The Research of Probability of Informed Trading under Short-Sell Constraints

Jingxia Xu[1, 2, a*], Susheng Wang[3, b], Jijin Geng[2, c] and Yun Xiong[4, d]
[1]School of Urban Planning and Design, Peking University, Nanshan District, Shenzhen, Guangdong, 518000, China
[2]Shenzhen Land and Real Estate Exchange Center, Futian District, Shenzhen, Guangdong, 518000, China
[3]Finance Department, South University of Science and Technology, Nanshan District, Shenzhen, Guangdong, 518000, China
[4]Ping An Bank Co., Ltd, Shenzhen, Guangdong, 518000, China

Keywords: Short-Sell Constraints, Probability of Informed Trading, Trading Spread.

Abstract: The probability of informed trading is an important indicator for regulators supervising market order. Classic models of the probability of informed trading allow traders short unlimited with private information. However, it has short-sell constraints in China's stock market at present, which would make the measurement deviation occurs if directly apply classic models to China's stock market. Under this condition, this research adds two short-sell constraint parameters to the classic model, named SC-TPIN model, to measure the probability of informed trading of stocks with bad event. By selecting eligible stocks as the sample stocks, this research estimates the probability of informed trading and relevant parameters of those stocks before and after the disclosure day, and analyze and summarize the time characteristics and microscopic characteristics of these parameters. This research proves that the SC-TPIN model is consistent with the order flow information, and the parameters and probability of informed trading estimated by the SC-TPIN model are in line with the actual situation of sample stocks. Compared with the TPIN model, the SC-TPIN model has strong explanatory power in explaining the same time series spreads and strong predictive power in forecasting future spreads in China's stock market. Therefore, the SC-TPIN model is valid.

1 INTRODUCTION

The supervision on the insider trading caused by bad events is somewhat weakness in China's stock market at present. We consult insider trading events handled by China Securities Regulatory Commission, and find that these insider trading cases are mainly caused by good events, rarely relate to bad events. Since 2011, there are only 4 insider trading cases caused by bad events, meanwhile, there is no bad insider trading case relate to underlying stocks of margin trading, which show that the regulation of insider trading caused by bad events should be improved. Insider trading is part of informed trading, and the regulation on informed trading can effectively prevent insider trading events to occur. The probability of informed trading model is a feasible method to infer informed trading and observe the dynamic change of probability of informed trading. There are short-sell constraints in China's stock market at present. Effectively calculating stocks' probability of informed trading under China's current market condition, screening stocks with higher probability of informed trading, and hosting supervision on such stocks, could provide a feasible direction for regulating insider trading caused by bad events in China's stock market.

The informed trading measurement model which accepted widely is EKOP model proposed by Easley (1996) (Easley, 1996), known as the classical EKOP model. The EKOP model reflects the situation of informed trading through the imbalance of orders, that is, the order arrival rate of informed traders and uninformed traders are different due to the differ of their private information. Although the model is found by observing the rules of the market maker, its principle can also be applied to the order driven market. For example, Yang et al. (2004) assumes that there is a hidden market maker who makes deal with informed and uninformed investors through submitting limit orders, and they applied the EKOP model directly to the Shanghai Stock Exchange (Yang, 2004). Many scholars have improved the model in order to correctly estimate the probability of

Xu, J., Wang, S., Geng, J. and Xiong, Y.
The Research of Probability of Informed Trading under Short-Sell Constraints.
DOI: 10.5220/0011731700003607
In *Proceedings of the 1st International Conference on Public Management, Digital Economy and Internet Technology (ICPDI 2022)*, pages 137-144
ISBN: 978-989-758-620-0

informed trading under various trading rules. such as Qin Lei (2005) (Lei, 2005) had research on the New York Stock Exchange and found that the buy and sell order arrival rate of uninformed traders are different, so they introduced the TPIN model by setting the buy and sell order arrival rate of uninformed traders with different parameters based on the classic EKOP model. The model is rational and reasonable through deduction and demonstration, and is used by more and more scholars. Duarte and Young (2009) proposed a modified PIN model. They added the market order flow shock in the classical EKOP model, which make the correlation of buy and sell orders implied in the model positive, in order to better match the actual data (Duarte, 2009).

No matter the classic EKOP model, nor the TPIN model, they both don't involve short-selling constraints, and default that trader can short freely. While in China's stock market, naked short is forbidden, and traders could short only when they reach a certain threshold, which restrict lots of traders to short. Therefore, if we want to calculate the probability of informed trading accurately, we should choose models involving short-sale constraint variables. Yuan et al. (2011) (Yuan, 2011) divide the short-sale constraint into four types, and divide traders into full short selling, restricted short selling, prohibited short selling, and selling, and set parameters for those traders respectively. Parameters of this model are too many, and some traders may sell and short sell at the same time, which may lead to repeating calculations. Wang, Guo et al (2013, 2013) (Guo, 2013; Wang, 2013) introduced a short-sale constraint factor θ into the classical EKOP model, with $0<\theta<1$, then the model became $PIN = \alpha\mu(1-\delta+\theta\delta)/(\alpha\mu(1-\delta+\theta\delta)+2\varepsilon)$. Due to $0<\theta<1$, the PIN value calculated by this model is less than the PIN value calculated by the EKOP model. When good news come, informed traders would buy stocks, and in this case there is no short selling restrictions, but because $\theta \neq 0$ and $\theta \neq 1$, the PIN value estimated by the model would not match with actual situation.

Considering the status quo of short-sell constraints in China's stock market, we build the SC-TPIN model through adding two short-sell constraint parameters to the TPIN model and deducing the model equation by using the decision tree. Then we illustrate step by step that our SC-TPIN model is suitable for current China's stock market by order information flow derivation, estimation results analysing, explanatory power and predictive power verification to the information asymmetry proxy indicator. We prove that our SC-TPIN model is more effective in estimating stocks' probability of informed trading in China's stock market compared with TPIN model, which provide a reference for measuring probability of informed trading of stocks caused by bad events in China's stock market.

The contents of this paper are as follows: the second part is the model construction, we construct our SC-TPIN model and deduce its order information flow. The third part is the empirical results analysing, we analyse the distribution of SCTPIN value and parameters from the perspective of time and micro characteristics. The fourth part is the model validity verify, we analyse the sensitivity of short-selling constraint parameters, and verify the explanatory power and predictive power of SCTPIN value to the trading spread. The fifth part is the conclusion.

2 MODEL CONSTRUCTION

China's securities market sets different restrictions on financing trading and short selling, and investors react different to good news and bad news (Xie, 2015). In order to make the model correctly reflect the actual market situation, we only take into account the calculation of the probability of informed trading of stocks with bad events happened in this paper. Based on the TPIN model proposed by Qin Lei (2005) (Lei, 2005), we add short-sell constraint parameters into the TPIN model, and get our probability of informed trading model which could be used under short-sell constraint condition, denoted as Short-sale Constraint TPIN model (SC-TPIN model). This model is mainly used to calculate the probability of informed trading of stocks with bad events under the condition of short-sell constraint. The value of the probability of informed trading estimated by the SC-TPIN model is recorded as SCTPIN value.

2.1 TPIN Model

There are three kinds of information state in the stock market: good news, bad news and no news. At the beginning of each trading day, information events are independently distributed and occur with probability α, and the information is only mastered by informed traders. The probability that the information is bad news is δ, while that good news is $1-\delta$. Assuming that the buy and sell order arrival rate of uninformed traders in one day submit to the Poisson distribution with parameter of ε_b and ε_s respectively. When the information arrives, the order arrival rate of informed traders submits to the Poisson distribution with parameter of μ .

By using the high-frequency transaction data, we can estimate parameters above from the maximum likelihood estimation bellow:

$$L(\theta|B,S)=(1-\alpha)\frac{e^{-\varepsilon_b}\varepsilon_b^B}{B!}\frac{e^{-\varepsilon_s}\varepsilon_s^S}{S!}+\alpha\delta\frac{e^{-\varepsilon_b}\varepsilon_b^B}{B!}\frac{e^{-(\varepsilon_s+\mu)}(\varepsilon_s+\mu)^S}{S!} \quad (1)$$
$$+\alpha(1-\delta)\frac{e^{-(\varepsilon_b+\mu)}(\varepsilon_b+\mu)^B}{B!}\frac{e^{-\varepsilon_s}\varepsilon_s^S}{S!}$$

Then we can get the value of TPIN

$$TPIN=\alpha\mu/(\varepsilon_b+\varepsilon_s+\alpha\mu) \quad (2)$$

2.2 Short-Sale Constraint TPIN Model (SC-TPIN Model)

The TPIN model assumes that when informed traders learn the information of one stock arrives, they can trade according with their private information without cost and restriction. However, if there are short-sale constraints in the market, or even lack of short mechanism, it would prevent informed traders to short, and change the distribution of market information.

At present, China's stock market has the following short-sale constraints: only underlying stocks of margin trading are allowed to be shorted; naked short selling is not allowed; the cost of short selling is higher, only investors who meet a certain threshold are allowed to short, and the securities lending amount of those investors is also limited by their credit and margin line. In this case, uninformed traders usually behave as liquidity traders or noise traders. Short restriction and high threshold of margin trading will prevent uninformed traders to short, while informed traders will choose to short only when they have strong sign that the price is going to fall. Therefore, margin trading distinguishes informed and uninformed traders to some extent.

According to the TPIN model, we still assume that the information arrive rate is α , and the information is only mastered by informed traders. The probability that the information is bad news is δ , while that good news is $1-\delta$. The buy and sell order arrival rate of uninformed traders on one day submit to the Poisson distribution with parameter of ε_b and ε_s respectively. When the information arrives, under the unlimited shorting status, the order arrival rate of informed traders submits to the Poisson distribution with parameter of μ . We assume that the proportion of informed traders who hold the target stock is h , $0 \leqslant h \leqslant 1$, and informed traders prefer to sell their holding first. The proportion of informed traders who short the target stock is k , and $0 \leqslant k \leqslant 1$. So when the bad news of one stock arrives, informed traders who hold the target stock will take sale or short sell strategy, this part of informed traders is h , the proportion of informed traders who don't hold the target stock but short it is $(1-h)k$, while the proportion of informed traders who do not hold the target stock and cannot short it because of short-sell constraints is $(1-h)(1-k)$.

Other assumptions of this model are consistent with other probability of informed trading models without short-selling constraints. The transaction process can be described by the decision tree of figure 1.

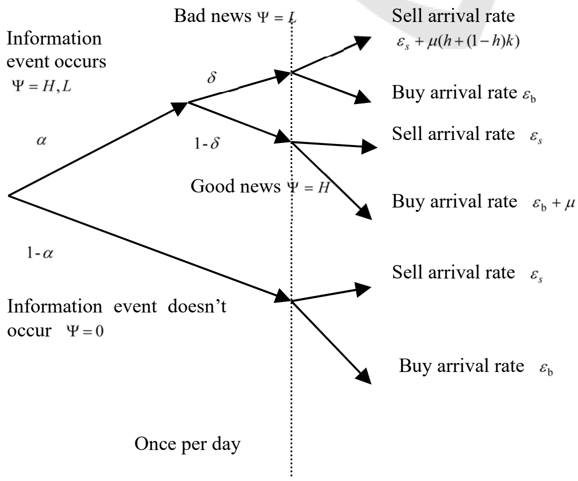


Figure 1: The decision tree existing short-sell constraints.

After introduce parameters of h and k, the order arrival rate of informed traders is

$$\alpha\mu\delta(h+(1-h)k)+\alpha\mu(1-\delta)$$

And the order arrival rate of uninformed traders is

$$\alpha\delta(\varepsilon_b+\varepsilon_s)+\alpha(1-\delta)(\varepsilon_b+\varepsilon_s)+(1-\alpha)((\varepsilon_b+\varepsilon_s))=\varepsilon_b+\varepsilon_s$$

Thus the probability of informed trading is

$$\begin{aligned} PIN &= \frac{\alpha\mu\delta(h+(1-h)k)+\alpha\mu(1-\delta)}{\alpha\mu\delta(h+(1-h)k)+\alpha\mu(1-\delta)+\varepsilon_b+\varepsilon_s} \\ &= \frac{\alpha\mu[\delta(h+(1-h)k)+1-\delta]}{\alpha\mu[\delta(h+(1-h)k)+1-\delta]+\varepsilon_b+\varepsilon_s} \end{aligned} \tag{3}$$

The maximum likelihood estimation is adopted to estimate unknown parameters in the SC-TPIN model. In this case, the likelihood estimation function of parameter $\theta=(\alpha,\delta,\varepsilon_b,\varepsilon_s\mu,h,k)^T$ is

$$\begin{aligned} L(\theta|B,S) &= (1-\alpha)\frac{e^{\varepsilon_b}\varepsilon_b^B}{B!}\frac{e^{\varepsilon_s}\varepsilon_s{}^S}{S!}+ \\ &\alpha\delta\frac{e^{\varepsilon_b}\varepsilon_b^B}{B!}\frac{e^{[\varepsilon_s+\mu(h+(1-h)k)]}[\varepsilon_s+\mu(h+(1-h)k)]^S}{S!} \\ &+\alpha(1-\delta)\frac{e^{(\varepsilon_b+\mu)}(\varepsilon_b+\mu)^B}{B!}\frac{e^{\varepsilon_s}\varepsilon_s{}^S}{S!} \end{aligned} \tag{4}$$

Easley (2008) indicated that, the daily trading data contains important information about the order arrival rate of informed traders and uninformed traders (Easley, 2008). We set TT as the total number of trades per day, then the expected value of the total trades is $E[TT]$, which is the sum of the Poisson arrival rate of informed traders and uninformed traders.

The arrival rate of the buy order is

$$E[B]=\alpha\delta\varepsilon_b+\alpha(1-\delta)(\varepsilon_b+\mu)+(1-\alpha)\varepsilon_b=\alpha\mu(1-\delta)+\varepsilon_b$$

the arrival rate of the sale order is

$$\begin{aligned} E[S] &= \alpha\delta[\varepsilon_S+\mu(h+(1-h)k)]+\alpha(1-\delta)\varepsilon_S+(1-\alpha)\varepsilon_S \\ &= \alpha\mu\delta(h+(1-h)k)+\varepsilon_s \end{aligned}$$

and the expected value of the total trades is

$$\begin{aligned} E[TT] &= \alpha\mu\delta(h+(1-h)k)+\alpha\mu(1-\delta)+\varepsilon_b+\varepsilon_s \\ &= \alpha\mu[\delta(h+(1-h)k)+1-\delta]+\varepsilon_b+\varepsilon_s \end{aligned}$$

The expected value of the trade imbalance $K=S-B$, when $\varepsilon_b=\varepsilon_s$

A more informative quantity is the absolute value of the trade imbalance. The first-order term of this expectation relates directly to the arrival of the informed trades

$$\begin{aligned} E[|K|] &= \alpha\mu\delta(h+(1-h)k)+\alpha\mu(1-\delta) \\ &= \alpha\mu[\delta(h+(1-h)k)+1-\delta] \end{aligned}$$

The expect balance order $TT-K$ is

$$E(TT-|K|)=\varepsilon_b+\varepsilon_s$$

It is clear from the above equation that, after h and k are introduced, the unbalanced order K include the arrival information of informed traders, while the balance order $TT-K$ contains the arrival information of uninformed traders, which is consistent with Easley (2008) (Easley, 2008).

The calculation of PIN value needs to know the trade direction. The most commonly used method to judge the trade direction is the method proposed by Lee and Ready (1991) (Lee, 1991). However, the accuracy of this method has always been questioned by scholars. Some scholars believe that the inaccurate judgment of the trade direction will lead to the underestimation of PIN. Therefore, in order to reduce the unnecessary errors in the calculation process, we use the high frequency data with trade direction to conduct our empirical test.

3 MODEL VALIDITY TEST

3.1 Samples and Data

Due to the China's stock market crash in June, 2015 (Wu, 2016), stocks price illegitimately limited up and limited down affected by other external factors, during which the transaction data were at abnormal level. Therefore, we abandon samples during that period, and limit our sample time interval from 2011 to 2014. Learning from Karpoff (2010) (Karpoff, 2010) and considering the reliability of event source, we selected those two types of bad news: (1) Listed companies which had poor performance in the annual report during 2012 and 2014. (2) Listed companies which was punished by CSRC during Jan, 2012 and March, 2015 due to the following reasons: short-term trading, illegal disclosure, major accident and connected transaction.

Because time points of the selected events are dispersed, we use the multi-object asynchronous event study method in this paper. By taking the disclosure day as the benchmark, and recording it as the event date, this is, the day 0, we set the estimation window start from 100 days to 11 days before the event day, denoted as [-100, -11]. The event window is 10 days before and after the event day, denoted as [-10, 10]. This is to say, sample stocks must have 100 consecutive trading days before the event day and 10 consecutive trading days after the event day. In order to ensure the validity of the data and eliminate abnormal samples, we also eliminated the ST, PT stocks, and finally got 208 stocks, of which there are

67 stocks chose from type (1), and 141 stocks chose from type (2).

We choose our sample stocks from Shenzhen A-share market and Shanghai A-share market, and get our microscopic characteristics data from CSMAR database and RESSET database, and get our high-frequency trading data from Giant Financial Platform.

We break the tick-by-tick transaction data into 5-minute data. The reasons are: on the one hand, private information integrating into the data needs trading for a certain time, the 5-minute data accumulates the information containing in the tick-by-tick data. On the other hand, the computation amount required by the tick-by-tick data is too large, and it is easy to overflow during the parameter estimation process, resulting in false value.

3.2 Parameters Sensitivity Analysis

We add two new parameters *h* and *k* in our SC-TPIN model. In order to clarify the relationship between the two parameters and SCTPIN, we make the following sensitivity analysis: Firstly, we find the partial derivative of PIN respect to *h* and *k* respectively by formula derivation, to analyse the relationship between PIN with *h* and *k* at [0, 1]. The partial derivative of PIN respect to *h* and *k* are as follow:

$$\frac{\partial PIN}{\partial h}=\frac{AC}{(Ah+B)^2} \qquad \frac{\partial PIN}{\partial k}=\frac{DC}{(Dk+F)^2}$$

Where $A=\alpha\mu\delta(1-k)$, $B=\alpha\mu\delta k+\alpha\mu-\alpha\mu\delta+\varepsilon_b+\varepsilon_s$, $C=\varepsilon_b+\varepsilon_s$, $D=\alpha\mu\delta(1-h)$, $F=\alpha\mu\delta h+\alpha\mu-\alpha\mu\delta+\varepsilon_b+\varepsilon_s$, and A, B, C, D, and F are all greater than or equal to 0.

We can see that when *h* and *k* changes at [0, 1], $\partial PIN/\partial h>0$, and $\partial PIN/\partial k>0$, so PIN is the increasing function of *h* and *k* respectively, and PIN get its maximum and minimum when $h=1$ ($k=1$) and $h=0$ ($k=0$). We use the figure to display the change of SCTPIN when *h* and *k* change at [0, 1] intuitively. As shown by figure 2.

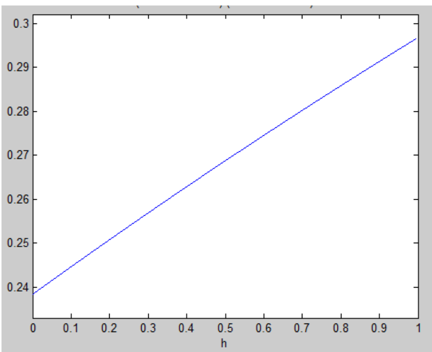
The horizontal axis in figure 2 represent the values of *h* and *k* at [0, 1], and the vertical axis represents the change of SCTPIN. After we fixe other values, the relationship between h and PIN presents the form of inverse proportional function, when h changes at [0, 1], the value of the PIN presents positive and approximate linear form in figure 2, this is, PIN is a strictly increasing function when h changes at [0, 1]. The relationship between *k* and PIN is approximately the same as that of *h*.

3.3 Model Validity Verification

Bid-ask spread is a common method used to measure the information asymmetry between informed and uninformed traders (O'hara, 2007). Reference to the method used by Easley (1996) (Easley, 1996) and Qin Lei (2005) (Lei, 2005), we verify the contribution our SC-TPIN model in explaining asymmetric information by measuring the explanatory power of SCTPIN to the spread, which also can verify the rationality of our SC-TPIN model apply to China's stock market. Because China's stock market is the order-driven market, it lacks corresponding bid-ask spread data. Based on the availability of data and acceptance of calculation method by scholars, we choose the trading spread with volume suggested by Stoll (2000) (Stoll, 2000) to calculate stocks' spread. The equation of the trading spread with volume TSW is as follows:

$$TSW=\frac{\sum_{i=1}^{n}P_i^BQ_i^B}{\sum_{i=1}^{n}Q_i^B}-\frac{\sum_{j=1}^{m}P_i^sQ_i^s}{\sum_{j=1}^{m}Q_i^S} \tag{5}$$

Where P_i^B and P_j^S are the price of the i th buy and sell in unit time respectively, Q_i^B and Q_i^S are corresponding volume respectively. The unit time is



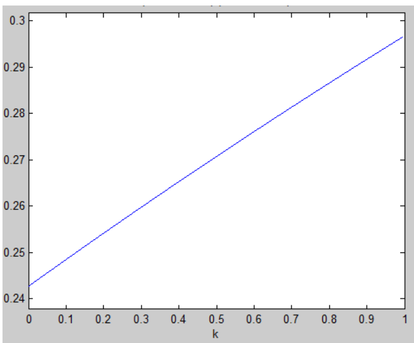


Figure 2: The sensitivity analysis of *h* and *k*.

Table 1: Regression results for equation (6).

Independent variable	Opening spread	Closing spread	Average spread
VSCTPIN	0.001817 (5.0499)***	0.001027 (5.6804)***	0.000825 (3.3543)***
VTPIN	0.001524 (4.1844)***	0.000115 (0.6280)	0.001002 (4.0258)***
VOL	0.001948 (3.0735)**	-0.000229 (-0.7192)	-0.001182 (-2.7288)**
R- squared	0.170043	0.084857	0.108927

Note: when the significance level is α =0.1, Z = 1.645; when α =0.05, Z = 1.96; when α =0.01, z=2.33; when α =0.001, Z = 3.29.

5 minute.

For the trading spread, we follow the method used by Easley (1996) (Easley, 1996) and Qin Lei (2005) (Lei, 2005), and select the opening spread, closing spread and average spread as the dependent variable respectively. After removing missing and invalid data, we get the 5 minute opening spread (excluding the call auction data), the 5 minute closing spread (excluding the call auction data) and the average spread (the average value of 5 minute spread per trading day) of 187 sample stocks.

3.3.1 The Explanatory Power of SCTPINs

Consistent with Easley (1996) (Easley, 1996) and Qin Lei (2005) (Lei, 2005), we use the panel regression (6) to test the explanatory power of SCTPINs:

$$\Sigma_{i,t} = \beta_0 + \beta_1 VSCTPIN_{i,t} + \beta_2 VTPIN_{i,t} + \beta_3 VOL_{i,t} + \varepsilon_{i,t} \quad (6)$$

Here $\sum_{i,t}$ is the spread, VSCTPIN is the product of SCTPIN and stock price, VTPIN is the product of TPIN and stock price, VOL is the trading volume defined as the product of stock price and share volume, ε is the residual, and $t \in [-10,-1]$. Existing researches show that the probability of informed trading has a positive effect on the spread, and VOL has a negative effect on the spread (Li, 2010), so the expected coefficient of VOL is negative. As competing measures of information asymmetry, VTPIN and VSCTPIN are expected to have positive coefficients. If one of the two measures completely subsumes the other in explaining spread, then we expect to see a significant positive coefficient for the dominant measure and an insignificant one for the other. The regression results of equation (6) are shown in Table 1, and the brackets are the values of t-statistic.

As can be seen from Table 1, the regression coefficient of VOL is significant when explaining the opening spread and the average spread, and the regression coefficient is negative when explaining the average spread. The coefficient is negative when explaining the closing spread, but it is not significant. The coefficient of VTPIN is significant in explaining the opening spread and the average spread, but it can't explain the closing spread. VSCTPIN has significant explanatory power for all three spreads, and its regression coefficients are all positive, especially when explain the opening spread and the closing spread, the coefficients of VSCTPIN are larger than that of VTPIN. Since the sample mean of VSCTPIN is larger than VTPIN, the overall explanatory power of VSCTPIN is higher than that of VTPIN (Lei, 2005).

3.3.2 The Predictive Power of SCTPINs

In order to test whether the SCTPINs is more informative than other measures of information asymmetry, we run the following panel regression to compare the predictive power of these measures for predicting the spread of the next trading day.

$$\begin{aligned}\Sigma_{i,t+1} = \beta_0 + \beta_1 VSCTPIN_{i,t} + \beta_2 VTPIN_{i,t} + \beta_3 VOL_{i,t} \\ + \beta_4 OIMB_{i,t} + \beta_5 RVOL_{i,t} + \beta_6 ME + \varepsilon_{i,t+1}\end{aligned} \quad (7)$$

$\sum_{i,t+1}$ refers to the next day's trading spread, VSCTPIN is the product of SCTPIN and stock price, VTPIN is the product of TPIN and stock price, VOL is the trading volume defined as the product of stock price and share volume, OIMB is the order imbalance or absolute net order flow in number of trades, as the events we selected are the bad events, the OIMB here equal to daily sell trades minus daily buy trades. ME is the market value of equity, and RVOL is the volatility of returns. Chordia et al. (2002) argue that order imbalances reduce liquidity, so the predicted sign for absolute order imbalance is positive (Chordia, 2002), that is, the coefficients of VSCTPIN, VTPIN, and OIMB should be positive. Stocks with large market cap generally have good liquidity, so the coefficient of ME is expected to be negative. Inventory theory holds that stocks with large earning volatility tend to have large spread

Table 2: The regression results of equation (7).

Independent variable	**Opening spread**	**Closing spread**	**Average spread**
VSCTPIN	0.002189 (6.066)***	0.000839 (4.6845)***	0.000964 (3.9971)***
VTPIN	0.001442 (3.9179)***	0.000278 (1.5303)	0.000927 (3.7821)***
VOL	0.003491 (4.5418)***	0.000218 (0.5720)	-0.000907 (-1.7655)*
RVOL	0.037095 (1.1571)	-0.030371 (-1.9084)*	0.026972 (1.2584)
OMBI	6.90E-09 (0.5175)	-2.84E-09 (-0.4296)	-4.16E-09 (-0.4671)
ME	-0.002089 (-2.3631)**	-0.000563 (-1.2839)	-0.000895 (-1.5147)
$R-squared$	0.200612	0.081735	0.120732

Note: when the significance level is α =0.1, Z = 1.645; when α =0.05, Z = 1.96; when α =0.01, z=2.33; when α =0.001, Z = 3.29.

(Lei,.2005), so the expected sign for RVOL is positive. The regression results of equation (7) are shown in table 2

As can be seen from table 2, the regression coefficients of VSCTPIN are all positive and significant when explaining the opening spread, the average spread, and the closing spread, indicating that VSCTPIN has significant explanatory power for all three spreads of one day after. VTPIN has significant explanatory power for the opening spread and the average spread, but its explanatory power for the closing spread is 0. Meanwhile, the regression coefficients of VTPIN are smaller than that of VSCTPIN. VOL has significant explanatory power for the opening spread and the average spread, but the coefficient is negative only when explaining the average spread. For other variables, only the coefficient of RVOL and ME are significant when explaining the closing spread and the opening spread respectively. So we believe that SCTPIN is a better and more robust measure in predicting future spreads, even after controlling for other competing measures of information asymmetry.

From the results above, we can see that, compared with TPIN, SCTPIN has strong explanatory power in explaining the same time series spreads and strong predictive power in forecasting future spreads, indicating that our SCTPIN model has strong power in explaining the information asymmetry in China's stock market, so our SC-TPIN model is effective.

4 CONCLUSIONS

The classic models of the probability of informed trading set no limitation on short selling based on private information, while it has short-sell constraints in present China's stock market, which could result in measurement deviation when applying the classic models to China's stock market directly. In this paper, we develop a SC-TPIN model by incorporating two short-sell constraint variables into the classical model, and select eligible sample stocks to verify it. By parametric characteristics analysis, order flow information analysis, and explanatory and predictive power test in explaining trading spreads, we prove that our SC-TPIN model is valid, and can better estimate the probability of informed trading of stocks with bad events in China's stock market.

By analyzing the time characteristics of the results of our SC-TPIN model, we found that stocks with high pre-event PIN value have significantly higher PIN value before the event day than that after the event day, while stocks with low pre-event PIN value have no significant difference before and after the event day, indicating that stocks with higher PIN value are more likely to be informed traded before bad news disclosure.

Through analyzing the microscopic characteristics of the results of our SC-TPIN model, we find that stocks with high institutional ownership, low turnover, small market cap, small securities lending scale and low price characteristics have higher probability of informed trading, and informed traders tends to short stocks with large volume and low institutional ownership when bad event arrives.

In addition, compared with TPIN model, our SC-TPIN model has stronger explanatory power in explaining the same time series spread and stronger predictive power in forecasting future spread.

Our model can be used to provide reference for securities regulators investigating insider trading timely, and it can also provide a relatively reliable way for uninformed traders avoiding stocks with bad events. However, our model does not consider the interaction between different types of traders, which could be suggested as the research direction in future.

ACKNOWLEDGMENT

This research is the achievement of Shenzhen Humanities and Social Sciences Key Research Base.

REFERENCES

Chordia T, Roll R, Subrahmanyam A. Order imbalance, liquidity, and market returns. Journal of Financial Economics 2002, 65: 111–130.

Duarte J, Young L. Why is PIN priced? Journal of Financial Economics, 2009, 91(2): 119-138.

Easley D, Kiefer N, O'Hara M, Paperman J B. Liquidity, Information, and Infrequently Traded Stocks. Journal of Finance, 1996, 51(4):1405-1436.

Easley D, Engle R F, O'Hara M, Wu L. Time-Varying Arrival Rates of Informed and Uninformed Trades. Journal of Financial Economics, 2008, 6(2): 171-207.

Guo H, Wang C F, Fang Z M. Influence of Information Asymmetry on Liquidity in View of Short-sale Constraint in A-share's Market. Journal of Xidian University (Social Science Edition), 2013, 23(2): 47-54.

Karpoff J M, Lou X X. Short Sellers and Financial Misconduct. The Journal of Finance, 2010, 65(5): 1879-1973.

Lei Q, Wu G J. Time-varying Informed and Uninformed Trading Activities. Journal of Financial Markets, 2005, 8: 153-181.

Lee C, Ready M J. Inferring Trade Direction from Intraday Data. The Journal of Finance, 1991, 46(2): 733-746.

Li G C, Liu S C, Qiu W H. The probability of informed trading in continuous order driven market: A new method. *Journal of Management Sciences in China, 2010,* 13(10): 8-20.

O'Hara M. Market microstructure theory. Blackwell Publishers, London, 1997:

Stoll H. Presidential address: friction. Journal of Finance, 2000, (4): 1479-1514.

Wang C F, Guo H, Fang Z M. Research on update of A-share's trade arrival rate and innovation digestion in the perspective of high-frequency data. Management Review, 2013, 25(8): 32-38.

Wu X Q. Stock Market Crisis: Structural Defects and Regulatory Reform. Finance & trade economics, 2016, (1): 22-32.

Xie H B, Fan K K, Zhou M. A study on the difference between the reactions of Chinese stock market to good and bad news. System Engineering Theory and Practice, 2015, 35(7): 1777-1783.

Yang Z S, Yao S Y. An Empirical Study on the Spread and Information Based Trading of the Shanghai Stock Exchange. Journal of Financial Research, 2004, (4): 45-56.

Yuan H Y. Short selling Mechanism and Operation Performance of China's Securities Market. *Economic Science Press*, 2011: 38-39.