Detecting Collusive Cliques in Futures Markets Based on Trading Behaviors from Real Data

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Abstract

In financial markets, abnormal trading behaviors pose a serious challenge to market surveillance and risk management. What is worse, there is an increasing emergence of abnormal trading events that some experienced traders constitute a collusive clique and collaborate to manipulate some instruments, thus mislead other investors by applying similar trading behaviors for maximizing their personal benefits. In this paper, a method is proposed to detect the hidden collusive cliques involved in an instrument of future markets by first calculating the correlation coefficient between any two eligible unified aggregated time series of signed order volume, and then combining the connected components from multiple sparsified weighted graphs constructed by using the correlation matrices where each correlation coefficient is over a user-specified threshold. Experiments conducted on real order data from the Shanghai Futures Exchange show that the proposed method can effectively detect suspect collusive cliques. A tool based on the proposed method has been deployed in the exchange as a pilot application for futures market surveillance and risk management.

Keywords: Futures markets, Financial trading behaviors, Collusive cliques, Correlation coefficient, Weighted graph, Unevenly-spaced time series.

1. Introduction

In financial markets, trading behaviors roughly refer to operations and actions conducted by individual investors to buy and sell financial instruments through an exchange institute. Although normal trading activities are dominating, abnormal market behaviors (for example, price manipulation and circular trading) happen now and then, especially in the emerging financial markets [1–5]. These abnormal behaviors not only impact market running mechanism and pricing mechanism, but also threaten the safety of financial markets and hurt the interests of righteous investors. What is worse, there is an increasing emergence of abnormal trading events that for maximizing their personal benefits, some traders constitute a collusive clique and collaborate with each other to manipulate the movement of some instruments, thus mislead other investors. Collusive trading activities [4–6] are becoming a threatening and concealed type of financial market manipulations. And discovering the hidden collusive cliques from numerous market participants and massive trading data poses a tough challenge to financial market surveillance and risk management, which thus has attracted increasing attention of market regulators and researchers in recent years. This is reasonable and natural when we consider this issue under the situation that the world is still struggling from the financial crisis.

The goal of this study is to detect collusive cliques in futures markets based on similar trading behaviors of investors. Empirical observation and analysis of trading operations of the market participants can provide the clue to detecting the collusive cliques in futures trading. The members of a clique are usually similar to each other in trading behavior while different from the those outside the clique. The similar trading behavior indicates that the members buy or sell a certain instrument
roughly at the same time point and even their order volume is correlated. On the contrary, the trading behaviors of ordinary (normal) investors who do not belong to any collusive clique have little possibility of being correlated. Admittedly, some “clever” traders may attempt to take different operations for counteracting collusive behaviors, which makes their activities appear just as normal investors so that they can escape from being detected. However, successful disguising needs not only high financial operation skills on one hand but also extra cost on the other hand, which prevents such collusive behaviors from happening popularly. This paper focuses on detecting the first kind of collusive behaviors where individual investors show (roughly) similar trading pattern, and leaves the problem of detecting the second kind of collusive behaviors where individual investors must not have similar trading fashion as future work.

In this paper, we propose an effective method to identify the collusive cliques from numerous market participants. We first select the dataset of real order records from the Shanghai Futures Exchange\(^1\) by conducting a comparative analysis on major information of futures trading activities. Then, taking signed order volume as the characteristic variable of futures trading activities, which can reliably reflect the trading intentions of investors, we define a unified aggregated time series to alleviate the disturbance caused by time difference of trading event occurrences, and calculate the correlation coefficient between any two eligible unified aggregated series. Next, based on the correlation matrix of one trading day, a weighted graph is constructed by using the edges whose weights are above a predefined threshold. After that, the separate connected components in the weighted graphs of multiple trading days are combined into an integrated weighted graph where the weight of each edge is the sum of its occurrences in different weighted graphs, and these edges whose weights below a predefined threshold are given up. Finally, the connected subgraphs in the integrated graph are taken as suspect collusive cliques. Our method is mainly inspired by the empirical observation and analysis on the real trading data, and we put the first priority on the method’s practicality in real applications of market surveillance and risk management.

This paper is organized as follows: In Section 2 we provide a survey of some of the related work. The real dataset used in our study is introduced in Section 3. Section 4 gives the detail of the proposed detection method and the concrete algorithms. Experimental results are presented in Section 5. Finally, Section 6 concludes the paper and highlights some future works.

2. Related Work

To the best of our knowledge, there is no related work that detects collusive cliques in futures markets based on similar trading behaviors as studied in this paper. However, some works have dedicated to the problem of detecting abnormal trading activities in financial markets from different perspectives. For example, price manipulation, one of major fraudulent trading activities, have been investigated by various methods, including pattern recognition based approach [1], behavioral statistic model [2, 4, 7, 8], rational expectation theory of corners [9] and domain driven data mining [10].

As an emerging kind of abnormal activities in financial markets, collusive activities among investors recently have been investigated from different aspects for explaining market manipulation. For distinguishing the irregular trading patterns from the regular trading operations, Franke et al [11] developed detection approaches based on spectral clustering method. They generated a trader network to represent the trading behaviors of traders and thus characterized the market. If the actual market behaviors deviate from the allowed trading behaviors in the market, then irregularities are reported. However, this study was conducted on an experimental stock market. Palshikar et al [5] proposed a graph clustering algorithm for detecting a set of collusive traders who have heavier trading among themselves compared to their trading with the other traders. They constructed stock flow graph with synthetic trading data to represent the trading relationships between traders, and applied the graph clustering method to find collusive traders. Cao et al [6] argued that market manipulation derives from the activities of a group of hidden manipulators who collaborate with each other to manipulate three trading sequences: buy-orders, sell-orders and trades, through carefully arranging their prices, volumes and time. They proposed a a coupled Hidden Markov Models(HMM)-based approach to describing the interactive behaviors among group members, and further to detecting abnormal manipulative trading behaviors on orderbook-level stock data.

Comparing with these works above, our study in this paper has three distinct features as follows: first, our work addresses collusive clique detection in futures markets, while the existing works all studied irregularity discovery in stock markets. Although both futures and stock are financial products, their trading mechanisms

\(^1\)http://www.shfe.com.cn
are quite different. Second, we build weighted graphs to characterize the interactions among the investors based on their trading behaviors, which is different from the existing works that also used graph based approaches. Last but not least, our method is inspired by and evaluated with real order data of futures trading in the Shanghai Futures Exchange. However, most existing works (not including Cao et al [6]) evaluated their methods by synthetic data.

In fact, the detection of collusive behaviors has also studied in other fields, including online auction systems [12, 13], online recommender systems [14–17], online reputation systems [18–20] and P2P file sharing networks [21, 22]. Solutions of these systems are effective in the respective scenarios, but none of them could be applied to the detection of collusive cliques in the futures market for three reasons. First, trading activities in the futures markets are complicated. For example, every investor can continuously open or close long/short positions in any futures contract. Second, there are hundreds of thousands of order recodes submitted to futures trading systems in one typical trading day. Such large scale data sets could not appear in most online auction systems or reputation systems. Last but not least, behavioral ratings and interaction between two colluders are not the ideal description of collusion behaviors for high frequent order sequences in the futures trading systems.

In our study, one key technique for detecting of collusive cliques is the measure of similarity between a pair of unevenly-spaced time series. The similarity of time series has been measured by various metrics, including Euclidean distance (ED) [23, 24] and more sophisticated metrics, such as Dynamic Time Warping (DTW) [25, 26], Edit distance with Real Penalty (ERP) [27], distance based on Longest Common Subsequence (LCSS) [28], Edit Distance on Real sequences (EDR) [29], Spatial Assembling Distance (SpADe) [30] and Sequence Weighted ALignmEnt model (SWALE) [31]. These representation and distance measures mentioned above have been comprehensively evaluated by comparative experiments in [32] for querying and mining of time series database. These methods try to identify matching elements between time series. However, the trading behavior similarity of two investors in collusive clique detection is characterized by the conformity and correlation between the pair of corresponding time series of signed volume, which emphasizes the shape similarity instead of magnitude similarity. Time stamp of trading activity is a principal characteristic to evaluate the similarity between two time series of signed volume. Two time series even with the same shape happening in different time periods could not been considered to be similar. For these reasons, correlation measurement is more appropriate for our study.

3. The Dataset

Data is the key to data mining. Understanding the data is crucial to the design of data mining algorithms. In this section, we will introduce the dataset used in our study for detecting collusive cliques in futures markets.

In futures trading, there are different types of data, such as order records, trade results and position changes, which can provide clue to describing the trading behavior of a market participant. An order is an instruction to buy or sell instruments, submitted by an investor to the electronic trading platform of the exchange institute. The order record indicates the trading intention of the investor to buy or sell how much volume of a specific instrument at the price of the moment. The eligible orders from buyers and sellers are matched according to a certain rule via the electronic trading platform, and trade reports are sequentially generated for the investors. Both the dealing prices and the trade volumes of the transactions are derived from the corresponding orders and are dependent on the current market situation such as the last prices and the order volumes of counterparts. The trading results will lead to position changes of the involved investor. Therefore, both trading results and position changes are the derivative consequences of order records, they can only partly represent the investors’ intentions. However, order information can properly characterize the investors’ trading behaviors.

The dataset used in our investigation is entirely from the real order series of the Shanghai Futures Exchange, which is the largest one in China’s domestic futures market and has considerable impact on the global derivative market. Currently, the electronic trading platform of the exchange institute receives only limit orders submitted by the investors. There are hundreds of thousands of order records from market investors in one typical trading day, which is comprised of the open call auction (8:55 - 8:59) and four continuous auction sessions (9:00-10:15, 10:30-11:30, 13:30-14:10 and 14:20-15:00). We collect a representative order dataset that cover three active futures contracts, including copper, fuel oil and natural rubber in the nine trading days from Sep 16, 2008 to Sep 26, 2008. The dataset contains 1,893,519 order records and involves 66,861 market participants.

The statistic information of the order records of the three futures contracts is given in Table 1. A limit order
Table 1. The statistic information of the order dataset of three futures contracts, including copper, fuel oil and natural rubber in the nine trading days from Sep 16, 2008 to Sep 26, 2008.

| Futures         | Number of orders | Number of investors |
|-----------------|------------------|---------------------|
| copper          | 441,104          | 19,414              |
| fuel oil        | 650,079          | 22,537              |
| natural rubber  | 802,336          | 24,910              |

record includes a virtual ID representing the investor, bid/ask indicator, order price and volume. All other sensitive information is filtered out for privacy preservation reason.

4. Methodology

In this section, we will describe the detail of the method employed to detect collusive cliques by calculating correlation coefficients between trading series and constructing weighted graphs from the correlation coefficient matrices. The algorithms for implementing the method are also given.

4.1. Selection of the Target Variable

A limit order refers to an order submitted by an investor to buy or sell an instrument at a specific price (rather than a market price), thus it contains the fundamental information such as bid/ask indicator, order price and order size. For these fields of a limit order record, which one can be used as a representative data item to describe the trading intention of an investor? To answer this question, let us first check these fields in detail.

As a piece of crucial information, the bid/ask indicator indicates whether the order is a buy limit order or a sell limit order and whether the investor wants to own or to abandon the asset. The order price is a specific price at which the investor hopes the order will be filled. Generally, the price that is close to the latest trade price of the market will be immediately filled, and the prices of orders submitted during a short period are almost the same. Consequently, the price that is dependent on the market situation does not distinguish the investors’ intentions. The order volume reflects the amount of asset that a investor intends to buy or sell.

Based on the preceding analysis of different fields in limit order records, we decide to combine the order volume and the bid/ask indicator into a signed order volume as the proper representation of a participant’s trading intention. A signed order volume sequence denotes the bid indicator with positive sign for buy order, and denotes the ask indicator with negative sign for sell order. That is, in a signed order volume sequence, the volume of a buy order is positive while the volume of a seller order is negative. By using signed order volume to describe a trading event of a certain investor at the moment of submitting her/his order, a discrete event sequence over a period of trading time can naturally characterizes the trading behavior of an investor.

For a futures investor, we denote by \( v(t_i) \) the signed order volume of an order submitted by her/him at time \( t_i \) \((i=1, 2, \ldots, N)\). \( N \) is the length of the sequence \([v(t)]\), which may be different for different investors, and the time points of the sequences for different investors can also be different. Thus, the time series \([v(t_i)]\) of the signed order volume is an unevenly-spaced event sequence.

Example 1. Table 2 illustrates the construction of two signed order volume sequences from the limit order sequences of two investors #1 and #2. In the table, the first five columns are the information fields of limit orders, and the last column represents the signed order volume. The timestamp of limit order is in the format using the colon as the separation character.

4.2. Aggregated Time Series

The event series of signed order volume above is not appropriate to calculate the behavior similarity of different investors due to two reasons as follow. On one hand, even though two investors belonging to a clique desire to apply the same order strategy, their operations can not be accurately synchronous in practice, usually there exists a little lag for some reasons (e.g., network speed or the queuing policy of the exchange). On the other hand, the active speculators such as day traders always issue a large number of order records, their long event sequences make the computation of behavior similarity more complex. Therefore, here we introduce an aggregated sequence to replace the original signed order volume sequence to represent the behavior of an investor.

We specify the size \( \delta_i \) of a time window. Given a signed order volume sequence, we split the sequence from its starting timestamp into a series of consecutive windows (or segments) of length \( \delta_i \), each of which is labeled by its time index whose value is an positive integer starting from 0. That is, the first window is labeled by 0, the second one is by 1, and so on. For the \( i \)-th window, its time index is denoted by \( s_i \), and it covers the scope of time \([s_i \delta_i, (s_i + 1) \delta_i)\). We aggregate the signed volumes of different orders happening within each window into a single value. Concretely, for the \( i \)-th window,
Table 2. The limit order sequences of two investors and the corresponding signed order volume sequences. The first five columns are the information fields of limit orders. The last column represents the signed order volume whose positive sign means buy order and negative sign means sell order.

| Investor | Timestamp | Indicator | Price | Volume | Signed volume |
|----------|-----------|-----------|-------|--------|---------------|
| 1        | 09:00:30  | Buy       | 3211  | 2      | 2             |
| 1        | 09:03:06  | Sell      | 3216  | 2      | -2            |
| 1        | 09:03:12  | Sell      | 3214  | 1      | -1            |
| 1        | 09:08:02  | Sell      | 3206  | 2      | -2            |
| 1        | 09:08:26  | Buy       | 3204  | 6      | 6             |
| 1        | 09:10:28  | Sell      | 3205  | 3      | -3            |
| 2        | 09:00:40  | Buy       | 3211  | 3      | 3             |
| 2        | 09:03:04  | Sell      | 3216  | 4      | -4            |
| 2        | 09:03:10  | Buy       | 3214  | 2      | 2             |
| 2        | 09:08:05  | Sell      | 3206  | 3      | -3            |
| 2        | 09:08:30  | Buy       | 3204  | 10     | 10            |
| 2        | 09:12:02  | Buy       | 3201  | 2      | 2             |

the aggregation value $V(s_i)$ is the sum of all signed volumes of orders happening in $[s_i, s_i + 1)$. Formally,

$$V(s_i) = \sum_{s_i \leq t < s_i + 1} v(t_j). \quad (1)$$

Above, $v(t_j)$ is the signed volume of an order happening at the timestamp $t_j$ in the signed order volume sequence under study. Thus, a signed order volume sequence can be transformed to an aggregated sequence, denoted by $\{(s_i, V(s_i))\} (s_i=0, 1, 2, \cdots)$. Furthermore, we discard any aggregated point $s_i$ whose aggregated value $V(s_i)=0$, then get the final aggregated signed order volume sequence, which is an aggregated time series.

Example 2. For the data in Table 2, let $\delta_t=60$ seconds and the starting timestamp of the order series is 09:00:00, we can get the time index sequences of the aggregated sequences for the two investors #1 and #2 are $\{0, 3, 8, 10\}$ and $\{0, 3, 8, 12\}$, respectively. And the two signed order volume sequences are aggregated into two aggregated signed order volume sequences as follows: $\{(0, 2), (3, -3), (8, 4), (10, -3)\}$ and $\{(0, 3), (3, -2), (8, 7), (12, 2)\}$.

In practice, there will be no aggregated data in a certain time span if there is no order event occurring at all during that period, thus the aggregated time series is unevenly spaced. The time window size $\delta_t$ determines the granularity of aggregation and the length of the aggregated series. By enlarging the window size, buying and selling volumes within a window may counteract, which thus makes the aggregated value of that window smaller and consequently degrades the calculation result. Therefore, a reasonable time window size is critical to the calculation of behavior correlation coefficient.

Furthermore, the collusive investors tend to frequently place orders to influence the market, they easily become the active traders in the market. Consequently, the investors with few orders will very possibly be excluded from the detected potential collusive cliques because they will not be highly correlated with these investors who have more orders. To reduce the unnecessary computation and thus boost efficiency, we filter out some investors who have few orders before correlation coefficient computation. Concretely, we compare the length of each aggregated time series with an empirical threshold ($\delta_L$), and only these with a length no shorter than the threshold are kept for further processing. We call these aggregated time series eligible aggregated signed order volume series. So only the eligible aggregated signed order volume series will be used for correlation coefficient computation and potential collusive cliques detection.

4.3. Unified Aggregated Time Series and Correlation Measure

The trading behavior similarity between two investors is evaluated by the strength of association between the corresponding aggregated time series, which is commonly measured by correlation coefficient [33, 34]. In statistics, correlation coefficient is used as an indicator of the degree to which an event or phenomenon is associated with, related to, or can be predicted from another, as well as a strength measure of linear relationship between two variables. It has been widely applied...
in the financial area. We adopts correlation coefficient as the similarity measure of two investors’ trading behaviors.

Let us consider two investors $A$ and $B$, and their aggregated time series are denoted by $V_A$ and $V_B$, respectively. Both aggregated time series are unevenly spaced and discrete, and their time indices $s^A_i$ and $s^B_i$ with the same subscript $i$ are not necessary the same, thus the methods for evenly-spaced time series are not applicable here. We merge their time index sets $s^A$ and $s^B$ into a unified time index set $s$, i.e., $s = s^A \cup s^B$. Based on the unified time index set, we define the unified aggregated time series of signed order volume of investor $A$ as follows:

$$U_A(s_k) = \begin{cases} V_A(s_k), & s_k \in s^A \\ 0, & \text{otherwise} \end{cases}$$

(2)

Similar definition is applied to the aggregated time series $V_B$ of investor $B$, and we get the unified aggregated time series $U_B$ of investor $B$.

**Example 3.** Following Example 2, we go further to compute the unified aggregated time series of investor #1 and #2. The unified time index set is $\{0, 3, 8, 10\} \cup \{0, 3, 8, 12\} = \{0, 3, 8, 10, 12\}$. According to Equation 2, we have the unified aggregated time series $U_1$ and $U_2$ as follows: $U_1 = \{(0, 2), (3, -3), (8, 4), (10, -3), (12, 0)\}$, $U_2 = \{(0, 3), (3, -2), (8, 7), (10, 0), (12, 2)\}$.

The correlation coefficient is evaluated between unified aggregated time series. For $U_A$ and $U_B$, their correlation coefficient $r_{AB}$ is defined as follows:

$$r_{AB} = \frac{\langle U_A U_B \rangle - \langle U_A \rangle \langle U_B \rangle}{\sqrt{\langle U_A^2 \rangle - \langle U_A \rangle^2} \sqrt{\langle U_B^2 \rangle - \langle U_B \rangle^2}}$$

(3)

where the angular brackets $\langle \cdots \rangle$ represents the average over all the aggregated events (or points) in the series. The correlation coefficient $r$ is between -1 and 1. A positive $r$ value indicates the existence of positive correlation, while a negative $r$ value implies negative correlation. A zero $r$ means no correlation and the two time series are independent from each other. For collusive clique detection, negative correlation is little significant because it means the trading behaviors of two investors are almost opposite. In fact, only positive correlation is of significance for collusive cliques detection.

**Example 4.** Following Example 3, according to Equation 3, the correlation coefficient between the two unified aggregated time series $U_1$ and $U_2$ is 0.956, which means that the trading behaviors of the two investors are strongly positive correlated.

When considering $N$ investors, the correlation coefficients between any two investors $i$ and $j$ build a correlation matrix $R$, which is an $N \times N$ matrix where the entry $r_{ij}$ indicates the correlation coefficient between two unified aggregated time series $U_i$ and $U_j$. The correlation matrix is symmetric because the correlation between $U_i$ and $U_j$ is the same as the correlation between $U_j$ and $U_i$. The diagonal elements in the matrix are the self-correlation coefficients of all unified aggregated time series, and the values are 1.

### 4.4. Discovery of collusive cliques

With the correlation coefficient matrix, we construct a weighted graph in which a node represents an investor in the market, and an edge is added to connect two nodes if the correlation coefficient between the two nodes’ corresponding unified aggregated time series is larger than a user-specified threshold ($\delta_w$). Note that the weighted graph constructed does not contain loop edges and there is no more than one edge between any two nodes, and the weight of each edge is the correlation coefficient. The resulting graph is not necessary a connected graph, very possibly it may includes some isolated nodes and some connected components (subgraphs). An isolated node has no link to any other nodes, and a connected component may be a complete graph, which means that all nodes in the component are highly similar to each other but weakly similar to the other nodes outside the component. Obviously, the connected components conform to the criterion of potential collusive cliques. Certainly, the value of correlation coefficient threshold $\delta_w$ will surely influence the number of resulting connected components. As the threshold increases, the number of resulting connected components will reduce, and the detected result will be more reliable but some suspect traders may be neglected. On the contrary, when decreasing the threshold, the number of false collusive cliques (noise) will rise, which will degrade the detection performance. Therefore, a proper threshold $\delta_w$ is of substantial importance to guarantee the detection performance.

It is always the case that we do not know how many collusive cliques exist and who belongs to which clique in the market. Fortunately, some practical observation can help us to make the decision. That is, a collusive clique will conduct cooperative and abnormal actions repeatedly. So if a doubtful clique happens in multiple trading days, it is reasonable to believe that it is a suspect collusive clique. Thus we consider multiple con-
tions for each trading day, and construct one weighted graph for each trading day, then combine the connected components in the daily graphs into an integrated weighted graph in which the weight of each edge is the sum of its occurrences in different weighted graphs. Finally, the connected subgraphs in the integrated graph are output as suspect collusive cliques by eliminating the isolated nodes and the edges whose weights are below a predefined threshold ($\delta_f$).

4.5. The algorithms

Our method of collusive clique detection by similar trading behavior analysis mainly consists of two stages:

- Computing the unified aggregated time series of signed order volume for each investor, and calculating the correlation coefficient matrix based on all eligible unified aggregated time series, and
- Identifying suspect collusive cliques by combining the connected components in the weighted graphs of multiple continuous trading days into an integrated weighted graph.

We develop two algorithms to implement the tasks of the two stages above. They are outlined in Algorithm 1 and Algorithm 2.

Algorithm 1 aggregates the signed order volumes of a market investor in every time window of a trading day to a single value, and filters out the short aggregated time series, and then calculates the correlation coefficient between any two unified aggregated time series. This algorithm’s input is the preprocessed order records set of one futures contract in a single trading day and each order record includes the investor’s virtual ID, signed order volume and a second-based timestamp converted from the time format that uses the colon as separation character.

With the correlation coefficient matrix, Algorithm 2 is developed to detect collusive cliques. It first constructs one weighted graph for each of trading day, and then merges the connected components of the daily graphs into an integrated weighted graph. For each connected component in the integrated weighted graph, if the weights of all its edges are no less than the threshold $\delta_f$, then the connected component is output as a suspect collusive clique.

5. Experiments and Discussions

In this section, we will present the experimental results with real order data of three futures contracts from the Shanghai Futures Exchange. The experimental results confirm the effectiveness of the proposed method in detecting collusive cliques.

5.1. The Effect of Time Window Size $\delta_t$

In aggregating time series of signed order volume, the length of time window $\delta_t$ is an important parameter that will directly influence the correlation coefficient calculation. For examining the impact of window size $\delta_t$ on correlation coefficient, we choose two time series of signed order volume from the trading data of fuel oil futures on September 25, 2008, which are shown in Fig. 1(a). We aggregate the two time series with different sizes of time window. Fig. 1(b) shows the aggregated time series with the time window size $\delta_t=60$ seconds. Then we calculate the correlation coefficient between the two resulting aggregated time series with the time window size increasing from 1 to 200 seconds. The results are shown in Fig. 2. We can see that the
Algorithm 2: Detecting collusive cliques

**Input:** Correlation coefficient matrix set \( \{ R^d \} \) for one futures contract in multiple trading days, threshold \( \delta_w \) for constructing weighted graphs, edge weight threshold \( \delta_f \) for the integrated weighted graph.

**Output:** Candidate collusive cliques

1. For each correlation matrix \( R^d \) do
   - Construct a simple weighted graph using \( R^d \) as the adjacent matrix, in which an edge exists if its weight is greater than \( \delta_w \);
   - Obtain the connected components set \( S^d \) of the graph;
2. Merge \( \{ S^d \} \) into an integrated weighted graph \( G \), in which the weight of each edge is the sum of its occurrences in \( \{ S^d \} \);
3. Eliminate the edges whose weights are below \( \delta_f \);
4. The connected subgraphs in \( G \) are output as potential collusive cliques;

The correlation coefficient increases as the size of time window enlarges, and it reaches asymptotically to a stable value at about 60 seconds. The result is analogous to the Epps effect [35–38] that the stock return correlation decreases as the sampling frequency of data increases. From Fig. 2, we argue that a time window of size 60 seconds is a reasonable choice in our experiments.

### 5.2. Determining the Length Threshold (\( \delta_L \)) of Aggregated Time Series

For the whole data set, the cumulative distribution function \( F(L) = P(L < L) \) of the length \( L \) of aggregated time series is shown in Fig. 3. As the figure shows, about 90% time series are less than 15 in length and are excluded from correlation coefficient calculation. There are only 10% investors included in collusive detection, which reduces the complexity of correlation calculation. Therefore, we choose 15 as the empirical threshold (\( \delta_L \)) value for filtering the short aggregated time series, which means that an investor should have placed orders in at least 15 time windows in a trading day to be included in the collusive clique detection procedure. This choice conforms to the long-term surveillance practical experience in the exchange institute.

### 5.3. The Effect of The Correlation Coefficient Threshold \( \delta_w \)

Now, we consider the order record data of the copper futures contract in one typical trading day (September 18, 2008) to demonstrate the process of collusive clique detection. After aggregating and filtering the time series of signed order volume, we obtain 819 eligible aggregated time series for computing the correlation coefficient matrix \( M_c \).

We construct four weighted graphs based on \( M_c \) with different correlation coefficient threshold values. In Fig. 4, the number of connected components are 10, 8, 6 and 4, corresponding to the threshold values 0.80, 0.85, 0.90 and 0.95, respectively. The number of resulting connected components gradually decreases as the threshold value grows. We notice that the connected component with six nodes is (almost) a complete graph in all the sub-figures. The reason is that the similarity between any pair of nodes in the component is very low.
large. In practical applications, the supervisors of the exchange institute can choose different threshold values according to real surveillance requirements to observe the suspect investors in different monitoring levels.

5.4. The Performance of the Proposed Method

According to the experimental results above, we choose the following parameter values for the detection method: $d_t = 60$ seconds, $d_s = 15$, $d_a = 0.90$ and $d_f = 2$. We construct the daily weighted graphs of the three futures contracts (see Table 1) in nine consecutive trading days, and merge the connected components occurring at least twice in the daily graphs into an integrated weighted graph. We illustrate the integrated weighted graphs for the copper, fuel oil and natural rubber futures contracts respectively in Fig. 5(a), Fig. 5(b) and Fig. 5(c). There are eighteen connected subgraphs in these figures. We can see that all the subgraphs are complete graphs except the two ones (22069, 12633, 1680, 33473, 3956) in Fig. 5(b) and (24139, 21244, 29020) in Fig. 5(c), and most subgraphs just appear twice in the nine trading days, while the four subgraphs including (24686, 28000) in Fig. 5(a), (12509, 21255, 11668) in Fig. 5(b), (1680, 3203, 4324, 10032, 12633, 17891, 22069) and the largest component in Fig. 5(c) occur at least three times. This means that these subgraphs can be considered as suspect collusive cliques. The four subgraphs occurring more than three times can be more confidently regarded as collusive cliques.

Furthermore, by carefully checking the figures, we notice that the set of investors $\{1680, 12633, 22069, 4324, 3203, 7891\}$ forming a connected subgraph in Fig. 5(a) and Fig. 5(c), and part of it $\{1680, 12633, 22069\}$ appears in Fig. 5(b). In addition, the two sets of investor $\{3956, 33473\}$ and $\{4162, 4937, 4987\}$ appear in Fig. 5(b) and Fig. 5(c), and the two sets of investors $\{3956, 33473\}$ and $\{1680, 12633, 22069\}$ are correlated in the fuel oil futures for they unify together to a single subgraph in Fig. 5(b). So we assert that these investor sets form collusive cliques with high probability, which will be further confirmed by related background data.

The experimental results for all the three futures contracts are summarized in Table 3. The average number $N_e$ of eligible aggregated time series in all the trading days are much smaller than the number of corresponding investors in Table 1. This indicates that a large number of short aggregated time series are excluded by the filter threshold $d_t$ and only the active investors are kept for further processing. In Table 3, there are many connected components that occur only once in the nine trading days, though our method will not classify them into suspect collusive cliques, the exchange institute still needs to pay attention to them in the following trading days. Certainly, these detected suspect collusive cliques should be further probed and confirmed via the regulatory procedure of the supervision system in the exchange institute. In practice, these suspect cliques,
Fig. 4. The weighted graphs obtained by using different threshold $\delta_w$ values for the copper futures contract in a trading day. The number of resulting connected components reduces as the threshold value increases. The threshold value is adjusted for different monitoring levels in practical surveillance requirements.

even not confirmed, will be added to the “black” list of the surveillance system.

Up to now, we have found some suspect collusive cliques. Are they really collusive cliques? or can we give some explanation on why they are treated as collusive cliques. For this purpose, we firstly examine the detected suspect collusive cliques carefully against the surveillance archival data of the exchange. The archival data covers the background information of all investors and companies involved in the futures market. The findings are interesting and promising. For most suspect collusive cliques, their members are interrelated in one or another way. They either come from the same community of a city or belong to the same company, or even they are from a family. We also find that the accounts of some cliques are controlled and operated by a backstage manipulator. The interrelation information implies great possibility to concert trading actions of members in a clique. Now we come to the final step of this study: validate the detected suspect collusive cliques in terms of verified collusive cliques of the surveillance system and judgement of experienced domain experts from the exchange institute. There are seventeen suspect collusive cliques verified as collusive cliques. The numbers of verified collusive cliques (the column $N_t$ in Table 3) are 4, 4 and 9 for the futures contract copper, fuel oil and natural rubber, respectively. Furthermore, we tracked and analyzed the order records of the members of these cliques, and the verified results were reconfirmed. The only detected suspect collusive clique that is not verified is from the fuel oil futures contract. The reason is that we can not find enough evidence. For privacy reason, we can not provide any more detail of these detected cliques.
Table 3. The experimental results of three futures contracts (including copper, fuel oil and natural rubber) in nine consecutive trading days. \( N_s \): the average number of eligible aggregated time series in the nine trading days; \( N_c \): the number of the connected components in all weighted graphs; \( N_s \): the number of the connected subgraphs in the integrated weighted graph, i.e., the number of detected suspect collusive cliques; \( N_i \): the number of the verified collusive cliques by surveillance archival data of the exchange institute.

| Futures           | \( N_s \) | \( N_c \) | \( N_s \) | \( N_i \) |
|-------------------|-----------|-----------|-----------|-----------|
| copper            | 480       | 14        | 4         | 4         |
| fuel oil          | 955       | 14        | 5         | 4         |
| natural rubber    | 1123      | 20        | 9         | 9         |

It is worthy of pointing out that the detected suspect collusive cliques or even the verified collusive cliques are not equal to real collusive criminal cliques in financial markets. Nevertheless, the detection results are still valuable to the market supervision department as they can provide informative targets to the supervision department for further probing, which is better than to search potential financial criminal cliques from numerous investors and massive trading data without any target.

6. Conclusion and discussion

A method for detecting collusive cliques in futures trading markets has been proposed under the framework of correlation analysis of traders’ behaviors and graphs merging. The proposed method defines the aggregated time series to summarize signed order volume series to achieve robust results, and then calculates correlation coefficient matrix over all eligible unified aggregated time series of signed order volume to construct weighted graphs, finally merges the connected components from multiple weighted graphs corresponding to multiple trading days into an integrated weighted graph. Experiments are conducted to determine reasonable values for different parameters, including the size of time window and other thresholds, and detect suspect collusive cliques from real order data of three futures contracts from the Shanghai Futures Exchange. The major innovation of the proposed method lies in two aspects: a) the aggregated time series used to summarize signed order volume series to alleviate the impacts of timestamp difference between different order series and data fluctuation, and b) the effective scheme to compute the correlation coefficient between two unevenly-spaced time series from irregular events. The proposed method can also be applied to investigating other behavior similarity of investors, for example, position changes per trading day. Experimental results validate the effectiveness of the proposed method. As a pilot application, a tool based on the proposed method has been deployed in the Shanghai Futures Exchange, to assist futures market surveillant and risk management.

As for future work, we are considering to further optimize the method by utilizing the data of two neighboring time windows for balancing the uneven data distribution. We also plan to take into account more trading information such as canceled orders and trade reports to enforce the information for detecting collusive. Furthermore, we will explore effective approaches to detecting collusive cliques that show “different” trading behaviors.

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References

[1] G. K. Palshikar, A. Bahulkar, Fuzzy temporal patterns for analysing stock market databases, Proc. Int. Conf. on Advances in Data Management (2000) 135.
[2] C. Zhou, J. Mei, Behavior based manipulation, Unpublished working paper 03028, NYU Stern School of Business, 2003.
[3] C. E. Walter, F. J. T. Howie, Privatizing china: The stock markets and their role in corporate reform, New York: Wiley 2003.
[4] A. I. Khwaja, A. Mian, Unchecked intermediaries: Price manipulation in an emerging stock market, Journal of Financial Economics 78 (2005) 203.
[5] G. K. Palshikar, M. M. Apte, Collusion set detection using graph clustering, Data Min. Knowl. Discov. 16 (2008) 135.
[6] L. Cao, Y. Ou, P. S. YU, G. Wei, Detecting abnormal coupled sequences and sequence changes in group-based manipulative trading behaviors, KDD (2010) 85.
[7] J. Hansen, C. Schmidt, M. Strobel, Manipulation in political stock markets c preconditions and evidence, Applied Economics Letters 11 (2004) 459.
[8] R. K. Aggarwal, G. Wu, Stock market manipulations, Journal of Business 79 (2006) 1915.
[9] F. Allen, L. Linov, J. Mei, Large investors, price manipulation, and limits to arbitrage: an anatomy of market corners, Review of Finance 10 (2006) 645.
[10] Y. Ou, L. Cao, C. Liao, C. Zhang, Domain-driven local exceptional pattern mining for detecting stock price manipulation, PRICAI (2008) 849.
[11] M. Franke, B. Hoser, J. Schröder, On the analysis of irregular stock market trading behavior, GfKl (2007) 355.
[12] J. Trevathan, W. Read, Detecting collusive shill bidding, ITNG (2007) 799.
[13] J. Trevathan, W. Read, Investigating shill bidding behaviour involving colluding bidders, Journal of Computers 2 (2007) 63.
[14] S. K. Lam, J. Riedl, Shilling recommender systems for fun and profit, WWW (2004) 393.
[15] X.-F. Su, H.-J. Zeng, Z. Chen, Finding group shilling in recommendation system, WWW (2005) 960.
[16] P.-A. Chirita, W. Nejdl, C. Zamfir, Preventing shilling attacks in online recommender systems, WIDM (2005) 67.
[17] S. Zhang, A. Chakrabarti, J. Ford, F. Makedon, Attack detection in time series for recommender systems, KDD (2006) 809.
[18] H. Zhang, A. Goel, R. Govindan, K. Mason, B. v. Roy, Making eigenvector-based reputation systems robust to collusion, Workshop on Algorithms and Models for the Web Graph (WAW) 2004.
[19] J.-C. Wang, C.-C. Chiu, Recommending trusted online auction sellers using social network analysis, Expert Syst. Appl. 34 (2008) 1666.
[20] Y. Liu, Y. Yang, Y. L. Sun, Detection of collusion behaviors in online reputation systems, Proceeding of Asilomar Conference on Signals, Systems and Computers (2008) 1368.
[21] M. Feldman, K. Lai, I. Stoica, J. Chuang, Robust incentive techniques for peer-to-peer networks, Proceeding of EC (2004) 102.
[22] Q. Lian, Z. Zhang, M. Yang, B. Y. Zhao, Y. Dai, X. Li, An empirical study of collusion behavior in the maze p2p file-sharing system, ICDCS (2007) 56.
[23] R. Agarwal, C. Faloutsos, A. R. Swami, Efficient similarity search in sequence databases, FODO (1993) 69.
[24] E. Keogh, S. Kasety, On the need for time series data mining benchmarks: a survey and empirical demonstration, KDD (2002) 102.
[25] D. J. Berndt, J. Clifford, Using dynamic time warping to find patterns in time series, KDD (1994) 229.
[26] E. J. Keogh, M. J. Pazzani, Scaling up dynamic time warping for datamining applications, KDD (2000) 285.
[27] L. Chen, R. Ng, On the marriage of lp-norms and edit distance, VLDB (2004) 792.
[28] M. Vlachos, G. Kollios, D. Gunopulos, Discovering similar multidimensional trajectories, ICDE (2002) 673.
[29] L. Chen, M. T. özsu, V. Oria, Robust and fast similarity search for moving object trajectories, SIGMOD (2005) 491.
[30] Y. Chen, M. A. Nascimento, B. C. Ooi, A. K. H. Tung, Spade: On shape-based pattern detection in streaming time series, ICDE (2007) 786.
[31] M. D. Morse, J. M. Patel, An efficient and accurate method for evaluating time series similarity, SIGMOD (2007) 569.
[32] H. Ding, G. Trajcevski, P. Scheuermann, X. Wang, E. Keogh, Querying and mining of time series data: experimental comparison of representations and distance measures, VLDB (2008) 1542.
[33] J. L. Rodgers, W. A. Nicewander, Thirteen ways to look at the correlation coefficient, Am. Stat. 42 (1988) 59.
[34] S. M. Stigler, Francis galton’s account of the invention of correlation, Stat. Sci. 4 (1989) 73.
[35] T. W. Epps, Comovements in stock prices in the very short run, J. Am. Stat. Assoc. 74 (1979) 291.
[36] R. Renò, A closer look at the epps effect, Int. J. Theor. Appl. Finan. 6 (2003) 87.
[37] B. Tóth, J. Kertész, On the origin of the epps effect, Physica A 383 (2007) 54.
[38] B. Tóth, J. Kertész, The epps effect revisited, Quant. Financ. 9 (2009) 793.
Fig. 5. The integrated weighted graphs of the copper (a), fuel oil (b) and natural rubber (c) futures by combining connected components of daily weighted graphs in nine consecutive trading days. The weight of each edge is the sum of its occurrences in each daily weighted graphs. Only those edges with weight no less than 2 are survived. Eventually, four (for copper), five (for fuel oil) and nine (for natural rubber) connected subgraphs are obtained, which will be output as suspect collusive cliques by our method. For the largest connected component at the bottom-right part of the figure (c), the edge weights are not shown due to space limit on the figure. However, we have computed the average value of its edge weights, which is 3.28.