Trends, cycles and seasonal components in primary commodities: state space modeling and the Kalman filter

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Abstract

Decomposing economic time series into their temporary and permanent components have followed two broad paths: trend versus difference stationary models and detrending versus filtering). Whereas the former breaks down due to their inability to capture the underlying data generation process (dgp), the latter are either one sided filters or are based on *ad hoc* procedures in achieving parsimony. In this paper we propose structural time series models in which trends, cycles and seasonal components are treated as stochastic and which contains the traditional approach as a special case. Cast in state space form, and estimated using maximum likelihood via the Kalman filter, these models accurately predict the behaviour of commodity prices through time. Using data on agricultural raw materials and metal price indices for the 1957(1) to 2008(4) period we document the frequency and duration of commodity prices, key elements for designing policies aimed at smoothing terms of trade shocks and the resulting macroeconomic effects associated with price disruptions. We found that the individual dgp have varied over time and are best captured as stochastic rather than deterministic trends. Moreover, we uncover multiple structural breaks and outliers, far beyond what extant results would like us to believe. Finally, the models remain robust in an out of sample forecast.

Key words: commodity prices, terms of trade shocks, trends, cycles and state space models.

JEL: C51, Q11, E32

1. Introduction

Prior to the 2007/2008 asset price bubble the world economy was hit by two shocks: a *tsunami* of energy and food price rises. At the end of 2006, the price of crude oil was about \$60/barrel and, about \$90/barrel at the end of 2007. It leapt from around \$100/barrel and reached an all time peak of \$145/barrel before receding with the recession. The increasing energy costs brought to the fore another shock, described as the 'silent *tsunami*'[1]: explosion in world food prices. A worldwide commodity price boom picked up pace in 2007, with the IMF commodity price index indicating a 45% hike since the end of 2006, mirroring earlier price run-ups in other commodities such as tin, nickel, soybeans, corn, wheat, and rice. In 2007 wheat prices rose 77% and, rice 16%. Record prices for fuel and food gave a vicious twist to inflation, pushing up the cost of living for workers, cut backs on air travel due to high surcharges and arguably, are partly to blame for propelling industrial and emerging economies closer to a recession even before the explosion in the sub prime mortgage sector[2].

At the heart of the global commodity price shock is a confluence of demand and supply factors, plus a mix of bad luck and bad policy. Strong food demand from emerging economies, reflecting stronger per capita income growth, accounted for much of the increase in consumption of both grain and crude oil. The sustained growth in global income contributed to depleting global inventories. At the same time, the diversion of agricultural production to bio-fuels (mainly in response to the high cost of crude oil), added to the demand for corn and rapeseeds oil, spilling over to other foods through demand and crop substitution effects[3]. At the supply side, prices have been slow to

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[1] The phrase 'silent *tsunami*' as applied to the global food conundrum was first used by Josette Sheeran, Executive Director of the World Food Programme.

[2] Admittedly, however, in real terms, prices of many commodities, particularly food, remained well below their highs in the 1970s and early 1980s, with the main exceptions of crude oil, lead, and nickel. In addition, the inflationary pressure such high prices induced is nowhere near earlier decades.

[3] The IMF estimates that the increased in consumption of major food crops in 2007 was related to bio fuels, mostly because of corn-based ethanol production in the US; and the new bio fuel mandates in the US and the EU that favour domestic production will continue to put pressure on prices (see IMF, 2008: www.imf.org).

adjust. Drought conditions and crop failure in major wheat-producing countries (e.g., Australia and Ukraine), higher input costs (animal feed, energy, and fertilizer) have been widely cited.

Evidence indicates that not only has bad luck been at play, but also bad policy response to these shocks has exacerbated the crises. Of 58 countries whose reactions are tracked by the World Bank, 48 imposed price controls, consumer subsidies, export restrictions or lower tariffs (see Economist, April 19-25, 2008). These twin shocks raise questions about the evolution of commodity prices, particularly, the long-run permanent trend, and the short-run cycles. The long-run evolution of commodity prices and their inter-relationships are important for both importing and exporting countries. For the former, it enables a more efficient planning at the production level and reduces the uncertainties that impede manufacturing activities. For the latter it enables to better cope with price risks in international markets and to limit interventions at the domestic level that may have undesirable spillover effects.

Extant knowledge on commodity price modeling so far fall under two broad headings: trend and difference stationary models and their various extensions that account for structural breaks and, detrending procedures based on Beveridge and Nelson (1981), BV for short, type decomposition and Hodrick and Prescott (1980), HP for short, style of detrending. While the former suffer from low power, imposes a restrictive deterministic time trend plus a stationary component which is sometimes misleading and indeed unnecessary (see Harvey, 1997), the latter, notably, BV techniques are based on *ad hoc* procedures in their model selection, while the HP filters employ mechanical means to separate the long-run from the short term components.

To investigate the long-run trends and short-run cyclical fluctuations in primary commodities, we adopt unobserved components time series models that typically consist of interpretable components such as trend, cycle, seasonal and irregular components. Each component is set up in such a way that the dynamic stochastic process depends on normally distributed disturbances. With regards to commodities, this seems to be the most plausible way of decomposing trends and cycles as opposed to the alternative analysis based on HP filter and BV decomposition. The deterministic trend is a limiting case in which the hyperparameters which allow the level and slope to change are equal to zero. This allows us to investigate the long-run and short-run dynamics of commodity prices, while modeling the observed and unobserved components associated with them. Following Harvey (1989), Harvey and Koopman (2000), our approach is cast in the spirit of state space models and the resulting maximum likelihood estimation is carried out via the Kalman filter. In contrast to extant results that assumes a single exogenous break, and or allow for two endogenous breaks, our technique is able to yield more refined and interesting dynamics of commodity price series by identifying multiple structural breaks without forcing any particular pattern on the data. Breaks in the level, slope and trend are accounted for and the possibilities of outliers are also imbedded.

Moreover, as Harvey and Jaeger (1993) have argued, a model based on trend cycle decomposition is to be preferred and can avoid the detection of spurious cycles in the time series. Working with unobserved components models has the additional advantage that they can also be used to produce forecasts, where more weight is put on the most recent observations, and, the faster the level and slope change, the more past observations are discounted.

Our results indicate that seasonally unadjusted data produce much better results when a seasonal component is added to a model. This is true for metals; constrained supply and robust demand in autumn tend to boost demand (1.83% increase autumn and 0.9% fall in summer). For agricultural raw materials, agronomical cycles confound the seasonal patterns. Our commodity price indices depict 3 main cycles ranging between 2 and 7 years for metals and 3 and 8 years for agricultural raw materials. The speed with which commodity prices rise and fall is estimated to average 1.39, very persistent, in both boom and slump phases. The duration and persistence of these cycles are key elements for designing policies to smooth terms of trade shocks and the resulting macroeconomic effects that price disruptions bring about and also to craft efficient counter cyclical policies to cope with price fluctuations. The long-run permanent trend is rather characterized by significant outliers, and level shifts. Metals reveal 4 outliers and level breaks while agricultural raw materials show 2 outliers and 6 level breaks. These are both statistically significant and are of economic importance for commodity price behaviour, and represent a departure from the usual two structural breaks documented in extant results. We also showed that metals tend to grow and slow faster than agricultural raw materials. Finally, unobserved components models perform well both in, and, out-of-sample.

The plan of this paper is as follows: we take a brief look at the literature in section 2 and focus particularly on the techniques employed. We argue here that the trend versus difference stationary models and the detrending versus filtering procedures are inadequate to understanding commodity price evolution. We argue in section 3 that structural time series models, cast in state-space form can uncover dynamics in the components that previous studies have failed to identify. Section 4 presents the empirical results, and 5 analyses and throw light on the policy implications of our results.

2. Commodity price behaviour: a brief review and methodological critique

Nearly all the literature on the long-run behaviour of commodity prices, particularly, dealing with terms of trade shocks either begins and/or end with the work of Prebisch (1950) and Singer (1950). Independently developed in the late 1940s, what subsequently became known as the Prebisch-Singer Hypothesis (PSH for short) postulates that there is a secular decline in the terms of trade of primary commodities relative to manufactured goods. The driving force behind this observation, argued Prebisch and Singer, is the propensity for developing countries to export primary commodities and import manufactures. Moreover, markets for manufactured goods are noted to be imperfectly competitive compared with those for primary products, thus accounting for the wide gap between the price of manufactured goods and their cost of production as compared with primary products. It further suggested that union organisation in manufacturing sectors of industrialised countries raises wages of manufacturing labour relative to those of primary sector workers in developing countries. Prebisch and Singer examined data over the 1870-1945 periods and suggested that the terms of trade for primary commodity exporters did have a tendency to decline. Although slightly outdated[4], and in fact, a mere observation, the PSH has become the dominant paradigm for examining the long-run evolution of commodity prices.

The literature testing a secular decline in the terms of trade can be summarised under two headings: the first group involves models that assume deterministic trend and or impose stationarity on the data generation process (dgp). Here the Dickey and Fuller(1979) style of unit roots tests and their various extensions that account for serial correlation, one or two structural breaks(this may be endogenous or exogenous breaks), Perron (1989), Zivot and Andrews (1992) and Lumsdaine and Papell (1997) respectively, have been the most popular and widely employed techniques.

The early empirical evidence tended to favour the position of a deterministic time trend. Spraos (1980) presents evidence of a stable declining commodity terms of trade and Sapsford (1985) collaborates this evidence, albeit with qualifications on the stability of Sproas results. The PSH was given further boost particularly with the construction of new datasets that made the testing of the PSH possible.

Grilli and Yang (1988)[5] henceforth, G-Y, used a newly constructed index of commodity prices and two modified indices of manufactured good prices, and find that from 1900 to

[4] The composition of global trade in recent time has raised questions about the validity of the PSH. There has been an upsurge of manufactured exports from developing Asia, while at the same time OECD countries such as Australia, export primary products. Thus the terms of trade for developing versus developed countries are no longer as closely related to the net barter terms of trade for primary and manufactured goods. However, the PSH is still relevant for Sub-Saharan African countries that rely extensively on the export of primary commodities for their export revenues.

[5] The G-Y commodity price index is one of the most widely used commodity price series in the commodity price evolution literature. The GY series of the commodities terms of trade (COMTT) are the ratio of an index of non-fuel commodity prices (COM) and a price index of manufactures (MUV). COM is an index of prices of 24 internationally traded non-fuel commodities weighted by the 1977–1979 values of world exports of each commodity. MUV is the United Nations index of export unit values of manufactures, in which G-Y filled the two gaps that this index had during 1914–1920 and 1939–1947. The original G-Y data set covered the period 1900–1986. Cashin and McDermott (2002) extended the data set to 1998, using the G-Y weights and the IMF commodity price indices, which are very close to those of the World Bank.

1986 the relative prices of all primary commodities fell on trend by 0.5% a year and those of nonfuel primary commodities by 0.6 % a year. They thus confirm the sign, but not the magnitude, of the trend implicit in the PSH. They then show that the evolution of the terms of trade of nonfuel primary commodities is not the same as that of the net barter terms of trade of non-oil-exporting developing countries. However, the deterministic trend adopted in these studies tends to be too restrictive. An alternative dgp is represented by the difference stationary model thus shifting most of the empirical work on commodity price evolution to difference stationary models.

Evidence based difference stationary as opposed to trend stationary models faulted the PSH. Cuddington and Urzua (1989) showed that the G-Y index of commodity prices should be represented as an integrated variable, and the corresponding first difference model found a non-significant long-run trend in the period 1900-83. Cuddingtion (1992) applies this methodology to the analysis of the 24 commodities that comprise the index (plus oil and coal), and found that 21 of them present zero or positive trends, thus rejecting the PSH in most cases. Kim et al (2003) finds only 5 of the 24 commodities in the G-Y index had negative trend as predicted by the PSH. These studies however failed to account for possible breaks in the commodity series. As Perron (1989) argue, "most macroeconomic time series are not characterized by the presence of a unit root. Fluctuations are indeed stationary around a deterministic trend function. The only 'shocks' which have had persistence effects are the 1929 crash and the 1973 oil price shock" (Perron, 1989, p.1361). Perrons procedure thus includes dummy variables to account for one known or exogenous structural break. The break point of the trend function is fixed (exogenous) and chosen independently of the data, and allows for breaks under both the null and alternative hypothesis. This approach has been tagged as data mining. Cochrane (1991) argues that the test could not successfully distinguish a trend and difference stationary models, and in small samples the technique is severely limited. Christiano (1992) shows that the data based procedures are typically used to determine the most likely location of the break and this invalidates the distribution theory underlying conventional testing.

Since then several tests have endogenised the break date, most notably unit root tests developed by Zivot and Andrews (1992), Lumsdaine and Papell (1997), and these later extensions have yielded useful results in terms of accounting for more than one structural break (see Lumsdaine and Papell, 1997). Consequently, the commodity price debate has applied these techniques to uncover further dynamics in the PSH. Using the Zivot and Andrews (1992) test that endogenises the break Leon and Soto (1997) showed that 17 of the 24 commodities in the G-Y index have negative long-run trends, 3 are trendless and four have positive trend, thus confirming the validity of the PSH for most commodities. More recently Kellard and Wohar (2006) extended the work of Leon and Soto (1997) and applied Lumsdaine and Papel (1997) unit root test that allow for two structural breaks. Zanias (2005) using Lumsdaine and Papell (1997) found that over the 20th century the relative prices of primary commodities dropped to nearly 1/3 of their level at the beginning of the century in two installments, when random shocks led to structural breaks, and not in a gradual way as implied by either a deterministic or stochastic trend. More recently, Kaplinsky and Santos-Paulino (2006) decomposed the unit price trends of EU imports relying on both Augmented Dickey Fuller (ADF) type regressions, and applied the Kalman filter to extract the trend and slope in the disaggregated unit import prices.

As argued in Harvey (1997), unit roots may be misleading and unnecessary! The autoregressive models on which they are based can display poor statistical properties when the autoregressive approximation is a poor one. Nelson and Plosser (1982) show that most economic series cannot be handled by a deterministic time trend plus a stationary component. So far the commodity price literature has not uncovered structural breaks beyond two, and this is both intriguing and important. First commodity series are subject to the same kind of shocks that most macroeconomic series experience and are likely to be subject to structural breaks and outliers; second and most importantly, failure to account properly for structural breaks cast doubt on the empirical results and the resulting policy implications. Thus an obvious way to present a more reasonable model is to make it flexible by letting the level and slope parameters change over time.

The second strand of models resort to detrending or filtering to decompose economic series into their permanent and temporary components. Beveridge and Nelson (1981) proposed the use of ARIMA to decompose non-stationary US business cycle indicators into long-run trend and transitory cycle. In this decomposition, the systematic part of the series is the combined effects of its transitory/ cyclical and its long-run/permanent component. In the long-run however, the transitory component fades away and the series converges to its long-run equilibrium, namely, its permanent component. The BV decomposition does not, assume a priori, a deterministic trend; however, the fact that it is based on an ARIMA model is a major weakness because for such a structure it is quite frequent that more than one specification fit the same data, thus rendering the model selection somewhat arbitrary (see also Harvey, 1985). Another approach is to use a filter such as the one proposed by Hodrick and Prescott (1980). However the HP filter imposes properties on the estimated cycle by construction, when in fact the properties of the cycle may be exactly what is in question. As Harvey and Jaeger (1993) argue the HP filter is only suited for US GDP, and can lead to the discovery of spurious cycles in other series.

We re-examine the time series properties of commodity prices using structural time series models. We favour this model based as opposed to the model free procedures found in the literature as they capture the trend, cyclical and seasonal components of commodity prices, while at the same time treating the traditional approach as a special case. These components capture the salient features of the data that are useful in analysing and predicting its behaviour. Moreover, structural time series offer the benefit of providing statistical tests and prediction algorithms. Additionally, it is easy to incorporate changing seasonal patterns and to introduce additional features such as explanatory variables and interventions. The set up follows Harvey (1989) and Harvey and Koopman (2000).

3. The set up

The logarithm of commodity prices y_t can be represented with stochastic unobservable components as follows:

$$y_t = \mu_t + \gamma_t + \psi_t + \varepsilon_t \ , \ \varepsilon_t \sim \mathrm{NID}(0, \sigma_\varepsilon^2) \quad t=1, 2\ldots, T \qquad (1)$$

where μ_t is the trend component, γ_t is the seasonal, ψ_t the cyclical and ε_t is the white noise irregular component. The stochastic specification of the trend component is represented by the following:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t\,, \quad \eta_t \sim \mathrm{NID}\left(0, \sigma_\eta^2\right)$$

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

where β_t represents the drift or slope of the trend, μ_t, and the disturbances η_t, ξ_t and ε_t are mutually uncorrelated at all leads and lags for t=1, 2…, T. Some notable limiting case of this specification include: if $\sigma_\xi \to 0$ while σ_η is non zero the trend is a random walk with drift β_1; if $\sigma_\eta \to 0$ while σ_ξ is non zero the trend follows a smooth integrated random walk; when both tend to zero μ_t reverts to a stochastic linear deterministic trend. The trend thus specified captures the long-run permanent component of commodity prices, and it could technically include demand and supply conditions, and any unobserved factor that evolves in a fairly continuous manner. Its stochastic manner means that shifts can be taken into account, without altering the parameters of interest—i.e. if we specify interventions or explanatory variables.

The seasonal component γ_t can be specified as a sum of time varying trigonometric cycles. Specifically, in a model for a time series with length s, we have

$$\begin{pmatrix} \gamma_{i,t+1} \\ \gamma^*_{j,t+1} \end{pmatrix} = \begin{bmatrix} \cos\lambda_j & \sin\lambda_j \\ -\sin\lambda_i & \cos\lambda_j \end{bmatrix} \begin{pmatrix} \gamma_{j,t} \\ \gamma^*_{j,t} \end{pmatrix} + \begin{pmatrix} \omega_{j,t} \\ \omega^*_{j,t} \end{pmatrix}, \begin{pmatrix} \omega_{j,t} \\ \omega^*_{j,t} \end{pmatrix} \sim \mathrm{NID}\left(0, \sigma_\omega^2 I_2\right) \tag{3}$$

with $\lambda_j = 2\pi_j/s$ for j=1,2,….[s/2] and t=1, 2…, T.

The seasonal component reflects the fact that the supply conditions of primary commodities, most notably agricultural commodities are influenced by weather conditions. Further structural reforms and economic policies can induce changes in commodity price behaviour and these are well approximated by the seasonal component. It has also been shown that seasonally adjusted data may not have the desirable properties, particularly if the seasonality pattern changes in a way that is not accounted for by the adjustment technique (see Harvey and Jaeger, 1993).

Given that many macroeconomic variables fluctuate around the business cycle we incorporate the effects of cyclical dynamics in the model by looking at the stochastic cyclical component ψ_t which is given by

$$\begin{pmatrix} \psi_{t+1} \\ \psi^*_{t+1} \end{pmatrix} = \rho \begin{bmatrix} \cos\lambda^c & \sin\lambda^c \\ -\sin\lambda^c & \cos\lambda^c \end{bmatrix} \begin{pmatrix} \psi_t \\ \psi^*_t \end{pmatrix} = \begin{pmatrix} \kappa_t \\ \kappa^*_t \end{pmatrix}, \begin{pmatrix} \kappa_t \\ \kappa^*_t \end{pmatrix}, \begin{pmatrix} \kappa_t \\ \kappa^*_t \end{pmatrix} \sim \mathrm{NID}\left(0, \sigma^2_\kappa I_2\right) \qquad (4)$$

where the unknown coefficients $\lambda^c, \rho, \sigma^2_\kappa$ represent the cyclical frequency , the damping factor and the cyclical disturbance respectively. The period of the cycle is given by $2\pi/\lambda^c$. Specified in this way the cyclical component has obvious interpretation: just like macroeconomic cycles, commodity markets are punctuated by booms and slumps, and these are well addressed by a model that account for such cyclical behaviour.

The specification of the trend, cycle and seasonal components in this way avoids the arbitrary use of proxies, introduces greater flexibility in the measure of what is basically unobservable influences, and contains the deterministic specification(constant trend, deterministic cycle and fixed seasonal effects) as special cases when $\delta_\omega = \sigma_\xi = \sigma_\kappa = 0$.

3.1. State Space form

The general formulation of unobserved components models in state space form is given by the observation or measurement equation

$$y_t = \mathbf{Z}_t \alpha_t + \mathbf{d}_t + \varepsilon_t, \ \varepsilon_t \sim \mathrm{NID}\left(0, \sigma^2_\varepsilon\right) \qquad (5)$$

y_t is the $n \times 1$ vector of observed variables, α_t is the state vector that contains the unobserved components and additional variables to enable the specification of the dynamic processes of the components, and $\mathbf{d_t}$ is a vector of predetermined variables. The matrix of coefficients $\mathbf{Z_t}$ is the observation matrix. The disturbance scalar ε_t is assumed to be distributed with conditional expectations zero and a covariance matrix. $\mathbf{H}_t$.

The essential difference between state space models and conventional linear models is that in the former the state of nature is time varying. The state space formulation is completed by specifying the state or transition equation which describes the law of motion for the unobserved components as

$$\alpha_t = \mathbf{T}_t \alpha_{t-1} + \mathbf{c}_t + \mathbf{R}_t \eta_t, \quad \eta_t \sim \mathrm{NID}(0, \mathbf{H}_t) \tag{6}$$

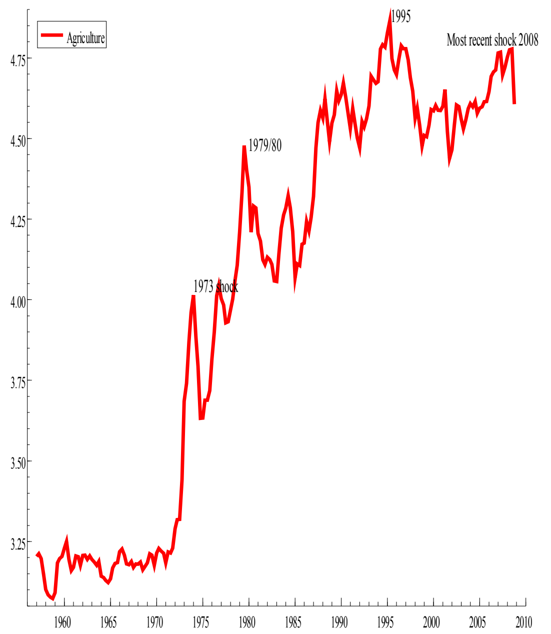
The state vector is thus modeled as a VAR (1). Exogenous components can be added in $\mathbf{c}_t$. The transition matrix is $\mathbf{T}_t$ and $\mathbf{R}_t$ is a matrix factorising the innovations in the state vector. The dimension of α_t is independent of y_t. For instance y_t could be a scalar and α_t a vector, implying that y_t was a function of several unobserved components; alternatively, y_t could be a vector and α_t a scalar, implying that the elements of y_t were a function of a single state of nature or a common factor.

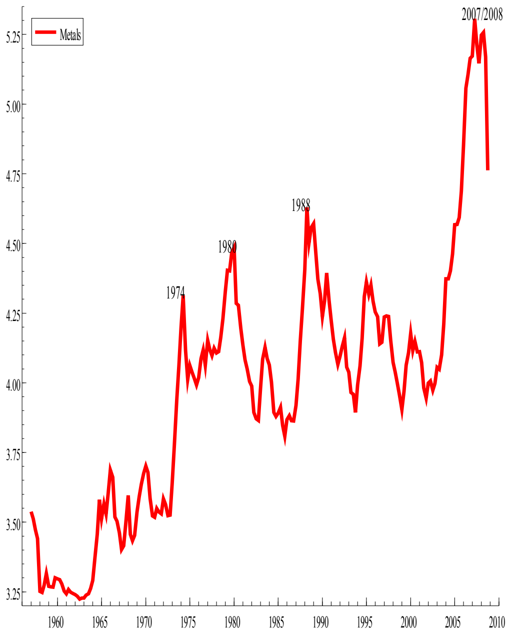
Cast in the state space form, there are now two sets of unknowns: the parameters of the model $\mathbf{T}_t, \mathbf{Z}_t, \mathbf{d}_t, \mathbf{c}_t, \mathbf{R}_t$ and $\mathbf{H}_t$ and the elements of the state vector α_t.These are easily estimated using maximum likelihood and the Kalman filter. The Kalman filter is a recursion algorithm which makes inference about the state vector.

4. Commodity prices: data considerations and some stylized facts

The data set is data is quarterly from 1957(1) to 2008(4) for two commodity price indices: metals and agricultural raw materials. The two indices track important commodities traded internationally. The components of the agricultural raw materials index and their respective weights in the International Financial Statistics (IFS) calculations are; cotton (1.1%), hides (3.1%), rubber (1.1%) timber (5%) and wool (1.1%). The metals index has aluminum (6.1%), copper (5.1%), iron ore (1.8%), lead (0.3%), nickel (1.2%), tin (0.3%), uranium (0.7%) and zinc (0.9%). We provide the logarithms of the two series in Figure 1.

Figure 1: Logarithms of commodity prices





The graphs shows a clear upward trend from 1957(1) to 2008(4). We can infer from the graph that before 1973 commodity prices have been relatively stable, with metal prices depicting more volatility than agricultural raw materials. The entry of the cartel OPEC in the 1970s and the subsequent 1973 oil price shock drove all commodity prices upward, including those under investigation. In a space of just one year, metal prices went up by 18.6% from 3.5% in 1972 to 4.3% in 1973. Agricultural raw materials also rose by 20% during the same period. Commodity prices have continued their upward trend since then, punctuated by slumps. The end of the sample shows that rate of growth of metal prices has been faster than agricultural raw materials. Although the prices of most commodities such as food and most agricultural raw materials , in real terms, have remained well below their highs in the 1970s and early 1980s, the same cannot be said of lead and nickel, which enjoyed massive price runs in addition to crude oil just before the onset of the 2007/08 financial crises.

A cursory look at the graph reveals that the booms are punctuated by slumps, very typical of business cycles. But more tellingly, commodity price shocks seem to precede economic downturns. After their high run ups in 1973 the subsequent recession sent metal prices down to 5.4% in 1975, 25% in the 1980s recession and all time drop of 34.7% in 1993. Agricultural raw materials followed similar patterns with 19.2% drop in 1975, 12.9% in 1980 and 14% in 1990. These swings would suggest that the long-run permanent trend has been characterized by breaks and such evidence holds an important key in formulating policies that would smooth the path of such variations. The end of the sample indicates that commodity prices by the end of 2008 begun to weaken, even faster for metals. The slump in global growth from the first quarter of 2008, subdued demand from industrialized economies and the lackluster performance of emerging markets, notably India and China, account for the recent weakness. At the heart of the commodity price trends shown in Figure 1 are episodes of swings and outlying patterns. In the structural time series parlance we designate these as trends, cycles and seasonal components, and the subject of the decomposition of the series into these components will occupy us for the rest of the paper.

4.1. Commodity price decomposition

Given the basic features of the data in Figure 1 we adopt a stochastic component approach for the trend, cycle and seasonal. The faster the level and slope change, the more past observations are discounted. The deterministic trend is a limiting case. We put our model in state space form. The underlying processes that govern the unobserved state vector and variance parameters along with the loading matrices, the damping factor and the frequency of the cycle are jointly estimated by maximum likelihood using the Kalman filter technique. The computations are implemented using the STAMP package of Koopman et al (2007). We discuss the results for metal and agricultural raw materials prices indices below. The linear unobserved components with trend, trigonometric seasonal and cycle components together with the usual white noise disturbance are presented in Table 1, the corresponding graphs of the components are shown in Figures 2 and 3.

Table 1: Estimated hyperparameters for commodity prices

parameters	Metals	agriculture
$\hat{\sigma}^2_\eta$	0.00022	0.0002
$\hat{\sigma}^2_\xi$	0.0001	8.2×10^{-6}
$\hat{\sigma}^2_\omega$	1.33×10^{-7}	5.51×10^{-7}

$\hat{\sigma}^2_{\kappa 1}$	0.00064	0.0003
$\hat{\sigma}^2_{\kappa 2}$	0.00045	0.00023
$\hat{\sigma}^2_{\kappa 3}$	6.07×10^{-5}	8.78×10^{-5}
$\hat{\sigma}^2_{\varepsilon}$	0.000	0.000
LogL	533.4	582.8
$N(\chi^2_2)$	3.64	9.78
$H_{63}(F_{63,63})$	1.6	1.68
DW	1.812	1.94
$Q_{12}(\chi^2_9)$	15.81[0.200]	14.15[0.398]
R^2	0.482	0.398

Note: figure in [ ] are p-values

Figure 2: Trends, Cycles and seasonality in metal prices

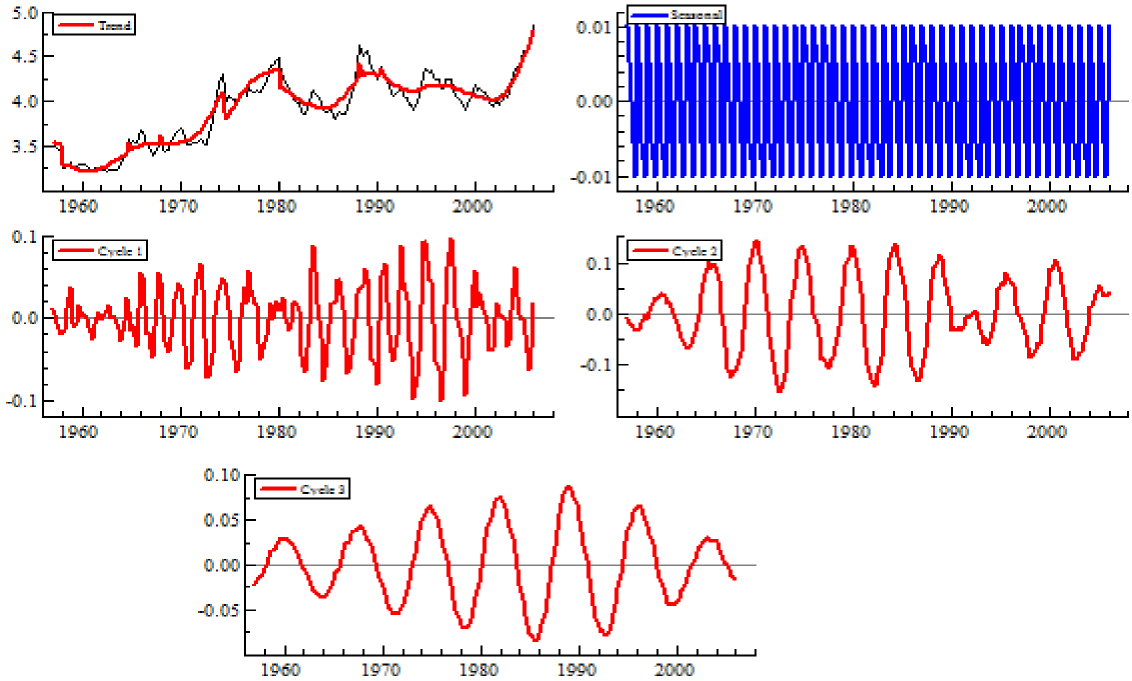
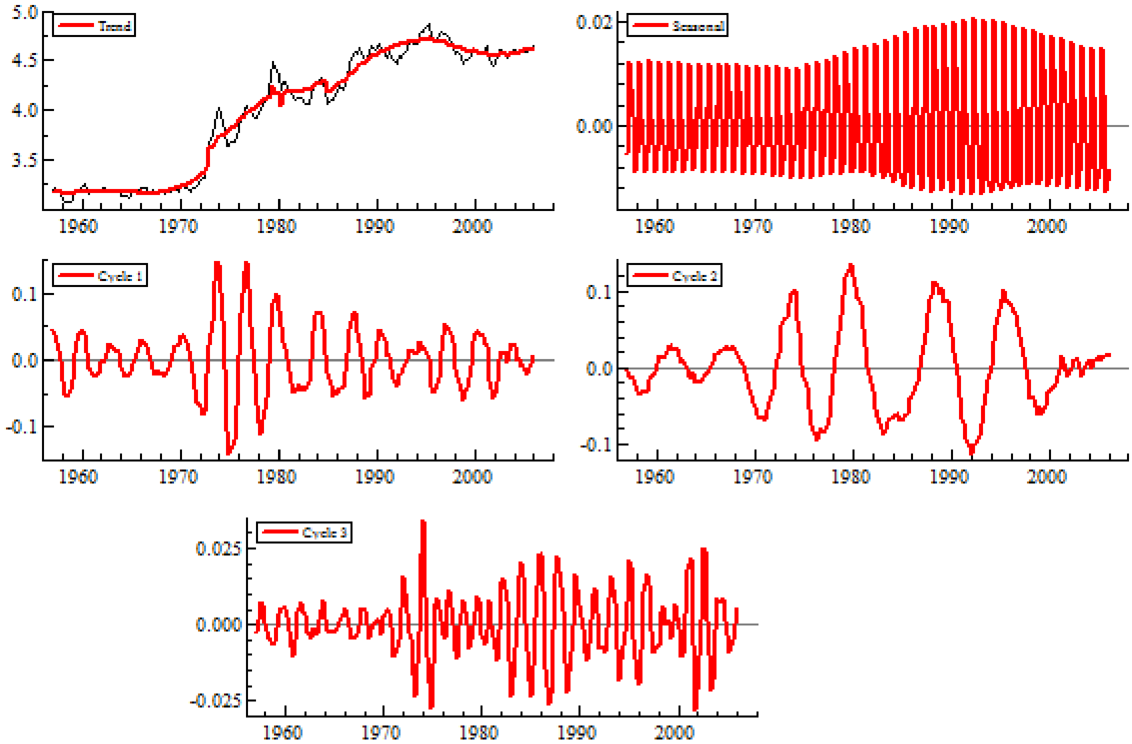


Figure 3: Trends, Cycles and seasonality in Agricultural raw materials



The maximum likelihood estimates of the parameters in equations (1), (2), (3) and (4), where the log likelihood value of the model is evaluated at the maximum likelihood of the parameters. The diagnostic tests based on the one step ahead prediction errors $f_t^{-1/2} v_t$ are shown below the log likelihood value where N is a normality statistic based on the third and fourth moments, H_m a heteroscedasticity statistic based on the ratio of the sample for the first one third of the prediction errors, Q_l is the Box-Ljung serial correlation statistic up to 12 lags. The null distributions of the tests are given between parentheses. The goodness of fit statistic and diagnostics indicate that the fit is fine.

4.1.2. Short-run fluctuations: seasonal and cycles

As shown in Table 1, the irregular component in metal and agricultural raw material prices are zero, implying that all the variations in the two series are attributed to the seasonal and cyclical components. The seasonal variations can be interpreted as the factors by which we multiply the trend. We allowed for the possibility of two main seasons for metal prices which we interpret as autumn and summer season[6]. Our estimates of the seasonal variance in Table 1 is non-zero, $\hat{\sigma}_{\omega}^2 = 1.33 \times 10^{-7}$, which indicates there are changes in seasonal patterns in the metal index. The seasonal factors are 1.018 [0.000] and 0.986[0.000] for the autumn and summer seasons respectively, where the numbers in square brackets indicate the p-values which are highly statistically significant. The seasonal patterns shown in Figure 2 confirm that metal prices tend to follow short-run seasonal effects according to demand and supply conditions. The demand for metals is about 1.83% higher in the autumn and this typically follows the boom face for metals. The autumn to late autumn months are good for copper and base metals such as zinc, iron, and nickel and lead. The simultaneous effects of robust demand and constrained supply around this period tend to give favorable response to metal prices. This finding is particularly supported by the copper price index as it has always performed best in October, November and January, usually coinciding with the boom phase for metals. Given that copper has one of the largest weight in the metal price index (5.1%), such seasonal variations in copper prices alone could account for some of the seasonal changes in demand. Conversely, metal prices tend to experience modest performance during the summer months. We found that in the summer there is a drop of 1.39% in demand for metals. Thus autumn is the best time to invest in metals. For agricultural raw materials

[6] The data rejects four seasons as the model parameters tended to be insignificant for the spring and winter seasons.

the seasonal effects are often production driven, with one year for annual crops and up to six years for perennial crops. It must be pointed out however that demand and external shocks tend to confound these agronomical cycles. The seasonal variance for agricultural raw materials is $\hat{\sigma}^2_{\omega} = 5.51 \times 10^{-7}$ and our estimates yielded -1.039[0.000], 1.475[0.000], 0.611[0.018] and -1.024[0.000] for the seasons 1, 2, 3 and 4 respectively. The cyclical components are shown in Table 2.

Table 2: Cycles paprameters

parameters	Metals	agriculture
$2\pi / \lambda_{c1}$	2.4	3.4
$2\pi / \lambda_{c2}$	4.7	2.5
$2\pi / \lambda_{c3}$	7.1	8.03
λ_{c1}	0.65(period =9.6)	0.46(period=13.5)
λ_{c2}	0.32(period=19.1)	0.61(period=10.4)
λ_{c3}	0.21(period=28.5)	0.19(period=32.1)
ρ_1	0.9	0.99
ρ_2	0.97	0.95
ρ_3	0.98	0.95

Following Koopman et al (2007) we fit 3 cycles in both series. As shown in Table 1 the cyclical variance appear to be significant for all three cycles and jointly with Table 2 we can see the cyclical patterns in more clear terms. To gauge the cyclical behaviour of the two commodities we extracted the smoothed cycles. The attraction of this model based approach, in contrast to HP and BV style filtering and detrending is that the filters implicitly defined by the model are consistent with each other and with the data (see Harvey and Trimbur, 2002). Moreover, they automatically adapt to the ends of the sample, and if desired, root mean square errors can be calculated. The filtered cycles are presented in Figures 4 and 5. The smoothed cycle leads to a more attractive decomposition and are capable of modeling the kind of pseudo-cyclical behaviour inherent in the two commodity series.

Figure 4: Filtered Cycles: Metals

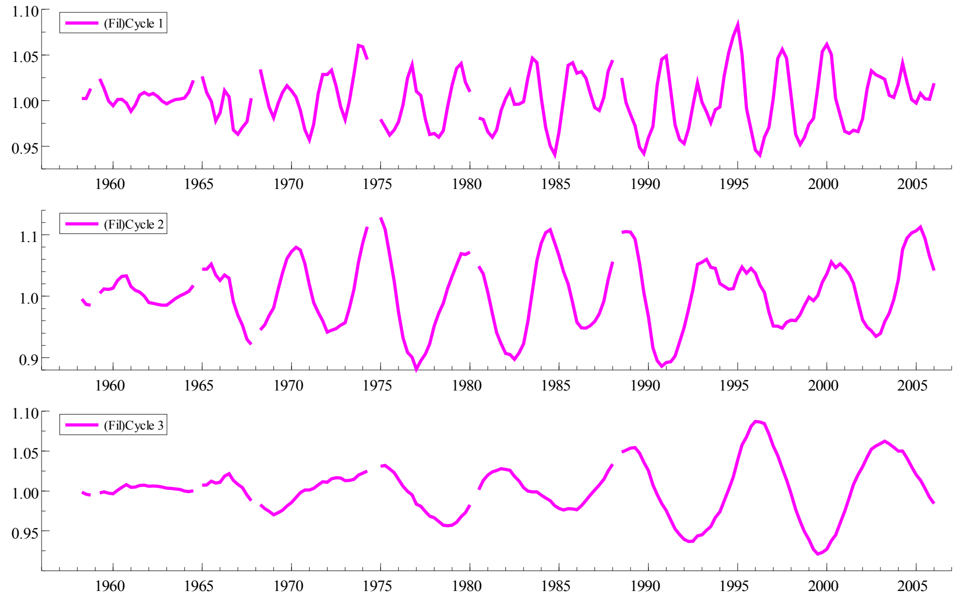
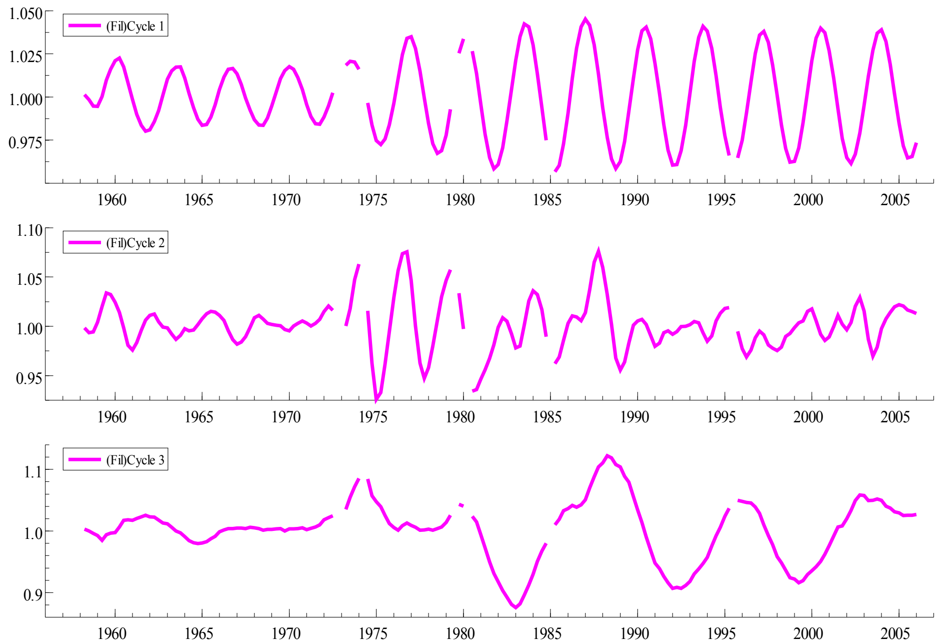


Figure 5: Filtered Cycles: Agricultural Raw materials



The cyclical variances for metals are small $\hat{\sigma}^2_{\kappa 1} = 0.00064, \hat{\sigma}^2_{\kappa 2} = 0.00045$, and $\hat{\sigma}^2_{\kappa 3} = 6.07 \times 10^{-5}$ for the first, second and third cycles respectively. The cyclical disturbances for agricultural raw materials are equally small as shown in Table 1. The first cycle for metals in Table 2, is estimated by about 9 quarters. For agricultural raw materials the first cycle lasts longer, almost 14 quarters. In terms of years, $2\pi / \lambda_{c1}$, is 2 and 3 years respectively for metals and agricultural raw materials. For both commodities, the longer cycle tends to be the third cycle which takes up to 28 quarters for metals and about 32 quarters for agricultural raw materials. The period of the second cycle for metals is approximately 5 years, corresponding to a plausible business cycle. However, the remaining cycles for both commodities are either in advance (the third cycle) or lies below (the first cycle) macroeconomic cycles. Thus, although commodity prices tend to follow macroeconomic cycles in some cases, the evidence is less clear whether they directly mimic economic cycles, for prices tend to slow faster or are slightly sticky in response to booms and slumps. Furthermore, the estimates of the cycle parameters indicate high degree of persistence. Thus the swings in commodities have tended to vary in their duration and amplitude. For instance as seen in Table 2 the damping factor for both commodities, averages 0.97 for the 3 cycles. These pieces of evidence thus provide important information for commodity market participants who may want to hedge the risk inherent in the cyclical fluctuations and also to make informed decisions about production and purchasing choices.

4.1.3. The long-run permanent component: trend

Next we address a topical issue in commodity prices which has dodged empirical analysis in the commodity price literature so far. Numerous studies, *inter alia,* Cuddington and Urzua (1989), Powell (1991), Deaton and Laroque (1992) present conflicting results concerning the time series properties of commodity prices. Apart from the finding that real commodity prices exhibit a high degree of persistence and autocorrelation, there is little agreement whether commodity prices are stationary or are characterized by structural breaks. This surprising gap in the literature is attributed to the conventional weaknesses in the techniques employed. We analyze the trends in this section. In contrast to previous studies, we account for multiple structural breaks (the literature so far has examined two breaks, see Kellard and Wohar, 2006 and Zanias, 2005). From the outset we introduce intervention variables to take account of outlying observations and structural breaks. These data irregularities may arise from a specific event, such as the oil price shocks in the case of an outlier or a change in policy such as the signing of new international commodity agreements in the case of structural breaks. We introduce an impulse intervention which takes the value of one at a particular time of the outlier and zero elsewhere. A break in the level of the series results in a shift up or down and is modeled as a step intervention variable which is zero before the event and one thereafter. The results of applying our interventions are shown in Table 3 and the resultant smooth trend plus interventions in Figure 6.

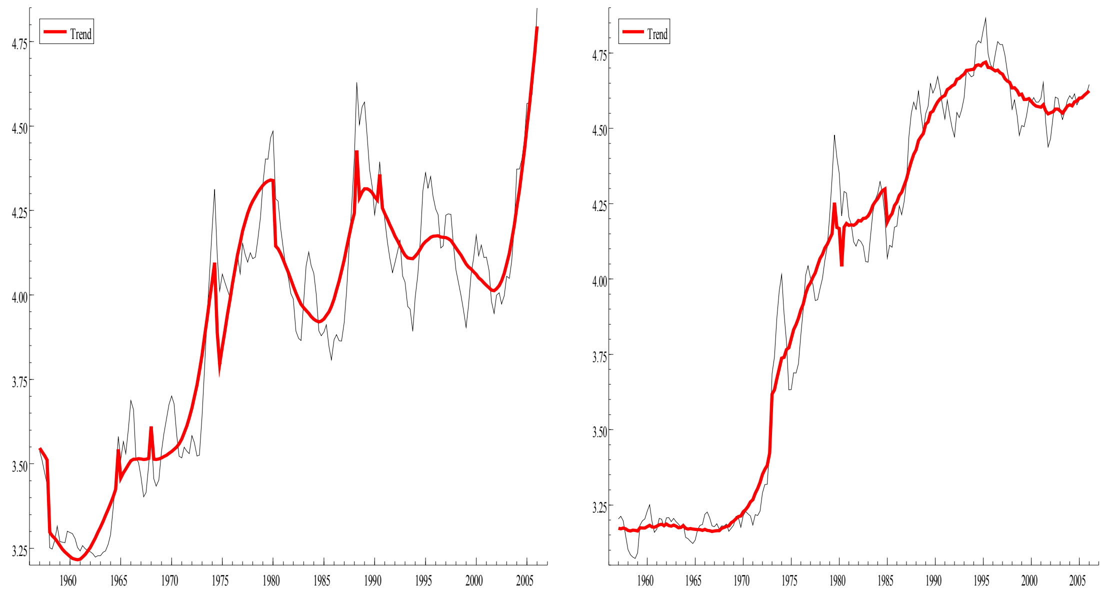
Table 3: Interventions

Metals		**agricultural raw material**	
1964(4) outlier	0.1007***(4.233)	1979(3) outlier	0.088***(4.053)
1968(1) outlier	0.095***(4.016)	1980(2) outlier	-0.125***(-5.714)
1988(2) outlier	0.159***(6.724)	1973(1) level break	0.228***(6.37)
1990(3) outlier	0.085***(3.608)	1985(1) level break	-0.137***(3.965)
1958(1) level break	-0.202***(-5.102)	1972(4) level break	0.1412***(3.941)
1974(3) level break	-0.262***(6.142)	1974(2) level break	-0.132***(-3.793)
1974(4) level break	-0.145***(-3.404)	1995(3) level break	-0.106***(3.082)
1980(2) level break	-0.189***(-4.797)	2001(3) level break	-0.111***(-3.196)

Note: *** indicates significance at the 1% level

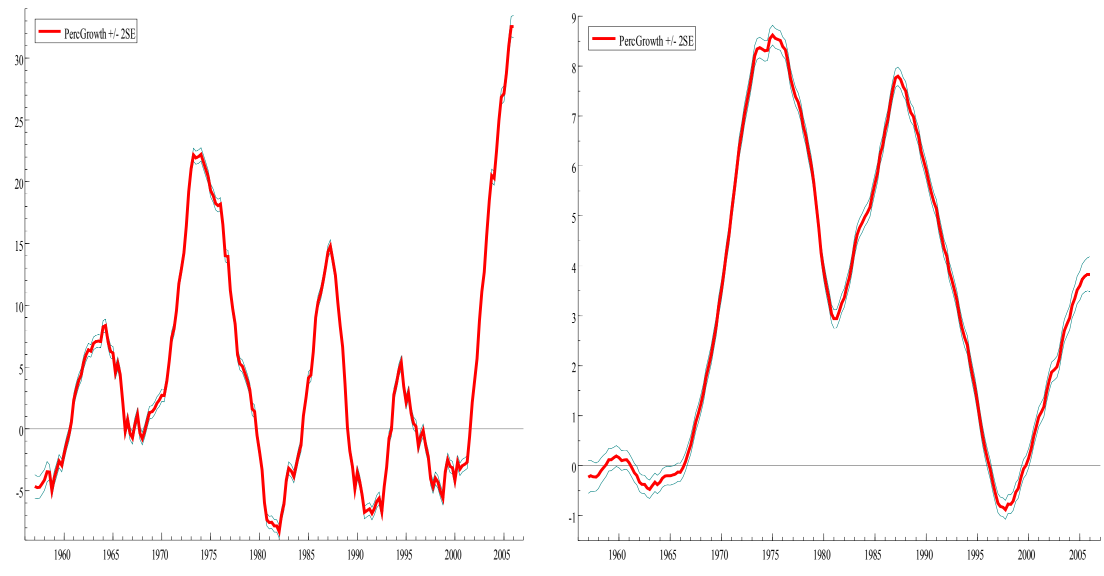
The interventions reported are statistically significant in Table 3 as judged by the t-distributions. The two sided probability values are shown in square brackets. With regards to agricultural raw materials the outliers uncovered appear in 1979(3) and 1980(2). As shown in Figure 6(b), a sudden rise in the agricultural commodity price index in 1979 preceded the subsequent 1980 decline in industrial production in western economies and the resultant recession that led to a drop in the level of agricultural raw materials by 12.5%. Interestingly, the IMF used business cycle dating methods based on downturns in industrial production to capture the fall in the agricultural commodity price index level to be 12.9%! The long-run trend of agricultural raw materials also witnessed another break in 1973(1), with 22% increase in the level and a subsequent drop following the oil price shock in the last quarter of 1973 whose effects were felt with a lag by a drop of 13% in the level in 1974(2). Further breaks in the level occurred in 1985(1), 1995(3) and 2001(3), with 14%, 10% and 11% respectively fall in the level of agricultural raw materials index.

Figure 6: Trend plus Interventions



a) trend plus interventions (metals) **b) trend plus interventions (agriculture)**

Figure 7: Growth rate of trend



a) % trend growth (metals) **b) % trend growth (agriculture)**

The striking feature of all these events is that they track the various downturns in industrial production that has been well documented in the business cycles dating literature. Our findings stand out in the sense that previous studies on commodity price trends have not yielded breaks beyond two. Further, we can argue that, at least for agricultural raw materials the downturns tend to be preceded by initial up turns. This is true for the 1980 and 1973 recessions.

The metal price index depicts more outliers than the agricultural raw material index, an important indication that both commodity classes respond differently to shocks. The unusual events are captured most notably in 1964(4), 1968(1), 1988(2) and 1990(3). The pre-1990 outliers are very telling. A look at Figure 6(a) indicates that metal prices have been relatively stable before 1960. A surge in demand for metals in the mid to late 60s accounted for much of the sharp rise in the levels of the index. Breaks in the trend are apparent in 1958(1), 1974(3), 1974(4) and 1980(2). For two successive quarters the metal price index slumped by 26% and 14% in 1974(3) and 1974(4) respectively. For both commodities, the restriction of our sample to 2006 prevents the discovery of the most recent outliers and breaks which might be present in the data following the 2008 sub prime mortgage crises and the consequent recession. The sample has been restricted to enable us carry out of sample forecasts, which is one other innovation in this paper. Figure 7 presents the growth rate of the trend. We present these graphs based on smooth estimates of the slope of the trend. For metals we estimated the growth rate to be 32% per year, while agricultural raw materials are estimated to be 3.8%.

4.1.4. Auxiliary residuals

Although we provided diagnostic check of our model based on the residuals, i.e., the one step ahead prediction errors—in unobserved components models, it is very important to check auxiliary residuals—estimators of the disturbances associated with the unobserved components. They can often yield information that is less apparent in the innovations (see Harvey and Koopman, 1992). The auxiliary residuals are reported in Table 4. The components for metals are generally well behaved, with N=2.5, 0.006 and 1.15 for the level, irregular and slope residuals respectively. Also the third and fourth moments are satisfactory. For agricultural raw materials, the level and irregular residual are satisfactory. However, the kurtosis statistic is high for the slope residual, 5.54.

Table 4. Residual Diagnostics for commodities

metals	S	K	N
Level	2.13[0.1129]	0.08[0.774]	2.59[0.273]
Irregular	4.95×10^{-5} [0.004]	0.006[0.935]	0.006[0.995]
Slope	0.171[0.679]	0.988[0.320]	1.159[0.599]
Agriculture			
Level	0.294[0.587]	0.964[0.326]	1.259[0.533]
Irregular	0.205[0.651]	0.298[0.584]	0.504[0.777]
Slope	0.982[0.322]	5.54[0.019]	6.435[0.04]

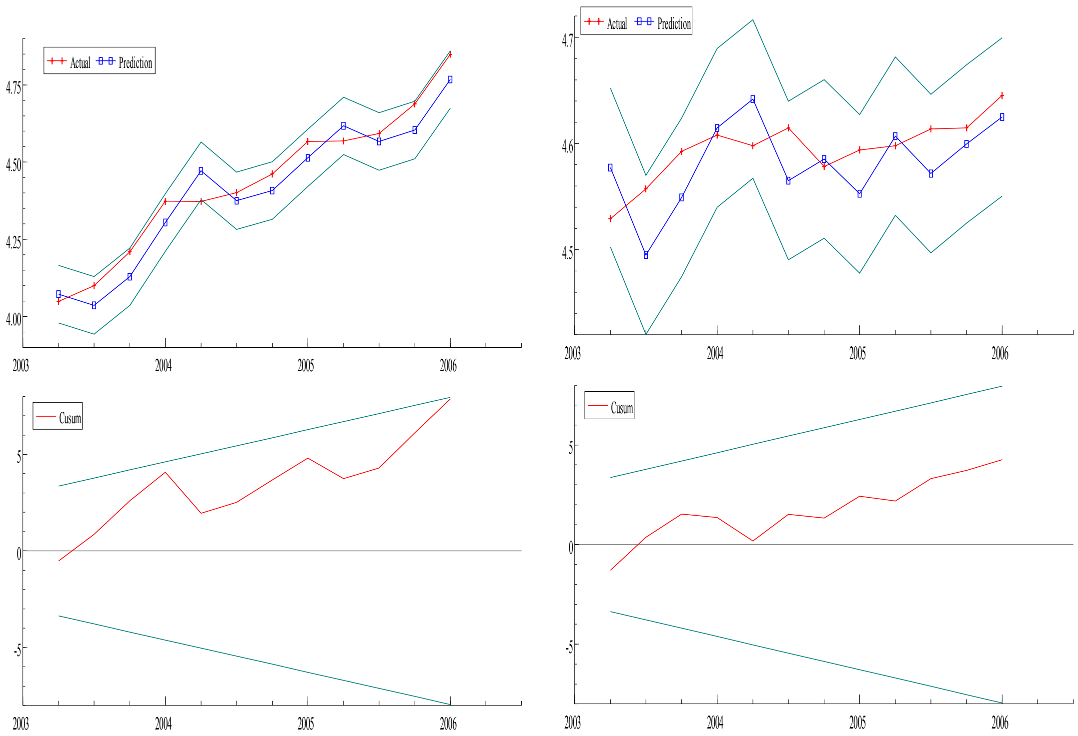
Notes: S-skewness, K-kurtosis and N=normality

Shifts in the level in 1958, 1974, and 1980 are thus well accounted for in the metals index, and the 1973, 1972, 1974, 1995 and 2001 level shifts in agricultural raw materials index. Most of the outliers clearly show up in the level for metals and less so for the slope and irregular.

4.1.5. Forecast

Forecast constitutes an important part of modeling time series patterns in commodity prices. Indeed, some econometricians would argue that the statistical adequacy of a model, in terms of its violations of the classical linear regression assumptions or whether it contains insignificant parameters, is largely irrelevant if the model produces accurate forecasts. In this section we are interested in knowing whether our fitted model is able to perform well even out of sample. We estimated the models from 1957(1) to 2006(1) and reserved 2006(2) to 2008(4) for out of sample forecast. Figure 8 shows the forecast errors and a CUSUM plot, obtained by assuming that the values of the trend and cyclical component remain constant over the period 2006(2) to 2008(4).

Figure 8: Prediction Quality from 2006(2) to 2008(4)



a)Metals **b) Agricultural raw materials**

The forecast for both commodities is generally satisfactory. The top part of Figure 8 shows that the forecast of the trend is never more than two standard errors from the observed value. The CUSUM plot below the actual and predicted values tests the parameter stability and forecast accuracy and indicates the forecast performance is generally accurate.

5. Discussion and concluding remarks

This paper analyzed the evolution of two important primary commodity prices: metal and agricultural raw materials indices. Although some developed economies now export raw materials, the predominant paradigm in commodity markets remain the same as it was 100 years ago—demand is largely driven by western economies, while the supply side is accounted for by mainly developing countries. This in turn has several implications for the terms of trade for developing countries whose export mix is mainly raw materials and import manufactured products to bolster their economies. Extant studies on commodity prices often resort to difference and/ or trend stationary models, and detrending and /or filtering to decompose the short-run from the long term components. Whereas the former is less informative about the underlying data generation process, the latter resort to mechanical and/or *ad hoc* procedures with the possible effects of discovery spurious cycles. The key innovation in this paper is the use of structural time series models to overcome the problems inherent in extant studies. We set up the class of unobserved components models consisting of stochastic trend, cycle, seasonal and irregular components. The model is estimated by maximum likelihood, and the specification checked by both the usual diagnostics and auxiliary residuals. The trend, cycle and seasonal components are extracted by the state-space smoothing algorithm. Our approach yielded several interesting facts about commodity prices.

We showed that demand and supply forces that drive commodity prices such as metals, coupled with production cycles in agricultural raw materials makes model based seasonal modeling far superior to seasonally adjusted data. By incorporating a seasonal component in commodity prices we found the demand for metals is about 1.83% higher in the autumn and this typically follows the boom phase for metals such as copper, zinc, iron, and nickel and lead. Thus the simultaneous effects of robust demand and constrained supply around this period tend to give favorable response to metal prices, compared to summer months where demand for metals is at their lowest levels. In agricultural raw materials prices, the existence of different agronomical cycles tends to confound these seasonal variations.

We also documented the frequency and duration of cycle in the two commodities. We identified three main cycles. For metals the time span of the first cycle shows periodicity of 9.6 quarters, approximately 2 years. This is similar to the second cycle for agricultural raw materials, where the cycle is about 2.5 years. For metals we document that the second cycle approximate that of a normal business cycle, estimated to be about 5 years in length. The third cycle for both commodities is longer, 7 years for metals and 8 years for agricultural raw materials. The speed with which commodity price cycles rise and fall are quite persistent, estimated to average 0.9 for the three cycles in both commodities. The existence and persistence of these cycles raises important policy questions about the stabilization and consumption and income of both producing and consuming nations alike, given that these short-run fluctuations may produce hysteresis type effect with attendant consequences such as hastening recessions or even making them more severe. The role of stabilization funds, agricultural boards and international commodity agreements as intervention measures for the cyclical fluctuations in agricultural produce have been discussed in Reinhart and Wickham (1994). For the metal industry and exporting countries these cyclical patterns suggests that a strategy to smooth the path of income and consumption over the commodity cycle would be important in sustaining the mining industry. Perhaps metal producing developing countries will do well with an attempt to process their metals for export and also reduce dependence on external markets by encouraging local demand, while at the same time managing export receipts to serve as a buffer in stormy times. The timing of investments in new projects could be designed to take advantage of the cyclical upturns and thus improve project profitability. Moreover, for traders and exporting nations these results point to the importance of hedging the downside risk associated with slump in metal prices that typically occur anywhere between 2 to 7 years. As we showed in our results, most of the commodity price hikes have often preceded some of the recessions (1970s, 1980s and most recently 2008), and the severe distortions such fluctuations impose on vulnerable commodity exporters should serve as a guide to all commodity market participants.

The long-run permanent trend is as important as the short-run cyclical fluctuations. So far analysis of commodity prices has failed to pin down the evolution of the trend. Conflicting results about the existence of structural breaks have been reported and most the analysis does not go beyond two structural breaks (see most recent papers Zanias, 2005 and, Kellard and Wohar, 2006). This is important not least because policies required to deal with the permanent component are patently different from those that focus on the temporary component. False reading of trends, or even inability to uncover structural breaks might engineer unwarranted policies that could further compound the problems associated with commodity price fluctuations. We identified numerous outliers in metal prices, most notably associated with some of the unusual events such as 1964/68, 1988/90 one time jumps in metal prices. For agricultural raw materials the outliers appear in 1979/80. By modeling the trend with interventions we found that there are more structural breaks in the levels of commodity prices than previous literature suggests. The 1973/4 level break occurs in both commodities and very significantly both statistically and in economic sense, where agricultural raw materials fell by 12.5% and metals 13%. Our approach essentially picks out all the major swings in commodity prices and estimate the magnitude and sign of these breaks in the levels of the series, and we argue that, level breaks, tend to track well the behaviour of commodity prices. Finally, while commodity prices respond to shocks differently over the economic cycle, so the growth rate of the long-run permanent component differs across time and space. Metals tend to grow faster (32% p.a.) and experience rapid fluctuations, than agricultural raw materials (3.8% p.a)

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