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MODELLING INTERNATIONAL OILSEED PRICES: AN APPLICATION OF THE STRUCTURAL TIME SERIES MODEL

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Abstract

The fundamentals characterizing agricultural commodity prices have often been debated in research and policy circles. Building on limitations in the existing literature, the present study conducts an integrated test and empirically analyses the international price of palm and soybean oil from 1960(1) to 2016(8). For this purpose the univariate Structural Time Series Model based on the state space framework is applied. This approach allows flexibility to model complex stochastic movements, seasonality, cyclical patterns and incorporate intervention analysis. Estimation is based on the Maximum Likelihood method via the Kalman Filter. The results establish that both series exhibit a stochastic long term trend punctuated by multiple breaks. The findings also uncover the presence of cyclicality which results in price swings of varying duration and amplitude. The model works well as a description of oilseed prices and improves awareness of their separate structural components. These are fundamental to design country and commodity specific policy strategies and respond to volatile market conditions. The results underscore that contrary to previous price spikes most of the drivers of the mid 2000s price spikes are structural and on the demand side. These new drivers in oilseed markets suggest the possibility of fundamental change in price behaviour with longer-lasting effects.
Keywords: *International prices, Oilseeds, Structural Time Series, Trend, Cycle.*
JEL Codes: *C22, Q2, Q11*

1. Introduction and Background

The past decade has witnessed a large increase in the international prices of food commodities, such as foodgrains and oilseeds, despite a fall during the global financial crises. The boom has brought the analysis of agricultural commodity prices in the forefront of economics research by stimulating empirical studies. These recent price spikes have also drawn concern and raised questions regarding their causes and prospects for future price movements. This issue gains particular importance for economic analysts, policy makers, and investors alike as agricultural commodities are important determinants of food security, particularly in developing and underdeveloped countries. Price movements of agricultural commodities are chiefly in response to supply and demand fundamentals such as technological infrastructure, change in cultivated area, income and taste change, variation in prices of related goods and exogenous shocks such as sudden policy shifts.

The present study focuses on inspecting the international price of two important oilseeds: palm and soybean oil. Edible vegetable oils are one of the most indispensable cooking ingredients and are popularly utilized in the production of consumer goods. Palm and soybean oil are the first and second widely consumed oil crops in the world and in 2015 they accounted for 30.7 and 23.8 percent of world edible oil production respectively (Oilworld Annual, 2015). Both are predominantly utilized in the manufacture of food products and have recently been used in biodiesel production. Palm oil production takes place almost entirely in Malaysia and

Indonesia while soybean is cultivated extensively in the U.S., Brazil and Argentina. For both oilseeds prices are driven by international supply and demand and exporting countries utilize a flexible export tax rate. Palm and soybean oil are considered substitutes as food processors move between them when prices fluctuate. While theoretically this should limit their price variability in practice disparity arises due to supply complications in producer regions (such as adverse weather conditions) or demand shifts (such as perceived health effects of consuming different types of fats and oils).

The objective of this paper is to elaborate a state space specification to investigate the formation of international palm and soybean oil prices while exploring the nature of the causes leading to price spikes since mid-2000s. In particular, the study examines whether the Structural Time Series Model (STM) with intervention variables is suitable to adequately represent price fundamentals and generate efficient forecasts. Oilseed prices are typically characterized by the following stylized features: they demonstrate stochastic (i.e. time varying) trends, exhibit structural breaks and/or outliers and are prone to short term fluctuations. These empirical properties are effectively incorporated into a formal modelling framework while enriching the literature with new insights into the drivers of price changes.

Existing empirical studies utilize a diverse range of econometric techniques to ascertain the growth patterns manifested by agricultural commodity prices. A widely applied method is to model price movements using common autoregressive or fixed coefficient trend models, such as the Autoregressive Integrated Moving Average (ARIMA) model, proposed by Box and Jenkins (1976). Their chief feature is the requisite of stationarity achieved either through de-trending or differencing techniques. Another extensively employed approach is to analyze price spikes using Vector Autoregressive model recommended by Sims (1982). These models investigate unit roots to specify the presence of trends or seasonality relying on differencing technique and the addition of a co-integrated relationship among the variables representing their common trend. A major limitation of both these approaches is that the differencing technique can eliminate the trend and seasonality of the data while using the sample autocorrelation function for model identification integrates high sampling variability. An alternate is the Structural Time Series Model (STM) which is based on the state space form and was first introduced by Kalman (1960). The STM provides a regression-like decomposition of the data into separate components to derive a fully specified statistical model at the end of the estimation. It does not aim to represent the underlying data generating process but the stylized features of the data to provide a better understanding of the response series and its intertemporal changes. The STM differs from the more popular approaches mentioned above as it does not mandate unit root tests thus eliminating the requirement for differencing the data to attain stationarity. On the contrary the non-stationary properties of the data are explicitly represented through the inclusion of stochastic components. Notably while all three model categories mentioned above focus on modelling price by circumventing the obligation to utilize a fully specified model the structural nature of the STM allows for direct economic interpretation.

Previous research shows that the STM class of models has been used in selective studies to investigate complex stochastic growth patterns in agricultural markets over related sample periods. In particular, Labys et al. (1996) examine primary commodity prices to establish the presence of short-term cycles. In their study, Bhar and Hamori (2007) investigated corn, soybean and sugar futures' prices to extract information about the short and long-term dynamics of each series. Alagidede (2009) applied the STM to agricultural and metal price index from 1951 to 2008 and established the presence of a time varying trend and short term fluctuations. In a recent paper, Rezitis et al. (2015) showed that the long-term real price trend of wheat and rice, over the period 1861 to 2010, was composed of a deterministic trend, seasonality and cyclical terms.

In light of the preceding discussion, this paper applies a univariate Structural Time Series Model to decompose palm and soybean oil prices in their structural components of trend, seasonal, cyclical, and irregular terms without searching for any commonalities in the two oilseeds. Being a contrast to the more specific approaches prevalent in the literature it has a number of advantages. Firstly, it incorporates the possibility of trend variation, through specification of a stochastic level and/or slope, while allowing for short term deviations to model the observed and unobserved components associated with them. The included terms are largely interpretable and are defined so that the dynamic stochastic process is reliant on normally distributed disturbances. Secondly, the more common autoregressive models can be obtained as limiting cases of the STM, by imposing restrictions on the hyperparameters, to attain a parsimonious specification. Thirdly, this approach can incorporate multiple structural breaks without the imposition of any specific pattern on the data. Finally in the context of forecasting the STM adjusts to the endpoints of a sample and allows extraction of trend and cycles by filters that are optimal and mutually consistent at the beginning and end of the series. This enables testing of functional forms related to time trends and cyclical patterns when the exact length is not known.

The empirical findings underscore the suitability of introducing a state space specification for a better assessment of oilseed prices. The results show that both series present stochastic trend and cyclical behavior. Inclusion of structural breaks and outliers from the outset, through dummy intervention variables, further improves the model. The results identify the role of multiple demand variables in the path of events that led to the mid 2000 price spikes while emphasizing the significance of commodity and country-specific policy measures. The rest of the paper is organized as follows. Section 2 presents a discussion of the data and the theoretical modelling framework. Estimation results are provided in Section 3 which also includes related statistics and graphical expositions to highlight the dynamics of price development. The state space specification provides a practical tool for forecasting and the estimated models are extended to generate out-of-sample forecasts. Discussion and conclusions are presented in section 4 and 5 respectively.

2. Empirical Strategy and Data Sources

The present study employs monthly palm and soybean oil prices from 1960 to as recent as 2016. The price data were taken from the World Bank and are quoted in U.S. dollars per tonne. The primary criterion for selecting these series is that they reflect competitive price behaviour on international markets capturing both demand and supply forces. While several previous studies utilize annual and quarterly data the present analysis employs monthly series as cyclical behaviour is best analyzed using frequent period of observation (Moore, 1980). Furthermore to reflect underlying market behaviour nominal prices have been employed relative to real prices. While the latter are suitable to study objectives such as terms of trade and industrial adjustments in the present case employment of a price deflator could distort the cyclical properties of the related price series.

Figure 1 shows the time series plot of logged real prices for both oilseed crops. The graphical exposition puts the evolution of data into broader perspective. Firstly, linear, quadratic and cubic curves are fitted to the data using all sample points. For both tested series the cubic trend (denoted by the dotted line) is a much closer fit to the data than either the linear or quadratic one. The latter two yield weak upward trending curves in contrast to the cubic trend which also serves to reduce persistence. Secondly, both series display a high rate of deviation from the trend suggesting a strong possibility of short term fluctuations such as seasonal and cyclical movements. Specifically the periods of mid 1970s and 2000s stand out due to increased volatility and periodic spikes while the uprising trend becomes much steeper. The most significant spike since 1970s occurred post mid-2000. After 2008 prices decrease briefly but return to persist at high levels. Finally, the data are punctuated by incidents of swings suggesting a strong possibility of outliers and structural breaks.

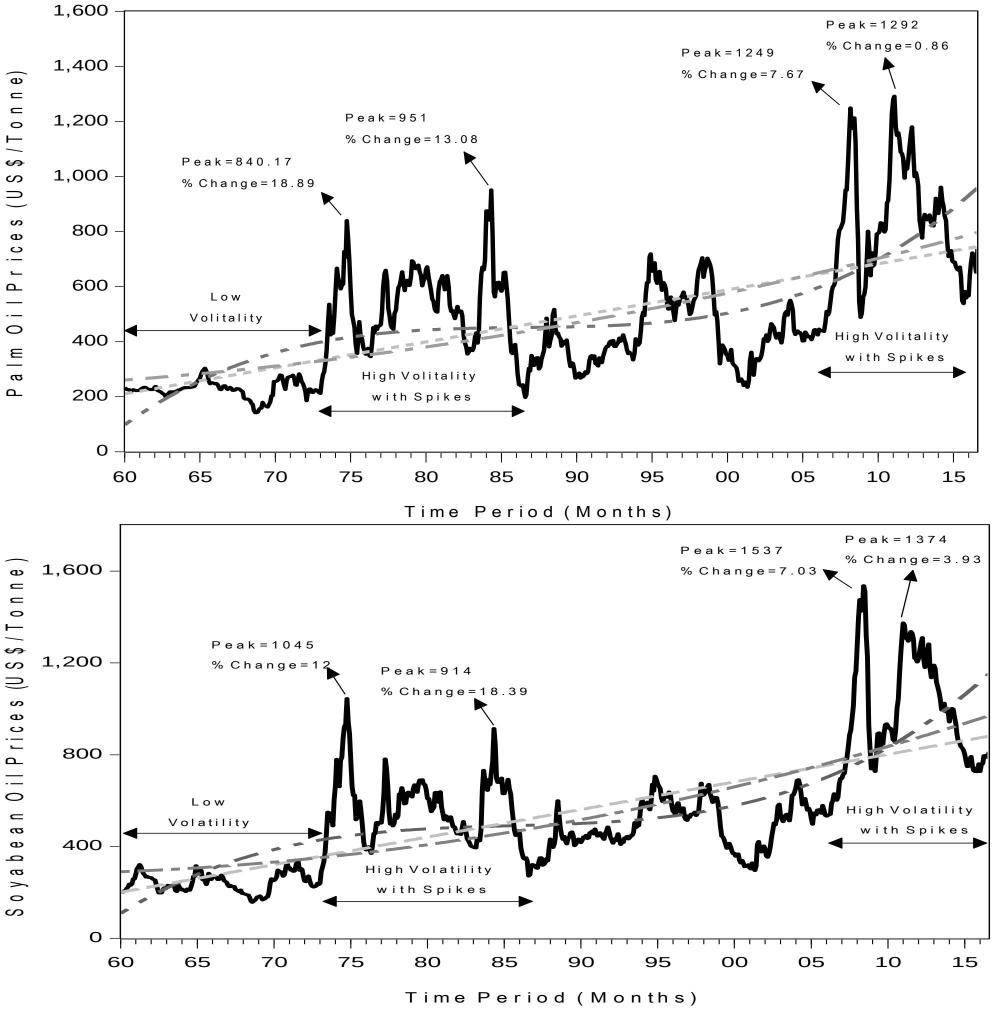

Figure 1. Log Real Prices and Trend Lines - 1960(1)-2016(8)

Table 1 presents the descriptive statistics of palm and soybean oil prices in levels and logarithms.

Table 1: Descriptive Statistics for Palm and Soybean Oil Prices

Statistic	Palm Oil	Log-Palm Oil	Soybean Oil	Log-Soybean Oil
Mean	477.6855	6.052039	540.9803	6.168913
Maximum	1292.000	7.163947	1537.000	7.337588
Minimum	141.7300	6.053264	504.0000	6.222574
Standard Deviation	235.7840	4.953924	157.0000	5.056246
Observations	680	680	680	680

2.1. The Structural Time Series Model

The Structural Time Series Model by Harvey (1989) is applied to decompose palm oil and soybean oil prices into different constituents. The model mandates an explicit formulation of stochastically time-varying terms to arrest features specific to the time series. Letting the logarithm of real prices be denoted by p_t the model is defined as given.

$$p_t = \mu_t + \gamma_t + \psi_t + \sum_{j=1}^{i} \lambda_j d_{j,t} + \varepsilon_t \qquad \text{where } \varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2) \quad t = 1, 2, \dots, T \tag{1}$$

Where p_t represents the logged price, μ_t denotes the trend, γ_t pertains to the seasonal term, ψ_t refers to the cycle, $d_{j,t}$ is the dummy variable and ε_t is the irregular component which is specified as a white noise term with a normal and independent distribution. The state equation for the long term trend can be denoted with a stochastic intercept and slope as given.

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \qquad \text{where } \eta_t \sim NID(0, \sigma_\eta^2) \tag{2}$$

$$\beta_t = \beta_{t-1} + \xi_t \qquad \text{where } \xi_t \sim NID\left(0, \sigma_\xi^2\right) \tag{3}$$

Where μ_t and $\beta_t$denote the level and slope terms. The residuals η_t and ξ_t are uncorrelated and conform to normal and independent distribution**.** Variances in equations 2 and 3 indicate stability. For example $\sigma_\eta^2 = 0$ specifies a constant trend while $\sigma_\xi^2 = 0$ allows trend fluctuations. The above equations can be generalized to nest different specifications. If $\sigma_\xi^2 > 0$ and $\sigma_\eta^2 = 0$ the trend evolves in a smooth pattern yielding the smooth trend model (SMTM), if $\sigma_\eta^2 > 0$ and $\sigma_\xi^2 = 0$ the slope remains constant and the trend evolves as a random walk with drift and finally if $\sigma_\eta^2 = \sigma_\xi^2 = 0$ i.e. both error terms are reduced to zero the trend is deterministic. While positive values of β_t represent an upward drift in the data the trend itself is time dependent as the slope is allowed to vary.

Seasonal fluctuations due to periodic events are a common source of variation in de-sesonalized data. Inclusion of seasonality rectifies these trend variations and their total impact is null over the complete season cycle (displayed through a zero sum term $\sum_{i=0}^{s-1} \gamma_{t-i} = 0$). It can be modelled in dummy variable form as follows.

$$\sum_{i=0}^{s-1} \gamma_{t-i} = \omega_t \qquad \text{where } \omega_t \sim IID(0, \sigma_\omega^2) \tag{4}$$

Alternatively seasonality can be presented as a sum of trigonometric cycles with seasons of varying frequencies as follows:

$$\gamma_t = \sum_{j=1}^{[s/2]} \gamma_{j,t}, \quad \gamma_{j,t} = a_j \cos(\lambda_j \text{t-} b_j) \tag{5}$$

Where $a_j$and b_j are the amplitude and the phase respectively of the cosine function $\gamma_{j,t}$.

$$\begin{pmatrix} \gamma_{j,t} \\ \gamma_{j,t}^* \end{pmatrix} = \begin{bmatrix} cos\lambda_j & sin\lambda_j \\ -sin\lambda_j & cos\lambda_j \end{bmatrix} \begin{bmatrix} \gamma_{j,t-1} \\ \gamma_{j.t-1}^* \end{bmatrix} + \begin{pmatrix} \omega_{j,t} \\ \omega_{j.t}^* \end{pmatrix} \qquad \text{where } \begin{pmatrix} \omega_{j,t} \\ \omega_{j.t}^* \end{pmatrix} \sim NIID(0, \sigma_\omega^2) \tag{6}$$

Seasonal frequency is measured in radian and specified as $\lambda_j = 2\pi j/s$ for $j = 1, \dots, [s/2]$ and $t = 1, \dots, n$. The seasonal disturbance terms are serially and mutually independent of each other and other disturbances with zero mean and common variance. The seasonal terms capture the aspect that supply conditions in the case of agricultural commodities bear the influence of weather and are also impacted by structural reforms and economic policies which can lead to changes in price behaviour. Furthermore seasonally adjusted data may not inculcate desirable properties more specifically if the changes in the seasonal patterns are not accounted for by the adjustment technique (see Harvey and Jaeger, 1993).

Based on visual evaluation of the graphs in Figure 1, cyclical terms are included in equation 1. Cycles are often seen in long economic time series as fairly regular oscillations and its basic form is trigonometric which can be statistically specified as given below:

$$\begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} = \rho_\psi \begin{bmatrix} cos\lambda_C & sin\lambda_C \\ -sin\lambda_C & cos\lambda_C \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{bmatrix} + \begin{bmatrix} v_t \\ v_t^* \end{bmatrix} \tag{7}$$

Where ρ denotes the damping factor $(0 < \rho < 1)$ and shows the pace at which the fluctuations dampen. The frequency in radians is given by $\lambda_C (0 < \lambda_C \leq \pi)$ and denotes the number of oscillations per time unit. The length of the cycle is specified as $2\pi/\lambda_C$. It signifies the time interval between two subsequent peaks and shows the time taken to complete one fluctuation. The irregular terms ($\mathrm{v_t}$ and $\mathrm{v_t^*}$) are normally and independently distributed with zero mean and common variance σ_v^2.

A fundamental question while specifying a univariate model, with both long (trend) and short term (seasonal and cycle) state equations, is how much the former should be allowed to vary. If both level and slope are permitted to fluctuate the trend will almost match the actual data and the included fluctuations will exhibit a short duration and small disturbance variance. Such a specification will contain no useful information and generate poor forecasts. To maintain a balance between the trend and short term movements, restrictions can be imposed on the level and /or slope terms to smoothen the trend. Constraining the level yields a random walk model with constant drift which is suitable for datasets that display linear trends. On the other hand restraining the slope provides a smooth trend model which is appropriate to capture variation in growth. The SMTM is selected for the present study as it allows the trend to evolve in smooth patterns and remains unaffected by small shocks in the near future. Post estimating the trend, the rest of the variation will be explained by the included short term components.

Finally when working with time series data, in addition to the unobserved components, it is often valuable to include explanatory regression coefficients to explicitly model the effect of external factors.[i] Equation 1 includes observable explanatory variables to incorporate the impact of structural breaks and outlying observations. The former refers to exogenous events that cause a shift in the series while the latter represents temporary disruptions in the data which can occur due to price shocks or policy changes. In the present study the de Jong and Penzer (1998) approach is used to check for the presence of irregularities in each series. Having established its position in the data, dummy pulse and step variables are generated for the identified breaks and outliers respectively. These are included in the estimated STM model. If any break term is insignificant it is dropped and only the statistically significant terms are retained in the final model.

3. Analysis of Empirical Results

For both palm and soybean oil prices the most suitable model consists of a smooth trend, seasonality, cycle, intervention and irregular terms (SMTM-SCI). Estimation is carried out using Maximum Likelihood as demonstrated by Harvey (1989). In this procedure first the hyperparameters (σ_ξ^2, σ_γ^2,σ_ψ^2 and σ_ε^2) are obtained and then the integrated terms (μ_t and ψ_t) are extracted based on a smoothing algorithm contained in Koopman et al (2009). Table 2 reports the variance and cycle parameters of the SMTM-SCI. The latter include the frequency at which the random components are centered, a damping factor to capture the dispersion of the random components around the central frequency and finally the variance of the cyclical components.

The outcome of the full sample period, for both palm and soybean oil prices, is provided in the right column of Table 2, along with in-sample results to validate accuracy of the estimates. The results are largely reliable across both samples periods. The irregular components, for both series, are zero indicating that all variations are credited to the other included terms. The slope variance is significant confirming a stochastic growth over the sample period and seasonal variations are non-zero. These can be interpreted as factors which are multiplied by the trend. The seasonal patterns are depicted in Figure 2 to substantiate that the series tend to follow seasonal effects.

A single cycle is fit to both series and parameter estimates show that their variances are significant. Interpretively, cyclical behaviour arises in response to a multitude of short term demand and supply influences such as demand shifts and changes in market structure. These aspects integrate a high measure of arbitrariness causing the cycles to exhibit stochastic properties. For palm oil the cycle covers a duration of 50.53 months (or 4.21 years) while for soybean it lasts longer, almost 52.42 months (or 4.36 years). The cycles for palm and soybean oil exhibit small central frequency, 0.12 and 0.11, and high-damping factors, 0.95 and 0.96, respectively. In other words the cycles reveal a large number of runs above or below the trend but remain close to the central frequency. Moreover they are highly persistent with swings that vary in duration and amplitude. These pieces of evidence can be effectively used to circumvent the risk inherent in cyclical fluctuations and make informed decisions about oilseed production and purchases.

Table 2 also shows the q-ratios. It is the ratio of each variance to the largest and illustrates the relative volatility of the included components. Results indicate that cyclical fluctuations are responsible for maximum variation in the data followed by the slope while the irregular and seasonal terms display negligible q-ratio.

Table 2. Estimation Results of the SMTM-SCB Models

Hyperparameters	**In Sample Period 1960(1) to 2014(8)**		**Full Sample Period 1960(1) to 2016(8)**	
	Palm Oil	Soybean Oil	Palm Oil	Soybean Oil
Level (σ_η^2)	0 (0)	0 (0)	0 (0)	0 (0)
Slope (σ_ξ^2)	0.00000483** (0.001295)	0.00000320** (0.001164)	0.00000479** (0.001295)	0.00000324** (0.001209)
Season (σ_γ^2)	3.84542E-14 (1.03E-11)	7.70639E-14 (2.80E-11)	3.47733E-14 (3.48E-14)	8.40184E-14 (3.14E-11)
Cycle (σ_ψ^2)	0.00373* (1)	0.00275* (1)	0.00370* (1)	0.00268* (1)
Irregular (σ_ε^2)	1.55655E-11 (4.17E-09)	2.87699E-11 (1.05E-11)	9.7619E-11 (2.04E-05)	2.38736E-11 (8.91E-09)
Cycle Parameters				
Duration ($2\pi/\lambda$)	50.53915*	52.42094*	50.59226*	52.62472*
Damping Factor (ρ)	0.95908*	0.95962*	0.95917*	0.95969*
Frequency (λ_C)	0.12432	0.11986	0.12419	0.11940
Variance (σ_v^2)	0.04654	0.03480	0.04625	0.03393

*Note: q-ratios are reported in parentheses. * and ** denote statistical significance at the 1% and 5% levels respectively*

Table 3 presents the Maximum Likelihood estimates of the final state vector (level and slope parameters) and regression effects (intervention terms). These are treated as fixed regression coefficients with state disturbances equal to zero. Model parameters illustrate that only the level component is significant for both series. Furthermore all identified intervention effects are statistically significant. For palm oil all four interventions are related to structural breaks. A single break in 2001(7) has a positive effect on the price level while a downward shift is represented by the 1973 (9), 1984 (7) and 2008 (10) breaks. For soybean oil there are five breaks and a single outlier. The structural breaks in 1983(8), 1988(6) and 2001(7) are associated with an upward shift while a downward shift is indicated by the two breaks in 1986(8) and 2008(10) and a single outlier in 1973(11). The findings of the present study stand out in the sense that the existing literature does not yield an integrated multiple break test for oilseeds. Few breaks are common while others relate to specific events. More importantly all identified intervention terms arrest significant rise or decline in palm and soybean oil market.

Table 3.State Vector Analysis and Regression Effects in Final State

Coefficients of Final State	**In Sample Period 1960(1) to 2014(8)**		**Full Sample Period 1960(1) to 2016(8)**	
	Palm Oil	Soybean Oil	Palm Oil	Soybean Oil
Level (μ_t)	7.368*	6.596*	7.142*	6.327*
Slope (β_t)	-0.006	-0.006	-0.005	-0.008
Level-1973 (9)	-0.289*	-	-0.288*	-
Level-1983 (8)	-	0.298*	-	0.298*
Level-1984 (7)	-0.282*	-	-0.280*	-
Level-1986 (8)	-	-0.209*	-	-0.209*
Level-1988 (6)	-	0.222*	-	0.222*
Level-2001 (7)	0.268*	0.263*	0.269*	0.264*
Level-2008 (10)	-0.312*	-0.256*	-0.313*	-0.256*
Outlier-1973 (11)	-	-0.154*	-	-0.153*

** denotes statistical significance at the 1% level*

To obtain a clear assessment and highlight the variability of separate structural terms historical decomposition for palm and soybean oil is calculated and presented in Figure 2. The first column shows that the long term trends are projected fairly well by time varying parameters while the break terms are instrumental in shifting the trend lines. The fluctuations in the slope are highly similar in both cases. The second column illustrates the deterministic pattern of the seasonal components over the estimation span and the last column graphs the cycles extracted from log prices. The cycles are highly persistent causing price swings to vary in their duration and amplitude while the seasonal components are less volatile. Due to a large number of runs above and below the trend (see Table 2) these cycles drive prices farther away from the long term trend. The amplitude of both cycles typically remains in the range of -0.25 and -0.3 to 0.25 and 0.3 but there is a discernible rise in mid 1970s and then post mid-2000. Notably the cycles capture the influence of short term supply and demand fundamentals while the intervention analysis arrest random effects on prices such as unpredictable movements. These findings are largely similar to those derived by Alagidede (2009) for agricultural commodity price index and Rezitis et al. (2015) for food grains crops (wheat and rice).

Diagnostics employed for model evaluation are based on one-step-ahead prediction errors. These include the mean squared error, the root mean squared error, the mean absolute percentage error, the maximum percentage error, the R^2 and the adjusted R^2. Table 4 shows that the above mentioned statistics do not give evidence of misspecifications and confirm a good agreement between the model and the data.

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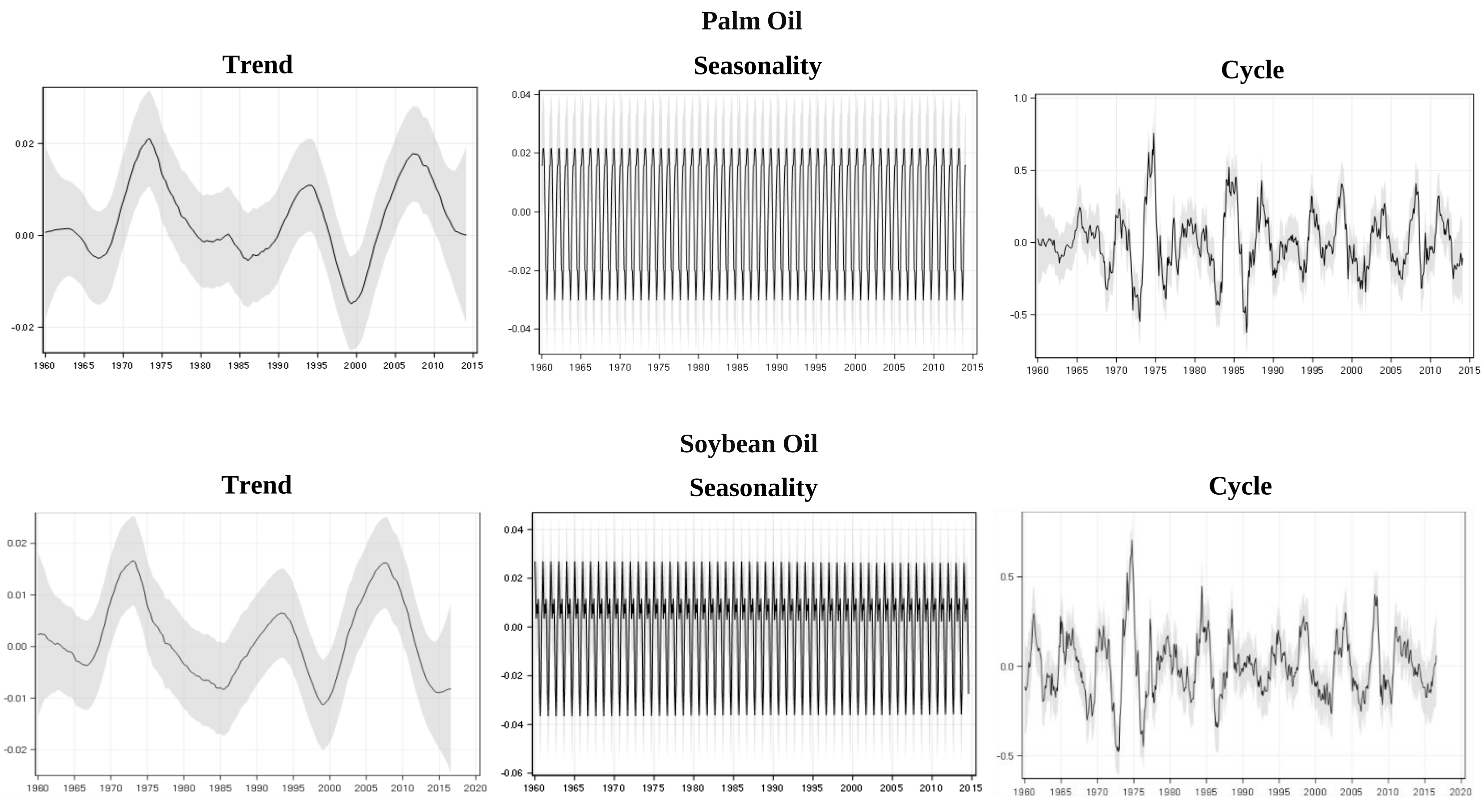

Figure 2. Decomposition of Prices into Trend-Seasonality-Cycle

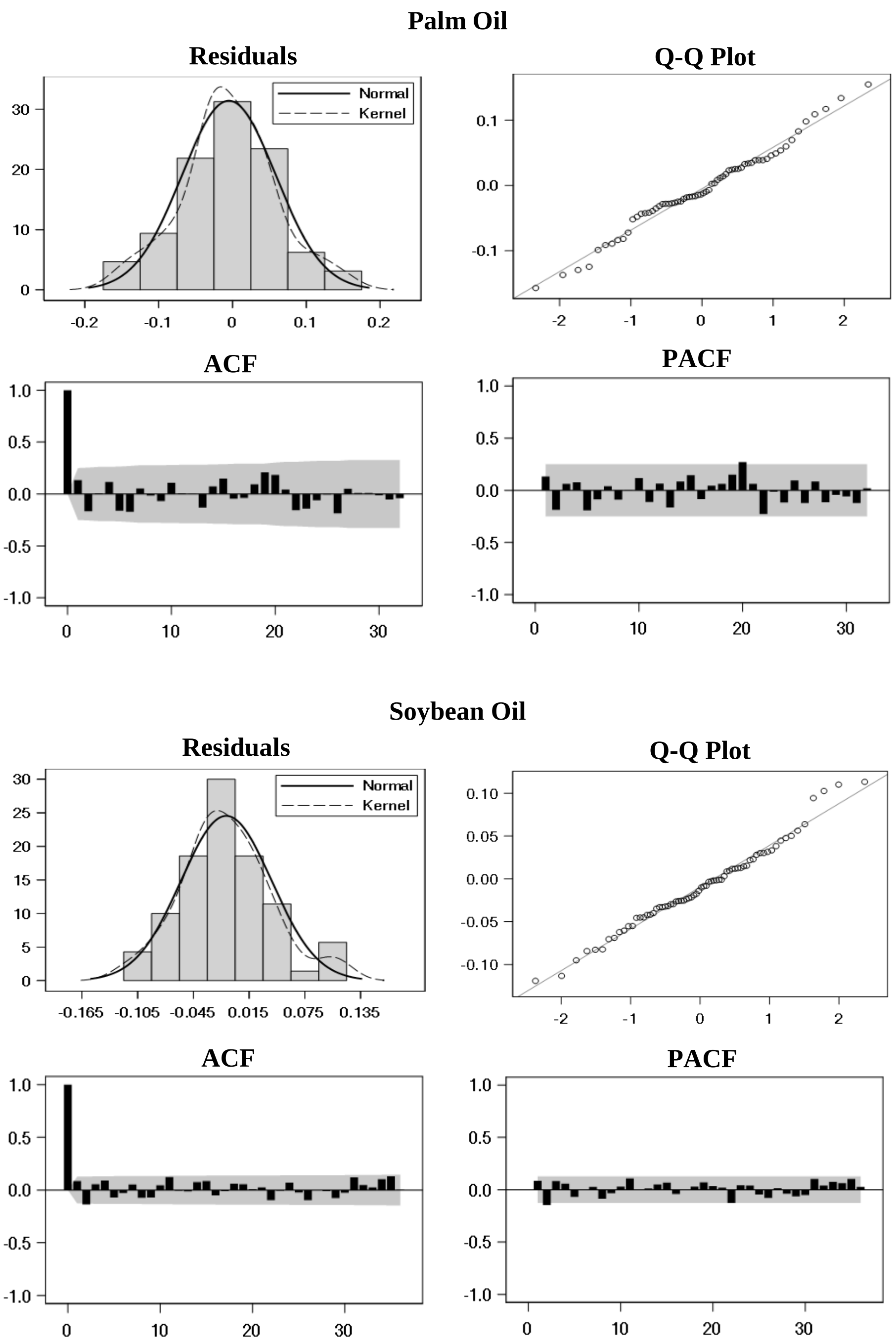

Figure 3. Residual Diagnostics

Table 4. Fit Statistics Based on Residuals

Statistics	Palm Oil	Soybean Oil
Mean Squared Error	0.003	0.002
Root Mean Squared Error	0.062	0.049
Mean Absolute Percentage Error	0.726	0.560
Maximum Percentage Error	2.035	1.696
Adjusted R^2	0.903	0.913
R^2	0.910	0.919

Additionally, Figure 3 presents supplementary residual diagnostic plots. These consist of the classical tests of normality (histogram and Q-Q plot) and whiteness [residual autocorrelation function (ACF) and partial residual autocorrelation function (PACF)]. The residuals exhibit normal and independent distribution for a correctly specified model. The first two columns demonstrate no serious breach of normality. The histogram is practically symmetric and lies quite close to the normal density. On the other hand the Q-Q plot remains close to the line of reference. The ACF and PACF are shown in columns 3 and 4 and clearly do not breach the assumption of whiteness as correlations at all nonzero lags are insignificant. The statistics presented in Table 4 and diagnostics depicted in Figure 3 validate that for both oilseeds the SMTM-SCI are robust and free from misspecification.

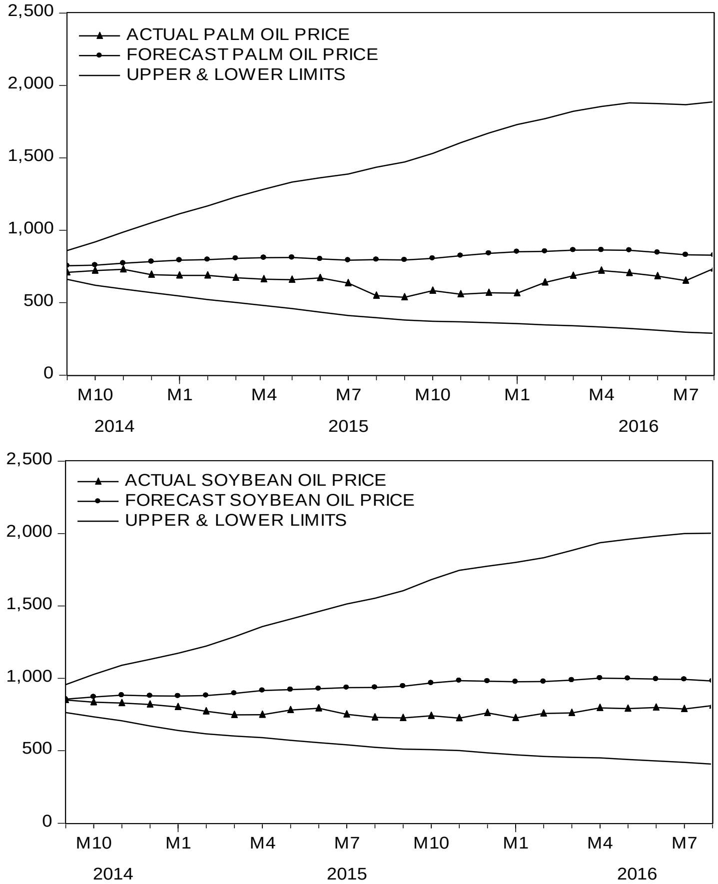

Figure 4. Prediction Testing from 2014(9) to 2016(8)

The measure of success for a model depends not only on its proficiency in capturing and explaining the fundamentals of the data series but also in forecasting. An important objective for producers and consumers is to generate regular price forecasts for agricultural commodities. These are directed to cater to both general and specific requirements such as investment evaluation, capacity development, and production. Once the final models are found to be satisfactory, they can be used to generate forecasts. The present paper utilizes the information acquired from the past behavior of the series, using the SMTM-SCI, to generate forecasts. The sample has been restricted to the period 1960(1) to 2014(8) in order to enable out of sample forecasts for 24 time periods covering the duration 2014(9) to 2016(8).

The predictions for palm and soybean oil prices are displayed in Figure 5. The validity of these forecasts can be verified by comparing the forecasted and actual data points. This comparison attests that both estimated models provide an effective description of the dynamic features contained in the data. Moreover the forecast errors are obtained by assuming that the values of the trend and cyclical component remain constant over the period. The forecast in all cases is generally satisfactory and is never more than two standard errors from the observed value. Thus, the estimated SMTM-SCI for palm oil and soybean oil are proved appropriate.

Notably a major feature of using the STM to generate forecasts is that the application of the Kalman filter calculates maximum likelihood estimates of the parameters along with optimal (minimum mean-square error) estimates of the state variables. Being a forward looking procedure, it recursively estimates the values of the state variables at each point in time using all of the information available up to that point, and hence is well suited for forecasting.

4. Discussion

For the period under investigation palm and soybean oil markets have undergone stochastic growth and cyclicality in prices specifically in the mid-1970s and 2000s. Market fundamentals of supply and demand have also led to permanent (structural breaks) as well as transitory (outliers) shocks. The collective influence of these factors governs price movements.

Oilseed prices remained relatively stable prior to 1970 but from beginning to mid-1970s production shortfalls and adverse weather conditions combined with high demand led to price run-ups. Exporting countries insulated domestic markets by adopting export taxes, restrictions, and bans, while importers reduced tariffs, rebuilt stocks and subsidized consumer prices. These policy actions further tightened global market conditions and the period of high prices ended only when economic expansion was curtailed due to the debt crisis in developing countries which constrained consumption. During 1980s palm oil production doubled in response to area expansion in producer countries. The rise was specific in Indonesia led by the government's encouragement of foreign investment through trade, economic liberalization and policy deregulation. Post mid 1990s oilseed stocks gradually reduced, in response to spillover effects from cereals markets, and reached their lowest level of 35 years in 2007 (Kingsbury, 2007). Specifically the El Niño event in 1997/98 caused world oilseed stocks (including palm and soybean) to fall to a low of 12 million tonnes in September 1998. Stocks increased through the subsequent three year period to before falling in 2003. For both series fluctuations grew more persistent since mid-2000 peaking in 2008. The literature proposes a converging agreement that few economic variables coincided with the spikes. Firstly, since 2000 oilseed trade grew more liberalized and reduced the need for individual countries to hold stocks. The global aggregate stocks-to-use ratios declined to less than 15 percent, the lowest level since 1970. As stocks are important to equilibrate markets and smooth price variations these low levels were inadequate to cope with market shocks manifesting in higher prices and increased volatility. Secondly, biofuel production which started around 1990, accelerated in 2000 reaching significant levels by mid-2000 (OECD, 2008). Specifically in 2007 the United States expanded maize area by 23 percent to meet the growing demand for ethanol production leading to a 16 percent decline in production and 75 percent rise in soybean prices. Thirdly, crude oil price rose gradually since 2000 and its volatility reached its peak of 147 U.S. dollar per barrel in July 2008 before subsiding in November, pushed by demand from China and India. In the same vein speculation, dollar depreciation and restrictive policy responses on the part of both importers and exporters, further influenced price formation and exacerbated these developments. In 2007 tariff reduction by India, the second largest importer of palm and soybean oil, further intensified the demand situation. Despite temporary easing prices again soared in 2011 amid declining export availability and growing global demand, specifically in major importing countries such as China. To eliminate the demand and supply discrepancy, on both domestic and international fronts, major stock-holding countries released a significant part of their inventories in 2012 once again causing stock-to-use ratios to reach critically low level.

The novelty of the present study is the employment of the structural time series analysis which uses separate components to give size and shape to factors that affect price formation. The empirical results establish that both palm and soybean oil prices exhibit a slowly-evolving long term trend with hard evidence of significant acceleration during the latter part of the sample period. Price volatility is instrumental in defining movements and specifically post mid 2000s it became incorporated in the trend leading to spikes. The emergence of biofuels as a major source of demand, specifically the expanded biodiesel demand in the European Union, is an additional factor that coincides with the recent price spikes in the oilseed market. It is principally on the demand side that plausible explanations for the spikes price hike can be located. On the supply side the chief drivers contributing to price fluctuations are concerned with production shortfalls and policy measures (for example restrictive export policies) and tend to be short-lived. Notable the sharp increase since mid-2000 is a distinguished from earlier spikes as the latter were not characterized by a comparable change in the makeup of global demand and instead were caused by supply side shocks. Demand shocks involve a higher degree of complications as oilseed markets do not instantly adjust to shocks. Moreover supply shocks are relatively less persistent than demand shocks. While these results do not contradict the relevance of traditional supply factors of high prices they strain that these cannot justify the unusual price peaks and volatility in prices. These new drivers in oilseed markets suggest the possibility of fundamental change in behaviour of oilseed prices combined with longer-lasting effects.

Finally knowledge of the price structure will enhance policy efforts to counterbalance the negative effects of cyclicality and vulnerability to exogenous factors. Since the present study shows that palm and soybean oil prices are affected by short-run fluctuations that govern price formulation in the long run, these measures should be enhanced relative to longer term ones. Prospective measures consist of stock building. To counter its rigidity and expense the government can enter joint stock-building with other net-importing countries and encourage involvement of the private sector to ease the financial burden. For developed countries the effects of prices on inflation is a more pressing matter relative to food security. Due to a high degree of integration with global markets these countries are adept at isolating their farmers from volatility in international markets and would benefit from cooperating with the less developed countries on mitigating the undesirable effects of food inflation. Moreover eliminating trade barriers and non-essential programs that segregate agriculture resources will enable flexible responses to drastic price changes. This discussion clearly indicates that policy makers require the right mix of policies depending on their position in the oilseed market and their country's economic strength. In this way, structural time series analysis can be a valuable tool for policy makers. More specifically, faced with increased prices that threatened the food security of their countries resorting to counter measures (such as export bans and subsidized prices) aids in the short term but lose their effectiveness in the absence of long-term measures.

5. Conclusions

The context of recent agricultural commodity price increase has been the subject of contentious discussion. Several studies examine price trends using standard autoregressive models. However due to the mandate of achieving stationarity this class of studies fails to capture the stylized features inherent in the data. To account for this limitation, this paper empirically analyzes real prices of two important oilseed crops, palm and soybean oil, using a Structural Time Series Model from 1960(1) to 2014(8). Founded on a state space representation, it allows the included components to evolve stochastically over the sample period while incorporating disruptions and outlying observations.

This paper holds methodological as well as substantive conclusions. From a methodological standpoint the study contributes to the literature on agricultural commodities by utilizing a method that is founded on the stylized facts that govern the data and highlights its properties without the prerequisite of attaining stationarity (a difficult factor given the presence of intense price spikes). Furthermore, consisting of multiple state equations, the model does not impose unnecessary parameter restrictions or compel deterministic specification on the included terms. Extended to allow for the effects of intervention variables it produces an acceptable set of out-of-sample predictions. Substantively, the empirical results give size and shape to the cyclicality and intervention terms of palm and soybean oil prices, which are shown to be the drivers of the price formation mechanism. Oilseed price cycles indicate high responsiveness to both market and non-market influences over the selected sample period. Identifying the interrelationship of several fundamental factors with the mid-2000 price spikes would not be possible without the information acquired by the structural analysis. The paper does not state that the absence of this occurrence would have cancelled the price spikes, but it has identified that a major factor that held back the growth rate of prices ceased to exist. Finally, the outcome of this study emphasizes the importance of considering oilseeds as separate commodities requiring country-specific and commodity-specific policy measures.

References

Alagidede, P. (2009). *Trends, Cycles and Seasonal Components in Primary Commodities: State Space Modelling and the Kalman Filter.* Stirling: University of Stirling.

Bhar, R., & Hamori, S. (2007). Component Structures Of Agricultural Commodity Futures Traded on the Tokyo Grain Exchange. *Asia-Pacific Financial Markets*, 13(1), 1–9.

Box, G. E. P., & Jenkins, G. M. (1976). *Time Series Analysis: Forecasting and Control*. Revised edition. San Francisco: Holden–Day.

de Jong, P., & Penzer, J. (1998). Diagnosing Shocks in Time Series. *Journal of the American Statistical Association*, 93(442), 796–806.

Harvey, A. C. (1989). *Forecasting, Structural Time Series Models and the Kalman Filter*. London: Cambridge University Press.

Harvey, A. C., & Shephard, N. (1993). Structural Time Series Models. In C. R. Rao, & H. D. Vinod, (Eds.), *Handbook of Statistics* (pp. 261-302). Amsterdam: North Holland.

Harvey, A. C., & Trimbur, T. M. (2003). General Model-Based Filters for Extracting Cycles and Trends in Economic Time Series. *Review of Economics and Statistics*, 85(2), 244-255.

Kalman, R. E. (1960). A New Approach to Linear Filtering and Prediction Problems. *Transactions of the ASME–Journal of Basic Engineering*, 82(Series D), 35–45.

Kingsbury, K. (2007, November 16). After the Oil Crisis, a Food Crisis?, TIME, Retrieved from http://www.time.com/time/business/article/0, 8599,1684910,00.htm.

Koopman, S. J., Harvey, A. C., Doornik, J. A. & Shephard, N. (2009). *Structural Time Series Analyser, Modeller and Predictor,* London: Timberlake Consultants.

Labys, W. C., & Kouassi, E. (1996*). Structural Time Series Modeling of Commodity Price Cycles.* Research Paper 9602. West Virginia University: Regional Research Institute.
Moore, G. H. (1980). *Business Cycles, Inflation, and Forecasting,* Cambridge: National Bureau of Economic Research.
Oil World. (2015). *Annual Report*. Hamburg: ISTA Mielke Gmbh.
Organization for Economic Cooperation and Development. (2008). *Rising Food Prices Causes and Consequences.* Paris: OECD publishing.
Rezitis, A. N., Ntinou, A. G. & Pachis. D. N. (2015). Investigating the International Prices of Wheat and Rice. *Agricultural and Food Economics*, 3(1), 3:16.
Sims, C. (1982). Macroeconomics and Reality. *Econometrica*, 48(1),1-48.

[i] Regressors can be included either in the observation equation (unobservable components) or added to the component equations (for example the trend equation). In the former case the static regressor will impact the dependent variable in the given time period i.e. t. In the latter case the regressor will impact the independent variable in the currant and all later time periods. This is because the trend in period t+1 depends on the trend in time period t which is impacted by the dependent variable.