

A Non-Linear Dependence Analysis of Oil, Coal and Natural Gas Futures with Brownian Distance Correlation

Germán G. Creamer

Stevens Institute of Technology
Castle Point on Hudson, Hoboken, NJ 07030
gcream@stevens.edu

Bernardo Creamer

CIAT - IFPRI, Washington, DC
ASTEC, Ecuador
jbernardoc@gmail.com

Abstract

This paper proposes the use of the Brownian distance correlation to conduct a lead-lag analysis of financial and economic time series. When this methodology is applied to asset prices, the non-linear relationships identified may improve the price discovery process of these assets.

The Brownian distance correlation determines relationships similar to those identified by the linear Granger causality test, and it also uncovers additional non-linear relationships among the log prices of oil, coal, and natural gas.

1 Introduction

The final report of the bi-partisan Project 88 of the US Congress (Stavins 1989) concluded that the environmental and economic debt the nation has acquired by not establishing appropriate environmental regulations was ineludible. The negative effects of SO_2 emissions have been thoroughly evaluated, especially, health deterioration issues caused by acid rain and other unwanted impacts which generate significant social costs. Acid rain caused by sulfate acid deposition can be detrimental to ecosystems, plants and animals, both aquatic and terrestrial (Smith et al. 2010).

The US Congress passed the Clean Air Act (CAA) Amendments of 1990 that included, under Title IV, an allowance market for the control of sulfur dioxide (SO_2) emissions, by way of the acid rain control initiative. This constituted a market based mechanism for controlling the cost of abating SO_2 emissions and a movement away from more traditional command-and-control regulations. (Carlson et al. 2000) argued that savings in SO_2 emissions abatement costs in the electric power sector were \$700 to \$800 million per year when adopting this mechanism compared to traditional command and control regulation procedures.

The regulation of SO_2 and NO_x emissions mostly affects the electric power sector (Banzhaf, Burtraw, and Palmer 2002). This is mainly because 37.4% of the electricity produced in the US in 2012 is based on burning coal (see Table 1), which accounts for nearly 70% of the total SO_2 emissions. Furthermore, coal-sourced electricity is likely to be a principal source of energy for at least several more decades given that the US has the largest amount of coal

Year	Coal	Oil	Nat.gas	Nuclear	Ren.En.	Other
2000	51.72%	2.92%	15.81%	19.83%	9.38%	0.35%
2001	50.96%	3.34%	17.10%	20.57%	7.70%	0.32%
2002	50.10%	2.45%	17.91%	20.22%	8.90%	0.42%
2003	50.83%	3.07%	16.74%	19.67%	9.15%	0.55%
2004	49.82%	3.05%	17.88%	19.86%	8.85%	0.53%
2005	49.64%	3.01%	18.77%	19.28%	8.82%	0.48%
2006	48.97%	1.58%	20.09%	19.37%	9.49%	0.51%
2007	48.51%	1.58%	21.57%	19.40%	8.49%	0.45%
2008	48.21%	1.12%	21.44%	19.57%	9.25%	0.42%
2009	44.45%	0.98%	23.31%	20.22%	10.57%	0.45%
2010	44.78%	0.90%	23.94%	19.56%	10.36%	0.45%
2011	42.27%	0.74%	24.72%	19.27%	12.52%	0.48%
2012	37.42%	0.56%	30.35%	18.97%	12.22%	0.47%

Table 1: Net electricity generation: Participation of energy source. Ren. en. refers to renewable energy. Source: US Energy Information Administration

reserves in the world (World Energy Council 2010). In the US alone in 2008, the electric power industry produced and emitted nearly 7.9 million tons of SO_2 emissions as a byproduct of their activity, out of a total of 9.5 million tons (Environmental Protection Agency 2008). SO_2 emissions generated by electric power plants accounted for 83.3% of the total sulfur emissions in 2008. Despite the fact that SO_2 emissions have consistently been reduced since the start of the CAA Amendments in 1990, they are still considered to be high and new restrictions are being planned.

The major contaminant effects of coal and the reduction of natural gas prices since 2005 have led to a contraction in the proportion of coal and an increase in the share of natural gas used in the production of electricity in the US since the year 2000 (see Table 1). According to one of the future scenarios considered by the EIA (U.S. Energy Information Administration 2013), natural gas and coal will account for 43% and 27% of total electricity generation in 2040, respectively. The share of oil on electricity generation has also decreased since 2000 in the US; however, it is still important at the world level, where its share is about 5% (U.S. Energy Information Administration 2011).

This analysis shows that the main fossil fuels (oil, coal and natural gas) have some common elements that affect all fuels, such as emissions control. Markets and political forces also affect fuel prices, especially, in the case of oil. It is

also possible their prices are mutually determined or that one price depends on another one. (Mohammadi 2011) finds that in the case of the US, the oil and natural gas prices are globally and regionally determined, respectively, and coal prices are defined by long-term contracts. (Mohammadi 2009), using cointegration analysis, exposes a strong relationship between electricity and coal prices and an insignificant relationship between electricity and oil and/or natural gas prices. (Asche, Gjolberg, and Volker 2003) and (Bachmeier and Griffin 2006) find very weak linkages among oil, coal and natural gas prices using cointegration analysis, while crude oil and several refined product prices are integrated (Asche, Gjolberg, and Volker 2003). (Hartley, Medlock, and Rosenthal 2008) notice an indirect relationship between natural gas and oil prices. Even more, (Aruga and Managi 2011) detect 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.

(Mjelde and Bessler 2009) observe that oil, coal, natural gas and uranium markets are not fully cointegrated. (Asche, Osmundsen, and Sandsmark 2006) indicate that the U. K. energy market between 1995 and 1998 was highly integrated where the demand was for energy rather than for a particular source of energy. (Brown and Yucel 2008) show that oil and natural gas prices have been independent since 2000; however, when weather and inventories are taken into consideration in an error correction model, crude oil prices have an effect on natural gas prices. Similar results are obtained by (Ramberg 2010) using cointegration analysis. (Amavilah 1995) observes that oil prices influence uranium prices.

The causality analysis is also used to evaluate the relationship between spot and future commodity prices. (Asche, Gjolberg, and Volker 2008)—using a non-linear Granger causality test—shows that neither the futures nor the spot crude oil market leads the relationship.

Most of the studies mentioned are based on cointegration analysis and Granger causality; however, none of these studies have used a non-linear correlation measure to evaluate the lead-lag relationship among the fossil fuels.

This paper proposes to use the Brownian distance correlation to conduct a non-linear lead-lag dependence analysis of coal, oil and gas. Section 2 introduces the different methods explored in this study; Section 3 presents the data used; Section 4 explains in detail the estimation techniques; Section 5 presents the results of our tests; Section 6 discusses the results, and Section 7 draws some conclusions and final comments.

2 Methods

2.1 Granger causality

Granger causality ((Granger 1969; 1980) and (Granger 2001)) is a very popular methodology used in economics, financial econometrics, and in many other areas of study, such as neuroscience, to evaluate the linear causal relationship among two or more variables. According to the basic definition of Granger causality, the forecasting of the dependent variable Y_t with an autoregressive process using Y_{t-l} as its lag- l value, should be compared with another autoregres-

sive process using Y_{t-l} and the vector X_{t-l} of independent variables. So, 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:

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

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

where the residual 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 based on the F-test. The order of the autoregressive model is selected based on the Akaike information criterion (AIC) or the Bayesian information criterion (BIC).

2.2 Brownian distance

(Székely and Rizzo 2009) have proposed a multivariate dependence coefficient called distance correlation that can be used with random vectors of multiple dimensions.

(Székely and Rizzo 2009) also proposed the Brownian distance covariance, which captures the covariance with respect to a stochastic process. Distance covariance ($\nu(X, Y)$) between the random vectors X and Y measures the distance between $f_X f_Y$ and $f_{X,Y}$ and is obtained as the square root of $\nu^2(X, Y) = \|f_{X,Y}(t, s) - f_X(t)f_Y(s)\|^2$ where $\|\cdot\|$ is the norm, t and s are vectors, 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 .

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 paper this test is the distance covariance test of independence.

Likewise, distance variance ($\nu(X)$) is the square root of $\nu^2(X) = \|f_{X,X}(t, s) - f_X(t)f_X(s)\|^2$.

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

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

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

This paper proposes to evaluate the non-linear dependence of the current value of Y (Y_t) on the l lagged value of X (X_{t-l}) with the Brownian distance correlation $R(X_{t-l}, Y_t)$. We particularly want to explore the lead-lag relationship among the time series under study. In general, 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 $R(X_t, Y_{t-l}) =$

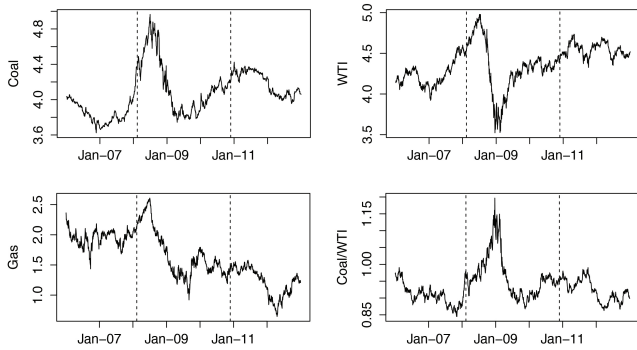


Figure 1: Log prices by product. Horizontal lines represent structural breaks according to the Bai-Perron test of the Coal/WTI log prices ratio

0 then there is no lead lag relationship between X and Y (Tsay 2010).

3 Data

We used the daily time series of one month forward futures log prices of the fossil fuel series for the period 2006-2012: West Texas Intermediate oil (WTI), the Central Appalachian [bituminous] coal (Coal) and natural gas (Gas) from the New York Mercantile Exchange (NYMEX) (see Figure 1). These series have some relevant autoregressive effects according to the autocorrelation function (ACF) and the partial ACF (see Figure 2); however, the emphasis of this paper is on the lagged cross-correlation, which will be explored in the next sections.

4 Estimation Techniques

We evaluated the stationarity of the series using the augmented Dickey-Fuller (ADF) test. We applied the Bai-Perron (Bai and Perron 1998) test to detect structural breaks of the coal/WTI log prices ratio, considering that these are the most dominant products of the causality analysis. The Bai-Perron test is particularly useful when the break date is unknown and there is more than one break date. For the complete series and for each of the periods identified with the Bai-Perron test, we tested the non-linearity of the series using the White (Lee, White, and Granger 1993) and the Terasvirta test (Terasvirta, Lin, and Granger 1993). We also conducted a non-linear lead-lag relationship analysis using the Brownian distance correlation between each pair of variables and up to seven lags (one week). We compared these results with the Granger causality test and evaluated the cointegration of the different pairs using the Johansen test (Johansen 1988b; 1988a) to decide if we had to use the VAR error correction model. In our analysis, \rightarrow denotes relationship. For instance, $X \rightarrow Y$ indicates that X Granger causes Y when Granger causality is used or Y is dependent of X when the Brownian distance correlation is used. Therefore, the p-value of every test only evaluates the effect of one variable into another one, and is not affected by other time series.

	2006-12	Pre-crisis	Crisis	Recovery
WTI	-1.70	1.72	-1.21	-2.48
Coal	-2.13	-1.57	-1.14	-2.74
Gas	-2.78	-3.36	-1.43	-1.35

(a) Log Prices

	2006-12	Pre-crisis	Crisis	Recovery
	-13.25**	-7.07**	-9.24**	-8.13**
	-10.93**	-7.61**	-9.54**	-7.72**
	-11.09**	-8.11**	-8.86**	-7.88**

(b) Log returns

Table 2: ADF test by product and period for log prices and log returns. *: $p \leq 0.05$, **: $p \leq 0.01$.

5 Results

The ADF test indicates that all log price series are non-stationary (see Table 2) and, as expected, the log return series are stationary. So, we used the log returns (the first difference of the log price) to conduct the causality tests. The Bai-Perron test applied to the coal/WTI ratio series split the data into the following periods: January 3, 2006 - January 17, 2008 (pre-crisis period), January 18, 2008 - November 17, 2010 (financial crisis period), and November 18, 2010 - December 31, 2012 (recovery period) (see Figure 1). We conducted our analysis in these different periods and in the complete series 2006-2012.

Table 3 includes the descriptive statistics of the log price series and their cross-correlation values. The correlations between the series significantly increase during the crisis period, as can be observed by the convergence of all the series in Figure 1. In the pre-crisis period the correlation between WTI and Coal is 0.64; however, after the crisis this correlation falls to 0.08. The opposite happens with the correlation between Coal and Gas where this value increases from 0.29 to 0.82, while the correlation between Gas and WTI changes from 0.07 to -0.15. These cross-correlation changes indicate a high interrelationship among the three fossil fuel series; however, the long-term dynamic linkages are better captured by the lead-lag and Granger causality analysis included in Table 4.

As none of the log price pairs are cointegrated in the different periods at the 5% significance level according to the Johansen test, we used a vector autoregressive (VAR) model of the log return series to run the Granger causality test with 7 lags instead of using the VAR error correction model.

6 Discussion

During the complete period 2006-2012, WTI and Coal show a feedback relationship according to the Brownian distance, and only the WTI \rightarrow Coal relationship is maintained conforming to the Granger causality test with a 5% significance level (see Table 4). Coal also Granger causes Gas for the lags 5 and 6. Additionally, the Brownian distance recognizes the following dependences (lags between parentheses): Gas (1, 7) \rightarrow Coal, Coal (2, 3) \rightarrow Gas, and WTI (1) \rightarrow Gas. Very

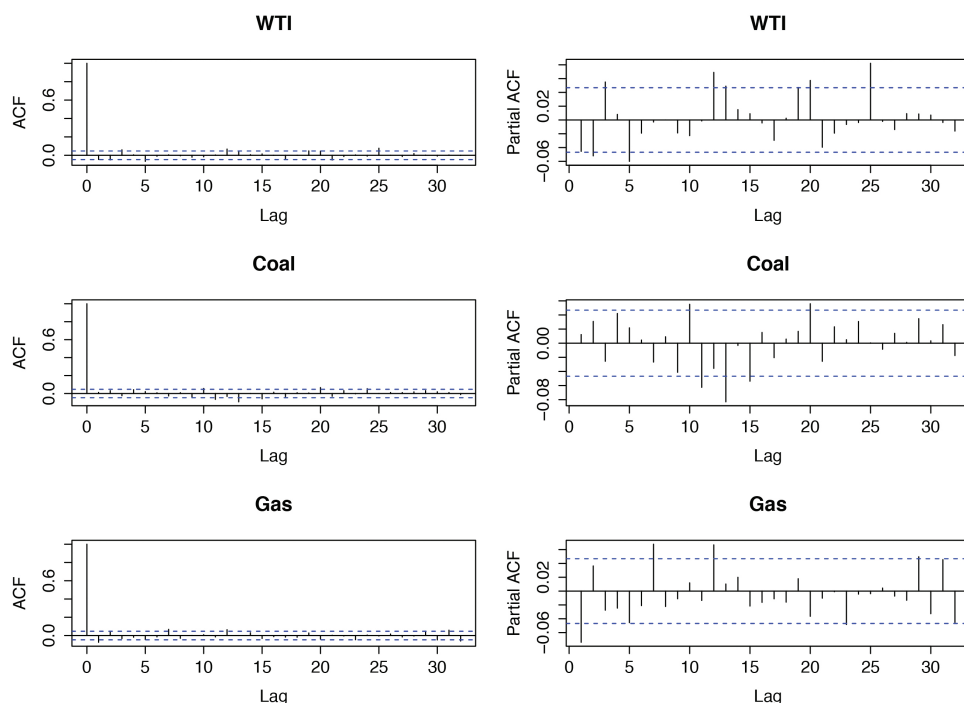


Figure 2: ACF and Partial ACF by product

2006-12			
	Coal	WTI	Gas
Mean	4.08	4.37	1.62
St.dev.	0.26	0.25	0.41
Skewness	0.79	-0.47	0.05
Kurtosis	0.34	0.48	-0.63
Correlation Matrix: 2006-12			
WTI	0.64		
Gas	0.16	-0.03	1
Pre-crisis			
WTI	0.55		
Gas	0.29	0.07	1
Crisis			
WTI	0.67		
Gas	0.85	0.65	1
Recovery			
WTI	0.08		
Gas	0.82	-0.15	1

Table 3: Descriptive statistics and correlation matrix of the log price series

similar relationships are observed during the crisis period (2008-2010). Both tests indicate that the Gas \rightarrow WTI dependence is relevant during the pre-crisis period, and the Brownian distance recognizes the importance of the relationship WTI (1) \rightarrow Coal and Gas (1,2) \rightarrow Coal. During the recovery period, only the Coal \rightarrow Gas relationship is relevant for both tests, especially for the Granger causality tests. Most of the additional relationships observed using the Brownian distance test, which were not recognized by the Granger causality test, were confirmed to be relevant non-linear relationships according to the White and Terasvirta tests (see Table 4). Hence, the Brownian distance correlation recog-

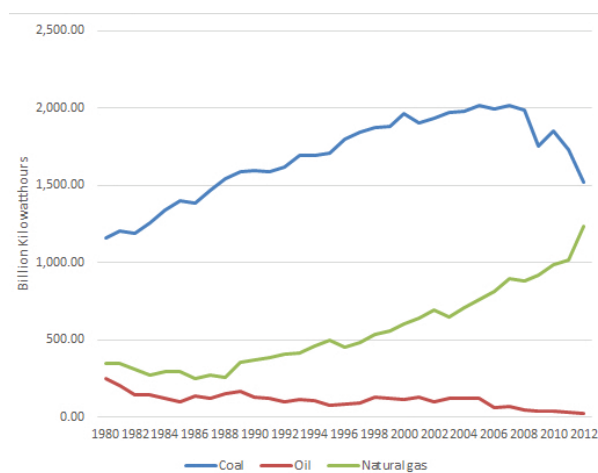


Figure 3: Evolution of net electricity generation by energy source. Source: US Energy Information Administration

nizes an important number of dependences, and some of them are confirmed by the Granger causality test. The non-linear relationships identified by the Brownian distance correlation challenge the traditional view that commodity prices are mostly determined by international market and political forces. Examples of these forces are the decisions of the Organization of the Petroleum Exporting Countries (OPEC) to curtail oil production or a political crisis in the Middle East. These non-linear relationships may have an impact on the

Periods	Lags/Effects	1	2	3	4	5	6	7
2006-12	WTI → Coal	**	**	**	**	**	**	**
	Coal → Gas					**	**	*
Pre-crisis	Gas → WTI	**	**	**	*	*		
	WTI → Coal	**	**	**	**	**	**	**
Crisis	Coal → Gas					*	*	
	Coal → Gas	**	**	**	*	*		

(a) Granger Causality: significance level

Periods	Lags/Effects	1	2	3	4	5	6	7
2006-12	WTI → Coal	0.12**	0.07**	0.09**	0.07**	0.08**	0.08**	0.07**
	Gas → Coal	0.06*	0.06	0.05	0.04	0.04	0.06	0.07*
	Coal → WTI	0.09**	0.08**	0.09**	0.10**	0.08**	0.09**	0.07*
	Coal → Gas	0.05	0.08**	0.07*	0.05	0.06	0.05	0.05
Pre-crisis	WTI → Gas	0.09**	0.05	0.04	0.04	0.04	0.05	0.04
	WTI → Coal	0.18**	0.09	0.09	0.09	0.07	0.07	0.09
	Gas → Coal	0.12*	0.11*	0.08	0.07	0.08	0.09	0.09
Crisis	Gas → WTI	0.12*	0.08	0.07	0.08	0.07	0.07	0.08
	WTI → Coal	0.16**	0.11*	0.11*	0.10*	0.11	0.11*	0.10
	Gas → Coal	0.08	0.07	0.09	0.06	0.07	0.08	0.11*
	Coal → WTI	0.13**	0.11*	0.12**	0.14**	0.13**	0.13**	0.09
Recovery	Coal → Gas	0.08	0.11*	0.12*	0.07	0.10	0.07	0.09
	WTI → Gas	0.11*	0.07	0.07	0.07	0.07	0.06	0.08
	Gas → Coal	0.07	0.09	0.09	0.07	0.08	0.09	0.07
	Coal → Gas	0.09	0.13*	0.08	0.07	0.08	0.07	0.09

(b) Brownian distance correlation

Table 4: Granger causality (panel a) and Brownian distance correlation (panel b) of log return series. Granger causality panel only includes this information. Non-relevant relationships are not are excluded. Yellow indicates non-linearity according to either the White or Terasvirta test, and green means that both tests detect non-linearity with a 5% significance level. *: $p \leq 0.05$, **: $p \leq 0.01$.

selection of inputs used to generate electricity in the US. Figure 3 shows that electricity generated with coal reached its peak in 2007 and substantially decreased afterwards. On the contrary, electricity generated with natural gas has been increasing since 1990, especially since 2009. Between the years 2000 and 2012, the proportion of electricity generated by coal and oil have decreased from 51.7% and 2.9% to 37.4% and 0.6% respectively while the proportion of electricity generated by natural gas almost doubled from 15.8% to 30.4% (see Table 1). The increase of the electricity generated with natural gas is equivalent to the contraction of electricity generated with coal. This can be partially explained by the decline of natural gas log prices since December 2005 to April 2012 (see Figure 1). The CAA restrictions on SO_2 emissions and the relative reduction of natural gas prices led the power plants to partially substitute coal with natural gas as their main input. As more power plants have increased their consumption of natural gas, its price has also increased following similar trends of oil and coal. The linear and non-linear lead-lag analysis also indicates that coal's price has an important effect on natural gas price, especially during the crisis and recovery period. This particular case illustrates the non-linear dynamic among the prices of the different commodities studied and the major interrelationship that exists among the three fossil fuel series. The main application of these non-linear relationships is to improve the forecast of commodity prices as demonstrated by (Creamer 2015).

7 Conclusions

This paper proposes the use of the Brownian distance correlation to conduct a lead-lag analysis of financial and economic time series. When this methodology is applied to asset prices, the non-linear relationships identified may improve the price discovery process of these assets.

The Brownian distance correlation determines relationships similar to those identified by the linear Granger causality test, and it also uncovers additional non-linear relationships among the log prices of oil, coal, and natural gas. The reduction of gas prices since 2005 shifted the demand from coal to natural gas by US electric power plants; however, this change eventually led to an increase in gas prices.

This research can be extended to explore the lead lag relationship between spot and future prices of complex assets such as commodities and foreign currencies applied to different markets.

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