect. As mentioned before, our focus was not only on the generality of price impact, but also on the different features of liquidity pricing among futures varieties.

Liquidity effects vary significantly among different commodity futures because of differences in major investor types, trading patterns, and the market’s maturity. Sophisticated traders usually base algorithmic trading strategies on the market trends, which are determined using statistics, to make a short-term profit. In fast-moving markets, getting in or out of a trade a few seconds earlier can make a big difference in the trade’s outcome. For the soybean market, most medium- and short-term investors, including informed traders and uninformed traders, tend to close positions on Friday to lock in gains; thus, the lower liquidity cost guarantees a higher future return. The unconventional thinking that better liquidity leads to higher returns is particularly outstanding at the end of each week, because of the potential to easily dispose contracts to lock in profits, which is consistent with some standpoints of Kadlec and Mcconnell [19] and Bongaerts et al. [26], but also conflicts with the liquidity premium theory of Amihud [18]. In the corn market, the Monday effect presents an opposite relationship between liquidity and returns. This is because informed traders should pay for liquidity to trade timely before transmission and diffusion information cumulated over the weekend, and more returns should be gained to ensure their enthusiasm in trading after paying for more liquidity costs. This paper argues that the main reasons for the seasonality effect of market liquidity are the information accumulation during the non-trading periods and the investors’ investment decisions caused by the suspension of trading over weekends. Hence, we suggest regulatory authorities not to release new information at non-trading periods, especially over weekends.

6. Conclusions

Based on high-frequency data on real-time transaction details of soybean and corn from the Dalian Commodity Exchange (DCE), this paper empirically analyzed the liquidity of the Chinese agricultural futures market and its impact on futures price. We undertook two key steps. Firstly, we explored the price impacts of futures trades and their intraday seasonality using a basic regression framework. Secondly, we investigated how transaction costs affect asset pricing and their periodic features using an asset pricing model. We found that variances in investor components, trading patterns, and market activeness across agricultural commodities produce economically meaningful differences in liquidity and seasonality. In addition, these results highlight the importance of establishing an early warning system, improving market transparency, and perfecting the information disclosure system.

The first contribution of this research is it being able to provide traders with the necessary information to successfully utilize futures markets. It can help investors become better informed when facing public and market-wide resources, and discover trade opportunities by predicting short-term price movements. Another contribution is that the research provides a new perspective into studying the price impact of trading activities and market liquidity. Most importantly, it encourages researchers to take heterogeneity among markets into account and to focus on the different features of price impact among varieties. Although the empirical findings were based on relatively short time periods, they were accepted by the robustness tests, which are not listed in this paper to keep the paper reasonably concise. We agree that further analyses on transaction cost analysis and algorithmic trading should be carried out to provide additional insight into price impacts and the informative role of futures trading.

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