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A model for probability of informed trading under short-sell constraints: study in china's stock market

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Abstract. The classic models of informed trading probability allow traders short unlimited with private information. It has short-sell constraints in China's stock market at present, which would make the measurement deviation occurs if we directly apply classic models to China's stock market. Under this condition, we add two short-sell constraint parameters to the classic model, named SC-TPIN model, to measure the informed trading probability of stocks with bad event. By selecting eligible stocks as the sample stocks, we estimate the informed trading probability 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. We prove that our SC-TPIN model is consistent with the order flow information, and the parameters and informed trading probability estimated by the SC-TPIN model are in line with the actual situation of sample stocks. Compared with the TPIN model, our 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, our SC-TPIN model is valid.

Key words. Short-sell constraints, informed trading probability, trading spread, bad event.

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

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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 informed trading probability model is a feasible method to infer informed trading and observe the dynamic change of informed trading probability. There are short-sell constraints in China's stock market at present. Effectively calculating stocks' informed trading probability 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.

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. 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.introduced a short-sale constraint factorθinto 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.

2. Mathematical Model

China's securities market sets different restrictions on financing trading and short selling, and investors react different to good news and bad news [6]. In order to make the model correctly reflect the actual market situation, we only take into account the calculation of informed trading probability of stocks with bad events happened in this paper. Based on the TPIN model proposed by Qin Lei et al. [3], we add short-sell constraint parameters into the TPIN model, and get our informed trading probability 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 informed trading probability of stocks with bad events under the condition of short-sell constraint. The value of the informed trading probability estimated by the SC-TPIN model is recorded as SCTPIN value.

(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 probabilityα, and the information is only mastered by informed traders. The probability that the information is bad news isδ, 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 $\varepsilon_b$and $\varepsilon_s$respectively. When the information arrives, the order arrival rate of informed traders submits to the Poisson distribution with parameter ofμ.

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

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

Then we can get the value of TPIN

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

According to the TPIN model, we still assume that the information arrive rate isα, 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$\varepsilon_b$and$\varepsilon_s$respectively. When the information arrives, under the unlimited shorting status, the order arrival rate of informed traders submits to the Poisson distribution with parameter ofμ. We assume that the proportion of informed traders who hold the target stock is$h$,$0\leq h\leq 1$, and informed traders prefer to sell their holding first. The proportion of informed traders who short the target stock is$k$, and$0\leq k\leq 1$. 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 can't short it because of short-sell constraints is$(1-h)(1-k)$.

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

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

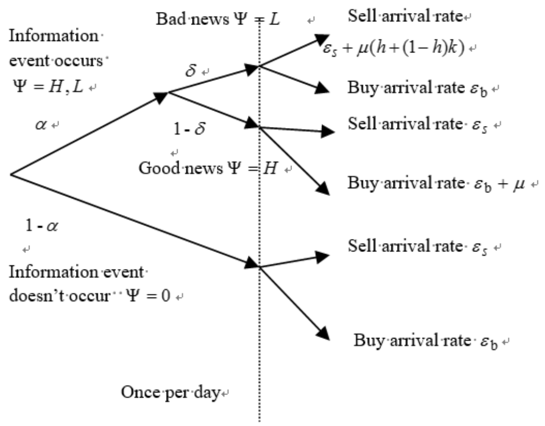

Fig. 1. The decision tree existing short-sell constraints

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

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

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

Ealsey (2008) indicated that, the daily trading data contains important information about the order arrival rate of informed traders and uninformed traders [9]. We set TTas the total number of trades per day, and the expected value of the total trades is$E[TT]$, which is the sum of 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

$$E[S] = \alpha\delta[\varepsilon_s + \mu(h + (1-h)k)] + \alpha(1-\delta)\varepsilon_s + (1-\alpha)\varepsilon_s = \alpha\mu\delta(h + (1-h)k) + \varepsilon_s$$

And the expected value of the total trades is

$$E[TT] = \alpha\mu\delta(h+(1-h)k)+\alpha\mu(1-\delta)+\varepsilon_b+\varepsilon_s = \alpha\mu[\delta(h+(1-h)k)+1-\delta]+\varepsilon_b+\varepsilon_s$$

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

$$E[|K|] = \alpha\mu\delta(h + (1-h)k) + \alpha\mu(1-\delta) = \alpha\mu[\delta(h + (1-h)k) + 1-\delta]$$

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 Kinclude the arrival information of informed traders, while the balance order$TT-K$contains the arrival information of uninformed traders, which is consistent with Easley et al. [9].

3. Empirical Result Analysis

3.1. Samples and Data

Due to the China's stock market crash in June, 2015 [8], 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 et al. [9] 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.

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.

3.2. Results Analysis

3.2.1. Time Characteristic Analysis Analyzing the estimation results can help us to understand the trading change between informed traders and uninformed traders before and after bad news disclosure. We will take the Mann-Whitney U test Method to analyze the change of the SCTPIN value and parameters estimated by the SC-TPIN model during the 21 trading days before and after bad news disclosure. Results are shown in table 1.

1) The mean and median ofαandδdon't show significant difference before and after the event day, but the mean value of $\alpha$is about 0.52, the mean value of δ is about 0.58, they are all greater than 0.5. As our sample stocks are all stocks which have bad event happened, the two value estimated by the SC-TPIN model are reasonable.

2) The mean value of μ is 2736 before the event day and 3021 after the event day. The mean result of the rank sum test is significant at 5% significance level, but the median result is not significant. The mean result of $\varepsilon_b$and $\varepsilon_s$are significant at 5% significance level, while the median result are not significant. The mean of these

three parameters after the event day are larger than before the event day.

3) The mean value of $h$after the event day is higher than it is before the event day, but the rank sum pairing test is not significant. When we cut off 1% extreme samples and revalue it, we found that it is significant at10% significance level, that is, the mean of $h$increases after the event day, indicating that the non-significant mean change of $h$is caused by individual stocks, traders holding the target stock sell more after bad news disclosure. The short constraint parameter $k$does not show significant difference before and after the event day, but both its mean and median value before and after the event day are greater than 0.5, and less than$h$.

4) The mean of the SCTPIN is 0.305 before the event day, and it reduces to 0.298 after the event day. The rank sum result is significant at the 10% significance level, indicating that the informed trading probability of sample stocks is significantly higher before the event day. When we divide our sample stocks into two groups according to the mean of the SCTPIN during the 10 days before the event day, and compare the difference of the two groups before and after the event day, we find that the mean difference of the large SCTPIN group is significant at 5% significance level, and the pre-event value is greater than the post-event value, while the mean difference of the small PIN group has no significant difference between the pro-event value and post-event value. The result shows that stocks with high pre-event SCTPIN value have significantly higher SCTPIN value before the event day than that after the event day, while stocks with low pre-event SCTPIN value have no significant difference before and after the event day. And the large SCTPIN group has higher mean value before and after the event day than the small SCTPIN group, indicating that stocks with large SCTPIN value are more seriously informed traded before bad news disclosure.

3.2.2. Microscopic Characteristics Analysis In order to specifically analyze the distribution of SCTPIN and parameters, we group the SCTPIN value and parameters according to the median of turnover, market value, securities lending scale, institutional ownership, volume, and price. We mark stocks with value greater than the median as group 1, and the others as group 2. Since our sample stocks are selected from two different types of bad events, we use the type of bad event as a grouping indicator, and mark sample stocks select from the negative annual report event as group 1, and sample stocks from the penalty event as group 2. We use the Mann-Whitney U test to compare the difference of group 1 and group 2 respectively.

as the object stocks by informed traders. Stocks with higher institutional ownership have lower proportion of liquid stocks. Influenced by the constraint of securities lending amount, the short-sell constraint of those stocks would be more obvious when bad event occurs. Meanwhile, most of informed traders are institutional investors, who have broader information channels and have further researches on stocks. Before the disclosure of bad news, such investors who informed of the news or predict the news advance will sell or short relevant stocks, resulting in higher probability of informed trading for stocks with higher institutional ownership. Wang et al. [12] found that companies with large scale, high equity concentration and low turnover have high information trading probability. Stocks with higher price have greater price volatility when bad news occurs. Traders can get more revenue when they buy or sell the same amount of such stocks, so informed traders prefer to sell or short stocks with higher price. Listed companies have earnings pre-announcement before the official disclosure, While penalty events are generally emergency events, therefore, the informed trading phenomenon of the penalty event group would be more obvious.

1) The arriving rate parameters of uninformed traders ε_b and$\varepsilon_s$have the same significance in all groups, their specific performance are: they all significantly larger in groups of large turnover, large market cap, large securities lending scale, large volume, and negative annual report event, while have no significant difference in institutional ownership and price groups.

2) The arriving rate parameter of informed trader μ shows significant difference in all groups. It has significantly larger mean value in groups of large turnover, large market cap, large securities lending scale, large volume, and negative annual report event, and has significantly larger mean value in groups of low institutional ownership and low price.

3) The significance of short-sell constraint parameters $h$and k in groups are different. h has significantly larger mean value in groups of large turnover and large market cap, and has significantly larger mean value in group of low institutional ownership, while has no significant difference in securities lending scale, volume, price and bad event type groups. k has significantly larger mean value in groups of large volume, and low institutional ownership, while has no significant difference in turnover, market cap, securities lending scale, price, and bad event type groups, indicating that informed traders tend to short stocks with large volume and low institutional ownership. The mean value of $k$are always less than the mean value of h at all groups.

4. Model Validity Test

4.1. 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 analyze the relationship between PIN with h and k at [0, 1]. The partial derivative of PIN respect to h and k are as follow:

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

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 $h = 0(k = 0)$.

Secondly, we use the figure to display the change of SCTPIN when h and K change at [0, 1] intuitively. As shown by fig. 2. The horizontal axis in fig.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.

4.2. Model Validity Verification

Bid-ask spread is a common method used to measure the information asymmetry between informed and uninformed traders . Reference to the method used by Esaly et al. [1] and Qin et al. [3], 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 to calculate stocks' spread. The equation of the trading spread with volume TSW is as follows:

$$TSW = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{P}_{\mathrm{i}}^{\mathrm{B}} Q_i^B}{\sum_{\mathrm{i}=1}^{\mathrm{n}} Q_i^B} - \frac{\sum_{\mathrm{j}=1}^{\mathrm{m}} \mathrm{P}_{\mathrm{i}}^{\mathrm{s}} Q_i^s}{\sum_{\mathrm{j}=1}^{\mathrm{m}} Q_i^S} \tag{1}$$

Where $P_i^B$and P_j^S are the price of the ith buy and sell in unit time respectively, $Q_i^B$and$Q_i^S$are corresponding volume respectively. The unit time is 5 minute.

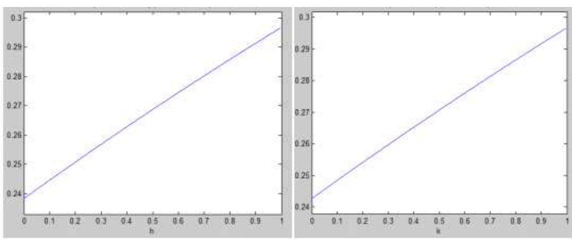

Fig. 2. The sensitivity analysis of h and k

For the trading spread, we follow the method used by Ealsy (1996) [1]and Qin Lei (2005) [3], 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.

(1)The explanatory power of SCTPINs

Consistent with Ealsy et al. [1] and Qin et al. [3], we use the panel regression equation (6)to test the explanatory power of SCTPINs:

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

In equation (6), $\sum_{i,t}$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,$\varepsilon$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 , 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 3, and the brackets are the values of t-statistic.

(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.

$$\Sigma_{i,t+1} = \beta_0 + \beta_1 VSCTPIN_{i,t} + \beta_2 VTPIN_{i,t} + \beta_3 VOL_{i,t} + \beta_4 OIMB_{i,t} \qquad (2)$$

In equation (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. argue that order imbalances reduce liquidity, so the predicted sign for absolute order imbalance is positive, 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 [3], so the expected sign for RVOL is positive. The regression results of equation (7) are shown in table 4.

Table 3. 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 isα=0.1, Z = 1.645; whenα=0.05, Z = 1.96; whenα=0.01, z=2.33; when α=0.001, Z = 3.29.

Table 4. The regression results of equation (7)

Independent variable	Opening spread	Closing spread	Average spread
VSCTPIN	0.002189 (??)***	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 isα=0.1, Z = 1.645; whenα=0.05, Z = 1.96; whenα=0.01, z=2.33; when α=0.001, Z = 3.29.

As can be seen from table 4 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.

5. Conclusion

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 informed trading probability of stocks with bad events in China's stock market.

By analyzing the time characteristics 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 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 informed trading probability, 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.

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