

Time-Varying Causality between Oil and Commodity Prices in the Presence of Structural Breaks and Nonlinearity

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Abstract

The recent commodity price boom has spurred interest to understand determinants of commodity price movements. This paper investigates the causal relationship between oil prices and the prices of 25 other commodities, which include both metals and agricultural products, in the presence of instability and nonlinearity. For this purpose, we make use of a long annual time series dataset spanning from 1900 to 2011, and analyze time-varying Granger causality test, since the inference drawn based on linear Granger causality tests could be invalid due to structural breaks and nonlinearity – which we show are present in the relationship between the variables of interest. We find that, under the case of time-varying causality there are fewer rejections of the null, than under the standard linear Granger causality test, thus highlighting the importance of accounting for instability and nonlinearity. Relying on the time-varying causality test, we observe stronger evidence of other commodity prices in predicting (in-sample) oil prices (15 cases) than the other way around (7 cases).

Key Words: Oil prices, commodity prices, stability, causality, linear, time-varying

JEL Classification: C32, Q11, Q47, F2, G00

1. Introduction

The recent commodity price boom has increased interest in understanding the determinants of commodity price movements. The most pronounced explanation for the observed price increases in commodities is the increased demand for basic materials from rapidly growing emerging markets, quantitative easing monetary policy and speculative demand for commodities in the stock market (Frankel & Rose, 2010). High commodity prices, whether or not related to oil prices, have high macroeconomic impacts such as (but not limited to) high inflationary pressures, high food prices and growth prospects (Avalos, 2011). It is thus important for policy makers to understand the movements in commodity prices.

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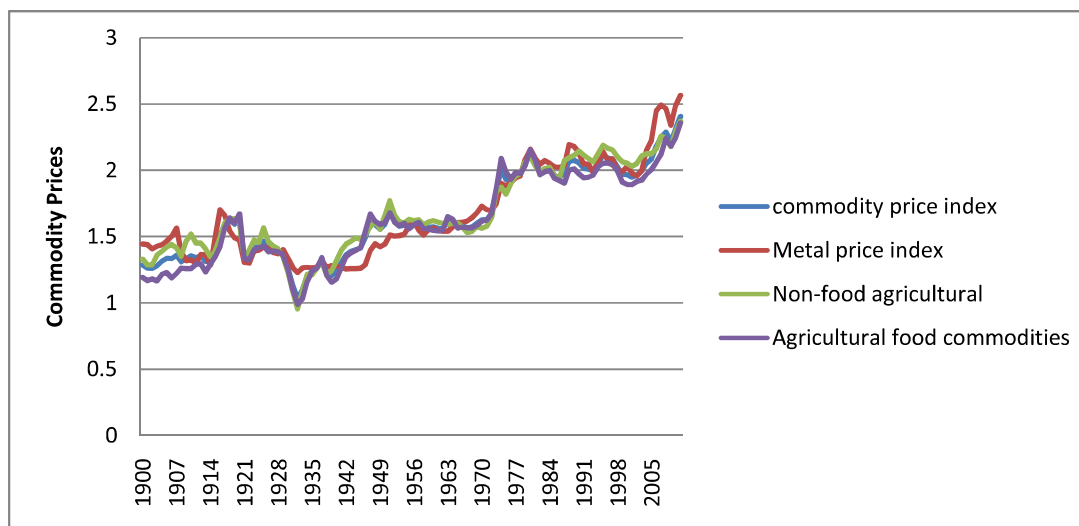
Several techniques have been employed to study the relationship between oil and commodity prices. Most of the research has studied long-run relationships, and have applied linear co-integration methods, while research on the nonlinear relationship has been carried out using threshold co-integration approaches. In contrast to earlier research, this paper will analyse the short-run relationship between oil and 25 selected commodity prices, for the annual period 1900 to 2011, using both linear and time-varying (nonlinear) Granger causality tests. While, analysis of long-run relationships between oil and other commodity prices are important; existence of which implies existence of causality at least in one direction (in a bivariate model), but it does not tell anything specifically about which variable is the causal variable, and if there is possibly bi-directional causality. Understandably, cointegration does not necessarily provide the full picture, which, policy makers might actually need for proper formulation of policies. Also, unlike the literature on commodity prices and oil, which have either looked at oil and precious metal prices or oil and agricultural commodity prices, we consider simultaneously both varieties of commodities in studying their relationship with oil over the same period, to give us a more complete analysis of what drives oil price and, are, in turn, driven by it. Finally note that, the decision to use nonlinear causality test over and above the standard linear Granger causality test stems from the possibility that the relationship between oil and commodity prices is likely to encounter structural breaks, especially given that we look at over a century of data, and also be characterized by nonlinearity (which is in fact what we do show below, based on statistical tests), thus invalidating inference based on linear tests. To the best of our knowledge, this is the first study to analyze time-varying causality between oil prices and 25 selected other commodity prices using 112 years of data.

The rest of the paper is structured as follows: Section 2 provides a discussion of various studies closely related to our paper. Section 3 presents the methodology and Section 4 discusses the data and empirical results. Section 5 concludes the paper.

2. Literature review

Commodity markets have been going through numerous changes since the start of the twenty first century, undergoing a steady and continuous upward trend up until mid-2008 (when a collapse of prices resulted due to the financial crisis). Prices in these markets picked up again from 2009 to 2011. This pattern signifies an apparent disruption from the pattern seen during the 1980s and 1990s when prices were falling at a rate of approximately 1% one average per annum. The magnitude as well as the timing of changes in the different segments of commodity markets (e.g. energy, metals, non-ferrous metals, agricultural/food, beverages, etc.) have generally differed over time, however, this changed with the price increase that started in late 2001 that spread into all commodity markets by 2004-2005 amidst the steady world economic growth (Brémond, Hache and Joëts, 2013). Figure 1 depicts commodity price indices for the period 1900 to 2011, and it shows that there have been considerable changes in commodity markets along with the clear upward trend in prices.

Figure 1: Log of Commodity Price indices, 1900 - 2011



The (causal) relationship between oil prices and commodity prices has for a long time been of great interest, and this has led to the vast literature that examines the different aspects of this linkage along with the use of wide ranging methodologies. This interest is mostly spurred by the need to understand the characteristics and determining factors of long-term commodity price movements. Bakhat and Würzburg (2013) argue that the causal relationship between oil prices and commodity prices (and therefore the understanding of this link) is important for various reasons, and these include (but not limited) to the fact that the oil markets experiencing high volatility along with high price levels since the 1970s (first) oil crises, and both high oil and commodity prices have an effect on economic growth and purchasing power.

Oil prices are thought to impact commodities other than energy and food, with some researchers arguing oil prices potentially have a causal relationship with the prices of other commodities as long as these make use of oil in their production process. Oil prices drive an index comprising different commodity prices that include metals commodities, agricultural commodities, etc. Furthermore, oil prices influence real exchange rates along with countries' industrial production, which in turn, impact commodities' demand worldwide, (Bakhat and Würzburg (2013).

The focus of the studies into this subject matter has differed depending on the specific interests of investigators. For example, there is literature that specifically looks into the relationship between oil prices and agricultural/food commodities such as that by Gozgor and Kablamaci (2014), Pala (2013), Nazlioglu (2011) and Saghaian (2010). Le and Chang (2011), Soytaş et al (2009), and Hammoudeh and Yuon (2008) specifically study the linkages

between oil prices and the prices of metals, and lastly Brémond, Hache and Joëts (2013), Bakhat and Würzburg (2013) investigate the association between oil prices and a wide range of prices comprising commodities from different groupings. Another difference in these studies is the type of relationship investigated in terms of the direction of the relationship in prices, i.e. other studies take a look at the bi-directional relationship between oil and commodity price while other studies are explicitly focused on the causal relationship running from oil to commodity prices.

Additionally, these investigations utilise different datasets, for example, Brémond, Hache and Joëts (2013) use daily data from July 2000 to July 2011, Nazlioglu (2011) uses weekly dataset spanning from 1994 to 2010, Pala (2013) and Gozgor and Kablamaci (2014) use monthly data between the periods of 1990 to 2008 and 1990 to 2013 respectively, while Sanders et al (2012) employ annual data from 1980 to 2010. The differences in these datasets, especially the length of time they cover, will have obviously impacted the results and conclusions from the studies. Bakhat and Würzburg (2013) and Brémond, Hache and Joëts (2013) have indicated that there has been considerable changes in the prices of both oil and commodities over time, and Brémond, Hache and Joëts (2013) further go on to indicate that there have been three periods of sharp market increases in commodity prices in the history of commodity markets. The oil market has also experienced a number of price shocks throughout its history including the above mentioned 1970s crises. One would then expect structural breaks in long time series and these should be accounted for.

Saghaian (2010) investigates the possible causal relationship between oil and agricultural commodity price, and the study's results show the presence of a strong correlation between oil and commodity prices, however, the evidence of a causal link running from commodity prices to oil prices is mixed. Soytaş (2009) does not find a causal linkage between oil and precious metal prices in Turkey leading to the conclusion that there are no predictive properties between these prices. Brémond, Hache and Joëts's (2013) results indicate that there is no linkage between oil and commodity prices in the long term. Their results however show evidence of a short-run relationship, particularly one running from oil to commodity prices.

Different methodologies have been employed to study the causal relationship between oil and commodity prices including the ones already mentioned above. What is clear from all these is that, there is a shift towards the use of methodologies that make use of nonlinear causality tests. Pala (2013) uses both the Johansen Cointegration test and the Granger causality by VECM to test for the relationship between crude oil and food prices. Pala (2013) does this making use of monthly data from 1990 to 2011 and accounts for structural breaks, particularly the one resulting from the 2008 global financial crisis. From the results found, Pala (2013) concludes that there is a significant relationship between crude oil and food prices, with causation running in two directions.

The study by Bakhat and Würzburg (2013) is another one that takes nonlinearity into account when investigating the link between oil prices and commodity. They apply a combination of non-linear cointegration and threshold techniques on a wide range of commodity prices and

oil prices. From these they find that crude oil prices lead to prices of certain commodities, e.g. under metals, they find causality running from crude oil to prices of aluminium and nickel; they find a strong interdependence between crude oil and food prices; and they also find evidence of linkages between crude oil and natural gas prices in the long run, with short-run shocks being transferred from the oil market to the gas market.

3. Methodology

3.1 Linear (Classical) Granger Causality Test

Granger (1969) developed a means (and hence also a test) of defining causality between two variables, X_t and Y_t . Variable X_t is said to “Granger” cause variable Y_t if Y_t can be predicted more accurately by making use of past values of both X_t and Y_t , *ceteris paribus*. This concept states that if we have two stationary series X_t and Y_t , X_t is said to Granger cause Y_t if the process of predicting Y_t is improved by also utilising historical values of X_t , as opposed to predicting based on past values of Y_t only.

The Granger causality test for the two series X_t and Y_t that are assumed to be stationary and of length n involves the estimation of the following p -order linear vector autoregressive (VAR) model:

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} X_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix}$$

Where:

p : optimal lag order of process

$\alpha_1, \alpha_2, \beta$'s : constants; β 's : parameters

$\epsilon_t = (\epsilon_{1t}, \epsilon_{2t})'$: a white noise process of zero mean and covariance matrix $\Phi = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$

In the above VAR model, the Granger causality test can be set up as follows: the series X_t noncauses series Y_t if and only if zero restrictions $\beta_{12} = 0$ for $(= 1, 2, \dots, p$. For the purposes of this study, the series X_t represents oil prices while the series Y_t represents other commodity price, and the null hypothesis that oil prices do not Granger cause commodity prices by imposing the above mentioned zero restrictions, i.e. $\beta_{12} = 0$ for $(= 1, 2, \dots, p$. Imposing this restriction means that oil prices do not contain any predictive properties for commodity prices if the joint zero restrictions under the null hypothesis (H_0) is not rejected.

$$H_0 : \beta_{12} = \beta_{12} = \dots = \beta_{12} = 0$$

3.2 Time-Varying Granger Causality

Due to the simplicity of the classical linear Granger causality tests, it is one of the most frequent approaches used to test Granger causality. However, this method is not suitable in cases where the VAR coefficients are time-varying, which may occur in cases of crisis or even governmental policies. In order to overcome this limitation, Sato et al. (2007) have suggested a methodological approach combining elements of the theory of locally stationary processes (Dahlhaus et al., 1999) and function expansions. The authors introduced a time-varying VAR, which could be used to test for time-varying Granger causality.

In this study, we considered a specific case of the model proposed by Sato et al. (2007) by considering the following bivariate dynamic VAR (DVAR) process

$$\begin{aligned} \mathbf{y}_t = & \alpha_1(t) + \alpha_2(t) \mathbf{y}_{t-1} + \dots + \alpha_3(t) \mathbf{y}_{t-2} + \alpha_4(t) \mathbf{y}_{t-3} + \dots + \alpha_5(t) \mathbf{y}_{t-4} + \mathbf{z}_t \end{aligned}$$

$$\mathbf{y}_t = \alpha_4(t) + \alpha_5(t) \mathbf{y}_{t-1} + \dots + \alpha_6(t) \mathbf{y}_{t-2} + \alpha_7(t) \mathbf{y}_{t-3} + \dots + \alpha_8(t) \mathbf{y}_{t-4} + \mathbf{z}_t$$

Where \mathbf{z}_t and \mathbf{z}_t are innovation terms with mean zero and variance σ^2 , $\alpha_1(t)$ and $\alpha_4(t)$ are time-varying intercepts, and $\alpha_2(t)$, $\alpha_3(t)$, $\alpha_4(t)$ and $\alpha_5(t)$ are the time-varying autoregressive coefficients. Note that DVAR is an extension of conventional VAR model and it provides a parameterization of the intercept and autoregressive coefficients as functions of time. The main idea is then to decompose these functions by using a linear combination of basic functions such as B-splines (Eilers and Marx, 1996). Thus, the time-varying coefficients are expanded as $\alpha_k(t) = \sum_{g=1}^M \alpha_{k,g} \beta_g(t)$ where $\alpha_{k,g}$ is the coefficient corresponding to the B-splines function $\beta_g(t)$, $k = 0 \dots M$, $\beta_g(t) = 1$, and M is the number of functions used in this expansion.

Thus, by using this representation, the DVAR model can be approximated by a linear multiple regression model, which can be estimated by using the ordinary least squares method, similarly to the estimation of conventional VAR models. In addition, Sato et al. (2007) have shown that not only the parameters estimation but also hypothesis testing on the coefficients might be carried out by using standard methods of General Linear Models (Graybill, 1976). As a result, time-varying Granger causality from \mathbf{y}_1 to \mathbf{y}_2 can be tested by using a Wald test to evaluate whether all the coefficients $\alpha_{k,g}$ are equal to zero. These coefficients relates the lagged values of \mathbf{y}_1 with the present values of \mathbf{y}_2 in a time-varying manner. Further information can be found at Sato et al. (2006, 2007). In this study, we used this DVAR model to test for the presence of Granger causality considering time-varying influences. Due to the reduced number of observations, we considered a DVAR of order 1 ($p = 1$) and $M=3$. Understandably, for the sake of comparability, the constant parameter Granger causality tests are also based on a lag-length of 1.

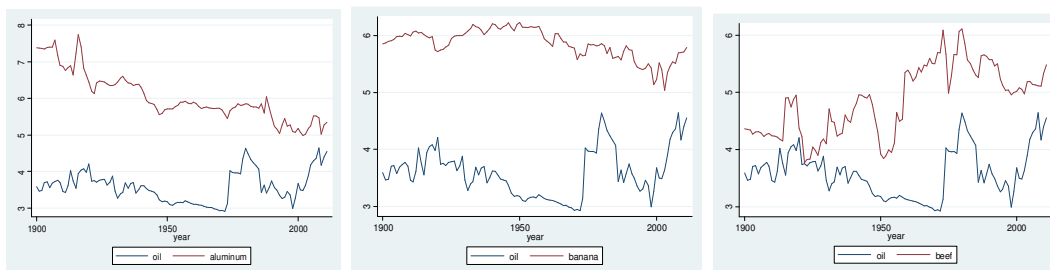
4. Data and Empirical Results

4.1 Data

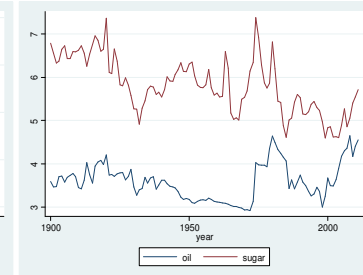
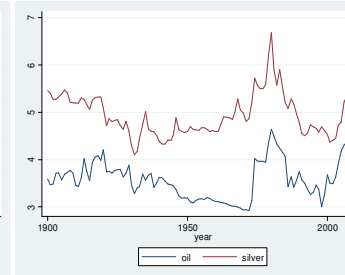
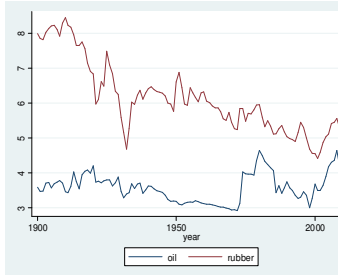
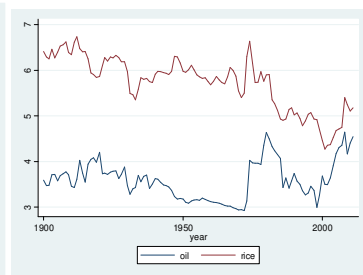
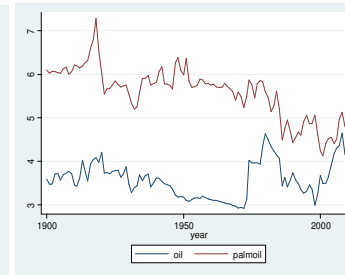
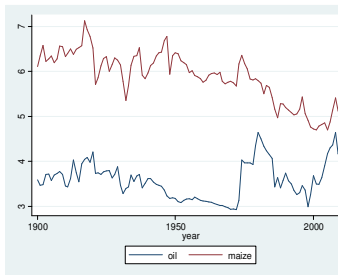
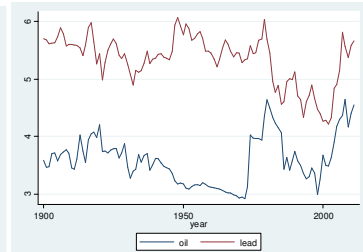
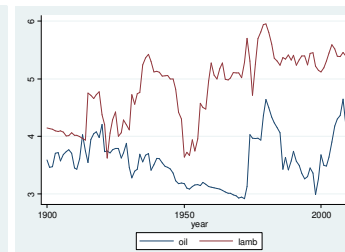
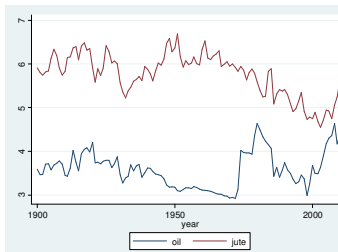
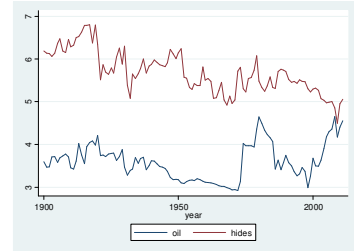
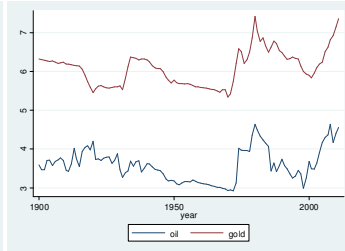
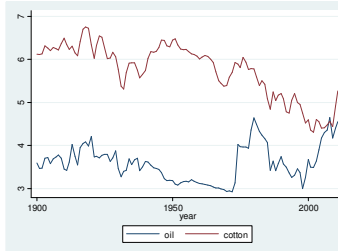
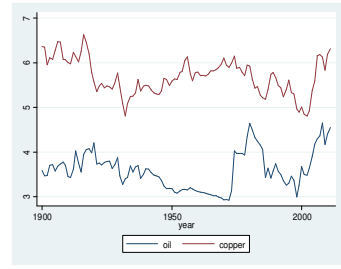
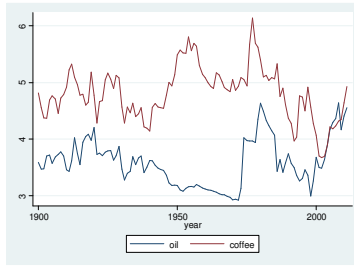
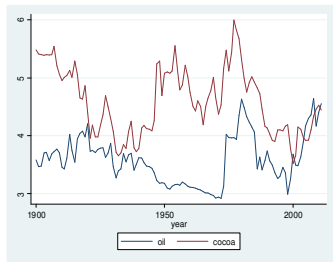
For the purpose of the analysis, we use an extended Grilli and Yang (1988) annual commodity prices for 23 commodities for the period 1900 to 2011, obtained from the webpage of Professor Stephan Pfaffenzeller.² The 23 commodities comprise of aluminium, banana, beef, cocoa, coffee, copper, cotton, hides, jute, lamb, lead, maize, palm oil, rice, rubber, sugar, tea, timber, tin, tobacco, wheat, wool, and zinc. Gold and silver prices are obtained from www.kitco.com, while the West Texas Intermediate (WTI) oil price is obtained from the Global Financial Database. All 26 commodity prices are expressed in constant 2011 US\$ and deflated by US CPI, which is also obtained from the Global Financial Database. Understandably, the start and end dates of our sample is purely driven by availability of data on all the 26 prices involved.

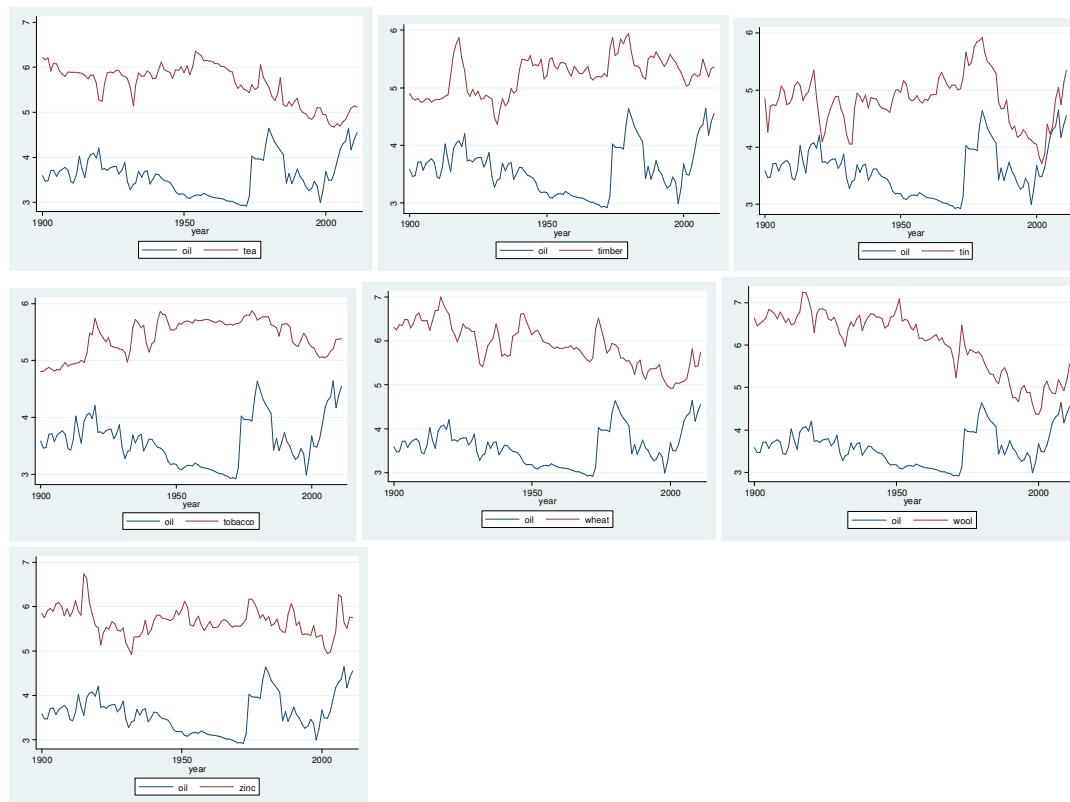
Figure 2 depicts the movement of the 25 commodity prices along with that of oil prices from 1900 to 2011. Without performing any statistical test, this figure already suggests that there might be a strong relationship between some of these commodity prices and oil prices. For example, there appears to be a somewhat strong co-movement of oil prices and the prices of commodities such as aluminium, beef, tobacco, gold and rubber.

Figure 2: Natural Logarithm of world commodity prices, 1900 – 2011.



² <http://www.stephan-pfaffenzeller.com/cpi.html>.





Furthermore, preliminary correlation results analysis (see Table A1 in the appendix) shows that there exists a positive relationship between the oil price and 21 of the 25 commodity prices as well as a negative relationship between the oil price and 4 commodity prices, with varying degrees of strength. For instance there exist a strong positive relationship between WTI oil price and tin price, while the relationship between WTI oil price and tobacco seems to be fairly weak.

4.2 Unit Root testing

The empirical analysis in this study commences with testing for unit roots in all the variables used, i.e. in the oil price and the 25 commodity prices. The augmented Dickey-Fuller (1979, ADF) as well as the Phillips-Perron (1988, PP) tests are utilised for this purpose. The results, reported in Table 1, from the two tests for all the variables, barring Zinc, indicate the presence of unit roots. Since both the linear Granger causality tests and the time-varying Granger causality tests require mean-reverting data, we work with returns data, i.e., first differences of the logarithms of the data, even for Zinc for the sake of comparability with the other commodity prices. Table A2 in the Appendix presents the summary statistics of the real returns for the 26 commodities over 111 observations, i.e., 1901-2011. Not surprisingly, in all cases, normality is overwhelmingly rejected. Gold has the highest mean returns, while rubber has the lowest value. In terms of volatility, rubber has the highest standard deviation, and WTI oil the lowest.

Table 1: Unit Root Test Results of the Various Commodity Prices: 1900 - 2011

Unit root Tests								
	Augmented DF Test				Phillips-Perron Test			
	Level		First difference		Level		First difference	
	Intercept	Trend and intercept	Intercept	Trend and intercept	Intercept	Trend and intercept	Intercept	Trend and intercept
Aluminium	0.3255	0.0273	0.0000	0.0000	0.3803	0.1061	0.0000	0.0000
Banana	0.2992	0.192	0.0000	0.0000	0.3689	0.2212	0.0000	0.0000
Beef	0.3471	0.2141	0.0000	0.0000	0.3242	0.1493	0.0000	0.0000
Cocoa	0.1897	0.5029	0.0000	0.0000	0.0663	0.2225	0.0000	0.0000
Coffee	0.0628	0.2023	0.0000	0.0000	0.0628	0.2023	0.0000	0.0000
Copper	0.0222	0.1293	0.0000	0.0000	0.0611	0.3009	0.0000	0.0000
Cotton	0.6972	0.3006	0.0000	0.0000	0.5629	0.225	0.0000	0.0000
Gold	0.388	0.4176	0.0000	0.0000	0.8816	0.737	0.0000	0.0000
Hides	0.0602	0.0014	0.0000	0.0000	0.104	0.0015	0.0000	0.0000
Jute	0.5035	0.3044	0.0000	0.0000	0.2458	0.0994	0.0000	0.0000
Lamb	0.3241	0.0974	0.0000	0.0000	0.3006	0.559	0.0000	0.0000
Lead	0.1233	0.2918	0.0000	0.0000	0.0848	0.1877	0.0000	0.0000
Maize	0.2288	0.014	0.0000	0.0000	0.2783	0.0173	0.0000	0.0000
Palm oil	0.4371	0.1514	0.0000	0.0000	0.1783	0.0375	0.0000	0.0000
Rice	0.4811	0.2199	0.0000	0.0000	0.4944	0.1013	0.0000	0.0000
Rubber	0.2481	0.4324	0.0000	0.0000	0.2698	0.3264	0.0000	0.0000
Silver	0.5298	0.8187	0.0000	0.0000	0.2979	0.6545	0.0000	0.0000
Sugar	0.0288	0.0151	0.0000	0.0000	0.043	0.0139	0.0000	0.0000
Tea	0.2754	0.1995	0.0000	0.0000	0.3995	0.2392	0.0000	0.0000
Timber	0.0233	0.0262	0.0000	0.0000	0.0668	0.081	0.0000	0.0000
Tin	0.0509	0.1715	0.0000	0.0000	0.106	0.3187	0.0000	0.0000
Tobacco	0.0617	0.2474	0.0000	0.0000	0.1961	0.6599	0.0000	0.0000
Wheat	0.425	0.002	0.0000	0.0000	0.3068	0.0786	0.0000	0.0000
Wool	0.7149	0.0937	0.0000	0.0000	0.5778	0.1177	0.0000	0.0000
WTI oil price	0.2787	0.5482	0.0000	0.0000	0.3147	0.5999	0.0000	0.0000
Zinc	0.0005	0.0018	0.0000	0.0000	0.0018	0.0055	0.0000	0.0000

Notes: Entries indicate p-values for the ADF and PP tests.

4.3 Standard Linear Granger causality Tests

We start off with the standard Granger causality tests reported in Tables 2 and 3. As can be seen from Table 2, the null hypothesis that oil price does not Granger cause the other commodity prices is rejected at least at the 10 percent level for banana, beef, copper, cotton, lead, rubber, timber, tin, tobacco and wool, i.e., in 10 instances. On the other hand, as can be seen from Table 3, there are 16 cases (aluminium, beef, copper, cotton, gold, hides, lamb,

lead, rice, rubber, silver, timber, tin, wheat, wool and zinc) for which the null is rejected, indicating stronger evidence of other commodity prices influencing oil price. Putting the results of Tables 2 and 3 together, a bi-directional causality relationship is found to exist between oil price and the prices of beef, copper, cotton, rubber, timber, tin and wool, i.e., 7 cases.

Table 2: Constant-Parameter Granger Causality Test: Causality from Oil to commodity Prices

Independent Variable: Oil			
Dependent variable	<i>p</i> -value	Dependent variable	<i>p</i> -value
Aluminium	0.2049	Palm Oil	0.4983
Banana	0.0002	Rice	0.4003
Beef	0.0134	Rubber	0.0794
Cocoa	0.2156	Silver	0.2140
Coffee	0.4298	Sugar	0.5992
Copper	0.0192	Tea	0.7961
Cotton	0.0047	Timber	0.0115
Gold	0.266	Tin	0.0224
Hides	0.1435	Tobacco	0.0480
Jute	0.1545	Wheat	0.5818
Lamb	0.1699	Wool	0.0490
Lead	0.0203	Zinc	0.1358
Maize	0.3188		

Notes: Bold entries indicate the rejection of the null at least at the 10 percent level of significance.

Table 3: Constant-Parameter Granger Causality Test: Causality from Commodity to Oil Prices

Independent Variable (s): Commodities			
Dependent variable	<i>p</i> -value	Dependent variable	<i>p</i> -value
Aluminium	0.0306	Palm oil	0.4258
Banana	0.4236	Rice	0.0139
Beef	0.0068	Rubber	0.0498
Cocoa	0.2314	Silver	0.0002
Coffee	0.5260	Sugar	0.7145
Copper	0.0592	Tea	0.8501
Cotton	0.0727	Timber	0.0025
Gold	0.0002	Tin	0.0029
Hides	0.0699	Tobacco	0.6702
Jute	0.7672	Wheat	0.0551
Lamb	0.0014	Wool	0.0007
Lead	0.0111	Zinc	0.0052
Maize	0.0522		

Notes: Bold entries indicate the rejection of the null at least at the 10 percent level of significance.

4.4 Structural Break Tests

Now one of the crucial assumptions behind the standard Granger causality tests is that the parameter estimates of the VAR model remains constant over the entire sample. However, this is less likely to be the case in reality and especially when we are analysing over a century of data. Given this, we test for structural breaks. The *Sup-F*, *Ave-F* and *Exp-F* tests, proposed by Andrews (1993) and Andrews and Ploberger, (1994) were performed to investigate parameter stability of each of the two equations of the constant parameter $VAR(p)$ model. At least one tests, i.e *Sup-F*, *Ave-F* and *Exp-F* must fail to reject the null hypothesis of parameter stability for us to conclude that the $VAR(p)$'s parameters are unstable. Note that, we follow Andrews (1993) by trimming off 15 percent of the ends of all three stability tests and therefore run the stability tests only on [0.15 0.85] of the sample. The results are reported in Tables 4 and 5 with oil price and the various commodities as dependent variables respectively. With oil price as the dependent variable structural instability is detected in the cases of aluminium, banana, rice, maize and wheat, while, with the individual commodities as the dependent variable, the existence of structural breaks cannot be rejected for aluminium, beef, cocoa, gold, hides, lamb, rice, silver, tin and zinc. So, there are a total of 13 cases out of the 25 relationships, where we observe structural breaks. Recall that, it is possible that there could be breaks that we cannot capture in the trimming zones.

Table 4: Structural Breaks Tests

Dependent Variable: Oil	Sup ρ -value	Exp ρ -value	Ave ρ -value	Dependent Variable: Oil	Sup ρ -value	Exp ρ -value	Ave ρ -value
Aluminium	0.068	0.063	0.114	Palm oil	0.413	0.760	0.812
Banana	0.079	0.071	0.685	Rice	0.095	0.053	0.034
Beef	0.885	0.887	0.880	Rubber	0.562	0.453	0.421
Cocoa	0.461	0.286	0.236	Silver	0.132	0.417	0.639
Coffee	0.783	0.789	0.770	Sugar	0.526	0.443	0.407
Copper	0.369	0.427	0.480	Tea	0.436	0.442	0.397
Cotton	0.441	0.611	0.606	Timber	0.913	0.886	0.875
Gold	0.712	0.782	0.797	Tin	0.844	0.934	0.936
Hides	0.505	0.715	0.702	Tobacco	0.579	0.435	0.395
Jute	0.830	0.843	0.832	Wheat	0.164	0.076	0.048
Lamb	0.883	0.660	0.612	Wool	0.459	0.430	0.408
Lead	0.782	0.843	0.865	Zinc	0.776	0.906	0.907
Maize	0.140	0.069	0.048				

Notes: Bold entries indicate the rejection of the null at least at the 10 percent level of significance.

Table 5: Structural Breaks Tests

Dependent Variable: Commodity	Sup p-value	Exp p-value	Ave p-value	Dependent Variable: Commodity	Sup p-value	Exp p-value	Ave p-value
Aluminium	0.081	0.455	0.698	Palm oil	0.794	0.971	0.979
Banana	0.132	0.106	0.102	Rice	0.084	0.238	0.428
Beef	0.000	0.001	0.009	Rubber	0.299	0.277	0.287
Cocoa	0.005	0.017	0.088	Silver	0.046	0.283	0.520
Coffee	0.336	0.661	0.710	Sugar	0.552	0.718	0.701
Copper	0.906	0.768	0.729	Tea	0.539	0.712	0.696
Cotton	0.752	0.897	0.901	Timber	0.256	0.461	0.498
Gold	0.098	0.470	0.664	Tin	0.020	0.201	0.435
Hides	0.062	0.133	0.139	Tobacco	0.562	0.493	0.509
Jute	0.838	0.775	0.766	Wheat	0.300	0.377	0.398
Lamb	0.000	0.000	0.004	Wool	0.271	0.398	0.426
Lead	0.709	0.728	0.707	Zinc	0.032	0.338	0.809
Maize	0.445	0.774	0.802				

Notes: Bold entries indicate the rejection of the null at least at the 10 percent level of significance.

4.5 Test of Nonlinearity

Table 6: BDS Linear Dependence Tests

Dependent Variable: Oil	Decision: Reject/Do not Reject the null hypothesis (linear dependence) at $\alpha=0.10$	Dependent Variable: Oil	Decision: Reject/Do not Reject the null hypothesis (linear dependence) at $\alpha=0.10$
Aluminium	Reject H_0 (2,3,6)	Palm oil	Reject H_0 (2,3,6)
Banana	Reject H_0 (2,3)	Rice	Reject H_0 (2,6)
Beef	Reject H_0 (2,3,6)	Rubber	Reject H_0 (2,3,6)
Cocoa	Reject H_0 (2,3,4,6)	Silver	Do not Reject H_0
Coffee	Reject H_0 (2,3,6)	Sugar	Reject H_0 (2,3,6)
Copper	Reject H_0 (2,3)	Tea	Reject H_0 (2,3,6)
Cotton	Reject H_0 (2 to 6)	Timber	Reject H_0 (2,3,6)
Gold	Reject H_0 (2,3,6)	Tin	Reject H_0 (2,3,6)
Hides	Reject H_0 (2,3,6)	Tobacco	Reject H_0 (2,3,6)
Jute	Reject H_0 (2,3,6)	Wheat	Reject H_0 (2)
Lamb	Reject H_0 (2,3,4,6)	Wool	Reject H_0 (2,3)
Lead	Do not Reject H_0	Zinc	Reject H_0 (2,3,4,6)
Maize	Reject H_0 (2,3,6)		

Notes: H_0 : Linear dependence; we reject H_0 at 10% level of significance if p-value is less than 0.1; Numbers in parentheses refer to the dimensions of the test that reject H_0 .

Besides structural breaks, the relationship between the commodities and oil could be inherently nonlinear, thus invalidating the linear structure in the VAR model used to test

Granger causality. Given this, we apply the BDS test (Brock, Dechert, Scheinkman and Le Baron, 1996) on the residuals of the two equations of the constant parameter VAR model. The results have been reported in Tables 6 and 7. When oil price is the dependent variable the null hypothesis that the residuals are i.i.d. is rejected for 23 out of the 25 cases, barring lead and silver. While, when oil price is the independent variables, the null is rejected in 17 of the 25 cases, with the exceptions being banana, beef, cocoa, coffee, jute, timber, wheat and zinc. All in all, there is quite strong evidence of omitted non-linear structure which was not captured by the linear specification, and hence there is non-linearity in the relationship between oil and the other commodities.

Table 7: BDS Linear Dependence Tests

Dependent Variable: Commodity	Decision: Reject/Do not Reject the null hypothesis (linear dependence) at $\alpha=0.10$	Dependent Variable: Commodity	Decision: Reject/Do not Reject the null hypothesis (linear dependence) at $\alpha=0.10$
Aluminium	Reject H_0 (2,3,4,5,6)	Palm oil	Reject H_0 (2,3,4,5,6)
Banana	Do not Reject H_0	Rice	Reject H_0 (6)
Beef	Do not Reject H_0	Rubber	Reject H_0 (2,3,6)
Cocoa	Do not Reject H_0	Silver	Reject H_0 (2,3,4,5,6)
Coffee	Do not Reject H_0	Sugar	Reject H_0 (2,3,4,5,6)
Copper	Reject H_0 (4,5)	Tea	Reject H_0 (2,3,4,5,6)
Cotton	Reject H_0 (4,5,6)	Timber	Do not Reject H_0
Gold	Reject H_0 (2,3,4,5,6)	Tin	Reject H_0 (2,3,4,5,6)
Hides	Reject H_0 (2,3,4,5,6)	Tobacco	Reject H_0 (2,3,4,5,6)
Jute	Do not Reject H_0	Wheat	Do not Reject H_0
Lamb	Reject H_0 (2,3,4,5,6)	Wool	Reject H_0 (2,3,4,5)
Lead	Reject H_0 (3,4,5)	Zinc	Do not Reject H_0
Maize	Reject H_0 (3,4,5,6)		

Notes: H_0 : Linear dependence; we reject H_0 at 10% level of significance if p-value if less than 0.1; Numbers in parentheses refer to the dimensions of the test that reject H_0 .

4.5 Time-Varying Granger Causality Test

Based on structural break and the nonlinearity tests reported in Tables 4 to 7, we observe that, barring the case of lead, there are either structural breaks or nonlinearity or both, in the relationship between oil and the other commodities. But, it is possible, given that we trim 15 percent of the observations from both ends of the sample in the structural break tests, we could have missed the possible breaks during these periods, especially given that, the trimming point at the end of the sample involves the recent financial crisis. So, in general, we can say that it is important to account for structural breaks and nonlinearities in the relationship between oil and other commodity prices to check for the robustness of the results based on the standard Granger causality test reported in Tables 2 and 3. The time-varying Granger causality test allows us to do exactly this, since the test, by considering each point in time as a different regime, controls for both structural breaks and nonlinearity and hence, is a more general approach.

The results from the time-varying (nonlinear) Granger causality test are reported in Tables 8 and 9. As can be seen, as far as oil causing other commodity prices are concerned, we have 7 cases, namely, aluminium, banana, beef, cotton, timber, tobacco and zinc. While, for the case of causality running from the commodity prices to oil is concerned, we now have the rejection of the null in 15 cases: aluminium, beef, cocoa, gold, lamb, lead, maize, rice, rubber, silver, timber, tin, wheat, wool and zinc. This implies that there is bi-directional causality for aluminium, beef, timber and zinc.

When we compare these results with that of the standard Granger causality, the results have lesser cases (by 4) of the rejection of the null, i.e., evidence of causality, especially for the case of commodity prices causing oil price. Also, bi-directional causality is now reduced by 3 cases. The cases that carries over from standard Granger causality tests to the time-varying test when we test the null that oil price causes other commodity prices, are that of banana, beef, cotton, timber and tobacco, with copper, lead, rubber, tin and wool falling out and aluminium and zinc getting added in. On the other hand, when we look at the cases of other commodity prices causing the oil price, the common set of results across the standard and time-varying approaches are that of aluminium, beef, gold, lamb, lead, rice, rubber, silver, timber, tin, wheat, wool and zinc. The causality for copper, cotton and hides in the case of the linear granger causality test is replaced by cocoa and maize. Barring the cases of beef and timber, the 5 other bi-directional causality results from the constant parameter Granger causality test, does not carry over to the time-varying test. So, while there are similarities, especially for the case of other commodities causing oil prices, the total evidence on Granger causality is weaker in the time-varying case.

Table 8: Time-Varying Granger Causality Test: Causality from Oil to commodity Prices

Independent Variable: Oil			
Dependent variables	<i>p</i> -value	Dependent variables	<i>p</i> -value
Aluminium	0.00	Palm oil	0.681
Banana	0.00	Rice	0.23
Beef	0.05	Rubber	0.285
Cocoa	0.684	Silver	0.736
Coffee	0.261	Sugar	0.881
Copper	0.176	Tea	0.677
Cotton	0.031	Timber	0.015
Gold	0.815	Tin	0.113
Hides	0.176	Tobacco	0.012
Jute	0.68	Wheat	0.541
Lamb	0.599	Wool	0.304
Lead	0.166	Zinc	0.01
Maize	0.661		

Notes: Bold entries indicate the rejection of the null at least at the 10 percent level of significance.

Table 9: Time-Varying Granger Causality Test: Causality from Commodity to Oil Prices

Dependent Variable: Oil			
Independent variables	<i>p</i> -value	Independent variable	<i>p</i> -value
Aluminium	0.046	Palm oil	0.943
Banana	0.465	Rice	0.000
Beef	0.036	Rubber	0.011
Cocoa	0.035	Silver	0.014
Coffee	0.796	Sugar	0.721
Copper	0.194	Tea	0.941
Cotton	0.288	Timber	0.006
Gold	0.012	Tin	0.049
Hides	0.211	Tobacco	0.226
Jute	0.510	Wheat	0.001
Lamb	0.012	Wool	0.007
Lead	0.02	Zinc	0.043
Maize	0.011		

Notes: Bold entries indicate the rejection of the null at least at the 10 percent level of significance.

5 Conclusion

This paper investigates the causal relationship between oil prices and the prices of 25 other commodities, which includes both metals and agricultural products, using a long time series dataset spanning from 1900 to 2011. We start off by using the standard linear Granger causality test. However, since we detect structural breaks and nonlinearity in the relationships between the commodity prices and oil, we resort to a more robust time-varying Granger causality test. This approach, by considering each point in time as a different regime, controls for both structural breaks and nonlinearity and hence, is a more general approach than the standard Granger causality test. We find that, under the case of time-varying causality there are fewer rejections of the null of no causality, than under the standard linear Granger causality test. This result highlights the importance of accounting for instability and nonlinearity, ignoring which, is likely to lead to incorrect inferences in many cases. Relying on the more robust time-varying causality test, we observe stronger evidence of other commodity prices in predicting (in-sample) oil prices (15 cases) than the other way around (7 cases). In other words, oil price movements are likely to be more predictable based on certain commodity prices, than the predictions of commodity prices based on oil price.

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Appendix

Table A1: Correlation of world commodity prices, 1900 – 2011

Commodity Prices	Correlation with Oil Price
Tin	0.5693
Silver	0.4916
Copper	0.4484
Gold	0.4276
Timber	0.3853
Maize	0.3843
Wheat	0.3665
Sugar	0.3515
Jute	0.3466
Cotton	0.3375
Lead	0.3362
Rubber	0.3174
Zinc	0.3143
Rice	0.3064
Palmoil	0.2258
Aluminium	0.1885
Tea	0.1674
Beef	0.1040
Cocoa	0.0399
Banana	0.0367
Tobacco	0.0104
Lamb	-0.0335
Wool	-0.0544
Hides	-0.0830
Coffee	-0.1247

Table A2. Summary statistics of real returns of the various commodities

	Mean	Std. Dev.	Maximum	Minimum	Skewness	Kurtosis	JB <i>p</i> -values	Observations
Aluminium	-12.56	167.56	903.25	-731.20	0.21	17.78	0.00	111
Banana	-0.19	28.09	83.35	-84.37	-0.10	3.91	0.14	111
Beef	1.47	39.94	144.04	-150.54	0.10	8.58	0.00	111
Cocoa	-1.40	37.01	171.06	-90.24	0.98	7.65	0.00	111
Coffee	0.15	40.58	170.32	-166.50	0.44	8.46	0.00	111
Copper	-0.23	68.28	236.79	-208.80	0.03	5.05	0.00	111
Cotton	-2.36	64.15	201.37	-263.35	-0.11	5.66	0.00	111
Gold	9.17	117.18	722.00	-533.81	1.43	18.30	0.00	111
Hides	-2.97	97.35	305.77	-324.66	-0.97	6.39	0.00	111
Jute	-1.52	88.94	246.85	-333.40	-0.41	4.89	0.00	111
Lamb	2.34	32.50	107.53	-97.30	0.28	4.81	0.00	111
Lead	-0.11	45.54	163.30	-121.30	0.38	4.74	0.00	111
Maize	-1.52	113.62	520.21	-502.62	-0.41	10.05	0.00	111
Palmoil	-2.27	113.07	536.29	-770.23	-1.92	25.21	0.00	111
Rice	-3.90	75.63	303.29	-295.04	0.14	7.12	0.00	111
Rubber	-22.74	284.80	1249.81	-903.31	0.81	9.06	0.00	111
Silver	2.41	65.95	312.10	-431.80	-1.06	24.03	0.00	111
Sugar	-5.26	221.03	1030.96	-1119.40	0.11	13.59	0.00	111
Tea	-3.03	48.11	175.50	-142.89	0.64	5.72	0.00	111
Timber	0.71	34.17	114.65	-108.60	-0.13	5.32	0.00	111
Tin	0.74	28.59	104.78	-83.40	-0.03	5.08	0.00	111
Tobacco	0.86	25.06	87.90	-74.84	0.76	6.08	0.00	111
Wheat	-2.11	84.32	288.26	-222.47	0.61	4.84	0.00	111
Wool	-4.52	122.89	520.36	-475.42	0.17	7.64	0.00	111
Wtioilprice	0.53	9.66	33.16	-39.39	-0.10	7.03	0.00	111
Zinc	-0.26	83.79	516.76	-309.26	1.92	17.38	0.00	111

Notes: JB stands for Jarque-Bera test of normality.