ENERGY PRICE DYNAMICS IN THE REAL ECONOMY: CAUSAL EVIDENCE

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ABSTRACT

The variation of energy prices has been a traditional source of shocks to the real economy. In many cases, this variation has manifested in jumps in energy prices that were characterized by some persistence. From another perspective, energy price volatility has historically been noted and its effects on real economy debated. Historically, the importance of the shocks to the real economy has led them to be labeled as energy crises, as they were argued to have resulted in substantial changes in real prices that induced changes in behavior on the demand and supply sides of the many markets. This paper re-examines evidence of such a linkage by considering the transmission of energy prices into soft commodity prices. This nexus lies within the core of any real effects as softs include food-related commodities. The paper contributes to the literature by re-examining this linkage with a close eye on the role played by structural breaks within a time series and by considering the question of causality within a nonlinear framework. The paper finds that functional form is a critical specification that conditions inference. Using linear forms, we find no cointegration between energy and food in the full sample under the maintained hypothesis that there are no structural breaks. Using linear nonparametric methods, we examine the series for structural breaks and find evidence of their importance. Based on subdivisions of the sample period as suggested by the structural break examination, within the structural break intervals identified we find evidence of co-integration. We next reconsider the issue within the context of nonlinear functional forms posing the question of whether evidence of structural breaks based on linear methods follow from underlying nonlinearity. Our results confirm the importance of functional form specification and we find evidence of nonlinear causality between energy and soft commodity prices.

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INTRODUCTION

The variation of energy prices has been viewed as an important source of shocks to the real economy. In many cases, this variation has manifested in jumps in energy prices that were characterized by some persistence. From another perspective, energy price volatility has historically been noted and its effects on real economy debated. Historically, the importance of the energy price shocks to the real economy has led them to be labeled as energy crises, as they were argued to have resulted in substantial changes in real effects on productivity, output, employment, and prices that induced changes in behavior on the demand and supply sides of the many markets. Indeed, Hamilton's (1983) suggestion that oil price shocks were the predominant cause of recessions in the post-War period continues to be examined and debated. For several decades, the sheer magnitude of oil price shocks has understandably peaked interest in establishing their real effects. Most notable among these crises were those in 1973 following an OPEC embargo, those following political and social disruptions and war include those 1979 following the Iranian revolution, the global oil excess supply that followed as energy demand responded to high prices, the 1990 oil price shock coincident with the Iraqi invasion of Kuwait, a decade long crisis at the start of new millennium associated with a series of unanticipated events that led to a nearly five-fold increase in oil prices.

In each case, these periods were associated with unanticipated perceived shifts in supply availability, procurement panics, and dramatic oil and energy price increases that were often cited as causing periods of more general price increases, inflation, expansion in national deficits in oil importing countries, recession, reduced productivity, and associated exchange rate depreciation, see e.g. Barsky and Kilian (2004), Hamilton (1994, 2004). In fact, early work to establish the empirical relations included a series of papers finding a negative relation between energy prices and various indicators of macroeconomic performance, see e.g. Hamilton (2003) for a review. The strong conclusion of Hamilton (1983) the oil price shocks played a major role in causing recessions continues to motivate reconsideration.

As Segal and others have noted, both policy and behavioral response to oil and energy shocks has often been substantial and this may explain the stream of empirical results that find a weak to no relationship between such shocks and the real economy. From the fiscal perspective, recognition of potential real effects has led to strong support for increased exploration (e.g. Alaskan oil from Prudhoe bay), R&D for improved energy efficiency, for alternative energy sources, and for new extraction technologies. From a monetary perspective, recognition of potential real effects has led to monetary policy actions, see e.g. Segal (2011). At the agent level, evidence of adaption and mitigation is strong. Together, these economic responses suggest the relationship between energy prices and the real economy may be weaker than first thought and at least it would be dependent on the time frame analyzed. As early work by Hooker (1996) showed, the time frame analyzed is important given variation in initial economic conditions as well as policy and economic behavioral response to oil price shocks.

Consistent with this intuition, a stream of papers have re-examined the real effects and found inconclusive results in support of negative effects. Within this stream, Darrat et al. (1996) and Hooker (1996) noted the importance of sample period and specification issues such as functional form. Barsky and Kilian (2002) noted the need to establish causal ordering of any relationship, while Kilian (2009) showed results that highlight the differential roles of demand and supply side shocks. A series of more recent papers have considered nonlinearity and presence of structural breaks in the relationships, see Hooker (2002), LeBlanc and Chinn (2004), van den Noord and Andre (2007) and Gregorio et al. (2007) each found evidence of nonlinearity and a diminution of energy price pass-through to inflation. Consistent with these results, Chen (2009) reported findings that indicate that currency depreciation, active monetary policy, and greater openness in international trade has led to diminution of oil price pass-through to inflation. Chen also reports evidence of variation of Phillips curve relationships over time.

While the aggregate effects of oil price shocks have received continued attention, the specific nature of these effects on prices requires a finer lens. Within this context the impacts of oil shocks on food commodities, as well as wholesale and retail prices is of interest. The nexus of food and energy prices has persistently raised concerns as energy price transmission into food prices can be expected to directly impact consumer welfare. Clearly, from the supply side, the energy intensiveness of the crop and animal production, processing and logistics suggests a strong linkage should exist. However, more recently, attention has been drawn to demand side dynamics with the emergence of biofuel which would seem to have amplified this nexus as crop land has shifted to biofuel crops reducing food supply, see Chen et al. 2010, McCalla (2009), Timmer (1975), Abbott et al. (2008), FAO (2008), Mitchell (2008), and OECD (2008). Despite this intuition, a majority of studies have found no evidence of causation between oil and agricultural commodity prices, e.g. see Yu et al. (2006), Zhang and Reed (2008), Kaltalioglu and Soytas (2009), Gilbert (2010), Lombardi et al. (2010), Mutuc et al. (2010), Nazlioglu and Soytas (2012). Nonetheless, several studies have reported unidirectional causation from oil to food commodities, see Hameed andArshad (2008), Arshad and Hameed (2009), Cooke and Robles (2009), and more recently, Zhang et al.(2010) who find biofuel crop prices (sugar) cause oil prices.

To re-examine the stability of any relationship between energy and food prices, a very limited number of studies have considered the issues of nonlinearity and structural breaks. Nazlioglu (2011) reconsiders linear causality using the Toda and Yamamoto (1995) nonparametric approach and nonlinear causality using the Diks and Panchenko (2006) method. Results for the linear case show no evidence of causality while results for nonlinear causality show evidence of causality from oil to maize and soy commodity prices. Nazlioglu and Soytas (2012) use monthly prices ranging from January 1980 to February 2010 and a panel of twenty four agricultural products to examine panel cointegration and Granger causality. In a model of the world crude oil and agricultural product prices, and real effective US dollar exchange rate, they find strong evidence of impact of world oil price changes on agricultural commodity prices.

Given the results from Phillips curve studies already cited (see Hamilton (2010) for a summary), it is not surprising that functional form might constitute an important specification for study of energy price transmission to other prices. However, these past studies have not addressed the question of structural change in the relationships as noted in the macro real effects literature. Campiche et al. (2007) note the need to consider parameter variation within the context of cointegrated VAR models, perhaps using tests introduced by Hansen and Johansen (1999).

Penaranda and Micola (2009) use the Bai and Perron (1998, 2003) method to identify structural breaks in the relationship between oil and non-energy (grains, softs, livestock, and metals) commodity futures prices. Using daily data for 1990-June 2011, they find univariate evidence based on a linear specification of structural breaks and changes in relationships within identified intervals.[1] Chen (2009) examined oil price pass-through to inflation in a country-level panel data set using a time-varying parameter VEC model based on one-time structural breaks using the method of Andrews (1993) and Andrews and Ploberger (1994). Avalos (2013) examines evidence in US data of a discrete break following 2006 US biofuel policy implementation and rejects structural stability and finds after that break point an increased strength of transmission of oil price innovations to corn, feedback from corn to oil and soybean prices, and existence of cointegration between oil and corn prices. Baumeister and Kilian (2013) use a similar approach based on a discrete time of break (May 2006).

Methods to identify and estimate time points of change in underlying parameters have been adopted in a limited number of studies, e.g. Du et al. (2011), Qui et al. (2012) use the Bai et al. (1998) and Bai and Perron (1997) method of estimating discrete changes in parameters of multivariate representations such as VARs or VECs. In the tradition of the long literature on detection of structural breaks as parametric changes, these approaches follow the early work of Chow (1960) and Quandt (1960). This approach searches for breaks using conventional F statistics. However, this approach requires the underlying DGM to be stable such that observed realizations of time series are stationary. Despite this shortcoming, recent work has continued to explore these methods using continuously varying parameter specifications, see Enders and Holt (2012). However, while smooth dynamics in parameters characterizes structural change, it is of interest to identify discrete points of change in the underlying data generating mechanisms. This type of change must be distinguished from structural breaks focused on parameter shifts.

This paper re-examines evidence of such a linkage by considering the transmission of energy prices into soft commodity prices. This nexus lies within the core of any real effects as softs include food-related commodities. The paper contributes to the literature by re-examining this linkage with a close eye on the role played by structural breaks within a time series and by considering the question of causality within a nonlinear framework. This builds on initial work considering inference relative to nonlinearity and structural breaks, see Koop et al. (2000). Koop et al. note that structural breaks interpreted as shifting parametric structure may well reflect underlying nonlinearity in relationships.

The paper finds that functional form is a critical specification that conditions inference. Using linear forms, we find no cointegration between energy and food in the full sample under the maintained hypothesis that there are no structural breaks. Using linear nonparametric methods, we examine the series for structural breaks and find evidence of their importance. Based on subdivisions of the sample period as suggested by the structural break examination, within the structural break intervals identified we find evidence of co-integration relying on the CUSUM method of Xiao and Phillips (2002). We next reconsider the issue within the context of nonlinear functional forms posing the question of whether evidence of structural breaks based on linear methods follow from underlying nonlinearity. Our results confirm the importance of functional form specification and we find evidence of nonlinear causality between energy and soft commodity prices.

[1] The B-P use a linear OLS to examines evidence of an unknown number of break points. They allow for correlation and heteroskedasticity in residuals and allow for change in distributions in the errors and the regressors across break intervals. As OLS is the base, stationary data in needed. The logic of their approach is to examine an increasing number of breaks using sum of squared residuals.

PAST LITERATURE

Past literature has examined both short- and long-run relationships among soft commodity prices and in some cases among selected soft commodities prices and crude oil price, see the recent reviews by Serra and Zilberman (2013), and Zhang et al. (2010). Early work focused on correlation, e.g. Malliaris and Urrutia (1996) who highlighted substantial agricultural future contracts of corn, wheat, oats, soybeans, soybean oil and conclude that they are correlated.

Tyner and Taheripour (2008) emphasized the relation between rise in oil prices and the increase in corn prices. Gilbert (2010) suggests that all agricultural markets are affected by the change in oil prices; namely the oil prices influence the food prices either by increasing the production costs or by using food as an input for biofuel production. The author suggests also that the cost of food production were affected by the transport and fertilizer cost.

Using a vector error correction model, Campiche *et al.* (2007) found no conclusive evidence of a relationship between crude oil prices and corn, sorghum, sugar, soybeans, soybean oil, and palm oil prices during the 2003-2005 period whereas evidence was reported that suggested corn prices and soybean prices were cointegrated with oil prices during the 2006-2007 time period.

Yu *et al.* (2006) results support the inference of long-run independence between major edible oil and crude oil prices and conclude that shocks in crude oil prices do not have a significant influence on the variation of edible oil prices.

Zhang and Reed (2008) examined the impact of the crude oil price on feed grain (corn and soybeans) and pork prices in China and report no evidence to support a . The results obtained with time series analysis has shown non-significant crude oil price fluctuation over the study period (2000-2007). Similar results are found by Nazlioglu and Soytas (2011) for Turkey.

Harri *et al.* (2009) examined the relationship between agricultural commodity goods and the oil price and concluded that there is an increasing connection between corn and oil. They suggested this is because of the growing use of corn for ethanol and the greater use of petroleum-based inputs in both corn and cotton markets.

Gobin and Chantret (2010) using a CGE model examined the role of macro-economic linkages in analyzing the relationship between food and energy prices. They concluded that although food and energy prices are mostly positively correlated, the correlation could be negative when the real income effect is considered.

Muruc *et al.* (2010) investigated the relationship between cotton and oil price and concluded that they are not cointegrated and that the response of cotton price to fluctuation in oil price is greatly different depending on whether the fluctuation is demand-driven or supply-driven.

Nazlioglu (2011) by examining the relationships between oil and ag-commodities corn, soybeans, and wheat has found evidence of nonlinear causality between oil and agricultural commodity prices; in another work, Nazlioglu and Soytas (2012) have found strong evidence of the world oil price changes on agricultural commodity prices using the panel cointegration and Granger causality methods.

Moving to the relations oil – biofuel - crops, Serra *et al.* (2010a) find that the prices of oil, ethanol and corn for the US to be positively correlated, and the existence of a long term equilibrium relationship between these prices, with ethanol. In Brazil, using the sugar as feedstock Serra *et al.* (2010b) demonstrate that sugar and oil prices are exogenously determined; by focusing their attention on the response of ethanol prices to changes in these two exogenous drivers, these authors conclude that ethanol prices respond relatively quickly to sugar price changes, but more slowly to oil prices.

Serra and Gil (2012) explain the price volatility of agricultural commodities affected by the energy prices, corn stocks and global economic conditions. Their findings support evidence of price volatility transmission between ethanol and corn markets. While the impacts of stocks in the very short-run are very high relative to the effects of energy price and macroeconomic instability, in the long-run the ethanol price and interest rate volatility are found to have the strongest impacts.

Bastianin *et al.* (2013) examined the linkages between the distributions of biofuels and commodity food prices, instead of the sample means and volatilities. They concluded that the distribution of the ethanol returns can be predicted using field crops returns, but not vice versa.

Considering now the role of trade policy intervention, Esposti and Listorti (2013) investigate about the national and international markets; trade policy regime has an important role in price transmission mechanisms and the trade policy intervention to mitigate the impact of price exuberance is considered. The authors analyze agricultural price transmission during price bubbles, in particular, considering Italian and international weekly spot (cash) price data over the years 2006–2010. Their results suggest that the bubble had only a slight impact on the price spread and the temporary trade-policy measures, when effective, have limited this impact.

METHODOLOGY

2.1 Notations

Let $Pi^0(t,\omega)$ represents the price of product i at time t, where $i = 1, \dots, 7$ and $t \in \{1, \dots, T\}$ where $T = 574$. Take log transformation, let $Pi(t,\omega) = \log\left(Pi^0(t,\omega)\right), for\ i = 1, .., 7$. Note that for $i = 1, \dots, 7$, for a fixed $t_0 \in \mathbb{N}, Pi(t_0,\omega)$ is a random variable in $\omega \in \Omega$, where Ω is the underlying sample space. We assume that $\int_\Omega Pi(t_0,\omega)^2 dP(\omega) < \infty$. And for $i = 1, \dots, 7$, for a fixed $\omega_0 \in \Omega, Pi(t,\omega_0)$ is a realization of $Pi(t,\omega)$. The dataset is a part of a realization of such data generating mechanism. Later in this paper, we will abbreviate $Pi(t,\omega)$ as $Pi(t)$ because the underlying probability space is fixed.

2.2 Tests

2.2.1 Stationarity Test

For a time series $Pi(t)$, if we can write it as an Autoregressive (AR) process:

$$Pi(t) = v + \alpha_{i1}Pi(t-1) + \alpha_{i2}Pi(t-2) + \cdots + \alpha_{ip}Pi(t-p) + \varepsilon$$

and $|1 - \alpha_{i1}z - \alpha_{i1}z^2 - \cdots - \alpha_{i1}z^p| \neq 0\ for\ |z| \leq 1$, then we call $Pi(t)$ is stable. And hence $Pi(t)$ is (asymptotically) stationary. A stationarity test we use in this paper is augmented Dickey-Fuller (ADF) test. Note $Pi(t)$ as an AR process, it can be written as

$$\Delta Pi(t) = vi + (\rho_i - 1)Pi(t-1) + \sum_{j=2}^{p} \alpha_{ij}Pi(t) + u_i(t) \quad for\ i = 1, .., 7$$

Let $\widehat{\rho_i}$ be the least square estimator of ρ_i. The null hypothesis of ADF test is $\rho_i = 1$. The test statistic is

$$t_{\hat{\rho}-1} = \frac{\hat{\rho} - 1}{\widehat{\sigma_\rho}}$$

Under the null hypothesis,

$$t_{\hat{\rho}-1} = \frac{\hat{\rho} - 1}{\widehat{\sigma_\rho}} \xrightarrow{d} N(0,1)$$

2.2.2 Linear and Nonlinear Granger Causality Tests

By the definition of Granger Causality, $Pi(t)$ is not Granger Causing $Pj(t)$ if

$$Pj(t+1)|Pj(t), Pj(t-1), \dots Pj(t-ly+1); Pi(t), \dots, Pi(t-lx+1) \sim Pj(t+1)|Pj(t), Pj(t-1), \dots Pj(t-ly+1)$$

for any $lx \; and \; ly$ finite lags. In the linear case, suppose $\begin{bmatrix} Pi(t) \\ Pj(t) \end{bmatrix}$ has a canonical MA representation with $lx = ly = p$, then we can write

$$\begin{bmatrix} Pi(t) \\ Pj(t) \end{bmatrix} = \begin{bmatrix} \mu i \\ \mu j \end{bmatrix} + \begin{bmatrix} \alpha_{ii,1} & \alpha_{ij,1} \\ \alpha_{ji,1} & \alpha_{jj,1} \end{bmatrix} \begin{bmatrix} Pi(t-1) \\ Pj(t-1) \end{bmatrix} + \dots + \begin{bmatrix} \alpha_{ii,p} & \alpha_{ij,p} \\ \alpha_{ji,p} & \alpha_{jj,p} \end{bmatrix} \begin{bmatrix} Pi(t-p) \\ Pj(t-p) \end{bmatrix} + \begin{bmatrix} u_i(t) \\ u_j(t) \end{bmatrix}$$

The null hypothesis is $Pi(t)$ does not Granger cause $Pj(t)$, or equivalently, $\alpha_{ij,k} = 0 \; for \; all \; k = 1, \dots, p.$ Under the null hypothesis, the test statistic is

$$\hat{F} = \frac{(RSS1 - RSS2)/p}{RSS2/(n-4p-2)} \sim F(p, n-4p-2)$$

where $RSS_1 \; and \; RSS_2$ are the residual sum of squares of restricted model ($\alpha_{ij,k} = 0 \; for \; all \; k = 1, \dots, p$) and the unrestricted model respectively.

In the nonlinear case, $Pi(t)$ not granger causing $Pj(t)$ is equivalent to

$$\frac{f_{Pj(t+1),\dots Pj(t-ly+1), Pi(t),\dots,Pi(t-lx+1)}(p_{jt+1}, \dots, p_{jt-ly+1}, p_{it}, \dots, p_{it-lx+1})}{f_{Pj(t),\dots Pj(t-ly+1), Pi(t),\dots,Pi(t-lx+1)}(p_{jt}, \dots, p_{jt-ly+1}, p_{it}, \dots, p_{it-lx+1})} = \frac{f_{Pj(t+1),\dots Pj(t-ly+1)}(p_{jt+1}, \dots, p_{jt-ly+1})}{f_{Pj(t),\dots Pj(t-ly+1)}(p_{jt}, \dots, p_{jt-ly+1})}$$

Following Dicks& Panchenko (2006), let $X_t^{lx} = [Pi(t), \dots, Pi(t-lx+1)]$, $Y_t^{ly} = [Pj(t), \dots, Pj(t-ly+1)], Z_t = Pj(t+1)$. Further, to keep a compact notation, let $X = X_t^{lx}, Y = Y_t^{ly}, Z = Z_t$. Then the previous equation can be written as

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \frac{f_{Y,Z}(y,z)}{f_Y(y)}$$

This implies $q = \mathbb{E}\left[\left(\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} - \frac{f_{X,Y}(x,y)}{f_Y(y)} \frac{f_{Y,Z}(y,z)}{f_Y(y)}\right) g(x,y,z)\right] = 0$ for any weight function$g(x,y,z) > 0$. If we choose $g(x,y,z) = f_Y^2(y)$, then

$q = \mathbb{E}\left[f_{X,Y,Z}(x,y,z) f_Y(y) - f_{X,Y}(x,y) f_{Y,Z}(y,z)\right]$. A natural estimator of q is

$$Tn(\varepsilon) = \frac{(2\varepsilon)^{-dx-2dy-dz}}{n(n-1)(n-2)} \sum_i [\sum_{k \neq i} \sum_{j \neq i} (I_{ik}^{XYZ} I_{ij}^{Y} - I_{ik}^{XY} I_{ij}^{YZ})]$$

where $I_{ij}^V = I(\|Vi - Vj\|_{sup} < \varepsilon)$. If let $\hat{f}_W(w_i) = \frac{(2\varepsilon^{-dW})}{n-1} \sum_{j \neq i} I_{ij}^W$, then we can rewrite $Tn(\varepsilon)$ as

$$Tn(\varepsilon) = \frac{(n-1)}{n(n-2)} \sum_i (\hat{f}_{X,Y,Z}(Xi, Yi, Zi)\hat{f}_Y(Yi) - \hat{f}_{X,Y}(Xi, Yi)\hat{f}_{Y,Z}(Yi, Zi))$$

Under the null hypothesis that the $Pi(t)$ is not Granger Causing $Pj(t)$, for a sequence of bandwidths $\varepsilon_n = Cn^{-\beta}$ $with\ C > 0\ and\ \beta \in (\frac{1}{4}, \frac{1}{3})$, the DP test statistic

$$\sqrt{n}\frac{\left(Tn\sqrt{\varepsilon_n} - q\right)}{Sn} \xrightarrow{d} N(0,1)$$

where S_n^2 is a robust estimation of $Var(Tn)$. Dicks and Panchenko suggest that the optimal bandwidth is $\varepsilon_n^* = C^* n^{-\frac{2}{7}}$, where $C^* = (\frac{18 \cdot 3q_2}{4(E[s(W)])^2})^{1/7}$.

2.2.3 CUSUM Test for structural breaks

If there is a long run relationship between Pi and Pj, then we can write $Pi(t) = \beta_{ij}Pj(t) + v_{ij}(t)$. If the parameters change with time, we write $Pi(t) = \beta_{ij}(t)Pj(t) + v_{ij}(t)$. Let $\widetilde{v_{ij}}(t)$ be the recursive residuals such that $\widetilde{v_{ij}}(t) = Pi(t) - \widehat{\beta_{ij}}(t)Pj(t)/f(t)$ where $f(t) = (1 + P_j^2(t)\left\{[Pi(1), \dots, Pi(t-1)]\begin{bmatrix} Pj(1) \\ \vdots \\ Pj(t-1)\end{bmatrix}\right\}^{\frac{1}{2}}$ and $\widehat{\beta_{ij}}(t)$ is the least square estimator in $Pi(t) = \beta_{ij}(t)Pj(t) + v_{ij}(t)$. The null hypothesis is $\beta_{ij}(t)$ does not change over time. The CUSUM test statistic is

$$T_{CUSUM} = \max_{K \le r \le T}\left\{\frac{\frac{\sum_{t=K+1}^{r}\widetilde{v_{ij}}(t)}{\hat{\sigma}\sqrt{T-K}}}{1 + 2\frac{r-K}{T-K}}\right\}$$

where $\hat{\sigma}^2$ is a consistent estimator of the variance of $v_{ij}(t)$. Under the null hypothesis,

$$T_{CUSUM} \xrightarrow{d} \sup_{0 \le r \le 1}\left\{\left|\frac{W(r)}{1+2r}\right|\right\}$$

where $W$is a Brownian bridge. We reject the null hypothesis when T_{CUSUM} is large.

2.3 Models

In this section, we specific models depending on the test results.

Model 1: VAR(p) in the level price

If $Pi(t)$ is stationary for $\forall i = 1, \dots, 7$, we can construct a bivariate VAR(p) on $\begin{bmatrix} Pi(t) \\ Pj(t) \end{bmatrix}$ as follows:

$$\begin{bmatrix} Pi(t) \\ Pj(t) \end{bmatrix} = \begin{bmatrix} \mu_i \\ \mu_j \end{bmatrix} + \sum_{k=1}^{p} A_k \begin{bmatrix} Pi(t-k) \\ Pj(t-k) \end{bmatrix} + \begin{bmatrix} u_i(t) \\ u_j(t) \end{bmatrix}$$

where A_k are coefficient matrix.

Note usually the VAR(p) model estimated is $P(t) = \mu + \sum_{k=1}^{p} Ak[P(t-k)] + u(t)$,where $P(t) = [P_1(t), \dots, P_7(t)]^T$. However, in this article, we use bivariate VAR to test linear and nonlinear granger causality in comparison with a bivariate VECM.

Model 2: VAR(p) in the first differenced prices

If $\Delta Pi(t)$ is stationary for $\forall i = 1, \dots, 7$, we can construct a bivariate VAR(p) on $\begin{bmatrix} \Delta Pi(t) \\ \Delta Pj(t) \end{bmatrix}$ as follows:

$$\begin{bmatrix} \Delta Pi(t) \\ \Delta Pj(t) \end{bmatrix} = \begin{bmatrix} \mu_i{}' \\ \mu_j{}' \end{bmatrix} + \sum_{k=1}^{p} B_k \begin{bmatrix} \Delta Pi(t-k) \\ \Delta Pj(t-k) \end{bmatrix} + \begin{bmatrix} u_i{}'(t) \\ u_j{}'(t) \end{bmatrix}$$

where B_k are coefficient matrix.

Model 3: Bivariate VECM

If $Pi(t)$ is not stationary for some $i \in \{1, \dots, 7\}$ but $\Delta Pi(t)$ is stationary for any $i \in \{1, \dots, 7\}$, then rewrite VAR(p) as VECM model as follows

$$\begin{bmatrix} \Delta Pi(t) \\ \Delta Pj(t) \end{bmatrix} = \Pi \begin{bmatrix} Pi(t-1) \\ Pj(t-1) \end{bmatrix} + \sum_{k=1}^{p-1} \Gamma_k \begin{bmatrix} \Delta Pi(t-k) \\ \Delta Pj(t-k) \end{bmatrix} + \begin{bmatrix} u_j(t) \\ u_j(t) \end{bmatrix}$$

where $\Pi = -(I_k - A_1 - \cdots - A_p)$ and $\Gamma_k = -(A_{i+1} + \cdots + A_p)$. If $rank(\Pi) = 0$, then we have model 2; if $rank(\Pi) = 2$, then we have model 1. If $rank(\Pi) = 1$, then we can decompose Π as $\begin{bmatrix} \alpha_i \\ \alpha_j \end{bmatrix} [1 \quad -\beta_{ij}]$. Then model 3 can be rewritten as

$$\begin{bmatrix} \Delta Pi(t) \\ \Delta Pj(t) \end{bmatrix} = \begin{bmatrix} \alpha_i \\ \alpha_j \end{bmatrix} [1 \quad -\beta_{ij}] \begin{bmatrix} Pi(t-1) \\ Pj(t-1) \end{bmatrix} + \sum_{k=1}^{p-1} \Gamma_k \begin{bmatrix} \Delta Pi(t-k) \\ \Delta Pj(t-k) \end{bmatrix} + \begin{bmatrix} u_j(t) \\ u_j(t) \end{bmatrix}$$

Then we have a long run relationship between Pi and Pj, i.e., $Pi(t) = \beta_{ij} Pj(t) + v_{ij}(t)$, where $v_{ij}(t)$ is stable and stationary as a combination of$u_j(t)$, $\Delta Pi(t)$, $\Delta Pj(t)$ and their lags.

Model 4

If further β_{ij} is allowed to change with time, model 3 changes to

$$\begin{bmatrix} \Delta Pi(t) \\ \Delta Pj(t) \end{bmatrix} = \begin{bmatrix} \alpha_i \\ \alpha_j \end{bmatrix} [1 \quad -\beta_{ijt}] \begin{bmatrix} Pi(t-1) \\ Pj(t-1) \end{bmatrix} + \sum_{k=1}^{p-1} \Gamma_k \begin{bmatrix} \Delta Pi(t-k) \\ \Delta Pj(t-k) \end{bmatrix} + \begin{bmatrix} u_j(t) \\ u_j(t) \end{bmatrix}$$

and $Pi(t) = \beta_{ijt} Pj(t) + v_{ij}(t)$. Here the change of β_{ijt} with time characterizes the change in the long run relationship between Pi and Pj.

Model 5

If the conditions of model 3 hold but there exists nonlinearity, we can use a Bivariate nonlinear model, such as

$$\begin{bmatrix} Pi(t) \\ Pj(t) \end{bmatrix} = f\left(\begin{bmatrix} Pi(t-1) \\ Pj(t-1) \end{bmatrix}, \dots, \begin{bmatrix} Pi(t-k) \\ Pj(t-k) \end{bmatrix} \right) + \begin{bmatrix} \varepsilon_i(t) \\ \varepsilon_j(t) \end{bmatrix}$$

where f is a function from $\mathbb{R}^2$ to $\mathbb{R}^2$ for fixed $t \in \mathbb{N}$, and $\begin{bmatrix} \varepsilon_i(t) \\ \varepsilon_j(t) \end{bmatrix}$ is stationary. In this article we do not specific the function f and hence model 5. But we assume model 5 is the underlying DGM in nonlinear granger causality testing.

DATA

We employ weekly data from January 2000 through December 2010 for a corn, wheat, soybeans a subset of "softs" commodity prices for European and US, and European Brent blend. The Italian prices of maize and wheat are obtained from DATIMA provided by ISMEA. The US prices of wheat, corn and soybeans are provided by FAO sourced from USDA. Data are weekly prices monitored for a length of time that started in February 2005 and ended in February 2010. The prices in $/ton are converted in €/ton using the official $/€ exchange rate. Missing values are replaced by using an imputation algorithm and the corresponding R-package AMELIA II (King *et al.*, 2001; Honaker *et al.*, 2009). For the fuel prices, the weekly United States spot prices and weekly Europe (UK) Brent blend spot price are converted to € per barrel.

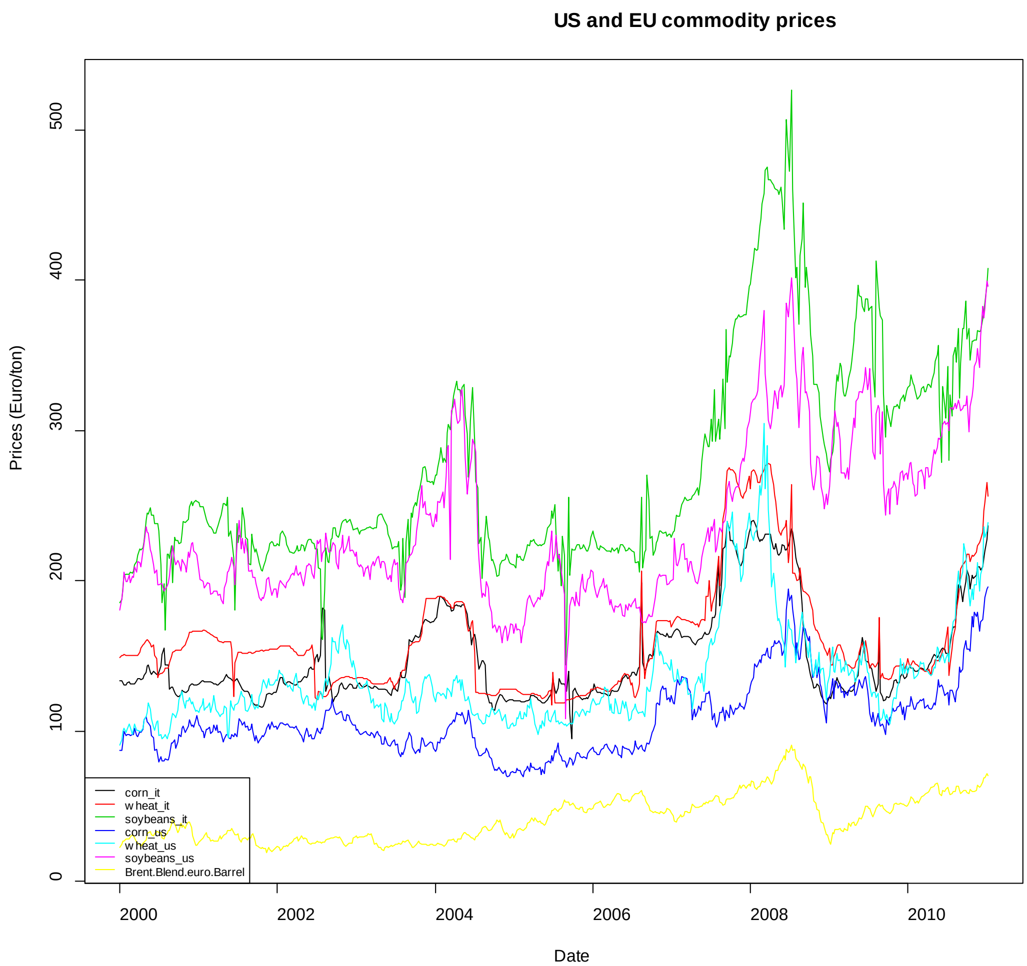
We analyze the natural logarithms of these prices. Table 1 shows the high bivariate correlations across these softs as well as between EU and US prices for the same commodity. In contrast, the correlation between softs and the Brent blend price is less striking. have some positive correlation, indicating there maybe cointegration between them. The causal direction, if we can construct a stable system, is not clear. This motivates our following causality analysis. Figure 1 presents graphic evidence of this correlation in price levels.

Table 1 Bivariate Correlation

	EU_corn	EU_wheat	EU_soybeans	US_corn	US_wheat	US_soybean
EU_corn	1.000					
EU_wheat	0.910	1.000				
EU_soybean	0.720	0.731	1.000			
US_corn	0.650	0.679	0.804	1.000		
US_wheat	0.788	0.835	0.726	0.721	1.000	
US_soybean	0.664	0.630	0.911	0.832	0.666	1.000
Brent Blend	0.572	0.501	0.692	0.609	0.566	0.556

Notes: The correlation matrix is for the period from January 2000 to December 2010.

Figure 1. Weekly Prices (US and EU softs and energy)



Notes: Weekly price levels for the period January 2000 to December 2010.

EMPIRICAL RESULTS

To examine the characteristics of any underlying univariate data generating mechanisms (DGM) using Augmented Dickey-Fuller test (ADF test) to test the stationarity of both original and the first difference of the data, see Table 2.

Table 2. Augmented Dickey Fuller unit root test

	Level	First Diff.
EU_corn	-2.371643	-7.876299 ***
EU_wheat	-1.723259	-8.777176 ***
EU_soybean	-2.45791	-10.147263 ***
US_corn	-1.876364	-10.346361 ***
US_wheat	-2.627275	-8.847174 ***
US_soybean	-2.493837	-10.511357 ***
Brent Blend	-2.775068	-9.743351 ***

Notes: The statistics are the t-statistic for ADF test. The critical values are -3.96, -3.41 and -3.12 for 1%, 5% and 10% respectively. ***, ** and * denote statistical significance at 1% and 5% level of significance, respectively.

The results indicate that no price series is stationary in level while rejection of the hypothesis of unit roots in the first differences support the inference that these series are stationary implying each series is integrated by order (1) and hence may share a common stochastic trend. If a linear system of all level variables can be constructed such that it is stationary, then a vector error-correlation model (VECM) can be used to represent the underlying joint DGM. Accordingly, we next examine cointegration of pairs of the differences series using the Johansen trace test (Johansen, 1998) is employed. For each bivariate pair, the null hypothesis is that the series are cointegrated to order r where $r \leq 0$. When the null hypothesis is rejected, we conclude that the bivariate pair cointegrated and infer the existence of a long run relationship between them. Results reported in Table 3 indicate that: 1) all pairs of European agricultural commodities prices are cointegrated; 2) US wheat and US soybean are cointegrated with most other commodities; 3) the Brent Blend price is not cointegrated with any the softs prices. The first and second of these conclusions are consistent with the observation of high correlation noted above and the fact that agricultural markets are highly integrated by arbitrage. However, our finding of no evidence for cointegration between the Brent blend and commodities prices does not agree with the positive correlation between many of them. Although similar results have been reported (see e.g. Yu et al., 2006; Zhang and Reed, 2008; Kaltalioglu and Soytas, 2009; Gilbert, 2010; Lombardi et al., 2010; Mutuc etal., 2010),we note this finding is also consistent with the existence of structural breaks or nonlinearity. We next examine these possibilities using cointegration tests with structural breaks and a nonlinear Granger causality test.

Table 3. Johansen trace test for cointegration within the full sample

	EU_corn	EU_wheat	EU_soybean	US_corn	US_wheat	US_soybean
EU_corn						
EU_wheat	35.247***					
EU_soybean	36.241***	33.658***				
US_corn	21.956	17.328	22.946*			
US_wheat	30.500***	33.571***	35.222***	23.352*		
US_soybean	27.011**	23.624*	35.454***	20.559	24.258*	
Brent Blend	18.453	13.182	16.882	13.374	16.139	16.007

Notes: The critical values are 30.45, 25.32 and 22.76 for 1%, 5% and 10% respectively. ***, ** and *denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Evidence reported above of no cointegration between Brent blend and agricultural commodities in the full sample does not reject the hypothesis that structural breaks exist and define time intervals within which cointegration exists. To identify such intervals we implement an nonparametric approach to examine linear relationships for each bivariate pair within identified structural breaks. Based on these results, we partition the full sample into subsamples according to these structural breaks and examine cointegration within each subsample. To identify the structural breaks, we test for structural breaks over the full sample using OLS-CUSUM, MOSUM, supF, and expF tests. Conditional on test results that support the presence of structural breaks, we identify structural breaks based on a Schwarz criterion (BIC) and RSS with maximum of 5 structural breaks followed by re-application of the approach within identified subsamples to identify the presence of further structural breaks. After the subsamples are identified, cointegration tests are conducted within subsamples.

Structural break dates identification and test results of cointegration between Brent blend and commodity within subsamples are illustrated in Table 4. By allowing for structural breaks, we find stronger evidence of cointegration within subsamples. In contrast of no cointegration between Brent blend and commodities prices in the whole sample, evidence supports the inference that the Brent blend price is cointegrated with European soybeans price from week 1 2000 to week 36 2003, European wheat prices from week 54 2004 to week 33 2006 and US wheat price from week 8 2008 at significant levels of 1%, 5% and 10% respectively.

Table 4.a Structural breaks identification

		EU_corn	EU_wheat	EU_soybean	US_corn	US_wheat	US_soybean
Brent Blend	Break Dates		2004w53 2006w33	2003w36	2007w34	2008w8	

Table 4.b Cointegration test results within subsamples

		EU_corn	EU_wheat	EU_soybean	US_corn	US_wheat	US_soybean
Brent Blend	Statistics	18.453	14.45 26.53** 14.73	35.60*** 10.66	12.15 6.46	10.35 24.10*	16.007

Notes: The critical values are 30.45, 25.32 and 22.76 for 1%, 5% and 10% respectively. ***, ** and * denote statistical significance at 1%, 5% and 10% level of significance, respectively.

Nonlinear Granger Causality tests

We next examine evidence of nonlinearity in relationships between each bivariate pair of commodities and Brent blend prices given that linear causality tests, such as the Granger test (1969), can fail to reveal nonlinear relationships (see e.g. Baek and Brock, 1992; Hiemstra and Jones, 1994). Hiemstra and Jones (1994). Based on Baek and Brock (1992), we implement a nonparametric approach based on the correlation integral to detect nonlinear causal relations between the time series. However, before moving to the nonlinear Granger causality test, a linear Granger causality test based on a VAR of first differenced series is conducted for comparison. It is expected the results should be with consistent with the cointegration test results. Consider the VAR(p) model:

$$P_t = A_1 P_{t-1} + \cdots + A_p P_{t-p} + W_t = \sum_{i=2}^{p} A_i P_{t-i} + W_t$$

and the associated first-differenced VAR with the form:

$$\Delta P_t = B_1 \Delta P_{t-1} + \cdots + B_p \Delta P_{t-p} + U_t = \sum_{i=2}^{p} B_i \Delta P_{t-i} + U_t$$

In contrast, the VECM consistent with a VAR in price levels has the form:

$$\Delta P_t = \Pi P_{t-1} + \sum_{i=1}^{p-1} A_i^* \Delta P_{t-i} + V_t$$

where $\Pi + I = \sum_{j=1}^{p} A_j$

$$A_i^* = -\sum_{j=i+1}^{p} A_j$$

Although the VECM in level and VAR in first difference provide tests based on different parameters (cointegration on Π and Granger-causality test on $\{B_i\}$), the two models have similar form and hence are expected to provide similar inference. Results are reported in Tables 5 for linear Granger causality tests.

Table 5.a Granger causality tests on the first differenced VAR

	EU_corn	EU_wheat	EU_soybean	US_corn	US_wheat	US_soybean
Brent Blend	0.544	0.686	0.402	0.114	0.017**	0.315

Notes: The null hypothesis is that column variables do not granger cause row variables. This table reports the probability of first type error. ***, ** and * denote statistical significance at 1% and 5% level of significance, respectively.

Table 5.b Granger causality tests on the first differenced VAR with subsamples

	EU_corn	EU_wheat	EU_soybean	US_corn	US_wheat	US_soybean
Brent Blend	0.544	0.599 0.397 0.099*	0.068* 0.890	0.270 0.211	0.369 0.733	0.315

Notes: The null hypothesis is that column variables do not granger cause row variables. This table reports the probability of first type error. ***, ** and * denote statistical significance at 1% and 5% level of significance, respectively.

These results are consistent with the cointegration test results. Granger causality in at least on direction is not rejected for agricultural commodity, a result that is consistent our finding that most agricultural commodities price pairs are cointegrated. We also find evidence supporting the inference that Brent blend price Granger causes US wheat price (5% significance level). This inference is not consistent with the cointegration test results in the full sample, though cointegration found in the subsample may account this conclusion.

Next, we turn to nonlinear Granger causality test results presented in Table 6. The results suggest that causal relationships are more extensive than those suggested linear causality results. In particular, evidence supports the inference that the Brent blend price causes the price of European corn, US corn and US soybean and that each US commodity price causes the price of Brent blend. These results are dramatically different results than those found with cointegration and linear causality tests. In particular, results suggest causality in both direction exists between the Brent Blend and US corn and US soybean prices.

Table 6. Nonlinear Granger causality tests

	EU_corn	EU_wheat	EU_soybean	US_corn	US_wheat	US_soybean	Brent Blend
EU_corn		0.001***	0.004***	0.006***	0.041**	0.023**	0.291
EU_wheat	0.294		0.002***	0.004***	0.297	0.005***	0.402
EU_soybean	0.017**	0.007***		0.005***	0.007***	0.011**	0.604
US_corn	0.041**	0.318	0.081		0.008***	0.005**	0.003***
US_wheat	0.482	0.044**	0.500	0.042**		0.129	0.033**
US_soybean	0.055*	0.020**	0.066**	0.003***	0.172		0.032**
Brent Blend	0.061*	0.173	0.384	0.001***	0.118	0.010***	

Notes: The null hypothesis is that column variables do not granger cause row variables. This table reports the probability of first type error. The lag is chosen as 2 and the bandwidth is chosen 0.5 by Schwarz criterion. ***, ** and * denote statistical significance at 1% and 5% level of significance, respectively.

Conclusions

By comparison to existing results they reconsider the role of structural breaks. To place these results in context, Nazlioglu found that allowing for endogenous (but common across series) structural breaks led to evidence of coint between corn & oil prices, and some evidence for wheat & oil prices. Nazlioglu found no evidence for linear Granger causality using residuals from the cointegration models, however, by relaxing linear functional form he found evidence of nonlinear feedbacks from oil to corn and soy prices, and two-way causality between oil and wheat prices.

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Appendix

The augmented Dickey-Fuller test (ADF test) to test for stationarity of both original and the first difference of the data are based on:

$$\Delta x_t = \alpha_0 + \gamma x_{t-1} + \sum_{2}^{k} \lambda_i \Delta x_{t-i+1} + \varepsilon_t$$

where the null H0: $\gamma = 0\ (unit\ root)$ against the alternative hypothesis of Ha : $\gamma \neq 0\ (no\ unit\ root)$ is tested using:

$$\tau = \frac{\gamma - 0}{SE(\gamma)} \sim t$$

A VECM (*p*) form is written as the first difference of the VAR above:

$$\Delta x_t = \begin{bmatrix} \Delta\ x_t^1 \\ \Delta\ x_t^2 \end{bmatrix} =$$

$$= \begin{bmatrix} \gamma_{10,t} \\ \vdots \\ \gamma_{(k+l)0,t} \end{bmatrix}^T \begin{bmatrix} x_{t-1}^1 \\ x_{t-1}^2 \end{bmatrix} + \sum_{i=2}^{p} \begin{bmatrix} \lambda_{11,t-i} & \cdots & \lambda_{1(k+l),t-i} \\ \vdots & \ddots & \vdots \\ \lambda_{(k+l)1,t-i} & \cdots & \lambda_{(k+l)(k+l),t-i} \end{bmatrix} \begin{bmatrix} \Delta x_{t-i}^1 \\ \Delta x_{t-i}^2 \end{bmatrix} + \begin{bmatrix} \nu_{1,t} \\ \vdots \\ \nu_{(k+l),t} \end{bmatrix}$$

$$where\ \Sigma = \begin{bmatrix} \sigma_{1,t}^2 & & 0 \\ & \ddots & \\ 0 & & \sigma_{(k+l),t}^2 \end{bmatrix}.$$

or

$$\Delta x_t = \gamma x_{t-1} + \sum_{2}^{p} \lambda_i \Delta x_{t-i+1} + \varepsilon_t$$

where Δ is the differencing operator, such that $\Delta x_t = x_t - x_{t-1}$ and x_t is a $(k + l) \times 1$ vector. The VECM has an equivalent VAR (*p*) representation as described in the preceding section.

$$x_t = a_0 + \sum_{i=1}^{p} \left(I_{(k+l)} + \gamma + \lambda_i\right) x_{t-1} + \sum_{i=2}^{p-1} (\lambda_i - \lambda_{i-1}) x_{t-i} - \lambda_{p-1} x_{t-p} + \varepsilon_t$$

where the null H0: r<=0 where r is the order of cointegration (no bivariate cointegration) is tested using the following test statistic:

$$L_{tr}(r) = -(T - kp) \sum_{i=r+1}^{k} \ln(1 - \lambda_i)$$

$$L_{tr}(r) \sim tr\{[\int_0^1 W_v(u) d\, W_v(u)']'[\int_0^1 W_v(u) W_v(u)' du]^{-1}[\int_0^1 W_v(u) d\, W_v(u)']\}$$

where v=r and $\mathrm{W_v(u)}$ is a v-dimensional standard Brownian motion process.

Details on the CUSUM tests and variations such as supF test can be found in Brown, Durbin and Evans (1975). For a linear regression with k regressors

$$y_t = x_t' \beta + \epsilon_t$$

the CUSUM statistic is defined as

$$CUSUM = \max_{k+1<r\leq T} \left|\frac{\sum_{t=k+1}^{r} \widetilde{v_t}}{\hat{\sigma}\sqrt{T-k}}\right| /(1+2\frac{r-k}{T-k})$$

where $\hat{\sigma}^2$ is a consistent estimate of the variance of ϵ_t.

$\widetilde{v_t} = \frac{y_t - x_t'\widehat{\beta_{t-1}}}{f_t}$ and $f_t = (1 + x_t'(X_{t-1}'X_{t-1})x_t)^{1/2}$

The asymptotic distribution of CUSUM is:

$$CUSUM \xrightarrow{d} sup_{0\leq r\leq 1} \left|\frac{W(r)}{1+2r}\right|$$

where *W(r)* is a unit Wiener process defined on (0,1). [Sen, 1982]

The null hypothesis for each test statistic is H0: no structural break in the interval.

The *sup-Wald* test statistic is defined as

$$sup_{\lambda_1 \in \Lambda_\epsilon} W_T(\lambda_1; q)$$

where $W_T(\lambda_1) = [SSR(1,T) - SSR(1,T_1) - SSR(T_1+1,T)]/\{[SSR(1,T_1) + SSR(T_1+1,T)]/T\}$

where *SSR*(*i,j*) is the sum of squared residuals from regressing y_t on a constant using data from data *i* to date *j, i.e.*

$$SSR(i,j) = \sum_{t=i}^{j}\left(y_t - \frac{1}{j-i}\sum_{t=i}^{j} y_t\right) = \sum_{t=i}^{j}(e_t - \sum_{t=i}^{j} e_t)$$

The asymptotic distribution of *sup-Wald* test statistic is:

$W_T(\lambda_1) \xrightarrow{d} \frac{1}{\lambda_1(1-\lambda_1)}[\lambda_1 W(1) - \lambda_1 W(\lambda_1) - (1-\lambda_1)W(\lambda_1)]^2$

Note, here $W_T(k)$ is monotonic transformation of $S_T(k)$. So it follows that

$\left(\widehat{T_1}, \dots \widehat{T_m}\right) = argmin_{(T_1,\dots T_m)} S_T(T_1 \dots T_m) = argmin_{(T_1,\dots T_m)} W_T(T_1 \dots T_m)$

Hence, the estimator obtained by minimizing the sum of squared residuals is the same as maximizing Wald-type statistics.

To examine evidence of cointegration between Brent and ag commodity prices based on subsamples suggested by the structural break examination, we test the null H0: r<=0 where r is the order of cointegration (no bivariate cointegration) using the following test statistic:

$$L_{tr}(r) = -(T-kp)\sum_{i=r+1}^{k} \ln(1-\lambda_i)$$

$$L_{tr}(r) \sim tr\{[\int_0^1 W_v(u)d\,W_v(u)']'[\int_0^1 W_v(u)W_v(u)'du]^{-1}[\int_0^1 W_v(u)d\,W_v(u)']\}$$

where v=r and $W_v(u)$ *is a v-dimensional standard Brownian motion process.*