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Dynamic Anomaly Detection in the Chinese Energy Market During Financial Turbulence Using Ratio Mutual Information and Crude Oil Price Movements

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Abstract: Investigating the stability of and fluctuations in the energy market has long been of interest to researchers and financial market participants. This study aimed to analyze the Chinese energy market, focusing on its volatility and response to financial tensions. For this purpose, data from eight major financial companies, which were selected based on their market share in Shanghai's and Shenzhen's financial markets, were collected from January 2014 to December 2023. In this study, stock prices and trading volumes were used as the key variables to build bootstrap-based minimum spanning trees (BMSTs) using ratio mutual information (RMI). Then, using the sliding window procedure, the major network characteristics were derived to create an anomaly-detection tool using the multivariate exponentially weighted moving average (MEWMA), along with the Brent crude oil price index as a benchmark and a global oil price indicator. This framework's stability was evaluated through stress testing with five scenarios designed for this purpose. The results demonstrate that during periods of high oil price volatility, such as during the turbulence in the stock market in 2015 and the COVID-19 pandemic in 2020, the network topologies became more centralized, which shows that the market's instability increased. This framework successfully identifies anomalies and proves to be a valuable tool for market players and policymakers in evaluating companies that are active in the energy sector and predicting possible instabilities, which could be useful in monitoring financial markets and improving decision-making processes in the energy sector. In addition, the integration of other macroeconomic factors into this field could strengthen the identification of anomalies and be considered a field for possible research.

Keywords: energy market dynamics; anomaly detection; ratio mutual information (RMI); financial network analysis; bootstrap-based minimum spanning trees (BMSTs); multivariate exponentially weighted moving average (MEWMA)

Citation: Xiao, L.; Sioofy Khoojine, A. Dynamic Anomaly Detection in the Chinese Energy Market During Financial Turbulence Using Ratio Mutual Information and Crude Oil Price Movements. *Energies* **2024**, *17*, 5852. https://doi.org/10.3390/en17235852

Academic Editor: Peter V. Schaeffer

Received: 13 October 2024
Revised: 11 November 2024
Accepted: 19 November 2024
Published: 22 November 2024

1. Introduction

1.1. Motivations

The stock market of companies active in the field of energy and its effects on the economies of countries have always been popular topics for researchers and activists in this field. In most studies, analysis of the stock market is mainly conducted based on examining the stock prices of companies [1]. However, this approach comes with challenges; for example, the price of a stock may increase over a certain period of time, while its trading volume does not change. Therefore, any analysis of financial markets that does not simultaneously consider the role of price time series and the volume of transactions seems incomplete. In one research work, Khoojine and Dong investigated the Chinese stock market crisis in 2015 and, in this analysis, they both considered the time series of prices and the trading volume in order to achieve a more comprehensive understanding of the market dynamics [2].

The stock market of companies that play a role when assessing the energy market status of a country can be considered an important indicator when examining its economic and financial condition from a macroeconomic perspective [3]. Thus, taking a closer look at the situation and movements in this type of market can be considered to be a solution to many ambiguous issues in economic and financial problems and for making informed decisions that aid countries' economies [4]. This study discusses this topic within a new and creative framework in order to provide an appropriate tool for investigating and monitoring this type of financial market, as well as comprehensively scrutinizing the behavior of financial markets in special situations.

In the analysis of financial markets, numerous challenges arise due to the inherently complex and multifaceted structure of these systems. One of the challenges in network analysis of financial markets is that most studies attempt to implement linear methods to model the distance between nodes, which, given the nonlinear dynamics of financial phenomena, can lead to a misunderstanding of the performance of these types of markets; therefore, it is necessary to overcome this issue through the use of nonlinear methods. Methods based on entropy or information theory can be an appropriate way to address nonlinearity in the real world. For example, in one study, Khoojine et al. investigated the turbulence of the U.S. financial market using a method based on mutual information, and in their article, they investigated the difference between linear and nonlinear methods [5]. Meanwhile, in this study, we attempt to use the ratio mutual information (RMI) method to find the distances between companies, as this method aids us in normalizing the weight of the edges and capturing the nonlinear nature of financial turbulence.

Another noteworthy aspect that can be observed in the study of financial markets is the use of a fixed period of time to analyze the behavior of financial markets. Although this type of study has recently been on the decline, the majority of studies have been based on considering fixed and long-term time periods [6]. In one article, Wu et al. investigated the relationships between international commodity future prices. A static dependency network for a vector of variables was constructed using partial correlations; the results were analyzed alongside another constructed dynamic network, and the findings were compared. The results obtained showed similarities to real-world oil price movements [7]. Therefore, in this study, we decided to apply a dynamic method instead of a static one.

China's economy is one of the economies that has made significant progress in recent decades and has been able to gain a major part of the global economy [8]. China, one of the largest suppliers in the global supply cycle, has a significant impact on the state of regional and even global financial markets. Considering the massive volume of production in this country and its dependence on energy supply, this study aims to analyze its energy financial market and measure the effects of oil price fluctuations on this market [9]. China, as an emerging economy, is a good input for modeling the energy market while taking the fluctuations in the global oil supply into account. Fang et al. analyzed the Chinese energy market by developing an analytical model to scrutinize the external factors affecting China's energy market [10]. Another study by Abdullah and Huo was conducted to analyze the time-varying relationships between the Chinese equity market, commodity markets, and international oil prices, and they emphasized that there is a robust correlation between the Chinese stock market and the oil market [11]. Chien et al. studied the relationship of external effects with the energy markets of the three countries of the U.S., the U.K., and China using wavelet-based Granger causality tests [12]. Gong et al. examined the complex interplay between geopolitical risks and the international energy market, focusing on how extreme events influence risk contagion across these networks. Using empirical data on crude oil prices and geopolitical risk indices, this study reveals that traditional energy markets exhibit stronger risk spillovers than clean energy markets, with Russia being identified as a primary risk contributor during shocks and geopolitical tensions, amplifying contagion in global energy markets [13]. Filipovic et al. introduced a comprehensive energy security index (ESI) that integrates economic, environmental, political, and social factors to provide a more nuanced measurement of energy security. Using principal component analysis, their study found that GDP per capita, country risk, carbon intensity, and energy intensity are among the most influential factors, while renewable energy share and energy dependence have weaker impacts on the index values [14]. All the above studies show that there is a strong relationship between external factors, such as oil price movement, and the energy market's behavior [15]. The need to monitor energy markets to understand their effects on the overall economy—at both the national and global levels—inevitably arises [16]. Therefore, this study aims to develop a reliable framework for comprehending the volatility of energy markets while addressing the previously mentioned challenges and considering earlier findings.

The focus of this study is addressing the existing research gap in the limited use of dynamic network analysis to understand the stability of China's energy market, especially under financial instability. Traditional anomaly-detection methods do not have sufficient ability to show changes and interactions between companies in response to external shocks such as oil price fluctuations. In addition, advanced measures, such as information theory indicators [2] and bootstrap-based minimum spanning trees (BMSTs) [17], have had limited application in this field, and few studies have used more complex models, such as the multivariate exponentially weighted moving average (MEWMA), for anomaly detection [18]. This research attempts to fill these gaps and more accurately identify financial anomalies by developing a new framework that combines BMSTs, the MEWMA, and dynamic network criteria.

To handle the research gap mentioned earlier, the methodology used in this study consists of three main steps: data collection and network construction, anomaly detection, and multivariate weighted moving average (MEWMA) monitoring. Initially, data such as stock prices, trading volume, and Brent crude oil prices were collected for eight energy companies. Then, a dynamic network was constructed for each company using the bootstrap-based minimum spanning tree (BMST) approach. This method, which is based on bootstrap sampling, allows us to calculate the reliability of network connections and confidence levels and to observe changes in dependence and interactions between firms over time. In the second step, network variables such as the node degree, strength, centrality, and connection scores were used to detect anomalies and were measured using the ratio mutual information (RMI) distance to identify nonlinear relationships between firms' performance and periods of critical volatility. Finally, in the third step, we used the MEWMA statistic to track the temporal changes in the BMST network characteristics with respect to global oil price trends. This tool is designed to identify outliers and significant market changes while, at the same time, proving its strength and stability through stress tests in simulated conditions. The objectives of this study are as follows:

- The identification and analysis of sensitive and unstable periods in the Chinese energy market, especially periods that are affected by global oil price fluctuations.
- The design of an algorithm that uses network features and oil price data to detect market anomalies early.

This analysis offers valuable insights into the influence of network structures on market behavior and decision-making within the energy sector. By examining the interdependencies among companies and tracking the flow of information across the market, we can develop a nuanced perspective that highlights both the operational efficiency and competitive positioning of major players. This comprehensive view not only identifies the firms that are pivotal to market stability but also sheds light on how these companies adjust to economic fluctuations, deepening our understanding of overall market dynamics.

1.2. Background

With the expansion of network theory and its applications in various fields over the last three decades, this theory began to be deployed in financial markets [19]. The idea of examining complex systems by considering the main members of a system as agents and finding internal connections between them, as well as finding their common effects on each other based on network theory, is used in different scientific fields [20,21]. In these fields, such as chemistry, genetics, neuroscience, and engineering, which include a wide range of applications of network theory, defined networks can be utilized in order to analyze the components of complex systems with tools derived from complex network theory [22].

One of the early works in the field of using network theory in financial markets was the work of Mantenga, who opened a new window for the analysis of financial markets by means of network theory tools for financial market researchers [23]. Many articles were written in this field, each of which highlighted an aspect of this new field of science [24]. This method was used on various data, and it was able to prove two characteristics of financial networks: the small-world and power law properties [25]. Various methods were tested to define the agents, which are referred to as nodes in network theory [26]. However, in order to find the relationship between these components and their relationships with each other, various methods were used, each of which had its own advantages and disadvantages; for more details, the reader can refer to [27,28].

The formation of financial networks has been studied from various perspectives by researchers in this field, and algorithms, which are mainly borrowed from graph theory, have been designed and implemented to improve their methods [29]. Additionally, Pearson correlation has been employed in numerous studies to determine the distance between network nodes. However, this approach has caused challenges for some researchers; various methods from different fields of mathematics have been utilized to handle this approach [30–32]. Some of this research includes the use of Granger causality, partial correlation, and distances based on a copula [33,34].

Studying the behavior of energy markets from the perspective of complex networks is one of the topics discussed in the field of financial markets, and various methods have been used to investigate it [35]. Li et al. investigated the effects of turbulence in the US financial market by selecting ten stock companies related to energy markets in NASDAQ and forming a network from them [36]. As an example of the creative formation of financial networks, Huajiao Li et al., choosing the main shareholders of energy companies as network nodes and common shares between them as links between the nodes, were able to analyze the behavior of shareholders in China's energy markets [37]. In another example of the application of complex networks in the analysis of energy markets, Gu et al. selected eight energy financial markets and collected their data between 2010 and 2020 to scrutinize the mutual effect of energy markets and the impacts of sustainability. This study shows the importance of studying the effects of different factors on energy financial markets [38]. A different study on energy markets by Huang et al. showed flexibility in building financial networks using various mathematical modeling tools, and they applied wavelet theory and network theory to create a network for bivariate oil price time series [39].

Other studies have been conducted on energy financial markets from different perspectives; for example, Restrepo et al. dealt with the spread of systemic risk in a financial market by forming a network of energy companies [40]. A further study from the point of view of forming a network of financial indicators of energy markets was implemented by Xian Xi et al. In this study, the structural features of the indicator network and its clustering were analyzed [41]. In another article, Liu et al. investigated the structural changes in the Chinese new energy market by constructing interaction networks between energy share companies by utilizing network theory tools [42]. In an additional study, Huang et al. used data from Chinese energy companies between 2013 and 2018 and employed the entropy method to form a network of energy companies and identify the influential members within this network [39].

Anomalies in financial markets are a topic that has always attracted the attention of financial market researchers [43]. Therefore, paying attention to how financial market anomalies are formed and making appropriate decisions when they occur can be a solution for many economic activists and governments. Among the studies that have been performed in the field involving the investigation of financial market turbulence through creating networks of agents of these markets, we can mention the work carried out by Khoojine and Dong. In this study, the financial fluctuations in the Chinese stock market in 2015 were investigated, and it was indicated that there were topological changes in the network and its characteristics before and after the financial turmoil [17]. Another study by Millington and Niranjan indicated similar findings by analyzing the returns of three stock markets: the DAX 30, S&P 500, and FTSE 100 (U.K.), from Germany, the U.S., and the U.K., respectively. In this study, a network of interconnected components of these stocks was created, and the shifts in the network over time were analyzed [44]. Ahelegbey and Giudici created a network of stock prices and then constructed an indicator of transmitting risk and its relationship with financial crises; after that, they analyzed the major crises in recent years, such as COVID-19, using this indicator [45].

The framework of this study is organized as follows: In Section 2, we discuss the data collection and methodology used in this study. In Section 3, we present the results of the analysis, and in Section 4, the robustness of the procedure for monitoring the Chinese energy market is discussed. Finally, in the closing section, we conclude the study and offer directions for further research.

2. Methodology

In this section, we create a structure to analyze the dynamic behavior of the bivariate energy market and use it to find potential anomalies.

2.1. Data Collection

The stock prices and traded volume of eight energy-related companies were collected from the Shanghai and Shenzhen stock markets within the period of 2014 to 2023 from the official websites of these markets (www.sse.com.cn and www.szse.cn). The companies selected for this study are among the eight largest energy companies in China due to their high market share and extensive influence on China's energy sector. These companies play major roles in the energy market and cover a wide range of industries, including oil, gas, and renewable energy. The strong performance and prominent financial position of these companies, especially in response to changes in global oil prices, make them suitable options for analyzing network dynamics and identifying market anomalies. The names and tickers of these companies are shown in Table 1.

Table 1. List of the selected Chinese energy market companies and their tickers.

No	Company Name	Ticker	City	Province
1	Shanxi Meijin Energy Co., Ltd.	000723	Taiyuan	Shanxi
2	Qianjiang Resources Development Co., Ltd.	600283	Wuhan	Hubei
3	Hengli Petrochemical Co., Ltd.	600346	Dalian	Dalian
4	Tongwei Co., Ltd.	600438	Chengdu	Sichuan
5	Shanxi International Energy Group Co., Ltd.	600546	Taiyuan	Shanxi
6	Huadian Energy Co., Ltd.	600726	Harbin	China
7	LONGi Energy Technology Co., Ltd.	601012	Xi'an	Shaanxi
8	PetroChina Co., Ltd.	601857	Beijing	Beijing

Let the datasets for the crude oil prices and energy market indices be given as follows:

$$P_i(t) = \{p_1(t), p_2(t), \ldots, p_8(t)\}, \quad V_i(t) = \{v_1(t), v_2(t), \ldots, v_8(t)\} \tag{1}$$

where $p_i(t)$ and $v_i(t)$ represent the time series of stock prices and traded volumes of stock i, respectively, t denotes the time index, and $p_i(t)$ and $v_i(t)$ denote the vectors of the companies' stock prices and traded volumes, respectively.

To reduce the effect of scale differences and make the data comparable, we normalize both the stock price and traded volume indices as follows:

$$R_i(t) = \frac{P_i(t)}{V_i(t)} \tag{2}$$

where $R_i(t)$ is the vector of the price–volume ratio for stock i at time t. To avoid zeros in the data, we add a small constant $\epsilon = 0.01$ to any value that would be zero.

In this section, we outline the procedure of the analysis conducted using Algorithm A1.

Figure 1 depicts the stock prices and traded volumes of the selected eight companies from 2014 to 2023. As shown in these two graphs, volatility in both stock prices and trading volumes is evident in 2015, 2020, and 2021; however, they do not exhibit a consistent co-movement pattern. Therefore, an aggregate index of these two metrics is necessary. The stock price graph shows a minor fluctuation in 2015, but a major volatility began in 2019, peaked in 2020, and then declined steadily. In contrast, the trading volume graph reveals a significant spike in trading activity in 2015 and another surge in 2020. Thus, we can expect market turbulence during the aforementioned periods.

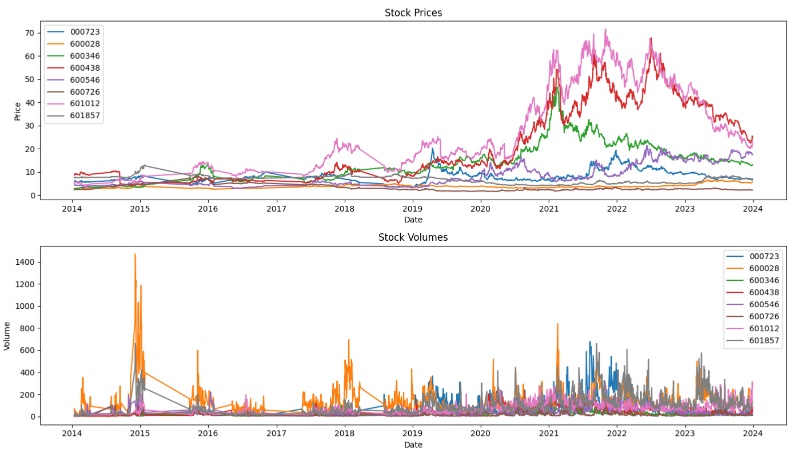


Figure 1. Time series of stock prices and the traded volumes of the eight energy-related companies in the Chinese stock market from 2014 to 2023.

2.2. Sliding Window Procedure

To create a dynamic time series of the distance constructed in (2), we use the sliding window method. To build the dynamic time series, we split the time series of each company i for overlapping windows as follows.

Let T be the number of entries, w be the size of the window (i.e., the number of entries within a time window), and n_w be the number of windows. In the scenario of a one-day interval for the sliding window, we have

$$n_w = T - w + 1 \tag{3}$$

Let R indicate the set of stock–volume ratios in the selection; then, for companies i and j, the k-th windows are $W_{i,k} = (r_{i,k}, r_{i,k+1}, \ldots, r_{i,k+w-1})$ for $k = 1, 2, \ldots, n_w$ and $W_{j,k} = (r_{j,k}, r_{j,k+1}, \ldots, r_{j,k+w-1})$, where the vector $W_{,k}$ indicates the collection of observations of stock declines in the k-th time window, while the small $r_{i,k}$ refers to the k-th entry in the time series for stock i. Afterward, we construct the distance matrices $\delta_1, \ldots, \delta_{n_w}$ of correlations between companies for each window constructed above. For instance, the distance matrix of the k-th windows is as follows:

$$\delta_k = \begin{pmatrix} 0 & \delta_{12}^k & \cdots & \delta_{1n}^k \\ \delta_{21}^k & 0 & \cdots & \delta_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{n1}^k & \delta_{n2}^k & \cdots & 0 \end{pmatrix} \tag{4}$$

where δ_{ij}^k is the distance between companies i and j in the $k - th$ window.

2.3. Dynamic Measure Construction

Mutual information (MI) is a nonlinear metric that captures the dependency between two variables. In this study, we use the MI to encapsulate the dependencies among the companies in the aggregated sample constructed using the sliding window procedure. The MI is defined as follows:

$$MI(W_{i,k}; W_{j,k}) = \sum_{w_i \in W_i} \sum_{w_j \in W_j} p(w_i, w_j) \log\left(\frac{p(w_i, w_j)}{p(w_i)p(w_j)}\right) \tag{5}$$

where $W_{i,k}$ and $W_{j,k}$ represent the two time series of stock–volume ratios, $p(w_i, w_j)$ represent the joint probability distribution, and $p(w_i)$ and $p(w_j)$ denote the marginal probability distributions.

In this study, to standardize the measures created using mutual information (MI), we apply the ratio mutual information (RMI), which is constructed as follows:

$$RMI(W_{i,k}; W_{j,k}) = \frac{MI(W_{i,k}; W_{j,k})}{max\{E(W_{i,k}), E(W_{j,k})\}} \tag{6}$$

where $E(W_{i,k})$ and $E(W_{j,k})$ represent the entropy of the two variables $W_{i,k}$ and $W_{j,k}$, respectively. The entropy $E(W_{i,k}$ is given by

$$E(W_{i,k}) = -\sum_{w_i \in W} p(w_i) \log p(w_i) \tag{7}$$

To establish a metric distance between the nodes, we create the normalized distance using the following:

$$d(W_{i,k}; W_{j,k}) = 1 - RMI(W_{i,k}; W_{j,k}) \tag{8}$$

Using the computed distance values between each pair of market indices, we construct a dynamic network where

- Each node represents an energy market or crude oil price.
- The edges between nodes are weighted by the distance values.

The adjacency matrix $A(k)$ at time window k is given by

$$A_{ij}(k) = \begin{cases} d(W_{i,k}, W_{j,k}) & \text{if } d(W_{i,k}, W_{j,k}) > \epsilon \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where $W_{i,k}$ and $W_{j,k}$ are included.

Now, we use three matrix norms to find the difference between two consecutive δ_k values. We define $d_1(k)$, $d_2(k)$, and $d_3(k)$ as follows for $k = 1, \ldots, n_w$.

$$d_1(k) = \| \delta_k - \delta_{k-1} \|_\infty = \max_{1 \le i \le m} \sum_{j=1}^{n} |(\delta_k - \delta_{k-1})_{ij}| \tag{10}$$

$$d_2(k) = \| \delta_k - \delta_{k-1} \|_2 = \sigma_{\max}(\delta_k - \delta_{k-1}) \tag{11}$$

$$d_3(k) = \| \delta_k - \delta_{k-1} \|_F = \left(\sum_{i=1}^{m} \sum_{j=1}^{n} |(\delta_k - \delta_{k-1})_{ij}|^2 \right)^{\frac{1}{2}} \tag{12}$$

After finding the time windows with high volatility, we analyze the characteristics of their constructed networks by bootstrap-based minimum spanning trees (BMSTs). To create the BMSTs of the volatile windows, in this approach, we construct 10,000 matrices. The columns of these matrices are the resampling of the dataset of the adjacency matrix for a time window with a replacement. Then, for each edge, we calculate the reliability score and then construct a BMST based on these scores. With this method, it is not necessary to know the distribution of the scores. After constructing the BMSTs of the critical time windows, we can analyze the key network metrics, such as the node degree, node strength, closeness centrality, eigenvalue centrality, and communicability scores of the constructed BMSTs. The definitions of these metrics are summarized in Table 2.

Table 2. Summary of network metrics: node degree, node strength, eigenvalue centrality, closeness centrality, and communicability score.

Metric	Definition	Mathematical Formula
Node Degree	Number of edges connected to a node, representing direct connections to other nodes.	$k_i = \sum_j A_{ij}$
Node Strength	Sum of edge weights connected to a node; this applies to weighted graphs.	$s_i = \sum_j w_{ij}$
Eigenvalue Centrality	Measurement of node influence based on connections to highly connected nodes.	$x_i = \frac{1}{\lambda} \sum_j A_{ij} x_j$
Closeness Centrality	Reciprocal of the sum of the shortest path distances to all other nodes.	$C_c(i) = \frac{1}{\sum_j d(i,j)}$
Communicability Score	Measurement of communication potential.	$G(i,j) = (e^A)_{ij} = \sum_{k=0}^{\infty} \frac{A_{ij}^k}{k!}$

2.4. Multivariate Exponentially Weighted Moving Average (MEWMA) Procedure

To monitor the impact of oil price movement on the energy market, we use a tool to detect the anomalies of the multivariate time series of the oil price and the characteristics of the constructed BMSTs, namely the node degree, node strength, eigenvalue centrality, closeness centrality, and communicability score. The MEWMA statistic at time t, which is denoted as Z_t, is computed recursively as follows:

$$\mathbf{Z}_t = \lambda \mathbf{x}_t + (1 - \lambda)\mathbf{Z}_{t-1} \tag{13}$$

Here, $\mathbf{x}_t$ is the vector of BMST characteristics $(x_1, \ldots, x_5)$ at time t, with x_1 representing the node degree, x_2 representing the node strength, x_3 representing the eigenvector centrality, x_4 representing closeness, and x_5 representing the communicability score. Z_t is the MEWMA statistic from the previous time step, and λ is a smoothing parameter such that $0 < \lambda < 1$. The parameter λ controls the weight assigned to the most recent observation; smaller values of λ emphasize past data more, while larger values give greater weight to recent data.

The covariance matrix of $\mathbf{Z}_t$, Σ_Z, changes over time, and after an initial transient phase, it converges to

$$\Sigma_Z = \frac{\lambda}{2 - \lambda} \Sigma_x$$

where Σ_x is the covariance matrix of the BMST characteristic vector $\mathbf{x}_t$ and the oil prices defined above. If T_t^2 exceeds a determined control limit, the process is supposed to be out of control, which means that there is high volatility in the energy market. The overall procedure of the methodology for detecting the anomalies in the energy market is shown in Algorithm A1.

3. Results

In this section, we outline the results from energy companies' data by applying the procedure detailed in Algorithm A1. Figure 2 depicts the price–volume ratio of the stock prices and traded volumes of eight selected companies calculated using Equation (2). From the figure, it is evident that there was significant volatility in 2015, as well as some other fluctuations around 2020. This standardized measure provides a better understanding of the co-movement between the stock prices and traded volumes of the companies.

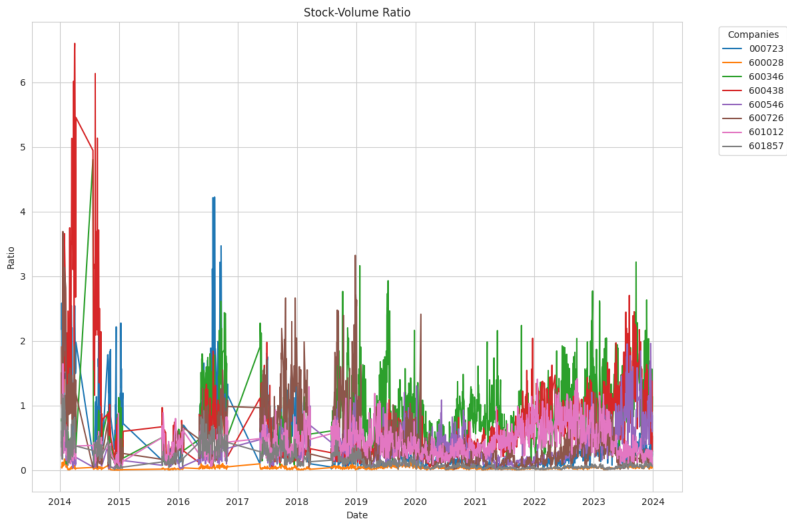


Figure 2. Price–volume ratios of the eight selected companies from 2014 to 2023.

Examination of the status of stock returns and purchase volumes in Figure 3 shows that during critical periods of stock turbulence, buyers reacted to these changes, which influenced their decisions to buy or sell. Three stocks—600346, 600546, and 601012—have a significant relationship in the co-movement of the stock price and transaction volume. However, stocks such as 601857 and 600283 are relatively more stable in the face of high purchase volumes. We apply these facts in the following sections to interpret the volatility results.

After creating the dynamic windows, we construct the adjacency matrix for each window using the RMI, which was defined in Equation (6). The minimum, maximum, and mean of the RMI and related distances for the created windows are mentioned in Table 3.

Table 3. Summary statistics of the ratio mutual information (RMI) and distance for the constructed dynamic windows.

Ratio Mutual Information (RMI)			Distance		
Minimum	**Maximum**	**Mean**	**Minimum**	**Maximum**	**Mean**
0.007	0.74	0.33	0.26	0.98	0.67

After creating the distance matrices, as defined in Equation (9), we applied three different norms, as outlined in Equations (10)–(12). Each norm represents the difference between two consecutive time windows. Figure 4 illustrates the aggregated stock price and volume for eight selected energy market companies. This figure shows that the d_1 norm fluctuates within the range of 0 to 0.4, with occasional peaks approaching 1, demonstrating moderate fluctuations across the time windows with few deviations. The middle plot, d_2, ranges from 1 to 2.5, with a few windows exceeding a norm value of 2.5. The third plot, d_3, fluctuates between 1.5 and 2.5, with some windows being more than 2.5. The comparison reveals that d_1 exhibits the least variability, d_2 displays a wider range of deviation, and d_3 shows the most extreme changes, with a higher number of outliers.

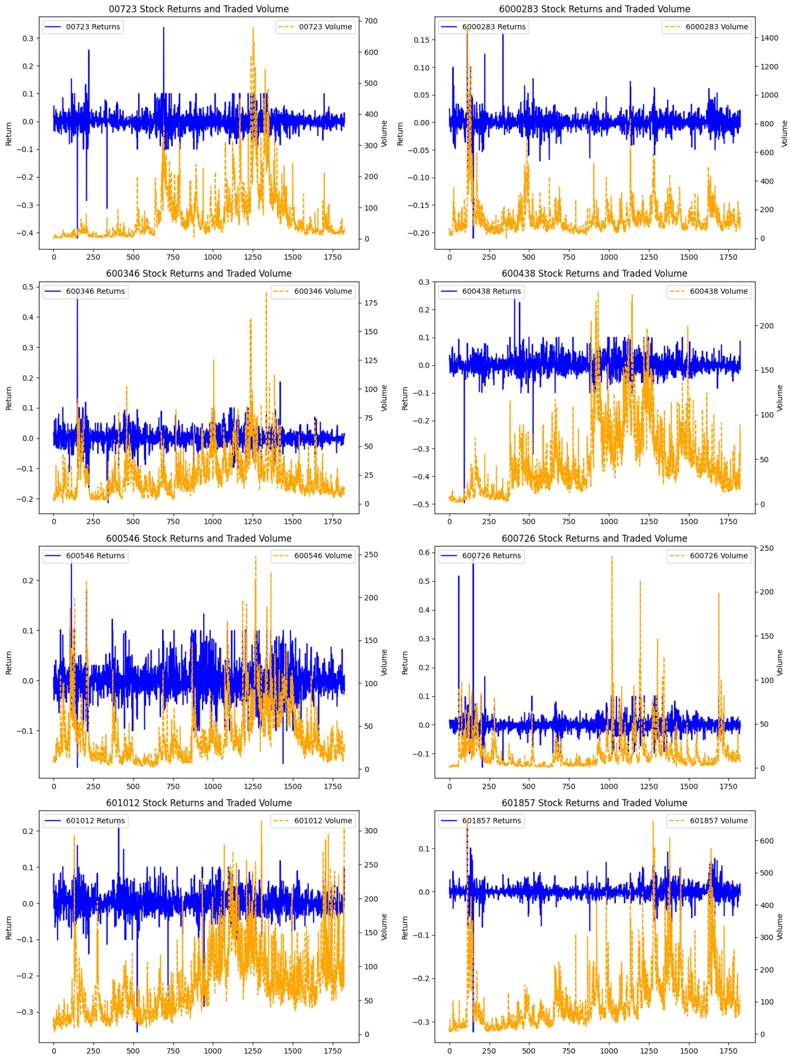


Figure 3. Stock returns and traded volumes for the eight companies from 2014 to 2023.

The common critical windows are identified by analyzing the calculated norms across all 1750 generated windows, where each window was assessed using three distinct norms: norm d_1, norm d_2, and norm d_3. Consequently, comparing the results from all three norms, we were able to isolate the windows that exhibit outlier behavior consistently across all three measures. The results of this analysis that showed the windows common to all norms are summarized in Table 4.

Table 4. Common critical windows across all three norms (d_1, d_2, and d_3).

Window	Norm d_1	Norm d_2	Norm d_3
29	1.196	2.473	3.641
59	0.766	2.055	2.754
850	0.677	2.183	2.837
880	1.152	2.860	3.711
953	0.807	2.912	3.479

Having isolated the critical common windows of the three norms—d_1, d_2, and d_3—we now analyze the characteristics of the constructed networks based on these windows. As mentioned earlier, we constructed BMSTs using the critical windows, and reliability scores were obtained through a bootstrapping method involving 10,000 iterations. Following the construction of these BMSTs, we derived four network metrics—the node degree, node strength, eigenvalue centrality, and closeness centrality—for each window. The results of these metrics are displayed in bar plots in Figure 5.

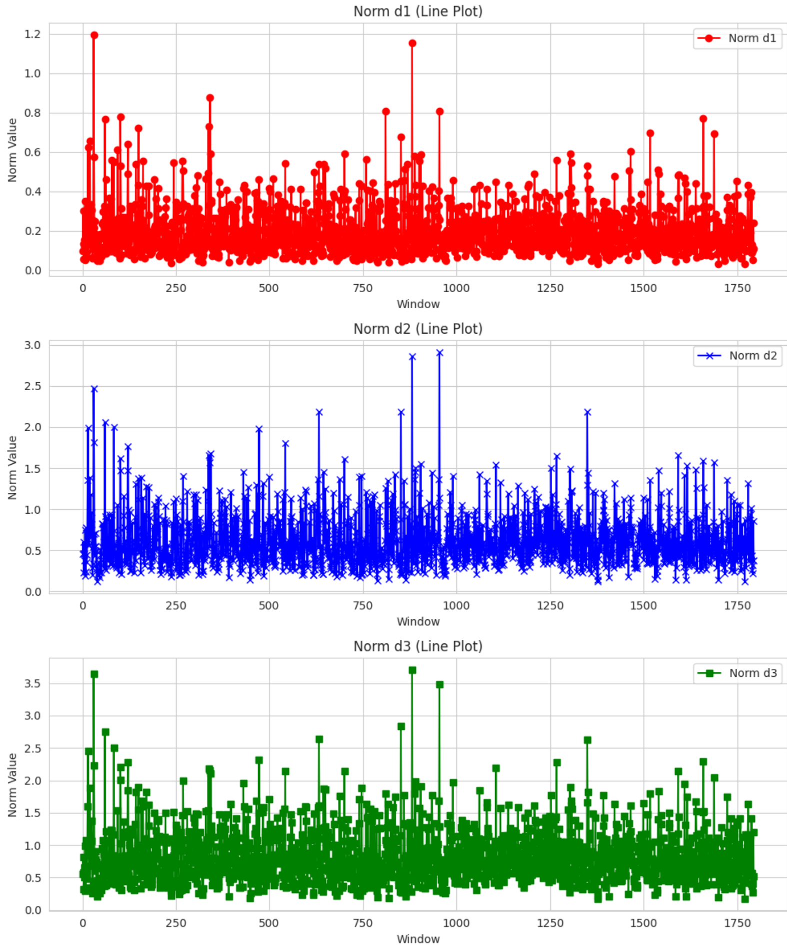
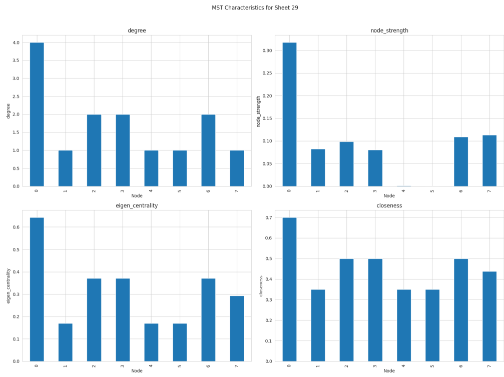


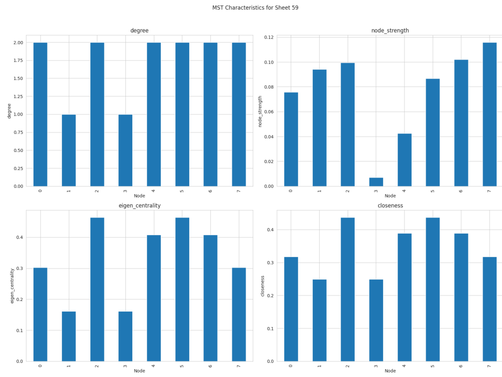
Figure 4. Fluctuations in the d_1, d_2, and d_3 norms in stock prices and volumes of the eight selected energy companies from 2014 to 2023.

The network metrics—the node degree, node strength, eigenvector centrality, closeness, and communicability score—reveal various dimensions of connectivity and influence in the financial network and provide a deeper understanding of market stability and possible paths of contagion. The degree and strength of a node are indicators of the concentration of activity in the market to identify stocks or systemically important sectors, and high values indicate the systematic importance of these elements. Any shock in these nodes can have significant effects on the market and make these nodes the key actors that can be observed in times of instability. The eigenvector centrality, however, determines the importance of a node based on its relationship with other important nodes. Higher eigenvector centrality of assets can amplify market shocks through chain effects. This feature provides valuable information for policymakers and investors seeking to manage systemic risk. In addition, the communicability score shows the flow of information transfer across the network. Additionally, higher communicability scores mean faster information diffusion and market reactions in volatile conditions; this allows traders and fund managers to assess a market's reaction speed and respond to sudden changes in a timely manner.

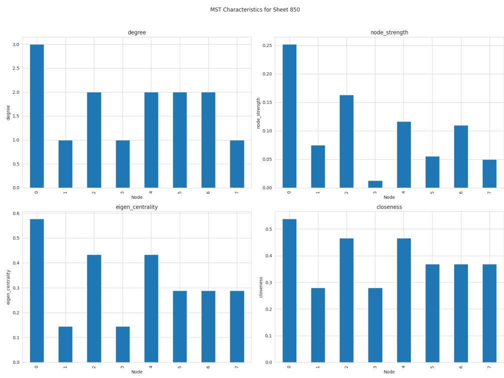
After analyzing the results of the three different norms, we derive the common critical windows among them. The comparative analysis of critical windows 29, 59, 850, 880, and 953 reveals both consistent patterns and shifts in the network dynamics of the eight companies over time. In addition, 000723 and 600726 emerge as key central figures across multiple windows, frequently leading in various centrality measures, such as the degree, node strength, eigenvalue centrality, and closeness; 000723 holds a dominant position in the earlier windows 29 and 850, while 600726 gains influence in the later windows 880 and 953, especially in terms of the degree and closeness centrality. Additionally, the leading companies in eigenvalue and closeness centrality shift across windows, reflecting changing levels of influence and network importance over time; these changes suggest that while certain companies maintain central roles, the structure of the network adapts, with different companies becoming more prominent in different periods.



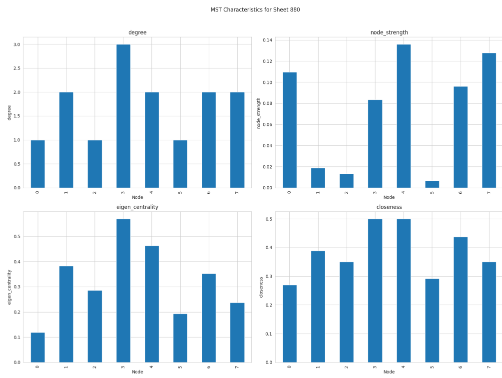
(**a**) Window 29



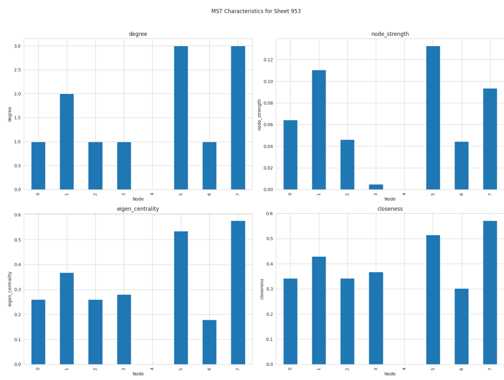
(**b**) Window 59



(**c**) Window 850



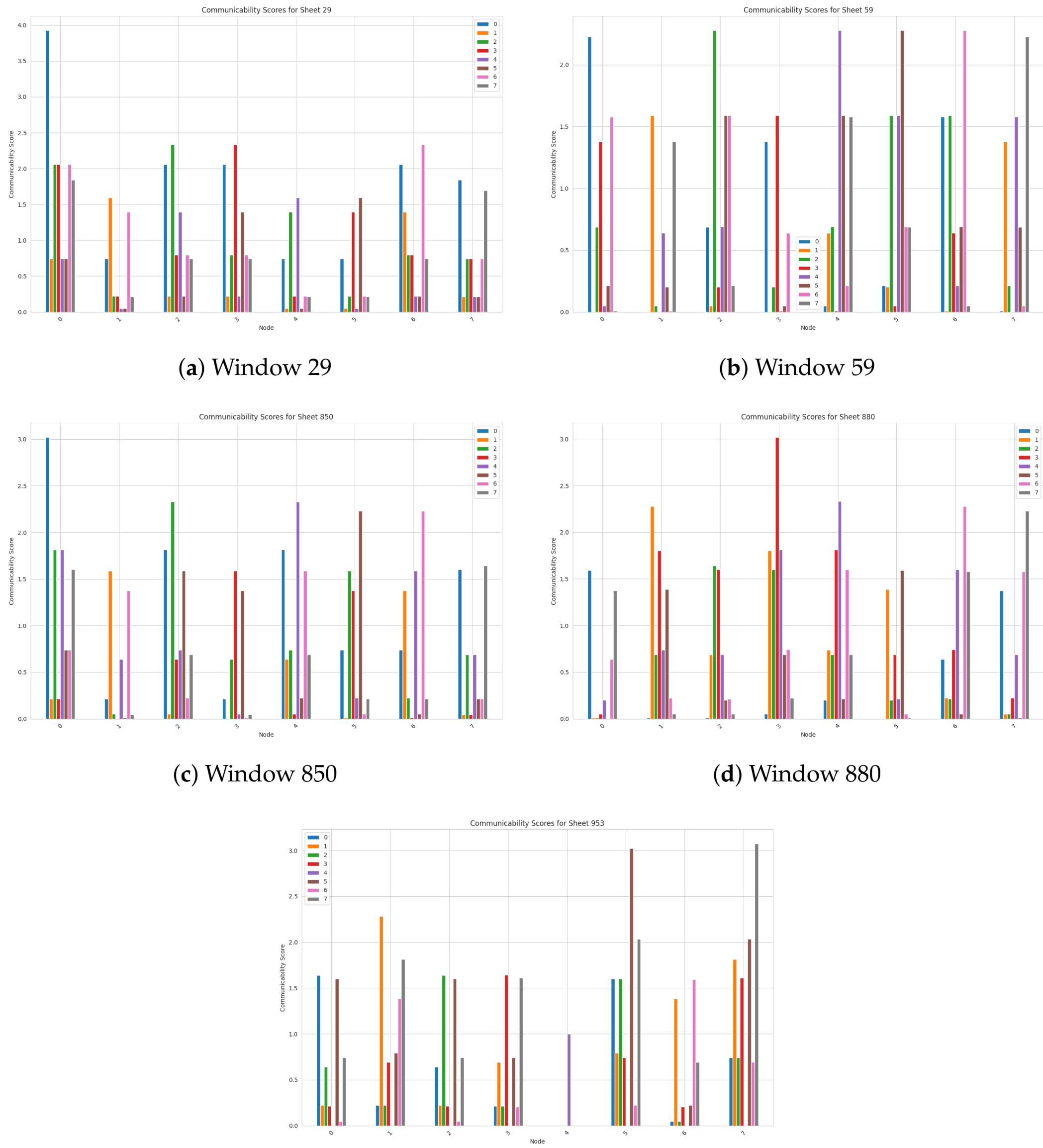
(**d**) Window 880



(**e**) Window 953

Figure 5. Bar plot illustrating the network characteristics—node degree, node strength, eigenvalue centrality, and closeness centrality—of the BMSTs constructed from the critical windows.

According to Figure 6, in Windows 29, 59, 850, 880, and 953, the connection points for the eight companies show how connected each company is in the network. In all critical windows, 000723 has a high connectivity index, and this shows the importance of this company in the built network. However, companies 600028 and 600726 maintain high connectivity in many windows, which indicates the effective communication of these two companies with other companies in the networks in critical periods of time. In Window 59, companies such as 600028 and 601857 show significant scores, indicating a balanced distribution of communication roles, unlike other windows, where one or two companies dominate. In contrast, some firms, such as 600546 and 600726, show low connectivity in some windows, implying weaker connections or more isolated roles. However, 600546, which initially had average scores, becomes stronger in later windows such as 880 and 953, indicating improved connectivity in the network. Figure 6 shows that while some firms maintain strong and central communication roles over several windows, others show fluctuating levels of influence, reflecting dynamic changes in their connectivity across the network during different critical windows. This analysis helps to identify which companies act as important communication hubs and may need to improve their network participation.



(**a**) Window 29 (**b**) Window 59

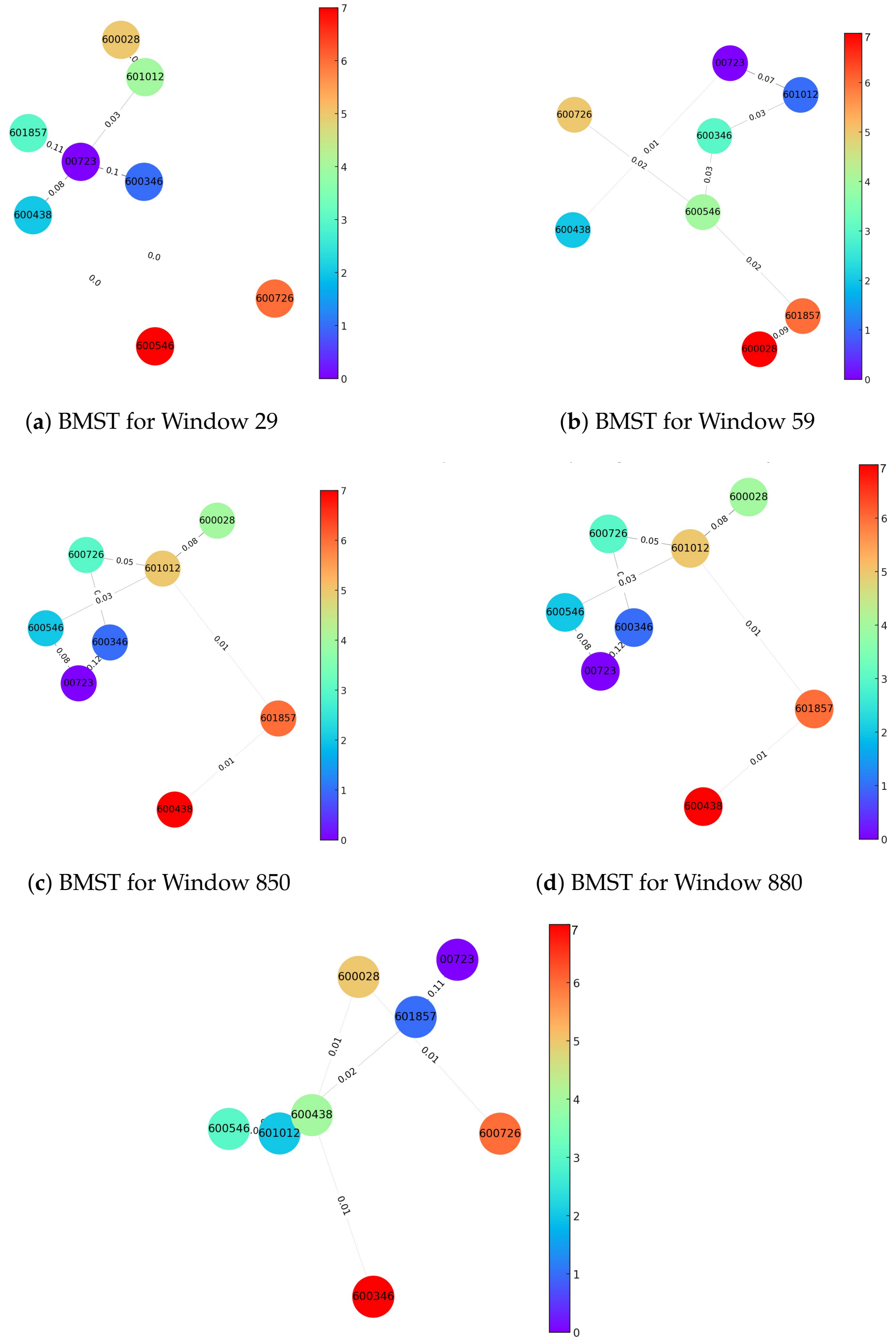
(**c**) Window 850 (**d**) Window 880

(**e**) Window 953

Figure 6. Bar plot illustrating the communicability scores of the BMSTs constructed from the five critical windows: 29, 59, 850, 880, and 953.

Figure 7 shows the BMSTs built in five critical windows. Topological analysis of these windows can give us useful information about critical periods. As can be seen in Window 29, a hub with 000723 as its center was formed. This pattern can also be seen in Windows

880 and 953 with a focus on other companies, but in the other two windows, a more linear mode can be seen. In times of financial turbulence, it seems that companies tend to form a hub centered on one company. In Window 880, the network topology undergoes subtle changes that reflect changes in connection strengths or node relationships. Finally, Window 953 shows a more compact structure with fewer clusters, suggesting potentially optimized paths or reduced connections between nodes.



(**a**) BMST for Window 29

(**b**) BMST for Window 59

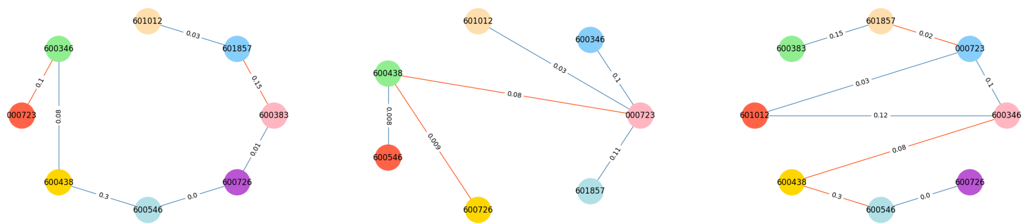
(**c**) BMST for Window 850

(**d**) BMST for Window 880

(**e**) BMST for Window 953

Figure 7. Bootstrapped-based Minimum Spanning Trees of the critical Windows 29, 59, 850, 880, and 953, with reliability scores as edge weights.

After examining the topological behavioral similarities of networks that are in critical periods, in order to analyze the behavior of these networks compared with networks with fewer fluctuations, we compare the structure of Window 29, which is known as an outlier window in all three norms, with that of its surrounding windows, 28 and 30. In Figure 8, it is clearly seen that in Window 29, a hub is formed around a specific company, and the network has a centralized structure. However, in the networks before and after this window, this pattern is not established. The former network is designed linearly, and the latter network tends to return to the linear state.



(**a**) Pre-Turbulence (**b**) Turbulence (**c**) Post-Turbulence

Figure 8. Circular layout of the bootstrapped-based minimum spanning trees: pre-turbulence, turbulence, and post-turbulence in windows 28, 29, and 30.

4. Discussion

4.1. Anomaly Detection Using the MEWMA Procedure

In this section, we seek to complete the process of finding anomalies in the created networks whose relative locations we previously observed. According to the explanations provided in the introduction, to understand the factors affecting fluctuations in the energy market, we discuss the impact of the Brent crude oil price index as a benchmark for the global oil price index on the Chinese energy market in this section. Figure 9 shows the movement of the Brent crude oil price from 2014 to 2023, where two significant price fluctuations can be observed in 2015 and 2020.

Figure 9. Movement of Brent crude oil price from 2014 to 2023 with the critical periods highlighted.

Using the process described in the methodology section, after constructing BMSTs based on the ratio mutual information distance and extracting their key features with metrics such as the node degree, node strength, eigenvalue centrality, closeness centrality, communicability scores, and Brent crude oil price movement, a MEWMA statistic was created. According to Equation (13), $\mathbf{x}_t$ is the vector of BMST characteristics $(x_1, \ldots, x_5)$ at time t, with x_1 representing the node degree, x_2 representing the node strength, x_3 representing the eigenvector centrality, x_4 representing closeness, x_5 representing the communicability score, and x_6 representing the Brent crude oil price movement; therefore, the MEWMA statistics are calculated.

In this case, upper and lower control limits of 0.05 were selected. Values above or below these limits indicate market fluctuations, while values within this range suggest either insignificant fluctuations or stable market activity. Most of the MEWMA statistics are within the control limits, which indicates that the system remains robust for this period; however, several points surpass both the upper and lower control limits, suggesting moments where the system deviated from expected behavior, potentially signaling outliers or process shifts.

Figure 10 shows the MEWMA statistics for Window 29, which is identified as one of the critical windows based on the three norms of the d_1, d_2, and d_3 procedures. After deriving the five network metrics for the constructed BMSTs for this window and aggregating them in a vector with price movements, the MEWMA statistic for this critical period was calculated. This critical period is categorized into three phases.

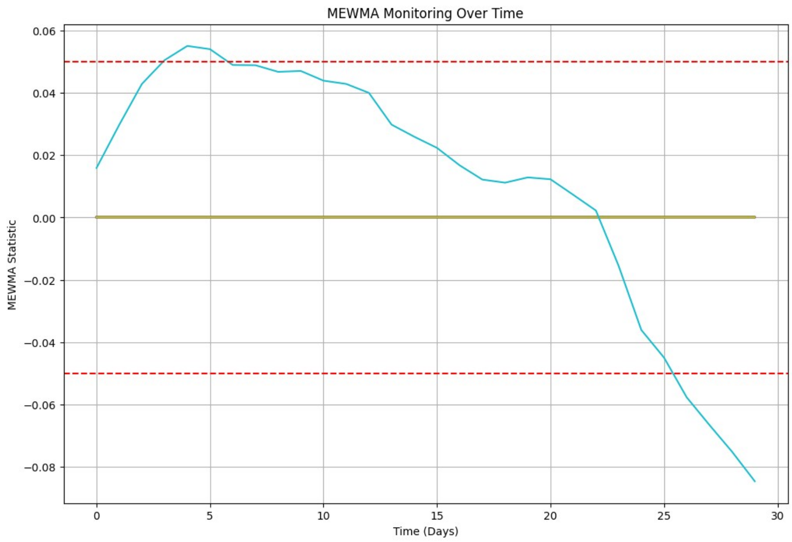


Figure 10. The MEWMA statistic over the period of time for Window 29 with its upper and lower control limits shown as dashed lines.

The multivariate exponentially weighted moving average (MEWMA) statistic provides a comprehensive indicator of overall market stability by combining the five main network metrics along with oil price movements. In this system, the control ranges are set based on a threshold of 0.05 that differentiates "normal" market conditions from "abnormal" ones. When the MEWMA index exceeds these limits, it indicates market instability and a possible deviation from the usual economic patterns. This mode is often accompanied by increased volatility, prompting investors to adopt conservative approaches, such as hedging against potential market corrections. In contrast, when the MEWMA index remains within the control limits, this indicates a stable environment that can be suitable for more aggressive investment strategies.

The high sensitivity of the MEWMA index to deviations and changes makes it valuable as an early warning system for financial managers. By alerting stakeholders and financial market regulators, this indicator helps them identify conditions that may require portfolio adjustments or risk reduction. In the MEWMA chart, three distinct phases—the volatile phase, the less volatile phase, and the period approaching volatility—reflect broader economic cycles. For example, a volatile phase in which the MEWMA exceeds the upper control limit may indicate market corrections or crises, driving investors to safer assets.

The less volatile and stable phase, which is characterized by MEWMA values in the control range, represents stability and can create favorable conditions for growth-oriented investments. Finally, the nearly volatile period, where the MEWMA approaches the lower control limit, is a warning of an impending turbulent period and calls for investors to take a cautious approach in anticipating possible market volatility.

4.2. Stress Testing

To test the developed process, we need a tool that can evaluate the entire designed algorithm. The stress test for the created process provides a comprehensive overview of its weak points. This stress test is conducted by considering factors that can cause changes in the network, specifically focusing on two critical factors: stock price and oil price fluctuations. By creating different scenarios based on previously experienced realities, we investigate the resilience of the developed process and test it accordingly.

The considered scenarios include five distinct situations, which are summarized in Table 5. For each of these scenarios, data on stock prices and oil prices are updated. Subsequently, windows are formed, correlations are calculated, and networks are established. As previously mentioned, the five metrics of the network introduced in Table 2 are calculated, and then the maximum values are determined. We performed this analysis for the 29th window across all five scenarios, and as shown in the table, all the values align well with the actual data. Consequently, the algorithm was able to issue the necessary alarms for approaching critical periods.

Table 5. Summary of scenarios for stock and oil price changes with the maximum MEWMA statistics.

Scenario	Description	Fact	Max of the MEWMA
Scenario 1	20% Decline in Stock Prices	A minor market correction following a period of overvaluation, similar to historical corrections seen in 2015 and 2018.	0.08
Scenario 2	30% Decline in Oil Prices	A significant decline due to reduced global demand during a recession, akin to what happened during the COVID-19 pandemic in 2020.	0.09
Scenario 3	25% Decline in Stock Prices and 15% Decline in Oil Prices	A combination of factors such as economic slowdown and increased production from OPEC countries, similar to the 2014 oil price collapse.	0.06
Scenario 4	15% Increase in Stock Prices and 20% Decline in Oil Prices	A scenario where technology or renewable energy advancements boost the stock prices of energy companies despite falling oil prices.	0.07
Scenario 5	Simultaneous 10% Increase in Stock Prices and 10% Increase in Oil Prices	An economic recovery scenario where demand for oil increases due to economic growth, leading to simultaneous increases in both stock and oil prices.	0.04

Stress test scenarios that involve simulating real-world market conditions in order to evaluate the flexibility of the financial system against economic pressures provide the possibility of analyzing market behavior under the influence of various economic shocks. Each scenario models specific events in the market and provides a picture of how shocks affect financial stability. In Scenario 1, a 20% decline in stock prices is used as an example of a common market correction that reflects investor caution following periods of overvaluation. Scenario 2 simulates a 30% drop in oil prices, which is similar to demand shocks, such as the shocks that occurred during the COVID-19 pandemic, which led to the exposure of vulnerabilities in the oil-dependent sectors and wider effects on the market. Scenario 3, which reflects the simultaneous decline in stock and oil prices, indicates economic stagnation. These are conditions in which compound pressures increase market sensitivity and provide the possibility of asset correlation analysis in challenging economic conditions. On the other hand, Scenario 4 reflects trends such as an increase in stock prices at the same time as a decrease in oil prices, which is often caused by the trend towards renewable energy and refers to the reallocation of investments in the energy sector. Finally, Scenario 5, which deals with a simultaneous increase in stock and oil prices, shows economic growth to provide guidance for investment strategies in high-growth markets. By monitoring specific indicators and creating an early warning mechanism, these analyses enable asset managers to adjust risks and allow policymakers to implement appropriate financial measures.

The findings of this study not only confirm those of previous studies in various key areas but also extend their scope. The network topology changes observed during market turbulence are consistent with the results of Khoojin and Dong [17] for the 2015 Chinese stock market crisis, particularly in showing how the market structure adapts during periods of stress. However, the present study goes beyond their work by simultaneously using price and volume data and provides a deeper insight into market dynamics. Additionally, during periods of turbulence, we observe the formation of hub networks, which are based on the analysis of nonlinear relationships. Our observation that firms tend to center around specific institutions during times of financial turmoil provides new insight into the reorganization of energy markets under stress.

The results of the MEWMA analysis show several improvements over traditional market monitoring methods. While previous studies used various statistical methods for anomaly detection, our combined approach of network metrics along with oil price changes provides an advanced early warning system. The three distinct phases that we identified—consisting of volatile, low-volatility, and near-volatile periods—align with the broader economic cycles and provide a detailed approach to the transmission of market behavior. In particular, the stress test results provide a deeper understanding of market resilience. The five tested scenarios showed how network structures respond to various market pressures. These findings emphasize the following three main factors:

- Quantification of network reactions to different market conditions.
- Identification of key companies that are more stable in periods of stress.
- Documenting the changes in network centralities criteria in different scenarios.

The strong relationship that we observed between oil price changes and network structure, especially for companies 000723 and 600726, provides empirical support for the theoretical frameworks constructed in this study—in particular, how different firms obtain central positions under various market stresses.

5. Conclusions

This study examined the Chinese energy market in the period from 2014 to 2023, analyzing the performance of the top eight energy companies in terms of their energy market share in the Chinese stock market. In this study, an attempt was made to provide a framework for finding anomalies in different periods. Additionally, the impact of global oil prices on China's energy market during this period was investigated, and an algorithm was developed to detect possible anomalies. Through collecting stock prices and daily transaction data, reliable information on market fluctuations was generated by calculating the ratio of the two. These data were processed using a sliding window method with 30-day intervals, which enabled us to analyze the financial system dynamically. For each window, a network was constructed using the minimum spanning tree method based on bootstrap sampling with 10,000 repetitions, and a confidence level was calculated for each edge. The distances between networks were then calculated using ratio mutual information (RMI), which is a nonlinear approach for measuring the distances among nodes. Then, three different matrix norms were applied to find the difference between two consecutive matrices.

Windows that significantly deviated from their preceding and subsequent windows were identified. Specifically, five critical windows—20, 59, 850, 880, and 953—among the 1750 created windows were recognized as key, and the corresponding time periods were extracted for further analysis. In the meantime, the characteristics of these critical windows were extracted, including the node degree, node strength, eigenvalue centrality, closeness centrality, and communicability scores. The results show that the identified critical networks exhibit dynamic changes. In some windows, a compact and central structure emerged, with strong connections between companies. In these critical networks, we observed the formation of hubs centered around dominant companies; in Windows 29 and 953, Company 000723 demonstrated strong centrality, and the characteristics of each network provide valuable insights into the status of the companies within the complex network. This allowed us to identify key companies within the network structure and analyze their significance; additionally, some companies showed variable behavior across different time frames, highlighting the waning of their influence over the studied period.

After examining the critical network structure using minimum spanning trees to monitor the Chinese energy market and utilizing changes in global oil prices, we employed the multivariate exponentially weighted moving average (MEWMA) procedure. In this way, we incorporated the features of the previously extracted network along with global oil prices into the MEWMA process, creating a statistic to monitor the market and generate appropriate alarms when critical market conditions are approaching. This algorithm performed well and successfully identified the critical windows that we had previously detected using the three different norms. To verify the stability of the designed algorithm, we created five scenarios based on real-world occurrences, calculated the MEWMA statistic, and found that the algorithm worked effectively.

This research has important implications for stakeholders and policymakers. By identifying influential companies and understanding network structures during volatile periods, decision-makers can better anticipate and respond to market fluctuations. The anomaly-detection framework, which is grounded in the BMST and RMI methods, provides a practical tool for early warning signals in financial markets, assisting in risk assessment and potentially guiding investment strategies within the energy sector.

While the framework captures structural changes effectively, it primarily considers oil prices, stock prices, and trading volumes. This limited scope may overlook other critical factors that could impact the Chinese energy market, such as geopolitical shifts, regulatory changes, or regional economic conditions. Additionally, reliance on historical data may limit the model's applicability to future, unforeseen market conditions.

Future research could expand this framework by incorporating additional factors, such as environmental events, policy shifts, and international trade tensions, in order to enhance predictive power. Moreover, extending the model to other energy markets or sectors could provide comparative insights and validate its broader applicability. Further refinement of the anomaly-detection model could also enable real-time monitoring and more nuanced interpretations of complex market networks, making it valuable for a wide range of stakeholders.

Author Contributions: Conceptualization, L.X. and A.S.K.; methodology, A.S.K.; resources, L.X. and A.S.K.; data curation, L.X. and A.S.K.; writing—original draft preparation, L.X. and A.S.K.; writing—review and editing, A.S.K.; supervision, L.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: The authors acknowledge the Faculty of Economics and Business Administration of Yibin University for their assistance in preparing this manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Algorithm A1 Dynamical Anomaly Detection in the Chinese Energy Market

1: **Input:** Stock prices $P_i(t)$ and traded volumes $V_i(t)$ for energy companies $i = 1, \ldots, 8$ over time period $t = 1, \ldots, T$.
2: **Output:** Dynamic BMSTs and MEWMA statistics for monitoring energy market stability.
3: Extract the stock price $P_i(t)$ and traded volume $V_i(t)$ data from the Shanghai and Shenzhen stock markets for each company i, as well as the Brent crude oil price.
4: Normalize the data by computing the price–volume ratio for each company i:

$$R_i(t) = \frac{P_i(t)}{V_i(t)} \quad \text{for } i = 1, \ldots, 8$$

5: Apply the sliding window method by splitting the time series $R_i(t)$ into overlapping windows of size w:

$$W_{i,k} = \{r_{i,k}, r_{i,k+1}, \ldots, r_{i,k+w-1}\} \quad \text{for } k = 1, \ldots, n_w$$

6: For each window k, construct the distance matrix δ_k based on correlations between companies i and j:

$$\delta_{ij}^k = \text{Distance}(W_{i,k}, W_{j,k})$$

7: Compute mutual dependencies between time series using mutual information (MI) and standardize them using ratio mutual information (RMI):

$$RMI(W_{i,k}; W_{j,k}) = \frac{MI(W_{i,k}; W_{j,k})}{max\{E(W_{i,k}), E(W_{j,k})\}}$$

then construct the metric distance using

$$d(W_{i,k}; W_{j,k}) = 1 - RMI(W_{i,k}; W_{j,k})$$

8: Construct a dynamic network for each window, where nodes represent companies and edges are weighted with $D(W_{i,k}, W_{j,k})$. The adjacency matrix is defined as

$$A_{ij}(k) = \begin{cases} d(W_{i,k}, W_{j,k}) & \text{if } d(W_{i,k}, W_{j,k}) > \epsilon \\ 0 & \text{otherwise} \end{cases}$$

9: Measure changes between consecutive distance matrices δ_k using the following matrix norms:

$$d_1(k), d_2(k), d_3(k)$$

10: For high-volatility windows, construct bootstrap-based minimum spanning trees (BMSTs) by resampling and calculating reliability scores for each edge.
11: Analyze the network structure using key metrics such as the node degree, closeness, eigenvalue, and communicability scores.
12: Apply the multivariate exponentially weighted moving average (MEWMA) procedure to monitor changes in the multivariate time series of BMST characteristics:

$$\mathbf{Z}_t = \lambda \mathbf{x}_t + (1 - \lambda)\mathbf{Z}_{t-1}$$

where $\mathbf{x}_t$ represents the vector of BMST characteristics and the oil price at time t. Monitor the MEWMA statistic and evaluate whether T_t^2 exceeds the control limit, indicating high volatility in the energy market.
13: Test the robustness of the procedure using a stress test with different scenarios.

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