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Volatility and Risk in the Energy Market: A Trade Network Approach †

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Abstract: This paper evaluates the effect of energy trade networks on the price volatility of coal, oil, natural gas, and electricity. This research conducts a longitudinal analysis using a time series of static coal trade networks to generate a dynamic trade network. It uses the component causality index as a leading indicator of the price volatility of the energy market. This research finds out that the component causality index, based on degree centrality, anticipates or moves together with coal volatility and, to a lesser degree, with natural gas and electricity volatility for the period 1998–2014. The proposed index could be integrated into a risk management system for investors and regulators. The broad impact of this research lies in the understanding of mechanisms of the instability and risk of the energy sector as a result of a complex interaction of the network of producers and traders.

Keywords: social networks; link mining; risk management; volatility forecast; energy finance; computational finance

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1. Introduction

The contraction of oil prices since 2014 has had a negative systemic effect worldwide, mainly for oil-producing countries and oil and energy companies. In this respect, the volatility of the energy market has internal determinants, such as reducing natural gas prices since 2005, technological advances in the production of electricity with fewer contaminant effects, the financial crisis of 2008, and the geopolitical changes that have affected the oil supply. Even though the simultaneous evaluation of these factors is complicated, the purchase and sale of coal by power plants, where coal is the primary input in electricity production, capture the internal transformation of the energy sector due to technological and energy price changes. This transformation is even more critical considering that coal prices are closely associated with electricity, oil, and natural gas prices.

Mohammadi [1] found that U.S. oil and natural gas prices are globally and regionally determined, respectively, and long-term contracts define coal prices. Mohammadi [2] exposed a strong relationship between electricity and coal prices and an insignificant relationship between electricity and oil and/or natural gas prices. Hartley et al. [3] noticed an indirect relationship between natural gas and oil prices. Furthermore, Aruga and Managi [4] detected a weak market integration among a large group of energy products: WTI oil, Brent oil, gasoline, heating oil, coal, natural gas, and ethanol futures prices.

Another recent line of research is the prediction in economic networks. Dhar et al. [5] proposed a product network to forecast product demand, and Creamer and Stolfo [6] integrated the metrics of an extended corporate interlock (social network of directors and financial analysts) with fundamental corporate variables and analysts' predictions to forecast the trend of the cumulative abnormal return and earnings surprise of U.S. companies. Creamer et al. [7] also predicted return and volatility using a corporate network of European companies based on the common topics of corporate news, and Adamic et al. [8] used a traders network to quantify the flow of information through financial markets. After the financial crisis of 2008, the finance literature has explored the linkages among financial institutions and corporations as drivers of the crisis and indicators of financial stress.

The third line of related research is the study of trade networks, as presented in the following section. This paper integrates the interrelationship among the energy prices and the network perspective, considering that the trade and distance among coal mines and power plants can significantly impact efficiency. Therefore, this research proposes and evaluates if an indicator called component causality index associated with the dynamic evolution of a longitudinal coal trade network among U.S. states might be a leading indicator of the volatility of the energy market.

The network literature has become increasingly interested in financial problems and risk evaluation, especially since the financial crisis of 2008. This literature has explored the linkages among financial institutions and corporations as indicators of financial stress and drivers of the crisis. The difficulty with these models is that the financial data are very restricted by the regulators and financial institutions, especially when it requires some microeconomic data that may reveal the identity of the agents as it happens with trade networks. For this reason, an important part of the financial network models is based on overnight payments among financial institutions or proxies of corporate distance for financial prediction as proposed by Mantegna [9] such as correlations among returns of different institutions [10–22]. Billio et al. [23], Zheng et al. [24] and Casnici et al. [25] have extended this network approach to study volatility and risk. The main idea is that these measures may overcome the restrictive perspective of the standard signals of market risk endorsed by the Basel accords such as Value at Risk (VaR) or Conditional VAR (CVaR) only based on financial profits.

The trade network literature also explores problems of sectoral and international trade, as in the case of Hidalgo and Hausmann [26] who created a bipartite network to represent global trade and the interaction between countries and their products. They concluded that variations in economic complexity can explain differences in income across countries. Kali et al. [27] used a similar trade network; however, they concluded that density and trade network proximity are the determinant factors that explain high-growth country rates. Cole et al. [28] found that Japanese firms' emissions are affected by the emissions of neighboring firms, and Chintrakarn and Millimet [29] observed that trade among U.S. states has a negative environmental impact; however, these two last articles are not based on trade networks.

We are not aware of previous studies that have evaluated a coal trade network among different U.S. states. In this research, we follow the tradition of this section of trade networks to study volatility and an energy trade network where every node represents an agent, and the outcome depends on the topology and the dynamic of the network.

The rest of the paper is organized as follows: Section 2 presents the methodology used; Section 3 describes the data and the coal market; Section 4 explains in detail the research design; Section 5 presents the results of our models, and Section 6 concludes.

2. Methods

This section describes the following methods used to study the networks and evaluate the causality among the time series under analysis.

2.1. Granger Causality

Granger causality [30,31] is a prevalent methodology in economics, financial econometrics, as well as in many other areas of study, such as neuroscience, to evaluate the linear causal relationship between two or more variables. According to the basic definition of Granger causality, the forecasting of the variable Y_t with an autoregressive process using Y_{t-l} as its lag-l value, should be compared with another autoregressive process using Y_{t-l} and the vector X_{t-l} of potential explanatory variables. Thus, X_{t-l} Granger causes Y_t when X_{t-l} happens before Y_t, and X_{t-l} has unique information to forecast Y_t that is not present in other variables.

Typically, Granger causality is tested using an autoregressive model with and without the vector X_{t-1}, such as in the following bivariate example:

$$Y_t = \sum_{l=1}^{L} \alpha_l Y_{t-l} + \epsilon_1 \tag{1}$$

$$Y_t = \sum_{l=1}^{L} \alpha_l Y_{t-l} + \sum_{l=1}^{L} \beta_l X_{t-l} + \epsilon_2 \tag{2}$$

where the residual ϵ_j is a white noise series: $\epsilon_j \sim N(0, \sigma)$, j = 1,2.

X_{t-l} Granger causes Y_t if the null hypothesis $H_0 : \beta_l = 0$ is rejected or, in general, if:

$$E(Y_t|\underline{Y}_{t-1}, \underline{X}_{t-1}) \neq E(Y_t|\underline{Y}_{t-1}) \tag{3}$$

where $\underline{Y}_{t-1} = (Y_{t-1}, Y_{t-2}, ...)$ and $\underline{X}_{t-1} = (X_{t-1}, X_{t-2}, ...)$ [32].

The main limitation of the Granger causality test is that it is based on a linear model while numerous studies show the existence of nonlinear causal relationships among different finance variables [33–41]. In response to this limitation, Baek and Brock [42] proposed a nonlinear bivariate version of the Granger causality test, Hiemstra and Jones [36] revised it and Bai et al. [43] extended it to a multivariate setting. In general, these tests run a nonlinear Granger causality test with the residuals of the linear test.

2.2. Brownian Distance

Székely and Rizzo [44] proposed a multivariate nonlinear dependence coefficient called Brownian distance correlation that can be used with random vectors of multiple dimensions or with strongly stationary time series. These authors also proposed the Brownian distance covariance, which captures the covariance of a stochastic process. Distance covariance between the random vectors X and Y measures the distance between f_X, f_Y and $f_{X,Y}$ where f_X and f_Y are the characteristic functions of X and Y, respectively, and $f_{X,Y}$ is the joint characteristic function of X and Y and is obtained as:

$$\nu(X, Y) = \sqrt{\|f_{X,Y}(t,s) - f_X(t) f_Y(s)\|^2} \tag{4}$$

where t and s are vectors and $\|.\|$ is the norm.

Empirically, $\nu(X, Y)$ evaluates the null hypothesis of independence $H_0 : f_X f_Y = f_{X,Y}$ versus the alternative hypothesis $H_A : f_X f_Y \neq f_{X,Y}$. In this proposal, this test is the distance covariance test of independence.

Likewise, distance variance is:

$$\nu(X) = \sqrt{\|f_{X,X}(t,s) - f_X(t) f_X(s)\|^2} \tag{5}$$

Once the distance covariance is defined, the distance correlation $R(X, Y)$ is obtained from the following expression:

$$R^2 = \begin{cases} \frac{\nu^2(X,Y)}{\sqrt{\nu^2(X)\nu^2(Y))}}. & \nu^2(X)\nu^2(Y) > 0 \\ 0, & \nu^2(X)\nu^2(Y) = 0 \end{cases} \tag{6}$$

The distance correlation takes a value of zero in case of independence and one when there is complete dependence.

Unlike the previous versions of the nonlinear Granger causality tests, we evaluate the nonlinear dependence of any financial time series, such as the current value of Y (Y_t) on the l lagged value of X (X_{t-l}) with the Brownian distance correlation $R(X_{t-l}, Y_t)$ directly. In particular, we wish to explore the lead-lag relationships among the time series under study directly. If $R(X_{t-l}, Y_t) \neq 0$ and $l > 0$, then X_{t-l} leads the series Y_t. Additionally, if $R(X_{t-l}, Y_t) \neq 0$, $R(X_t, Y_{t-l}) = 0$ and $l > 0$, then there is a unidirectional relationship from X_{t-l} to Y_t. However, if $R(X_{t-l}, Y_t) \neq 0$, $R(X_t, Y_{t-l}) \neq 0$ and $l > 0$, then there is a feedback relationship between X and Y. On the contrary, if $R(X_{t-l}, Y_t) = 0$ and $R(X_t, Y_{t-l}) = 0$, then there is no lead lag relationship between X and Y [45].

2.3. Machine Learning Algorithms

In this section, we review the machine learning algorithms used to forecast volatility assuming that the training set Y consists of N pairs $(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)$. x_i are the features of a particular observation, and $y_i \in \{-1, 1\}$ is its class label.

2.3.1. Random Forests

Random Forests (RF) calculates many decision trees (θ_i) using uniform bootstrap samples with replacement of Y and from a predefined number of features X randomly selected. The combination of these trees leads to a forest, and the final decision of a classification problem is the majority vote of these trees or predictors $\psi(X, \theta_i)$ [46].

2.3.2. Support Vector Machine

Support Vector Machine (SVM) as a classification algorithm projects the input matrix X in a higher dimensional space using mathematical functions called kernels [47]. The algorithm calculates a hyperplane $\{X : F(X) \doteq X^T\beta + \beta_0 = 0\}$, where $||\beta|| = 1$ and $\text{sign}(F(X))$ is the prediction rule [48]. This hyperplane is in the middle point between the planes of the two input categories where it maximizes the margin (M) or the distance between these planes:

$$\begin{aligned} &\underset{\beta,\beta_0,||\beta||=1}{\text{Max}} \quad M \\ &\text{subject to} \\ &y_i(x_i^T\beta + \beta_0) \geqslant M,\ i = 1, \ldots, N \end{aligned}$$

2.4. Centrality, Connectedness and Network Structure

Degree centrality is the sum of the edges of a vertex v_i:

$$D_c(v_i) \doteq \sum_j a_{ij} \tag{7}$$

where a_{ij} is an element of the adjacent matrix A of the undirected graph $G(V, E)$, $V = v_1, v_2, \ldots, v_n$ is the set of vertices, E is the set of edges, and e_{ij} is the edge between vertices v_i and v_j

We also use the Krackhardt connectedness score [49] as a density measure of the digraph $C(V, E)$. Krackhardt connectedness is the proportion of all pairs of vertices v_i and v_j that have an undirected path between them:

$$connectedness \doteq 1 - \frac{V}{\frac{N(N-1)}{2}} \tag{8}$$

where V represents the number of pairs of vertices that are not mutually reachable while $\frac{N(N-1)}{2}$ represents the total number of pairs of vertices. The range of the connectedness score is from zero for the null graph to one for the weakly connected graph.

We apply the following methods for community detection on directed graphs to explore the structure of trade networks in different periods:

1. Brandes et al. [50] proposed an algorithm (Brandes algorithm) that finds the optimal community structure with subgraphs or clusters based on the maximal modularity score;

2. Pons and Latapy [51] introduced the Walktrap algorithm that finds an efficient community structure according to a measure of similarities between vertices based on random walks as short-random walks typically stay in the same community.

Modularity measures the quality of a partition based on the number of edges connected to every cluster above an expected random number of edges. A high level of coal volatility may lead to a more irregular pattern of trade between states. Therefore, the community structure of the trading network would be less well defined. As a result, high volatility could be associated with low modularity [52].

3. Data and the Coal Market

This research explores the impact of the monthly coal trading dynamic among U.S. states and the coal, oil, natural gas, and electricity spot price volatility from January 1998 to December 2014. This period is affected by the dot-com burst of 2000–2001 and the credit crisis of 2008–2010. We also selected this period as the U.S. coal production reached a maximum point in 2008, and after this year, it declined. So, our sample captures a change of regime that may have a significant impact on coal volatility.

We used the monthly time series of the spot log prices of the fossil fuel series for the period 1998–2014: West Texas Intermediate oil (WTI), the Central Appalachian (bituminous) coal (Coal), and natural gas (Gas) from the New York Mercantile Exchange (NYMEX). The electricity prices are the total electricity prices for each state from the sales, revenues, and prices statistics of the U.S. Energy Information Administration. The bituminous and sub-bituminous coal prices and coal traded come from fuel purchases by steam electric generating plants of 50 megawatts or higher for 39 U.S. states (see Table 1) reported in the FERC Form No. 423 [53]. There are about ten times more records for bituminous coal purchases than for sub-bituminous coal purchases.

Table 1. U.S. Census Bureau Regions. * denotes states selected for this research.

Region	ID	Region/Division	States Included
Northeast	R1	New England	CT *, ME *, MA *, RI *, VT
	R2	Middle Atlantic	NJ, NY, PA *
Midwest	R3	East North Central	IL *, IN *, MI *, OH *, WI *
	R4	West North Central	IA, KS *, MN *, MO *, NE, ND *, SD *
South	R5	South Atlantic	DC *, DE *, FL *, GA *, MD *, NC *, SC *, VA *, WV *
	R6	East South Central	AL *, KY *, MS, TN *
	R7	West South Central	AR *, LA *, OK, TX
West	R8	Mountain	AZ *, CO *, ID *, MT *, NM *, NV *, UT *, WY *
	R9	Pacific	AK, CA *, HI *, OR, WA

The U.S. states that provide most of the coal consumed in the U.S. can also be reorganized in the following three regions:

- Western region and Powder River Basin (Wyoming and Montana);
- Interior region (Illinois, Indiana, and Kentucky);
- Appalachian Basin (West Virginia and Kentucky).

The sub-bituminous coal from the Powder River Basin has low sulfur content, but a slightly lower heat content per ton. The Western region provides almost all the low sulfur sub-bituminous coal consumed in the U.S. Mining in this region is done on the surface, which eases coal extraction and dramatically reduces prices at the mine's location.

The other two regions produce medium to high volatility bituminous coal with high sulfur content. Mining is done underground and is more labor-intensive than in the Western region.

Mines and coal producers have narrowed down the sulfur dioxide (SO_2) emissions of bituminous and sub-bituminous coal from 1985. This contraction is partially explained by the reduction of sulfur in both types of coal. In the 1970s, electric power plants used bituminous coal extensively. This tendency, however, changed over time mainly due to the new Clean Air Act (CAA) environmental regulations and the opening of new, inexpensive sources of low sulfur coal. As the Powder River Basin provided substantial amounts of cheap sub-bituminous coal, the prices of sub-bituminous coal dropped, and its consumption for electricity production increased. Since 2009, almost 90% of the coal purchased by plants was either bituminous or sub-bituminous coal. For this reason, this analysis concentrates on bituminous and sub-bituminous coal only.

4. Research Design

We built a national network based on the total coal purchased where the nodes are U.S. states, similar to agents in an agent-based framework. The weight of each edge is the amount purchased from one state to another state. We conducted a longitudinal analysis using a monthly time series of static networks to generate a dynamic trade network from January 1998 to December 2014. We calculated degree centrality for each node of the monthly network and obtained the monthly average of these indicators.

The degree centrality of each state of a network may represent the importance that a state has at the national level. Additionally, the centrality of a state might also be associated with the volatility of coal, natural gas, WTI, and electricity prices, as the change of these prices may also lead to a shift in trading patterns or vice versa. The association between degree centrality and volatility might become more critical during periods of crisis as risk increases and the trade among states may also change.

For the analysis of the volatility of the energy market, we used an index called Component Causality Index (CCI) proposed by Creamer [54] which is the proportion of components of a particular system or index that have significant causal relationships with a dependent variable over a given period. In this research, the components are the U.S. states that act as agents. The dependent variables are electricity, coal, and bituminous coal volatility, as most of the coal traded is bituminous coal. The main idea is that if there are substantial changes in the components of a system or an index, the system's volatility will also be affected. Therefore, it could be anticipated by the shift in the behavior of its components. We used the CCI as a leading indicator of volatility, evaluating the impact of the network variables on the subsequent period's volatility for the complete time series. We calculated monthly volatility as the standard deviation of the last 12 months. The volatility of coal, natural gas, WTI, and electricity could be used to calculate the risk for each particular energy market.

Using a moving window based on the previous 12 months, we evaluated if degree centrality has a causal relationship or affects the next period's return and volatility of electricity, coal, and bituminous coal prices by state. Based on these results, we calculated the CCI as the proportion of states that show significant dependence between degree centrality and the subsequent period return and volatility of each state using the Brownian distance test of independence. Finally, we evaluated if seven lags of the CCIs for electricity, coal and bituminous coal volatility have a significant causal relationship on the return of electricity and coal, and volatility of prices of electricity, coal, bituminous coal, sub-bituminous coal, WTI, and natural gas using the Granger causality test and the Brownian distance test of independence. We also applied the Bonferroni correction for the p-values of the Brownian distance test and the Granger causality test. We selected seven lags to evaluate the CCI impact from one day, a week, and a share (one-third) of a month. As we present in Section 5.2, each of the seven lagged values of the dependent variables has more importance for forecasting coal volatility than most of the rest of the features.

We developed several predictive models for coal volatility to test the CCI's predictive value. For our base model, the independent variables are the seven lags of the dependent variable. Our forecast model includes the seven lags of the dependent variable, CCI for electricity return (CCIR) and volatility (CCI), CCI for coal volatility (CCIC), and CCI for bituminous coal volatility (CCIBC). The model for the sub-bituminous coal volatility trend omits the variable CCIBC as this is not relevant for this product. We forecasted as dependent variables the volatility direction of coal, bituminous coal, and sub-bituminous coal using the SVM and RF algorithms introduced in Section 2. We established as positive and negative trends those observations that are greater or less than the median, respectively.

We calibrated our models finding the best combination of the following parameters according to an exhaustive cross-validation search with 10 folds (we used the GridSearchCV function from the scikit-learn python package to conduct the exhaustive cross-validation search):

1. For RF: Number of trees: 1, 11, 21,..., 91 in 10 increments;
2. For SVM: C penalty parameter of the error term: 0.1, 1 (default) and 100.

We split our observations into training and test datasets using 70% and 30% of the observations, respectively. We split the test dataset in three folds of 15 observations each and compared the average Matthews correlation coefficient (MCC) and the test error of our forecast and base model using the *t*-test of the mean difference. MCC [55] or the ϕ coefficient, as it is also known, is $|MCC| \doteq \sqrt{\frac{\chi^2}{n}} \doteq \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$. n is the number of observations, and T.P., F.P., TN, and F.N. stand for true positive, false positive, true negative, and false negative observations. Here, 1, 0, and -1 represent perfect, random, and inverse prediction, respectively. MCC is equivalent to the Pearson correlation coefficient for binary cases.

We applied the Bai–Perron [56] test to detect structural breaks on the time series of coal volatility. The Bai–Perron test is particularly useful when the break date is unknown, and there is more than one break date.

This research used the Energy, SNA and strucchange packages for R to calculate the Brownian distance test of independence, network measures, and the structural brakes (information about R can be found at <http://cran.r-project.org> (accessed on 1 October 2015)).

5. Results

Most of the results of Granger causality are not significant; however, those few cases that are significant are also significant for the Brownian distance correlation (see Tables 2 and 3). Therefore, the following analysis refers to the results using the Brownian distance correlation.

Table 2. Brownian distance correlation between lagged component causality index (CCI) and the return of energy products. Columns 1 to 7 represent lagged values. **, *, and .: p-value $\leq$ 0.01, 0.05 and 0.1, respectively, with Bonferroni correction. None of these tests are significant according to the Granger causality test with the Bonferroni correction.

Lags	1		2		3		4		5		6		7	
CCI for electricity volatility														
Electricity	0.11		0.14		0.15		0.11		0.09		0.10		0.14	
Coal	0.20	**	0.16	.	0.21	**	0.25	**	0.23	**	0.33	**	0.31	**
CCI for coal volatility														
Electricity	0.11		0.14		0.15		0.14		0.12		0.12		0.14	
Coal	0.23	**	0.22	**	0.22	**	0.20	*	0.22	**	0.20	*	0.24	**
CCI for bituminous volatility														
Electricity	0.11		0.10		0.12		0.10		0.10		0.12		0.08	
Coal	0.23	**	0.26	**	0.27	**	0.25	**	0.26	**	0.24	**	0.19	**

The evolution of the bituminous coal trade network included in component I of Figure 1 shows that very few hubs are essential coal providers, in particular, those from the Mountain region. This process is noticeable for the sub-bituminous coal trade network presented in component II of Figure 1 where Wyoming, and with less importance, Colorado and Montana, are primary fuel providers. New Mexico and Arizona connected with the rest of the network during the 2000s, even though they were disconnected from the network during the 1990s. These states are part of the Mountain region. Plants of this region and those of West South Central may have boosted their productivity due to their proximity to the Powder River Basin, a sizeable sub-bituminous area.

Table 3. Brownian distance correlation between lagged component causality index (CCI) and the volatility of energy products. Columns 1 to 7 represent lagged values. **, *, and .: p-value $\leq$ 0.01, 0.05 and 0.1, respectively, with Bonferroni correction. This table also includes the p-values with Bonferroni correction for the Granger causality test applied to the same variables: ‡ indicates p-values $\leq$ 0.05.

Lags	**1**		**2**		**3**		**4**		**5**		**6**		**7**	
CCI for electricity volatility														
Electricity	0.18	*	0.13		0.15		0.14		0.14		0.20	**	0.19	* ‡
Coal	0.15		0.27	**	0.29	**	0.32	**	0.28	**	0.32	**	0.35	**
Bit. Coal	0.19	* ‡	0.23	**	0.24	**	0.26	**	0.30	**	0.37	**	0.37	**
Sub-bit. Coal	0.14		0.12		0.17	*	0.21	**	0.18	*	0.14		0.20	*
WTI	0.11		0.13		0.21	**	0.15		0.12		0.12		0.16	
Gas	0.14		0.22	**	0.13		0.16	.	0.15		0.18	*	0.19	*
CCI for coal volatility														
Electricity	0.11		0.12		0.10		0.14		0.12		0.10		0.11	
Coal	0.25	**	0.25	**	0.25	**	0.26	**	0.27	**	0.27	**	0.25	**
Bit. Coal	0.23	**	0.23	**	0.23	**	0.25	**	0.25	**	0.24	**	0.23	**
Sub-bit. Coal	0.18	*	0.18	*	0.15	.	0.18	*	0.17	*	0.19	*	0.17	*
WTI	0.21	** ‡	0.18	.	0.16		0.20	*	0.16		0.20	*	0.20	*
Gas	0.14		0.15		0.12		0.17	.	0.15		0.13		0.17	.
CCI for bituminous volatility														
Electricity	0.11		0.11		0.12		0.14		0.12		0.12		0.12	
Coal	0.23	**	0.24	**	0.24	**	0.21	**	0.23	**	0.21	*	0.21	*
Bit. Coal	0.21	*	0.20	**	0.21	**	0.18	*	0.20	**	0.19	*	0.17	*
Sub-bit. Coal	0.16		0.14		0.18	*	0.14		0.15	.	0.13		0.14	
WTI	0.17		0.18	*	0.17	.	0.16	.	0.17	.	0.16	.	0.18	.
Gas	0.20	**	0.19	*	0.22	**	0.22	*	0.21	*	0.20	*	0.21	**

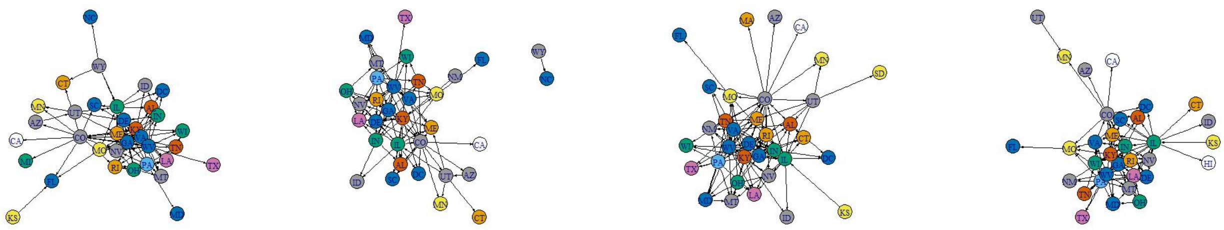
The CCIs for electricity, coal and bituminous coal volatility do not directly impact electricity return. However, they all have a direct impact on coal return (see Table 2). They also have a significant correlation at all lags with bituminous coal volatility, and in most cases, with coal volatility. The correlation is much weaker with sub-bituminous coal and WTI volatility (see Table 3). Our research on fuel energy products volatility extends the results of previous investigators [2–4,57–60] who have studied the relationship and the level of cointegration among fuel energy prices.

As indicated by the CCI definition, the different CCIs have a powerful impact on the volatility of their products. For instance, the CCI for electricity volatility shows significant correlations with electricity volatility (lags 1, 6, and 7). This CCI also correlates with natural gas volatility (lags 2, 4, 6, and 7) (see Table 3). The CCI for coal volatility impacts both sub-bituminous and bituminous coal volatility as coal includes both types of coal. As natural gas has partially substituted coal in the power plants, especially bituminous coal, this may explain that all the lags of the CCI for bituminous coal volatility show a significant correlation with natural gas volatility. Even though the power plants need some time to adjust to price changes, a contraction of natural gas prices may increase the demand for natural gas and reduce the demand for bituminous coal or vice versa. These changes increase the volatility of both products.

The graphs of the time series also show that the CCI for bituminous coal volatility follows more closely bituminous coal and natural gas volatility (Figure 2) than other time series. The CCI for bituminous coal volatility sharply increases about 4–5 months before the significant spikes in bituminous coal volatility (first quarter of 2001, the fourth quarter of 2004, and 2009). In general, the causality analysis shows that the CCIs for electricity, coal, and bituminous coal act as leading indicators of periods of high volatility, especially of the coal market.

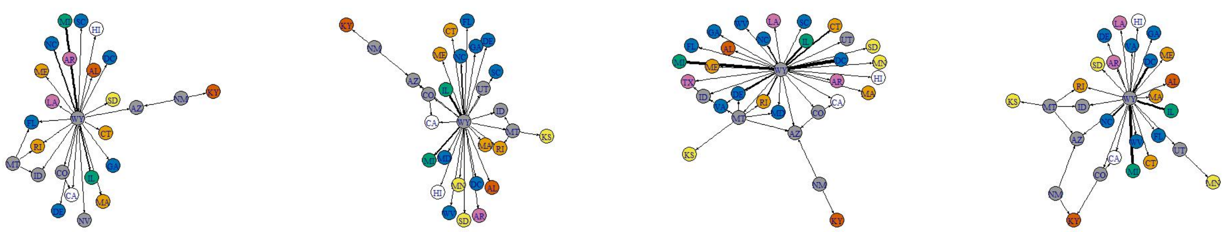
The impact of the different CCIs on WTI volatility is much weaker, considering that WTI prices are mainly influenced by geopolitical factors that affect the oil supply and demand.

[I. Bituminous coal]



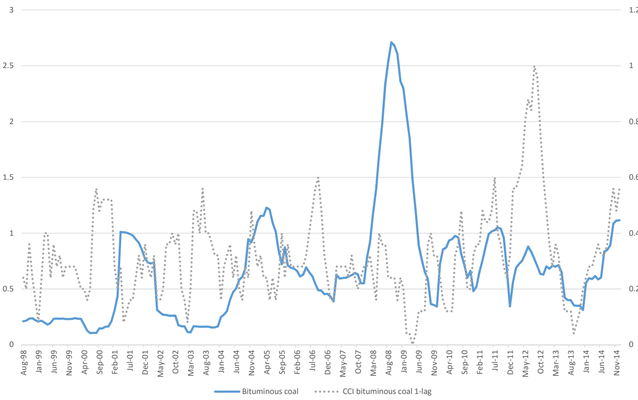
(**a**) 2000 (**b**) 2004 (**c**) 2008 (**d**) 2012

[II. Sub-bituminous coal]

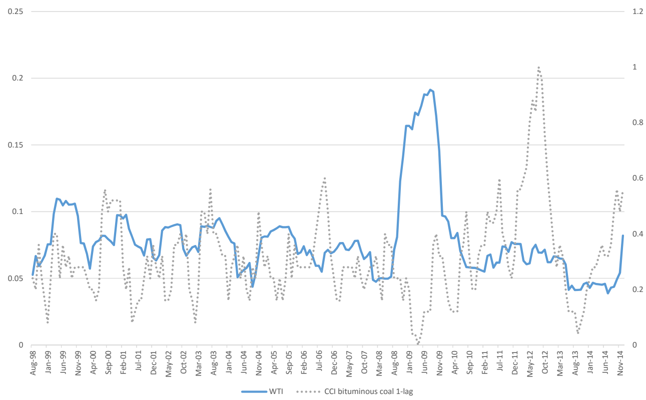


(**a**) 2000 (**b**) 2004 (**c**) 2008 (**d**) 2012

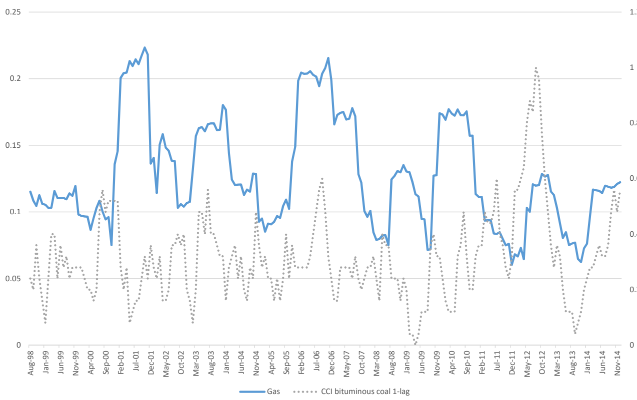
Figure 1. Bituminous (I.) and sub-bituminous coal (II.) trade network among states. Every node includes the abbreviation of the relevant state. The widths of the arrows are associated with the amount traded, and color represents geographic regions: 1. New England (dark yellow), 2. Middle Atlantic (light blue), 3. East North Central (green), 4. West North Central (light yellow), 5. South Atlantic (dark blue), 6. East South Central (orange), 7. West South Central (pink), 8. Mountain (gray), and 9. Pacific (white).



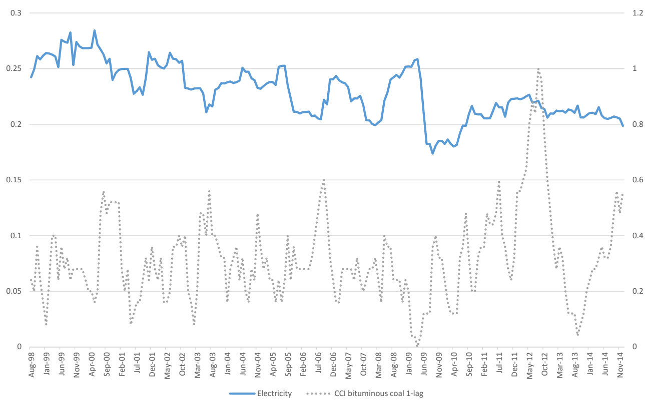
(**a**) Bituminous coal



(**b**) WTI



(**c**) Gas



(**d**) Electricity

Figure 2. Coal bituminous, WTI, natural gas, and electricity volatility, and 1-lag CCI used to forecast bituminous coal. Right *Y*-axis is for CCI. Dashed line is 1-lag CCI bituminous coal.

5.1. Network Structure

A final remaining question is if the changes of the complete network structure might be related to volatility. One way to explore this problem is through the relationship between network connectedness and volatility. In this respect, the correlation between these two variables is 0.312.

The Bai–Perron test [56] applied to the coal volatility series split the data into the following periods: pre-crisis (before December 2007), financial credit crisis (December 2007–July 2009), and recovery (since July 2009). Figure 3 indicates that an increase in connectedness happened during the financial credit crisis period and anticipated a substantial increase in coal volatility in September 2008 when the production of coal contracted significantly. During crises, the market tends to converge and become more integrated. This implies stronger connections among the agents at the trade network level, as we can observe in this case. In particular, the 5% most and least volatile observations have average standard deviations of 25.3 and 2.95 and average Krackhart connectedness scores of 0.8 and 0.74, respectively.

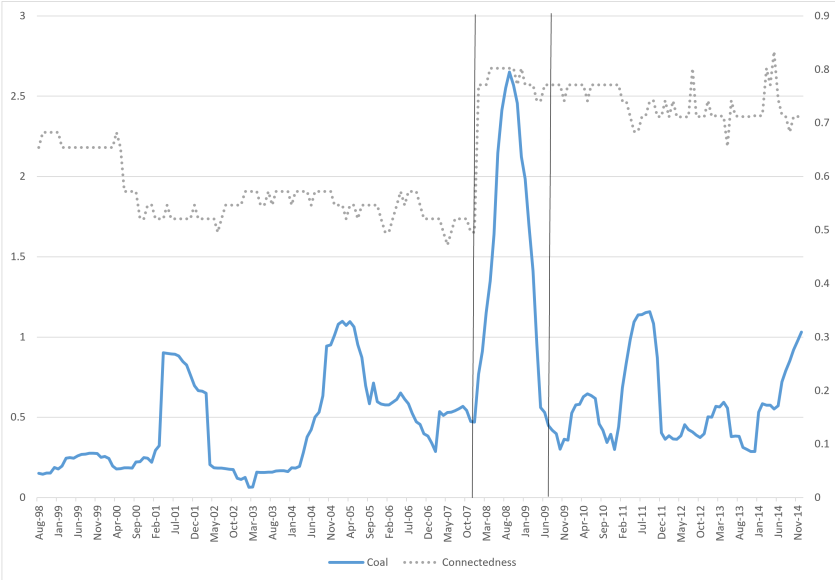


Figure 3. Coal volatility (**left** axis) and Krackhardt connectedness (**right** axis) during the period 1998–2014. Vertical lines are structural brakes according to the Bai–Perron test [56].

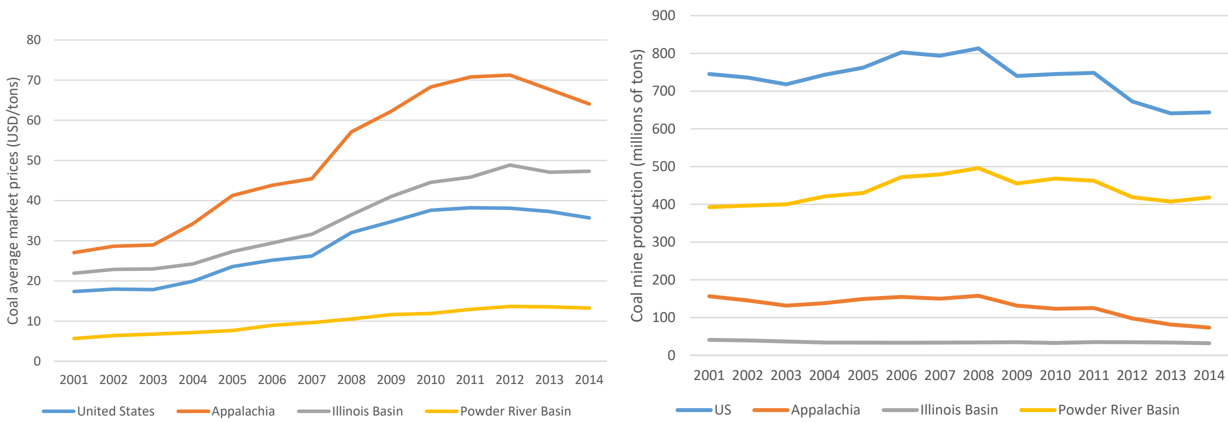
A second perspective to evaluate the impact of the network structure on coal volatility is through changes in the network's clusters using the maximal modularity measure as an indicator of community structure as proposed by the Brandes et al. [50] algorithm. High coal volatility may lead to more chaotic changes in the pattern of trade between states, and therefore low modularity. During the period 1998–2014, the correlation between modularity and coal volatility for each period is −0.47, and −0.53 to bituminous coal volatility. Additionally, the modularity for months of maximum and minimum volatility is below and above the average modularity, respectively, for the period 1998–2014 according to the Brandes algorithm and the Walktrap algorithm used as a baseline algorithm (see Table 4).

Even though 25 U.S. states produce coal, the most critical coal producer states are in three regions: the Powder River Basin (Wyoming and Montana), the Appalachian Basin (West Virginia and Kentucky), and the Illinois Basin (Illinois and western Kentucky). The competition among these regions, declining and changing prices (see Figure 4a) and reduction of the most accessible, lowest-cost coal reserves led to an uneven contraction of the coal production of these three regions by 16%, 53%, and 7%, respectively, from 2008 to 2014 (see Figure 4b). These changes in prices and production also affected the trade network structure between high and low volatility periods, as we saw above.

Table 4. Modularity for periods of maximum and minimum coal volatility according to the algorithms of Brandes et al. [50] and Pons and Latapy [51] (Walktrap as a baseline).

	Walktrap	**Brandes**
Maximum volatility	0.34	0.42
Minimum volatility	0.43	0.47
Average (1998–2014)	0.41	0.44

Forecasting the volatility of the energy market is very important for the stability of the world economy and for the millions of persons that work in this sector and consume its products. So, even though it would be desirable to interpret the impact of the causalities found significant, our objective in this paper is to find new ways to detect leading indicators of the energy market volatility. They could become inputs of a multivariate time series model that combines the autoregressive effect with the patterns of a dynamic trade network.



(**a**) Coal prices (**b**) Coal production

Figure 4. U.S. coal average market prices (**a**) and mine production (**b**) by regions. Source: [61].

5.2. Forecasting

CCI for coal volatility is the most critical indicator to forecast the different types of coal volatility besides the lagged values of the dependent variables according to the feature importance ranking (see Table 5). Even though the first two lags of the dependent variables are the most relevant variables, the rest of the lags are more important than the rest of the variables in most cases.

The rest of CCI variables are also essential to forecast volatility, especially the CCI for electricity return. This last finding is understandable considering that coal is the primary input to generate electricity. Hence, any change in electricity prices may also affect coal volatility.

Table 5. Feature importance for coal volatility direction according to the Gini importance coefficient using Random Forests. The score represents the reduction of the impurity in the classification by each feature.

	Coal	Bituminous Coal	Sub-Bituminous Coal
1 lag dependent variable	23.16%	18.83%	23.18%
2 lag dependent variable	13.78%	13.77%	27.75%
3 lag dependent variable	9.03%	11.51%	8.76%
4 lag dependent variable	7.63%	10.33%	2.11%
5 lag dependent variable	9.11%	8.90%	1.50%
6 lag dependent variable	11.55%	10.03%	7.67%
7 lag dependent variable	7.66%	6.25%	18.11%
CCI for electricity volatility	3.58%	5.68%	3.75%
CCI for coal volatility	6.20%	5.64%	2.97%
CCI for bituminous coal volatility	3.73%	3.97%	
CCI for electricity return	4.57%	5.10%	4.21%

Our model significantly outperforms the base model using the SVM and RF algorithms according to the Matthews correlation coefficient and the test error (Tables 6 and 7, respectively). The p-value that compares the results of both algorithms of our model against the base model is 1.6% for the MCC and 7.4% for the test error. SVM shows a better result than RF and a more remarkable improvement to the base model. Additionally, the forecast of coal volatility shows the best results, followed by the bituminous coal volatility representing its major component.

These results confirm our previous analysis and show that CCI indicators of a coal trading network improve coal's volatility forecast.

Table 6. Matthews correlation coefficient between the CCI and the base model. Base is the model with seven lags of the dependent variable and CCI includes these variables and the CCI variables. *p*-value is based on the *t*-test mean difference between all the versions of the CCI and the base model.

		CCI		**Base**	
		SVM	**RF**	**SVM**	**RF**
Coal volatility	MCC	0.728	0.768	0.590	0.583
	Standard error	0.012	0.007	0.166	0.112
Bituminous	MCC	0.656	0.498	0.622	0.557
coal volatility	Standard error	0.215	0.160	0.154	0.173
Sub-bituminous	MCC	0.553	0.472	0.000	0.256
coal volatility	Standard error	0.188	0.139	0.000	0.078
Total	MCC	0.646	0.579	0.404	0.465
	Standard error	0.098	0.084	0.122	0.089
	p-value	0.016			

Table 7. Test error between the CCI and the base model. Base is the model with seven lags of the dependent variable and CCI includes these variables and the CCI variables. *p*-value is based on the *t*-test mean difference between all the versions of the CCI and the base model.

		CCI		**Base**	
		SVM	**RF**	**SVM**	**RF**
Coal volatility	Test error	0.131	0.110	0.221	0.243
	Standard error	0.002	0.019	0.102	0.097
Bituminous	Test error	0.303	0.390	0.414	0.349
coal volatility	Standard error	0.069	0.051	0.050	0.022
Sub-bituminous	Test error	0.514	0.536	1.000	0.394
coal volatility	Standard error	0.175	0.159	-	0.086
Total	Test error	0.316	0.345	0.545	0.329
	Standard error	0.082	0.081	0.117	0.049
	p-value	0.074			

6. Conclusions

This paper demonstrates that the dynamic and structure of the coal trade network, particularly the component causality index, have a significant relationship with the next period of coal volatility.

Changes in the trading network structure are also related to coal volatility. An increase in the connectedness of the trading network anticipates a rise in coal volatility. Likewise, less structured networks characterized by low modularity are associated with highly volatile periods. In general, high volatility may lead to significant changes in the trading pattern between states. Therefore, the trading network structure becomes less stable.

A nonlinear correlation such as the Brownian distance correlation helped to detect additional indicators that were not recognized by the linear Granger causality test. Hence, the forecast of a financial time series may improve using these features identified by a nonlinear approach.

Even though the U.S. states are large economies and, in many cases, more affluent than many countries, this paper shows that they still act as live trade agents. Their behaviors impact the energy market volatility and stability. In this research, rather than modeling the states' response as trade agents, our interest is to learn from their behavior and extract relevant signals that could help anticipate future energy market movements.

As the trading activity is closely related to energy price movements, the behavior of a particular market's components may impact market risk. In this respect, the proposed CCI could be integrated with another set of features, not alone, into a risk management system for investors and regulators.

The broad impact of this research lies in the understanding of mechanisms of the instability and risk of the energy sector as a result of a complex interaction of the network of producers and traders.

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