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Sharp Breaks or Smooth Shifts? An Investigation of the Evolution of Primary Commodity Prices*

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Abstract

This paper explores the behavior of real commodity prices over a 50–year period. Attention is given to how the shifting means for various commodity prices have changed with a special emphasis on behavior since the mid 2000s. To identify structural changes in commodity prices, we estimate shifting–mean autoregressions by using: the Bai and Perron (1998) procedure for determining structural breaks; low frequency Fourier functions; and a procedure that specifies shifts to be smooth logistic functions of time. We find that the pattern in the timing of shifts is suggestive of the causal factors underlying the recent boom.

Keywords: Nonlinear Trends, Shifting–Mean Autoregression, Unit Root Tests

JEL Classification Codes: C22; C52; E3; Q2

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1 Introduction

In recent years the prices for many commodities have experienced a significant and sustained boom. Moreover, this boom has extended beyond the "usual suspects," that is, beyond oil and precious metals, to include a diverse set of goods such as cotton, maize, wheat, soybeans, sugar, edible oils, and coffee, among others. The situation is summarized in Figure 1, where monthly World Bank aggregate price indices, 1960–2010, for energy, grains, and edible fats and oils are plotted.[1] As illustrated there, sustained increases began for each of these (nominal) price categories sometime during the early 2000s. Indeed, nominal prices for all three indices reached all–time highs during 2008. As also indicated in Figure 1, while there were steep declines in these indices following the onset of the recent financial crises, since then the prices for many commodities have substantially recovered.

There are many reasons underlying the recent commodity price surge. A primary driver is almost certainly the rapid income growth of emerging economies, most notably for China and India. With rising purchasing power, there appears to be concomitant "Westernization" of diets in many emerging economies, with consumers increasingly demanding a richer, more varied diet, and one tilted more towards protein (Zhang and Law, 2010). Likewise, income growth in emerging economies has also corresponded with rapidly increasing demands for energy. See Hamilton (2009) and Kilian (2009). Not only is energy a major input into agricultural production, but the demands for energy and food are increasingly linked because of biofuel production; see Abbott, Hurt, and Tyner (2008). Since passage of the Energy Policy Act of 2005, the United States has established a renewable fuel standard while simultaneously pursuing a policy of subsidizing ethanol production and restricting its import. In consequence two of every five bushels of corn now produced in the United States are used in ethanol production (U.S. Department of Agriculture, 2011). Weather shocks have also reduced commodity supplies in some instances (see, e.g., World Bank, 2011), the result being that for some commodities (e.g., maize, rice, and wheat) global stock levels relative to overall use have been unusually low in recent years. Other factors that have possibly played a role in recent commodity price runs include speculation and expansionary monetary policies, although establishing these as true causal factors is difficult.

A variety of approaches could be used to explore the recent surge in commodity prices. One would be to construct a comprehensive structural supply–demand system that attempts to account for the myriad factors influencing commodity markets. While this approach has merit, it is data intensive, costly to implement, and is sensitive to assumptions (e.g., do agents possess rational expectations, naïve expectations, or something in between?). Although it can be advantageous, the problem with the structural approach is that any hypothesis tests are actually joint tests involving the assumptions embedded in the structural model. An alternative approach, and one used extensively in the literature (see, e.g., Carter and Smith, 2007), is to model commodity prices in a reduced form manner, typically by using univariate or multivariate time series methods. We pursue this second approach because we want to model a large number of commodity prices in a consistent fashion. Our main interest is in estimating the timing of shifts in sixteen different commodity prices. However, to address the issue, we must determine whether prices are stationary around an unspecified number of, possibly smooth, mean shifts. The econometric task is to estimate the number of breaks, the dates at which breaks occur, and whether series are stationary after controlling for shifts. As noted by Newbold and Vougas (1996), answering these questions is paramount in obtaining a deeper understanding of commodity price behavior, and is therefore material to attaining insights into recent commodity price movements.

There is a small but relevant literature that has examined the time series properties of commodity prices. Much of this work has sought to examine the long–term behavior of commodity prices vis–à–vis some numéraire, for example, the producer price index. The goal is to determine if (real) commodity prices are trend stationary, and if so whether there has been a long–term secular decline. Recent examples of work in this area include Kellard and Wohar (2006), Balagtas and Holt (2009), and Harvey et al. (2010). Others such as Wang and Tomek (2007) have examined the issue conceptually and empirically; they argue that, due to storability and biological production constraints, prices for agricultural commodities should not follow a unit root process. They also discuss specification issues in testing for unit roots in commodity prices and present empirical evidence that several common price series appear to be trend stationary once mean breaks are accounted for.

As Wang and Tomek (2007) observe, the production processes for agricultural commodities in the presence of costly storage means that price changes are serially correlated. The autocorrelation is a result of: (1) the biological constraints that prevent an instantaneous supply response to changes in market conditions; and (2) the changes in inventories that help smooth consumption and hence price changes over time. The argument applies equally well to temporary and permanent changes in market fundamentals. For example, in response to a permanent increase in demand, the price could overshoot its long–run level if short–run supply were sufficiently inelastic. Although inventory adjustments would mitigate the possibility of overshooting (since stocks would decline when prices are relatively high), the key point is that prices would gradually adjust to their new long–run level. As such, price adjustments would tend to be gradual, even if shifts in the underlying market conditions occur quickly.

Prior research has not investigated the possibility that commodity prices are best represented as a stationary process that incorporates a set of smooth shifts as opposed to a series of discrete, one–off sharp breaks. However, the recent time series literature has made substantial progress in testing for unit roots in the context of models that not only include trends but also smooth shifts. See, for example, Becker, Enders, and Lee (2006a) and Enders and Lee (2011). The situation where commodity prices are potentially stationary around a smoothly shifting mean is also relevant for examining the most recent boom. For example, did observed price spikes during the past five–six years reflect a true mean shift, indicating the possible change in some underlying fundamental? Or did they simply result from a series of random disturbances? And assuming the former is true, is there any discernable pattern to the timing of shifts across commodities? These and related questions can be examined once the time series properties of the price data have been firmly established.

Considering the above, the goals of this paper are as follows: (1) to use new methods to examine the unit root hypothesis for commodity prices vis–à–vis a trend stationary model with smooth shifts; and (2) for commodities for which shifting–mean stationarity is deemed appropriate, to determine the timing of and the extent to which the most recently observed shifts occur. In the empirical analysis we examine monthly primary commodity price data collected from World Bank Pink Sheets and the International Monetary Fund (IMF) Financial Statistics Database, 1960–2010. Commodities examined include maize, soy, wheat, rice, cotton, and crude oil, among others. In so doing we employ a set of new tools for examining smooth shifts in commodity prices. Specifically, we implement two variants of a smooth shifting–mean autoregressive (SM–AR) process: one due to Becker, Enders, and Hurn (2004; 2006b) that is based on a Fourier flexible form; and one due to González and Teräsvirta (2008) that is based on a time–varying autoregressive (TV–AR) model. Because SM–AR models do not force structural change to be sharp they represent a reasonable alternative to the more common Bai and Perron (1998) approach, the results of which are also included for comparison.

The outline of the paper is as follows. In the next section we present an overview of the methods employed to investigate shifting means in commodity prices. In section three we describe the data, while section four reviews unit root testing in the presence of shifting means and reports the results of these tests applied to the commodity price data. In section five we detail the Bai and Perron (1998), the Fourier, and the González and Teräsvirta (2008) methodologies and compare the estimated break dates found by each. Section six discusses the implications of our analysis for the timing and possible causes of changing commodity prices. The final section concludes.

2 A Framework for Modelling Shifting Means

Let cp_t denote a primary commodity price, and let p_t denote the producer price index. The basic building block for our investigation of shifting means in commodity prices is a univariate autoregressive (AR) model, which is written as:

$$(1) \qquad \Delta y_t \;=\; \tilde{\delta}(t) + \sum_{j=1}^{p} \theta_j \Delta y_{t-j} + \rho y_{t-1} + \varepsilon_t, \quad t = 1, \ldots, T,$$

and where $y_t = ln(cp_t/p_t)$, Δ denotes a difference operator such that $\Delta z_t = z_t - z_{t-1}$, $\tilde{\delta}(t)$ is a time–varying intercept, and $\varepsilon_t \sim iid(0, \sigma^2)$. Here Δy_t denotes the monthly (real) inflation rate for a commodity price. By examining real commodity prices we abstract from price movements caused by changes in the overall price level.

Regardless of the approach used to specify $\tilde{\delta}(t)$, once parameter estimates have been obtained it is a straightforward matter to uncover an estimate of the shifting mean. Assuming that $\rho < 0$ in (1), that is, by assuming that the real commodity price is stationary around a shifting mean, the underlying unconditional mean at time t is

$$(2) \qquad E(y_t) \;=\; -\tilde{\delta}(t)/\rho,$$

where E denotes the expectation operator.

2.1 Bai–Perron Procedure

A now standard methodology for modelling $\tilde{\delta}(t)$, developed by Perron (1989) and Bai and Perron (1998), is to assume the series of interest is stationary around a small set of discrete breaks in its unconditional mean. In other words, commodity prices might behave as a process that is piecewise stationary. In the context of (1), the idea is as follows. Rewrite $\tilde{\delta}(t)$ as:

$$(3) \qquad \tilde{\delta}(t) \;=\; \delta_0 + \sum_{i=1}^{k} \delta_i I_{\tau_i},$$

where I_{τ_i} is defined as a Heaviside indicator function such that $I_{\tau_i} = 1$ if $t > \tau_i$ and is 0 otherwise. Additionally, k denotes the number of discrete breaks in the unconditional mean of the series and δ_i and τ_i, $i = 1, \ldots, k$, are additional parameters to be estimated.

In contrast to a Chow test where break dates are known, Andrews and Ploberger (1994) develop a test for the case of a single sharp break (i.e., $k = 1$ in (3)) occurring at an unknown date. The procedure involves searching for τ_i by performing a Chow test for every possible break date. To ensure an adequate number of observations for each regression, it is standard to use "trimming" such that breaks do not occur at the very beginning or end of the sample. If a break is present, the value of τ_i producing the best fit is a consistent estimate of the break date. The null hypothesis of structural stability is tested against the alternative of a one–time break using the Andrews and Ploberger (1994) supremum test. Bai and Perron (1998, 2003) generalize this methodology to allow for the possibility of $k > 1$ breaks.

Although the Bai–Perron method is arguably the current "industry standard," it is problematic as to whether it can capture the smooth shifts shown in Figure 1. For equation (3) to approximate the recent gradual and sustained increases in commodity prices, it is necessary to combine the sharp breaks into a step-function. Yet, for any type of gradual change, the first step will necessarily come after the initial price increase.

2.2 Fourier Series Approximation

Instead of viewing breaks in $\tilde{\delta}(t)$ as being sharp, Becker, Enders and Hurn (2004, 2006b) show that the essential characteristics of a series containing breaks can often be captured using a modification of Gallant's (1984) flexible Fourier form. Specifically, define:

$$(4) \qquad \tilde{\delta}(t) \;=\; \delta_0 + \delta_1 t + \sum_{i=1}^{n} \left\{ \delta_{ci} \cos\left(2\pi f_i^* t/T\right) + \delta_{si} \sin\left(2\pi f_i^* t/T\right) \right\}, \quad n \leq T/2,$$

where f_i^* are low frequency Fourier terms. The choice of a Fourier approximation to model the smoothly evolving time–varying intercept is driven by three considerations. First, it is well–

known that a Fourier approximation can capture the variation in any absolutely integrable function of time. Hence, the behavior of the time–varying intercept can be readily captured by trigonometric expressions even if the actual function in question is not periodic. Although a Fourier approximation works best when the breaks are smooth, Becker, Enders and Hurn (2004), Becker, Enders, and Lee (2006a) and Enders and Lee (2011) show that trigonometric functions do reasonably well in approximating certain sharp breaks. Second, unlike a Taylor series approximation using powers of $t, t^2, t^3, \ldots$, the sum of a small number of trigonometric components is bounded and projections into the future are necessarily finite. Although a Taylor series is valid at a particular point in the sample space, a Fourier approximation is a global (rather than a local), approximation. Third, the estimation of (4) is easily accomplished by using OLS; for each desired frequency f_i^*, form the variables $\sin(2\pi f_i^* t/T)$ and $\cos(2\pi f_i^* t/T)$ and include them in the estimating equation. Hypothesis testing is also straightforward since the values of $\sin(2\pi f_i^* t/T)$ and $\cos(2\pi f_i^* t/T)$ are orthogonal to each other and Gallant and Souza (1991) show that their joint distributions are multivariate normal.[2]

Throughout, we select various model components including lag lengths, p, and the number of cumulative frequencies, n, by using Akaike's Information Criterion (AIC), determined as:

$$\text{AIC} = T \log\left(\sum_{t=1}^{T} \hat{\varepsilon}_t^2\right) + 2r, \tag{5}$$

where r is the number of estimated parameters and $\hat{\varepsilon}_t$'s are the SM–AR's estimated residuals.

2.3 Logistic Function Components

González and Teräsvirta (2008) also assume the series in question moves around a deterministically shifting mean while allowing shifts to be either sharp or smooth. Specifically, they consider:

$$\tilde{\delta}(t) \ = \ \delta_0 + \sum_{i=1}^{k} \delta_i g(\eta_i, c_i, t^*), \tag{6}$$

where, again, δ_i's are "mean–shift" parameters and $g(.)$'s is a logistic function, defined as:

$$g(\eta_i, c_i, t^*) \ = \ \big(1 + \exp(-\gamma(\eta_i)(t^* - c_i)/\hat{\sigma}_{t^*})\big)^{-1}, i = 1, \ldots, k, \tag{7}$$

where $\gamma(\eta_i) = \exp(\eta_i)$, $t^* = t/T, t = 1, \ldots, T$; $\hat{\sigma}_{t^*}$ is the estimated standard deviation of t^*; and where η_i and c_i are parameters. Specifically, η_i is finite but is otherwise unrestricted. As well, $c_i \in [0, 1]$ is a centrality parameter where the value of $c_i T$ indicate the date at which the shift is centered. By construction each $g(.)$ component in (7) is bounded on the unit interval.

Given (7), it follows that the unconditional mean can, depending on the magnitude of η_i, experience either sharp or slowly evolving changes. Specifically, as the normalized value of η_i becomes large, $g(.)$ effectively becomes a Heaviside indicator function, I_{c_i}, as in (3). Alternatively, for small values of η_i the function $g(.)$ approaches a linear trend, while for intermediate values it has a sigmoidal shape. By varying k additional flexibility can be achieved. Significantly, the shifting mean could include a combination of discrete and smooth changes as well as a linear trend. In this sense the logistic function approach is also a generalization of Bai and Perron's (1998) methodology.

We use the following procedure to estimate the SM–AR's parameters with logistic function components:

1. Define a set of candidate transition functions by evaluating (7) for a grid of values for η and c. Let $\Theta_N = \left\{\left(\mathrm{H}_{N_\eta} \times C_{N_c}\right)\right\}$, where $\mathrm{H}_{N_\eta} = \{\eta_s : \eta_s = \eta_{s-1} + \kappa_\eta, s = 1, \ldots, N_\eta\}$ and $C_{N_c} = \{c_s : c_s = c_{s-1} + \kappa_c, s = 1, \ldots, N_c\}$, and where κ_η and κ_c are values used to initialize the grid.

2. Estimate the AR model in (1) by setting $\tilde{\delta}(t) = \delta_0$. The minimized sum of squared errors is computed and saved.

3. Determine the first smooth break as

$$(\hat{\eta}_1, \hat{c}_1) = \underset{(\eta_s, c_s) \in \Theta_N}{\operatorname{argmin}} \sum_{t=1}^{T} \left\{ \Delta y_t - \hat{\delta}_0 - \hat{\delta}_1 g\left(\eta_s, c_s, t^*\right) - \sum_{j=1}^{p} \hat{\theta}_j \Delta y_{t-j} - \hat{\rho} y_{t-1} \right\}^2$$

where estimates of $\hat{\alpha} = \left(\hat{\delta}_0, \hat{\delta}_1, \hat{\theta}_1, \ldots, \hat{\theta}_p, \hat{\rho}\right)'$ are obtained as follows. Define $w_t\left(\eta_s, c_s\right) = \left(1, g\left(\eta_s, c_s, t^*\right), \Delta y_{t-1}, \ldots, \Delta y_{t-p}, y_{t-1}\right)'$. Then

$$\hat{\alpha}\left(\eta_s, c_s\right) = \left(\sum_{t=1}^{T} w_t\left(\eta_s, c_s\right) w_t\left(\eta_s, c_s\right)^T\right)^{-1} \left(\sum_{t=1}^{T} w_t\left(\eta_s, c_s\right) \Delta y_t\right).$$

4. Repeat step 3 until $k = \overline{k}$. For each pass, k, treat $(\hat{\eta}_1, \ldots, \hat{\eta}_{k-1}, \hat{c}_1, \ldots, \hat{c}_{k-1})$ as fixed. Compute and save the AIC(k) as defined in equation (5). Determine the number of logistic function components to use in the final model as $\hat{k} = \operatorname{argmin}_{k \in \left(1, \ldots, \overline{k}\right)}$ AIC(k).

Simply put, we use a two–dimensional grid search to estimate logistic function parameters. For this reason we name our estimation strategy SlowShift, as opposed to González and Teräsvirta's (2008) QuickShift procedure. The advantage of SlowShift is that with a fine enough grid, the in–sample mean square prediction error is effectively minimized.

3 Data

Commodity price data were obtained from World Bank (various issues). We also examine the behavior of ocean freight rates for bulk products, a series collected by Lutz Kilian; see Kilian (2009). Although a large array of commodity prices are available, we focus on sixteen series: maize, soy, wheat, sorghum, palm oil, rice, cotton, coffee, cocoa, sugar, beef, logs, rubber, oil, coal, and ocean freight rates. The data are monthly and, as described in the Technical Appendix, generally span the period 1960–2010 (612 observations). This group includes important food and feed grains (maize, soy, wheat, sorghum, and rice) as well as prices for other primary food and fibre items (palm oil, cotton, coffee, cocoa, sugar, and beef). Logs and rubber are important products used extensively in manufacturing, construction, and production of consumer items. The price of oil is included because of its universal importance as a primary input in manufacturing, food production, and transportation. As well, and as noted previously, oil and maize prices have become more intertwined in recent years due to increased biofuel production. Oil, while important, is not the only energy source, and for this reason we also include coal. Ocean freight is included to reflect general global economic activity; the cost of ocean transport is also an important consideration in commodity trade. A detailed description of the data used including units, sample periods, and sources may be found in the Technical Appendix.

All prices are deflated by the producer price index (PPI). The PPI is used because most commodities can be regarded as intermediate inputs. We also transform each real price series by multiplying by 100 and then by taking the natural logarithm.

4 Unit Root Testing in the Presence of Smooth Shifts

Before estimating a model in the form of (1), it is crucial to know whether or not the series in question is stationary around a shifting mean. Of course $H_0 : \rho = 0$ is a testable hypothesis, and one that should be verified for (2) to be defined. However, it is well known that typical unit root tests lose power in the presence of one or more mean shifts (Perron, 1989). Moreover, smooth shifts add another complicating factor in that a gradually changing series is not likely to be piecewise stationary in the sense of Prodan (2008). For example, when capturing a smooth break with a Bai-Perron stair–step function, the series will not generally be stationary within any of the selected intervals.

Several papers have proposed unit root tests for SM–AR models including Leybourne, Newbold, and Vougas (1998), who examined the null of a unit root against a TV–AR model with a single logistic component. Nevertheless, since our series are likely to have multiple structural breaks, we adopt another estimation strategy that is consistent with (1) and (4). Becker, Enders and Lee (2006a) (BEL) modify the Kwiatkowski, Phillips, Schmidt and Shin (1992) (KPSS) test, which examines the null of stationarity against a unit root alternative. The BEL test allows for flexibility in the specification of mean shifts by using selected frequency components from a Fourier function. An advantage of KPSS–type tests is that the problem of low power associated with standard unit root tests is avoided. Moreover, the null hypothesis that commodity prices are stationarity seems more in tune with economic theory than the null hypothesis of a unit root (Wang and Tomek, 2007).

To implement the BEL test, the following regressions are estimated:

$$y_t = \delta_0 + \sum_{i=1}^{n} \{\delta_{ci} \cos(2\pi f_i^* t/T) + \delta_{si} \sin(2\pi f_i^* t/T)\} + e_t, \tag{8a}$$

$$y_t = \delta_0 + \delta_1 t + \sum_{i=1}^{n} \{\delta_{ci} \cos(2\pi f_i^* t/T) + \delta_{si} \sin(2\pi f_i^* t/T)\} + e_t, \tag{8b}$$

where (8a) is appropriate when the null hypothesis is level–stationary and (8b) when the null is trend–stationary. Let $\tilde{e}_t$ denote the residuals from the estimates of (8). The BEL test statistics are then

$$\tau_\mu(n) \text{ or } \tau_\tau(n) = \frac{1}{T^2} \frac{\sum_{t=1}^{T} \tilde{S}_t(n)^2}{\tilde{\sigma}^2}, \tag{9}$$

where $\tilde{S}_t(n) = \sum_{j=1}^{t} \tilde{e}_j$ and where $\tilde{e}_t$ are from the regression in (8a) for τ_μ or from (8b) for τ_τ. The test statistic can be viewed as a comparison of an estimate of the short–run variance to that of the long–run variance, $\tilde{\sigma}^2$. An estimate for the long–run variance is also needed, and is typically given by:

$$\tilde{\sigma}^2 = \tilde{\gamma}_0 + 2\sum_{j=1}^{\ell} w_j \tilde{\gamma}_j,$$

where ℓ is the truncation lag, $\tilde{\gamma}_j$ is the jth sample autocovariance of the residuals, $\tilde{e}_t$, from estimates of either (8a) or (8b), and w_j are a set of weights. Alternatively, $\tilde{\sigma}^2$ could be obtained by augmenting (8) with lags of Δy_t, as indicated by Leybourne and McCabe (1994). Becker et al. (2006a) discuss the properties of the test statistics in (9), and present simulated critical values. They also illustrate that these tests have good power to ascertain U–shaped breaks and smooth breaks even near the end of the sample.

Enders and Lee (2011) develop an LM–type unit root test that also approximates breaks (shifts) in a series by using low frequency terms from a Fourier series. The test proceeds by estimating a regression analogous to (8a), but in first–difference form. That is,

$$\Delta y_t = \delta_0 + \sum_{i=1}^{n} \{\delta_{ci}\Delta \cos(2\pi f_i^* t/T) + \delta_{si}\Delta \sin(2\pi f_i^* t/T)\} + e_t. \tag{10}$$

Based on estimates of (10), a de–trended series is constructed as

$$\tilde{S}_t = y_t - \tilde{\delta}_0 - \sum_{i=1}^{n} \left\{\tilde{\delta}_{ci} \cos(2\pi f_i^* t/T) + \tilde{\delta}_{si} \sin(2\pi f_i^* t/T)\right\},\ t = 2, \ldots, T,$$

and the testing regression is therefore:

$$\Delta y_t = \varphi \tilde{S}_{t-1} + d_0 + \sum_{i=1}^{n} \{d_{ci}\Delta \cos(2\pi f_i^* t/T) + d_{si}\Delta \sin(2\pi f_i^* t/T)\} + \xi_t. \tag{11}$$

If y_t follows a unit root process then $\varphi = 0$ is true. The associated LM test, called the τ_{LM} test, is then simply a test of $\text{H}_0 : \varphi = 0$ in (11); Enders and Lee (2011) report critical values for such a test. Importantly, they also find that the τ_{LM} test has good size and power properties in the presence of logistic shifts of the sort described in (6) and (7).

We perform both versions of the Fourier tests. Stationary tests, such as the KPSS test and the BEL test, are known to have good power, but poor size properties. Tests with the null of a unit root, such as the usual Dickey-Fuller test and the τ_{LM} test, have good size but low power.

4.1 Unit Root and Stationarity Test Results

Table 1 shows the results of the Enders and Lee (2011) LM unit–root test and the Becker, Enders and Lee (2006a) KPSS–type stationarity test. The second column of the table shows the number of frequencies selected (by minimizing AIC) up to a maximum of $n = 3$. For that number of frequencies, n, the next column shows the sample value of the τ_{LM} test statistic for $\mathrm{H}_0 : \varphi = 0$. The lower panel of Table 1 indicates the 5% and 10% critical values for each n for a sample size of 500. For example, if $n = 3$, the corresponding 5% and 10% critical values are -5.42 and -5.16, respectively. For coffee, cocoa, and sugar, we cannot reject the null of a unit root at the 10% significance level, whereas for all other commodities we reject the null at the 5% level.

Columns 3 and 4 of Table 1 contain the sample test statistics for the BEL staionarity tests. The critical values for this test depend on whether there is a deterministic trend in the estimating equation. For $n = 3$, the 5% and 1% critical values are 0.0216 and 0.0265 in the presence of a trend and 0.0729 and 0.1157 without the trend.[3] Column 3 reports the results with a trend (the τ_τ test) while column 4 reports the results when the trend was found to be insignificant (the τ_μ test). For all commodities except cotton, logs, oil, and coal, we cannot reject the null hypothesis of stationarity at the 5% level; but even for these commodities we fail to reject stationarity at the 1% level. Nevertheless, for every commodity, at least one version of the test indicates that the series reverts to a smoothly evolving mean.

In an earlier version of this paper, we considered eight other commodities including gold, silver, iron ore, zinc, copper, tin, and lead. These commodities were found to have unit roots and so necessitate a different methodology to find breaks than that considered here. To save space, and because these commodities have no direct bearing on agricultural prices, results for these commodities are not reported here.

5 Estimation Results

In this section we apply the methods described previously for estimating shifting means to commodity prices. In every case we set the upper limit for the number of autoregressive parameters, p, to twelve; we use the AIC to determine the lag order of the autoregressive process by setting $\tilde{\delta}(t) = \delta_0$. The result is there are $T = 599$ sample observations, from February, 1961 through December, 2010 for all commodities save coal ($T = 479$) and ocean freight ($T = 503$). A detailed description of the data as well summary statistics for the best fitting constant–mean autoregressions (including results of several parameter non–constancy tests) are reported in the Technical Appendix; in each case the test results allow us to reject the null hypothesis that the model's intercept is constant.

5.1 Bai–Perron Results

We employ the Bai and Perron (1998, 2003) methodology setting the maximum number of breaks at 9. We use a trim factor such that the last of these breaks can occur no later than December, 2008 (2008:12).[4] Instead of using a sequential search, we estimate the model for every possible combination of 9 breaks imposing the restriction that there must be at least 24 observations between any adjacent break dates. The combination of break dates resulting in the smallest residual sum of squares is a consistent estimate of the vector of break dates. We test the null hypothesis of no breaks against the alternative hypothesis of some breaks by using the $UDmax$ critical values tabulated in Bai and Perron (1998).[5] Since we allow only the intercept to change across regimes, we can use the 90%, 95% and 97.5% asymptotic critical values of 8.78, 10.17 and 11.52, respectively. Although Bai and Perron (1998) indicate that the critical values are insensitive to the magnitude chosen for the upper value of k, we also perform tests for the null hypothesis of no breaks against the specific alternatives of exactly one break and exactly nine breaks (i.e., the sup–F test using a single break and using nine breaks). Given that we reject the null hypothesis of no breaks, we estimate every possible combination of breaks using models containing 1 through 9 breaks. We select the best fitting model using the Bayesian Information Criterion (BIC). This procedure is recommended by Prodan (2008) and seems reasonable for a large number of commodities with varying numbers of potential breaks.

Summary results for the final models estimated by using the Bai–Perron procedure are reported in the Technical Appendix. Here we focus on the timing of the last break found for each series. After all, if rising oil prices have caused run–ups in other commodity prices, we should find a positive jump in the price of oil that occurs prior to, or concurrently with, jumps in the prices of the other commodities.[6] Figure 2 shows the time paths of the estimated breaks superimposed over the actual price series. For clarity, the plots in Figure 2 focus only on the later part of the sample, beginning in 1995; plots for the entire sample period are reported in the Technical Appendix. Table 2 reports, for each commodity, the estimated date of the most recent break along with a 95% confidence interval (i.e., the columns headed Lower and Upper in the Table) for the break date. As should be clear from the Table, for oil, the last break occurs in December, 2004. This is earlier than the final jumps in the prices of maize (2006:08), soy (2007:04), rice (2008:01), cotton (2008:11), coffee (2008:10), and cocoa (2008:11). The oil price jump also precedes the jumps in the prices of wheat (2006:1) and sorghum (2006:08) that were followed by partial returns to their pre–jump levels. This is reasonably strong evidence in support of the claim that the rise in the price of oil reflected itself in a general rise in most other commodity prices. Of the commodities in our sample, only sugar and beef seem to be invariant to the jump in the price of oil. This argument is bolstered by the fact that the jump in the mean real price of oil was almost twofold.

The problem with the view that the oil price jump occurred prior to the other breaks is that the break dates are poorly estimated. Notice, for example, that a 95% confidence interval is such that the last break in the price of oil could have occurred as early as 2004:05 but as late as 2005:04. Part of the problem may be that breaks are gradual instead of sharp. Unless each break fully manifests itself at a single point in time, models with sharp breaks are misspecified. If you examine Figure 2, it is clear that sometime close to 1999, the (real) price of oil started to rise at a fairly steady pace. The Bai–Perron method captures this steady upward drift using sharp (upward) breaks at 1999:02 and 2004:12. If the price of oil actually did begin to rise in 1999, the prices of other commodities should have begun their increases around 1999 as well. Similar problems occur in the end–of–sample run–ups in the prices of soy, rice, coffee. The point is that if breaks are smooth, the Bai–Perron procedure necessarily relies on several or more reinforcing breaks to capture the sustained movement in the series. In these instances the estimated break dates are not especially informative of the actual change points in the series.

5.2 Fourier Results

Since breaks manifest themselves at the low end of the spectrum, Becker, Enders and Lee (2006a) recommend estimating (4) using a number of low frequencies, n. Unit root and stationarity tests lose power as the number of frequency components is expanded. Unlike these tests, where power is a particularly important issue, our aim is to precisely estimate the break dates. As such, we set $max(n) = 10$ and estimate each series in the form of (1) and (4). To avoid being *ad hoc*, we did not attempt to pare down the models by eliminating insignificant intermediate frequencies (e.g., for Maize, the value of n yielding the lowest AIC was $n = 6$ so that *sine* and *cosine* terms using frequencies f_1^* through f_6^* are included). For each commodity, the number of frequencies selected, estimates of ρ, and other regression diagnostics are reported in the Technical Appendix. Unlike the Bai and Perron (1998, 2003) specification, with a Fourier expansion, the number of breaks (shifts) in the data need not equal the number of frequencies used in the estimating equation.

For our purposes, the key piece of information is in the fifth column of Table 2 labeled "Last". Entries in this column show the date of the last trough of the estimated Fourier intercept and can be taken as an approximation of the last upward break in the series.[7] For example, if you examine the estimated time–varying mean for maize, $-\tilde{\delta}(t)/\rho$, shown as the long dashed line labeled "Trig" in Panel 1 of Figure 2, you can see that the last trough occurred in September of 2004 suggestive of an upward jump in the price of maize. Reading down column five, the last trough for oil occurred in July 2002. This clearly predates the last trough in all of the agricultural commodities except rice. Most importantly, the last upward shift for most commodities including maize (2004:09), soybeans (2005:10) and wheat (2005:03), occurred two or more years after the initial run–up in oil prices. Nevertheless, the Bai-Perron and Fourier results reinforce each other in supporting the claim that the recent run–up in agricultural commodities follows from an increase in the real price of oil.

5.3 SlowShift Results

In the implementation of SlowShift we set the upper limit for the number of mean shifts, $\overline{k}$, to ten. As well, when $k \geq 2$ we force SlowShift to pick a centrality parameter, c_i, that is at least 24 months away from its nearest neighbor.[8] We restrict our search for c_i's to 100 equally spaced values in the $[0.05, 0.95]$ interval (1963:07 to 2008:06) and for η_i's to 100 equally spaced values in the $[-1, 3.401]$ interval. In terms of $g_i = \exp(\eta_i)$, the corresponding grid is $[0.368, 30]$.[9] The result is that 10,000 regressions are estimated for each iteration of the SlowShift procedure.

The estimation results, including the number of shifts, parameter estimates, goodness–of–fit measures, and tests for serial correlation are summarized in the Technical Appendix. For all commodities save palm oil and ocean freight, the SlowShift procedure chooses at least two logistic function components. Moreover, in ten instances four or more shifts are included in the final model specification (i.e., for maize, soy, wheat, sorghum, rice, coffee, cocoa, sugar, beef, and coal). Results in Table 2 indicate that in some instances the shifts in underlying commodity price means are fairly sharp, that is, $\hat{\gamma} = \gamma_{max} = 30$. Even so, for most commodities there is at least one component for which the estimated value of γ is substantially less than 30, indicating that long–term mean shifts are a feature of the data. For example, although not reported here, long–term shifts were estimated for maize, soy, wheat, sorghum, cotton, coffee, sugar, beef, oil, coal, and ocean freight. See the Technical Appendix for details.

Additional results of interest, as reported in the Technical Appendix, are as follows. In mid–1986 the International Coffee Organization (ICO) failed in its attempts to ratify a new agreement, choosing instead to temporarily extend the 1983 agreement. During 1993–94 the ICO tried again to negotiate a new agreement to regulate international coffee prices, and did eventually have a new agreement ratified in late 1994. The new agreement, however, did not include provisions for regulating prices. In this instance the SM–AR model with logistic function components does a reasonable job of identifying these periods and the resulting impacts on international coffee prices.

Of interest here, as with the Bai–Perron and Fourier results, are the shifts that occurred in recent years, notably, since the early– or mid– 2000s. Results in Table 2 as well as in Figure 2 suggest that in many instances commodity price means did change rather sharply during this period. To illustrate, a rather abrupt increase in the mean for maize was centered around August 2006 (2006:08). Similar shifts were identified for soy (2007:02), wheat (2006:03), sorghum (2006:03), rice (2007:02), coffee (2008:06), cocoa (2007:07), and rubber (2008:06). Likewise, notable upward shifts in the prices of oil and coal were centered around December 2003 (2003:12). Similar to the results obtained by using alternative methods (i.e., Bai–Perron and Fourier frequencies), the SlowShift models indicate that means for oil and coal apparently shifted upward about three–to–four years in advance of the corresponding rise in the means for grains and food commodities.

6 Discussion and Analysis

A fundamental question is this: did the recent run–up in the price of oil cause subsequent upward shifts in prices of other commodities? While the results of our analysis do not allow us to make explicit causal statements, it seems unlikely that oil price jumps were the sole cause of subsequent shifts for other commodity prices. Unfortunately, it is not always straightforward to determine the beginning of a price movement. For example, for maize, the Bai–Perron method selects a last upward break date of 2006:08, the Fourier method 2004:09, and ShowShift selects 2005:8.[10] Since this last shift in the price of maize is rather sharp, the Bai–Perron method seems to capture this particular shift better than the other methods. Notice that the SlowShift and Fourier methods seem to smooth out the shift and, therefore, seem to select a somewhat early break date. However, in cases where the shift is gradual, the Bai–Perron method seems to be the most problematic. For oil (see Panel 15 of Figure 2), the Bai–Perron method finds a downward shift at 1997:01 followed by upward shifts in 1999:02 and 2004:12. The SlowShift and Fourier methods seem more plausible in that they capture the rise in the price of oil that began in late 2002. Finally, some prices, (such as wheat and ocean freight) began to increase, but then fell during the onset of the 2008 financial crisis. In an effort to be fair to each method, we used some judgment and, in Table 3, report what appear to be the start of the most recent run–up; notice that the commodities are listed chronologically from first to last shift date. As such, the results in Table 3 are not a simple ordering of the last upward shifts shown in Table 2.

Based on the rankings, we can categorize each method in terms of which commodities began to rise early, which rose later, and those which are unclear (or have non–applicable last breaks, i.e., a last break occurring prior to 2000:01). Notice that three commodities, specifically, rubber, coal, and oil seem to have the strongest evidence of early price shifts. Maize, sorghum, logs, palm oil, rice, and soybeans increase somewhat later. Finally, some commodities have no breaks occurring after 2000:01 (e.g., sugar for Bai–Perron and SlowShift); run–ups which begin quite late in the sample period (e.g., cotton); or downward shifts following a previous upward shift (e.g., freight).

The key point is the timing of the various jumps seems somewhat out of sync if in fact oil is the primary causal factor. Specifically, if oil is singularly the causal driver, the corresponding jumps in the prices for grains and other food items would have occurred sooner than they did. Moreover, the Bai–Perron and Fourier methodologies suggest that shifts in the prices for building materials (rubber and logs) preceded the increase in oil. As well, we are dubious that speculative activity has played a large and sustained role in the recently observed behavior for many commodity prices. Why? Because not all prices examined were associated conclusively with upward shifts at the end of the sample period including several heavily traded commodities such as wheat and sugar. Moreover, wheat and sugar are included in the widely used Reuters–Jefferies CRB index, which in turn has recently become a focal point of a number of exchange traded funds (ETFs). A priori it is not clear why speculative activity would result in sustained run–ups in prices for certain commodities and not others. Finally, note that these shifts are not simply due to changes in the overall level of inflation as we analyze only deflated commodity prices.

Other than negative oil supply shocks, there are at least two plausible candidates for the recent shifts in many primary commodity prices. First, and as noted in the introduction, there is solid reason to believe that demand shifts for many commodities may have occurred sometime in the mid 2000s and that, likewise, increases in supplies were not sufficient to offset these shifts. The demand shifts in turn were likely driven by higher real incomes in China, India, and in other emerging economies. The nature and timing of the various breaks revealed here suggest that the demand for energy and building materials increased first followed secondly by an increase in demand for food–related commodities. Secondly, and consistent with the conclusions of Abbott, Hurt, and Tyner (2008), we cannot rule out the possibility that for some commodities, and notably for maize as well as possibly for soy, wheat, and sorghum, that the explicit shift in the United States to a mandated ethanol fuel standard starting in 2006 also triggered a permanent shift in underlying price relationships for these goods. Indeed, it is very likely that the two factors are intertwined, that is, that both increasing demands for commodities in emerging economies as well as the rise of biofuel production are primary drives underlying much of the recently observed change in commodity prices.

7 Conclusions

In this paper we have examined the underlying behavior of a group of monthly commodity prices over a fifty year period. Specifically, we examine price movements in the context of mean breaks or shifts. We do so by using established methods for detecting multiple structural breaks in time series data (i.e., the procedures due to Bai and Perron, 1998, 2003) as well as several new procedures, specifically, Fourier and SlowShift approximations. Interestingly, all three methods appear to tell a similar story: in recent years changes in the price of oil and the prices for several building materials pre–dated (by several years) changes in the prices for grains and other food items. As such, it seems unlikely that shifts in the oil price alone caused shifts in other commodity prices. Indeed, a more plausible story seems to be that demand growth in emerging economies and the increasing utilization of certain crops for biofuels production have also contributed to the recent price runs.

Although this study has shed light on the timing and nature of recently observed commodity price movements, more work remains. For example, to what extent do some or all of the commodity prices examined here cotrend? To illustrate, do the price of oil and the price of maize share a common, nonlinear trend? In this regard it may be possible to use the SlowShift or Fourier SM–AR modelling framework presented here in conjunction with methods advanced by, for example, Bierens (2000) to examine this issue. This and related topics remain, however, as important future extensions of the analyses presented here.

Notes

[1]The commodities included in these indices are as follows: (1) energy (oil, coal, and natural gas); (2) grains (barley, maize, rice, sorghum, and wheat); and (3) edible fats and oils (coconut oil, copra, groundnut oil, palm oil, palmkernel oil, soybean meal, soybean oil, and soybeans).

[2]If the individual f_i^* are estimated, they become unidentified nuisance parameters under the null that $\delta_{ci} = \delta_{si} = 0$. In such circumstances, Becker, Enders and Hurn (2004, 2006b) develop a sup–F test along the lines of Davies (1987).

[3] The critical values get larger as the significance level decreases since the null hypothesis is that the data are stationary and the alternative is that they are nonstationary. To be 99% confident that the series is nonstationary requires larger critical values than to be 95% confident.

[4]Although not reported here, in earlier stages of the analysis we experimented with other trim factors, all of which were less favorable to the Bai–Perron methodology than the one utilized here.

[5]As discussed in Prodan (2008), searching for multiple breaks using the alternative sequential procedure is problematic. The problem is that finding a consistent estimate of the k-th break is contingent on successfully finding the first $k-1$ breaks. Yet, if there are k breaks the search for the $k-1$ breaks entails the use of a misspecified model. Papell and Prodan (2006), show that this problem is especially acute in searching for offsetting breaks, sometimes called U–shaped breaks. Similarly, sequential testing procedures can be problematic in that any test for the k-th break is conditional on the outcome of the tests for the other $k-1$ breaks.

[6]For some highly speculative commodities such as gold and silver, prices rises could occur

in anticipation of future events, including anticipated oil price inflation.

[7]Since our interest is in breaks occurring around the rise in oil prices, we do not consider troughs that occur before 2000:01 or after 2009:01.

[8]If two or more of the estimated c_i's are too close, and if the corresponding γ_i's are similar in magnitude, near singularity can result. By forcing c_i's to be at least 24 months apart we preclude this possibility.

[9]One advantage of searching over η versus γ is that an equally spaced grid on the former does not translate into an equally spaced grid for the later. As González and Teräsvirta (2008) note, there is less need to have an evenly spaced grid for relatively large values of γ. This principle is embedded here in our equidistant grid for η.

[10]To make comparisons comparable, we measure the beginning of the break for SlowShift as the date where the corresponding logistic function equals 0.10. See the column labeled 10% in Table 2.

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Table 1: Unit Root Test Results.

Commodity	n	τ_{LM}	$\tau_\tau(n)$	$\tau_\mu(n)$
Maize	3	-5.454	0.0210	–
Wheat	3	-5.652	0.0189	–
Soybeans	3	-6.378	–	0.041
Sorghum	3	-6.152	0.0200	–
Palmoil	3	-6.658	–	0.032
Rice	3	-5.432	–	0.022
Cotton	3	-6.175	**0.0221**	–
Coffee	3	**-5.022**	–	0.031
Cocoa	1	**-3.426**	0.0368	–
Sugar	3	**-5.003**	0.0195	–
Beef	2	-5.596	–	0.026
Logs	3	-5.495	**0.0224**	–
Rubber	3	-5.701	–	0.020
Oil	3	-6.221	**0.0234**	–
Coal	2	-5.309	**0.0330**	–
Freight	1	-5.859	0.0389	–

Critical Values:

	τ_{LM}		$\tau_\tau(n)$		$\tau_\mu(n)$	
n	5%	10%	5%	1%	5%	1%
1	-4.05	-3.78	0.0538	0.0714	0.1688	0.2696
2	-4.79	-4.52	0.0312	0.0397	0.1023	0.1614
3	-5.42	-5.16	0.0216	0.0265	0.0729	0.1157

Note: Entries in bold for the τ_{LM} test indicate that the unit root hypothesis is rejected at the 5% but not the 10% significance level. For the same test an entry that is in bold and underlined is not significant at the 10% level. For the KPSS–type tests, bolded entries indicate the null of stationarity can be rejected at the 5% but not the 1% significance level.

Table 2: Recent Upward Shifts and Shift Dates for Estimated SM–AR Models.

	Bai–Perron			Fourier	SlowShift				
Commodity	Lower	Date	Upper	Last	γ	c	10%	Center	90%
Maize	2003:11	2006:08	2007:08	2004:09	30	0.91	2005:08	2006:08	2007:09
Soy	2006:06	2007:04	2008:05	2005:10	30	0.92	2006:01	2007:02	2008:02
Wheat	2003:11	2006:01	2006:07	2005:03	30	0.90	2005:02	2006:03	2007:03
Sorghum	2006:03	2006:08	2006:09	2005:03	30	0.90	2005:02	2006:03	2007:03
					3.55	0.95	1999:07	2008:06	2017:05
Palm Oil	2004:08	2006:06	2007:01	2002:11	30	0.47	1983:05	1984:05	1985:06
Rice	2007:03	2008:01	2008:02	2001:11	30	0.92	2006:01	2007:02	2008:02
Cotton	2004:01	2008:11	2009:09	2007:10	2.97	0.55	1977:11	1988:06	1999:02
Coffee	2007:09	2008:10	2009:08	2007:05	25.11	0.95	2007:03	2008:06	2009:09
Cocoa	2007:12	2008:11	2010:05	2005:09	30	0.93	2006:06	2007:07	2008:08
Sugar	1981:01	1985:06	1992:09	2008:01	30	0.40	1980:03	1981:03	1982:04
Beef	1998:09	2003:06	2008:02	2007:06	30	0.67	1993:05	1994:05	1995:06
Logs	2003:07	2005:11	2008:08	2002:12	30	0.73	1996:07	1997:07	1998:08
Rubber	2008:01	2008:12	2010:12	2007:12	9.87	0.95	2005:04	2008:06	2011:09
Oil	2004:05	2004:12	2005:04	2002:07	30	0.86	2002:11	2003:12	2004:12
Coal	2006:11	2007:05	2007:07	2001:11	30	0.86	2002:11	2003:12	2004:12
					30	0.91	2005:08	2006:08	2007:09
Freight	2002:07	2003:02	2003:07	2006:09	3.40	0.28	1965:07	1974:11	1984:03

Note: Columns for Bai–Perron breaks indicate the most recent upward shift along with the upper and lower boundaries of a 95% confidence interval. For Fourier shifts last denotes the date of the last trough. Columns titled 10% (90%) denote the dates for which the relevant logistic function is associated with a value of 0.10 (0.90). Likewise, columns headed Center denote dates for which $t^* = \hat{c}$ for the respective logistic function.

Table 3: Last Upward Shift in Commodity Price Means.

Commodity	Bai-Perron	Commodity	Fourier	Commodity	SlowShift
		Commodities with Early Shifts			
Rubber	2001:12	Coal	2001:11	Oil	2002:11
Freight	2003:02	Rice	2001:11	Coal	2002:11
Beef	2003:06	Rubber	2002:12		
Coal	2003:10				
		Commodities with Intermediate Shifts			
Rice	2004:07	Oil	2002:07	Wheat	2005:02
Coffee	2004:08	Palm Oil	2002:11	Sorghum	2005:02
Oil	2004:12	Logs	2002:12	Rubber	2005:04
				Maize	2005:08
		Commodities with Late or Non Applicable Shifts			
Logs	2005:11	Maize	2004:09	Soy	2006:01
Wheat	2006:01	Wheat	2005:03	Rice	2006:01
Palmoil	2006:06	Sorghum	2005:03	Cocoa	2006:06
Maize	2006:08	Cocoa	2005:09	Coffee	2007:03
Sorghum	2006:08	Soy	2005:10	Palm Oil	NA
Soy	2007:04	Freight	2006:09	Cotton	NA
Cotton	2008:11	Coffee	2007:05	Sugar	NA
Cocoa	2008:11	Beef	2007:06	Beef	NA
Sugar	NA	Cotton	2007:10	Logs	NA
		Sugar	2008:01	Freight	NA

Note: NA denotes "Non Applicable" in that no shifts (breaks) occurred after 2000:01.

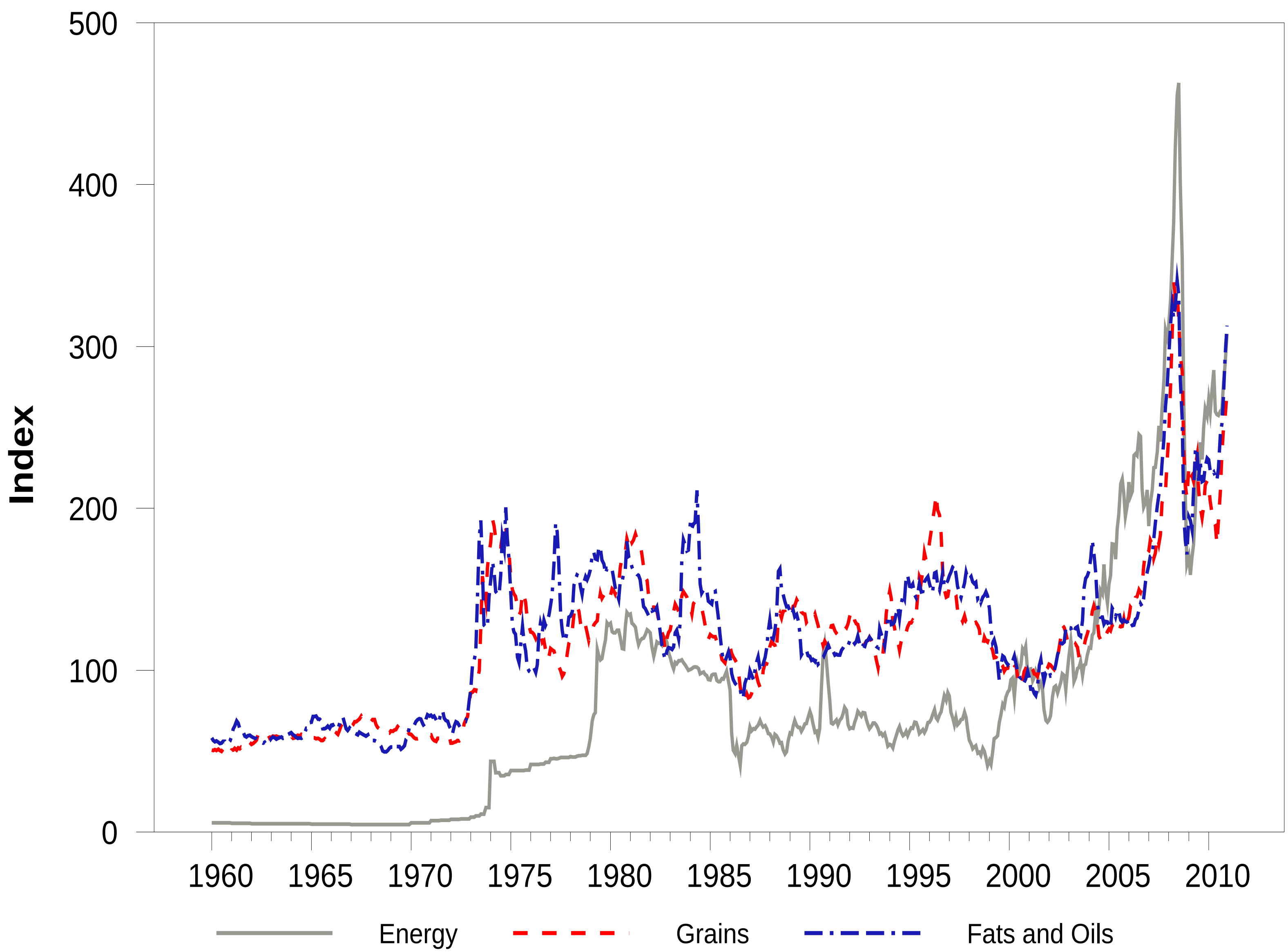

Figure 1: Commodity Price Indices for Energy, Grains, and Edible Fats and Oils, 1960–2010.

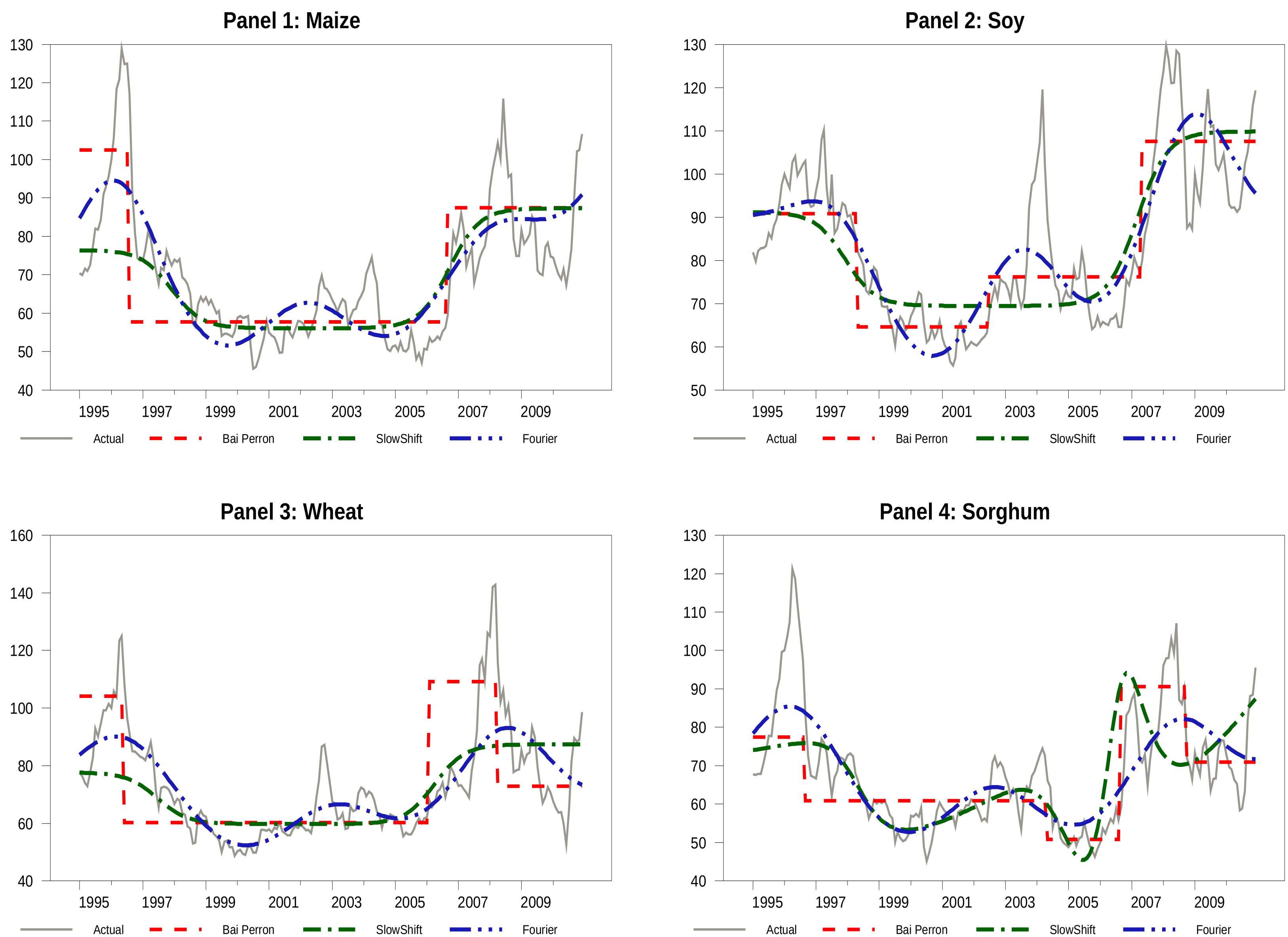

Figure 2: Commodity Prices, Actual Values and Shifting Means Obtained by Various Methods, 1995–2010.

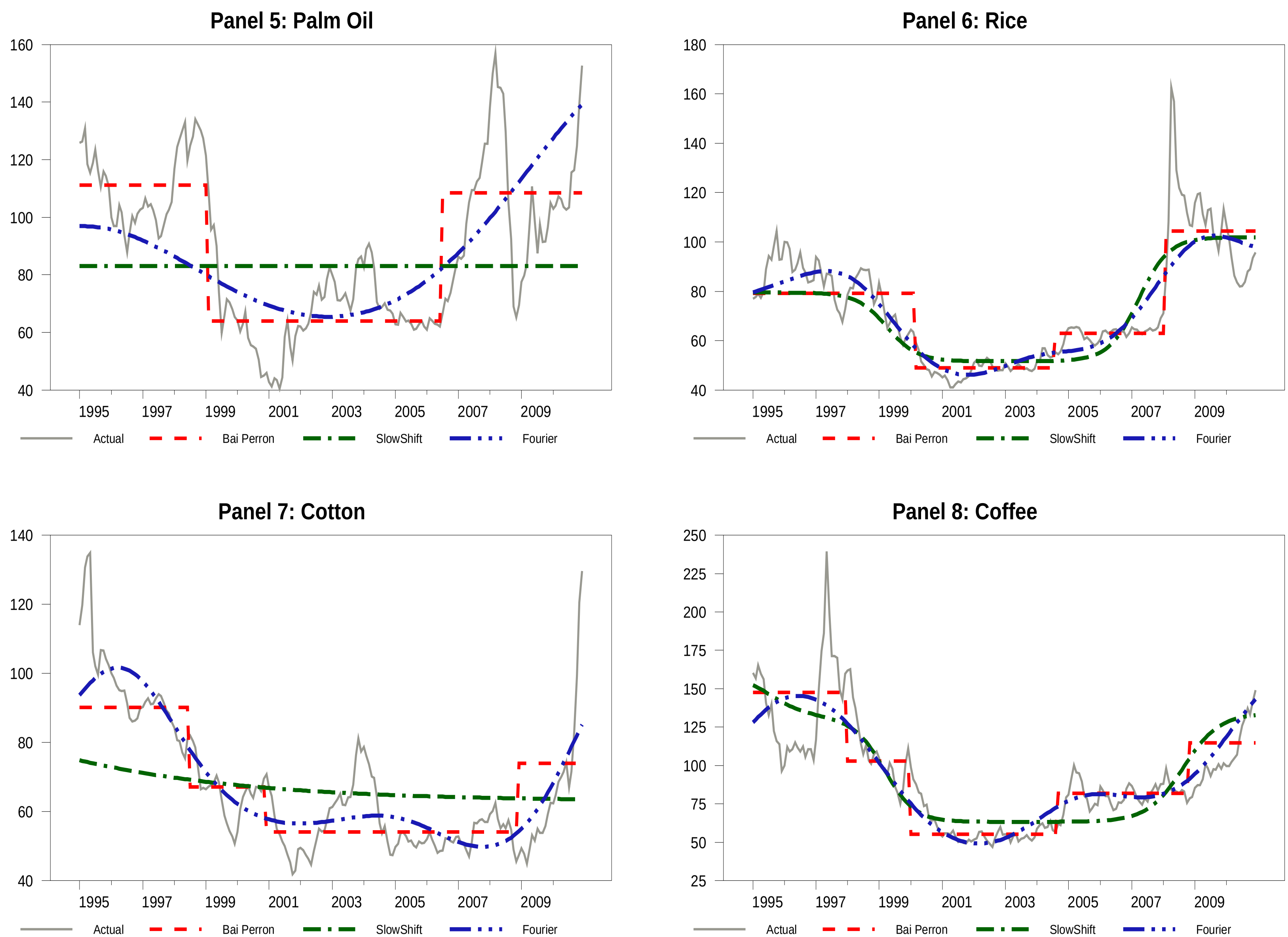

Figure 2: Commodity Prices, Actual Values and Shifting Means Obtained by Various Methods, 1995–2010 (Continued).

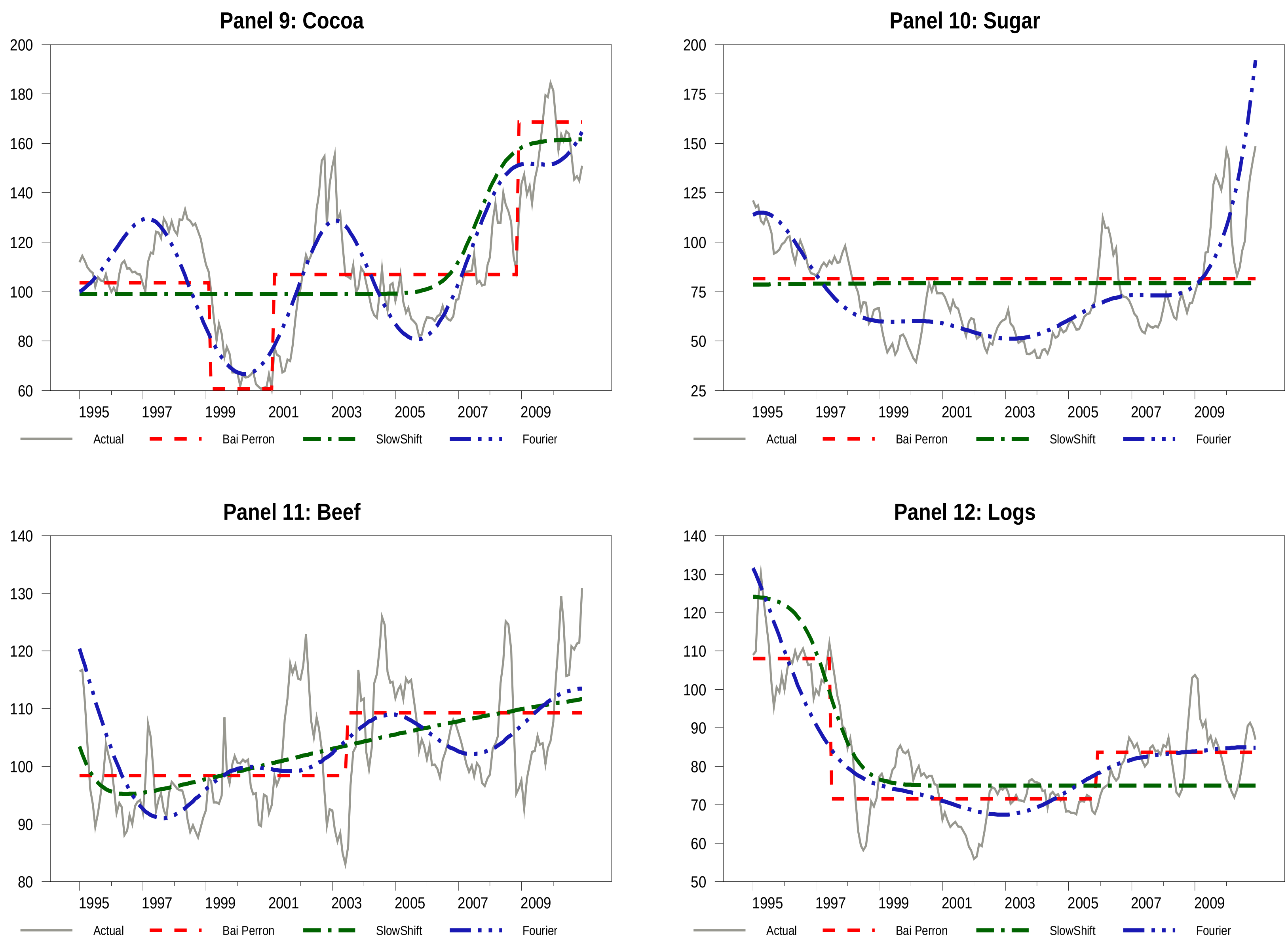

Figure 2: Commodity Prices, Actual Values and Shifting Means Obtained by Various Methods, 1995–2010 (Continued).

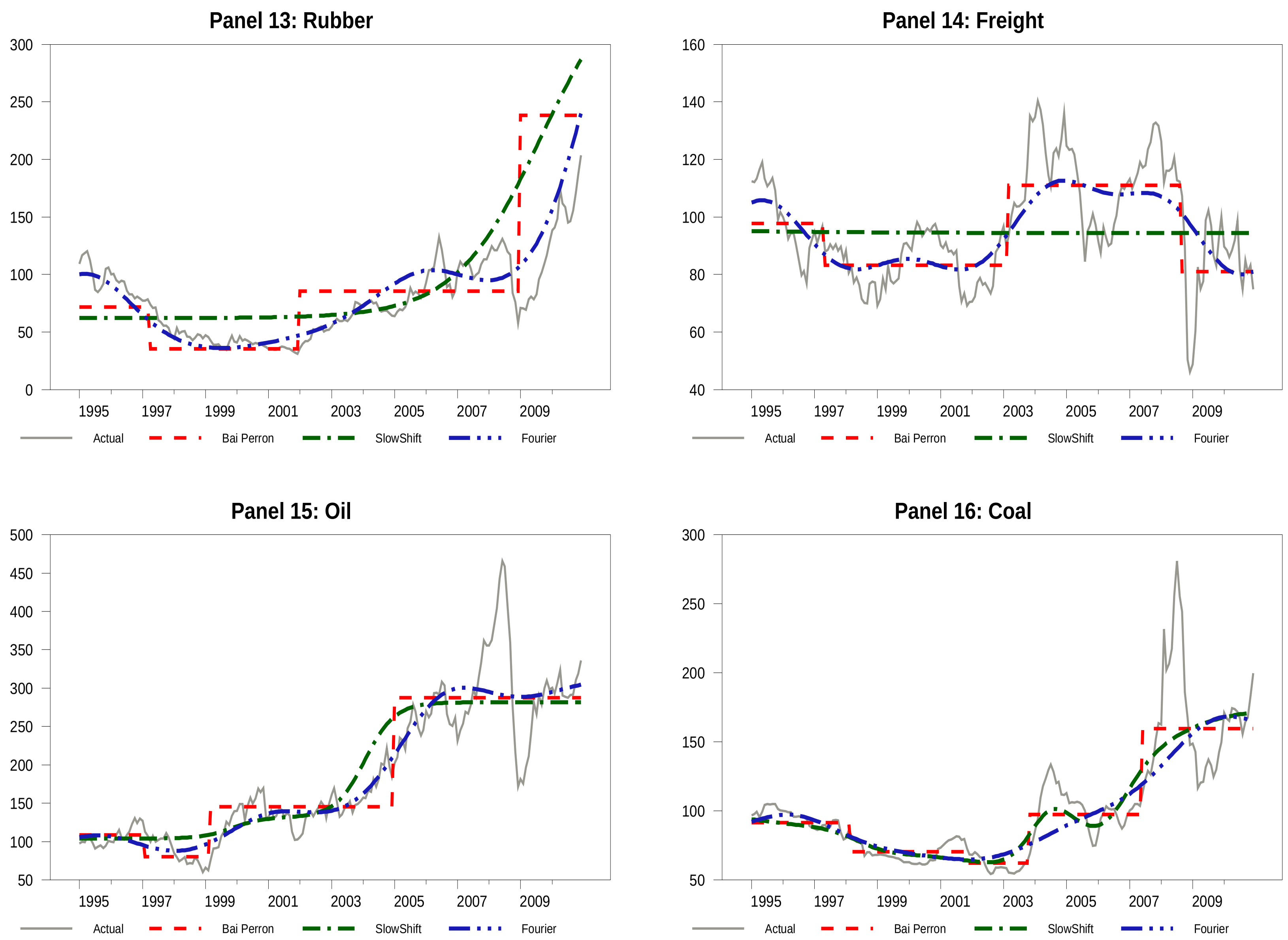

Figure 2: Commodity Prices, Actual Values and Shifting Means Obtained by Various Methods, 1995–2010 (Continued).