Trading Network and Systemic Risk in the Energy Market

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***Abstract*—This paper evaluates the effect of energy trading networks on the volatility of coal, oil, natural gas, and electricity. This research conducts a longitudinal analysis using a time series of static coal trading networks to generate a dynamic trading network, and uses the component causality index as a leading indicator of systemic risk. This research finds out that the component causality index, based on degree centrality, anticipates or moves together with coal volatility and in less degree with gas and electricity volatility during the period 2007-14. 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.**

I. Introduction

The contraction of oil prices since 2014 has had a negative systemic effect worldwide especially for oil producing countries and for oil and energy companies. In this respect, the volatility of the energy sector has internal determinants such as the reduction of natural gas prices since 2005, technological advances in the production of electricity with less contaminant effects, the final crisis of 2008, and the geo-political changes that have affected the oil supply. Even though the evaluation of these different factors is extremely difficult, the purchase and sale of coal by power plants, where coal is the major input in the production of electricity, capture the internal transformation of the energy sector due to technological and energy price changes. For this reason, this paper evaluates the nonlinear correlation between the dynamic evolution of energy trading networks and the volatility of the main energy products which are associated with the systemic risk of the energy sector.

II. The Coal Market

The following three regions provide most of the coal consumed in the US:

- Western region and Powder River Basin
- Interior region (Illinois, Indiana, and Kentucky)
- Appalachian region

The Western region provides almost all the low sulfur sub-bituminous coal consumed in the US. The sub-bituminous coal from the Powder River Basin has low sulfur content, but a slightly lower heat content per ton. Mining in this region is done on the surface, which eases the extraction of coal and dramatically reduces prices at mine mouth.[1]

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 SO_2 emissions of bituminous and sub-bituminous coal from 1985 to 2005. 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 due mostly 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 inexpensive 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.

A. *Trade networks*

The trade and distance among coal mines and plants can have a major impact on efficiency. Therefore, in this research we propose that a longitudinal coal trade network among US states may be closely associated with the volatility of energy prices. We are not aware of previous studies that have evaluated the coal trade network among different US states, although there are several previous studies of trade networks, especially, in the international markets. Hidalgo and Hausmann (2009) create a bipartite network to represent global trade and the interaction between countries and their products. They conclude that differences of income across countries can be explained by variations on economic complexity. Kali et al. (2013) use a similar trade network, however, they conclude that density and trade network proximity are the determinant factors that explain high growth country rates. Cole et al. (2013) find that Japanese firms' emissions are affected by the emissions of neighboring firms, and Chintrakarn and Millimet (2006) observe that trade among US states has

[1] Mine mouth refers to the mine's location.

a negative environmental impact; however, these two last articles are not based on trade networks.

III. Technical Approach

A. Methods

In this section, I describe the following methods used to build corporate news networks and evaluate the causality among the main time series under analysis.

1) Brownian distance: Székely and Rizzo (2009) 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 with respect to 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:

$$\nu(X,Y) = \sqrt{\|f_{X,Y}(t,s) - f_X(t)f_Y(s)\|^2} \quad (1)$$

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:

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

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

$$R^2 = \begin{cases} \frac{\nu^2(X,Y)}{\sqrt{\nu^2(X)\nu^2(Y))}}. & \nu^2(X)\nu^2(Y) > 0 \\ 0, & \nu^2(X)\nu^2(Y) = 0 \end{cases} \quad (3)$$

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

In this paper, I evaluate the non-linear 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 $R(X_{t-l}, Y_t)$. In particular, I wish to explore the lead-lag relationship among the time series under study. 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 an 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 (Tsay, 2010).

2) Centrality: Degree centrality is simply the sum of the edges of a vertex v_i:

$$D_c(v_i) \doteq \sum_j a_{ij} \quad (4)$$

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

B. Data

This research explores the impact of the monthly national trading dynamic among U.S. states and the coal, oil, natural gas, and electricity spot price volatility from January, 2007 to December, 2014. I selected a sample that includes two years before and four years after the financial crisis period of 2008-2010.

I used the monthly time series of the spot log prices of the fossil fuel series for the period 2007-2014: 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 comes from fuel purchases by steam electric generating plants of 50 MW or greater for 27 U.S. states (see Table I) reported in the FERC Form No. 423 Environmental Information Agency (2005). There are about 10 times more records for bituminous coal purchases than for sub-bituminous coal purchases.

C. Research design

I built a national network based on the total coal purchased where the nodes are US states and the weight of the edges is the amount purchased from one state to another state. I conducted a longitudinal analysis using a monthly time series of static networks to generate a dynamic trading network from January, 2007 to December, 2014. I calculated degree centrality (Bonacich, 1972, 2007) 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 change of trading patterns or vice versa.The association between degree centrality and volatility might become more important during periods of crisis as systemic risk increases and the trade among states may also change.

For the analysis of systemic risk, I use an index called Component Causality Index (CCI) proposed by Creamer (2016) which is the proportion of components of a particular system or index that have significant causal

TABLE I: 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, NV*, NM, UT*, WY*
	R9	Pacific	AK, CA, HI, OR, WA

relationships with a dependent variable over a given period. In the case of this research, the components are the U.S. states and the dependent variables are electricity and bituminous coal volatility as most of the coal traded is bituminous coal. The main idea is that if there are important changes in the components of a system or an index, the volatility of the system will also be affected, and therefore could be anticipated by the change of behavior of its components. I used the CCI as a leading indicator of systemic risk evaluating the impact of the network variables on the next period volatility for the complete time series. I calculated monthly volatility as the standard deviation of the last 12 months, and I used the volatility of coal, natural gas, WTI and electricity as the proxy of systemic risk for each particular market.

Using a moving window based on the previous 12 months, I evaluated if degree centrality has a causal relationship or have an effect on the next period volatility of electricity and bituminous coal volatility by state. Based on these results, I calculated the CCI as the proportion of states that show significant dependence between degree centrality and the next period volatility of each state using the Brownian distance test of independence. Finally, I evaluated if seven lags of the CCIs have a significant causal relationship on the volatility and return of coal, natural gas, WTI and electricity.

This research used the energy, and sna packages for R to calculate the Brownian distance test of independence and the degree centrality.[2]

IV. Results

The CCIs for electricity volatility and for bituminous coal volatility 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. All the lags of the CCI for bituminous coal volatility show significant correlations with coal and gas volatility. The CCI for electricity volatility also shows significant correlations with electricity volatility (lags 1, 6 and 7) and with gas volatility (lags 2, 6, and 7) (see Table II).

The graphs of the time series also show that CCI for bituminous coal volatility follows more closely coal and gas volatility (Figure 1). The CCI for bituminous coal volatility sharply increases about 4-5 months before the major spikes of bituminous coal volatility (first quarter of 2001, the fourth quarter of 2004, and the third quarter of 2009). In general, the causality analysis shows that certain CCIs act as leading indicators of periods of higher volatility or when the systemic risk increases.

The impact of CCI on WTI volatility is much weaker considering that WTI prices are mostly affected by geopolitical factors that affect the oil supply and demand.

The evolution of the bituminous and sub-bituminous coal trade network included in Section I of Figure 2 shows that very few hubs are important coal providers, specifically, those from the Mountain region. This process is more noticeable for the sub-bituminous coal trade network presented in Section II of Figure 2 where Wyoming, and with less importance Colorado and Montana, are major fuel providers. Even though New Mexico and Arizona were disconnected from the network during the 1990s, they connected with the rest of the network during the 2000s. These states are part of the Mountain region. Plants of this region, as well as those of West South Central, may have had a boost to their productivity due to the proximity to the Powder River Basin, a large sub-bituminous area.

V. Final Comments

This paper demonstrates that the coal trading network structure have a significant relationship with the next period market volatility or with systemic risk. The component causality index has been applied to this particular problem; however, it could also be used with other trading networks. Although the trading activity is closely related to energy price movements, the behavior of the components of a particular market or system may have an impact on the risk of the system. In this respect, the proposed CCI can also be integrated into a risk management model to forecast systemic risk when the CCIs are combined with main accounting, financial and economic variables.

The broad impact of this research lies in the understanding of mechanisms of financial instability and risk as a result of a complex interaction of the dynamics of social networks and financial products. Problems of global financial instability are generally solved using short term measures that limit the most evident effects of the crisis, not its causes.

[2]Information about R can be found at <http://cran.r-project.org>.

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 **
Coal bit.	0.19 *	0.23 **	0.24 **	0.26 **	0.30 **	0.37 **	0.37 **
Coal sub-bit.	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 bituminous coal 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 *
Bituminous coal	0.21 *	0.20 **	0.21 **	0.18 *	0.20 **	0.19 *	0.17 *
Sub-bituminous 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 **

TABLE II: Brownian distance correlation between lagged component causality index (CCI) and volatility of energy products. Columns 1 to 7 represent lagged values.

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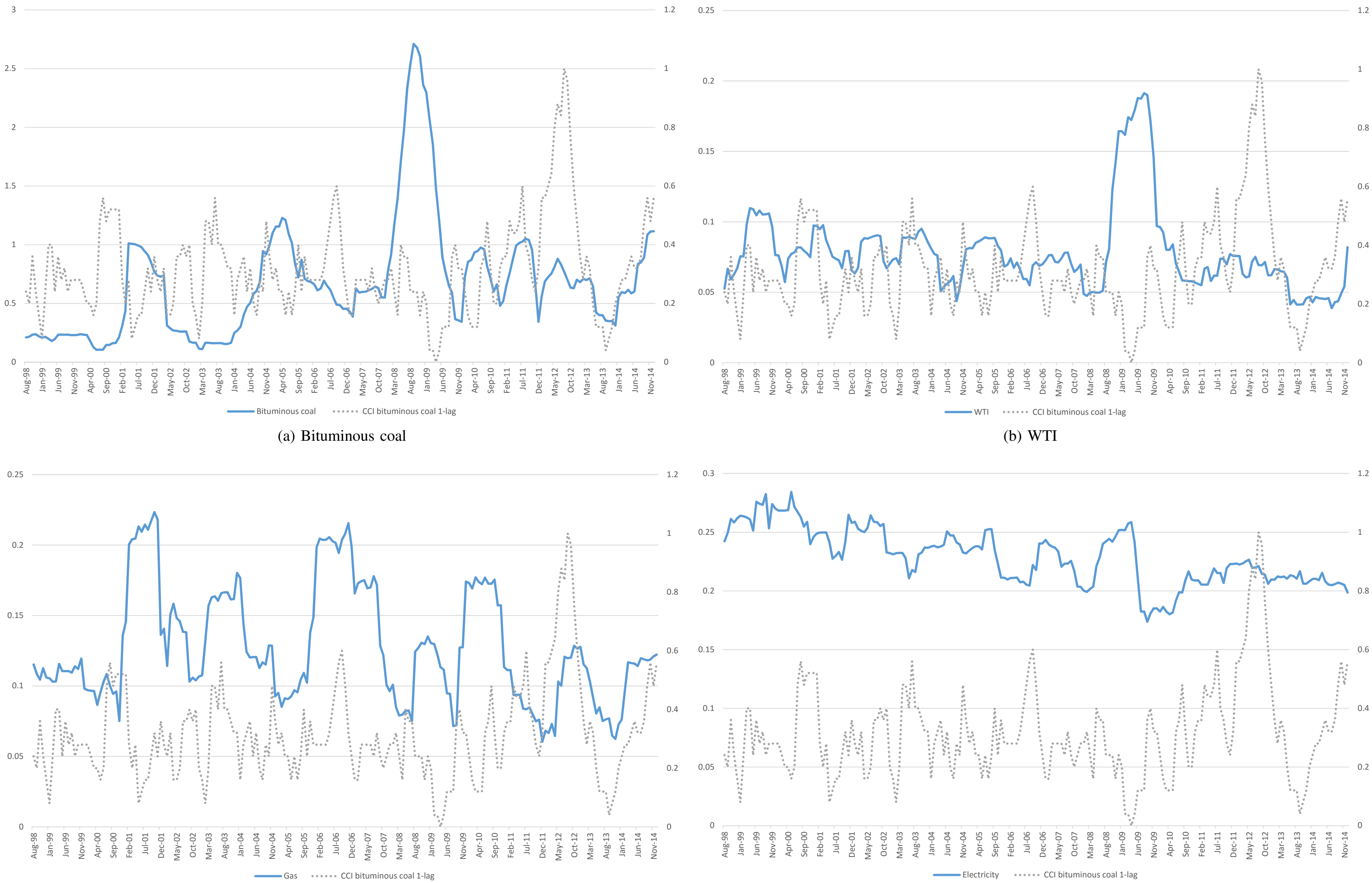


(a) Bituminous coal

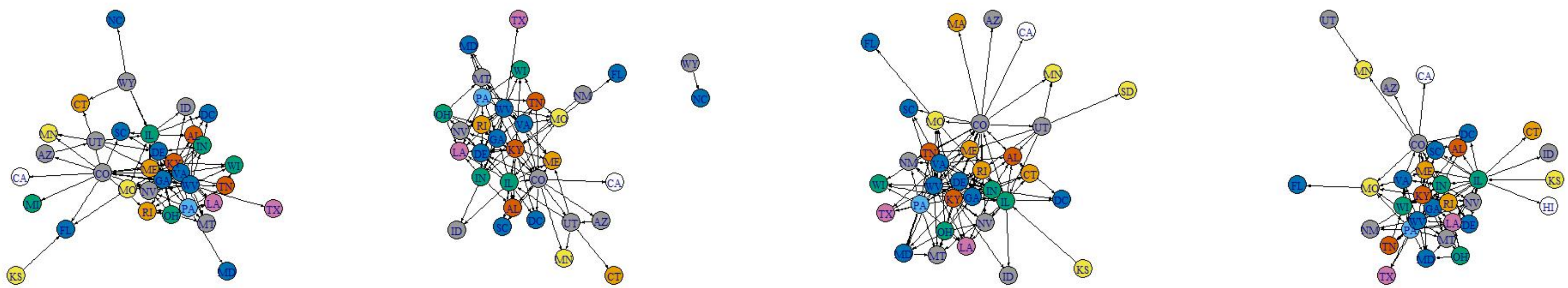
(b) WTI

(c) Gas

(d) Electricity

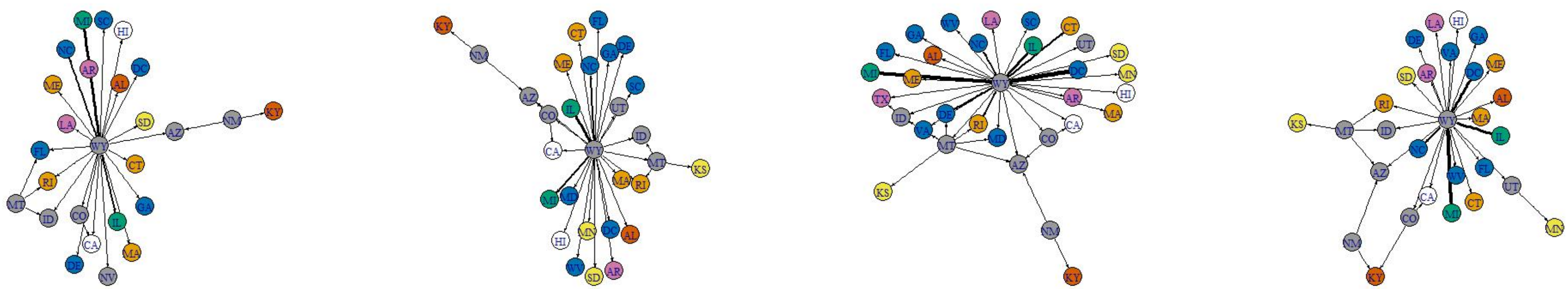
Fig. 1: Coal bituminous, WTI, gas, and electricity volatility, and 1-lag CCI used to forecast bituminous coal. Right Y axis is for CCI.

.[I. Bituminous coal]



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

.[II. Sub-bituminous coal]



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

Fig. 2: 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).