

Research Article

Study on Informational Transaction and Its Effect on China's Stock Index Futures Market

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Received 24 December 2013; Accepted 20 February 2014; Published 27 April 2014

Academic Editor: Fenghua Wen

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Information is one of the important factors that influence the behavior of investors and then have an effect on the price of the risky assets in the market. Firstly, the new procedure developed by Easley et al. (2011) is used to estimate the Volume-Synchronized Probability of Informed Trading (VPIN) of the Chinese stock index futures market. Then VPIN for special scenarios is depicted. As a result, we find that the future contracts generally have a larger number of information transactions. We also find that, for particular scenarios, the probability of informed trading in the market has obvious exceptions. The larger proportion of informed trader is, the higher the volatility of the price is.

1. Introduction

The capital market plays an important role in the efficient allocation of resources in socioeconomic operations because the market gathers all the scattered information into the price of the assets. It is often assumed traditionally that the traders on the market share the common integrated information in traditional finance. However, information is always asymmetrical in reality. It has been become common knowledge in the microstructure literature that the arrivals of orders contain important information of asset volatilities. However, it has become more difficult when the measurement of the order flow in a high frequency scenario is needed. In a framework where trading takes place in milliseconds, Easley et al. [1] introduced another conception. In this paper we apply this new technique to the Chinese stock index futures market.

The paper is organized as follows. Section 2 summarizes the principal approaches for analyzing the probability of informed trading. Section 3 illustrates the principal models. Section 4 briefly illustrates the VPIN model. Section 5 estimates the Volume-Synchronized Probability of Informed Trading of the Chinese stock index futures market. Section 6 depicts the Volume-Synchronized Probability of Informed Trading of special scenarios. Section 7 is the conclusion.

2. Literature Review

The former securities market information asymmetry research usually refers to the indirect measurement. Easley et al. [2] set up a mixed discrete and continuous time sequential model of the trading process. It is the first time to measure the market's degree of information asymmetry in a direct way. We will briefly explain it in the next section. Their model is developed on the basis of Easley and O'Hara's (1992) [3] studies. This microstructure model views trading as a game between informed traders and uninformed traders. The trading is repeated over trading periods. Since informed traders trade only when there is a signal, thus it is reasonable to assume that variations in the trading intensity are positively related to the behavior of informed traders. However, the model implies strongly that asset prices and the trading volume do not affect the traders' behaviour. Easley et al. [4] introduced the possibility that the traders condition their trades on the observed volume. They argue that uninformed traders will take into consideration the trading history in placing their orders. Other researchers (see Brockman and Chung [5], such as Grammig et al. [6]) have also conducted studies on this topic.

Venter and De Jongh [7], Lei and Wu [8] consider the arrival rate of traders as inconstant. Venter and Jongh assume

that the arrival rate of traders' orders obey the inverse Gaussian distribution, while Lei and Wu allow uninformed traders' order arrival rate with the behavioral characteristics of the district system to convert endogenously. Until 2008, Easley et al. [9] propose a dynamic econometric microstructure model of trading which depicts the time-varying PIN (probability of informed action-based trading).

There are a number of current studies on classifying buy and sell volumes. Jackson [10] expanded the EKOP model which does not need to distinguish the direction of volume, and Easley et al. [1] set up a new approach for classifying buy and sell volumes. They propose a new "bulk volume" classification algorithm in which they aggregate trades over short time intervals and then use the standardized price change between the beginning and the end of interval to approximate the percentage of buy and sell volumes. This approach is explained in details by Easley et al. in their article [11, 12]. While Anderson and Bondarenko [13] use tick data for S&P futures to establish the VPIN metric model in Easley et al. [1, 11, 12], dispute their empirical finding in papers, and argue that VPIN does not work well. Then Easley et al. [14] refute the outcome of Andersen and Bondarenko [13] and stress the importance of microstructure feature in understanding price dynamics.

There are also researches about Chinese stock market that are based on EKOP model (see [15–17]). These studies are consistent with Easley et al. [2]. However, Zheng and Yang [18] indicate that the EKOP model cannot accurately measure information risk of stocks. What is more, a new method to estimate probability of informed trading in continuous auction order driven market called Transaction Aggressiveness is proposed by Li et al. [19], and they find that their model performs better in explaining the spread of market price in comparison with classic models.

Handa et al. [20] models quote setting and price formation in a nonintermediated, order driven market where trading occurs since investors differ in their valuation about shares and the advent of news that is not common knowledge. They show that the size of the spread is a function of adverse selection and differences in valuation among investors. And the probability of informed trading is given by GMM estimation of the model parameters. Other related papers include Wang and Yang [21], An et al. [22], and Zhou and Yu [23].

In addition, Nyholm [24, 25] estimates the probability of trades being generated by privately informed traders. Inference is drawn on a trade-by-trade basis using data samples from the New York Stock Exchange. His model, formulated as a regime-switching expansion of the basic trade-indicator model, is validated. Nyholm [24] also discusses that whether the model can be applied to the continuous auction market. What is more, we need to test the Markov property before launching his model.

3. EKOP Model and Time Varying Information Model

3.1. EKOP Model. In this section we describe the sequential trade model introduced by Easley et al. [2], for those who

are not familiar with the EKOP approach. This model can be viewed as a benchmark for sequential trade models, since it captures all the essential features of these types of models. The settings of EKOP model are as follows.

The Market Mechanism. In the dealership market framework, some risk-neutral, competitive market-makers sequentially provide investors with the price of an asset and trade with these investors. The prices that are reported by market makers are then computed based on the past expected price of all transaction information.

Trading Period. They set up a mixed discrete and continuous time sequential model of the trading process. Trading days are indexed by i ($i = 1, \dots, I$) and, within a trading day, time is continuous, indexed by $t \in [0, T]$. Information events are independently distributed. At the end of each trading day, the price of an asset will fully reflect the event which has happened during the day. At the same time, there is an essential hypothesis that each investor just trade once during a trading day, and the transaction must be able to finish in time.

Investors. In this framework, trades arise because of the interaction of two types of economic agents: informed and uninformed traders. Trades not only depend on the arrival rates of informed and uninformed traders which are governed by independent Poisson processes, but also on the likelihood of the occurrence of three different types of information events (no news, good news, and bad news) which are naturally decided before the first trade take place every day. On any day, arrivals of uninformed buyers and uninformed sellers are determined by independent Poisson processes. Uninformed buyers and sellers arrive at rate ϵ . The arrival rate of informed buyers and sellers is represented by μ .

Asset. The likelihood of the occurrence of three different types of information events (no news, good news, and bad news) are chosen by nature everyday. Information events are independently distributed and occur with probability α . These events include good news with probability $1 - \delta$ and bad news with probability δ . At the end of trading on any day, the full information value of the asset is then realized. During day i , if an information event occurs, the value of the asset conditional on good news is \bar{S}_i and on bad news is \underline{S}_i .

Informed Trading Probability. Let $P(t) = \{P_n(t), P_b(t), P_g(t)\}$ be the market maker's prior beliefs in no news (n), bad news (b), and good news (g) of the events at time t . The unconditional priori beliefs at time 0 are equal to the probabilities with the information regime which is naturally determined: $P(0) = \{1 - \alpha, \alpha * \delta, \alpha * (1 - \delta)\}$. So at time t , the expected value of risky assets of the market makers is shown as

$$E(S_i | t) = P_n(t) * S_t^* + P_b(t) * \underline{S}_i + P_g(t) * \bar{S}_i \quad (1)$$

At time t the probability for the informed traders to sell the asset is given by $\mu * (P_b(t)/(\epsilon + \mu * P_b(t)))$. Similarly,

the probability for the informed traders to buy the asset is given by $\mu * (P_b(t)/(\varepsilon + \mu * P_b(t)))$. The bid and ask are given by the following equations:

$$\begin{aligned} B(t) &= E(S_i | t) - \mu * \frac{P_b(t)}{\varepsilon + \mu * P_b(t)} * [E(S_i | t) - \underline{S}_i], \\ A(t) &= E(S_i | t) - \mu * \frac{P_b(t)}{\varepsilon + \mu * P_b(t)} * [\bar{S}_i - E(S_i | t)]. \end{aligned} \quad (2)$$

These equations demonstrate the explicit role played by arrivals of informed and uninformed traders in affecting quotes. If there are no informed traders ($\mu = 0$), then trade carries no information, and as a result, the Bid and Ask are both equal to the prior expected value of the asset. Alternatively, if there are no uninformed traders ($\varepsilon = 0$), then the Bid and Ask are at the minimum and maximum prices, respectively. At these prices no informed traders will trade either, and the market, in effect, shuts down. Generally, both informed and uninformed traders will be in the market, and so the Bid is less than $E(S_i | t)$, and the Ask is greater than $E(S_i | t)$.

The Bid-Ask Spread at time t is denoted by

$$\begin{aligned} \sum(t) &= \mu * \frac{P_g(t)}{\varepsilon + \mu * P_g(t)} [\bar{S}_i - E(S_i | t)] \\ &+ \mu * \frac{P_b(t)}{\varepsilon + \mu * P_b(t)} [E(S_i | t) - \underline{S}_i]. \end{aligned} \quad (3)$$

The spread for the initial quotes in the period has a particularly simple form in the natural case in which good and bad events are equally likely. That is, if $\delta = 1 - \delta$, then

$$\sum = \alpha * \frac{\mu}{\alpha * \mu + 2\varepsilon} * (\bar{S}_i - \underline{S}_i). \quad (4)$$

So the probability that the opening trade in a period is information-based is given by

$$\text{PIN} = \alpha * \frac{\mu}{(\alpha * \mu + 2\varepsilon)}. \quad (5)$$

Difficulties in estimating the parameter arise because it is not possible to directly observe neither the occurrence of information events nor the associated arrival of informed and uninformed traders. However, it is possible to infer the values of daily arrivals of sell and buy using maximum likelihood and assuming that the trading process follows a Poisson process:

$$\begin{aligned} L &= \prod_{i=1}^n P[y_t = (B_t, S_t)] \\ &= \prod_{i=1}^n \left(\alpha * (1 - \delta) * e^{-(\alpha + 2\varepsilon)} * \frac{(\mu + \varepsilon)^{B_t} * \varepsilon^{S_t}}{B_t! * S_t!} \right. \\ &\quad \left. + \alpha * \delta * e^{-(\mu + 2\varepsilon)} * \frac{(\mu + \varepsilon)^{S_t} * \varepsilon^{B_t}}{B_t! * S_t!} \right) \\ &\quad + (1 - \alpha) * e^{-2\varepsilon} * \frac{\varepsilon^{(B_t + S_t)}}{B_t! * S_t!}. \end{aligned} \quad (6)$$

3.2. Time Varying Information Model. Easley et al. [9] consider the information content of trades, because the numbers of buys and sells contain information about arrival rates of informed and uninformed traders. They calculate the expected arrival rate of informed trades; the traders then use this information to update their arrival rate estimates. So at time t , the arrival rates of informed and uninformed traders in the market will be influenced by time $(t-n)$ ($n = 1, 2, 3, \dots$).

It is still essential to use maximum likelihood just as (6) to estimate the parameter of the time varying model. The difference is that trading order arrival rates for informed and uninformed traders change over time and the lag influences should be taken into consideration.

Time-varying information model has already been regarded applicable to study the high-frequency transactions on the financial markets. However, the huge advantage of the supercomputer has increased the speed of transactions to milliseconds. Just as Easley et al. [1] illustrate, studies updated from the perspectives of volume-time, rather than clock time make, the model more applicable to the high frequency world.

4. VPIN Model

Easley et al. [1] group sequential trades into equal volume buckets of an exogenously defined size V . A volume bucket is a collection of trades with total volume V . If the last trade needed to complete a bucket which has a size greater than required, the excess amount belongs to the next bucket. We let $\tau = 1, \dots, n$ be the index of equal volume buckets. If the deal is launched by the buyer, the buyer will launch volume aggregation marked V_τ^B or marked V_τ^S . Hence, the equation is as follows:

$$\frac{1}{n} \sum_{\tau=1}^n (V_\tau^B + V_\tau^S) = V. \quad (7)$$

From EKOP model and time varying model, we may know that

$$\begin{aligned} E(V) &= \underbrace{\alpha * (1 - \delta) * (\varepsilon + \mu + \varepsilon)}_{\text{volume resulting from good news}} \\ &\quad + \underbrace{\alpha * \delta * (\varepsilon + \mu + \varepsilon)}_{\text{volume resulting from bad news}} + \underbrace{(1 - \alpha) * (\varepsilon + \varepsilon)}_{\text{volume without news}} \\ &= \alpha * \mu + 2\varepsilon, \\ E(\text{OI}) &= B - S \\ &= \alpha * \delta * (\varepsilon - \mu - \varepsilon) + \alpha * (1 - \delta) * (\varepsilon + \mu - \varepsilon) \\ &\quad + (1 - \alpha) * (\varepsilon - \varepsilon) \\ &= \alpha * \mu * (1 - 2\delta), \end{aligned}$$

TABLE 1

Date	Natural proportion	Corporation proportion
August 20	0.946	0.054
September 6	0.983	0.017
September 17	0.946	0.054

TABLE 2

Date	Natural proportion	Corporation proportion
August 20	0.512	0.859
September 6	0.527	0.868
September 17	0.577	0.601

$$\begin{aligned}
E(|OI|) &= |B - S| \\
&= \alpha * \delta * (|\varepsilon - \mu - \varepsilon|) + \alpha * (1 - \delta) \\
&\quad * (|\varepsilon + \mu - \varepsilon|) + (1 - \alpha) * (|\varepsilon - \varepsilon|) \\
&= \alpha * \mu, \\
E[OI_\tau] &= E[|V_\tau^S - V_\tau^B|] \approx \alpha * \mu.
\end{aligned} \tag{8}$$

Generally speaking, information trading can be reflected by the unbalance order. So,

$$VPIN = \frac{\alpha * \mu}{\alpha * \mu + 2\varepsilon} = \frac{\alpha * \mu}{V} \approx \frac{\sum_{\tau=1}^n |V_\tau^S - V_\tau^B|}{n * V}. \tag{9}$$

5. The Information Trading of Chinese Stock Index Futures Market

5.1. The Discussions on the Market Mechanism. This model fully draw from Easley et al. [1]. What is more, the model of their paper is set up based on dealership market. However, China's stock index future market is a typical continuous bidding market. So the entrusted orders (limit order) may be delayed in dealing. In that sense, the explanatory ability of the model will be fragile. So we should firstly discuss the applicability of the model on CSI 300 stock index futures market in China.

By choosing CSI 300 stock index futures contract IF1009 on August 20, September 6, and September 17 trade-by-trade data, the results of the market structure are depicted in Table 1.

From Table 1, we can observe that natural investors are the most common group in Chinese stock index futures market. Then the dealing rate of these natural investors' orders may be helpful to answer the question about the applicability of the model in Chinese stock index futures market. The statistical results are given in Table 2.

From Table 2, more than 80% (weighted) limit orders could get a deal in Chinese stock index futures market. There is no existence of significant problem of bidding market compared with the dealership market. What is more, Nyholm [24] finds that the order-driven market limit order book provides the market with liquidity, whose essence is just similar to the market maker.

5.2. Data Sources and Instructions. The data we supplied are all from CFFEX, and the selected contracts are from all the listed contracts for trading from August 3, 2010, to November 19, 2010, in China's financial futures exchange, including dominant contract, next month contract, next season contract, and seasons contract (see Table 3).

Trade classifications follow the reporting conventions in CFFEX. We do not adopt these algorithms which are set up by Lee and Ready (1991) or Easley et al. [1].

It is worth noting that

- (1) we also treat each reported trade as if it was an aggregation of trades of unit size just as what has been argued by Easley et al. [1];
- (2) we also focus on V equal to 1/50 of the average daily volume and $n = 50$ (Easley et al. set up V equal to 1/50 of the average daily volume and $n = 50$);
- (3) the VPIN metric is updated after each volume bucket. Thus, when bucket 51 is filled, we drop bucket 1 and calculate the new VPIN based on buckets 2–51.

5.3. The Statistics of Order in the Volume Bucket. Firstly we investigate the CSI 300 stock index futures from August 3, 2010, to November 19, 2010, to find the statistical analysis of the executed contract.

Tables 4, 5, 6, and 7 show the buy volume, sell volume, and order imbalance in each volume bucket of the Chinese stock index futures market, including dominant contract, next month contract, next season contract, and seasons contract. We can find that the average volume becomes smaller progressively which means that the main contract is more attractive to investors.

5.4. Volume-Synchronized Probability of Informed Trading. From the values computed above, we can derive the Volume-Synchronized Probability of Informed Trading

$$VPIN \approx \frac{\sum_{\tau=1}^n |V_\tau^S - V_\tau^B|}{n * V}. \tag{10}$$

The results areas are shown in Table 8. We can find that the Volume-Synchronized Probability of Informed Trading of each contract is 9.96%, 15.03%, 29.02%, and 47.61%, and the future contract generally has larger and more fluctuational information transactions, meanwhile; the main contract is more stable.

Figures 1, 2, 3, and 4 provide a graphical illustration of the Volume-Synchronized Probability of Informed Trading for each contract.

As is shown in Figures 1, 2, 3, and 4, the horizontal axis of each figure represents the volume bucket, while

TABLE 3

Date	Dominant	Next month	Next season	Seasons
2010/08/03–2010/08/20	IF1008	IF1009	IF1012	IF1103
2010/08/23–2010/09/17	IF1009	IF1010	IF1012	IF1103
2010/09/20–2010/10/15	IF1010	IF1011	IF1012	IF1103
2010/10/18–2010/11/19	IF1011	IF1012	IF1003	IF1106

TABLE 4

	Buy	Sell	Order imbalance
Mean	2044	2048	406
Std.	258.36	258.36	319.58

TABLE 5

	Buy	Sell	Order imbalance
Mean	616	628	187
Std.	120.66	120.66	153.49

TABLE 6

	Buy	Sell	Order imbalance
Mean	21	22	13
Std.	7.93	7.93	9.44

TABLE 7

	Buy	Sell	Order imbalance
Mean	3	4	3
Std.	2.02	2.02	2.19

TABLE 8

	VPIN
Dominant contract	
Mean	0.0996
Std.	0.0143
Next month contract	
Mean	0.1503
Std.	0.0377
Next season contract	
Mean	0.2902
Std.	0.0437
Seasons contract	
Mean	0.4761
Std.	0.0715

the longitudinal axis refers to the Volume-Synchronized Probability of Informed Trading of each contract. We can also conclude that the information trading probability of contracts with lower active levels is higher than those with higher active levels.

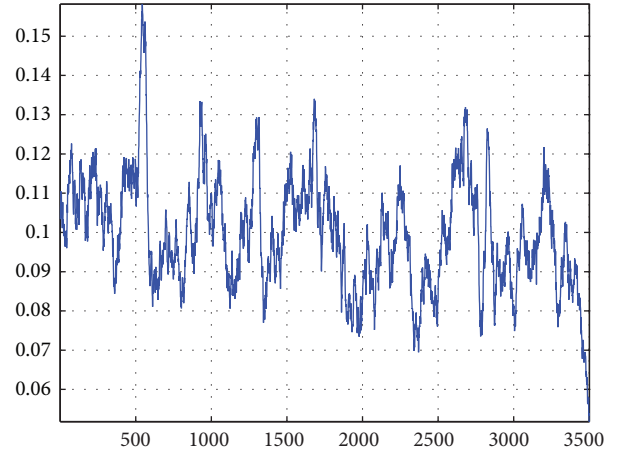


FIGURE 1: The VPIN of main contract.

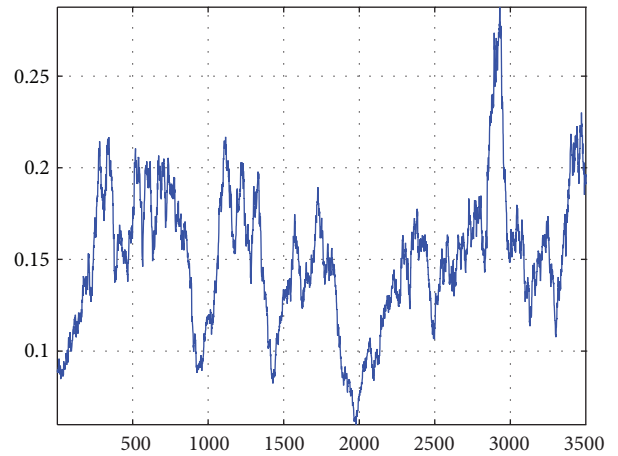


FIGURE 2: The VPIN of next month contract.

6. The Volume-Synchronized Probability of Informed Trading for Special Scenarios

Information is one of the important factors that may affect the trade behavior of investors within the market, just as Huang et al. [26] illustrate that, in the practical financial markets, the price volatility of financial asset is not continuous but containing jumps because of the influence of information shock on the market and the investors' irrational behavior. Investors can make judgement on the market trends and estimate gains from trade based on existing information. Therefore, monitoring the real-time information in the market is significant for securities trading and market supervision. In that sense,

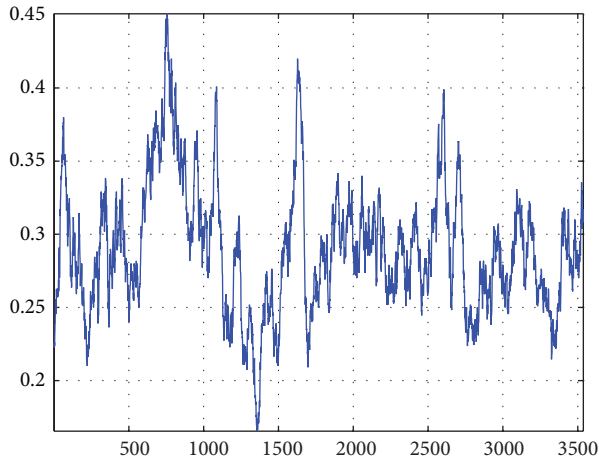


FIGURE 3: The VPIN of next season contract.

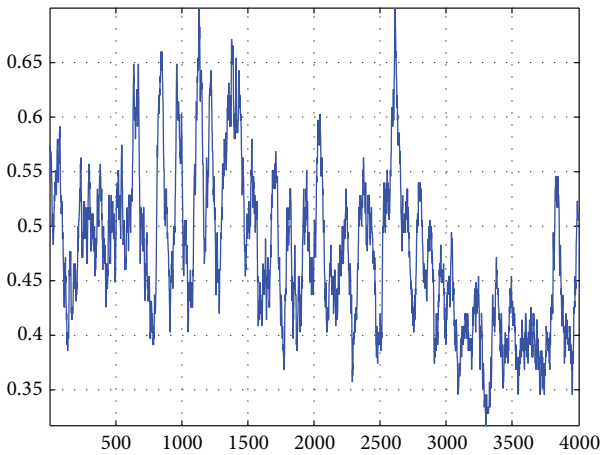


FIGURE 4: The VPIN of seasons contract.

this part of the paper will concentrate on two specific areas of information trading in the market.

Firstly we concentrate on the expiration day. Since the 1982 Kansas futures exchange (KCBT) first launched value line index futures contract, international regulatory, academia, and investors give high level of attention to the influence of maturity date (expiration day effects). The so-called expiration day effects not only refer to the yield and stability of both spot and stock index futures, but also the anomalous changes before the expiration dates for contracts of stock index futures. The previous research shows that the main reason for stock index futures expiration date effects is the market investors' behavioral changes. Therefore, studies on information trading probability on the delivery day of the stock index futures market contracts make contribution to deepen the understanding of market investors' behavior.

Secondly we focus on the information trading characteristics when CSI 300 stock index futures are initially listed in the market. We wonder the possible features that IF1005 may have and whether the VPIN model can be used to warn liquidity crisis as Easley et al. [1] point out.

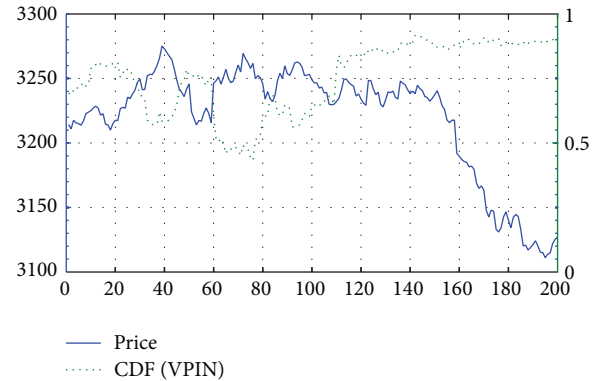


FIGURE 5

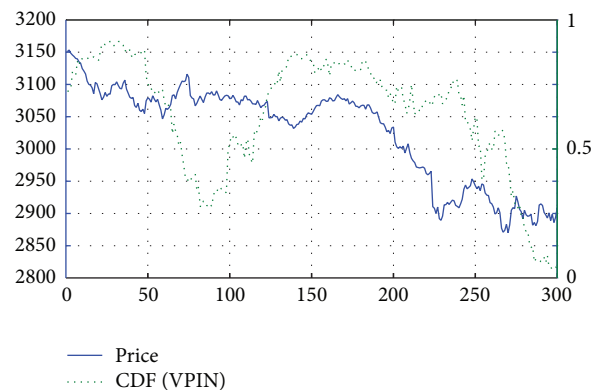


FIGURE 6

6.1. The Information Trading on the Expiration Day. Cai [27] point out that the effects of the direct (main) reason can be generalized as, under the existing framework, different market agents have changed the trading strategies near the maturity date of stock index futures. Existing research about expiration day effects of stock index futures focuses on the cash market, but abnormal changes on volume, quantity, and prices are also shown in the stock index futures market. So this section will be limited to reveal trading information in stock index futures market, and spot index market is not involved.

Data is selected from the high frequency data of main contract and the next month contract between August 3, 2010, and November 19, 2010, for this section, in which the evolution characteristics of information trading on the maturity date of stock index futures are then revealed. Specifically, the statistics for maturity date refer to the exact date for contract expiration and the day before expiry; this is because in normal market conditions, abnormalities in transaction volume have already appeared before the expiry day of contracts.

Having compared Tables 9, 10, 11, and 12, it can be concluded that information traded for the main contracts on the expiry dates appear downward trends and stability in contrast to that on expiration date. This shows that the arrival rate for information trading on maturity date

TABLE 9

	Unexpiration day	Expiration day
IF1008		
Mean	0.1065	0.0879
Std.	0.0145	0.0019
Buckets per day	69	5
IF1009		
Mean	0.1410	0.1754
Std.	0.0404	0.0185
Buckets per day	53	250

TABLE 10

	Unexpiration day	Expiration day
IF1009		
Mean	0.1033	0.0838
Std.	0.0117	0.0068
Buckets per day	61	11
IF1010		
Mean	0.1094	0.1700
Std.	0.0156	0.0246
Buckets per day	9	179

TABLE 11

	Unexpiration day	Expiration day
IF1010		
Mean	0.0926	0.0879
Std.	0.0102	0.0064
Buckets per day	42	11
IF1011		
Mean	0.1057	0.1472
Std.	0.0138	0.0144
Buckets per day	12	175

is not high, and on the expiry date, the sales volume of main contract decreases obviously. The phenomenon shows different results compared with previous studies about stock index futures expiration date that are generally believed that, on the contract's first delivery day, the sales volume for main contracts within the market will appear a magnified trend. This may be because of the insufficient hedgers and arbitragers in present CSI 300 stock index futures market in our country.

It is not difficult to find that the next month contract, the maturity date information trading volume, and volatility probability all appear amplification. This shows that informed traders will choose to trade on the next month contracts with more liquid and less risky features on the expiration dates of main contracts.

6.2. *The Probability of Informed Trading of IF1005.* Easley et al. (2010) [1] study the flash crash based on VPIN on May 6, 2010. They find that the VPIN metric for the E-mini S&P 500 future remained abnormally high level for at least one

TABLE 12

	Unexpiration day	Expiration day
IF1011		
Mean	0.0946	0.0556
Std.	0.0144	0.0021
Buckets per day	51	3
IF1012		
Mean	0.1426	0.1463
Std.	0.0441	0.1046
Buckets per day	54	92

week before the flash crash. And the VPIN metric reached its highest level on May 6, 2010. At the same time, China's CSI 300 stock index futures market also showed a relatively larger decline. Research (see, [28–30]) has specified the linkage between China and the U.S. stock market. Hence, this section will focus on the content whether the CSI 300 stock index future market would show a higher probability of informed trading.

Because of limitations on data, studies about the probability of informed trading for IF 1005 contracts in the CSI300 index futures market will be limited to the period from April 16, 2010, to May 14, 2010. During this period, IF1005 contract has decreased by 594.8 points in total, which is 17.2 percent alternatively. At the same time, because of the one minute frequency data, it is difficult to determine the buy and sell. We adopt the classification algorithm set up by Easley et al. [1]:

$$V_{\tau}^B = \sum_{i=t(\tau)+1}^{t(\tau)} V_i * Z \left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}} \right), \tag{11}$$

$$V_{\tau}^S = \sum_{i=t(\tau)+1}^{t(\tau)} V_i * \left[1 - Z \left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}} \right) \right] = V - V_{\tau}^B,$$

where $t(\tau)$ is the index of the last time bar included in the τ volume bucket and Z is the CDF of the standard normal distribution and is the estimate of the standard derivation of price changes between time bars. P is the last price of every minute. $\sigma_{\Delta P}$ refers to the standard deviation of price change.

We find that the probability of informed trading of IF1005 contract in the sample period is about 0.8733. This shows that during the initial listing period of stock index futures, the transactions remain frequent. In order to measure the relationship between the probability of information trading and sudden downturn within the market, we use Pearson's correlation between the natural logarithm of VPIN and the absolute price return ($\text{abs}(P_{\tau}/P_{\tau-1} - 1)$) over the following bucket.

Table 13 shows the distribution of absolute returns between two consecutive volume buckets under the conditions of previous VPIN level. We also do this by firstly grouping VPINs by 5% tiles and absolute returns in bins of size 0.15% (see, [1]), and each row adds up to 100%.

Table 13 shows that as VPIN levels increase, there is a transfer of probability from lower returns to higher returns.

TABLE 13

	0.0015	0.003	0.0045	0.006	0.0075	0.009	0.0105	>0.0105
0.7562	56.25%	22.92%	14.58%	2.08%	4.17%	0.00%	0.00%	0.00%
0.7999	60.42%	18.75%	12.50%	6.25%	2.08%	0.00%	0.00%	0.00%
0.8104	56.25%	25.00%	14.58%	0.00%	0.00%	4.17%	0.00%	0.00%
0.8185	66.67%	14.58%	12.50%	4.17%	2.08%	0.00%	0.00%	0.00%
0.8302	52.08%	33.33%	12.50%	2.08%	0.00%	0.00%	0.00%	0.00%
0.8465	56.25%	20.83%	18.75%	2.08%	2.08%	0.00%	0.00%	0.00%
0.8543	45.83%	35.42%	10.42%	4.17%	0.00%	2.08%	2.08%	0.00%
0.8605	58.33%	20.83%	14.58%	4.17%	2.00%	0.00%	0.00%	0.08%
0.8667	60.95%	28.80%	5.48%	2.47%	0.88%	0.71%	0.18%	0.53%
0.8739	61.39%	29.15%	4.83%	2.32%	0.77%	0.77%	0.19%	0.58%
0.8801	62.34%	28.09%	4.68%	2.55%	0.85%	0.64%	0.21%	0.64%
0.8851	61.61%	28.44%	4.74%	2.61%	0.95%	0.71%	0.24%	0.71%
0.8923	61.76%	29.14%	4.55%	2.41%	0.80%	0.53%	0.27%	0.54%
0.8976	63.50%	28.22%	3.68%	2.76%	0.61%	0.31%	0.31%	0.62%
0.9019	64.39%	26.62%	3.96%	3.24%	0.72%	0.36%	0.00%	0.72%
0.909	61.74%	27.83%	4.78%	3.91%	0.43%	0.43%	0.00%	0.86%
0.9151	60.99%	26.92%	6.04%	4.40%	0.55%	0.55%	0.00%	0.55%
0.9193	61.19%	26.87%	5.22%	4.48%	0.75%	0.75%	0.00%	0.75%
0.9236	60.47%	27.91%	3.49%	5.81%	1.16%	0.00%	0.00%	1.16%
0.9274	52.63%	31.58%	2.63%	10.53%	0.00%	0.00%	0.00%	2.63%

It shows that VPIN is useful as a predictive measurement of absolute returns.

Table 14 represents the distribution of prior VPIN levels conditional on the following absolute returns. The first row and column of Table 14 have the same meaning of Table 13. As these are probabilities of VPIN conditional on absolute returns, each column in Table 14 sums to one. Table 14 depicts that an alternative use of VPIN is as a warning measure.

The second half of this section will be inspected in the dynamic trend for market price of the CSI 300 stock index futures market under the conditions where the value for the distribution function of the probability of informed trading is above 0.8. The distribution of VPIN of IF1005 in the CSI 300 stock index futures market can be closely approximated by a log-normal.

For the five trading days from April 21, 2010, to April 27, 2010, IF1005 contract fell about 4 percent, and the biggest one-day point declined by 86 points. Figure 5 describes the CDF (VPIN), trend, and market prices within the five trading days.

The horizontal axis of the figure is the trading volume bucket (nearly 200 trading volume bucket), the cumulative distribution probability of values for VPIN corresponds to the right longitudinal axis, and the left vertical axis indicates the IF1005 contract market price. The connection in diagram represents the trend of market price, and the Green Line represents the trend of cumulative probability distribution for VPIN value. Therefore, we may observe that, before the start of the “fall” (about 130 point), the cumulative distribution probability of VPIN value exceeded 0.8 and fluctuated around 0.9 and the tendency continued till the end of the “slump.”

In addition, within five trading days of April 30, 2010, to May 7, 2010, the IF1005 contract fell about 6 percent; the

biggest decline in a single day (May 6) is 111.2 points. On May 7, the opening price lowered by 61 points, and the final one-day drop was 75.5 points. Figure 6 describes the CDF (VPIN) trend and market prices during the 5 trading days. Abscissa axis, two longitudinal axes, and the curve refer to the same meaning represented by those in Figure 5.

The first 0–50 trading volume bucket of Figure 6 is approximation for April 30, before the opening of the day, the values for cumulative distribution function of the probability of informed trading fluctuated around 0.9, and on May 4 (50–100 trading volume bucket), the probability of informed trading declined, whereas on May 5 (100–150 trading volume bucket), the probability of informed trading went up again, indicating that the informed traders trade frequently. With the pace of crash, the probability of informed trading is gradually declining.

This section mainly studies the probability of informed trading for a particular scenario. Firstly, dynamic changes of informed trading probability for both main contracts and the next month contracts on the settlement dates are examined based on that the study has found that the informed trading probability for main contract on the expiration date appears downward trend, while that for the next month contract shows magnified trend on both trading volume and volatility. Secondly we study the relationships between VPIN values and IF1005 contract price and we have observed that VPIN is useful in warning the sudden crash for IF1005 contracts.

7. Conclusion

Start from Easley et al. [1], we carry out the study about information transactions probability of CSI 300 stock index

TABLE 14

	0.0015	0.003	0.0045	0.006	0.0075	0.009	0.0105	>0.0105
0.7562	4.80%	4.31%	8.33%	3.85%	20.00%	0.00%	0.00%	0.00%
0.7999	5.16%	3.53%	5.95%	11.54%	10.00%	0.00%	0.00%	0.00%
0.8104	4.63%	4.71%	9.52%	0.00%	0.00%	28.57%	0.00%	0.00%
0.8185	5.52%	2.75%	7.14%	7.69%	10.00%	0.00%	0.00%	0.00%
0.8302	4.63%	5.88%	7.14%	3.85%	0.00%	0.00%	0.00%	0.00%
0.8465	4.63%	4.31%	9.52%	3.85%	10.00%	0.00%	0.00%	0.00%
0.8543	4.27%	5.88%	5.95%	7.69%	0.00%	14.29%	50.00%	0.00%
0.8605	4.80%	3.92%	7.14%	7.69%	0.00%	0.00%	0.00%	0.00%
0.8667	4.63%	4.71%	8.33%	7.69%	10.00%	0.00%	0.00%	0.00%
0.8739	4.63%	7.06%	3.57%	0.00%	0.00%	14.29%	0.00%	0.00%
0.8801	5.34%	5.10%	3.57%	3.85%	0.00%	0.00%	0.00%	0.00%
0.8851	5.16%	4.31%	3.57%	7.69%	10.00%	14.29%	0.00%	5.00%
0.8923	4.27%	6.67%	4.76%	0.00%	10.00%	14.29%	0.00%	5.00%
0.8976	4.98%	6.67%	2.38%	0.00%	0.00%	0.00%	50.00%	5.00%
0.9019	6.05%	4.71%	0.00%	0.00%	10.00%	0.00%	0.00%	10.00%
0.909	6.05%	5.10%	0.00%	0.00%	0.00%	0.00%	0.00%	20.00%
0.9151	4.63%	5.49%	4.76%	11.54%	0.00%	0.00%	0.00%	5.00%
0.9193	5.16%	5.49%	3.57%	3.85%	0.00%	14.29%	0.00%	5.00%
0.9236	5.69%	4.31%	2.38%	3.85%	10.00%	0.00%	0.00%	10.00%
0.9274	4.98%	5.10%	2.38%	15.38%	0.00%	0.00%	0.00%	35.00%

futures. The main body of this paper is divided into two parts: the first part, using Easley et al. [1] research, we estimate the probability of informed trading of CSI 300 index futures contracts from August 3, 2010, to November 19, 2010, including the main contract, the next month contract, the next quarter, and seasons contracts; secondly, we reveal the probability of informed trading for particular scenarios.

Based on EKOP model which is developed by Easley et al. [2], a new method named VPIN which is launched by Easley et al. [1] and applicable for high-frequency market is studied in the first part of our research. And then we use the model to calculate the stock index futures market in China. It has been found out that the probability of informed trading in stock index futures market shows an increasing trend with the approaching of expiry date. Also, future contracts generally have a larger number of information transactions, so the probability of informed trading for main contracts is more stable than others.

As for the second part, empirical research is firstly conducted to examine the tendencies of probability for informed trading on the expiration day. Information traders generally choose to trade the next-month contract on the expiration day. We have also found out that the probability of informed trading of stock index futures was generally large and the market is so unstable when the stock index future was initially listed.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This work is supported by NSFC (Projects 71320107003, 71131007, and 71271145), China Program for New Century Excellent Talents in University (NCET-07-0605), and Program for Changjiang Scholars and Innovative Research Team in University (IRT1028).

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