Impact assessment of international anti-dumping events on synchronization and comovement of the Chinese photovoltaic stocks

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Abstract

This study investigated the effects of international anti-dumping events on the stock prices of the photovoltaic (PV) sector using sample data from China. Nine international anti-dumping events were tested using the event study methodology, and we found that most of them had significant impact on the stock returns of PV companies. Then, we chose a threshold value to construct stock networks for the different phases of the event development. We studied the changes in the scale and strength of the stock price synchronization, the evolution of the stock price co-movement and the stability of the co-movement between adjacent stocks by analyzing the changes in the topological structure of the stock networks. We found that the international anti-dumping events had different effects on the evolution of the synchronization and co-movement of the prices of Chinese PV stocks. In addition, the stock market of the PV sector exhibits high sensitivity to certain events. This study provides a novel approach that combines the event study methodology and stock-network analysis to help us to better understand the effects of anti-dumping on the PV stocks.

Keywords: Chinese photovoltaic sector, Stock network, Event study, Synchronization, Comovement

Contents

1. Introduction .................................................. 460
2. Materials/methods ........................................ 461
   2.1. Data .................................................. 461
   2.2. Event study methodology ......................... 461
   2.3. Network construction ............................. 461
3. Effect tests of events ..................................... 462
4. Results ..................................................... 463
   4.1. Stock price networks based on events ......... 463
   4.2. Changes in the scale and strength of the stock price synchronization 463
   4.3. Evolution of the co-movement of stock prices, 465
   4.4. Effects of the events on the stability of the co-movement between adjacent stocks. 466
5. Discussion and conclusion ............................... 466
   5.1. Discussion .......................................... 466
   5.2. Conclusion ......................................... 468

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1. Introduction

Because of the huge global demand for solar power, which is one of the cleanest and most reliable energy sources presently available, the Chinese photovoltaic (PV) industry promises a huge development potential. First, China consumes huge amounts of energy. Second, China has a natural advantage of excellent solar resources \([1]\) and significant financial support from its government \([2]\). With the rapid development of the China’s renewable energy applications in the past 10 years, China has become the biggest producer of PV cells in the world \([3]\). Third, Chinese enterprises possess the greatest competitive advantage because of the comparatively low production cost of solar cells and module assembly \([4]\). A growing number of Chinese companies have joined the PV industry in recent years; a number of listed companies are taking advantages of the opportunities provided by this industry. Meanwhile, China’s PV industry is also going through a severe challenge, including that from the international trade conflicts, market competition, and so forth \([5,6]\). Between 2012 and 2013, several international anti-dumping efforts against solar products imported from China were launched by the U.S., the countries of the European Union and India. These events, to some extent, resulted in turbulence in the stock market in the Chinese PV sector. The market capitalization of many Chinese PV firms decreased significantly, and many firms even faced the dilemma of delisting, merger or bankruptcy. Crowley and Song has provided evidence showing that European trade policy had a larger negative influence on China’s PV private firms relative to state owned enterprises \([7]\).

Stock price synchronization and co-movement are the key topics in stock-market volatility studies. These are common behaviors of stock markets and can reflect the fluctuation patterns of stock markets. Stock price synchronization is the phenomenon that once a single stock price fluctuates, the average stock price may move up or down in the same direction. It describes the correlation between changes in a single stock price and the average stock-price changes of the stock market. Stock price co-movement refers to associated stocks or stocks of the same type that exhibit a simultaneous rising or falling phenomenon. Financial markets are very sensitive to economic instabilities. They can be impacted by material events. This influence will be reflected in changes in stock price synchronization and co-movement. Among previous studies, very few have considered the impact of material events on stock price synchronization and co-movement. Thus, it is interesting to investigate whether the synchronous and co-movement behavior of stock prices has changed with the occurrence of material events and, if so, how they evolved. Answering these questions can help us to better understand the mechanism that underlies the impact of material events on stock-market volatility behaviors.

However, a material event is likely to undergo a long process from beginning to end. During the process of event development, there are expected to be several sub-events. It is necessary to test whether all these sub-events have significant influences on stock markets. The event study methodology provides us a statistical technique for testing the significance of the effects of events on stock markets. The previous studies have illustrated that different types of events have different effects on the stock markets \([8–17]\).

In our work, we studied the impacts of international anti-dumping events on the evolution of the stock price synchronization and co-movement of the Chinese PV sector. These international anti-dumping events were launched by the U.S., the countries of the European Union and India. Several sub-events occurred during the process of the event development. We used the event study methodology to test the significant effects of each sub-event on the stock returns of Chinese PV firms. After examining the significant effects of the sub-events on the stock returns of PV firms, we then constructed the corresponding unweighted stock-price networks and weighted stock-price networks based on the day that each sub-event occurred. We tried to answer the following three questions: Firstly, did all these sub-events have significant impacts on the stock returns of Chinese PV firms? Secondly, how did the scope and strength of the stock price synchronization change with the occurrence of these international anti-dumping events? Thirdly, how did the stock price co-movement evolve?

This paper is organized as follows. In Section 2 we describe the financial data we used for our analysis and then introduce the methodology, including the event study methodology and the network construction. In Section 3, we analyze the effects of the events on the stock returns of Chinese PV firms. In Section 4, we present the numerical results of our analysis of the changes in the topological properties of the stock-price networks following the occurrence of the sub-events to answer the three questions we proposed above. The paper finishes with a discussion and conclusions.

2. Materials/methods

For analyzing the stock-price synchronisation and co-movement behavior, many scholars have studied financial market volatility using various econometric models \([18,19]\). Filer and Selover have found that the global stock market synchronization results from a “mode-locking” effect in a nonlinear system \([20]\). Synchronicity behaviors between the US and Chinese stock markets were present in the periods 1991–1998 and 1999–2008 \([21]\). Some researchers have quantified the synchronization among the top 40 UK companies using the minimal spanning tree and hierarchical tree methods \([22]\). Liow has found that the global real-estate stock correlations co-move significantly and positively with regional real-estate stock correlations and local real-estate stock correlations \([23]\). Li and Zou have investigated the impact of policy and information shocks on the co-movements of China’s T-bond and stock markets \([24]\). These studies of stock market synchronization and co-movement were based on cross-correlations between stocks. Using the correlations between stocks, some researchers have studied stock cross-correlations using minimal spanning trees \([25–27]\) or the random matrix approach \([26,28,29]\). Many econophysicists have constructed stock networks and investigated their topological properties or topological stability using complex network theory \([30–32]\). Sun et al. studied the stock market characteristics of China’s PV enterprises through building a hierarchical network model \([33]\). Via research concerning the topological properties of a financial network, we were able to analyze the synchronization and co-movement behavior of
the corresponding financial market [34,35] and obtained excellent results.

For analyzing the influence of material events on the stock markets, the event study methodology provides a useful tool. The method was first introduced in the 1930s by Dolley, who analyzed the effect of a stock split on the stock price [36]. Afterward, many scholars further developed the method, and it became popular when Ball and Brown [37] and Fama et al. [38] published two landmark papers. By the 1960s, event studies had made their way into leading business economics journals. This traditional methodology has been commonly used to test announcement effects of dividends [39,40], the announcement effects of earnings [41], and the effects of the existence of insider trading [42]. Nowadays, more and more researchers are beginning to use this method to analyze the effects of other events on stock markets. Moser and Rose assessed the consequences of news concerning regional trade agreements on the stock markets [43]. Schmid and Dauth have found that there are both positive and negative effects of internationalization on a firm’s stock price [44]. However, few studies focus on the effects of material events on the stock market of PV sector.

2.1. Data

For our analysis, we used data regarding the 65 listed PV companies in the Shanghai and Shenzhen A-share markets. There are 59 of them whose daily closing stock prices are available for the trading days from 4 January 2012 to 12 July 2013. The data can be downloaded from the public financial software at the website (www.tx.com.cn). Our analysis is based on the nine sub-events that occurred between 2012 and 2013 that were involved in the development of the international anti-dumping events. The event day is the time when the announcement of international anti-dumping activities against the Chinese export of PV products first appeared in the media.

2.2. Event study methodology

The event study methodology is used to measure abnormal returns, which can capture the abnormal or excess behavior of the stock prices of companies within the time range of each event. Normal return indicates the expected return if the event in question did not occur, while abnormal return indicates the difference between the observed return and the expected return after the event.

\[
R_A = \frac{p_t - p_{t-1}}{p_{t-1}}, \quad (1)
\]

\[
L = T_{-3} - T_{-4}, \quad (2)
\]

where \(p_t\) and \(R_A\) are the stock price and the observed return respectively of stock \(i\) at time \(t\). We define day \(T_0 = 0\) as the day of the media announcement of each sub-event and assume a time window of \(±3\) days around the event day as the event window, i.e., \(T_{-3} \sim T_{+3}\). The estimation window \(L\) is \(T_{-5} \sim T_{-4}\) and \(T_{0} \sim \) is the day after the event window of the previous event.

There are three primary types of models for estimating the expected return: the mean-adjusted return model, the market-adjusted return model and the market-and risk-adjusted model. Brown has concluded that there are no great differences among these methods [45], and it has been shown that the mean-adjusted model is superior to the market model for the Chinese market structure by Hanwen and Xiangmin [46]. Therefore, we choose the mean adjusted return model to estimate the stock returns for each event period. Thus, the expected return for each sub-event is defined as follows:

\[
ER_A = \left(1 - \frac{1}{T}ight) \sum_{t=T-4}^{T} R_A, \quad (3)
\]

where we define the abnormal returns \(AR_i(t)\) for the stock \(i\) during the event window as \(AR_i(t) = \begin{cases} AR_i(-3), & \text{if } t = -3 \\ AR_i(-2), & \text{if } t = -1 \\ AR_i(0), & \text{if } t = 1 \\ AR_i(+1), & \text{if } t = +1 \\ AR_i(+2), & \text{if } t = +3 \\ \end{cases}
\]

\[
AR_i(t) = R_i(t) - ER_i(t), \quad (4)
\]

The average abnormal return for all stocks (\(n\)) during the event period is \(AAR(t) (t = -3, -2, -1, 0, +1, +2, +3)\):

\[
AAR(t) = \frac{1}{n} \sum_{i=1}^{n} AR_i(t), \quad (5)
\]

Then, the cumulative abnormal return (CAR) of the stock \(i\) for the event period is defined by Eq. (6) as follow:

\[
CAR_i(t) = \sum_{j=-3}^{t} AR_i(j), \quad (6)
\]

The cumulative abnormal return is given as follows:

\[
CAR(t) = \sum_{j=-3}^{t} AAR(j), \quad (7)
\]

Finally, a hypothesis test is constructed to identify whether each sub-event had a significant impact on the stock returns of Chinese PV companies. We assume that the abnormal changes are distributed normally with a mean of zero. Hence, the null hypothesis \(H_0\) is modified as follows:

\[
H_0 : AAR(t) = 0, \quad CAR(t) = 0.
\]

\[
T_{AAR} = \frac{AAR(t)}{\sigma_{AAR(t)}} \quad (8)
\]

\[
T_{CAR} = \frac{CAR(t)}{\sigma_{CAR(t)}} \quad (9)
\]

The variance of \(AAR(t)\) and \(CAR(t)\) for each sub-event is calculated as follows:

\[
\sigma^2_{AAR(t)} = \frac{1}{n} \sum_{i=1}^{n} (AR_i(t) - AAR(t))^2, \quad (10)
\]

\[
\sigma^2_{CAR(t)} = \frac{1}{n} \sum_{i=1}^{n} (AR_i(t) - CAR(t))^2, \quad (11)
\]

2.3. Network construction

After examining whether the sub-events had significant effects on the stock returns, we then construct stock-price networks, i.e., unweighted stock networks and weighted stock networks, whose time windows are all based on the event day of each sub-event. A network is usually defined as a collection of “nodes” connected by “links” or “edges”. In our work, we define stock-price networks in which each stock is a network node. The edges of an unweighted stock network and a weighted stock network all depend on the threshold value and the cross-correlation between the stock prices in question. If the correlation coefficient is equal to or greater than the threshold value, then there is an edge between the nodes. If the correlation coefficient between two nodes is less than the threshold value, then there is no edge between them. For an unweighted stock network, the value of the edge is equal to 1 if there is an edge connecting two nodes; otherwise, it is 0. For a weighted stock network, the edge weight is equal to the Pearson’s correlation of the corresponding stock prices in a specified time period [47]. The cross-correlation between pairwise stocks is
calculated for each sub-event period. Thus, we analyze the effects of each sub-event on the stock network.

Let \( P_i(t) \) and \( P_j(t) \) be the daily closing stock prices of stocks \( i \) and \( j \), respectively, during the periods for each sub-event. Then, the cross correlation coefficient, \( \rho_{ij} \), between stocks \( i \) and \( j \) is defined as follows:

\[
\rho_{ij} = \frac{\sum (P_i(t) - \bar{P}_i)(P_j(t) - \bar{P}_j)}{\sqrt{\sum (P_i(t) - \bar{P}_i)^2} \sqrt{\sum (P_j(t) - \bar{P}_j)^2}}
\]

where \( \bar{P}_i \) and \( \bar{P}_j \) are the means of the time series, and the summations are taken over a specific sub-event. The Pearson’s correlation coefficient \( \rho_{ij} \) ranges from \(-1\) to \(1\). If \( \rho_{ij} = \pm 1 \), the stock prices are perfectly positively (or negatively) correlated with each other. If \( \rho_{ij} = 0 \), the stock prices are not related to one another. As the absolute correlation coefficient of the stock prices increases, the relation between the stock prices becomes more significant.

For an unweighted stock network, the value of any edge is equal to either 1 or 0. For a weighted stock network, each edge of the network has its own weight \( W_{ij} = W_{ji} \), which is calculated from the Pearson’s correlation coefficient \( \rho_{ij} \) over each sub-event period, i.e., \( W_{ij} = \rho_{ij} \). Thus, after constructing the unweighted stock networks and the weighted stock networks, we analyze the changes in the topological properties of the stock network based on the event situation and compare the differences among the changes caused by these sub-events.

The procedure for constructing a stock network in our study is as follows. We use the data from each sub-event period, creating networks of 59 nodes. There are two networks for each sub-event, i.e., an unweighted stock network and a weighted stock network. Each node corresponds to one of the stocks of the PV sector. For each pair of stocks, we evaluate the cross-correlation of the time series of the daily closing prices for each sub-event period. We specify a certain threshold value, \( \theta \), \(-1 \leq \theta \leq 1\). For the unweighted stock network, we add an edge of value 1 connecting the vertices \( i \) and \( j \) if the correlation coefficient \( \rho_{ij} \) is equal to or greater than \( \theta \). For the weighted stock network, we add a weighted edge connecting the vertices \( i \) and \( j \) if the correlation coefficient, \( \rho_{ij} \), is equal to or greater than \( \theta \). Different values of \( \theta \) define networks with the same set of vertices, but different sets of edges.

Let graph \( G = (V, E) \) represent an unweighted stock-price network, where \( V \) and \( E \) are the sets of vertices and edges, respectively. \( E \) is defined as follows:

\[
E = \left\{ \begin{array}{ll}
\epsilon_{ij} = 1, i \neq j \text{ and } \rho_{ij} \geq \theta \\
\epsilon_{ij} = 0, i \neq j \text{ and } \rho_{ij} < \theta,
\end{array} \right.
\]

(13)

Let graph \( G' = (V', E') \) represent a weighted stock-price network, where \( V \) and \( E' \) are the sets of vertices and edges, respectively. \( E' \) is defined as follows:

\[
E' = \left\{ \begin{array}{ll}
\epsilon'_{ij} = \rho_{ij}, i \neq j \text{ and } \rho_{ij} \geq \theta \\
\epsilon'_{ij} = 0, i \neq j \text{ and } \rho_{ij} < \theta,
\end{array} \right.
\]

(14)

3. Effect tests of events

In our study, we investigated the significant effects of the nine events on the stock returns of the 59 investigated companies from the PV sector using the event study methodology. For the nine events, the times of occurrence and the time ranges of the events are different from one another. As there are no uniform criteria for choosing the estimation window and the event window, we defined the event window as \( \pm 3 \) days around the day when the anti-dumping news was first announced by the media. We defined the time window of event 0 to be the estimation window for event 1. Specific descriptions of the nine sub-events are shown in Appendix A. In Appendix B, we show the estimation windows and the event windows for analyzing the effects of each event, i.e., events 1–9.

In Fig. 1, the distributions of the cumulative abnormal returns of each event day for the nine events are shown. It can be seen that the distributions of the cumulative abnormal returns for the nine events closely follow the normal distribution. In particular, more than 70% of the stocks had negative cumulative abnormal returns for events 1, 2, 6, and 9. We performed t-tests to determine whether these events had significant effects on the stock returns.

We tested the effects of the nine events on the stock returns for each event day using a t-test. The t-test results are shown in Table 1.

Null hypothesis \( (H_0) \): \( \text{AAR}(t) = 0 \), \( \text{CAR}(t) = 0 \)

Alternative hypothesis \( (H_1) \): \( \text{AAR}(t) \neq 0 \), \( \text{CAR}(t) \neq 0 \)

The t-test results for the nine events indicate that the \( p \)-values of all nine tests, except event 3, were less than 0.05, i.e., at the 5% significance level, which means that the population means are significantly different from the test mean (0) for the nine events except in the case of event 3. Moreover, the distributions of the cumulative abnormal returns on the event day of each event closely follow the normal distribution, as shown in Fig. 1. Therefore, for events 1, 2, 4, 5, 6, 7, 8, and 9, we rejected the null hypothesis, thereby concluding that all nine events, except event 3, had significant impacts on the stock returns of the PV firms. Then, we proceeded to analyze the changes in the stock-network structure by constructing stock-price networks for the nine events.

![Fig. 1. The distributions of the cumulative abnormal return of each event day.](image_url)

### Table 1

<table>
<thead>
<tr>
<th>Events</th>
<th>AAR</th>
<th>( T_{AAR} )</th>
<th>CAR</th>
<th>( T_{CAR} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Event 1</td>
<td>0.0275</td>
<td>-12.0038***</td>
<td>-0.0213</td>
<td>-4.23902***</td>
</tr>
<tr>
<td>Event 2</td>
<td>0.0192</td>
<td>-8.8813***</td>
<td>-0.0185</td>
<td>-24.35358***</td>
</tr>
<tr>
<td>Event 3</td>
<td>0.0054</td>
<td>5.6704***</td>
<td>0.0083</td>
<td>1.5610</td>
</tr>
<tr>
<td>Event 4</td>
<td>0.0186</td>
<td>9.1546***</td>
<td>0.0124</td>
<td>2.3644***</td>
</tr>
<tr>
<td>Event 5</td>
<td>0.0110</td>
<td>5.7271***</td>
<td>0.0163</td>
<td>8.0338***</td>
</tr>
<tr>
<td>Event 6</td>
<td>0.0047</td>
<td>-2.8063***</td>
<td>-0.0265</td>
<td>-9.1204***</td>
</tr>
<tr>
<td>Event 7</td>
<td>0.0051</td>
<td>2.7322***</td>
<td>0.0138</td>
<td>2.9313***</td>
</tr>
<tr>
<td>Event 8</td>
<td>0.0021</td>
<td>-0.6202</td>
<td>0.0195</td>
<td>3.0131***</td>
</tr>
<tr>
<td>Event 9</td>
<td>0.0059</td>
<td>-1.9764**</td>
<td>-0.0553</td>
<td>-7.2193**</td>
</tr>
</tbody>
</table>

* \( p \leq 0.10 \).
** \( p \leq 0.05 \).
*** \( p \leq 0.01 \).
4. Results

4.1. Stock price networks based on events

Based on the Pearson’s correlation coefficient, we constructed the pairwise correlation-coefficient matrix for the prices of the PV stocks. We then described the connectivity of the stocks in terms of the distribution of the correlation coefficients. Fig. 2 shows the correlation-coefficient distribution of the stock prices. The distribution indicates that most of the stocks (approximately 71%) are positively correlated. Because our work is mainly concerned with stock price synchronization and co-movement, we chose the positively correlated stocks to construct the stock networks.

The degree of vertex \( i \) in a network corresponds to the number of adjacent edges that connect to \( i \). The higher the degree of the vertex is, the more important that vertex will be. The vertex with the highest degree has the greatest influence on the network of all vertices in that network. In a stock network, this means that the stock represented by that vertex has the most significant influence on the stock market. We constructed unweighted and weighted stock networks for various threshold values in the range 0.50–0.95. Fig. 3 shows the number of vertices of positive degree for different correlation threshold values. The results indicate that the number of vertices of positive degree decreases as the threshold value, \( \theta \), increases. Only a few stocks have strong correlations with one another. When \( \theta > 0.70 \), there is a sharp decrease in the number of vertices of positive degree. For a weighted stock network, the vertex strength of vertex \( i \) refers to the sum of the weights of the adjacent edges that connect to \( i \). We found that the number of nodes whose vertex strength is greater than 0 also decreases as the threshold values increases, and a threshold value of 0.70 is the inflection point for the weighted stock network, as well.

Therefore, we chose 0.70 as the threshold value to construct the stock-price networks for the nine events [48,49]. The time windows of the stock networks, i.e., the unweighted stock networks and the weighted stock networks, are based on the event days of the nine events, as shown in Appendix A. If the correlation coefficient between stocks \( i \) and \( j \), \( \rho_{ij} \), is equal to or greater than 0.70, there is an edge that connects them in the unweighted stock network, and the edge weight between stocks \( i \) and \( j \) is equal to \( \rho_{ij} \) for the weighted stock network; otherwise, the number of edges or the edge weight is 0. The stocks that are connected by edges in the stock networks are positively and strongly correlated.

4.2. Changes in the scope and strength of the stock price synchronization

According to the definition of stock price synchronization provided above, changes in the scope of the stock price synchronization correspond to the changes in the scope of the correlation between the changes in a single stock price and the average stock-price changes of the stock market. Changes in the strength of the stock price synchronization correspond to changes in the extent of the correlation.

For the unweighted stock networks, the degree of vertex \( i \) is \( k_i = \sum_{j \neq i} e_{ij} \), which denotes the number of adjacent edges that connect to \( i \). It describes the extent to which a node is connected to other nodes. The vertex that has the largest degree is the hub vertex in the stock network. It correlates with other stocks in terms of price fluctuation. As we chose a threshold value of 0.7 to construct the stock networks, the stocks that are of positive degree in the stock networks are positively and strongly correlated. The stocks of high degree can most accurately reflect market behaviors [30]. When the stock price of the stock with the highest degree fluctuates because of an event, the average stock-price fluctuation of the stock market may also move upward or downward in the same direction. The degree distribution for the nine events is shown in Fig. 4.

According to Fig. 4, the maximum degree and the number of stocks of the same degree in the stock networks are smaller than
they were prior to the anti-dumping events for each of the nine events. This means that the scope of the stock price synchronization narrowed following the occurrence of the events with respect to the situation prior to the events. However, the maximum degree of the stock networks still changed with each individual event. After event 1 occurred, the maximum degree of the vertices in the unweighted stock network decreased sharply, by 53%. When event 2 occurred, the maximum degree of the stock network increased again by 62%. After event 3, the maximum degree dropped by 24%. The occurrence of event 4 caused the maximum degree to increase by 25%. When event 5 took place, the maximum degree decreased by 42.5% and reached the lowest maximum degree of all nine events. Event 6 caused the maximum degree to increase significantly, by 78%. When event 7 occurred, the maximum degree decreased by 24% and it then grew by 16% and 28% following events 8 and 9, respectively. Thus, following the occurrence of events 2, 4, 6, 8 and 9, the maximum degree of the vertices in the stock network grew. Events 2 and 6 were associated with particularly large increases. Furthermore, the number of stocks of the same degree also changed with the occurrence of each event. It can be seen that the numbers of stocks of the high degree (the degree greater than 30) for events 2, 4, 6, 8 and 9 were greater than those for events 1, 3, 5 and 7. Therefore, events 2, 4, 6, 8 and 9 caused the scope of the stock price synchronization to increase, which means that there were more stocks whose stock prices fluctuated in the same direction, and the average stock market of the PV sector may also have changed in the same direction as a result of events 2, 4, 6, 8 and 9, particularly event 2 and event 6, which caused the scope of the synchronization to expand considerably.

Fig. 5 illustrates that before the international anti-dumping events occurred, the degrees of most stocks (over 89%) were greater than 30. After event 1 took place, all stocks had low degrees of less than 30. Afterward, following the occurrence of event 2, the degrees of 14% of the stocks became greater than 40. When event 3 took place, the number of stocks with degrees of less than 30 increased to 98%. After event 4, most stocks were of low degree (less than 30), and the remaining 39% of the stocks had relatively high degrees of more than 30 but less than 40. When event 5 occurred, all stocks dropped to low degrees. Following event 6, 5% of the stocks had high degrees of greater than 40, and most stocks were of low degree. When event 7 occurred, the number of stocks with degrees of less than 30 increased to 98%. Following event 8, 78% of the stocks were of low degree. Following event 9, 37% of the stocks had degrees greater than 40. Events 1, 3, and 5 caused the degrees of almost all stocks to drop below 30, and most stocks were of low degree following the occurrence of events 7 and 8. This means that the scope of the stock price synchronization narrowed following these events. After events 2, 6, and 9, there was a minority of stocks of high degree (greater than 40), which can most accurately reflect the average fluctuation of the PV industry stocks. Fig. 6 shows the changes in the average degree and the changes in the number of vertices of a degree of no less than 40. The average degrees of events 2, 4, 6, 8 and 9 are greater than those of events 1, 3, 5, and 7. After events 2, 6 and 9, the number of stocks of high degree reached a peak level. Although these stocks were in the minority, a large number of stocks were connected with them. Thus, following the occurrence of events 2, 6, and 9, the scope of stock-price synchronization increased significantly and reached a peak level.

For the weighted stock networks, the vertex strength of $i$ is $S_i = \sum_{j=1}^{n} w_{ij}$, which denotes the sum of the weights of the adjacent edges that connect to $i$. It describes the strength of the stock price synchronization. The node that has the largest vertex strength has the strongest influence on the stock market of all nodes. The vertex-strength distributions for the nine events are shown in Fig. 7.

From Fig. 7, we found that the maximum vertex strength was decreased for the nine events with respect to the situation prior to the anti-dumping events. This means that the international anti-dumping events weakened the overall strength of the stock price synchronization relative to the previous situation. However, the strength of the stock price synchronization still changed with each individual event. According to Fig. 8, the total vertex strengths following events 2, 4, 6 and 9 were all greater than those following...
events 1, 3, 5, 7 and 8. This means that events 2, 4, 6 and 9 caused the strength of the stock price synchronization to increase, and it reached a peak for events 2 and 9.

Based on the analysis above, it can be seen that with respect to the situation prior to the anti-dumping events, the overall scope and strength of the stock price synchronization decreased after the occurrence of the nine events. Nevertheless, the scope and strength of the stock price synchronization changed with each individual event. Events 2, 4, 6, and 9 caused the scope and strength of the stock price synchronization to increase relative to the situations following the preceding events. This means that these four events stimulated the synchronization behavior of the stock prices. In particular, under the influence of events 2, 6, and 9, the scope of the stock price synchronization reached a peak level. Therefore, more stocks reflected a stock synchronous pattern.

4.3. Evolution of the co-movement of stock prices

The connectedness is a measurement of the extent to which each node is connected to other nodes. A network with high connectedness has characteristics such as power decentralization and scattered information, and the network is not controlled by the minority vertices. A network with low connectedness has the opposite characteristics of power centralization and centralized information, and the network is dominated by the minority vertices. Reachability is used to calculate the connectedness of a network based on Eq. 15 as follows:

$$C = 1 - \frac{V}{N * (N - 1) * 4}$$

where $C$ is the connectedness of the network, $V$ is the number of pairs that are not reachable, and $N$ is the scale of the network.

Stock price co-movement refers to associated stocks or stocks of the same type that exhibit simultaneous rising or falling phenomena. Changes in the connectedness of a stock network indicate changes in the scope of the stock price co-movement. When the connectedness of the stock network increases, the scope of the co-movement of the stock prices will shrink. When the network connectedness decreases, the scope of the co-movement of the stock prices will expand.

Fig. 9 shows the changes in the connectedness of the unweighted stock price network with the nine events. Before the international anti-dumping events occurred, the connectedness of the stock network was 0.93. When event 1 occurred, the connectedness decreased by 7%, and it decreased further, by 29%, during the period of event 2. Following event 3, the connectedness increased, and it reached a peak value of 1 after event 4 took place. The connectedness then decreased by 13% and 21% following events 5 and 6, respectively. Event 7 caused the connectedness to increase considerably, to 0.97, while the connectedness decreased by 6.7% following event 8, and event 9 caused the connectedness to decrease by 17%. These findings indicate that during the time windows of events 2, 6, and 9, the connectedness of the stock network was lower than it was for the other events. When events 1, 5, and 8 occurred, the connectedness began to decrease, and during the subsequent periods of events 2, 6, and 9, the connectedness reached its lowest points. During these low-connectedness periods, the scope of the co-movement of the stock market became larger.

Network structure entropy is used to measure the heterogeneity of a network. In a heterogeneous network, most vertices are of small degree, and a few vertices are of large degree. The network is dominated by the minority of vertices that are of high degree. Once the stock prices of the minority stocks fluctuate under the influence of certain events, the other stocks that are connected to them may co-move in the same direction. Thus, in a stock network, the network structure entropy may reflect the sensitivity of the stock price co-movement to such events. When the network structure entropy becomes smaller, the stock network becomes more heterogeneous, the connectivity of the network improves, the small-world property of the network becomes much more obvious, and the sensitivity of the stock price co-movement to events increases. A higher sensitivity means that the stock market starts the co-movement behavior caused by events. The network structure entropy is defined as follows:

$$E = -\sum_{i=1}^{N} I_i * \ln I_i$$

where $I_i = \frac{k_i}{\sum_{i=1}^{N} k_i}$.

$$\hat{E} = \frac{(E - E_{\min})}{(E_{\max} - E_{\min})} = \frac{-2 \sum_{i=1}^{N} I_i * \ln I_i - \ln 4(N - 1)}{2 \ln N - \ln 4(N - 1)},$$

where $\hat{E} \in [0, 1]$. 

Fig. 8. The total vertex strength for the nine events.

Fig. 9. The connectedness for the nine events.
4.4. Effects of the events on the stability of the co-movement between adjacent stocks

The weighted clustering coefficient of vertex $i$ reflects the extent of linkage between vertex $i$ and its adjacent vertices. The greater the weighted clustering coefficient is, the more frequently the two adjacent vertices will contact. The co-movement between vertex $i$ and its adjacent vertices will be much more stable. The weighted clustering coefficient of vertex $i$ is defined by Eq. (19) as follows [50]:

$$C_i^w = \frac{1}{\left\lfloor k_i \times (k_i - 1) \right\rfloor} \sum_{j,k} \left( w_{ij}^w * w_{jk}^w * w_{kj}^w \right)^{\frac{1}{3}},$$

where $k_i$ is the degree of vertex $i$, $w_{ij}^w = \frac{w_{ij}}{\max(w_{ij})}$, and $\max(w_{ij})$ is equal to 1 in our study. In a stock network, the weighted clustering coefficient corresponds to the stability of the co-movement of the stock market between adjacent stocks. The larger the weighted clustering coefficient is, the more stable the stock price co-movement between adjacent stocks will be.

Fig. 11 presents the changes in the average weighted clustering coefficient of the stock network with respect to the nine events. Before the international anti-dumping events occurred, the average weighted clustering coefficient was 0.39. After event 1 took place, the average weighted clustering coefficient dropped significantly, by 40%. Afterward, it decreased to 0.28 following event 2 and remained constant following event 8. Under the influence of event 9, it increased by 28% to 0.36. Therefore, it can be seen that when events 2, 4, 6, 9 took place, the average weighted clustering coefficient increased significantly with respect to the situations following the other events, meaning that the contact between adjacent stocks became more frequent. The stock price co-movement between adjacent stocks became more stable following these events.

5. Discussion and conclusion

5.1. Discussion

For this study, we chose the stock prices of the PV sector in the Shanghai and Shenzhen A-share markets from 4 January 2012 to 12 July 2013 as the sample data. We used the event study methodology to prove that the international anti-dumping events that occurred between 2012 and 2013 had significant impact on the stock returns of the PV firms. Then, we constructed ten unweighted stock-price networks and ten weighted stock-price networks based on the event day of each sub-event to analyze the changes in the topological structure of the stock network. Finally,
we found that the changes in the stock price synchronization and the evolution of the stock price co-movement were influenced by the anti-dumping events.

The results illustrate the changes in the maximum degree value, the changes in the degree distribution, the changes in the average degree and the changes in the number of vertices of high degree. We found that with respect to the situation prior to the anti-dumping events, the general level of the stock-price synchronization all decreased after the anti-dumping events occurred. However, different events had different effects on the scope of the stock-price synchronization. Compared with events 1, 3, 5 and 7, events 2, 4, 6, 8, and 9 caused the scope of the stock-price synchronization to increase. Furthermore, following events 2, 6, and 9, there was minority of stocks of high degree, and the scope of the stock-price synchronization reached a peak. More stocks reflected synchronous price behavior. Events 2, 4, 6, 8 and 9 represent the following occurrences: the U.S. ruled to levy an anti-dumping tax of 31.14–249.96%, which is a very high rate, on Chinese companies; the European Union confirmed that they would launch an anti-dumping investigation of imported Chinese solar cells and their components; the EU formalized their investigation of Chinese PV companies, and the U.S. decided to levy an anti-dumping tax of 18.32–249.96% and an anti-subsidy tax of 14.78–15.97% on the solar products imported from or produced by Chinese PV companies; foreign media reported that the EU would levy a punitive tariff at an average rate of 47% on Chinese PV products; and the EU ruled that they would levy a temporary anti-dumping tax of 11.8% on Chinese PV products. These events all concern the anti-dumping initiatives launched by the U.S. and the EU countries, which are the main importers of Chinese PV products. Therefore, when the U.S. ruled to levy an anti-dumping tax with an extraordinarily high rate, more stocks began to fluctuate in the same direction; the fluctuation of these stocks reflected the volatility of the stock market in the Chinese PV sector. These events all increased the scope of the stock-price synchronization with respect to the situation following the other events.

By analyzing the changes in the vertex-strength distribution and the changes in the total vertex strength of the PV sector, we found that with respect to the situation prior to the anti-dumping events, the overall strength level of the stock-price synchronization decreased after the international anti-dumping events occurred. However, the impacts of individual events on the strength of the stock-price synchronization differed. Compared with events 1, 3, 5, and 7, events 2, 4, 6, 8, and 9 caused the strength of the stock-price synchronization to increase. In particular, under the influence of events 2, 6, and 9, the strength of the stock-price synchronization reached a peak. To be specific, the events that involved the U.S. levying high-rate anti-dumping and anti-subsidy taxes or the EU launching an investigation of imported Chinese solar products or levying a temporary anti-dumping tax all increased the strength of the stock-price synchronization.

By investigating the changes in the connectedness of the stock network, we found that events 2, 6, and 9 enlarged the scope of the stock price co-movement of the PV sector. In other words, the events that involved the U.S. and the EU levying anti-dumping and the anti-subsidy taxes enlarged the scope of the co-movement of the stock prices in the PV sector. In addition, we also analyzed the sensitivity of stock price co-movement to certain events. We found that the stock price co-movement of the PV sector was sensitive to the occurrence of all nine events, to some extent. However, the sensitivity changed with individual events. Events 1, 5 and 8 were associated with their higher sensitivity of the co-movement of the stock prices than were the other events. The stocks of the PV sector exhibited stock price co-movement behavior when events 1, 5, and 8 occurred. These events include the U.S. ruling to levy a tax on Chinese PV companies via a temporary anti-subsidy tax; the U.S. Department of Commerce ruling to levy a tariff of 34–47% on solar panels and solar cells imported from China, subjected to the final decision of the U.S international trade commission; and the foreign media reporting that the EU would levy a punitive tariff at an average rate of 47% on Chinese PV products. These types of events such as levying a temporary anti-subsidy tax, waiting for a final decision concerning the levying of a high tax or foreign media reported news regarding the levy of an anti-dumping tax—are more likely to be a signal that the stocks will continue to exhibit co-movement in the near future.

We also analyzed the changes in the average weighted clustering coefficient. We found that the contact between adjacent stocks became more frequent following events 2, 4, 6, and 9, and stock price co-movement of the PV sector between adjacent stocks became more stable.

In this paper, we do not consider the influence of manufacturing overcapacity in our model. The manufacturing overcapacity is one of the factors that have impact on the profits of manufacturers [51]. There is a spiral mechanism between the manufacturing overcapacity and the stock market of PV sector in China. The investors tend to invest in the market of good prospects. Since the Chinese government introduces some supportive policies into the PV industry, there is a huge expansion of the PV production. With the speedy development of the industry, the investors expect that the stock prices of the PV sector will increase. Therefore, they will expand their investment into the PV industry, which may increase the stock prices of the PV sector. And the listed PV enterprises will then finance more funds to expand manufacturing, which may attract more investors to contribute more capital into the PV industry. Therefore, the stock prices of the PV sector may increase further. In China, the domestic consumption of PV products is in the bottleneck and mainly relies on the foreign markets, especially those of the United States and the European Union [52,53]. In 2012, the domestic consumption only amounted to 8000 MWp, which is no more than 35% of the total production [54]. The huge demand of the foreign markets triggers the fast expansion of the PV industry in China. As a result, plenty of funds flooded into the stock market of the PV sector, which may increase the stock prices of the PV sector. However, since the “double reverse” in the United States and the European Union to China’s PV companies, those companies have faced serious loss and become worse because of the high tariffs or punitive tariffs, which may ultimately have a negative impact on the stock prices of the PV sector. Since this paper is mainly focused on the impacts of international anti-dumping events on the movement of stock prices at the Chinese PV sector. The event study methodolody has been applied to test the significance of the impacts of the anti-dumping events on the PV stock market. Through constructing the stock network to show the changes of the topological structure of the stock network before and after the anti-dumping events we have provided a new perspective to analyze the influence of material events on the financial markets. Therefore, the influence of the manufacturing overcapacity is not the major factor in our current research, but it will be considered in our future research.

Previous study has found that the risk perception of financial markets is a result of investors or other financial market participants [55]. Social media has been considered as a factor that has influences on the stock market by some researchers. It has proved that there is a correlation between the sentiment from the social media and stock returns [56,57]. The influence of events on the stock markets varies with different types of the events. Positive (negative) events lead to higher (lower) predicted returns, whereas events related to
third-party opinions lead to smaller changes in predicted returns in short event windows [58]. In our study, the nine events studied here represent anti-dumping events in the PV industry. When a similar event occurs, the results of this analysis may provide essential information for investors to analyze stock price synchronization and stock price co-movement behavior.

As for the influence of spin doctors to the public and press perception of PV solar energy, there are two events which relate to the spin doctors, i.e. the event 4 and event 8. The event 4 occurred on the 3 September 2012. According to the media, the European Union had confirmed the anti-dumping investigation of solar cells and modules exported to Europe by Chinese enterprises. The event 8 occurred on the 9 May 2013. Foreign media reported that the EU would levy a punitive tariff at an average rate of 47% on Chinese PV products. Under these two events, the scope and the strength of stock-price synchronization all increased. We also found that the stock price co-movement of the PV sector was highly sensitive to the occurrence of event 8, while the interconnectedness between the adjacent stocks became more frequent following the event 4. In the future, we will choose more events related to the spin doctors to the public and press perception of PV solar energy and explore their influence on the stock behavior.

Inevitably, there will be noise that interferes with an event study, such as other events that may impact the stock market. However, according to the results of our analysis, most of these nine events had significant effects on the stock returns, as shown in Fig. 1 and Table 1. In addition, as our work focused on the influence of events on the stock price synchronization and stock price co-movement of a specific industry, we only investigated the anti-dumping events that impacted the stock market in the Chinese PV sector. In the future, we can choose more different types of events to analyze and determine the general rules regarding the changes in stock price synchronization and stock co-movement behaviors affected by material events. We may also extend the sample data to one or more other stock markets, which will have a more practical impact on our future research.

5.2. Conclusion

This study presents a novel approach to examine the effects of international anti-dumping events on the stock synchronization and co-movement of the Chinese PV sector. The event study methodology provides a method of testing whether events have a significant impact on stock returns. Based on the results of the test, we have proved that most of the anti-dumping events had significant effects on the stock returns. We then constructed unweighted stock networks and weighted stock networks. In constructing the stock networks, a threshold value was chosen. By analyzing the changes in the stock-network properties, we have found that different types of events have different impacts on the stock-network structure. The stock price synchronization and the stock price co-movement also change with the occurrence of different types of events. The U.S. levied a high anti-dumping tax rate, while the EU launched an investigation of imported Chinese solar products and levied a temporary anti-dumping tax; all these events increased the scope and strength of the stock price synchronization. These events also caused the stock price co-movement between adjacent stocks that became more stable. Moreover, anti-dumping and anti-subsidy taxes levied by the U.S. and the EU enlarged the scope of the stock price co-movement of Chinese PV stocks. In addition, the stock market of the PV sector has a high sensitivity to events such as the U.S. ruling to levy a tax on Chinese PV companies via a temporary anti-subsidy tax, the U.S. waiting for a final determination concerning the levying of a high-rate tariff on solar panels and solar cells imported from China, and the foreign media reporting that the EU would levy a high-rate punitive tariff on Chinese PV products. The stock market in the PV sector exhibited the stock price co-movement behavior following the occurrence of these types of events. To our knowledge, this study provides a new pathway to this type of study that combines the event study methodology and stock-network analysis to analyze the effects of material events on stock-volatility behaviors. We believe that it may lead to important applications of event study to the investigation of other issues related to financial networks and provide reference to the effects of anti-dumping on the PV industry.

Acknowledgment

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A. Appendix

See Table A1.

<table>
<thead>
<tr>
<th>Events</th>
<th>Event day</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>4 January 2012</td>
<td>Estimation window for event 1</td>
</tr>
<tr>
<td>1</td>
<td>20 March 2012</td>
<td>U.S. Department of Commerce ruled to levy tax on Chinese PV companies of 2.9–4.73% as a temporary anti-subsidy tax</td>
</tr>
<tr>
<td>2</td>
<td>18 May 2012</td>
<td>U.S. Department of Commerce ruled to levy anti-dumping tax on Chinese PV companies of 31.14–249.96%</td>
</tr>
<tr>
<td>3</td>
<td>24 July 2012</td>
<td>Some European companies requested the European Union Commission to investigate the dumping behaviors of Chinese PV companies</td>
</tr>
<tr>
<td>4</td>
<td>3 September 2012</td>
<td>Media reported that the European Union had confirmed the anti-dumping investigation of solar cells and modules exported to Europe by Chinese enterprises.</td>
</tr>
<tr>
<td>5</td>
<td>10 October 2012</td>
<td>U.S. Department of Commerce made the final ruling that they would levy a tariff of 34–47% on solar panels and solar cells imported from China but wait for the final determination of the U.S. International Trade Commission</td>
</tr>
<tr>
<td>6</td>
<td>8 November 2012</td>
<td>European Union formalized the investigation of Chinese PV companies. The U.S. decided to levy an anti-dumping tax of 18.32–249.96% and an anti-subsidy tax of 14.78–15.97% on solar products imported from or produced by the Chinese PV companies.</td>
</tr>
<tr>
<td>7</td>
<td>23 November 2012</td>
<td>Indian anti-dumping Bureau decided to launch an anti-dumping investigation of solar cells imported from mainland China, Chinese Taipei, Malaysia and the United States</td>
</tr>
<tr>
<td>8</td>
<td>9 May 2013</td>
<td>Foreign media reported that the EU would levy a punitive tariff at an average rate of 47% on Chinese PV products</td>
</tr>
<tr>
<td>9</td>
<td>5 June 2013</td>
<td>The EU ruled that they would levy a temporary anti-dumping tax of 11.8% on Chinese PV products from 6 June 2013 to 6 August 2013</td>
</tr>
</tbody>
</table>
B. Appendix

See Table B1.

Table B1

The estimation window and the event window of each event.

<table>
<thead>
<tr>
<th>Event</th>
<th>Estimation window</th>
<th>Event window</th>
</tr>
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<tbody>
<tr>
<td>Event 1</td>
<td>5 January 2012</td>
<td>T_1</td>
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<tr>
<td>Event 2</td>
<td>26 March 2012</td>
<td>T_1</td>
</tr>
<tr>
<td>Event 3</td>
<td>24 May 2012</td>
<td>T_2</td>
</tr>
<tr>
<td>Event 4</td>
<td>30 July 2012</td>
<td>T_3</td>
</tr>
<tr>
<td>Event 5</td>
<td>7 September 2012</td>
<td>T_3</td>
</tr>
<tr>
<td>Event 6</td>
<td>16 October 2012</td>
<td>T_4</td>
</tr>
<tr>
<td>Event 7</td>
<td>14 November 2012</td>
<td>T_4</td>
</tr>
<tr>
<td>Event 8</td>
<td>28 November 2012</td>
<td>T_4</td>
</tr>
<tr>
<td>Event 9</td>
<td>15 May 2013</td>
<td>T_3</td>
</tr>
</tbody>
</table>

References


[40] Liu YJ, Chi DJ. Stock market reaction to various dividend announcements: which kind of dividend announcement is more significant? J Test Eval 2014;42:996–1006.


