Explaining Commodity Prices through Asymmetric Oil Shocks: Evidence from Nonlinear Models

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Abstract: Linkages between oil and 25 other commodity prices are examined using annual data for 1900 to 2011. We identify long-run relationships using both linear and nonlinear ARDL models and capture short-run causalities through asymmetric Granger causality tests. Nonlinearity can't be rejected for oil and most commodity prices. Long-run positive impacts of oil price increases are found for 20 commodities and short-run negative impacts for 13 commodity prices. Oil prices don't have much impact on beverage or cereal prices once endogeneity is accounted for, but they have substantial impact on metal prices.

Key Words: Oil prices, commodity prices, symmetry, asymmetry, price volatility.

JEL Classification: Q20; E24; C33

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1. Introduction

With sharply rising commodity prices at the beginning of the 21st century and the subsequent dramatic collapse, there has been a surge of interest in understanding the determinants of commodity price movements. Explanations for the observed commodity price increases include increased demand for commodities from emerging markets, quantitative easing in monetary policy and speculative commodity demands in stock markets (Frankel & Rose 2010). Explanations of the subsequent price collapse include excessive expansion of production capacity for oil and key minerals, slowing Chinese economic growth and stagnation in the advanced developed economies.

Linkages between oil and other commodity prices are part of the overall dynamics of resource prices. They are of particular importance to resource companies and investors in designing portfolios of assets for the diversification risk. Understanding the linkages is also important in macroeconomic forecasting for countries, such as Australia, with heavy exposure to commodities in terms of exports or countries, such as Japan, with heavy exposure to commodities in terms of imports. Some of the poorest countries are particularly exposed to fluctuations in prices of their commodity exports, so understanding the linkages of their main exports to oil prices is particularly helpful in designing their development and macroeconomic policies (see Nissanke & Mavrotas 2010).

Most studies investigating the linkages between oil and commodity (mainly food, other agriculture, metals and energy) prices are undertaken within linear frameworks, assuming symmetry of the impact of oil price shocks, *i.e.* they assume that the impact of a

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positive price shock is identical, but opposite, to the impact of a negative shock. However, this assumption of linearity or symmetry is too restrictive, as in many cases there is potentially an asymmetric structure regarding the magnitude and direction of impacts. Asymmetries can reflect institutional arrangements, such as price cap regulation, and market structure, such marketing cartels, or the way production capacity reacts differently to positive and negative changes in current market conditions. In the last two decades, methods have been developed in the econometrics literature for dealing with nonlinearity (Balke & Fomby 1997; Hansen & Seo 2002; Psaradakis *et al.* 2004; and Kapetanios *et al.* 2006, among others). We utilize these methods to add a further dimension to the empirical literature examining the impact of oil prices on the prices of other commodities.

Imposition of the assumption of symmetry when in fact there are asymmetric responses to shocks in the oil price series can lead to bias in estimates of the impact of these shocks. Also, treating the effects of shocks as symmetric implies that volatility in oil prices has no impact on the net movement in the prices of other commodities. Equal positive and negative shocks in oil prices would have a net negative (positive) impact on the price of a commodity if the elasticity of the response to the negative shock were larger (smaller) than the elasticity of the of response to a positive shock. This can provide a possible channel for oil price volatility having negative impacts on the broader economy as found in Rafiq, *et al.* (2009).

We also diverge from much of the earlier research linking oil and commodity prices by estimating both long-run cointegration and dynamic interactions between oil and commodity prices by implementing two very recent nonlinear asymmetric estimation techniques, namely, the nonlinear ARDL (Autoregressive Distributed Lag) model due to Shin *et at*. (2014) and the asymmetric causality test of Hatemi-J (2012). With the application of these methods, we make four contributions to the literature. First, we estimate both long-run impacts and dynamic causalities running from oil prices to 25 other commodity prices. Second, these impacts and causalities are investigated through both linear and nonlinear frameworks. Third, we use a long time series of annual data from 1900 to 2011 for the purpose of capturing long-lasting relationships. Finally, we include a wide range of commodities to identify the variety of causal relationships, which can contribute to formulating diversification strategies for investors and policymakers.

The rest of this paper is organized as follows. Section 2 offers a brief overview of the time-series data for oil and other commodity prices and reviews the existing literature. This is followed by discussion of analytical models in Section 3. A description of data sources and discussion of the empirical results are presented on Section 4, while Section 5 discusses policy implications that emerge from the results and concludes the paper.

2. Linking Oil and Commodity Prices: Historical, Theoretical and Empirical Perspectives

In an anatomy of the commodity prices, Radetzki (2006) depicts three periods of sharp commodity price increases in the post-WW II period. The first boom is from 1950 to 1953 and is directly linked with the Korean War through increased insecurity regarding industrial material supply, which prompted a widespread build-up of strategic inventories. The second boom of 1970s is identified with three events, a substantially strong macroeconomic performance during 1972 and 1973, deficiency in inventories for both food and agriculture raw materials due to two consecutive years of widespread crop failures, and with oil price shocks. According to Radetzki (2006), the third boom from 2003 is identified with demand shocks in commodity markets, especially for oil and copper.

For the period prior to WW II, Brémond *et al*. (2013) indicate that sharp commodity price rises following the Great Depression of 1930s reflected recovery in commodity markets after the sharp decline during 1929-1932. Further instability in commodity prices in the period from 1939 to 1947 is attributable to the effects of international conflict and its aftermath. The historical pattern of individual commodity prices and their relationship with oil prices over the full course of the Twentieth Century is depicted in the graphical representations of prices in Appendix Figure 1.

Heady & Fan (2008) and Mitchell (2008) identify two major channels through which oil prices have positive linkages to other commodity prices. One is the increase in production cost and the second is an increase in transport cost. These two studies conclude that the combined increase in production and transport costs for major US food commodities, like corn, soybeans and wheat, account for 20-30% of the increase in the US export prices of these commodities. Offsetting these positive cost-push relationships, Gohin & Chantret (2010) identify a negative real-income effect between world commodity (food) and energy (oil) prices in terms of a reduction in consumer real income following an oil price increase eventually puts downward pressure on prices of other commodities. Of course, real income shocks from sources other than oil price changes may have common demand influences on prices of oil and other commodities.

Following the seminal work of Pindyck & Rotemberg (1990), estimation of the dynamic linkages between oil and commodity prices has been mostly undertaken within linear cointegration or causality frameworks. The majority of the studies focus on identifying the impact of oil prices on food, other agricultural, metal and other energy commodity prices. The results tend to vary according to the group of commodities studied, the sample period, data frequency and estimation method.

Divergent results regarding the co-movement of oil and other commodity prices are particularly evident for agricultural commodities. For example, using Johansen cointegration and Granger causality techniques, Abel & Arshad (2009) and Saghaian (2010) find long-run cointegrating relationships between oil and food prices, while Zhang *et al.* (2010) and

Baumeister & Kilian (2014) fail to find any. Using a linear ARDL cointegration approach, Chen *et al*. (2010) find significant linkages between oil and grain prices, whereas Sari *et al*. (2011) only demonstrate some weak causality.

Ambiguity in the relationship between oil and agricultural commodity prices is also found in studies using non-linear estimation. Peri & Baldi (2010) employ the Hansen & Seo (2002) threshold-based cointegration approach and find significant cointegration between rapeseed and diesel prices, while sunflower and soybean oil prices are found to have no cointegrating relation with diesel. Natanelov *et al*. (2011) use similar threshold analysis to investigate the price relationship of future contracts of crude oil, gold and eight food commodities and conclude that only cocoa, wheat and gold move together with crude oil in the long run over the entire sample period.

The relationship between oil and agricultural commodity prices is generally clearer when allowance is made for structural breaks. After identifying a structural break around 2008 financial crisis, Pala (2013) finds strong linkages between oil and food prices. Also, Nazlioglu (2011) and Nazlioglu & Soytas (2012) use panel data cointegration and Granger causality tests to find positive relationships between oil and agricultural prices. Finally, Gazgor & Kablamaci (2014) utilize second generation panel data estimation techniques under cross-sectional dependence and find statistically significant and positive interactions between oil and agricultural commodity prices.

Studies investigating the linkages between oil and other energy prices also tend to find significant positive relationships. Using Johansen and Breitung's cointegration tests, Brown & Yücel (2006) find significant positive long-term cointegration between oil and natural gas prices. Hartley *et al*. (2008) reach the same conclusion indirectly using the price of residual fuel oil, while Asche *et al*. (2006), Panagiotidis & Rutledge (2006) and Chevelliar

& Ielpo (2013) find significant positive cointegrating relationships between oil and natural gas prices.

A recent study by Gupta *et al*. (2014) employs the same long-run database as is used in our study. They perform time-varying causality tests to identify the linkages between oil and a wide range of commodity prices over more than 100 years, finding that oil price causes banana, beef, copper, cotton, lead, rubber, timber, tin, tobacco and wool prices. However, the analysis is only for short-run causality.

From the survey of the literature several conclusions are in order. First, most of the studies are performed with linear techniques and focus on food, agricultural and energy commodities. Second, with respect to non-linear studies, all of them employ long-run cointegration analysis, while only a very few identify short-term causal relationships. Third, none of the studies draw any conclusion regarding asymmetric relationships between oil and commodity prices.

In this paper we expand the range of methods employed in examining linkages between oil and other commodity prices by implementing both symmetric linear and asymmetric nonlinear methods to identify both long-run cointegration and short-run causality between oil and 25 commodity prices over a sample period of more than a century. For this purpose we employ two recent nonlinear techniques due to Shin *et al*. (2014) and Hatemi-J. (2012).

3. Analytical Framework

As discussed, standard time-series techniques of cointegration, error-correction modelling and Granger causality testing, are the dominant methods used in the literature linking oil with commodity prices. While these methods are appropriate for capturing both long-run and short-run interactions, they presume symmetric relations among the variables. Shin *et al*.

(2014) propose a simple nonlinear ARDL cointegration approach (NARDL) as an asymmetric extension to the well-known ARDL model of Pesaran & Shin (1998) and Pesaran *et al.* (2001), which captures both long-run and short-run asymmetries in variables of interest.

The Shin *et al.* approach has three desirable attributes. First, it is linear in parameters. Second, it is readily estimable by OLS. Third, it can accommodate combinations of persistent and stationary variables in a coherent manner (Greenwood-Nimmo & Shin 2013). Hence, in addition to performing symmetric linear ARDL models, we adopt this NARDL modelling approach to estimate the linkages between oil and commodity prices.

The NARDL model is built upon an asymmetric long-run relationship of the following form:

$$C_t = \beta^+ O_t^+ + \beta^- O_t^- + u_t, \quad \Delta O_t = v_t \tag{1}$$

where C_t is a scalar *I(1)* variable (a commodity price here), O_t is a the oil price series here defined such that $O_t = O_0 + O_t^+ + O_t^-$, where O_0 is the initial oil price and $O_t^+ = \sum_{j=1}^{t} \Delta O_j^+ = \sum_{j=1}^{t} \max(\Delta O_j, 0)$ and $O_t^- = \sum_{j=1}^{t} \Delta O_j^- = \sum_{j=1}^{t} \min(\Delta O_j, 0)$ are partial sum processes of positive and negative changes in oil pric. As in Shin *et al.* (2014), a single threshold value of zero is assumed to enable a clear economic interpretation of the model. It is worth mentioning here that, decomposing oil prices in this way leaves us with approximately 60:40 split in favor of a positive regime. Hence, we do not need to worry about estimation issues resulting from large differences in the regime possibilities.

The NARDL (*p, q*) in levels derived from Equation (1) can be written as follows:

$$C_t = \sum_{j=1}^{p} \phi_j C_{t-j} + \sum_{j=0}^{q} \left(\theta_j^+ O_{t-j}^+ + \theta_j^- O_{t-j}^-\right) + \varepsilon_t \,, \tag{2}$$

where the ϕ_j's are autoregressive parameters, θ_j^+ and θ_j^- contain the asymmetric distributed lag parameters, and ε_t is the idiosyncratic term with zero mean and constant variance, σ^2. The associated error-correction model is:

$$\Delta C_t = \rho C_{t-1} + \theta^+ O^+_{t-1} + \theta^- O^-_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta C_{t-j} + \sum_{j=0}^{q-1}\left(\varphi_j^+ \Delta O^+_{t-j} + \varphi_j^- \Delta O^-_{t-j}\right) + \varepsilon_t \tag{3}$$

where $\rho = \sum_{j=1}^{p} \phi_j - 1$, $\gamma_j = -\sum_{i=j+1}^{p} \phi_i$ for *j = 1, …., p-1*, $\theta^+ = \sum_{j=0}^{q} \theta_j^+$, $\theta^- = \sum_{j=0}^{q} \theta_j^-$, $\varphi_0^+ = \theta_0^+$, $\varphi_j^+ = -\sum_{i=j+1}^{q} \theta_j^+$ for *j=1,……..,q-1*, $\varphi_0^- = \theta_0^-$, $\varphi_j^- = -\sum_{i=j+1}^{q} \theta_j^-$ for *j=1,……..,q-1*, and $\beta^+ = -{}^{\theta^+}\!/_{\rho}$ and $\beta^- = -{}^{\theta^-}\!/_{\rho}$ are the asymmetric long-run parameters.

We identify causality running from oil prices to individual commodity prices through implementing the asymmetric causality test procedure of Hatemi-J (2012). At the outset, C_t (commodity price at time *t*) and O_t (oil price at time *t*) can be expressed as the following random walk process:

$$C_t = C_{t-1} + \varepsilon_{1t} = C_0 + \sum_{i=1}^{t} \varepsilon_{1i}, \tag{4}$$

and

$$O_t = O_{t-1} + \varepsilon_{2t} = O_0 + \sum_{i=1}^{t} \varepsilon_{2i}, \tag{5}$$

where *t=1,2,….T*, the constants C_0 and O_0 are the initial values and the variables ε_{1i} and ε_{2i} signify white noise disturbance terms. Positive and negative shocks are defined as: $\varepsilon_{1i}^+ = \max(\varepsilon_{1i}, 0)$, $\varepsilon_{2i}^+ = \max(\varepsilon_{2i}, 0)$, $\varepsilon_{1i}^- = \min(\varepsilon_{1i}, 0)$, and $\varepsilon_{2i}^- = \min(\varepsilon_{2i}, 0)$, respectively. Hence, we can write $\varepsilon_{1i} = \varepsilon_{1i}^+ + \varepsilon_{1i}^-$ and $\varepsilon_{2i} = \varepsilon_{2i}^+ + \varepsilon_{2i}^-$. Therefore:

$$C_t = C_{t-1} + \varepsilon_{1t} = C_0 + \sum_{i=1}^{t} \varepsilon_{1i}^+ + \sum_{i=1}^{t} \varepsilon_{1i}^-, \tag{6}$$

And likewise:

$$O_t = O_{t-1} + \varepsilon_{2t} = O_0 + \sum_{i=1}^{t} \varepsilon_{2i}^+ + \sum_{i=1}^{t} \varepsilon_{2i}^- \tag{7}$$

Finally, the positive and negative shocks of each variable can be defined in a cumulative form as $C_t^+ = \sum_{i=1}^{t} \varepsilon_{1i}^+$; $C_t^- = \sum_{i=1}^{t} \varepsilon_{1i}^-$, $O_t^+ = \sum_{i=1}^{t} \varepsilon_{2i}^+$ and $O_t^- = \sum_{i=1}^{t} \varepsilon_{2i}^-$.

The cumulative components above provide the possibility to implement asymmetric causalities between oil and commodity prices. For example, if we want to test causality between the positive components, then the vector that should be used is $P_t^+ = (C_t^+, O_t^+)$.

Afterwards, this vector can be used to estimate the following vector autoregressive model with the lag order k, *VAR (L)*:

$$P_t^+ = \vartheta + \alpha_1 P_{t-1}^+ + \cdots + \alpha_L P_{t-k}^+ + u_t^+, \quad (8)$$

where ϑ is the *2* X *1* vector of intercepts, and u_t^+ is representing a *2* X *1* vector of the errors, α_r is a *2* X *2* matrix of parameters for lag order r (where $r=1,\ldots\ldots,k$) to be estimated. The optimum lag order k is obtained based on the minimization of the information criterion presented below:

$$HJC = \ln(|\widehat{\Omega_j}|) + j\left(\frac{n^2 lnT + 2n^2 \ln(lnT)}{2T}\right), \qquad j=0,\ldots\ldots,p \quad (9)$$

where $|\widehat{\Omega_j}|$ signifies the determinant of the variance-covariance matrix of the error terms in the VAR model of lag order j, n is the number of equations in the model, while T is the number of observations.

Once, the optimum lag order is selected, we test the null hypothesis that the k th element of P_t^+ (O^+ in our study) does not Granger cause the w th element of Y_t^+ (C^+ here) by the following hypothesis:

H_0: the row w, column k element in α_r equals zero for $r=1,\ldots\ldots,k$ (10)

In order to define a Wald test in a compact form, the denotations are in order:

$$Y := (P_1^+, \ldots., P_T^+) \qquad (m \text{ X } T)\ matrix,$$

$$D := (v, \alpha_1, \ldots., \alpha_k) \qquad (m \text{ X } (1+mk))\ matrix,$$

$$Z_t := \begin{bmatrix} 1 \\ P_t^+ \\ P_{t-1}^+ \\ \vdots \\ . \\ P_{t-p+1}^+ \end{bmatrix} \qquad \big((1+mk) \text{ X } 1\big)\ matrix, for\ t = 1, \ldots\ldots, T,$$

$$Z := (Z_0, \ldots., Z_{T-1}) \qquad \big((1+mk) \text{ X T}\big)\ matrix, and$$

$$\delta := (u_1^+, \ldots., u_T^+) \qquad (m \text{ X } T)\ matrix.$$

The VAR(p) model can now be compactly presented as:

$$Y = DZ + \delta;$$

The null hypothesis in (10) of non-Granger causality, namely $H_0: R\beta = 0$, is tested through the following Wald statistic:

$$Wald = (R\beta)^{/}[R((Z^{/}Z)^{-1} \otimes S_U)R^{/}]^{-1}(R\beta), \qquad (11)$$

where $\beta = vec(D)$ and *vec* represents a column-stacking operator; $\otimes$ is the Kronecker product, and R is a k X m $(1+mk)$ indicator matrix with elements that are one for restricted parameters and zero for the rest. S_U is the variance-covariance matrix of the unrestricted VAR model estimated as $S_U = \frac{\hat{\delta}_U^{/}\hat{\delta}_U}{T-q}$, where q is the number of parameters in each equation of the VAR model. It is worth mentioning here that, when the assumption of normality is fulfilled, the Wald test statistic has an asymptotic χ^2 distribution with the number of degrees of freedom equal to the number of restrictions to be tested.

4. Data and Empirical Estimation Results

We use the extended version of Grilli & Yang (1988) dataset of annual prices for 24 primary commodities (obtained from Professor Stephen Pfaffenzeller's webpage at http://www.spephen-Pfaffenzeller.com/cpi.html), Gold (from http://www.KITCO.com) and West Texas Intermediate (from Global Financial Database) crude oil prices over 1900 to 2011. The time series are based on prices from the key world trading centres for each commodity (details are available from the database website). All prices are measured in US$ as this the dominant currency used for global trade in commodities. At the outset, we deflate all 26 commodity prices with US CPI to obtain constant 2011 US$ prices and take natural logarithms for greater convenience in explaining the results as well as to remove the influence of units of measurement. Arbitrage between different geographical markets limits the degree to which prices adjusted for exchange rates vary across countries.[2]

Co-movements in oil and most of the other 25 commodities especially after mid Twentieth Century can easily be observed by looking at the graphs presented in Appendix Figure 1. Simple correlation tests between oil and the other 25 commodity prices, which are reported in Appendix Table 1, confirm that all the 25 commodity prices are significantly correlated with oil prices.

At the beginning of the econometric exercise, we investigate predictor persistency, normality of distribution and model heteroscedasticity. These diagnostic tests are reported in Appendix Table 2. Columns 2 to 7 report AR (1), mean, standard deviation, skewness, kurtosis and the Jarque–Bera normality test results for all the commodities and positive and negative oil shocks. The last two columns report tests for hetroscedasticity and autocorrelation. All the commodity series seem to be reasonably persistent according to AR(1) findings. Oil price has similar magnitude of volatility as other commodity prices, but positive oil shocks are more volatile than the negative counterpart. Almost half of the commodity prices are found to be non-normal. With regards to heteroscedasticity and autocorrelation, the null hypothesis of no ARCH is strongly rejected with regards to four commodity prices and positive oil shock and the null of no autocorrelation is rejected at the 5% level for ten commodity prices, oil-price level and oil-price positive shock component.

We further employ three unit root tests, namely the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests as presented in Appendix Table 3. Using all of these tests makes it possible to test for both the null hypothesis of non-stationarity and stationarity, respectively. This process of combined use of

[2] Variation across countries in the rate of inflation or exchange rates could still lead to differences in the local price of traded commodities relative to purely domestic goods. However, the theory of purchasing power parity suggests that differences in exchange rates and inflation rates across currency areas tend to be offsetting.

unit root (ADF and PP) and stationarity (KPSS) tests is known as confirmatory data analysis (Brooks, 2002; Rafiq *et. al.*, 2009). The vast majority of the commodity series tend to be non-stationary in levels according to at least one of the tests, with only jute and wool price series failing to accept the null of both the ADF and PP tests as well as accepting the null of the KPSS test. All commodities reject the null for a unit root in first differences for both the ADF and PP tests as well accepting the null for the KPSS test. We also perform these unit root tests for the series of each of the asymmetric commodity price innovations. As reported in Appendix Table 4, all the positive and negative commodity price components are non-stationary at their levels and stationary at their first differences, at least for the ADF and PP tests. Thus, the findings from these tests suggest that these commodity prices along with their positive and negative components are predominantly integrated in the order of 1 *i.e. I(1)*. However, we still provide robustness checking of our results by using methods that avoid strong distributional assumptions.

In order to identify long-run linkages between oil and 25 commodity prices, we employ both linear ARDL and nonlinear NARDL models to estimate the linkages under four different model settings. One of the major reasons for the popularity of these autoregressive type models is that, the estimates from these tests achieved by bounds-testing approach are reliable regardless of the integration orders of the variables (Pesaran & Shin, 1998; Pesaran *et al*., 2001; Greenwood-Nimmo & Shin 2013; and Shin *et al*., 2014).The first model is a static linear regression of commodity prices on a constant, time trend and oil prices. Second is a static asymmetric model of the form of Equation (1). Third is a restricted symmetric ARDL regression.[3] Fourth is an unrestricted NARDL case, allowing for asymmetry in both the long and short runs. Results are given in Table 1.[4]

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[3] For, dynamic models, we follow the general-to-specific approach to select the final ARDL specification. The preferred specification is chosen by starting with max p = max q = 12 and dropping all insignificant stationary regressors.

[4] We summarize the results due to space constraint, but detailed results will be furnished upon request.

According to the Wald test results in the fifth column in Table 1 for the static asymmetric model and ninth and tenth columns for the dynamic model, asymmetry in the static model is significant for all but five commodities (cocoa, rice, wheat, silver and hides), while for the dynamic model asymmetry is significantly supported for all but seven of the commodities (cocoa, rice, sugar, beef, cotton, hides and tobacco) either in the short run or long run. These findings lend substantial support to undertaking nonlinear models for identifying the interactions between oil and commodity prices.

Table 1: Long-Run Elasticities based on ARDL and NARDL models

Linkages/Models	Static Linear	Static Asymmetric			Dynamic Linear	Dynamic Asymmetric			
	O	O^+	O^-	$W_{O^+=O^-}$	O	O^+	O^-	W_{LR}	W_{SR}
Coffee & Oil	0.2200***	0.5374***	0.2738***	15.30***	0.7215***	0.7850**	-0.6936	3.58**	6.35**
Cocoa & Oil	0.4382***	0.7360***	0.7495***	0.03	0.6595***	0.1598	0.4935	2.77	0.30
Tea & Oil	0.0766**	0.2919***	-0.0147	62.74***	0.5063***	0.3741**	-0.1122	3.97**	0.18
Rice & Oil	0.2704***	0.4105***	0.3587***	1.66	0.4505***	0.4798***	-0.4454*	0.06	1.30
Wheat & Oil	0.4284***	0.5238**	0.4784***	1.59	0.5385***	0.5713***	-0.5575***	0.02	3.99**
Maize & Oil	1.667***	0.3947***	0.2921***	7.76***	0.4218***	0.4276***	-0.3743**	0.33***	3.18**
Sugar & Oil	0.5242***	0.6288***	0.7345***	3.42*	0.5189***	0.0336	-0.3095	0.15	0.01
Beef & Oil	0.3433***	0.7711***	0.3135***	40.72***	0.7209	0.4544	0.2861	0.92	0.34
Lamb & Oil	0.4366***	0.7397***	0.1806*	105.91***	1.0085**	0.0258	0.2232	4.76***	0.43
Cotton & Oil	0.1979***	0.3384**	0.2450**	4.32**	0.3548***	0.3435**	-0.2621	0.28	2.04
Jute & Oil	0.1143**	0.3499***	0.1118	22.08***	0.4581***	0.5532***	-0.4956	0.11**	6.65***
Wool & Oil	0.1812***	0.2278***	0.1135	9.80***	0.2532***	0.2305***	-0.1591	3.67**	1.68
Gold & Oil	0.7988***	0.9009***	0.7148***	22.47***	1.2830***	0.3435**	-0.2621	2.82**	0.10
Copper & Oil	0.4678**	0.6765***	0.5733***	4.01*	1.2830***	0.6691***	-0.3418	4.94***	5.35**
Aluminium & Oil	0.5931***	0.5774***	0.7499***	28.53***	0.5078***	0.5858***	-0.6848***	3.75**	3.66**
Tin & Oil	0.4032***	0.6782***	0.5028***	10.14***	0.6806***	0.5893**	-0.2301	3.11**	3.48**
Lead & Oil	0.3086***	0.4810***	0.2682***	22.42***	0.5461***	0.4114***	-0.0593	4.94**	2.41
Silver & Oil	0.8095***	1.0432***	0.7499***	1.40	1.028***	0.8831***	-0.5939	3.14***	3.01**
Zinc & Oil	0.4410***	0.6311***	0.4344***	21.17***	0.7511***	0.5213***	-0.1674	4.82**	3.81**
Timber & Oil	0.3744***	0.6501***	0.2562***	68.24***	0.5148	0.3937	0.1238	3.87**	4.05**
Rubber & Oil	0.6478***	0.5883***	0.9934***	42.25***	0.4388***	0.5370***	-0.5765	4.04**	3.89**
Banana & Oil	0.2186***	0.3792***	0.0119	271.81***	0.7606***	0.5094***	-0.2284	5.48**	2.16
Palm oil & Oil	0.2689***	0.3958***	0.3082***	4.26**	0.3916***	0.3834***	-0.3019	5.50***	4.38***
Hides & Oil	0.4981***	0.5519***	0.5095***	0.88	0.5758***	0.5043***	-0.4242	0.18	0.02
Tobacco & Oil	0.1799***	0.4798***	-0.0237	121.43***	0.6382***	0.7030***	-0.5930	0.10	0.79

Note: O denotes the natural logarithm of oil prices. O^+ and O^- the associated positive and negative partial sum processes. $W_{o^+=o^-}$ denotes the Wald test of the equality of the coefficients associated with O^+ and O^-. W_{LR} refers to the Wald test of long-run symmetry (*i.e.* Long run $W_{o^+=o^-}$) while W_{SR} denotes the Wald test of the additive short-run symmetry condition. ***, ** and * represent 1%, 5%, and 10%, respectively.

The static linear model indicates a long-run positive elasticity for all of the commodities with respect to oil prices.[5] The static asymmetric regression finds positive shocks in oil prices exert statistically significant long-run impacts for all the commodities, but negative shocks in oil prices exert statistically significant long-run impacts for all but five commodities (tea, rice, wheat, silver and hides). Further, oil price rises generally have greater elasticities than oil price decreases, ranging from 0.2278 to 1.0432, while negative shocks have statistically significant elasticities range from 0.1806 to 0.9934.

As far as the dynamic model estimations from NARDL are concerned, here we present only the long-run elasticities.[6] As in the static linear model, oil prices have significant positive long-run impacts on almost all of the commodity prices, with only beef and timber as exceptions.[7] When the dynamic asymmetry of prices is brought into effect, the positive elasticities from positive shocks are significant for all commodities aside from cocoa, sugar, beef, lamb and timber. In contrast, at the five percent significance level there are negative elasticities from negative oil price shocks for only three commodities (wheat, maize and aluminum). This is further justification for the implementation of nonlinear methods, as not allowing for asymmetry might lead to making incorrect inferences.

According to the statistically significant dynamic asymmetric model results, in the long run a one percent increase in crude oil price leads to increases ranging from 0.2305 percent for wool prices to 0.8831 percent for silver prices. Other commodities with large elasticities with respect to positive oil shocks are coffee (0.78%), tobacco (0.70%), copper (0.67%), and tin (0.59%). In contrast, the elasticities for the very few significant negative oil price shocks are aluminum (-0.69%), wheat (-0.56%) and maize (-0.37%).

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[5] In order to accommodate the strong trending behavior of O, we include a deterministic time trend (ρ).

[6] The short-run causality directions are captured separately from the Hatemi-J. (2012) nonlinear causality test. Detailed results will be provided upon request.

[7] As in our results, Abdel and Arshad (2009) find significant long-run interaction between food and oil prices.

We employ symmetric and asymmetric causality tests to capture the short-run dynamics between oil and commodity prices.[8] The symmetric Granger causality test results are reported in Table 2 and the asymmetric causality test findings due to Hatemi-J (2012) are presented in Table 3. According to the symmetric causality test results, at the five percent level oil prices significantly Granger cause prices for twelve commodities; tea, rice, wheat, maize, sugar, banana, palm oil, cotton, wool, hides, tobacco and aluminum prices, which are all agricultural commodities aside from aluminum. Based on the asymmetric causality results, at the five percent level oil shocks Granger cause prices for eleven commodities; rice, wheat, beef, lamb, palm oil, hides, timber, copper, tin, silver and gold. Hence, under asymmetric causality test there are fewer rejections of the null of no causality for agricultural commodities than under symmetric Granger causality test, but more rejections for metals. This result again highlights the importance of accounting for nonlinearity, ignoring which, could lead to incorrect inferences in many instances.

Turning to the results for positive and negative oil shocks, at the five percent significance level a rise in oil prices Granger causes an increase prices for only three commodities; rice, wool, and gold. In contrast, at the five percent significance level a fall in oil prices Granger causes decreases in thirteen commodity prices; tea, wheat, maize, sugar, palm oil, cotton, jute, wool, hides, rubber, tin, lamb, silver, and lead.

Compared to other studies, tour results for wheat and gold prices are similar to Natanelov *et al*. (2011). They find that an increase in oil price has long-run positive impact on wheat and gold prices. Our results also suggest that decreases in oil prices reduce wheat prices both in the long and short run, while a positive shock from oil prices increases gold prices both in the long and short run. Zhang and Wei (2010) also find a significant positive

[8] To keep consistency with the primary research question and to conserve space here we are only reporting the results of unidirectional causalities running from oil prices to other commodity prices, while bi-directional causalities between the prices and/or uni-directional causalities running from other commodity prices to oil prices are also worth pursuing.

correlation between gold and oil prices. Our results are also consistent with Gupta *et al*. (2014) in that a positive shock from oil prices increases cotton prices in both the short and long run.

Table 2: Symmetric causality tests

Null hypothesis	Oil & Coffee	Oil & Cocoa	Oil & Tea	Oil & Rice	Oil & Wheat	Oil & Maize	Oil & Sugar	Oil & Beef	Oil & Lamb	Oil & Banana	Oil & Palm oil	Oil & Cotton	Oil & Jute
$O \neq> C$	4.31	2.96	6.41**	10.76***	14.23***	14.28***	12.06***	3.28	4.01	31.22***	12.47***	6.32**	4.021
	Oil & Wool	Oil & Hides	Oil & Tobacco	Oil & Rubber	Oil & Timber	Oil & Copper	Oil & Aluminium	Oil & Tin	Oil & Silver	Oil & Lead	Oil & Zinc	Oil & Gold	
$O \neq> C$	11.07***	8.10**	16.19***	3.24	0.36	1.36	10.65***	1.06	2.19	2.79	2.77	1.82	

Note: ***, ** and * represent 1%, 5%, and 10%, respectively.

Table 3: Asymmetric causality tests using the bootstrap simulations

Null hypothesis	Oil & Coffee	Oil & Cocoa	Oil & Tea	Oil & Rice	Oil & Wheat	Oil & Maize	Oil & Sugar	Oil & Beef	Oil & Lamb	Oil & Banana	Oil & Palm oil	Oil & Cotton	Oil & Jute
$O \neq> C$	3.39	4.48	4.64	11.66**	7.06**	5.84	6.49*	7.95**	9.44**	5.49	7.26**	4.81	3.76
$O^+ \neq> C^+$	1.91	0.94	5.32	15.49**	4.21	2.54	1.27	2.73	7.91*	8.624*	3.42	1.39	1.740
$O^- \neq> C^-$	3.34*	5.67*	9.49**	1.29	11.11***	13.08***	9.76**	1.79	0.20	0.637	12.22***	23.53***	18.10***
$O^+ \neq> C^-$	1.03	0.37	0.94	9.85**	0.41	0.35	1.39	1.45	1.48	0.770	2.32	0.184	0.66
$O^- \neq> C^+$	0.10	2.62	0.01	1.117	0.48	1.47	0.95	1.85	1.82	0.791	2.15	3.016	3.67
	Oil & Wool	Oil & Hides	Oil & Tobacco	Oil & Rubber	Oil & Timber	Oil & Copper	Oil & Aluminium	Oil & Tin	Oil & Silver	Oil & Lead	Oil & Zinc	Oil & Gold	
$O \neq> C$	8.35*	9.69***	4.72	3.74	12.51**	8.39**	3.40	15.423***	17.89***	5.37*	3.67	20.02***	
$O^+ \neq> C^+$	11.48***	4.83	0.68	0.57	2.69	2.69	4.26	2.29	2.03	0.67	4.00	21.75***	
$O^- \neq> C^-$	7.78**	8.31**	9.08*	11.05**	6.91*	6.91*	4.58*	19.78***	31.52***	14.59***	3.91	2.14	
$O^+ \neq> C^-$	0.74	0.87	0.55	0.29	1.61	1.61	1.79	0.45	3.28	0.40	1.02	10.41**	
$O^- \neq> C^+$	2.63	2.45	3.59	1.32	3.33	3.33	3.81	3.45	4.78	0.39	0.15	1.67	

Note: O stands for oil price and C is the respective commodity price. Cumulative positive and negative shocks are used. The denotation $O \neq> C$ means that variable O does not cause variable C. It should be mentioned that the $\chi 2$ critical values for one degree of freedom are 6.64, 3.84, and 2.71 at the 1, 5, and 10% significance levels. For two degrees of freedom the $\chi 2$ critical values are 9.21, 5.99, and 4.60 at the 1, 5, and 10% significance levels. ***, ** and * represent 1%, 5%, and 10%, respectively.

In summary, we find the presence of asymmetry in the linkages between oil and most of the commodity prices. From our dynamic asymmetric model, elasticities of oil price increases are significantly positive with respect to most of the commodity prices. However, impacts of oil price decreases are significant only for a few commodities. The asymmetric Granger causalities indicate that a positive oil price shock causes increases in a few commodities in the short run, but a decrease in oil price Granger causes decreases in about half the commodities. In a nutshell, we find that a decrease in prices has short-run impact in causing decreases in many of the commodity prices, but in the long run price decreases have very little impact. Price increases, in contrast, have long-lasting impacts in increasing almost all of the commodity prices, but have little short-run impact.

5. Robustness Checks: Predictive and Regime-Based Estimations

In this section, we examine the robustness of our results with respect to possible structural breaks in the data series for oil and the other commodities as well as for endogeneity of oil prices in the relationship to the other commodities. As discussed earlier, commodity prices have historically experienced abnormally large positive and negative shocks. To statistically capture such sharp price changes, we employ Lee & Strazicich (2003, 2004) tests for one and two structural breaks. The results of these tests are provided in Appendix Table 5.

According to the results, oil prices have a significant structural break during 1973, which is directly linked with first oil shock of 1970s. There is a break in cocoa prices during 1946 at a 1% level of significance, which might be an aftermath of the Second World War. Both rice and rubber prices experienced significant breaks during 1930-1931, which are linked with the Great Depression of 1930s. Beef prices have a significant break during 1958, which seems to be a market-based shock.[9] There is a break in gold prices in 1979 at a 1 percent significance level, which is linked with the oil shock of 1979 in the wake of the Iranian Revolution.[10]

As oil and other commodity price series with evidence of structural breaks might follow a nonlinear process, for cocoa, rice, rubber, beef and gold we examine short-run and long-run linkages based on both the linear and nonlinear time-series econometric techniques. Our break dates for oil, cocoa, rice, beef, rubber and gold are 1973, 1946, 1930, 1958, 1931 and 1979, respectively. Considering these dates as regime breaks, we estimate a structural regime-threshold model. This modification is inspired by the seminal contribution of Enders and Granger (1998) and Hansen (1999), which permits regimes to be identified by the one or multiple threshold variables. This methodological approach allows us to investigate how the dynamics of our benchmark models change conditional on the stage of the imposed thresholds identified at an earlier stage of the empirical analysis.

The new specification of our models for each of these commodities yields the following estimating equations for the various commodities:

$$\Delta Cocoa_{it} = [b_{11}\Delta Oil_{it}]\ I\ (\Delta Cocoa_{it} \leq 1946) + [b_{12}\Delta Oil_{it}]\ I\ (\Delta Cocoa_{it} > 1946) + [b_{11}\Delta Oil_{it}]\ I\ (\Delta Oil_{it} \leq 1973] + [b_{12}\Delta Oil_{it}]\ I\ (\Delta Oil_{it} > 1973) + v_{1it} \quad (12)$$

$$\Delta Rice_{it} = [b_{11}\Delta Oil_{it}]\ I\ (\Delta Rice_{it} \leq 1930) + [b_{12}\Delta Oil_{it}]\ I\ (\Delta Rice_{it} > 1930) + [b_{11}\Delta Oil_{it}]\ I\ (\Delta Oil_{it} \leq 1973] + [b_{12}\Delta Oil_{it}]\ I\ (\Delta Oil_{it} > 1973) + v_{2it} \quad (13)$$

[9] US Department of Agriculture (1983) identifies 1958 as the beginning of a second cycle in the cattle market. As stated, after the Korean Conflict cattle prices declined because of the 21 percent build up in numbers from 1950 to 1953. Growth in numbers continued as prices were going down until 1956, after several years of drought and a year of extremely low prices when the hog cycle and cattle cycle bottomed in 1955. As noted further, 1958 was the year of turnaround.

[10] This is the period when oil, gold and silver prices went up sharply in one of the greatest currency panics ever to hit the U.S. dollar.

$\Delta Beef_{it}$ = [$b_{11}\Delta Oil_{it}$] I ($\Delta Beef_{it} \leq 1958$) + [$b_{12}\Delta Oil_{it}$] I ($\Delta Beef_{it} > 1958$) + [$b_{11}\Delta Oil_{it}$] I ($\Delta Oil_{it} \leq 1973$] + [$b_{12}\Delta Oil_{it}$] I ($\Delta Oil_{it} > 1973$) + v_{3it} (14)

$\Delta Rubber_{it}$ = [$b_{11}\Delta Oil_{it}$] I ($\Delta Rubber_{it} \leq 1931$) + [$b_{12}\Delta Oil_{it}$] I ($\Delta Rubber_{it} > 1931$) + [$b_{11}\Delta Oil_{it}$] I ($\Delta Oil_{it} \leq 1973$] + [$b_{12}\Delta Oil_{it}$] I ($\Delta Oil_{it} > 1973$) + v_{4it} (15)

$\Delta Gold_{it}$ = [$b_{11}\Delta Oil_{it}$] I ($\Delta Gold_{it} \leq 1979$) + [$b_{12}\Delta Oil_{it}$] I ($\Delta Gold_{it} > 1979$) + [$b_{11}\Delta Oil_{it}$] I ($\Delta Oil_{it} \leq 1973$] + [$b_{12}\Delta Oil_{it}$] I ($\Delta Oil_{it} > 1973$) + v_{5it} (16)

where I(.) is the indicator function, while the remaining variables have been defined before.

The estimated parameters of all four models are reported in Appendix Table 6. Except for beef, oil seems to be impacting all of the commodity prices in most of the regimes, confirming the importance of oil price changes in these commodity markets.

To implement a test for endogeneity of oil price in our symmetric and asymmetric models, we first estimate the bivariate predictive model:

$$C_t = \alpha + \beta O_{t-1} + \varepsilon_{C,t} \tag{17}$$

where C_t is the log of commodity price in year t, and O_t is the oil price, positive oil shocks or negative oil shock in the same year. We then estimate:

$$O_t = \mu(1-\lambda) + \lambda O_{t-1} + \varepsilon_{O,t} \tag{18}$$

Here, $\varepsilon_{O,t}$ has mean zero and with variance, σ_O^2. If the residual terms from estimating equations (17) and (18) are correlated, then oil price is perceived to be endogenous. Thus, we test the linear linkage between the error terms by estimating the following simple equation using these residuals:

$$\varepsilon_{C,t} = \theta \varepsilon_{O,t} + \varepsilon_t \tag{19}$$

where, ε_t is the idiosyncratic term.

Results of the endogeneity tests are given in Appendix Table 7. As indicated by the significance of the Θ, the null hypothesis of no endogeneity of oil prices and positive oil shocks with regards to rice, wheat, maize, sugar, beef, lamb, palm oil, wool, hides, timber, copper, aluminum, tin, silver, lead, zinc and gold prices can be rejected at the 10% or higher level of significance. Thus, endogeneity appears to be an issue for the relationship between oil prices or positive oil shocks and many non-oil commodities.

Given the evidence of some structural breaks and substantial endogeneity, we check the robustness of our results through two separate estimation strategies. With regards to endogeneity, we follow Westerlund and Narayan (2012, 2014) and use GLS-based bias-adjusted estimators.[11] These estimators link earlier Equation (17) conditional on Equation (18), thus, removing the endogeneity effect and accounting for any persistence in the predictor indicator. Hence, the conditional predictive regression equation takes the following form:

$$C_t = \alpha + \theta\mu(1-\lambda) + \beta^{adj} O_{t-1} + \theta O_t + \varepsilon_t \tag{20}$$

where by construction, ε_t is independent of $\varepsilon_{O,t}$ in Equation (13) and $\beta^{adj} = \beta - \theta(\lambda - 1)$. Westerlund and Narayan's (2012, 2014) bias-adjusted GLS estimators (namely, β^{adj}) resolve the endogeneity issue and further account for potential conditional heteroscedasticity. According to the results presented in Appendix Table 8, fifteen out of seventeen commodity prices for which endogeneity is shown in Appendix Table 7 are significantly impacted by either oil price or its shock components. The only exceptions are rice and maize prices, which seem to be independent of oil price shocks after allowing for possible endogeneity. The outcome of this test is similar to our previous results in that positive oil shocks are more prominent in raising commodity prices than are negative oil shocks in decreasing prices.

[11] The coefficient estimates of Westerlund and Narayan (2012, 2014) are identical to the OLS estimates from Lewellen (2004), but the adjustment for heteroscedasticity means the power of the GLS test is greater.

6. *Conclusions*

In this study we investigate both long-run and short-run linkages between oil and 25 other commodity prices in the presence of both linear and nonlinear price impacts. To measure long-run impact of oil prices we implement both ARLD and the NARLD methods offered by Shin *et al*. (2014), while to capture the short-run dynamics we implement linear Granger causality and nonlinear causality tests due to Hatemi-J (2012). Considering a hundred and eleven years of time-series data, Wald test results support the presence of nonlinearity in the linkages between oil and most other commodity prices.

Our long-run asymmetry test results indicate that a positive shock in oil prices increases prices of at the least 20 commodities, with positive elasticities ranging from 0.2305 percent for wool prices to a maximum of 0.8831 percent for silver prices. In contrast, a decline in oil price decreases long-run prices at the five percent significance level for only wheat, maize and aluminum, with magnitudes varying from 0.37 to 0.68 percent. In the short run, our results show oil price decreases have significant impacts in lowering many commodity prices. Further, our findings from asymmetric Granger causality test indicate that a decline in oil prices causes a negative shock to at least 13 commodity prices, while a positive shock in oil price causes an increase in prices of only three commodities.

Our results also reveal that there are substantial differences in the impact of oil prices across commodity clusters. For example, while oil prices do not seem to have much impact on beverage market prices and cereal prices, especially once endogeneity is accounted for, they have substantial impact on non-food agricultural commodities and on metal prices even after controlling for potential endogeneity. This suggests a linkage through the use of commodities as raw materials in industrial production.

Differences in the impacts of oil prices across commodities and between the short and long run suggest possible diversification strategies for companies and countries in planning for long-run development. In the short-run context, recent studies by Fernandez (2015) and Reboredo and Ugolini (2016) using high frequency data over recent decades show that variation in the relationship between oil prices and prices of other commodities offers opportunities for diversification and hedging of commodity portfolios. Our results for price relationships over the past century using annual data correspondingly offer opportunities for companies or countries to choose a portfolio of investments in resource development to help reduce the variability of earnings from the portfolio. For example, an oil exporting country would benefit from investments in producing commodities whose prices don't vary with oil prices.

Our results point to asymmetry in the impact of positive and negative oil shocks in their impact on the prices of non-oil commodities. There are also substantial differences in the way oil prices impact on commodity prices between the short run and the long run. However, in spite of the variation in results there is still a preponderance of co-movement between oil prices and prices of other commodities. Thus, from the perspective of smoothing future global economic development, our results clearly lend support to the proposition that a stable oil price is conducive to short-run and long-run stability in the prices of other commodities. Any measures that would reduce oil price volatility would have widespread impact in reducing price volatility across the broad spectrum of commodity prices.

References

Abdel, H.A. and Arshad, F.M., 2009. The impact of petroleum prices on vegetable oils prices: evidence from cointegration tests. Oil Palm Industry Economic Journal 9(2), 31-40.

Asche, F., Osmundsen, P. and Sandsmark, M., 2006. The UK market for natural gas, oil and electricity: are the prices decoupled? Energy Journal 27(2), 27-40.

Bakhat, M., and Würzburg, K., 2013. Co-integration of oil and commodity prices: a comprehensive approach. WP FA05/2013, Alcoa Foundation.

Balke N.S., and Fomby T. B., 1997. Threshold cointegration. International Economic Review 38, 627-645.

Baumeister, C., and Kilian, L., 2014. Do oil price increases cause higher food prices? Economic Policy 29(80), 691-747.

Brémond, V., Hache, E. and Joëts, M., 2013. On the link between oil and commodity prices: A panel VAR approach. Les cahiers de l'économie - n° 93, IFP Energies nouvelles – IFP School - Centre Économie et Gestion.

Brown, S. and Yücel, M., 2006. What drives U.S. natural gas prices? Presented at the USAEE 26th Annual Conference. Ann Arbor, MI.

Chevelliar and Ielpo (2013), *The Economics of Commodity Markets*, Chichester, UK, Wiley-Blackwell.

Chen, S., Kuo, H. and Chen, C., 2010. Modeling the relationship between the oil price and global food prices. Applied Energy 87, 2517–2525.

Enders, W. and Granger, C.W.J., 1998. Unit root tests and asymmetric adjustment with an example using the term structure of interest rates. Journal of Business and Economic Statistics 16, 304-311.

Enders, W. and Siklos, P.L., 2001. Cointegration and threshold adjustment, Journal of Business and Economic Statistics 19(2), 166–176.

Fernandez, V. 2015. Influence in commodity markets: Measuring co-movement globally. Resources Policy 45, 151-164.

Frankel, J. and Rose, A. K., 2010. Determinants of agricultural and mineral commodity prices. HKS Faculty Research Working Paper Series RWP10-038, John F. Kennedy School of Government, Harvard University.

Gohin A. and Chantret F., 2010. The long-run impact of energy prices on world agricultural markets: The role of macro-economic linkages. Energy Policy 38, 333–339.

Gozgor, G. and Kablamaci, B., 2014. The linkage between oil and agricultural commodity prices in light of the perceived global risk. Agricultural Economics – Czech, 60(7), 332–342.

Greenwood-Nimmo, M. and Shin, Y., 2013. Taxation and the asymmetric adjustment of selected retail energy prices in the UK. Economics Letters 121(3), 411-416.

Grilli, E. R., Yang, M. C., 1988. Primary commodity prices, manufactured goods prices, and the terms of trade of developing countries: What the long run shows. World Bank Economic Review 2(1), 1-47.

Gupta, R., Kean, G. J.., Tsebe, M. A., Tsoanamatsie, N. and Sato, J. R. (2014). Time-varying causality between oil and commodity prices in the presence of structural breaks and nonlinearity, Department of Economics Working Paper Series, University of Pretoria.

Hansen, B.E., 1999. Threshold effects in non-dynamic panels: Estimation, testing, and inference. Journal of Econometrics 93, 345-368.

Hansen, B.E. and Seo, B., 2002. Testing for two-regime threshold cointegration in vector error-correction models. Journal of Econometrics 110, 293–318.

Hartley, P.R., Medlock, K.B. and Rosthal, J.E., 2008. The relationship of natural gas to oil prices, Energy Journal 29, 47–66.

Hatemi-J, A., 2012 Asymmetric causality tests with an application. Empirical Economics 43(1), 447-456.

Kapetanios, G, Shin, Y. and Snell A. 2006. Testing for cointegration in nonlinear smooth transition error correction models. Econometric Theory 22, 279-303.

Lee, J. and Strazicich, M.C., 2003. Minimum Lagrange multiplier unit root test with two structural breaks. Review of Economics and Statistics 85 (4), 1082–1089.

Lee, J. and Strazicich, M.C., 2004. Minimum LM unit root test with one structural break. Department of Economics, Appalachian State University.

Lewellen, J., 2004. Predicting returns with financial ratios. Journal of Financial Economics 74, 209-235.

Mitchell, D., 2008. A note on rising food prices. World Bank Policy Research Working Paper Series. No. 4682, World Bank.

Natanelov, V., Alam M.J., McKenzie A.M. and Van Huylenbroeck G., 2011. Is there co-movement of agricultural commodities futures prices and crude oil? Energy Policy 39, 4971–4984.

Nazlioglu, S., 2011. World oil and agricultural commodity prices: Evidence from nonlinear causality. Energy Policy 39, 2935–2943.

Nazlioglu, S. and Soytas U. 2012. Oil price, agricultural commodity prices, and the dollar: A panel cointegration and causality analysis. Energy Economics 34, 1098–1104.

Nissanke, M. and Mavrotas, G., (eds) 2010. *Commodities, Governance and Economic Development Under Globalization,* London: Palgrave.

Pala, A., 2013. Structural breaks, cointegration, and causality by VECM analysis of crude oil and food price. International Journal of Energy Economics and Policy 3(3), 238-246.

Panagiotidis, T. and Rutledge, E., 2007. Oil and gas markets in the UK: Evidence from a cointegrating approach. Energy Economics 29, 329–347.

Peri, M. and Baldi, L., 2010. Vegetable oil market and biofuel policy: An asymmetric cointegration approach. Energy Economics 32 (3), 687–693.

Pesaran, M.H. and Shin Y., 1998. An autoregressive distributed lag modelling approach to cointegration analysis. In Econometrics and Economic Theory: The Ragnar Frisch Centennial Symposium, Strom S (ed.). Cambridge: Cambridge University Press.

Pesaran, M.H., Shin, Y. and Smith, R. J., 2001. Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics 16, 289-326.

Pindyck, R.S. and Rotemberg, J.J., 1990. The excess co-movement of commodity prices. Economic Journal 100, 1173–1189.

Psaradakis, Z, Sola, M. and Spagnolo, F., 2004. On Markov error-correction models with an application to stock prices and dividends. Journal of Applied Econometrics 19, 69-88.

Radetzki, M., 2006. The anatomy of three commodity booms. Resources Policy 31, 56-64.

Rafiq, S, Bloch, H. and Salim, R., 2009. Impact of crude oil price volatility on economic activities: An empirical investigation in the Thai economy. Resources Policy 34, 121-132.

Reboredo, J.C. and Ugolini, A. (2016). The impact of downward/upward oil price movements on metal prices. Resources Policy 49, 129-141.

Saghaian, S. H., 2010. The impact of the oil sector on commodity prices: Correlation or causation? Journal of Agricultural and Applied Economics 42(3), 477–485.

Sari, R., Soytas, U. and Hacihasanoglu, E., 2011. Do global risk perceptions influence world oil prices? Energy Economics 33, 515–524.

Shin, Y., Yu, B. and Greenwood-Nimmo, M., 2014. Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In William C. Horrace and

Robin C. Sickles (Eds.), *Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications*. New York: Springer, 281-314.

US Department of Agriculture 1983. *Cattle Cycles: How to Profit from Them*. Washington DC, US Government Printing Office.

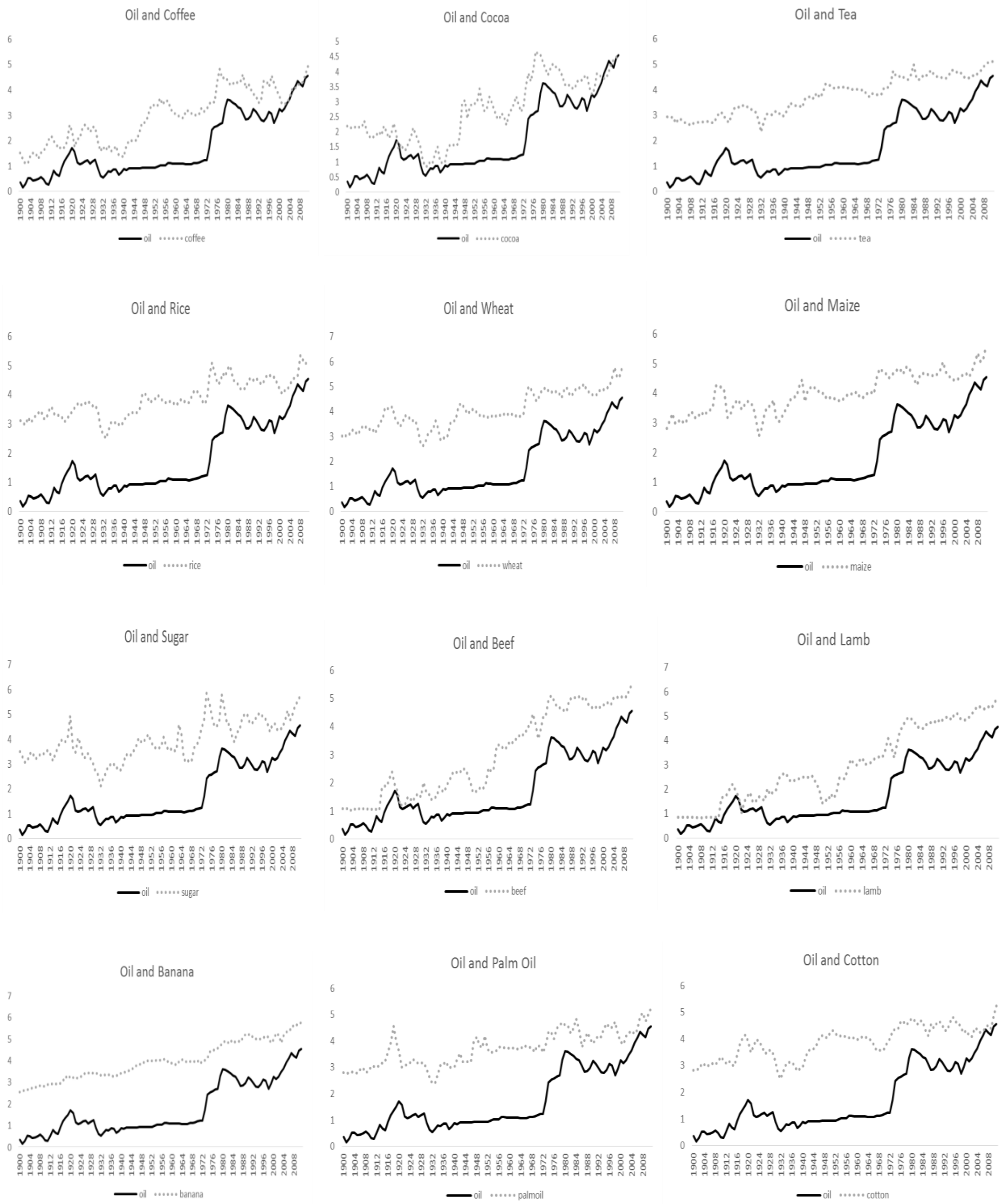
Westerlund, J. and Narayan, P.K., 2012. Does the choice of estimator matter when forecasting returns? Journal of Banking and. Finance 36, 2632–2640.

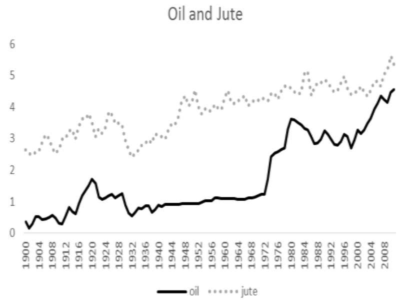
Westerlund, J. and Narayan, P.K., 2014. Testing for predictability in conditionally heteroskedastic stock returns. Journal of Financial Econometrics, 13(2), 342-375.

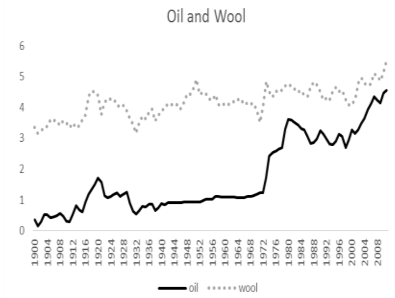
Zhang, Z., Lohr, L., Escalante, C. and Wetzstein, M., 2010. Food versus fuel: What do prices tell us? Energy Policy 38, 445–451.

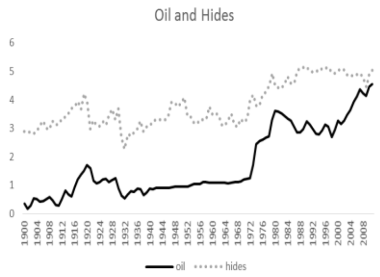
Zhang, Y.-J. and Wei, Y-M., 2010. The crude oil market and the gold market: Evidence for cointegration, causality and price discovery. Resources Policy 35, 168–177.

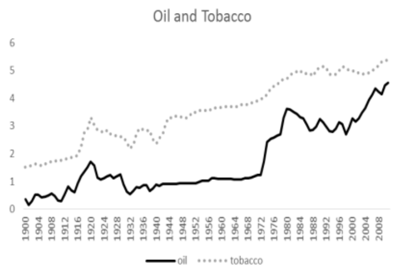
Appendix Figure 1: World commodity prices in natural logarithm, 1900-2011

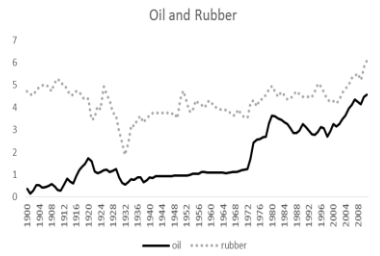


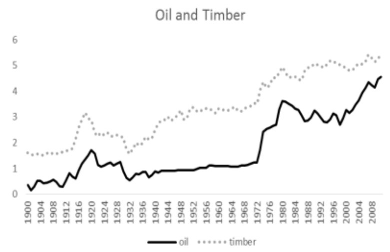


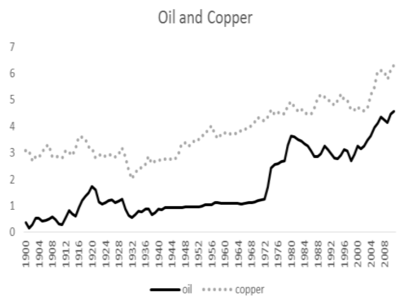


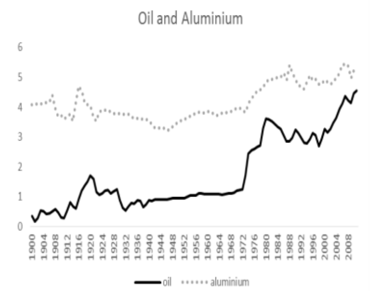


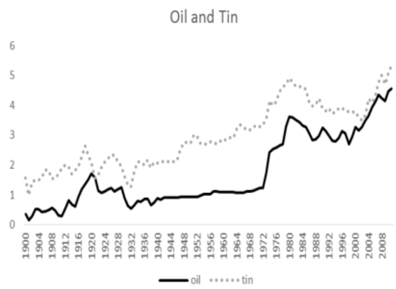


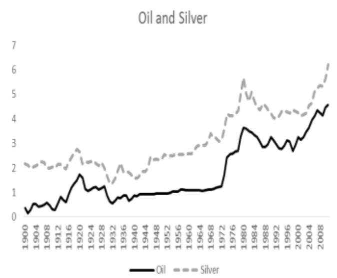


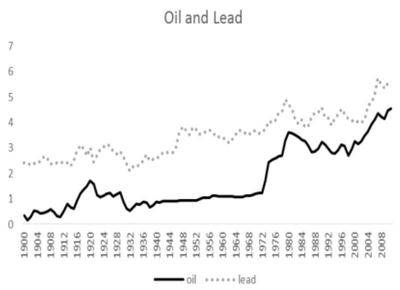


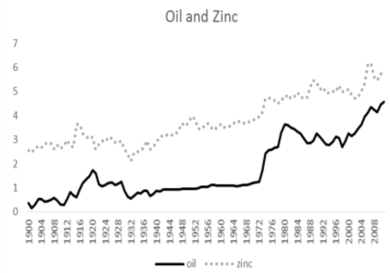


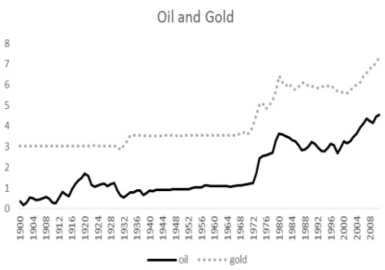












Note: All the variables are in their natural logarithmic forms.

Appendix Table 1: Partial correlations between oil and other commodity prices

Coffee	Cocoa	Tea	Rice	Wheat	Maize	Sugar	Beef	Lamb
0.28***	0.42***	0.19**	0.47***	0.67***	0.52***	0.56***	0.44***	0.59***
Banana	Palm oil	Cotton	Jute	Wool	Hides	Tobacco	Rubber	Timber
0.68***	0.46***	0.32***	0.19**	0.35***	0.64***	0.40***	0.59***	0.62***
Copper	Aluminum	Tin	Silver	Lead	Zinc	Gold		
0.59***	0.79***	0.56***	0.81***	0.49***	0.67***	0.84***		

Note: ***, ** and * represent 1%, 5%, and 10%, respectively.

Appendix Table 2: Selected descriptive statistics of the data

Variables	AR(1)	Mean	Std. Dev	Skew.	Kurt.	J-B	ARCH	L-B Q stat.
Coffee	0.060	2.94	1.06	-0.01	1.72	7.65**	1.21	0.20
Cocoa	0.955***	2.73	1.05	0.04	1.85	6.16**	0.39	0.05
Tea	0.955***	3.76	0.75	-0.03	1.69	7.94**	1.21	9.64***
Rice	0.925***	3.86	0.63	0.23	2.33	3.08	1.08	1.16
Wheat	0.929***	4.04	0.73	0.21	2.15	4.18	0.45	0.26
Maize	0.889***	4.01	0.65	0.03	2.24	2.72	0.68	0.09
Sugar	0.877***	3.95	0.80	0.28	2.43	2.98	0.82	4.05**
Beef	0.970***	2.98	1.51	0.18	1.43	12.06***	0.32	0.04
Lamb	0.965***	2.98	1.53	0.21	1.67	9.09**	0.46	1.89
Banana	0.961***	3.99	0.86	0.27	1.96	6.46**	3.59***	9.07***
Palm Oil	0.896***	3.71	0.65	0.14	2.16	3.68	1.01	7.80***
Cotton	0.919***	3.87	0.61	-0.28	2.09	5.44*	1.44	7.36***
Jute	0.929***	3.88	0.78	-0.21	1.98	5.59*	0.68	0.25
Wool	0.851***	4.18	0.49	-0.07	2.63	0.76	1.46	11.09***
Hides	0.927***	3.81	0.79	0.42	1.79	10.11	1.01	0.78
Tobacco	0.969***	3.55	1.17	-1.12	1.81	6.85**	1.16	6.48**
Rubber	0.867***	4.27	0.67	-0.46	4.19	10.62***	0.92	1.44
Timber	0.970***	3.35	1.25	0.13	1.69	8.32**	0.52	1.86
Copper	0.950***	3.82	1.00	0.51	2.42	6.42**	1.16	0.01
Aluminum	0.946***	4.17	0.61	0.52	2.00	9.69***	4.79***	17.46***
Tin	0.951***	2.95	1.08	0.31	1.95	6.92**	0.78	1.80
Silver	0.950***	3.09	1.19	0.63	2.15	10.76***	2.20**	16.79***
Lead	0.936***	3.47	0.87	0.47	2.58	4.98*	0.71	2.01
Zinc	0.953***	3.79	1.01	0.44	2.01	8.26**	0.63	0.59
Gold	0.964	4.22	1.30	0.74	1.97	15.28***	7.63***	42.88***
O	0.958***	1.73	1.20	0.77	2.19	14.19***	1.42	5.46**
O^+	0.965***	3.75	2.27	0.42	2.34	5.42*	2.58***	7.61***
O^-	0.965***	-2.38	1.21	0.15	2.44	1.83	1.19	0.59

Note: O denotes the natural logarithm of oil prices. $O^+$and O^- the associated positive and negative partial sum processes; Lag length chosen based on SIC; Std. Dev: Standard Deviation; Skew: Skewness; Kurt: Kurtosis; J-B: Jarque-Bera test of normality; ARCH: Autoregressive conditional heteroscedasticity test; and L-B Q-stat.: Ljung-Box Q Statistics. All the variables are in their natural logarithmic forms.

Appendix Table 3: Unit root tests of the data

Variables	*ADF*		*PP*		*KPSS*	
	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
Coffee	-2.8248	-9.7281***	-2.9758	-9.7003***	0.0726	0.0377
Cocoa	-2.2569	-9.5524***	-2.5478	-8.8152***	0.1395*	0.0574
Tea	-3.9499**	-9.5758***	-0.3611	-4.0509***	1.1750***	0.0836
Rice	-4.1333***	-8.8591***	-0.8513	-9.7818***	1.1771***	0.1288
Wheat	-3.6218**	-6.9907***	-0.6500	-8.0044***	0.1495**	0.0570
Maize	-3.8415**	-9.7431***	-1.1899	-15.098***	1.2258***	0.2790
Sugar	-3.4614**	-9.4926***	-1.6834	-11.607***	0.9762***	0.1594
Beef	-2.6965	-9.6364***	-2.8188	-9.6049***	0.1609**	0.0402
Lamb	-2.9180	-9.9000***	-3.0634	-9.8888***	0.1528***	0.0317
Banana	0.0740	-9.2261***	0.2274	-10.598***	1.2020***	0.0941
Palm Oil	-1.1784	-9.6289***	-1.4006	-9.5257***	1.1873***	0.0653
Cotton	-3.6756**	-8.1432***	-2.9522	-7.2880***	1.0816***	0.0497
Jute	-3.6505**	-10.293***	-3.6505**	-10.751***	0.0632	0.0486
Wool	-3.5627**	-9.0789***	-3.5095**	-11.6931***	0.0476	0.1018
Hides	-3.0892	-9.8664***	-3.0202	-13.031***	0.1977**	0.0591
Tobacco	-3.6435**	-7.4888***	-2.7734	-7.7599***	0.0581	0.0405
Rubber	-1.9461	-9.4112***	-1.9902	-9.7437***	0.2331***	0.0551
Timber	-2.1560	-8.1470***	-2.9179	-8.5600***	0.1795*	0.0366
Copper	-2.5269	-8.9891***	-2.0353	-9.0898***	0.2254***	0.0569
Aluminum	-2.0773	-9.8007***	-2.0237	-10.204***	0.2891***	0.0588
Tin	-2.7757	-9.4405***	-2.6222	-9.4423***	0.1150**	0.0461
Silver	-1.3506	-8.1933***	-1.5754	-7.8905***	0.2121**	0.0570
Lead	-2.6359	-9.6100***	-2.6359	-9.6210***	0.1850**	0.0436
Zinc	-3.0249	-9.4898***	-3.0353	-10.725***	0.2110**	0.0494
Gold	-1.7202	-7.0428***	-1.3206	-6.5239***	0.2320***	0.0547
O	-1.7243	-8.3955***	-1.4006	-7.1822***	0.2290***	0.0732
O^+	-1.7142	-2.8641**	-0.5678	-6.9362***	0.1987**	0.1080
O^-	-1.5484	-7.8043***	-1.5087	-7.6993***	0.1479**	0.1058

Note: *ADF*, *PP* and *KPSS* stand for Augmented Dickey-Fuller, Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin tests. For ADF and PP the null is non-stationarity while for KPSS the null is the series is stationary. Optimum lag length for ADF are selected based on Schwarz Information Criterion, and bandwidths for PP and KPSS are chosen through Newly West Bandwidth technique. * (**) *** denote statistical significance at 10%, 5% and 1%, respectively.

Appendix Table 4: Unit root tests for asymmetric components

Variables	*ADF*		*PP*		*KPSS*	
	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
Coffee+	0.1072	-9.8952***	0.1716	-9.9021***	1.2222***	0.0476
Coffee-	-1.7854	-9.3762***	-1.9360	-9.3701***	1.1864***	0.0818
Cocoa+	-2.1458	-8.3615***	-2.2858	-8.7023***	0.1476**	0.1134
Cocoa-	-2.4321	-8.1853***	-1.7212	-8.7693***	0.1850**	0.0979
Tea+	-2.7079	-8.4236***	-2.8774	-9.1371***	1.2163***	0.0668
Tea-	-2.3074	-9.7170***	-2.4918	-9.6978***	1.2071***	0.0758
Rice+	-2.4312	-8.4812***	-2.0357	-8.2926***	0.2068**	0.0397
Rice-	-2.5812	-8.3230***	-2.0153	-8.1622***	0.1639**	0.0453
Wheat+	-2.9109	-8.0584***	-2.5271	-7.9394***	1.2199***	0.0509
Wheat-	-1.9470	-7.8915***	-1.4121	-7.5746***	0.2264***	0.0793
Maize+	-1.9372	-8.4438***	-2.0328	-8.2380***	0.2516***	0.0854
Maize-	-1.5481	-10.060***	-1.3868	-10.434***	0.2631***	0.0801
Sugar+	-2.2706	-10.383***	-2.2420	-10.424***	0.1913***	0.0601
Sugar-	-2.0741	-8.9324***	-2.2563	-8.8871***	1.2024***	0.0584
Beef+	-0.0095	-10.517***	-0.0310	-10.485***	0.1242*	0.1068
Beef-	-2.6648	-7.5718***	-2.0949	-7.2863***	0.1302*	0.0625
Lamb+	-2.3725	-9.3108***	-2.7998	-9.3821***	0.0824	0.0769
Lamb-	-1.5238	-8.8966***	-1.8982	-8.9104***	0.2033**	0.0875
Banana+	0.0225	-9.8960***	-0.1565	-9.9233***	0.2666***	0.0806
Banana-	-0.9247	-9.6797***	-0.9882	-9.6511***	0.2482***	0.0517
Palm Oil+	-2.5681	-8.6423***	-2.3365	-8.7823***	0.1199*	0.0516
Palm Oil-	-2.8967	-8.3401***	-2.6100	-8.3024***	0.1231*	0.0530
Cotton+	-2.4000	-7.7922***	-2.0114	-7.5522***	0.1597**	0.0860
Cotton-	-1.5375	-7.6737***	-1.6195	-7.2819***	0.1398*	0.1073
Jute+	-2.7067	-9.5308***	-2.6500	-10.365***	0.1976**	0.0497
Jute-	-2.6940	-9.7122***	-2.6661	-9.9401***	0.1786**	0.0544
Wool+	0.2526	-8.0353***	-3.0949	-7.6384***	1.2237***	0.0760
Wool-	-0.2671	-10.303***	-0.2129	-10.506***	1.2166***	0.0523
Hides+	-1.5748	-11.534***	-1.4733	-11.674***	0.1371*	0.0659
Hides-	-1.2779	-10.084***	-1.3545	-10.076***	0.2420***	0.0642
Tobacco+	-2.1708	-7.0884***	-1.3643	-6.7569***	0.2472***	0.0490
Tobacco-	-1.2463	-7.8450***	-1.0918	-7.7864***	0.2233***	0.1161
Rubber+	-2.3646	-9.7302***	-2.4827	-9.7079***	0.1946**	0.0565
Rubber-	-0.6690	-8.8086***	-0.9989	-8.8918***	0.2571***	0.0667
Timber+	-2.8661	-8.1544***	-2.7953	-8.1172***	1.2171***	0.0475
Timber-	-1.5564	-9.1219***	-1.7121	-9.1277***	0.2242***	0.0645

Copper+	-2.2401	-8.9095***	-1.7930	-8.8040***	0.1461***	0.0812
Copper-	-2.4312	-9.2988***	-2.1636	-9.2445***	0.1976***	0.0972
Aluminum+	-1.2522	-8.2375***	-0.9670	-8.0978***	0.1880***	0.1159
Aluminum-	-1.6634	-8.6085***	-1.8389	-8.6737***	1.1000***	0.2002
Tin+	-0.0794	-8.5670***	0.0454	-8.5578***	1.2286***	0.0894
Tin-	-2.1714	-9.9757***	-2.1714	-9.9757***	0.1665***	0.1168
Silver+	-1.1942	-7.3007***	-1.3766	-6.9103***	0.2292***	0.0516
Silver-	-1.7643	-8.0588***	-1.7740	-8.0483***	1.1566***	0.0837
Lead+	-1.5439	-9.1045***	-1.9226	-9.0718***	0.1495**	0.0565
Lead-	-2.0875	-9.5714***	-2.0875	-9.5455***	1.1989***	0.0636
Zinc+	-2.8805	-10.307***	-3.0102	-10.4501***	1.2264***	0.0776
Zinc-	-1.7441	-10.264***	-1.7381	-10.264***	0.2098***	0.1104
Gold+	-1.2385	-5.4686***	-1.0350	-5.5608***	0.2590***	0.0641
Gold-	-1.2636	-8.7373***	-1.3182	-8.7373***	0.2694***	0.1120
O^+	-1.7142	-2.8641**	-0.5678	-6.9362***	0.1987**	0.1080
O^-	-1.5484	-7.8043***	-1.5087	-7.6993***	0.1479**	0.1058

Note: *ADF*, *PP* and *KPSS* stand for Augmented Dickey-Fuller, Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin tests. For ADF and PP the null is non-stationarity while for KPSS the null is the series is stationary. Optimum lag length for ADF are selected based on Schwarz Information Criterion, and bandwidths for PP and KPSS are chosen through Newly West Bandwidth technique. * (**) *** denote statistical significance at 10%, 5% and 1%, respectively.

Appendix Table 5: LM tests for structural break, Lee and Strazicich (2003, 2004)

Series	k	TB	S_{t-1}	B_t	*k*	TB_1	TB_2	S_{t-1}	B_{t1}	B_{t2}
Oil	2	1929	-0.05	-0.39	2	1929	1973	-0.06	-0.38	0.66**
			(-1.64)	(-2.36)				(-1.82)	(-2.45)	(4.27)
Coffee	2	1946	-0.15	0.31	3	1929	1986	-0.18	-0.55	-0.50
			(-3.02)	(1.30)				(-3.29)	(-2.41)	(-2.16)
Cocoa	4	1972	-0.10	0.68	2	1946	1972	-0.16	1.10***	0.65
			(-2.46)	(2.72)				(-3.07)	(4.85)	(2.88)
Tea	1	1946	-0.28**	0.27	1	1946	1973	-0.30**	0.29	0.19
			(-4.19)	(1.83)				(-0.41)	(1.99)	(1.27)
Rice	1	1930	-0.20**	-0.66*	2	1930	1984	-0.23*	-0.67**	-0.20
			(-3.85)	(-3.66)				(-3.75)	(-3.87)	(-1.14)
Wheat	4	1930	-0.16	-0.60	1	1930	1953	-0.17	-0.61	-0.15
			(-3.13)	(-3.21)				(-3.23)	(-3.29)	(-0.81)
Maize	1	1930	-0.18	-0.50	1	1930	1954	-0.20	-0.51	-0.19
			(-3.30)	(-2.24)				(-3.48)	(-2.31)	(-0.85)
Sugar	2	1924	-0.26**	-0.50	2	1924	1971	-0.30**	-0.47	0.47
			(-4.08)	(-1.49)				(-4.35)	(-1.44)	(1.44)
Beef	1	1958	-0.16	0.75**	3	1958	1972	-0.21*	0.78**	0.48
			(-3.11)	(3.87)				(-3.58)	(4.08)	(2.51)
Lamb	4	1975	-0.19	0.49	1	1947	1975	-0.22*	-0.39	0.50
			(-3.40)	(2.28)				(-3.68)	(-1.85)	(2.36)
Banana	2	1958	-0.12	-0.16	2	1958	1974	-0.14	-0.14	0.23
			(-2.66)	(-1.66)				(-2.86)	(-1.58)	(2.50)
Palm Oil	1	1930	-0.22*	-0.41	2	1930	1984	-0.23*	-0.42	-0.33
			(-3.67)	(-1.76)				(-3.77)	(-1.82)	(-1.43)
Cotton	2	1929	-0.10	-0.32	2	1915	1930	-0.11	0.38	-0.58
			(-2.48)	(-1.83)				(-2.59)	(2.21)	(-3.35)
Jute	3	1930	-0.23*	-0.43	1	1929	1946	-0.28**	-0.46	0.58
			(-3.83)	(-1.98)				(-4.20)	(-2.19)	(2.75)
Wool	1	1968	-0.10	-0.20	3	1968	2003	-0.13	-0.21	0.19
			(-1.65)	(-2.36)				(-1.81)	(-2.48)	(2.29)
Hides	3	1989	-0.08	-0.09	2	1989	1994	-0.10	-0.10	-0.11
			(-1.45)	(-1.77)				(-1.62)	(-1.89)	(-1.98)
Tobacco	1	1992	-0.11	-0.26	1	1930	1992	-0.13	-0.21	-0.26
			(-2.60)	(-2.14)				(-2.76)	(-1.76)	(-2.17)
Rubber	2	1929	-0.13	-0.79	3	1920	1931	-0.17	-1.01	-0.84**
			(-2.76)	(-2.77)				(-3.16)	(-3.01)	(-3.86)
Timber	2	1972	-0.13	0.50	2	1931	1972	-0.15	-0.36	0.50
			(-2.82)	(3.21)				(-2.99)	(-2.25)	(3.23)
Copper	1	1930	-0.13	-0.56	1	1920	1931	-0.17	-0.36	-0.54
			(-2.75)	(-2.99)				(-3.16)	(-1.98)	(-2.89)
Aluminium	1	1973	-0.09	0.26	3	1920	1973	-0.12	-0.36	0.25
			(-2.25)	(1.66)				(-2.64)	-(2.37)	(1.61)
Tin	3	1929	-0.12	-0.42	3	1929	1985	-0.14	-0.43	-0.47
			(-2.68)	(-2.05)				(-2.94)	(-2.16)	(-2.34)
Silver	2	1920	-0.07	-0.46	2	1929	1973	-0.09	-0.38	0.59
			(-2.07)	(-2.27)				(-2.29)	(-1.90)	(2.95)
Lead	1	1931	-0.15	-0.40	1	1931	1957	-0.16	-0.41	-0.21
			(-3.01)	(-1.99)				(-3.08)	(-2.08)	(-1.06)
Zinc	2	1920	-0.23*	-0.51	2	1929	1973	-0.28**	-0.44	0.55
			(-3.76)	(-2.51)				(-4.25)	(-2.25)	(2.80)
Gold	1	1979	-0.04	0.69***	1	1930	1979	-0.04	-0.23	0.70***
			(-1.54)	(5.28)				(-1.60)	(-1.85)	(5.34)

Note: TB_1 and TB_2 are the break dates, k is the lag length, S_{t-1} is the coefficient on the unit root parameter and B_{t1} and B_{t2} are the coefficients on the breaks in the intercept. The maximum lag length is set as eight (k_{max}=8), and optimum lag length is selected through t-significant' approach proposed by Hall (1994). Critical values for the LM test at 10%, 5% and 1% significant levels are -3.504, -3.842, -4.545. Other critical values follow the standard normal distribution. * (**) *** denote statistical significance at 10%, 5% and 1%, respectively.

Appendix Table 6: Estimates of the multiple-regime models

Linkages/Models	1st Regime			2nd Regime	
	Coeff.	*t*-stat.		Coeff.	*t*-stat.
Cocoa & Oil					
b_{11}	1.243607**	2.06	b_{12}	0.0368637	0.20
b_{13}	1.497441***	2.69	b_{14}	0.4017254	1.47
Rice & Oil					
c_{11}	1.183993***	3.41	c_{12}	0.1581152	0.21
c_{13}	1.283968***	4.30	c_{14}	0.8039821**	2.19
Beef & Oil					
e_{11}	-0.6266095	-1.21	e_{12}	0.0610881	0.40
e_{13}	0.7848593	1.64	e_{14}	0.0325218	1.54
Rubber & Oil					
f_{11}	1.029385**	2.00	f_{12}	0.3844302*	1.97
f_{13}	0.9574696***	2.66	f_{14}	0.0037304	0.14
Gold & Oil					
g_{11}	0.302036*	1.72	g_{12}	0.0222508**	1.84
g_{13}	-0.0863631	-0.42	g_{14}	0.3843691***	3.32

Note: *, **, and *** denote statistical significance at 10%, 5% and 1%, respectively.

Appendix Table 7: Results of endogeneity tests (Estimated values of θ)

Variables	O		O^+		O^-	
	Coefficient	*t*-stat.	Coefficient	*t*-stat.	Coefficient	*t*-stat.
Coffee	0.567562*	1.788	-0.145455	-0.350	0.041032	0.053
Cocoa	0.212685	0.657	1.039242	0.113	0.148624	0.160
Tea	0.230041	1.080	-0.101826	-0.443	0.083378	0.292
Rice	0.585808***	3.274	0.729779**	2.782	-0.140299	-0.273
Wheat	0.711289***	4.472	0.859484***	3.355	-0.107897	-0.191
Maize	0.719820***	4.382	0.697235***	2.969	0.409921	0.862
Sugar	0.692953***	2.796	1.679557***	4.334	0.439295	0.583
Beef	1.100024***	2.962	1.132089**	2.575	-0.694619	-0.743
Lamb	1.044783***	3.107	1.017172***	3.082	-0.874180	-1.079
Banana	0.211814	1.196	-0.041515	-0.322	1.117071	0.489
Palm Oil	0.692547***	3.652	0.327965***	4.335	0.409202	0.797
Cotton	0.543237	1.705	0.400564	1.428	0.472329	0.944
Jute	0.625780	2.563	0.302844	0.984	0.626456	1.149
Wool	0.559074***	3.374	0.421715*	1.904	0.651472*	1.722
Hides	0.517835**	2.577	0.897995***	2.905	-1.064809	-1.682
Tobacco	0.325699	1.139	-0.000386	-0.001	-0.914666	-1.549
Rubber	0.897668***	2.838	1.193131**	2.544	0.975538	1.285
Timber	1.009824***	3.768	1.015662***	3.453	-0.395279	-0.555
Copper	1.050007***	4.576	1.219403***	3.541	0.037509	0.050
Aluminium	0.426918***	2.703	0.828089***	2.844	-0.782288	-1.350
Tin	1.126421***	4.459	0.944436**	2.576	0.625992	0.818
Silver	1.155399***	5.813	1.614186***	4.027	-0.629819	-0.662
Lead	0.904489***	4.174	0.799477***	2.859	0.465371	0.807
Zinc	0.921228***	4.469	0.955067***	3.352	-0.069638	-0.104
Gold	0.770748***	4.088	1.136399***	3.645	-1.642095*	-1.917

Note: *, **, and *** denote statistical significance at 10%, 5% and 1%, respectively.

Appendix Table 8: Estimates of β^{adj}

Linkages	O	O^+	O^-
Rice & Oil	0.2896156	0.3897704	-0.6018847
Wheat & Oil	0.2591397	0.3955184	-0.9473457*
Maize & Oil	-0.3806227	0.2250788	-0.3806227
Sugar & Oil	0.6095702**	0.8260674**	0.2303804
Beef & Oil	0.953281***	1.038484**	-1.087629
Lamb & Oil	0.8859299***	0.9623433***	-1.408814*
Wool & Oil	0.3074286*	0.1543126	0.2211709
Gold & Oil	0.3888608**	0.5535947*	-1.875723**
Copper & Oil	0.5987739***	0.7628021**	-0.7860244
Aluminum & Oil	0.174498	0.5585638*	-1.206726**
Tin & Oil	0.6256072**	0.4978224	-0.2710919
Lead & Oil	0.4670422**	0.2690943	-0.1280742
Silver & Oil	0.599216***	0.8448819**	-0.8831***
Zinc & Oil	0.519006***	0.5483362*	-0.8217999
Timber & Oil	0.5816121**	0.475195	-0.9730306
Palm oil & Oil	0.4290784**	0.3447178	0.0371485
Hides & Oil	0.4253763**	0.846862***	-1.340665**

Note: O denotes the natural logarithm of oil prices. O+and O- are the associated positive and negative partial sum processes. ***, ** and * represent 1%, 5%, and 10%, respectively.