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PRIMARY COMMODITY PRICES: A TIME-SERIES ANALYSIS OF TRENDS AND CYCLES

John T. Cuddington and Carlos M. Urzúa

Abstract

This paper has two objectives. First, it uses time series techniques to re-examine the Prebisch-Singer hypothesis that the relative prices of primary commodities in terms of manufactured goods are characterized by secular deterioration. It considers 26 individual commodity prices over the period 1900 to 1983. Second, it studies cyclical behavior of commodity prices. In the cases where price series are found to be difference stationary (rather than time stationary), this is done by using the Beveridge and Nelson (1981) method for decomposing those economic time series into permanent (or "secular") and cyclical components.

1. Introduction

Primary commodity price movements have important implications for both producer and consumer countries. For example, many LDCs continue to depend heavily on commodity exports for the bulk of their foreign exchange earnings, although this dependence has declined during the post World War II period. 1/ Economic activity in industrialized countries is also affected by changes in commodity prices, as was amply demonstrated by the supply-side shocks of the 1970s.

Interest in commodity price movements focuses in part on their long-term trends, in part on their cyclical behavior, and in part on their unpredictable volatility (i.e., the residual noise after taking trends and cycles into account). Regarding long-term trends, the hypothesis of Prebisch (1950) and Singer (1950) that there has been a secular deterioration in the net barter terms of trade (NBTT) between primary products and manufactures has fostered perhaps more empirical studies than any other hypothesis in development economics. (For recent examples, see Spraos (1980) and Grilli and Yang (1988).) The presumed validity of the Prebisch-Singer hypothesis has provided a strong motivation for export diversification away from primary commodities towards manufactured goods in many developing countries.

For policy purposes, reasonable estimates of the magnitude, duration, and shape of commodity price cycles are as important as estimates of their

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1/ According to the World Development Report, 1987 (pp. 222-223), the ratio of primary commodity exports to their total merchandise exports was 80 percent in 1965, and fell to 60 percent in 1985 for LDCs taken as a group. For the "oil exporters" subcategory, however, the ratio fell only slightly, from 95 to 91 percent, while for the sub-Saharan African countries it rose from 92 to 94 percent over the same period.

underlying long-term trends. A good understanding of the cyclical behavior of commodity prices is, for example, essential when deciding when (or whether) to implement countercyclical stabilization policies in countries whose exports are dominated by one or two key commodities. The advisability of policies affecting production or export incentives in the agriculture or mining sectors, for example, hinges on expected world price performance. The financial viability (or budgetary costs) of national commodity stabilization funds, as well as the potential benefits and costs of international market-sharing agreements and multilateral arrangements such as the IMF's compensatory financing facility also depend critically on the nature of both long-term trends and cyclical movements.

This paper has two interrelated objectives. First, it uses univariate time series techniques to re-examine the Prebisch-Singer hypothesis that the relative prices of primary commodities in terms of manufactured goods are characterized by secular deterioration. Second, it decomposes various primary commodity prices into permanent (or "secular") and cyclical components in order to study their cyclical behavior. Being based on univariate techniques, our results should be interpreted only as statistical descriptions of the data. They leave open the question of the underlying economic causes of the trends and cyclical movements, although our characterization of the stylized facts is, of course, a prerequisite for such work.

As both Spraos (1980) and Grilli and Yang (1988) have emphasized, empirical conclusions regarding the Prebisch-Singer hypothesis depend importantly on the choice of price indices for capturing LDCs' terms of trade. To explore the possibility that our earlier empirical findings [Cuddington and Urzúa (1989)] and those of others are sensitive to the choice of a particular primary commodity price index, this paper takes a disaggregated approach. It studies the individual price movements of twenty-six commodities. The underlying nominal price data used in this study are free-market quotations compiled by the World Bank covering the period 1900-83; each nominal price is deflated by a manufactures unit value (MUV) index from Grilli and Yang (1988). 2/ These 26 commodities, which comprise the bulk of world commodity trade, include the 24 non-fuel commodities in a new primary commodity price index constructed by Grilli and Yang (1988) plus _two energy products_: oil and coal. 3/ The non-fuel group includes _eleven food commodities_: bananas, beef, cocoa, coffee, lamb, maize, palm oil, rice, sugar, tea, and wheat; _seven non-food agricultural commodities_: cotton, hides, jute, rubber, timber, tobacco and wool; and _six metals_: aluminum, copper, lead, silver, tin and zinc.

Section 2 briefly summarizes recent research on long-term trends in primary commodity prices to put our study into context. Section 3 discusses the statistical issues involved in estimating trends in economic time series. Of particular importance is the issue of whether there are unit roots in the stochastic processes generating commodity prices. The presence or absence of a unit root determines whether real commodity prices are more appropriately modelled as so-called _trend stationary_ (TS) processes, as virtually all previous research on commodity price trends implicitly assumes, or as

2/ This series corresponds to the MUV index compiled by the United Nations Secretariat except for two gaps: 1914-20 and 1939-47, which Grilli and Yang filled by interpolation.

3/ In a companion paper, Cuddington and Urzúa (1989), we use the same methodological approach taken here to study the trends in the terms of trade between primary commodities and manufactures, as measured by the new commodity price index constructed by Grilli and Yang (1988).

difference stationary (DS) processes [Nelson and Plosser (1982)]. Unless the appropriate model is chosen, consistent estimates of the secular trends in real commodity prices will not be obtained. Based on the unit root tests carried out in Section 3, Section 4 uses the TS and DS models as required to re-examine the empirical evidence on the long-term trends in primary commodity prices.

Section 5 discusses the decomposition of price movements into trend and cyclical components. This decomposition, too, depends critically on the choice of the TS or DS model. In situations where the DS model is chosen, we use the Beveridge and Nelson (1981) technique for decomposing economic time series into a permanent, trend, or secular component, on the one hand, and a temporary or cyclical component, on the other. Section 6 summarizes our conclusions.

2. A Brief Review of Recent Empirical Evidence

Spraos (1980) presents a detailed analysis of the Prebisch-Singer hypothesis using a number of alternative commodity price indices. Comparing the index used by Prebisch (1950) and Singer (1950) to others now available, he concludes that evidence supporting the Prebisch-Singer hypothesis of a secular deterioration in real commodity prices is stronger with the index they chose than with the other indices he considered. Using his preferred index, Spraos found (somewhat weaker) supportive statistical evidence for the seventy-year period ending with the outbreak of World War II. When he extended his analysis to include the post World War II period, however, the hypothesis was open to doubt. In a comment on Spraos' paper, Sapsford (1985a) found evidence of structural break in the data in 1950. After allowing for this break using dummy variables and correcting for first-order autocorrelation, he concluded that a significant downward trend prevails in the post-war period as well.

Noting shortcomings with existing commodity price indices, Grilli and Yang (1988) constructed several new indices. Following earlier authors, they estimated a simple log-linear model and found a significant downward trend in the NBTT, as well as three sub-indices of the individual commodity prices. This conclusion was robust to corrections for both first-order autocorrelation and structural instability.

Thirlwall and Bergevin (1985), using United Nations quarterly data from 1954 to 1982, also fit log-linear models to indices for different commodity groups and individual commodity prices. For all commodity groups and individual commodities, the terms of trade were found to be either trendless or deteriorating. Apparently, they did not examine the error terms of the fitted models for evidence of serial correlation. As is well-known, high serial correlation can lead to erroneous statistical inferences.

3. Estimating Trends in Commodity Prices

Existing empirical tests of the secular deterioration of commodity prices examine the sign of the time coefficient β in a log-linear model of the form:

$$ly(t) = a + \beta * TIME + e(t), \tag{1}$$

where ly(t) is the natural logarithm of the real commodity price. The residuals in such regression equations typically exhibit high serial correlation. It is well-known that failure to account for this serial correlation when estimating the time trend β produces inefficient estimates. More importantly, the standard errors on the regression coefficients, on which hypothesis tests regarding the trend are based, are inconsistent unless the error process in (1) is adequately modeled.

Most previous work on commodity price behavior has assumed that e(t) follows a simple AR(1) process. That is,

$$(2) \qquad (1 - pL)\, e(t) = u(t)$$

where u(t) is white noise. The error process is assumed to be stable (i.e. $p < 1$) and the Cochrane-Orcutt or other method is used to correct for first-order serial correlation when estimating (1).

A more general procedure, which eliminates the potential misspecification involved in assuming (2) when there is higher order serial correlation, would be to model e(t) as a mixed autoregressive moving-average (ARMA) process:

$$(3) \qquad C(L)e(t) = D(L)u(t).$$

The model (1) and (3) can then be identified and estimated using standard Box-Jenkins techniques. 4/

In recent years, estimating time trends has become somewhat of a growth

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4/ Although long lags are often disregarded in time series modeling on the grounds of "parsimony", there is a common belief in the commodity price literature that medium and long-term cyclical movements may be important. For this reason, we consider longer lag specifications in our models than would typically be used in Box-Jenkins methods. The text reports models with lags up to 12. Cuddington and Urzúa (1986) reports estimated models with lags as high as 30.

industry in the macroeconometrics literature, because of a number of interesting conceptual and statistical issues that arise. [See, e.g., Stock and Watson (1988).] The key statistical issue is whether the error process in the general model represented by (1) and (3) is in fact stable or whether it has a unit root. As we discuss below, this has important implications for the estimation of trends as well as the characterization of cycles about these trends. [See, e.g., Beveridge and Nelson (1981).]

To facilitate the discussion below, it is useful to factor (3) to isolate the root p with the largest modulus. The model (1)-(3) can then be written:

(4) $ly(t) = a + \beta * time + e(t)$

(5) $(1 - pL)\ A(L)\ e(t) = B(L)\ u(t).$

It is assumed that: (i) the lag polynomial A(L) is invertible, (ii) B(L) and hence $A^{-1}(L)*B(L)$ are stable polynomial lag operators, and (iii) the innovations u(t) in (5) are white noise. As long as $|p| < 1$, (4)-(5) is just the <u>trend stationary</u> (TS) model on which previous analyses of the Prebisch-Singer hypothesis were based.

If there is a unit root (p=1) in (5), on the other hand, the error process is nonstationary and difficult statistical problems arise in the estimation of (4)-(5). For example, the sampling distribution of the ordinary least squares (OLS) estimator of β in (4) is not well behaved. This can lead to OLS estimates that are not only biased in finite samples but, in many applications, also inconsistent. 5/ Nelson and Kang (1984, p. 80) emphasize

5/ Although the OLS estimator is always biased, Plosser and Schwert (1978) show that it turns out to be consistent in the special case where TIME is the only regressor (as it is in many of the empirical studies of the alarming size of this bias:

> A conventional *t* statistic for the least squares coefficient on time is a very poor test for the presence of trend in the sense of a dependence on time. Such tests lead to rejection of the null hypothesis of no dependence in 87% of the cases for a sample length of 100 at a nominal 5% level, when in fact there is no dependence on time. Attempts to correct for serial correlation in the residuals only partially correct this effect. An investigator applying first order AR correction based on sample autocorrelations of the residuals would still reject the true hypothesis at a nominal 5% level with 73% probability. (Nelson and Kang, 1984, p. 80.)

Thus, the presence of a unit root in the error process e(t) in the typical specification (1) would lead to misleading statistical inferences. In particular, it is extremely likely that researchers would conclude that commodity prices exhibit trends even if, in fact, no trends exist.

In the presence of a unit root, the correct procedure is to first difference the regression equation (4), thereby eliminating the unit root and achieving stationarity of the error process. The resulting model is the difference stationary (DS) model:

$$\text{dly}(t) = \beta + e(t). \tag{6}$$

Since $\text{dly}(t) = (1-L)\text{ly}(t)$, dly(t) is simply the growth rate of y(t). The mean growth rate β is the same as the coefficient on TIME in (4). The error process is ARMA: $A(L)e(t) = B(L)u(t)$.

Just as under-differencing (i.e. failing to recognize the presence of a unit root) can lead to incorrect statistical inferences, so can over-differencing. If, in fact, there is no unit root in (5), it is inappropriate to first-difference the model prior to estimation. Doing so will introduce a unit root into the error process of the first-differenced form of the model in (6) even though none existed in the original specification (4)-(5). It is clearly essential to tests for the presence of a unit root prior to estimation of the time trend if reliable evidence on the Prebisch-Singer hypothesis is to be obtained.

Before carrying out unit root tests, the time series of the real commodity prices were plotted and examined for any major breaks in the data that could not plausibly be attributed to the stochastic process generating the rest of the data series. This seemed to be the case for two of the commodities, coffee and oil, where level shifts in the series occurred in 1950 and 1974 respectively. As Perron (1987, 1988) has shown, such shifts render standard unit root tests invalid. He suggests a generalization of the Said-Dickey unit root test to deal with this situation. The Said-Dickey and Perron tests are briefly reviewed below before turning to our results.

The Said-Dickey and Perron Tests for Unit Roots

The issue of how to test for the presence of a unit root is complicated, particularly if the underlying error process in (5) does not take the very simple AR(1) form in (2). (See Dickey, Bell, and Miller, 1986, for a survey of recent work in this area.) Said and Dickey (1984) have proposed a test for the presence of a unit root in general ARMA models, which is based on a regression equation that approximates ARMA error processes with higher-order AR models. [6]/ Perron (1987, 1988) has recently extended the Said-Dickey procedure to allow for situations where there is assumed to be an exogenous

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[6]/ Schwert (1989) suggests that this test is considerably more robust against specification error than other tests in the literature.

shift in the level of the data series after time period T_B (where $0 < T_B < T$). As Perron stresses, the Said-Dickey test statistic is inconsistent when there is a break in the data. Using Monte Carlo simulations, Perron computes empirical cumulative density functions for unit root t-test statistics given various assumptions about where the break occurs in the data series. As $\lambda = T_B/T$ approaches zero or one, Perron's critical values will approach those for the Said-Dickey t-test. Thus we will discuss the Perron test, leaving the Said-Dickey test as a special case.

Let DUM be a "level" dummy variable that takes the value zero in all periods up through T_B and unity for all t from T_B+1 to T. DDUM is a "spike" dummy defined as the first-difference of DUM. Hence it takes the value zero in all period except T_B+1. Perron's generalization of the Said-Dickey unit root test [henceforth, the Said-Dickey-Perron test] is based on the following regression equation:

(7) $dly = \mu + \alpha * ly(-1) + b*TIME + c*DUM + d*DDUM + C(L)\ dly(t) + u(t)$

where C(L) is an lag polynomial of high enough order to render the residuals u(t) white noise. Under the null hypothesis that the time series process for ly(t) in (4)-(5) has a unit root, $\alpha = 0$ in (7). The t-test statistic $\tau_\alpha = \alpha/\sigma$, where σ is the standard error of the OLS estimator α, is not distributed according to the usual student t distribution. The empirical cumulative distribution of τ was calculated by Dickey and Fuller for the case where there are no breaks in the data. This empirical distribution can be shown to be the same as that reported in Fuller (1976, p.371-3). The appropriate distribution in Fuller depends on whether a constant term μ and TIME are or are not included among the regressors in (7), implying different alternative hypotheses. The inclusion of TIME results in confidence intervals that are considerably wider than those in the case where the model includes a nonzero constant but TIME is in fact insignificant. Thus if the price series is in fact stationary around a constant mean (no trend), the inclusion of TIME will reduce the power of the unit root test. When in doubt, however, the inclusion of TIME is advisable according to Schwert (1989, p.150):

> Including a time trend in [regression 7] even when the trend coefficient $\alpha=0$, makes the distribution of the autoregressive parameter estimate independent of [the unknown intercept] μ. In empirical applications in which knowledge of the value of the intercept μ is unavailable, inclusion of a time trend is probably a prudent decision in performing unit root tests.

As we were particularly interested in the alternative hypothesis of a trend stationary model, the Said-Dickey-Perron test based on regression (7) including both a constant and a time trend was used. We experimented with alternative lag specifications for C(L) ranging from 4 to 10 lags and examined the autocorrelation and partial autocorrelation function of the residuals for evidence of serial correlation in each case, because premature truncation of the lag distribution will render the estimate of $\tau_\alpha = \alpha/\sigma$ inconsistent. Excessive lags, on the other hand, will reduce the power of the test. [7]

Table 1 reports the <u>lowest</u> τ_α statistic from the various lag specifications 4 through 10 for each of the commodities. This is the test statistic least sympathetic to the null hypothesis that there is a unit root. Asterisks (*) in the Table indicate rejection of the null hypothesis at the 10% significance level. According to Fuller (1976, Table 8.5.2, p. 373), the

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[7] Lack of power against alternative models where the largest root is near unity is a well-known problem with existing unit root tests. Thus one should not be cavalier in the choice of lag length.

Table 1

Estimated "t" Statistics for Unit Root Hypothesis

	$\tau\alpha$	lags
Aluminum	-2.48	4
Bananas	-2.29	9
Beef	-2.95	4
Coal	-3.88*	7
Cocoa	-2.51	7
Coffee[1]	-4.31*	10
Copper	-2.39	6
Cotton	-2.52	7
Hides	-3.82*	4
Jute	-2.58	4
Lamb	-3.16*	10
Lead	-3.20*	4
Maize	-3.73*	4
Oil[2]	-3.16	10
Palm oil	-3.83*	4
Rice	-4.82*	7
Rubber	-2.62	4
Silver	0.87	4
Sugar	-2.79	6
Tea	-2.18	4
Timber	-3.75*	4
Tin	-2.82	4
Tobacco	-2.21	7
Wheat	-3.73*	5
Wool	-1.90	4
Zinc	-3.75*	4

[1] The unit root test for coffee incorporated level shift in the data in 1974. Thus the test statistic was obtained by estimating a Said-Dickey-Perron regression and comparing the t-statistic to the empirical distribution in Perron (1987, Table 4B) for the data breakpoint at $\lambda = 50/83 = .60$ in the sample. The crtical value at the 10% significance level for $\lambda = .60$ equals -3.47.

[2] As in the case of coffee, the Said-Dickey-Perron test was used to account for a level shift in the oil price data in 1974 (i.e. at $\lambda = .89$ in the sample). From Perron (1987, Table 4B), the critical value at the 10% significance level for $\lambda = .90$ equals -3.38.

hypothesis of a unit root would be rejected at the 10% level of significance whenever the value of τ_α is less than -3.18, -3.15, or -3.12 for sample sizes of 50, 100, and infinity respectively. For the two commodities with structural breaks, Perron (1987, Table 4B) calculates the asymptotic distributions of the t_α statistic in the model with a TIME trend for various values of λ.

Turning to the results of the unit root tests in Table 1, the asterisks indicate rejection of the unit root hypothesis for 11 of the 26 commodity prices, suggesting that these prices are best modelled as TS processes. For the remaining 15 commodities, the unit root hypothesis could not be rejected at the 10 percent level. Hence, the DS process is appropriate in these cases. [8]

4. Empirical Findings on the Deteriorating Trend (Prebisch-Singer) Hypothesis

TS Models. For the 11 commodity prices where the unit root hypothesis is rejected, TS models were identified and estimated. The resulting models are reported in Table 2. Examining the coefficients on TIME, we find that in 3 cases TIME is statistically insignificant at the 10 percent significance level. In 3 other cases, there are significantly positive price trends. The remaining 5 commodities (of the 11 commodities best modeled as TS processes) have statistically significant negative trends as conjectured by Prebisch and Singer.

The Box-Pierce statistic Q(12), reported in column 6 of Table 2, suggests that the error processes have been adequately modelled. It is distributed as

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[8] It might be noted that it is possible to have both a unit root and a log-linear time trend in (4)-(5). For the 26 commodities in this study, however, none appears to exhibit this characteristic.

Table 2
Estimated Trend Stationary (TS) Models

Commodity	Constant	Dummy	Time	error process	Q(12)	R^2
coal	-16.454 (-3.854)	n/a	.009* (4.057)	$(1-.716L)e_t=u_t$ (-9.428)	7.285	.769
coffee	-1.473 (-0.184)	.557D1950 (3.100)	.000 (0.060)	$(1-.646L)e_t=(1-.479L^{11})u_t$ (-6.120) (-3.660)	4.132	.779
hides	23.436	n/a	-.012* (-4.924)	$(1-.563L)e_t=u_t$ (-6.150)	8.303	.669
lead	1.226 (0.237)	n/a	-.001 (-0.278)	$(1-.730L)e_t=u_t$ (-8.580)	7.578	.483
lamb	-37.045 (-3.811)	n/a	.019* (3.713)	$(1-.782L)e_t=(1+.335L)u_t$ (-7.293) (2.942)	7.376	.867
maize	13.507 (3.743)	n/a	-.007* (-3.620)	$(1-.514L)e_t=u_t$ (-5.614)	9.340	.497
palm oil	12.164 (3.074)	n/a	-.006* (-3.036)	$(1-.818L+.240L^2)e_t=u_t$ (-7.372)(2.145)	3.688	.606
rice	12.475 (3.930)	n/a	-.006* (-3.835)	$(1-.937L+.399L^2)e_t=u_t$ (-9.010)(3.792)	12.008	.666
timber	-21.886 (-4.329)	n/a	.011* (4.235)	$(1-.773L)e_t=u_t$ (-10.885)	8.328	.863
wheat	14.781 (5.759)	n/a	-.007 (-5.603)	$(1-.846L+.221L^2+.172L^4)e_t=u_t$ (-7.674)(1.905)(2.117)	7.269	.733
zinc	-0.258 (-0.059)	n/a	.000 (0.062)	$(1-.639L)e_t=u_t$ (-7.452)	7.204	.410

a Chi-square with 12 degrees of freedom under the null hypothesis of no serial correlation from order one to 12 in the innovations u(t) in the estimated models.[9] As Table 2 illustrates, there is considerable variety in the specification of the error process across commodities. It is certainly not true that the simple AR(1) model is generally applicable.

DS Models. For each of the 15 commodity prices where the unit root hypothesis could not be rejected, the time series ly(t) was first-differenced to achieve stationarity. A low-order model for dly(t) was then identified and estimated using Box-Jenkins techniques. The results are reported in Table 3. Note that in the case of oil, a "spike" dummy that takes the value of 0 in every year except 1974 (D1974) is included to account for the one-time shift in the level of the data in that year.

Recall that estimated constant terms in Table 3 represent estimated (stochastic) time trends under the DS specification. Scanning these estimates, it is interesting to note that the time trend is insignificantly different from zero in all cases except for the real price of tobacco, where a statistically significant positive trend of 1.5 percent per year is found. As was the case with the TS model reported in Table 2, the error process in the DS models varied considerably across commodities, but this time MA processes appear more often than AR processes.

Recapping the findings from the TS models in Table 2 and the DS models in Table 3, we conclude that, out of our 26 commodity prices, five commodities

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[9] The residuals from all reported models were examined (i) visually, (ii) using autocorrelation and partial autocorrelation functions, and (iii) using the Box-Pierce Q statistic to insure that error processes were adequately modelled.

Table 3

Estimated DS Models

Commodity	Constant	Dummy	error process	Q(12)	R^2	Gain Function
aluminum	-.015 (-.945)	n/a	$e_t=(1+.355L-.286L^2-.236L^5)u_t$ (3.138) (-2.504) (-2.037)	5.174	.192	$dly(t)= -.015+833u_t$
bananas	.004 (.375)	n/a	$e_t=(1-.278L^2-.278L^{10})u_t$ (-2.436) (-2.362)	6.131	.116	$dly(t)= .004+.444u_t$
beef	.019 (.726)	n/a	$e_t=u_t$	7.422	.000	$dly(t)= .019+u_t$
cocoa	-.001 (-.035)	n/a	$e_t=(1-.359L^2)ut$ (-3.199)	4.821	.114	$dly(t)= -.001+.641u_t$
copper	-.005 (-.306)	n/a	$e_t=u_t$	10.003	.000	$dly(t)= -.005+u_t$
cotton	-.002 (-.174)	n/a	$e_t=(1+.254L-.424L^2-.269L^3)u_t$ (2.230) (-3.697) (-2.344)	4.252	.234	$dly(t)= -.002+.561u_t$
jute	-.001 (-.052)	n/a	$e_t=(1-.343L^2-.257L^5)u_t$ (-3.032) (-2.235)	5.141	.173	$dly(t)= -.001+.400u_t$
oil	.003 (0.203)	1.264*D1974 (8.342)	$e_t=(1-.215L^3-.284L^{11})u_t$ (-1.874) (-2.309)	2.952	.488	$dly(t)= .003+.501u_t$
rubber	-.025 (-.753)	n/a	$e_t=u_t$	9.667	.000	$dly(t)= -.025+u_t$
silver	.010 (.537)	n/a	$e_t=(1-.371L^2+.306L^2-.294L^8)$ (-3.252) (2.247) (-2.133)	6.921	.191	$dly(t)= .010+.641u_t$
sugar	-.008 (-.211)	n/a	$e_t=(1-.487L^2-.262L^5+.268L^6)u_t$ (-4.195) (-2.201) (2.261)	6.160	.240	$dly(t)= -.008+.519u_t$
tea	-.005 (-.309)	n/a	$e_t=(1-.280L^2)u_t$ (-2.478)	6.151	.072	$dly(t)= -.005+.720u_t$
tin	.012 (.680)	n/a	$e_t=(1+.235L^3-.244L^5)u_t$ (2.094) (-2.190)	5.238	.135	$dly(t)= .012+.991u_t$
tobacco	.015* (1.928)	n/a	$(1+.381L^4)e_t=u_t5.107$ (3.535)	.140		$dly(t)= .015+.781u_t$
wool	-.010 (-.485)	n/a	$e_t=(1-.208L-.449L^2)u_t$ (-1.862)(-4.013)	3.136	.196	$dly(t)= -.010+.343u_t$

(hides, maize, palm oil, rice, and wheat) have negative trends. Thus the estimated trends for these commodity prices provide support for the Prebisch-Singer hypothesis. Four commodity prices exhibit positive trends (coal, lamb, timber, and tobacco), while the remaining 17 real commodity prices are trendless (i.e. statistically insignificant).

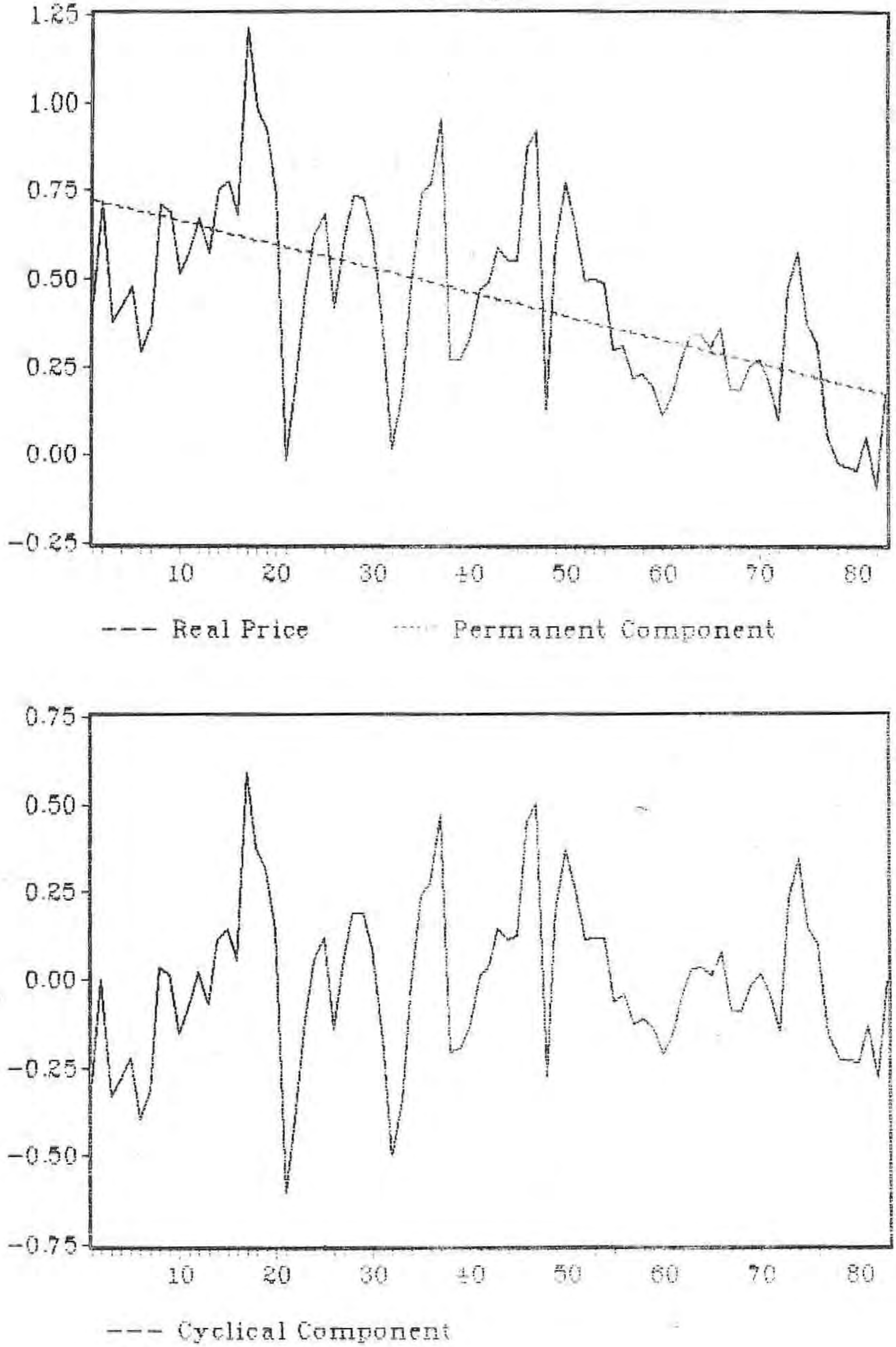
5. Cyclical Movements in the Commodity Prices

As mentioned in the Introduction, a knowledge of the cyclical behavior of commodity prices is at least as important as their long-term trends for policy purposes. Furthermore, the characterization of cycles depends critically on whether the TS or DS model is most appropriate.

TS Models The traditional approach for determining commodity price cycles is to fit a TS model like (1) above. As emphasized in Section 3, this approach is appropriate in the absence of unit roots in the stochastic processes generating prices. The cyclical component of ly(t), denoted lyc(t), is found by calculating the deviations between ly(t) and the exponential trend line. Since the error process e(t) in (1) is assumed to be stationary, the innovations in prices u(t) have no persistent (i.e. steady state) effect. That is, the TS model, implicitly assumes that the permanent component of ly(t) is completely deterministic ($a + \beta$*time) and shocks to prices are entirely cyclical in nature.

As an example of the TS Model, consider maize, which according to Table 2 follows a simple AR(1) process around a time trend of -0.7 percent per year. The natural logarithm of the real price of maize and its permanent (i.e. log-linear trend line) and cyclical components are shown in Figure 1. Deviations

FIGURE 1
REAL PRICE OF MAIZE
(in logs)



between the actual price and the trend line, of course, represent cyclical fluctuations, which can be quite persistent as the figure illustrates.

......Insert FIGURE 1 here......

DS Models   If the error process in the general model (4)-(5) has a unit root however, a hypothesis that we failed to reject using the Said-Dickey-Perron test for 15 of the 26 commodities, it is inappropriate to estimate the log-level form of the model. Not only will this lead to erroneous conclusions about the secular drift in prices, it will also distort our view of cycles. As Plosser and Nelson (1982) explain, when there is a unit root so that the DS model is appropriate, the growth rate in (4) in effect becomes stochastic rather than deterministic. In this framework, stochastic shifts in the level of the growth path are interpreted as permanent (secular) effects, while fluctuations around the (shifting) growth path are cyclical effects. Since this model allows for changes in the level of the growth path, it will typically reduce the relative importance of the cyclical component in commodity price data. [10/]

The innovations u(t), which may reflect shocks to supply and/or demand for the commodity, may cause the growth rate to be above or below of its mean rate for a period of time, with the length of this period depending on the process followed by e(t) in (3). Given that the error process is stationary, the effect of the shock dies out over time, so the growth rate reverts to its mean rate after the shock is dissipated. The shock, however, permanently

[10/] However, as shown in Cuddington and Winters (1987), there are some cases in which the cyclical component gets bigger, relative to the permanent component, rather than smaller.

alters the level of ly(t).

Following Beveridge and Nelson (1981), it is possible to decompose price shocks into permanent and cyclical components. An implicit assumption in their procedure is that the same fraction of each and every innovation is viewed as permanent; the remainder is cyclical. 11/ In order to determine the permanent and cyclical components of the price series, begin with the DS models identified and estimated in Table 3. To understand the movements in the permanent component, it is useful to look at the changes in the permanent component of ly(t), dlyp(t). This amounts to calculating the stochastic steady state of the model after the current realization u(t). As Cuddington and Winters (1987) show, this is easy to derive using the so-called gain function, which is obtained by setting the lag operator L equal to 1 in the estimated DS model in Table 3. (The gain function from each model is reported in the rightmost column of Table 3.) It indicates the functional relationship between price shocks or innovations and changes in the level of lyp(t). In the absence of any price shocks (u(t) = 0), the permanent component of relative commodity prices grows at its historical trend rate β. Diagrammatically, this assumption means that the growth path of ly(t) has the slope β; each innovation shifts the level of the growth path by an amount indicated by the gain function. 12/

The consequences of an innovation u(t) at period t are twofold. First,

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11/ A decision must be made on how to treat the dummy variable in the case of oil. The working assumption made here is to consider the entire impulse to be a change in the permanent component of the price series in the year when it occurs.

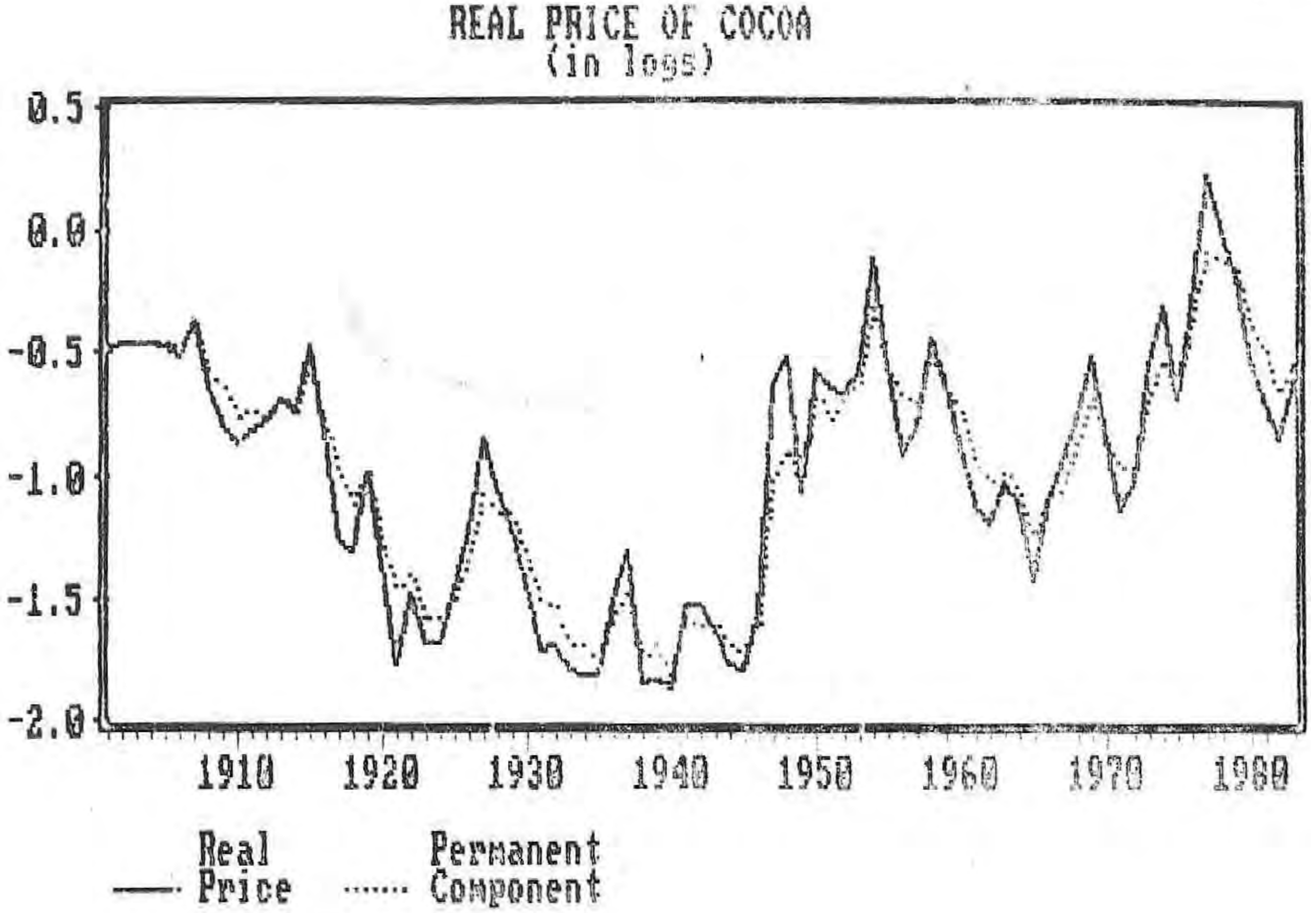
12/ The inclusion of DDUM(1974) in the gain function for oil insures that lyp jumps by the additional amount DDUM(1974) in the year when the structural break occurs.

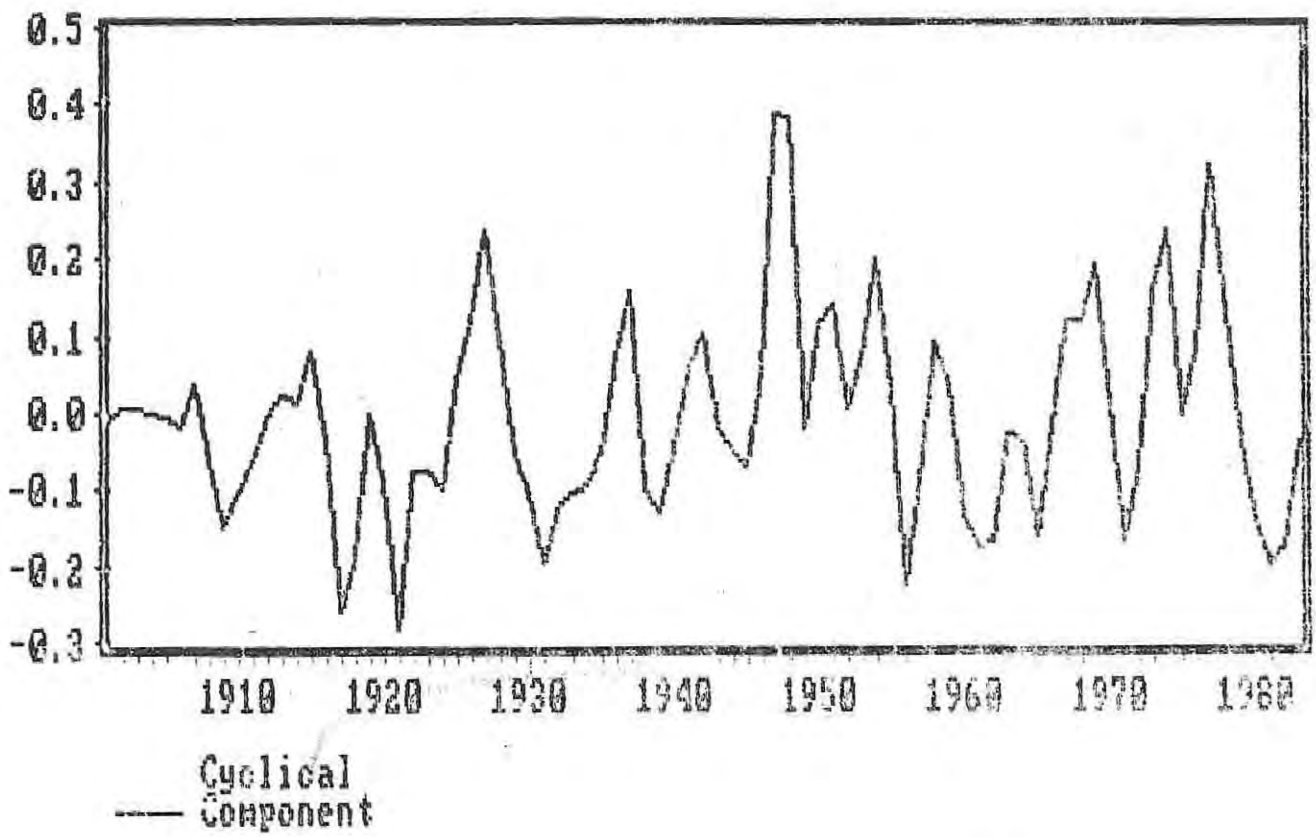
the growth path of ly(t) is shifted by the amount $\beta + B(1)^{-1}*A(1)\ u(t)$, causing the change in lyp(t) in period t to be somewhat greater or less than its trend rate of β, depending on the sign and magnitude of the coefficient on u(t) in the gain function. Second, the innovation sets in motion a cyclical movement in prices around the shifted trend path. The nature of these cyclical deviations of actual prices from their permanent level depends on the nature of the ARMA error process describing prices.

As an example of how to interpret the information in Table 3, consider cocoa. The constant term in the DS model indicates a point estimate of the trend in cocoa prices equal to -.001 (although this value is not significantly different from zero). The extent to which a shock should be viewed as permanent (secular) as opposed to temporary (cyclical) can be determined from the coefficient on u(t) in the gain function. For the cocoa gain function, this coefficient equals .641, indicating that 64.1 percent of the typical cocoa price shock is permanent; the remaining 35.9 percent is cyclical.

The error process in the model is MA(2), indicating that cocoa price shocks are dissipated in two years. In the absence of further innovations, there are no further shifts in the permanent price path, and actual prices eventually converge to the (new) permanent level. We infer from the MA(2) error process that an innovation of u(t) units, which shifts the trend line up by .641 u(t), leaves ly(t) above its trend by (1-.641) u(t) in the current period t. In the following period t+1 in the absence of further innovations, the price remains this amount above trend (because the estimated error process has no MA(1) term), as both the actual price and the permanent component grow at the rate $\beta = -.001$. In period t+2, e(t+2) changes by the amount β -.359 u(t), as reflected in two-period lag (i.e. the MA(2) term) of the error

FIGURE 2


REAL PRICE OF COCOA
(in logs)
0.5
0.0
-0.5
-1.0
-1.5
-2.0
1910
1920
1930
1940
1950
1960
1970
1980
Real Price
Permanent Component


0.5
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
1910
1920
1930
1940
1950
1960
1970
1980
Cyclical Component

process. This returns ly to its new stochastic trend-path. As mentioned, in the case of cocoa, price shocks persist for a total of two periods; they follow a humped pattern rather than an oscillatory movement until the long-run equilibrium is restored. The Beveridge-Nelson decomposition of real cocoa prices is illustrated in Figure 2.

.....insert Figure 2 here.....

The estimated models in Tables 2 and 3 indicate that the degree of permanence of price shocks varies greatly across commodities. For all 11 commodities in Table 2, all shocks should be viewed as completely transitory. At the other extreme, there are commodities like beef, copper, rubber, and tin where the gain equals one. The first three of these time series follow a random walk, implying that all innovations should be viewed as permanent, with no cyclical effect. In the case of tin, the innovation is ultimately 100 percent permanent, but there are short-term fluctuations about the new trend level for five years. The remaining commodities in Table 3 (the DS cases) have permanent components ranging from .343 of the innovation (wool) to unity (as just discussed). Although it is technically possible to have gain functions with u(t) coefficients in excess of one, no such cases occurred in our sample of 26 commodity prices.

6. Conclusions

This study has re-examined the empirical validity of the hypothesis that the relative prices of primary commodities in terms of manufactures are characterized by secular deterioration. Applying time series techniques to 26 individual commodity prices (deflated by the MUV) and allowing for the possibility of structural breaks and the presence of unit roots, we conclude that the majority (17) of the 26 prices are best characterized as trendless.

Our analysis demonstrates that there is a tremendous diversity in both trend and cyclical behavior across commodity prices, suggesting that blanket statements about commodity price trends and cycles based on aggregate indices may be quite misleading if one is trying to say something about the prospects for specific commodity prices, or the plight of primary commodity exporters in general ("typical developing countries", for example).

Some commodity prices were best modeled as trend stationary, while others were difference stationarity. In the TS model, the trend line for any commodity price is completely deterministic --i.e. the growth rate of real commodity prices is inalterably fixed; all innovations are entirely cyclical. In the DS model, on the other hand, each and every innovation is deemed to be x% permanent and (1-x)% cyclical. In the special DS case of a random walk, every innovation is 100 percent permanent, with no transitory component. Any of these assumptions seems a priori to be very restrictive. Of the various (real and nominal) shocks that impact the supplies and demands for commodities over time, some presumably reflect permanent shifts, such as resource discoveries or technological changes (e.g. the development of synthetic substitutes). Others reflect cyclical phenomena, such as crop failures or monetary shocks, which may indeed have real effects in the short run even though they are neutral in the long run.

These latter reservations lead to our earlier caveat: The analysis of trends as well as the trend-cycle decompositions in this paper are based on univariate techniques. Thus they ignore additional information about the precise cause of particular innovations or "shocks" that may be available to commodities analysts and market participants. In principle, such information could be incorporated into multivariate generalizations of the models used in this paper. Detailed structural econometric models may also be useful in obtaining more sophisticated characterizations of trends and cycles. In our view, this is an interesting direction for future research.

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