Electricity market dynamics: The influence of fuel prices and the spillover effect

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Abstract. Fossil energy power generation still plays a key role in the power generation industry, especially for countries where thermal power generation still dominates. With such potential considerable impact, this article aims to analyze the drivers of peak and valley electricity prices from the perspective of thermal power fuel. Specifically, the study uses data from the highly market-oriented US PJM power market to conduct an empirical analysis and focused on the links with coal, crude oil, and natural gas. Applying the Barunik and Krehlik index method to measure the spillover effect, we find that there is an obvious two-way spillover effect between the thermal power fuels and the electricity market. Besides, such an effect mainly occurs in the short time horizon, and natural gas plays a key role in transmitting the information to electricity prices. At last, this paper further builds a connectedness network based on the results of the pairwise spillovers, thereby visually displaying the cross-market connections.

1. Introduction
The marketization of electricity is an important access to promote the long-term development of the power industry, thus many countries are committed to improving the efficiency of power generation through market-based pricing of electricity. As far as the current situation is concerned, those countries with high power generation and power consumption mainly rely on thermal power generation, like USA, China and India. Thus, thermal power fuels could always bring an unavoidable impact on electricity prices. Understanding the impact of changes in the price of fossil fuels on the electricity market and the price spillovers between them will not only help grasp the overall operation of the energy market but also be benefit to promote the marketization of electricity.

In view of the importance of the price relationship between the electricity market and other energy markets, many scholars and papers have conducted detailed analyses on related issues[1-5]. Recently, Xia et al.[6] identify nonlinear causality between electricity and fuel source returns, which inspired the research ideas of this article. This paper employed the EEMD method to decompose the intrinsic mode
functions and detected the multi-scale connectedness among these markets. Though they obtain some informative findings, there is still an obvious defect in such research. That is, the frequency domain components decomposed by EEMD only pay attention to the characteristics of the time series itself, and the excessive frequency domains makes the economic significance of each component even thinner. Meanwhile, most of the studies ignore the difference between the peak and valley electricity prices, which also promote our further analysis in this field.

To fill such the knowledge gap, this paper applied the method of Barunik and Krehlik [7] on the spillover linkages between the electricity markets in both the peak and off-peak stages and fossil fuels prices in frequency domain. In specific, Barunik and Krehlik [7] proposed the measures in a similar VAR context as Diebold and Yilmaz [8-10], and it includes the spectral representation of variance decompositions instead of the forecast error variance decomposition. Hence, this framework could estimate unconditional connectedness relations in the frequency domain.

This paper contributes to the extant literature from the following three perspectives: (1) We studied the relationship between the fuel price changes and the two kinds of electricity prices, while most previous studies only focused on the off-peak condition. (2) This paper applied an effective approach BK spillover index to detect this issue, the corresponding results would be more informative than other methods, like EEMD based model. (3) We also consider the inherent diversity of the two markets and construct the complex networks of net-pairwise directional connectedness at different frequencies.

2. Methodology and data

2.1. Barunik and Krehlik Connectedness model

To analyze the information spillover effects among fossil fuel markets and the electricity market, this paper applies a newly established index method by Barunik and Krehlik [7]. The start point of the BK framework is the VAR (p) model for \( x_t = (x_{1,t}, \ldots, x_{N,t})' \), a covariance stationary N-variate process at \( t = 1, \ldots, T \).

Assuming that the roots of \( |\Phi(z)| \) lie outside the unit circle, VAR (p) model could be represented as an infinite moving average process:

\[
   x_t = \Psi(L)\varepsilon_t, \quad x_t = \sum_{k=0}^{\infty} \Psi_k(L) \varepsilon_{t-k} \tag{1}
\]

Introducing the frequency domain counterparts, we can construct the variance decomposition at a given frequency \( w \) as:

\[
   (\theta(w))_{i,j} = \frac{\sigma_{ik}^2 |\Psi(e^{-iw})\Sigma_{j,k}|^2}{\Psi(e^{-iw})\Sigma^w(e^{-iw})_{i,j}} \tag{2}
\]

Where \( \Psi(e^{-iw}) = \sum_n e^{-inw}\Psi_n \) is the Fourier transform of the impulse response of \( \Psi_n \). Following BK, the above equation could be standardized as the following:

\[
   (\bar{\theta}(w))_{i,j} = \frac{(\theta(w))_{i,j}}{\sum_{i=1}^{N}(\theta(w))_{i,i}} \tag{3}
\]

Then, the generalized variance decompositions at frequency band \( d \) are defined as:

\[
   (\bar{\theta}(d))_{j,k} = (\theta(d))_{j,k} / \sum_k (\theta(d))_{j,k} \tag{4}
\]

Where \( d = (a, b): a, b \in (-\Pi, \Pi), a < b \). From here, it allows us to define a variety of connectedness measures in the frequency domain. Firstly, we could obtain the overall connectedness based on the decomposition process above within the frequency \( d \). This is defined as:

\[
   C_d^d = \frac{\sum_{i=1}^{N}(\bar{\theta}(d))_{i,i}}{\bar{\theta}(d)_{i,j}} = 1 - \frac{\sum_{i=1}^{N}(\theta(d))_{i,i}}{\sum_{i=1}^{N}(\bar{\theta}(d))_{i,i}} \tag{5}
\]

The BK framework also allows the identification of the direction of spillovers, we could estimate the directional connectedness among markets within the whole system on the frequency \( d \) as:

\[
   C_{i\rightarrow j}^d = \frac{\sum_{k=1}^{N}(\hat{\theta}(d))_{i,j}}{\sum_{k=1}^{N}(\hat{\theta}(d))_{i,j}} \tag{6}
\]

\[
   C_{j\rightarrow i}^d = \frac{\sum_{k=1}^{N}(\hat{\theta}(d))_{j,i}}{\sum_{k=1}^{N}(\hat{\theta}(d))_{j,i}} \tag{7}
\]

Where \( C_{i\rightarrow j}^d \) represents within from connectedness, namely the contribution of all other markets \( j \) to market \( i \); \( C_{j\rightarrow i}^d \) represents within to connectedness, namely the contribution of the market \( i \) to all
other markets $j$. Note that $i \neq j$. Then, the within net connectedness could be computed as the difference between the above two connectedness indices:

$$\mathbb{C}^{d,\text{net}}_{i,j} = \mathbb{C}^{d}_{i\rightarrow j} - \mathbb{C}^{d}_{i\leftarrow j}$$

(8)

If the $\mathbb{C}^{d,\text{net}}_{i,j} < 0$ exists, we could conclude that the market $i$ is a net information receiver from all other markets in the system, otherwise, the market $i$ is a net information transmitter to all other markets.

Furthermore, the pairwise connectedness between two markets $i$ and $j$ is defined as:

$$\mathbb{C}^{d}_{i,j} = (\hat{\beta}_d)_{i,i} - (\hat{\beta}_d)_{i,j}$$

(9)

At last, the contribution of the frequency band $d$ to the overall system connectedness in the system is calculated as:

$$\mathbb{C}^d = \mathbb{C}^d \Gamma(d)$$

(10)

2.2. Data set and descriptive statistics

Since this paper mainly focuses on the question of how the peak and off-peak electricity market periods are connected with the prices of fossil fuels, our variables or datasets could be aggregatedly divided into two aspects. Considering that the electricity market with low marketization will inevitably not be able to effectively respond to changes in upstream fuel prices, the sample market should have a high market-oriented feature. Thus, we select the largest competitive power wholesale market US PJM electricity market and track its prices for both the cases of peak and off-peak stages. For the datasets of fossil fuel prices, we focus on the three main thermal power raw materials coal, natural gas, and crude oil (WTI). These three energy sources account for more than 60% of the total fuel for PJM power generation.

All the time series employed in this paper are sourced from the Datastream database. The data range is from July 2009 to July 2020, and the data is seasonally adjusted. Before the estimation process, we compute the continuously compounded returns series and describe the basic statistic results for them. Note that monthly range-based returns measure as $R_t = \ln(P_t/P_{t-1})$, where $P_t$ is the monthly closing price at time $t$. Table 1 presents descriptive statistics.

Table 1. Descriptive statistics for the green stock, green bond, and conventional financial assets.

|                  | Mean  | Max.  | Min.  | St.Dev. | Skewness | Kurtosis | J.B.     | ADF     |
|------------------|-------|-------|-------|---------|----------|----------|----------|---------|
| Peak price       | -0.164| 166.334| -156.1| 43.129  | 0.346    | 2.462    | 38.325***| -6.712***|
| Off-peak price   | -0.34 | 268.621| -144.67| 44.074  | 1.731    | 11.947   | 882.819***| -7.015***|
| Crude oil        | -0.399| 63.327 | -78.187| 12.242  | -1.02    | 15.696   | 1428.371***| -5.106***|
| Nature gas       | -0.536| 48.621 | -45.025| 11.663  | -0.01    | 3.523    | 72.196***| -5.007***|
| Coal             | -0.234| 25.836 | -21.28 | 7.02    | 0.261    | 1.293    | 11.684***| -4.7***  |

Notes: The abbreviations “Std. Dev.” and “J-B” stand for standard deviation and Jarque-Bera test of normality, respectively. The symbols *** indicate rejection of the null hypothesis of normality and unit root at 1% level of significance.

3. Empirical results

3.1. Spillover effect estimation

As mentioned above, we examine return spillovers using the Barunik and Kréhlik measures in the frequency domain. As our final model specification, we use a reduced-form VAR with two lags based on the Akaike Information Criterion (AIC) criteria. Following similar research [7,11], we mainly divide the estimation for two different frequency bands. The first one corresponds to movements from one to three months, indicating the short-term component; While the other frequency refers to the periods longer than three months, namely long-term components. Decomposing the computation into two different frequency components could enable us to understand the underlying differences between connectedness conditions at spectral bands. To start with the analysis, we compute the full static connectedness among different financial assets. The results have been reported in Table 2. Note that the
FROM_ABS (TO_ABS) is the measure of frequency connectedness in the absolute sense, and FROM_WTH (TO_WTH) is the measure of ‘within’ connectedness as introduced in Eq.6.

Table 2 The spillover effect matrix for electricity and fossil fuel markets.

|                | Peak price | Off-peak price | Crude oil | Nature gas | Coal | FROM_ABS | FROM_WTH |
|----------------|------------|----------------|-----------|------------|------|----------|----------|
| Peak price     | 70.670     | 18.520         | 1.960     | 2.410      | 1.280| 4.830    | 5.700    |
| Off-peak price | 26.130     | 63.400         | 0.980     | 2.450      | 0.970| 6.110    | 7.200    |
| Crude oil      | 0.960      | 1.110          | 73.240    | 1.930      | 2.250| 1.250    | 1.470    |
| Nature gas     | 5.940      | 7.780          | 1.580     | 64.630     | 4.700| 4.000    | 4.720    |
| Coal           | 0.700      | 0.320          | 11.340    | 1.710      | 57.180| 2.810    | 3.320    |
| TO_ABS         | 6.750      | 5.550          | 3.170     | 1.700      | 1.840| 19.010   |          |
| TO_WTH         | 7.960      | 6.540          | 3.740     | 2.000      | 2.170|          | 22.410   |

Panel B: The spillover table for a band: 0.63 to 0.00, Roughly corresponds to 3 months to Inf months.

|                | Peak price | Off-peak price | Crude oil | Nature gas | Coal | FROM_ABS | FROM_WTH |
|----------------|------------|----------------|-----------|------------|------|----------|----------|
| Peak price     | 2.930      | 1.300          | 0.060     | 0.760      | 0.110| 0.450    | 2.930    |
| Off-peak price | 0.970      | 4.210          | 0.030     | 0.530      | 0.330| 0.370    | 2.450    |
| Crude oil      | 0.150      | 0.100          | 19.000    | 0.560      | 0.700| 0.300    | 1.990    |
| Nature gas     | 0.190      | 0.140          | 0.830     | 11.110     | 3.100| 0.850    | 5.610    |
| Coal           | 0.120      | 0.250          | 3.730     | 1.620      | 23.020| 1.150    | 7.550    |
| TO_ABS         | 0.290      | 0.360          | 0.930     | 0.690      | 0.850| 3.120    |          |
| TO_WTH         | 1.900      | 2.360          | 6.120     | 4.570      | 5.590|          | 20.540   |

In general, we could observe that the overall spillover index ranges from 22.41 % to 20.54 % at different frequency bands, revealing that the connectedness weakens in the system as the frequency band rises. The static connectedness results also support the preliminary analysis form the unconditional correlation that nature gas shows the closet linkages with both the peak and off-peak electricity prices among three fossil fuels. Such a conclusion always exists in both high frequency and low-frequency bands. In a specific case of the short-term frequency band, the directional spillovers transmitted “TO_ABS” show that the estimated index of peak electricity price is larger than off-peak electricity, indicating the former is more susceptible to fuel price fluctuations. Meanwhile, we could find off-peak electricity prices may induce more opposite spillover effects on fossil fuels based on the results of “From_ABS”. Such findings would also exist in the long run or low-frequency band. The results based on frequency 2 illustrates that the “TO_ABS” and “From_ABS” index of both the two kinds of electricity prices are smaller than the case of frequency band 1, thus the spillover relations across the electricity market and fossil fuels may rise as the extension of the investment horizon.

In terms of ‘within’ connectedness (TO_WTH and FROM_WTH), the electricity market is the main contributor to the overall connectedness in the high-frequency band. Peak and off-peak prices respectively contribute 7.96% and 6.54% of the forecasting variance to other markets, which are the two most important factors that have an impact on the entire system. While fossil fuels show larger spillover contributions in the low frequency band, crude oil, natural gas, and coal transmit the largest spillover in the system, contributing about 6.12%, 4.57% and 5.59% of the overall system. Such results reveal that information from electricity markets are transmitted faster while the spillover effects from fossil fuels last longer, even the spillover effects from fuels to electricity are always weak. Though the main spillover contributors are different between the long and short term, some characteristics for the information spillover among electricity and fossil fuels could be gained. Firstly, the spillover relationship within the electricity market and the energy market is stronger than the cross-market spillover effect. We could infer that the demand shocks may play a more significant role in driving the
fluctuations in electricity prices. Additionally, fossil fuels bring different spillover effects on the two electricity prices. In specific, crude oil and natural gas would transmit more information on the off-peak electricity price than the peak electricity prices in the high-frequency band, while the spillover from the coal market shows the opposite features. And such differences may reverse in a longer time horizon. Such results show that the management methods for peak and off-peak electricity prices should be different to ensure the stability of electricity prices, and it should also be flexible for different time spectral.

3.2. Connectedness network
Then, to analyze the information connectedness for peak, off-peak, and three fossil fuel energies, this part constructs two-directional connectedness graphs based on the net pairwise directional connectedness. They have been shown in Figure 1. Each node represents a selected market and they are all colored in green. In this figure, the blue arrows represent the direction of the pairwise directional spillover, the thick of the arrow lines detail the intensity of such a connection. Namely, the darker the color and the thicker the arrow lines both indicate a stronger net spillover relationship from the markets in arrow source to arrow tip.

![Figure 1 Net pairwise directional connectedness network for two frequencies.](image)

On the whole, this figure evident that the pairwise connectedness would be more pronounced in the high-frequency domain than in the low-frequency domain. This illustrates that the cross-market links are mainly concentrated in the short-term (within a quarter). With the extension of the investment horizon, most of the pairwise spillovers would become weaker. Based on the direction indicated by the arrows, we could find that electricity markets are not always net information spillover receiver from fossil fuels. This phenomenon could be observed in both high-frequency and low-frequency domains. In specific, both the peak and off-peak electricity prices could produce the net information spillover on crude oil and coal in the high-frequency state. In other words, only the natural gas is the significant and net spillover transmitter for the electricity market. Such results illustrate that natural gas is a key driver for shaping the changes in electricity prices, the underlying origin for this situation may be its more fluctuated price and its important position in power production. Note that natural gas power generation is a relatively large source of power sold in the PJM power market (about 27.2%), the impact of its changes on electricity prices will be greater and more obvious than crude oil. Meanwhile, due to the high degree of financialization of the natural gas market and the strong regional nature of the coal market, the natural gas price changes could produce a significant impact on the overall PJM electricity price but the coal benchmark prices are difficult to directly correlate with the electricity market. In the low-frequency state, coal and crude oil price could weakly affect electricity prices but natural gas turned to be a net information receiver from the electricity markets. This reflects the phenomenon of long-term mean recovery in the process of market information transmission.

At last, it can be seen from the net spillover strength that off-peak prices are more closely related to the fuel markets in the short term, while peak prices have relatively more significant links with fuel prices in the low-frequency range. This shows that the two electricity prices have different cross-market connectivity characteristics. Off-peak electricity prices are more susceptible to power generation costs driven by changes in fuel prices.
4. Conclusions and management implications

The urging question of the current power industry and social economics is how to ensure the relative stability of electricity prices and sufficient pricing efficiency under the premise of marketization. Since the electricity production in most countries is still dominated by thermal power generation, changes in the price of fossil fuels as raw materials will inevitably affect the cost of electricity production and ultimately shock the price of electricity. In this context, the most influential and essential fossil fuels are crude oil, natural gas, and coal. Thus, we aim to investigate how the three commodities prices affect the electricity prices and detect the spillover effects among these markets. Since there are still few types of research providing in-depth empirical research on this area, and the behavior of energy policymakers and market participants may differ across various time horizons, this paper applies both the reduced VAR model and frequency domain connectedness index method to capture the influence and spillover effect of fossil fuels, respectively. To efficiently grasp the relationship between the electricity and the fossil fuel market, we firstly cover both the peak and off-peak electricity prices simultaneously.

Consequently, we obtain the findings as follows. (1) The connectedness matrix in the frequency domain reveals that natural gas has the closest linkages with the electricity market in the cases of both the high frequency and low-frequency bands. And it also indicates that fossil fuels bring different spillover effects on the two electricity prices and such effect may reverse in a longer time horizon. (3) Pairwise directional spillover networks provide some stronger evidence that spillover between each other is more significant in the high-frequency domain. Besides, off-peak prices are more closely related to the fuel markets in the short term, while peak prices have relatively more significant links with fuel prices in the low-frequency range.

Such findings may be useful for companies and policymakers. Companies should fully base on their own production time horizon when introducing more electricity into their production program, it is essential to understand how the electricity prices change and adjust production plans according to the characteristics of electricity prices during peak and valley periods. The results of this research imply that it is so difficult to balance the marketization of electricity and the stability of electricity prices. Thus, policymakers should effectively detect the price of power generation fuels that consume a lot and are often used for peak shaving, such as natural gas. Stabilizing the price of such fuels is of key significance to stabilize electricity prices.

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References

[1] Serletis, A., & Shahmoradi, A. (2006). Measuring and testing natural gas and electricity markets volatility: evidence from Alberta's deregulated markets. Studies in Nonlinear Dynamics & Econometrics, 10(3).

[2] Asche, F., Osmundsen, P., & Sandsmark, M. (2006). The UK market for natural gas, oil and electricity: are the prices decoupled?. The Energy Journal, 27(2).

[3] Mohammadi, H. (2009). Electricity prices and fuel costs: Long-run relations and short-run dynamics. Energy Economics, 31(3), 503-509.

[4] Mulder, M., & Scholtens, B. (2013). The impact of renewable energy on electricity prices in the Netherlands. Renewable energy, 57, 94-100.

[5] Liu, M. H., Margaritis, D., & Zhang, Y. (2013). Market-driven coal prices and state-administered electricity prices in China. Energy Economics, 40, 167-175.

[6] Xia, T., Ji, Q., & Geng, J. B. (2020). Nonlinear dependence and information spillover between electricity and fuel source markets: New evidence from a multi-scale analysis. Physica A: Statistical Mechanics and its Applications, 537, 122298.

[7] Barunik, J., & Krehlik, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. Journal of Financial Econometrics, 16(2), 271-296.
[8] Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal, 119(534), 158-171.

[9] Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of Forecasting, 28(1), 57-66.

[10] Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics, 182(1), 119-134.

[11] Ferrer, R., Shahzad, S. J. H., López, R., & Jareño, F. (2018). Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. Energy Economics, 76, 1-20.