Trading networks, abnormal motifs and stock manipulation

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We study trade-based manipulation of stock prices from the perspective of complex trading networks constructed by using detailed information of trades. A stock trading network consists of nodes and directed links, where every trader is a node and a link is formed from one trader to the other if the former sells shares to the latter. Specifically, three abnormal network motifs are investigated, which are found to be formed by a few traders, implying potential intention of price manipulation. We further investigate the dynamics of volatility, trading volume, average trade size and turnover around the transactions associated with the abnormal motifs for large, medium and small trades. It is found that these variables peak at the abnormal events and exhibit a power-law accumulation in the pre-event time period and a power-law relaxation in the post-event period. We also find that the cumulative excess returns are significantly positive after buyer-initiated suspicious trades and exhibit a mild price reversal after seller-initiated suspicious trades. These findings can be better understood in favour of price manipulation. Our work sheds new lights into the detection of price manipulation resorting to the abnormal motifs of complex trading networks.

Keywords: Stock trading network; Order flow; Abnormal motif; Price manipulation

1. Introduction

Price manipulation is a ubiquitous phenomenon in equity markets (Putniņš 2012). Cumming and Johan (2008) compose a rich list of manipulation techniques and Putniņš (2012) provides a taxonomy of manipulation techniques. In general, there are three categories of price manipulation: action-based manipulation, information-based manipulation and trade-based manipulation (Allen and Gale 1992). Action-based manipulation is based on actions that change the actual or perceived value of the asset, information-based manipulation is implemented by releasing false information or spreading false rumours, and trade-based manipulation is based purely on buying and selling securities without taking any publicly observable actions or spreading false information (Allen and Gale 1992). Unlike the first two categories, trade-based manipulation is easier to conduct and thus more common, and it is possible to design statistical approaches for the detection of trade-based manipulations.

Empirical studies have been conducted from the macro and micro view angles. At the macro level, researchers investigate the behaviour of stock price time series trying to identify abnormalities. Felixson and Pelli (1999) and Hillion and Suominen (2004) study the closing price manipulation, and Comerton-Forde and Putniņš (2011) propose an index of the probability and intensity of closing price manipulation. Mahoney (1999) and Jiang et al. (2005) study the alleged stock pools of the 1920s through abnormal turnover and returns and find evidence of informed trading rather than manipulation. Öğüt et al. (2009) and Diaz et al. (2011) design algorithms for the detection of stock-price manipulation based on data mining techniques.

Recently, owing to the availability of order flow data, there are also studies from the microscopic angle. Sun et al. (2010) investigate the distributions of the transaction number and trading volume of individual traders trading the same stock and find that the distributions of 45 non-manipulated stocks exhibit nice power-law tails, while the distributions for seven manipulated stocks do not have power-law tails and have an obvious hump. Sun et al. (2011) further investigate 100 non-manipulated stocks and 8 manipulated stocks. They uncover that the seller–buyer ratio is strongly correlated with the stock return for non-manipulated stocks, while the correlation is marginal for manipulated stocks. Sun et al. (2012) study stock complex trading networks and find that manipulated stocks have higher degree-strength correlations than non-manipulated stocks. These techniques have an important potential for the detection of manipulated stocks. Following the same idea, Sun et al. (2012) investigate the ratios of strength to degree for individual traders and are able to identify abnormal traders as candidates of manipulating traders.

There are also studies aimed at detecting collusive cliques or pools based on trading networks. To identify cliques that are defined as bidirectional complete subgraphs, Palshikar and Apte (2008) adopt graph clustering methods including the shared nearest neighbours algorithm of Jarvis and Patrick (1973), the mutual nearest neighbours algorithm of Gowda and Krishna (1978) and a new
collusion clustering algorithm. They find that the two latter algorithms perform well. Islam et al. (2009) propose a Markov clustering algorithm that is able to successfully detect circular trading, which cannot be identified using the methods in Palshikar and Apte (2008). In addition, Franke et al. (2006, 2008) apply spectral analysis of the trading networks of traders in a prediction market and successfully identify clusters of manipulators.

Alternatively, Wang et al. (2012) use the similarity of the trading activities among investors to detect candidate collusive cliques. In doing so, they construct the time series of aggregated order volumes calculated in given time intervals of individual traders and calculate the correlation matrix. When a proper threshold of correlation coefficient is set, the candidate collusive cliques of traders can be identified. This method is reminiscent of the works to classify trader clusters using random matrix theory on the inventory variation time series (Lillo et al. 2008, Zhou et al. 2012) or statistically validated networks of trading activity (Tumminello et al. 2012).

In this work, we report preliminary results on the behaviours of potential manipulating traders identified from the complex trading networks. For each stock, we can construct a trading network, where the traders are nodes and a directed link is assigned from one trader to another if the former sells some shares to the latter. We investigate the properties of three specific motifs that correspond to possible manipulation techniques. We find that these abnormal motifs do contain rich information. The underlying idea of this Letter is obviously different from those in Palshikar and Apte (2008) and Islam et al. (2009), who also work on trading networks of traders.

The study of security trading networks has a long history and can be at least traced back to Baker (1981, 1984). However, the progress is very slow. The situation changes gradually in recent years since trading data are easier to obtain and network science flourishes. Franke et al. (2006, 2008) analyse a prediction market to detect clusters of price manipulators. Wang et al. (2008) study the network topology of a prediction market which is an experimental futures exchange. Tseng et al. (2009) propose an agent-based model with ‘zero-intelligence’ traders under the continuous double auction market mechanism to explain the power-law degree distribution of the trading network. Tseng et al. (2010a) investigate the trading network of a prediction market to study the dynamics of wealth accumulation. Tseng et al. (2010b) study the statistical properties of a trading network in an agent-based double auction model.

There are also several studies focusing on real security markets. Adamic et al. (2012) construct trading networks using transaction-level data for the September 2009 E-mini S&P 500 futures contract and find that network metrics are highly contemporaneously correlated with returns, volatility, volume, duration, and market liquidity and strongly Granger-cause intertrade duration and trading volume. Jiang and Zhou (2010) explore the statistical properties of trading networks of a highly liquid stock traded on the Shenzhen Stock Exchange for the whole year of 2003. Wang et al. (2011) concerns with the statistical characteristics of the trading networks of all commodities traded on the Shanghai Futures Exchange from July to September, 2008. Sun et al. (2011, 2012) analyse the trading network of manipulated and non-manipulated stocks listed on the Shanghai Stock Exchange and report significant differences in the topological properties between the two categories of stocks.

2. Basic description

2.1. Data sets

The data sets under investigation are the history records of order flows of 43 stocks traded on the Shenzhen Stock Exchange during the whole year of 2003, including 32 A-shares and 11 B-shares. The list of codes for the A-share stocks are 000001, 000002, 000009, 000102, 000106, 000221, 000224, 000227, 000063, 000066, 000088, 000089, 000406, 000429, 000488, 000539, 000541, 000550, 000581, 000625, 000709, 000720, 000778, 000800, 000825, 000839, 000858, 000898, 000917, 000932, 000956 and 000983, and the list of codes for the 11 B-share stocks are 200002, 200012, 200016, 200024, 200429, 200488, 200539, 200541, 200550, 200581 and 200625. The A-share stocks are constituents of the Shenzhen Stock Exchange Component Index and the B-shares are associated with some of the A-share stocks.

Each submitted or cancelled order contains the following information: time stamp of order placement or cancellation, unique encrypted identity of the trader, limit order price, order size and buy–sell identifier (buy, sell or cancellation). We are thus able to reconstruct the limit order book and trace the transactions. In this work, only transactions in the continuous double auction are considered. For more information about the Shenzhen stock market, see Mu et al. (2010) and Zhou et al. (2012).

2.2. Construction of stock trading networks

We construct an entire trading network for each stock. The trading network construction approach is the same as in Jiang and Zhou (2010) and Sun et al. (2012). Each trader who bought or sold the stock enters the network as a node. A directed link is formed between two traders if they had transactions and the direction of the link is from the seller to the buyer. When a trader places an effective market order, it is possible that the order is executed by several orders on the limit order book submitted by different traders. In this case, the local network structure is a star-like graph with the central node acting as a source if the trader sells or a sink if the trader buys.

2.3. Determination of abnormal trading motifs

The constructed trading networks record the patterns of order execution in limit order book and of the flows of cash and stock shares among investors, which provides a potential opportunity to detect market manipulations of some traders and to further investigate their influences on the market’s behaviours. By scanning all the trading networks, we find that there are some motif patterns in contrast with the intuitions, which can be considered as evidence in
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favour of market manipulations of some investors. Network motifs are building blocks of complex networks (Milo et al. 2002, 2004), and motifs evolve in time-varying networks (Kovanen et al. 2011). When 3-node motifs are considered in directed networks, there are 13 possible motifs without self-loops (Milo et al. 2002). In this work, we investigate three motifs as depicted in figure 1. The determination of motifs is based on economic considerations.

**Motif A** in figure 1 is a self-loop, containing a single trader who sells shares to herself. Such motifs are reminiscent of wash sales, which are improper transactions in which the buyer and seller are the same person such that there is no genuine change in ownership (Putniņš 2012). If a trader utilizes the technique of wash sales, her trading behaviour will be identified as motif A from the trading network. On the other hand, a motif A trader is possibly not a manipulator, but the probability is very low.

**Motif B** in figure 1 is a two-node loop, in which two traders (or more precisely two stock accounts) exchange shares of the same stock. Motif B is the simplest structure embedded in the manipulation technique of stock pools. As described by Putniņš (2012), stock pools are a collusive group of manipulators trading shares back and forth among themselves. Cliques investigated in Palshikar and Apte (2008) or collusion sets of circular trading investigated in Islam et al. (2009) are special examples of stock pools. Motif B can be observed not only in cliques and some circular trading sets but also in other pools.

**Motif C** in figure 1 contains multiple (at least two) links with the same direction, which happens when one account repeatedly sells to or buys from the same counterparty. The occurrence of network structure of motif C is more common than motifs A and B. Motif C might correspond to a normal behaviour when a trader buys or sells the same stock several times and encounters the same counterparty by coincidence. On the other hand, motif C might also appear between two traders within a same pool.

3. **Topological properties of abnormal trading motifs**

For each stock, we have identified all motifs of the three types as depicted in figure 1. The occurrence numbers of different motifs identified are plotted in figure 2. In each plot, we also show the numbers of traders for each stock. Specifically, \( n_A, 2n_B \) and \( 2n_C \) are the numbers of traders exhibiting respectively motifs A, B and C. Hence \( n_M < N_M \) if there are overlapping \( M \)-motifs (or at least two motifs share a same trader) for a stock, where \( M = A, B \) or C. Otherwise, we have \( n_M = N_M \).

Figure 2(a) shows that \( n_A = N_A \) for 16 stocks whose motifs do not have multiple links in the self-loops and \( n_A < N_A \) for other 27 stocks. Figure 2(b) shows that there are 10 stocks that do not have motif B since \( N_B = 0 \), 18 stocks have isolated B-motifs since \( n_B = N_B \), and 15 stocks have overlapping B-motifs since \( n_B < N_B \). Figure 2(c) shows that all stocks have C-motifs and many of these motifs overlap since \( n_C < N_C \). The observation of \( n_M < N_M \) for some or all stocks provides further evidence of possible price manipulation.

To illustrate the complex structure of each motif type, we show in figure 3(a) the entire networks containing all \( B \)-motifs for four stocks. We find that most connected clusters have tree-like or star-like structures. Only one stock (200625) possesses a trading circle of four traders and no stock has cliques or other loops. Figure 3(b) illustrates the entire network containing all nodes and links in the identified C-motifs of a typical stock. We observe that there are two large sub-graphs and many small-size clusters including a lot of isolated C-motifs and three-node chains. There are also loops in some clusters. We note that the size distribution of the clusters of all stocks for motif C has a nice power-law behaviour:

\[
p(S) \sim S^{-(\alpha+1)},
\]

where the tail exponent is estimated to be \( \alpha \approx 3.5 \).

By definition, motif A is composed of only one edge and motif B is constituted by two edges. In contrast, a C-motif may contain double, trinary, quadruple and more

![Figure 1. Graphical illustration of abnormal trading motifs: (A) self-loop, (B) two-node loop and (C) two-node multiple arcs.](image1)

![Figure 2. The occurrence numbers of motifs A, B and C (\( N_A, N_B \) and \( N_C \)) and the associated characteristic numbers of traders (\( n_A, n_B \) and \( n_C \)) for different stocks. Each point corresponds to a stock.](image2)
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Figure 3. (a) The entire networks containing all nodes and all links in the identified $B$-motifs for four stocks: 000021 (♦), 000539 (▲), 200002 (■) and 200625 (●). Each edge in the plot represents a pair of bidirectional links. (b) The entire network containing all nodes and all links in the identified $C$-motifs for stock 200024. Each edge stands for multiple directed links.

Figure 4. The cumulative probability distribution of the number of edges in motif $C$ for five random chosen stocks. The data points of 000016, 000778, 200016 and 200541 are translated vertically by a factor of 100, 10, 0.1 and 0.01 for better visibility, respectively. The straight lines give the best fits to the data.

edges. Therefore, it is interesting to explore the distribution of the number of edges $n_{\text{Edges}}$ in each $C$-motif for each stock. Figure 4 plots the empirical cumulative distribution of $n_{\text{Edges}}$ for five random chosen stocks. It is found that there are $C$-motifs which have more than 100 edges and the cumulative distributions have power-law tails:

$$P(n_{\text{Edges}}) \sim n_{\text{Edges}}^{-\gamma}. \quad (2)$$

Following Clauset et al. (2009), we can obtain the estimates of the power-law exponent $\gamma$ and the low boundary $x_{\text{min}}$ of the power-law behaviours. The inset of figure 4 presents the values of $\gamma$ and $x_{\text{min}}$ for different stocks. The average value of the power-law exponents for the whole sample is $\langle \gamma \rangle = 3.19 \pm 0.23$. This power law might be a new stylized fact on the micro level, which can be used to test if some $C$-motifs are formed by chance or some $C$-motifs are abnormal containing some information of abnormal trading in future detailed analysis.

4. Market dynamics surrounding the abnormal trading edges

We investigate in this section the dynamics of four commonly used financial quantities before and after abnormal transactions associated with the identified motifs, including volatility $v$ determined as the absolute return of mid-price, trading volume $\omega_{\text{cum}}$ defined as the total trade size in each minute, average trade size $\omega_{\text{ave}}$ defined as the trading volume divided by the number of trades in each minute, and turnover value $f$ defined as the sum of transaction values (product of trade size and the corresponding transaction price) in each minute. All these variables exhibit pronounced intraday patterns. Consider a given financial variable $x(d, t')$, where $d$ identifies the trading days and $t' = 1, 2, \ldots, 240$ are 1-min intervals within each trading day. The intraday pattern is determined as follows (Jiang et al. 2009):

$$\bar{x}(t') = \frac{1}{N_d} \sum_{d=1}^{N_d} x(d, t'), \quad (3)$$

where $N_d$ is the number of trading days for the stock. We remove the intraday patterns before aggregating the events from different stocks:

$$x_r(d, t') = \frac{x(d, t')}{\bar{x}(t')} \quad (4)$$

To investigate the market dynamics around the detected abnormal trading motifs (or manipulation edges), we employ the approach commonly used for analysing market reactions to public news or announcements (Fleming and Remolona 1997, 1999, Joulin et al. 2008, Erenburg and Lasser 2009, Groß-Klußmann and Hautsch 2009) and...
for understanding market behaviours around predefined extreme price changes (Haminkel 2003, Zawadowski et al. 2004, 2006, Ammann and Kessler 2009, Ponzi et al. 2009, Tóth et al. 2009, Mu et al. 2010). Each directed link in the identified motifs stands for a transaction and is called an event in this work. We categorize the events into three groups according to the trade sizes of events. For each stock, we sort the events ensuring that the associated trade sizes are in the decreasing order. Twenty events are picked out into the large-size group in an iterative way. The first event with the largest trade size is chosen. The second event is chosen only if it does not occur on the same trading day as the first event. The third event is chosen only if it does not occur on the same trading days of previously chosen events. This procedure repeats until 20 events are chosen. The median-size group and the small-size group are determined in a similar way, ensuring that the events are around the median trade size and the smallest trade size, respectively. The chosen events in the large-size (median-size or small-size) groups of all stocks are put together to form the final large-size (median-size or small-size) group. We divide the trade size of each event in the three groups by the average trade size of the underlying stock and obtain the averages for the three groups which are 68.8, 0.88 and 0.0026, respectively.

We perform analysis for each group. Following the methodology of event analysis, we first determine the time point $t'_0$ when the event occurs. One can further extract the evolutionary trajectory of the financial quantity $\{x_{\kappa}(t) : t = -200, \ldots, -1, 0, 1, \ldots, 200\}$ from $x_{\kappa}(d, t')$, where $\kappa \in \{L, M, S\}$ and $t' = 0$ corresponds to $t'_0$. If the time to the opening or closing time is less than 200 min, we simply extend the time series to the previous or next trading day, which is rational since the intraday pattern has been removed (Zawadowski et al. 2004, Mu et al. 2010). The averages $\langle x_{\kappa}(t) \rangle$ over all events in each group can be obtained as follows:

$$\bar{x}_{\kappa}(t) = \frac{1}{\|\kappa\|} \sum_{\kappa \in \kappa} x_{\kappa}(t), \quad t = -200, \ldots, 200,$$  

where $\|\kappa\|$ is the number of events in group $\kappa$. If there is nothing abnormal in a group, we expect to have $\bar{x}_{\kappa}(t) \approx 1$ for all $t$ values.

Plots (a–d) of figure 5 show the pre-event and post-event dynamics of four representative financial variables for the three groups. Almost all the 12 curves exhibit a marked peak at $t = 0$, accompanied with a gradual accumulation when $t < 0$ and a slow decay when $t > 0$. We also observe that larger trade size causes more significant deviation of a financial variable from its normal value especially around the events: $\bar{x}_L(t) > \bar{x}_M(t) > \bar{x}_S(t)$. The results are qualitatively similar if we further divide the abnormal trading edges into two groups with seller-initiated trades and buyer-initiated trades.

It has been reported that the market dynamics surrounding large price changes exhibit power-law accumulations and relaxations for many financial variables (Zawadowski et al. 2004, 2006, Ponzi et al. 2009, Tóth et al. 2009, Mu et al. 2010). It is interesting to check if this feature applies to the current case. The plots (e–h) of figure 5 show the results in plots (a–d) in log–log scales, where the pre-event dynamics have been reflected with respect to $t = 0$. All curves exhibit nice power-law behaviours:

$$\bar{x}_{\kappa}(t) \sim |t|^{-\beta_{\kappa,\tau}}.$$  

(6)

The estimated power-law exponents using linear regression are presented in table 1. For pre-event dynamics, we find $\beta_{L,\tau} > \beta_{M,\tau} > \beta_{S,\tau}$ for all financial variables investigated. For post-event dynamics, we find $\beta_{L,\tau} > \beta_{M,\tau} \approx \beta_{S,\tau}$. If we compare the pre-event power-law exponent with the post-event power-law exponent, we find that $\beta_{L,\tau,\text{pre}} > \beta_{L,\tau,\text{post}}$ for all the four quantities and $\beta_{(M,S),\tau,\text{pre}} < \beta_{(M,S),\tau,\text{post}}$ except for $\beta_{S,\text{size}}$.

There are different possible explanations of the abnormal dynamics observed around the motif edges. One possible explanation is endogenous: The system evolves approaching a critical state through imitation and herding, which results in intermittent heavy trading activities. In such situation, the possibility to observe abnormal trading
relaxation such that to conjecture that large trades are more likely associated with collusive traders trying to manipulate the price. We argue that this can also explain the observed 

\[ \beta \] and \[ \omega \] behaviour in pre-event accumulation dynamics and explain the power-law distribution of the transaction volumes.

### Table 1. Estimated exponents of the power-law distribution for pre-event and post-event dynamics

| \( \kappa \) | \( \beta_{x,v} \) | \( \beta_{x,pre} \) | \( \beta_{x,post} \) | \( \beta_{x,f} \) |
|-------------|-----------------|-----------------|-----------------|-----------------|
| **Panel A: Pre-event dynamics** |
| \( L \) | 0.111(4) | 0.217(5) | 0.107(4) | 0.218(4) |
| \( M \) | 0.043(4) | 0.057(5) | 0.028(4) | 0.056(5) |
| \( S \) | 0.033(4) | 0.054(5) | 0.026(4) | 0.052(5) |
| **Panel B: Post-event dynamics** |
| \( L \) | 0.103(4) | 0.187(5) | 0.094(4) | 0.185(5) |
| \( M \) | 0.045(4) | 0.079(5) | 0.031(4) | 0.077(5) |
| \( S \) | 0.055(4) | 0.080(5) | 0.021(4) | 0.077(5) |

Note: All the returns have been multiplied by a factor of \( 10^5 \).

### 5. Price impacts

We investigate the price impact surrounding the transactions in the detected motifs though an event-study approach similar to the investigation of price impact of block trades (Holthausen et al. 1990, Gemmill 1996, Anderson et al. 2006, Frino et al. 2007). We calculate the raw trade-by-trade return series defined as the logarithmic difference of consecutive transaction prices. For each event \( m \in \mathcal{M} \), where \( \mathcal{M} \) is the set containing all transactions in the identified motifs, we extract a sequence \( \{ r_{mi,j} : i = -10, \ldots, 10 \} \), where \( r_{m,0} \) is the return between the transaction prices of the event and its preceding trade. For each event \( m \), we designate a control set of 20 benchmark trades. The benchmark trades are selected from the trades of the same stock on other trading days. To avoid introducing other influence factors, each benchmark trade is also required to satisfy the following conditions: The benchmark trade has the same type (i.e., buyer-initiated or seller-initiated) as event \( m \) and the transaction time of a benchmark trade must be close to that of the event when labelled in intra-day time. For each benchmark trade \( n \) in the control set, a detailed analysis is required to test these explanations and to explain \( \beta_{(M,S),x,pre} < \beta_{(M,S),x,post} \), which is, however, beyond the scope of this Letter.

### Table 2. Mean raw and excess returns 10 trades before and 10 trades after the buy-initiated and seller-initiated events.

| \( i \) | Buyer-initiated events | | Seller-initiated events | |
| --- | --- | --- | --- | --- |
| | \( (r_{mi,j}) \) | \( p \)-value | \( (\text{exc}_{mi,j}) \) | \( p \)-value | \( (r_{mi,j}) \) | \( p \)-value | \( (\text{exc}_{mi,j}) \) | \( p \)-value |
| **Panel A: Trade-by-trade return** |
| \(-10\) | 3.84 | .493 | 4.38 | .437 | -14.92* | .028 | -12.71 | .073 |
| \(-9\) | 6.80 | .220 | 9.39 | .097 | -2.09 | .740 | -0.60 | .927 |
| \(-8\) | -0.19 | .972 | -0.18 | .974 | 3.35 | .596 | 4.12 | .524 |
| \(-7\) | 8.62 | .136 | 12.18* | .040 | -3.93 | .495 | -2.02 | .732 |
| \(-6\) | -3.69 | .570 | -1.85 | .778 | -0.99 | .874 | -2.37 | .715 |
| \(-5\) | 18.99** | .001 | 20.87*** | .001 | -1.94 | .763 | -1.29 | .846 |
| \(-4\) | -7.65 | .186 | -6.48 | .276 | -2.12 | .726 | -4.11 | .517 |
| \(-3\) | 4.75 | .428 | 6.10 | .324 | -14.49* | .023 | -15.62* | .017 |
| \(-2\) | 11.77 | .083 | 17.61* | .010 | -2.91 | .609 | -6.70 | .262 |
| \(-1\) | -6.49 | .324 | 5.50 | .411 | -9.72 | .157 | -22.45*** | .001 |
| 0 | 144.61*** | .000 | 48.17*** | .000 | -157.81*** | .000 | -69.35*** | .000 |
| 1 | -78.37*** | .000 | -2.69 | .740 | 95.05*** | .000 | 27.96** | .001 |
| 2 | 16.37** | .009 | 12.32 | .053 | -9.49 | .212 | -8.81 | .192 |
| 3 | 1.85 | .766 | 1.27 | .843 | 5.66 | .417 | 8.73 | .219 |
| 4 | 9.18 | .118 | 7.68 | .204 | -9.96 | .130 | -8.81 | .192 |
| 5 | 5.69 | .333 | 8.59 | .155 | -8.00 | .273 | -7.52 | .311 |
| 6 | -4.51 | .468 | -5.25 | .410 | -0.94 | .887 | -0.89 | .894 |
| 7 | 9.89 | .111 | 11.40 | .076 | 1.55 | .800 | 1.73 | .783 |
| 8 | 3.56 | .538 | 4.26 | .473 | -6.77 | .267 | -6.84 | .270 |
| 9 | -0.77 | .895 | -1.33 | .823 | 11.90* | .049 | 9.31 | .140 |
| 10 | 5.83 | .292 | 5.04 | .376 | -9.87 | .087 | -8.99 | .129 |

Note: All the returns have been multiplied by a factor of \( 10^5 \).

*Statistical significant at 5% level.

**Statistical significant at 1% level.

***Statistical significant at 0.1% level.
sequence of trade-to-trade returns \( r_{i}^{ben} : t = -10, \ldots, 10 \)
are determined similarly. The mean benchmark returns \( r_{i}^{ben} \)
can be obtained as follows:
\[
r_{i}^{ben} = \frac{1}{20} \sum_{n=1}^{20} r_{i,n}^{ben}.
\]
(7)
The excess return \( r_{i}^{exc} \) can be estimated by subtracting mean
benchmark returns from the associated raw trade-to-trade returns
\[
r_{i}^{exc} = r_{i} - r_{i}^{ben}, \quad i = -10, \ldots, 10.
\]
(8)

Panel A of table 2 presents the averages of the raw
returns and the excess returns of buyer-initiated trades and
seller-initiated trades, as well as the \( p \)-values of \( t \)-tests on the
null hypothesis that an average is insignificantly different
from 0. When \( i = 0 \), the two average returns for buyer-initiated trades are positive and the two average returns for
seller-initiated trades are negative. All these averages are
significantly different from 0 at the significance level of
0.1%. These values are comparable to those of all trades as
shown in table 1 of Zhou (2012). There is a significant phe-
menon of price reversal at \( i = 1 \) after the events except
for the excess returns after the buyer-initiated events, which
is reminiscent of price reversal after large price move-
ments (Mu et al. 2010). In addition, there are significantly
positive average returns before buyer-initiated events and
significantly negative average returns before seller-initiated events.

In Panel B of table 2, we present the cumulative sums
of the trade-by-trade returns before and after the events. It is more evident that the raw cumulative return has the
same sign as the return at \( i = 0 \), which is followed by a
significant price reversal. This finding seems normal and
and can be explained by endogenous herding behaviours. How-
ever, we observe a positive value (41.29) of the cumulative
excess return after buyer-initiated events and a mild time
reversal after seller-initiated events. These results can be
explained in favour of possible price manipulations. When
a group of collusive traders (or accounts) proceed to make
profit by manipulating the price of a stock by the pump-and-
dump strategy, they buy shares first and try to make their
trades have larger price impact to pump the price. When
dumping their shares, they would prefer to make their trades
have ignorable price impact to hide their intention. This pic-
ture provide one explanation of why we observe continuous rise of the price after buyer-initiated trades and a mild time
reversal after seller-initiated events.

6. Conclusion
In summary, we have studied three types of abnormal motifs
in the trading networks of investors for 43 Chinese stocks.
Abnormal dynamics of several financial variables (volatility,
trading volume, average trade size, turnover value and
excess return) around the suspicious trades associated with
the links of the identified motifs have been observed. The
presence of price manipulation emerges as a possible expla-
nation of these findings. However, it does not rule out other
possible explanations.

Our analysis provides novel tools for the detection of
trade-based price manipulation. It is not irrational to con-
jecture that there should be some traces left in the trading
networks when price manipulations occur. Abnormal motifs
are the basic building blocks of the interactions of stock
pools. To provide conclusive evidence of manipulation,
one needs to perform further detailed analysis of the trad-
ing behaviours and the profits of the suspected traders. Our
work paces the first step towards the uncovering of collusive
manipulators. There is no doubt that techniques developed
in this line will be helpful to market supervisors and policy
makers.

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