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Detrended moving average partial cross-correlation analysis on financial time series

Ningning Zhang, Aijing Lin *, Pengbo Yang

School of Science, Beijing Jiaotong University, Beijing 100044, PR China

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A B S T R A C T

Cross-correlations between nonlinear time series widely exist in complex systems. It is of great importance to accurately measure the correlations between time series. In this work, we suggest a combination methodology of Detrended Moving Average Processing and Partial Cross-correlation Analysis to quantify the correlations between different time series, which we call as Detrended Moving Average Partial Cross-correlation Analysis (*DMPCCA*). This novel approach combines the advantages of Detrended Moving Average Processing and Partial Cross-correlation Analysis, not only exploring power-law cross-correlations between two signals but removing underlying impacts of other signals on those two signals. To demonstrate the advantages of this approach, we carry out experiments with synthetic data generated by correlated processes and compare the performance of this measurement to traditional cross-correlation techniques. It is found that this method can reveal the real cross-correlations between systems even when the indirect cross-correlations established by other common factors exist. Then we go further study into the application of *DMPCCA* to financial time series in order to report its performance in stock markets and investigate cross-correlations between different stock indices. Furthermore, the rolling windows method is used in conjunction with *DMPCCA* to capture the changes of cross-correlations between stock indices as time goes on. We notice that there is a special period when *DMPCCA* coefficients between stock indices are obviously different from those of other periods.

1. Introduction

In order to deeply understand complex systems, it is necessary to analyze the signals in complex systems. It is obvious that complex systems [1–5] involve a lot of cross-correlations between time series [6–8]. Correlation, as an important characteristic of the interactions of the time series in complex systems, has been widely studied recently [8–12]. The research methods of cross-correlations between time series were originally from the study of power-law autocorrelations of single time series. One of the most commonly used methods to study the power-law autocorrelations of nonlinear time series is Detrended Fluctuation Analysis (*DFA*) [13,14]. Its benefit is that it could help reveal the scale characteristics by cutting polynomial tendency. Later, as some researchers thought of extending the research of autocorrelations of time series to the cross-correlations between time series, the Detrended Cross-correlation Analysis (*DCCA*) based on *DFA* is proposed in [10], which contributes to the discovery of long-range cross-correlations between nonlinear signals. In recent times, another approach named Detrending Moving Average Cross-correlation Analysis (*DMCA*) has been introduced and

* Corresponding author.
E-mail address: ajlin@bjtu.edu.cn (A. Lin).

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applied to measure the power-law autocorrelations of nonlinear time series [15–17]. As we all know, trends may affect the discovery of power-law cross-correlations and result in interactions. *DCCA* cannot completely remove the influences of trends in signals by polynomial fitting. However, the *DMCA* is able to eliminate the trend using the moving average method, and can dynamically alter the fitted curve, which can improve the evaluation precision [18,19].

Both *DCCA* [13,20–22] and *DMCA* [16,17] show that trends can affect the detection of the cross-correlations of time series. If the common external factors make an indirect interaction between the two time series, it is necessary to use Partial Cross-correlation Analysis which can measure their intrinsic relationships between them [23–28]. Therefore, when non-stationarity and external factors are present, we propose Detrended Moving Average Partial Cross-correlation Analysis (*DMPCCA*) to measure cross-correlations between time series. We verify the effectiveness of this method using simulated data and compare its performance to the other approach. Considering that time series in complex systems have nonlinear characteristics and are associated with other time series, we apply this new approach to empirical financial data and investigate the cross-correlations between stock indices from America and China stock markets. Furthermore, we employ the rolling window approach to capture the changes of cross-correlations between stock indices with time.

This work is organized as follows. The Detrended Moving Average Partial Cross-correlation Analysis (*DMPCCA*) is presented in detail in Section 2. We compare the performance of *DMPCCA* with Detrending Moving Average Cross-correlation Analysis (*DMCA*) [29] on simulated data for testing the effectiveness of the new method. In Section 4, *DMPCCA* is applied to financial time series. Further, the rolling window approach is used to capture the time-varying changes of cross-correlations of stock indices. Finally, we draw some conclusions and future development prospects in Section 5.

2. Methodology

2.1. Detrended moving average partial cross-correlation analysis (DMPCCA)

Consider m time series $\{x^j(i) : i = 1, 2, 3, \ldots, n; j = 1, 2, 3, \ldots, m\}$, in which n denotes the length of each sequences. They may be stationary or non-stationary time series, and they may also be influenced by other external factors. Detrended Moving Average Cross-correlation (*DMCA*) technique can eliminate the trends and make the time series gradually stable so as to avoid the existence of trends which lead to erroneous correlation estimation.

Step 1: Construct profiles of these m time series

$$X^j(i) = \sum_{s=1}^{i} x^j(s), \tag{1}$$

where $i = 1, 2, 3, \ldots, n, j = 1, 2, 3, \ldots, m$.

Step 2: Compute the moving average function as follows

$$\tilde{X}_t^j(i) = \frac{1}{t} \sum_{k=\lfloor -(t-1)r \rfloor}^{\lceil (t-1)(1-r) \rceil} X^j(i-k) \tag{2}$$

where t denotes the width of window, and r represents the position ($r = 0, r = 0.5$ and $r = 1$ represent the backward, centered and forward moving average, respectively [17]). Parameters t and r together determine the location of the window, and the average fitting data in windows are to eliminate relative trend. The case of $r = 0$ means that the estimation of moving average function will be computed through previous data. Similarly, $r = 0.5$ implies that each window consists of halved previous data and halved latter data. $r = 1$ shows that the estimation of the moving average function takes into account the tendency of $n - 1$ data points.

Step 3: Define $F^2_{j_1,j_2}$, which can be seen as a detrended covariance

$$F^2_{j_1,j_2}(t) = \frac{\sum_{i=\lfloor t-r(t-1) \rfloor}^{\lceil n-r(t-1) \rceil} (X^{j_1}(i) - \tilde{X}_t^{j_1}(i))(X^{j_2}(i) - \tilde{X}_t^{j_2}(i))}{n - t + 1} \tag{3}$$

where $j_1, j_2 = 1, 2, 3, \ldots, m$. If power-law cross-correlations between x^{j_1} and x^{j_2} do occur, the square root of growing covariance over time would meet [15–17]:

$$F_{j_1,j_2}(t) \propto t^{h_{x^{j_1},x^{j_2}}} \tag{4}$$

Step 4: Obtain a covariance matrix,

$$F^2(t) = \begin{pmatrix} F^2_{1,1}(t) & F^2_{1,2}(t) & \cdots & F^2_{1,m}(t) \\ F^2_{2,1}(t) & F^2_{2,2}(t) & \cdots & F^2_{2,m}(t) \\ \vdots & \vdots & \ddots & \vdots \\ F^2_{m,1}(t) & F^2_{m,2}(t) & \cdots & F^2_{m,m}(t) \end{pmatrix} \tag{5}$$

Step 5: The degree of cross-correlations between considered signals, $x^{j_1}(i)$ and $x^{j_2}(i)$, could be defined as:

$$\rho_{j_1,j_2}(t) = \frac{F^2_{j_1,j_2}(t)}{F_{j_1,j_1}(t) \cdot F_{j_2,j_2}(t)}, \tag{6}$$

Step 6: Further, we can obtain the coefficients matrix

$$\rho(t) = \begin{pmatrix} \rho_{1,1}(t) & \rho_{1,2}(t) & \cdots & \rho_{1,m}(t) \\ \rho_{2,1}(t) & \rho_{2,2}(t) & \cdots & \rho_{2,m}(t) \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{m,1}(t) & \rho_{m,2}(t) & \cdots & \rho_{m,m}(t) \end{pmatrix} \tag{7}$$

where $\rho_{j_1,j_2}(t)$ is in the range $[-1, 1]$, and denotes the degree of cross-correlations on time scale t. Nevertheless, it represents the cross-correlations between sequences $x^{j_1}(i)$ and $x^{j_2}(i)$. When the considered sequences are affected by other time series, this cross-correlation measure may provide spurious correlations. Therefore, what we need is to eliminate the effects of other sequences on considered time series. Here, the partial cross-correlation is used.

Step 7: Calculate the inverse matrix of $\rho(t)$ by using the partial-correlation method [30],

$$C(t) = \rho^{-1}(t) = \begin{pmatrix} C_{1,1}(t) & C_{1,2}(t) & \cdots & C_{1,m}(t) \\ C_{2,1}(t) & C_{2,2}(t) & \cdots & C_{2,m}(t) \\ \vdots & \vdots & \ddots & \vdots \\ C_{m,1}(t) & C_{m,2}(t) & \cdots & C_{m,m}(t) \end{pmatrix} \tag{8}$$

Step 8: Accordingly, for the sequences $x^{j_1}(t)$ and $x^{j_2}(t)$, the degree of partial cross-correlation could be examined as,

$$\rho_{DMPCCA}(j_1, j_2; t) = \frac{-C_{j_1,j_2}(t)}{\sqrt{C_{j_1,j_1}(t) \cdot C_{j_2,j_2}(t)}} \tag{9}$$

where the coefficients $\rho_{DMPCCA}(j_1, j_2; t)$ could be adopted to measure cross-correlations between different signals on time scales t.

The above is the whole step of estimating Detrended Moving Average Partial Cross-correlation Analysis (*DMPCCA*).

3. The experiments of the simulated data

3.1. Simulated data

To investigate whether *DMPCCA* could indeed quantify the cross-correlations between time series, we generate two systems and compare the performances of *DMPCCA* with that of *DMCA* in the detection of cross-correlations. In this manner, we can control how one variable is related to the other variable. Specifically, the following simulated systems are tested:

(1) The stationary system has three variables with only nonlinear couplings ($x \to y$, $y \to z$) [31]

$$\begin{aligned} x_t &= 1.4 - x^2_{t-1} + 0.3x_{t-2} \\ y_t &= 1.4 - cx_{t-1}y_{t-1} - (1-c)y^2_{t-1} + 0.3y_{t-2} \\ z_t &= 1.4 - cy_{t-1}z_{t-1} - (1-c)z^2_{t-1} + 0.3z_{t-2} \end{aligned} \tag{10}$$

(2) The stationary system has three variables with only nonlinear couplings ($x \to y$, $x \to z$) [31,32]

$$\begin{aligned} x_t &= 3.4x_{t-1}(1-x_{t-1})^2 exp(-x^2_{t-1}) + 0.4\epsilon_{1,t} \\ y_t &= 3.4y_{t-1}(1-y_{t-1})^2 exp(-y^2_{t-1}) + 0.5x_{t-1} + y_{t-1}0.4\epsilon_{2,t} \\ z_t &= 3.4z_{t-1}(1-z_{t-1})^2 exp(-z^2_{t-1}) + 0.5x^2_{t-1} + 0.4\epsilon_{3,t} \end{aligned} \tag{11}$$

In order to simulate non-stationary systems, we use the Eq. (11) to generate data, and then add a square and cubic trend of time t to y and z sequences respectively.

3.2. Experimental results of simulated data

We apply the Detrended Moving Average Partial Cross-correlation Analysis (*DMPCCA*) and the Detrended Moving Average Cross-correlation Analysis (*DMCA*) methods to the simulated data described above, and obtain the results shown in Figs. 1–3.

Fig. 1 displays the results of the *DMPCCA* and the *DMCA* for System 1 from which one can find the *DMPCCA* could precisely detect cross-correlations between sequences. In Fig. 1, the three subgraphs of the first line are the images of

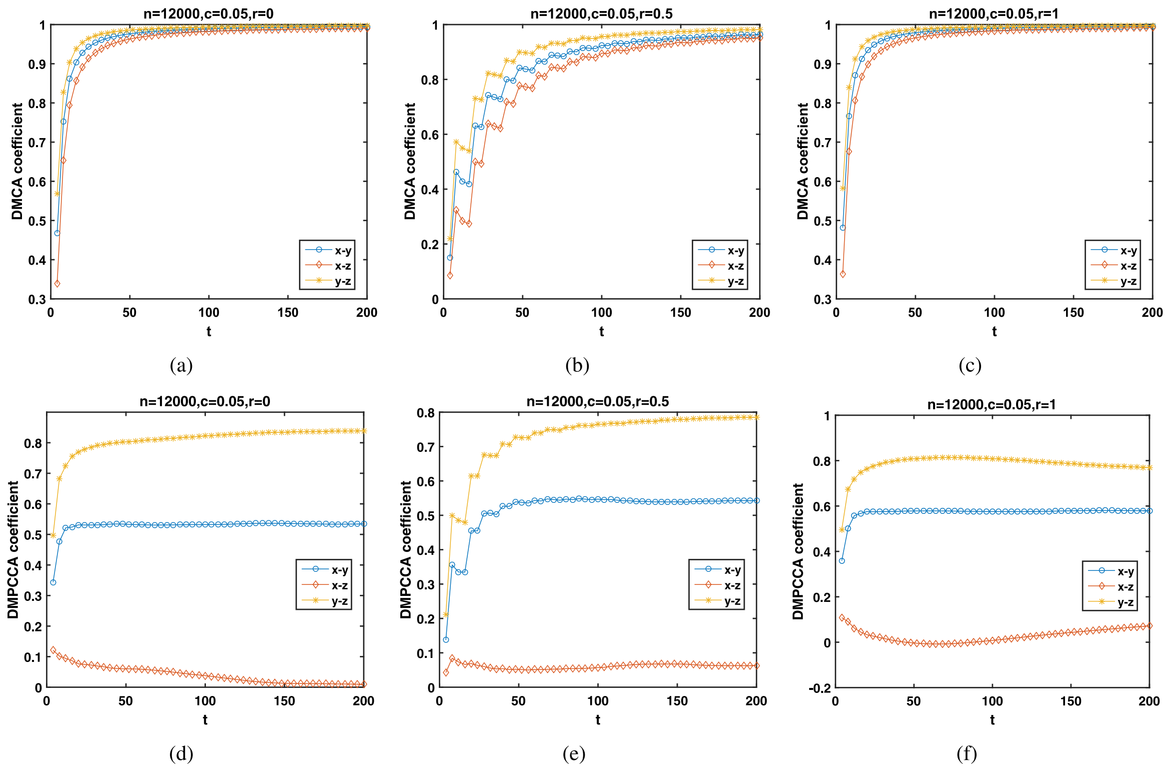


Fig. 1. Detrended Moving Average Partial Cross-correlation Analysis (*DMPCCA*) (the top panel) and the Detrended Moving Average Cross-correlation Analysis (*DMCA*) (the bottom panel) for $x-y, x-z, y-z$ of the System 1 in which variable x is not related to z. In each experiment, the value of the window size t is from 4 to 200. The different values of r represent 3 different *DMCA* methods (the backward moving average, the centered moving average and the forward moving average). By comparing the cross-correlation coefficients in each case, it is found that the *DMPCCA* coefficients are less than the *DMCA* coefficients. In particular, the DMPCCA cross-correlation coefficients between X and Z is almost 0, while *DMCA* coefficients are much larger.

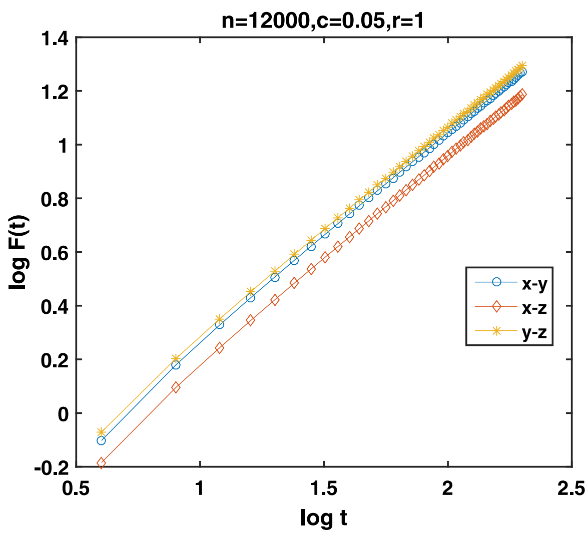
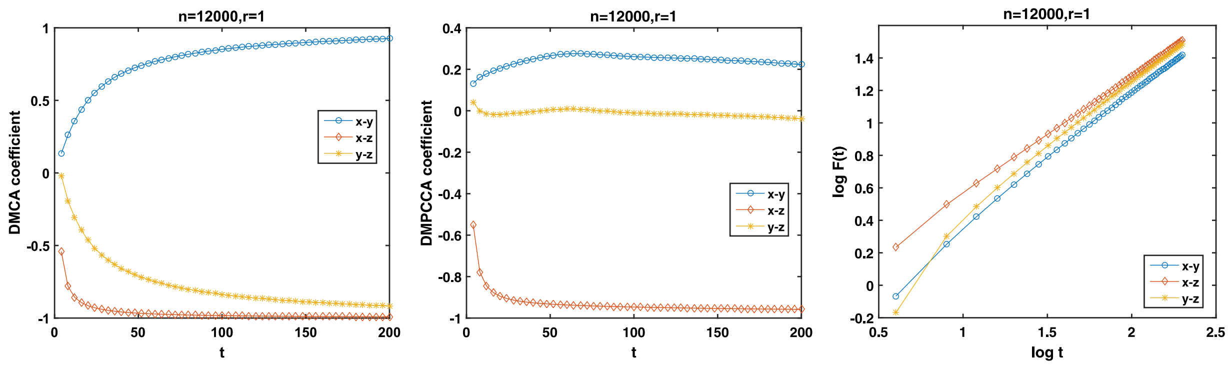


Fig. 2. The log–log plot for the square root of the detrended covariance F(t) vs. time scale t, from which one can find that power-law cross-correlation. The slopes of the three lines in the graph, that is, the h exponent in Eq. (4), are 0.7822 (x–y), 0.7807 (x–z) and 0.7801 (y–z) in turn.

the *DMCA* coefficients fluctuating with the size of the window when r (0, 0.5, and 1) takes different values. The bottom of Fig. 1 is the images of *DMPCCA* coefficients changing with the size of the window. It can be seen that in any cases, the *DMPCCA* coefficients between the sequences are smaller than the *DMCA* coefficients, which shows that our method



(a) (b) (c)

Fig. 3. Cross-correlation detection for data from system 2 (Data length n is 12000, and window size t ranges from 4 to 200). (a) Detrended Moving Average Cross-correlation Analysis (*DMCA*) for System 2. The results show that there is a positive cross-correlation between sequences x and y, while there is a negative correlation between sequence x and z and sequence y and z. (b) Detrended Moving Average Partial Cross-correlation Analysis (*DMPCCA*) for the time series generated by system 2. Compared with the *DMCA* coefficients, we find that the *DMPCCA* coefficients between sequence y and sequence z are almost 0, which means that the *DMCA* detects false correlation. (c) The log–log plot for the square root of the detrended covariance F(t) vs. time scale t. There is a linear relationship between $F(t)$ and window size t under the logarithmic scale.

Table 1
The list of four stock indices.

Num	Country	Index	Abbreviation
1	America	Nasdaq	NAS
2	America	Standard and Poor's 500 Index	S&P500
3	China	Shanghai Stock Exchange Composite Index	SSE
4	China	Shenzhen Component Index	SZSE

eliminates not only the influences of the trends on the correlations, but also the common impression of the additional factors on target sequences. In particular, the cross-correlation coefficients between x sequence and z sequence can be found that *DMPCCA* coefficients are much smaller than the *DMCA* coefficients and almost approach 0. From the process of generating data, there is no direct connection between x and z, and the indirect interaction between them is caused by the role of y. Fig. 2 illustrates the relationship between $F(t)$ and window size t based on Eq. (4). It could be seen that there are power-law cross-correlations between these three sequences generated by system 1. We also get similar results for different c values in Eq. (10), and we will not describe them repeatedly here.

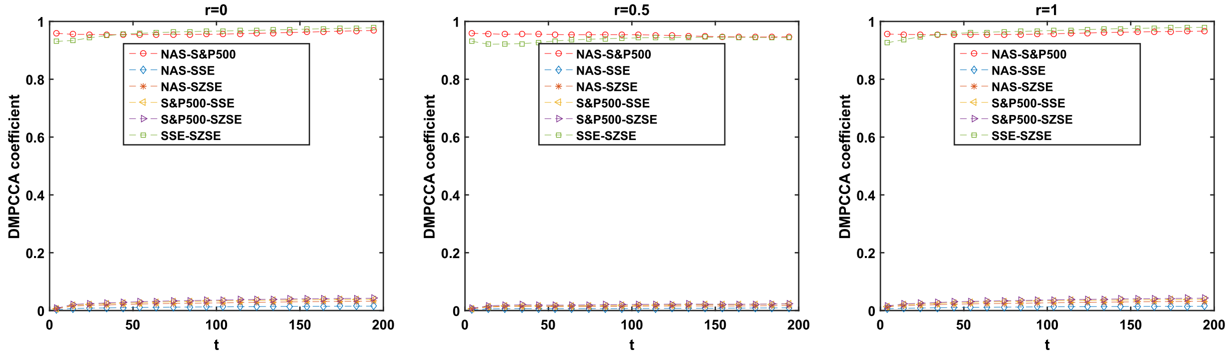
Fig. 3 presents the experimental results of cross-correlations between time series generated by system 2 using *DMCA* and *DMPCCA*. By comparing the *DMCA* coefficients and the *DMPCCA* coefficients, the results from the two methods are inconsistent for the cross-correlations between sequence y and sequence z (see Figs. 3(a) and 3(b)). There is no direct connection between y and z generated by Eq. (11). Therefore, the *DMCA* coefficients detect the spurious correlation between y and z. We can see from Fig. 3(c) that there are power-law correlation between the sequences generated by system 2.

4. Real-world stock data

As we all know, nonlinear time series are usually extracted from complex systems. These signals generally have nonlinear characteristics and are frequently associated with other time series. Thus, the *DMPCCA* can be extensively applied in diverse areas. In the next section, we will demonstrate the effectiveness of *DMPCCA* through interactions between stock indices.

In order to show the corresponding abilities of the *DMPCCA* method for stock markets, we analyze four stock indices of America and China stock markets. The NAS and S&P500, SSE and SZSE are the largest Chinese and American stock market index based on market capitalizations, respectively. The data set is listed in Table 1 spanning the period from January 3, 2006 to March 11, 2016. We gain data from the website of http://finance.yahoo.com. Let x_t denotes a stock indices' price on day t. In addition, for x_t, we calculate the logarithmic daily price return r_t, $r_t = ln(x_t) - ln(x_{t-1})$.

In Section 3, the performance of *DMPCCA* in detecting cross-correlations between time series has been confirmed through its performance on simulated data. Now, we further study the ability of this method to detect cross-correlations between stock indices stock markets. Fig. 4 displays that the *DMPCCA* coefficient changes with the window size t when r takes different values ($r = 0$, $r = 0.5$ and $r = 1$). In different cases, the performances of *DMPCCA* are similar. We can find that the *DMPCCA* coefficients are almost 0 between NAS and SSE, NAS and SZSE, S&P500 and SSE, S&P500 and SZSE, which are much smaller than that between NAS and S&P500, SSE and SZSE. This phenomenon illustrates that the stock indices



(a) (b) (c)

Fig. 4. *DMPCCA* coefficients of NAS and S&P500, NAS and SSE, NAS and SZSE, S&P500 and SSE, S&P500 and SZSE, and SSE and SZSE. (a) The *DMPCCA* coefficients are plotted versus the time scale t when $r = 0$. (b) The *DMPCCA* coefficients are plotted versus the time scale t when $r = 0.5$. (c) The *DMPCCA* coefficients are plotted versus the time scale t when $r = 1$.

of America and China stock markets have low cross-correlations. Moreover, the stock indices from the same country have the same economic environment which leads to higher cross-correlations.

To better understand the cross-correlations between stock indices, we further adopt the rolling window approach to analyze the correlation characteristics of the four stock indices over time when the time scale $t = 5$. Considering the choice of window size of the rolling window, the large window size is suitable for detecting long-term trends in market fluctuations, while the small window size is better able to observe short-term dynamics. It should be noted that we set the window size as 264 trading days, roughly equivalent to 1 year. Moreover, we adopt the window step is a trading day. In order to show that the cross-correlations estimated by our method are significant, we shuffle all the stock indices and calculate the *DMPCCA* coefficients between shuffled sequences as a reference. We get a 95% confidence interval of *DMPCCA* coefficients between shuffled time series, and when the *DMPCCA* coefficients between the original sequences fall into this interval, it would mean that the cross-correlations between original sequences are insignificant.

In Fig. 5, we display the *DMPCCA* coefficients between NAS and S&P500, NAS and SSE, and NAS and SZSE versus time. In all trading days, the curve of the *DMPCCA* between NAS and S&P500 is outside the gray dashed area (see Fig. 5(a)). Therefore, we can reject the hypothesis that there is no cross-correlation between the NAS and the S&P500. That is to say, the cross-correlations indeed exist between NAS and S&P500. From Figs. 5(b) and 5(c), we can see that there is a similar special period when the curve of *DMPCCA* exceeds the 95% confidence level: from June 2007 to November 2008, which corresponds to the 2008 American financial crisis. This interesting finding shows that to some extent the US stock market influences Chinese stock indices during economic crisis.

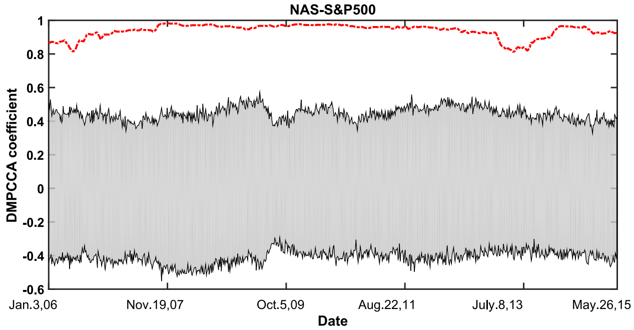
We illustrate the graph representations of the *DMPCCA* between S&P500 and SSE, and S&P500 and SZSE over time in Fig. 6. Since S&P500 is also a stock indice from the US, we found similar results with that of NAS. In Fig. 6, it can be seen that during the typical period, from June 2007 to November 2008, there is a more significant cross-correlation between S&P500 and SSE, S&P500 and SZSE. These results reveal the phenomenon that NAS and S&P500 have a very significant effect on SSE and SZSE at that time.

In Fig. 7, we can see that the *DMPCCA* coefficients between SSE and SZSE are approximately 1 while those between the shuffled SSE and SZSE fluctuate within the range of ± 0.6, which indicates a strong cross-correlation between SSE and SZSE. This conclusion confirms that there is a high correlation between stock indices from the same country.

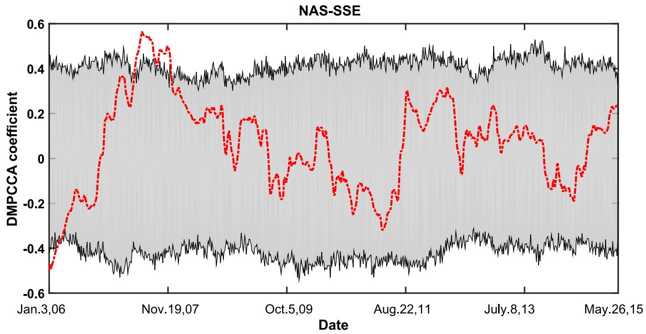
5. Conclusions

In general, complex systems are nonlinear and affected by multiple signals, which will bring many obstacles to us for understanding them. The existence of trends will have a certain impact on the detection of cross-correlations between time series. The classical Detrended Moving Average Cross-correlation Analysis method (*DMCA*) removes trend items by moving averages and estimates cross-correlations between nonlinear time series. Eliminating the trends will help us to accurately analyze the relationships between complex systems. On the other hand, if other external factors affect both target sequences at the same time, this will also lead to false cross-correlation estimation. Therefore, we consider using Partial Cross-correlation Analysis to eliminate the indirect cross-correlations between sequences caused by other common factors. This work introduces a novel methodology called Detrended Moving Average Partial Cross-correlation Analysis (*DMPCCA*) by integrating Detrended Moving Average Processing and Partial Cross-correlation Analysis.

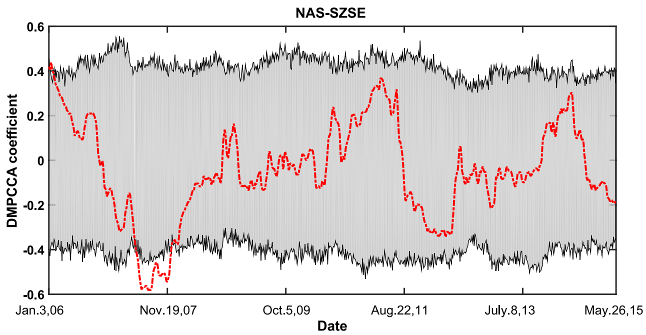
To illustrate the advantages of our method, we perform many simulated experiments. It is found that the *DMPCCA* performs better than Detrended Moving Average Cross-correlation Analysis. Furthermore, we estimate the cross-correlations between stock indices (NAS, S&P500, SSE and SZSE) using *DMPCCA* method. It is noted that the stock indices from the



(a)



(b)



(c)

Fig. 5. Time-varying of *DMPCCA* coefficients between NAS and S&P500, NAS and SSE, and NAS and SZSE using the rolling windows method. The window size is set to 264 trading days, and the window step is a single trading day. The red dotted line indicates the fluctuation curve of the *DMPCCA* coefficients, and the gray area indicates the 95% confidence interval of the *DMPCCA* coefficients between time series after complete disruption and rearrangement. The curve falling in this area indicates that there is almost no correlation. (a) *DMPCCA* coefficients between NAS and S&P500 are plotted versus time when $r = 0$. (b) *DMPCCA* coefficients between NAS and SSE are plotted versus time when $r = 0$. (c) *DMPCCA* coefficients between NAS and SZSE are plotted versus time when $r = 0$.

same country have stronger relations than those from different countries. Finally, to capture the time-varying of cross-correlations between those stock indices, we employ the rolling window method to the analysis of financial time series. Our analysis shows that abnormal changes of the *DMPCCA* coefficients can reflect irregular market activities, such as the 2008 US financial crisis.

We believe that the *DMPCCA* method can be used to detect the intrinsic interactions among multiple dynamical systems, and therefore it can be widely applied to many research fields. For example, in the context of the new interdisciplinary field of network physiology [33], where advanced time-series analysis techniques are employed to explore how integrated physiologic function arises from the network interaction of organ systems.

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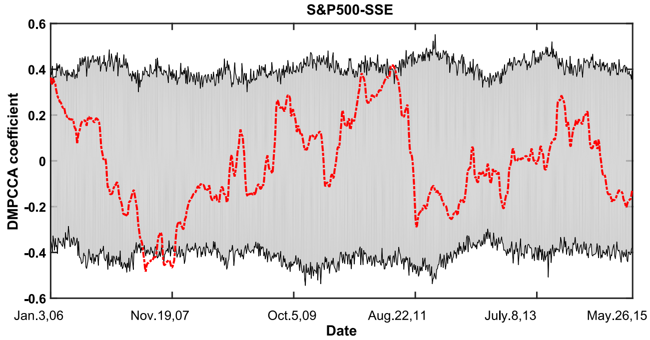
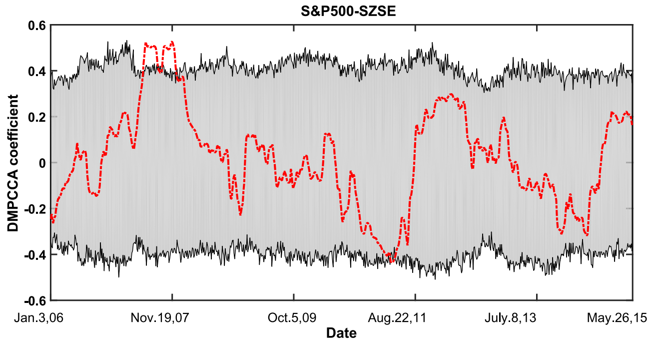


(a)



(b)

Fig. 6. Time-varying of *DMPCCA* coefficients between S&P500 and SSE (a), and S&P500 and SZSE (b) using the rolling windows method. The red dotted line depicts the fluctuation curve of the *DMPCCA* coefficients, while the gray dashed area represents the 95% confidence interval of the *DMPCCA* coefficients between time series after complete disruption and rearrangement.

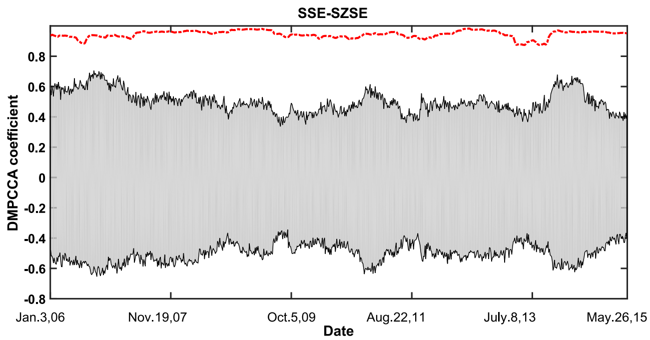


Fig. 7. Time-varying of *DMPCCA* coefficients between SSE and SZSE using the rolling windows method. The red dash line represents the *DMPCCA* coefficients, while the gray dashed area represents the 95% confidence interval of the *DMPCCA* coefficients. *DMPCCA* coefficients between SSE and SZSE are plotted versus time when $r = 0$.

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