Journal of Computing and Electronic Information Management
ISSN: 2413-1660 | Vol. 10, No. 1, 2023

The time-varying co-movements between energy market and global financial market

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Abstract: Since the global financial crisis in 2008, international energy markets have become more closely linked to financial markets and energy prices have exhibited more financial characteristics. Therefore, it is of great theoretical and practical significance to study the time-varying synergy between the energy market and the global financial market. This paper sets up a model for realizing the time-varying co-movements between energy markets and global financial markets: It uses the Diebold &Yilmaz spillover index method and its dynamic expansion model to test the spillover mechanism of market volatility shocks, applies the deep long and short-term memory (DLSTM) model to predict market prices. The results of this study show that, first, energy markets and global financial markets are closely linked networks, and the spillover effects have obvious time-varying characteristics. Second, from a static spillover perspective, the Global Financial Price Index shows the largest net exporter in both yield and volatility spillovers, suggesting that the global financial development market has the strongest influence on other markets. However, in the volatility spillover, the net spillover index shows alternating periods of positive and negative periods most of the time.

Keywords: Spillover index; Energy market; Global financial market; Deep learning.

1. Introduction

Energy is an important input to the modern economic system and provides the impetus for rapid economic and social development. Its impact on various components of economic performance has been extensively studied. Since the global financial crisis in 2008, the international energy market has become more closely connected with the financial market, and energy prices have shown more financial characteristics.

The rapid growth of the global economy in the last century relied heavily on the significant consumption of traditional fossil energy sources (coal, oil, etc.). In just a few decades, the global consumption of energy has been growing, and the level of national economic development is closely linked to energy consumption, such that the United States, the world's largest economy, is the second largest energy consumer in the world today, while China, the world's second-largest economy, is the first energy consumer in the world today. At the same time, the massive use of traditional energy sources has caused serious environmental pollution. In order to pursue a sustainable development path, new energy has become a way to maintain a balance between rapid economic development and environmental protection and has received strong support from governments at all levels. However, as a highly capital-intensive industry, innovation and industrial development of new energy technologies require large amounts of capital, which is not enough to rely on government financial support alone and requires financing through other channels to obtain development funds. The financial market, mainly the stock market, is an indispensable financing channel for the development of the energy industry. In addition, the price changes of energy are not only influenced by supply and demand, but also by the fluctuations of financial trading sub-markets such as the stock market, showing obvious financial market attributes. In the context of global integration and internationalization of energy, price changes in the energy market will be more and more likely to give rise to cross-market, cross-product, and cross-industry phenomena of volatility spillover risks.

A large academic literature exists that examines the correlation and spillover effects between energy and financial markets, mainly through empirical evidence. Oil has a special status in the economy, and international research on the linkage between the oil market and the global financial market started earlier. Scholars have conducted extensive research on the correlation between crude oil price changes and the overall stock market, but the academic community has not yet reached a consistent conclusion on the relationship between the two. As early as 1986, Chen, Roll, and Ross studied the effects of variables such as interest rates, inflation rates, bond yields, industrial output, and risk factors on stock market returns. They found no significant effect of the oil price index on stock returns. Sadorsky took the US data as a sample and used the vector autoregressive model to find that both the rate of yield and volatility of oil prices have a significant and asymmetric impact on the real return of US stocks. The research conclusions of the two are opposite, and the follow-up research will continue to develop further based on this. Agren used the BEKK model to study the volatility spillover effect between the oil market and the stock market. The study finds that the oil market has significant volatility spillover effects on the stock markets of the United States, Japan, Norway, and the United Kingdom. Park and Ratti used the data from the United States and 13 European countries from 1986 to 2005 as samples and adopted variables and methods similar to those of Sadorsky. The study finds that, except for Norway, a net oil exporter, changes in oil prices have a significant negative impact on stock returns in other countries. But the impact effect does not have a significant asymmetric effect. Shahzad et al. examine volatility spillovers between international crude oil markets and Islamic stock market indices. The study finds that there is an asymmetric risk spillover effect between the international crude oil market and the Islamic stock market, and this spillover effect changes over time. As international oil (as a commodity) has become part of investors' asset portfolios like stocks, commodity traders will also observe the stock market to judge the future development trend of the commodity market.

From the perspective of research methods, the latest research method on the linkage between energy market and global financial market is the DY Spill Index method and its expanded version. The core of the Diebold & Yilmaz spillover index method (DY for short) is the variance decomposition of the forecast error in the VAR model. The DY method is widely used because it can reveal rich information, such as the strength and direction of the spillover effect, and also provide visualization of the results. Alaa et al. combined deep learning methods and LSTM to propose a deep-length short-term memory (DLSTM) structure, which is an extension of traditional recurrent neural networks. The method can address the limitations of traditional forecasting methods and shows accurate predictions. In this paper, the method is also applied to forecast the prices of various markets. This part will be explained in detail below.

The structure of the article is as follows. The first section proposes research questions. The second section mainly describes the research methods of the paper. The third section is the results, and discussion and the last section is the conclusion.

2. Method

2.1. TVP-VAR-DY spillover index

By sorting out the current research results of scholars, the methods used in the research on spillovers mainly include VAR model and GARCH model (for example, GARCHBEKK, DCC-MGARCH). At present, GARCH-type models have two defects: one is that GARCH-type models cannot measure the size of spillover effects; the other is that a large number of parameters need to be estimated when using GARCH models, which is complicated to calculate and takes a long time. In addition, GARCH-type models cannot analyze dynamic spillover effects and cannot reflect the time-varying spillover relationship between variables. Diebold and Yilmaz (2020) improved the DY spillover index model in 2020. The improved DY spillover index model mainly measures the empirical results in two different ways: static spillover index table and dynamic spillover index chart, showing fluctuations between different markets. The dynamics of the conduction mechanism. The specific process of this method is as follows:

Firstly, construct a stationary N-variable P-order vector autoregressive model (VAR) model; under the above vector autoregressive model framework, the improved DY spillover index model adopts the model proposed by Koop et al., Pesaran and Shin. The KPPS method (Generalized Variance Decomposition) deals with the impact of the forecast residual term, and finally defines the spillover index. The total spillover index is used to measure the overall correlation between different markets. It uses the KPSS variance decomposition method to measure the contribution of information spillovers between all variables in the model to the total forecast residuals of the model. Directional overflow index. The directional spillover index can measure the size of the spillover effect of market i on all other markets j, and the size of the spillover effect of all other markets j received by market i. The net spillover index measures the net spillover of a single market to all other markets. The net spillover index is derived from the shocks transmitted from market i to all other markets minus the total shocks transmitted from other markets to market i. If there are multiple (more than two) markets under analysis, the net paired spillover index can be used to measure the volatility spillover effect between the different two markets.

Based on the 2009 version of the DY Spillover Index, Zhang studied the relationship between the yields of six global stock markets and oil shocks. Kang combined the Diebold & Yilmaz spillover index with the DCC-GARCH model to analyze the dynamic spillover and correlation between the stock, commodity, bond, and volatility index markets and proposed a hedging strategy to give the optimal investment combination. Corbet et al. combined the Diebold & Yilmaz spillover index and the DCC-FIGARCH conditional correlation framework to assess the linkage and volatility spillovers of different submarkets such as energy production, extraction, and transportation. The study focuses on mutual spillovers between oil prices and share prices of renewable energy companies during the novel coronavirus. It finds that during the specific period when WTI oil prices fell into negative territory, lower oil prices had significant spillover effects on renewable energy companies and coal companies.

2.2. DLSTM model

It has been widely proven that increasing the depth of neural networks is an effective way to improve overall performance. This paper applies a deep LSTM recurrent network for time series forecasting applications. In the proposed DLSTM, we can stack several LSTM blocks, as shown in Fig 1, connected one after another in a deep recursive network to combine the advantages of a single LSTM layer of the harvester. In the case of large or complex data, it is demonstrated that this deep architecture will generalize better due to a more compact representation than the shallow architecture.

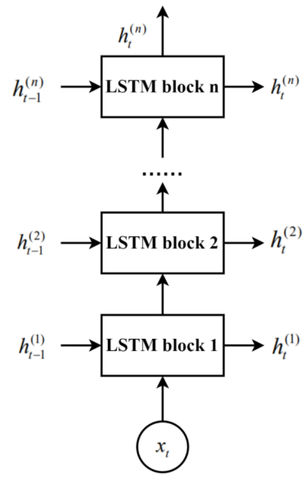


Fig 1. The architecture of DLSTM recurrent network.

The point of this stacking architecture is that each layer can process some part of the task and then pass its results to the next layer until the last layer provides the output. Another benefit is that this architecture allows each level of hidden state to operate on a different time scale.

3. Result and discussion

3.1. Data sources and descriptive statistics

The objective of this paper is to quantify the yield spillover and volatility spillover effects between energy markets and global financial markets.

Regarding energy markets, the S&P Global Clean Energy EURO TR (SPGCE), the MSCI Global Energy Price Index (MEPI), and West Texas Intermediate (WTI) crude oil futures are chosen as indicators of price changes in energy markets. (i) SPGCE is a global clean energy stock price index compiled by Standard & Poor's. SPGCE has been compiled since 2003 and has the advantage of being rich data and representative. Companies are weighted in the SPGCE based on their role in clean energy, their technological impact, and their importance in controlling pollution. In this paper, the index is chosen to measure the development of the global clean energy market. (ii) The MSCI ACWI Energy Index includes large and mid-cap securities across 23 Developed Markets (DM) and 24 Emerging Markets (EM) countries*. All securities in the index are classified in the Energy as per the Global Industry Classification Standard. In this paper, the index is chosen to measure the price trend of the energy market. (iii) West Texas Intermediate (WTI) is a benchmark price in the international oil market and is the underlying of oil futures contracts on the New York Mercantile Exchange. Regarding global financial markets, this paper selects representative financial data to measure the development of global financial markets, which are MSCI Global Information Technology Price Index (MIPI), MSCI Global Financial Price Index (MFPI), MSCI Global Daily Consumer Price Index (MCPI), and U.S. Ten-Year Treasury Bond Yield (USBOND). (i) Since the emergence of the third scientific and technological revolution, the high-quality economic development of all countries is inseparable from the progress of science and technology. The MIPI index is used to measure the development status of global information technology companies, which is an indispensable and important content in the global financial market. (ii) The MFPI is used to measure the overall development of global financial markets, including both developed and emerging market countries. (iii) Consumption plays a fundamental role in economic development. The MCPI is a daily consumption-based index designed to reflect the performance of daily consumption in economic development. All component indices are classified according to the Global Industry Classification (GICS). (iv) USBOND is the U.S. 10-year Treasury yield, which is used to measure the performance of U.S. In addition, the VIX Panic Index (VIX) and the U.S. Economic Policy Uncertainty Index (USEPU) are added to assess the risk of the future investment environment and simulate the uncertainty in the economic development process.

Considering the data availability of each market, the time interval of the empirical sample is from November 25, 2003 to August 31, 2022, and the data are obtained from Eikon with the DataStream and WIND information financial database, respectively. A total of 4563 observations are obtained after data preprocessing.

Table 1 lists the descriptive statistical data of price fluctuations in various markets. It can be seen from Table 1: the Jarque-Bera statistic rejects the null hypothesis at the 1% significance level, proving that each variable obeys the non-normality state distribution. The ADF test results show that each variable is stationary, so the DY spillover exponential model can be applied to the selected data.

3.2. Static spillovers between energy market and global financial market

By constructing a static volatility spillover index table, the static volatility spillover effect between the energy market and the global financial market is analyzed. In this paper, the lag order of the VAR model of each series is set to order 2, and the prediction error step H is set to 10 days with reference to Diebold and Yilmaz (2020). Table 2 shows the volatility spillover index among markets. The elements on the diagonal line in Table 2 represent the contribution of the prediction variance from the variable itself, and the elements on the off-diagonal line represent the contribution of the prediction variance from other variables, that is, the spillover effect. The values in the last column of Table 2 represent the spillover effects of all other variables on a variable; the values in the third-to-last row represent the spillover effects of a variable on all other variables; the values in the last row represent the net spillover effects of a variable.

Table 1. Descriptive statistics for each sequence

	SPGCE	MEPI	WTI	MIPI	MFPI	MCPI	USBOND	VIX	USEPU
Mean	0.018	0.015	0.024	0.038	0.005	0.024	-0.006	0.010	0.035
Median	0.051	0.050	0.048	0.088	0.05	0.049	0.000	-0.416	-0.429
Maximum	17.499	13.945	48.641	9.303	11.337	7.627	36.783	76.825	321.56
Minimum	-22.126	-22.281	-50.709	-15.88	-15.637	-9.247	-32.41	-35.05	-314.8
SD	1.813	1.622	3.602	1.222	1.330	0.788	2.750	7.556	54.023
Skewness	-0.616	-1.212	-0.450	-0.813	-0.719	-0.815	0.131	1.061	0.028
Kurtosis	19.251	25.733	53.774	17.052	18.779	17.690	29.497	9.567	4.557
JB	50487.340***	99348.370***	490180.200***	38035.51***	47722.590***	41521.920***	13346.7***	9053.779***	461.548***
ADF	-59.768***	-24.809***	-51.026***	-64.949***	-59.080***	-64.794***	-23.289***	-52.421***	-27.557***

*Notes: All values are measured in percentile units. *** denotes rejection of the null hypothesis at 1% significance levels.*

Table 2. Static spillover index table

	SPGCE	MEPI	WTI	MIPI	MFPI	MCPI	USBOND	VIX	USEPU	From others
SPGCE	35.01	12.78	1.33	15.35	14.15	10.13	2.80	8.46	0.00	64.99
MEPI	10.93	29.68	3.67	12.10	17.31	13.10	4.64	8.55	0.01	70.32
WTI	2.49	8.11	78.04	2.29	3.53	2.20	1.80	1.49	0.05	21.96
MIPI	12.39	11.46	0.97	28.25	16.01	14.09	3.55	13.28	0.01	71.75
MFPI	11.12	15.58	1.42	15.36	26.62	15.47	4.91	9.52	0.00	73.38
MCPI	8.87	13.38	1.05	15.20	17.59	30.25	2.84	10.84	0.00	69.75
USBOND	4.83	9.33	1.40	7.69	10.83	5.80	54.77	5.32	0.02	45.23
VIX	8.35	10.16	0.86	16.73	12.27	12.63	3.35	35.64	0.01	64.36
USEPU	0.16	0.14	0.08	0.24	0.23	0.15	0.02	0.31	98.66	1.34
To others	59.15	80.93	10.78	84.95	91.92	73.56	23.91	57.76	0.11	483.08
To all	94.15	110.61	88.82	113.20	118.54	103.81	78.68	93.41	98.77	TCI=
Net	-5.85	10.61	-11.18	13.20	18.54	3.81	-21.32	-6.59	-1.23	53.68

From an overall perspective, the total yield spillover index in the system is 53.68% and the total volatility index is 47.56%, indicating that half of the forecast errors in the total sample originate from shocks to the system itself and the remaining half from the cross-market transmission of shocks. Energy markets and financial markets are tightly connected networks with high overall linkages. From a market perspective, the directional spillover index and the net spillover index reveal the specific role of each market in shock transmission. In the yield spillover effect, MFPI has the strongest influence on other markets with a spillover output index of 91.92%. It is also the most influenced by price changes in other markets, with a spillover acceptance index of 73.38%, which indicates that MFPI is most closely linked to other markets. In contrast, the co-movements between USEPU and other markets are weaker, with a spillover output index of 0.11% and a spillover acceptance index of 1.34%. USEPU is relatively isolated from the system in terms of yield transmission.

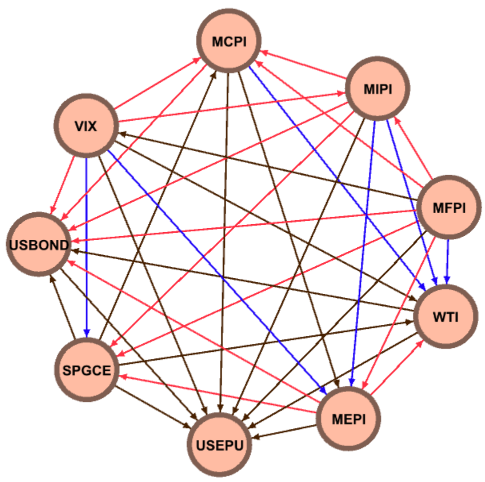


Fig 2. Pairwise plots of directional connectedness.

If we take the energy market and global financial market as the nodes of a complex network and the spillover effects between each market as the edges of the complex network, we can construct a network of spillover effects in the energy market and global financial market and analyze their transmission paths. In Fig. 2, we have plotted the net pairwise directional connectedness of the energy market and financial market in the time domain. The direction of the arrows represents net pairwise directional connectedness between series, and the color of the line represents the overflow strength between two nodes. The color of the lines explains the strength of pairwise directional connectedness from red (strongest) to blue and black (weakest). We use the average of the net pairwise spillover index and the spillover index of 0.5 as the dividing line.

The volatility net pair spillover has similarities to the yield net pair spillover. (i) In the full sample period, MFPI is the net pairwise contributor to spillovers and volatility in the system and plays a dominant role in the aggregate. Connectivity is closely followed by MIPI stock returns. (ii) USBOND, WTI, and USEPU can be considered net recipients of directional spillovers from other markets. In yield overflow, USBOND has a very small net contribution to WTI (0.402%), WTI has a very small net contribution to USEPU (0.033%), and USEPU has a very small net contribution to USBOND (0.005%). Moreover, our results explain the limited role of oil-energy price volatility, that is, oil shocks are not exogenous, they are part of financial markets and are affected by shocks in the global financial system. These findings contradict previous findings, which claimed that oil shocks play an important role in affecting stock market returns. However, our results support the study of Zhang, which concludes that oil shocks play a limited role in the global financial system.

3.3. Dynamic spillovers between energy market and global financial market

While the DY Spillover Index reveals a wealth of information on the linkages between energy markets and global financial markets, it is static essentially and does not capture the trend and volatility characteristics over time. Therefore, it is a reasonable assumption that the transmission of information between energy markets and global financial markets will also change over time. To test this hypothesis, this paper combines the TVP-VAR model with the DY spillover index method to conduct a dynamic analysis of spillover effects.

Fig 3 reveals the dynamic total spillover indices of yields between energy markets and global financial markets. The average degree of spillover of 60.93%. This indicates that the spillover effect between energy markets and global financial markets is somewhat stable and time-varying. There have been many relatively obvious peaks, which are all related to the profound changes in the global economic form or energy market. This shows that when systemic uncertainties rise or fall into trouble, the overall linkage between energy markets and global financial markets increases.

Figure 4 shows the dynamic trend of directional spillover index and net spillover index between energy market and global financial market. From the perspective of different markets, the following points can be summarized.

(i) MFPI and MIPI have the strongest time-varying spillover output and time-varying spillover receptivity and exhibit persistent positive net spillover effects. This suggests that they are the largest contributors to earnings spillovers, transmitting price information to other markets and leading stock price movements in energy markets and global financial markets. (ii) For the Global Energy Market Price Index (MEPI), we find that the spillover role it plays in the system is divided into two distinct phases using 2015 as the dividing line. Before 2015, the net spillover index of MEPI was largely positive, demonstrating that MEPI was systematically passing price information to other markets during this period. The net spillover index of MEPI, on the other hand, alternates between positive and negative after 2015, suggesting that MEPI acted as both a spillover recipient and a spillover contributor in the system during this period. This may be attributed to the frequent "Price Wars" in the international crude oil market after 2015, the rapid development of clean energy, and the drastic changes in the international energy landscape.

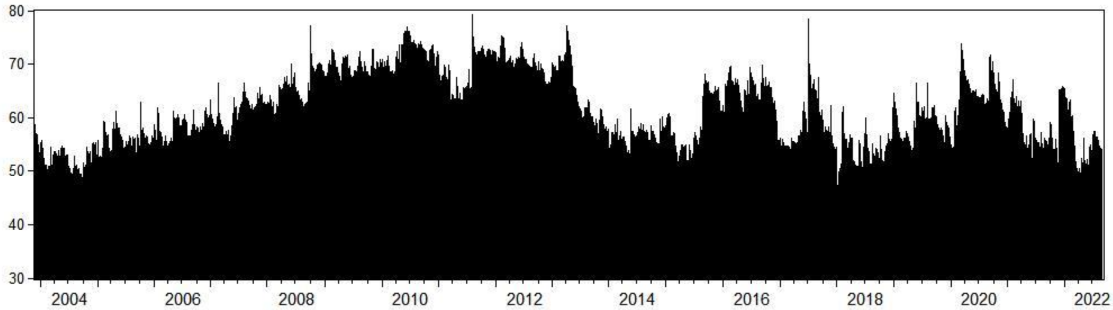
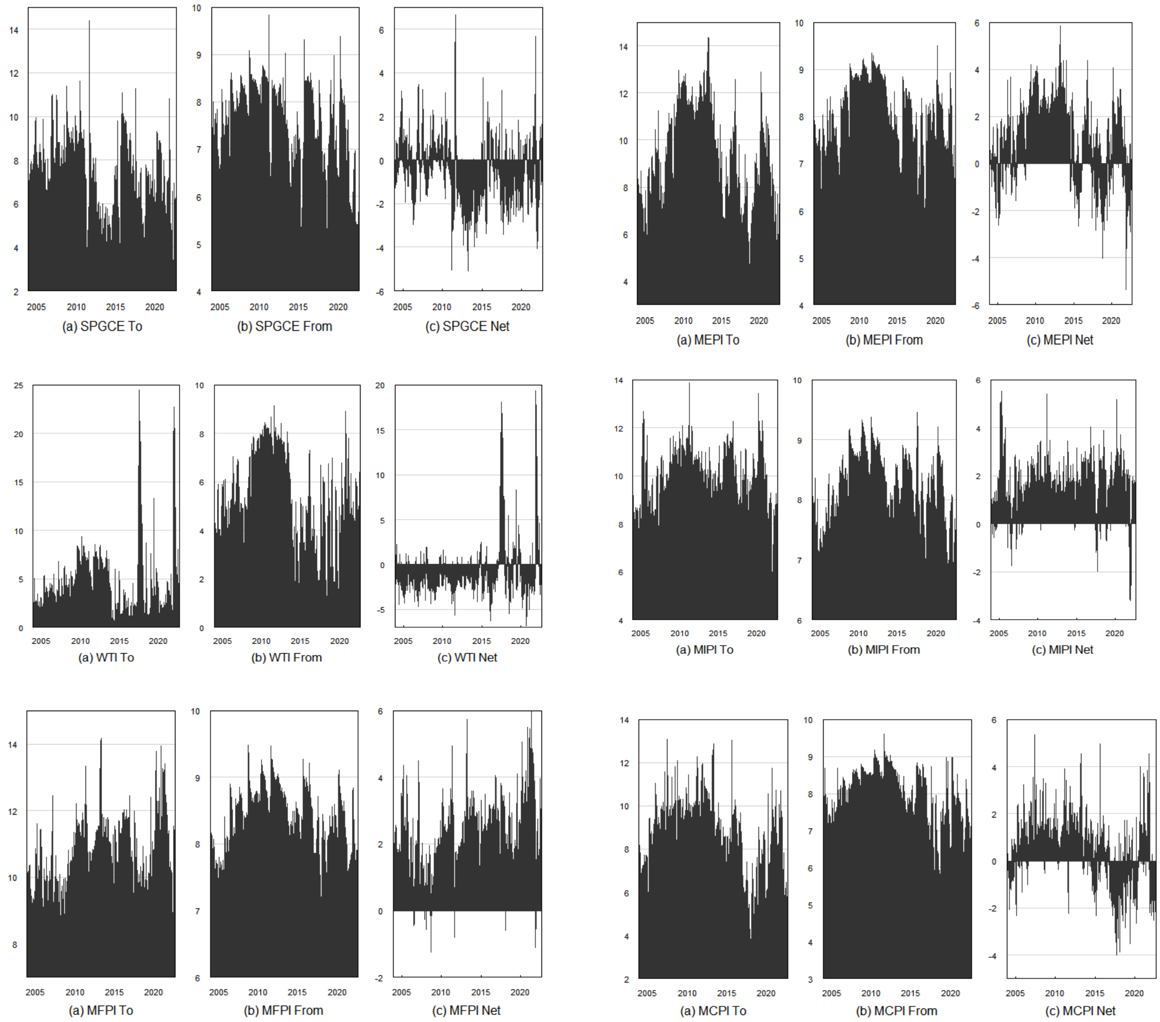


Figure 3. Dynamic total spillover indices.



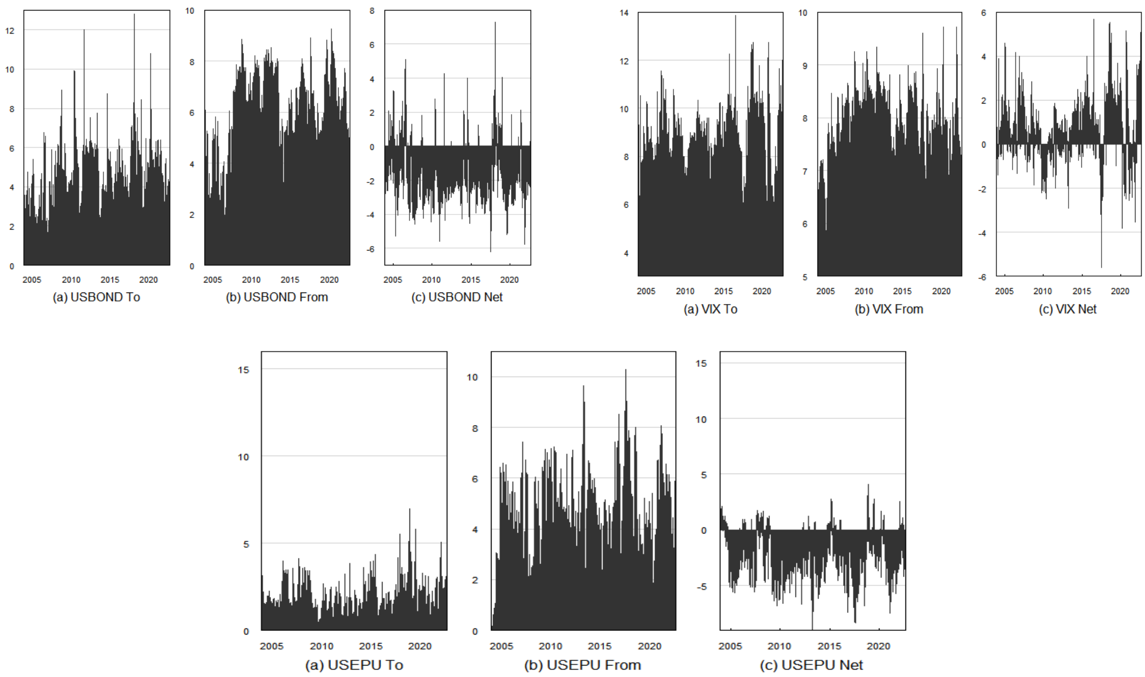


Figure 4. Dynamic net spillover effect

(iii) For most of the time during the sample period, the net spillover index of WTI performed negatively, which indicates that most of the time WTI plays the role of a net recipient of price information in the system. This is mainly due to the special position of crude oil in the global economic system, the volatility of financial markets, the game of oil-producing countries, and other factors are reflected in the crude oil market. It is notable that, similar to the MEPI, the net premium index for the international crude oil market (WTI) has seen several extreme peaks of positive values after 2015, most notably in August 2016 and September to October 2020, respectively. We considers this to be mainly due to the ongoing turmoil in the international oil market after 2015. (iv) USEPU and USBOND have weaker time-varying spillovers and time-varying spillover acceptance for the rest of the market prices, with average time-varying net spillover indices of -2.16% and -1.69%, respectively, suggesting that they act more as risk intermediaries in the system. This finding is consistent with Su et al. who suggest that financial uncertainty in the US does not have a significant spillover effect.

3.4. Market price forecasting based on DLSTM model

In the literature, for estimating forecast accuracy and forecast performance, two types of errors are usually measured, namely the Root mean square error (RMSE) and the Mean absolute error (MAE).

Mean absolute error (MAE). This type of error has the same magnitude as the original value and is more robust to outliers than the RMSE. it is also used as a loss function in the regression model. The mean absolute error can evaluate the degree of variation in the data. Root mean square error (RMSE). This error has the same scale as the data itself. Consequently, as a limitation, accuracy measurements based directly on this error cannot be used to make comparisons between series of different scales. The smaller the values of MAE and RMSE, the better the accuracy of the prediction model in describing the experimental data

Deep learning (DL) is an essential part of machine learning, where long short-term memory (LSTM) neural networks can efficiently solve time-series data learning problems. Most of the data in the stock markets are time series data, which makes LSTM technically and naturally applicable to the stock market and has the theoretical possibility for screening investment targets in the stock markets. In stock market investment practice, LSTM model can be more accurate in guessing the financial market trend, and the constructed portfolio can achieve better investment performance.

This study demonstrates the quantitative and visualization results of the proposed DLSTM model. The dataset contains 4562 price observations, of which the first 3649 observations (80% of the dataset) are used to construct or train the prediction model, and the remaining 913 observations (20% of the dataset) are given to test the performance of the prediction model. The performance of the trend forecasting results for a total of seven market segments price indices for energy markets and global financial markets is shown in Table 3, here based on the DLSTM calculations. In this paper, we construct the best results of DLSTM for static scenarios, where the number of layers and units hidden in the deep neural network are [1,3,3].

Table 3 shows that the performance of price forecasting based on the DLSTM model is positive for each market, and the values of MAE and RMSE are in an acceptable range. Among all market segments, the global consumer market (MCPI) has a smaller mean absolute error and root mean square error of 0.77 and 1.50, respectively, which suggests that DLSTM has the best prediction of price trends in this market. Fig 5 illustrates the relationship between the raw price data and the predicted values of the DLSTM model. We plot the results of the training and test sets uniformly, with the training set on the left of the black dashed line and the test set on the right. It can be observed that DLSTM also performs better on the test set, which indicates that our model is more robust.

Table 3. The best results of DLSTM in static scenes.

	SPGCE	MEPI	WTI	MIPI	MFPI	MCPI	USBOND
MAE	1.57118	1.54973	2.07188	1.31583	0.77431	0.67071	3.44848
RMSE	2.34985	2.40211	3.72662	1.99148	1.50243	1.10116	5.78638

Notes: SPGCE represents the yield series for that market, and the other series are similar.

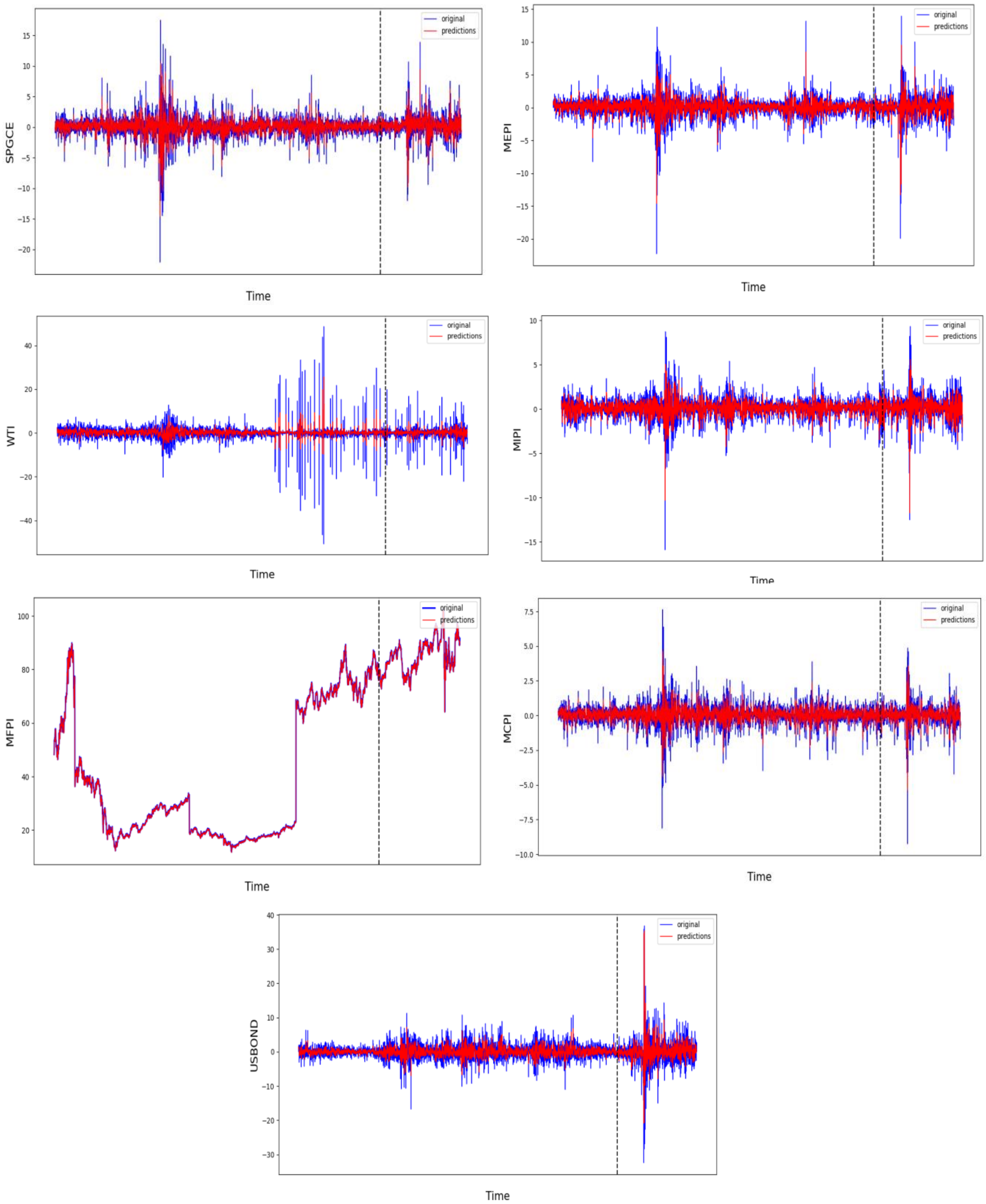


Figure 5. DLSTM-based price forecasting for each market

4. Conclusions

Based on the dynamic index spillover method and the deep short-term and short-term neural network, this paper studies the income spillover effect between the energy market and the global financial market. The selected sample data represents the daily closing prices of conventional and unconventional energy prices and global financial market indexes, covering the period from November 25, 2003 to August 31, 2022. The main conclusions are as follows.

The empirical results of static and dynamic spillover effects in the DY framework have the following findings. (i) The energy market and the global financial market are closely linked networks, and the spillover effects have obvious time-varying characteristics. (ii) From a static spillover perspective, the Global Financial Price Index (MFPI) shows up as the largest net exporter, indicating that global financial development markets have the strongest influence on other markets and are more likely to exist as price linkage centers and risk linkage centers. From a dynamic spillover perspective, the Global Financial Price Index (MFPI) and the Global Information Technology Price Index (MIPI) maintain the most significant influence, transmitting price information and risk to other markets. However, in the volatility spillover, the net spillover indexes show alternating periods of positive and negative periods most of the time, i.e., the role of each market in the spillover network is dynamically changing. (iii) The impact of the financial crisis on the role of each market in the spillover network is significant.

Due to limited time and ability, there is still room for improvement in this paper in terms of research content and research methods. First, when studying the spillover effects between the energy market and the global financial market, this paper only measures the strength and direction of yield spillovers from the perspective of time, while ignoring the relationship between market spillovers from the perspective of the frequency domain. Therefore, in the future, we can continue to study the frequency domain spillover effect between the energy market and the global financial market from the perspective of the frequency domain, and provide more research angles for the construction of investment strategies. Second, the application of the deep neural network is not sufficient. In the future, we can consider further developing the advantages of deep knowledge in financial data prediction and optimizing our model.

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