Breaks, bubbles, booms, and busts: the evolution of primary commodity price fundamentals

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Breaks, Bubbles, Booms, and Busts: The Evolution of Primary Commodity Price Fundamentals*

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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 fundamentals for various commodity prices have changed with a special emphasis on behavior since the mid 2000s. To identify changing commodity price fundamentals we estimate shifting–mean autoregressions by using: the Bai and Perron (1998) procedure for estimating structural breaks; a SlowShift procedure that specifies intercepts to be nonlinear, potentially smooth functions of time; and low frequency Fourier functions. We find that the pattern in the timing of the various shifts is suggestive of the causal fundamentals underlying the recent boom.

Keywords: Commodity Prices, Fundamentals, Nonlinear Trends, Shifting–Mean Autoregression

JEL Classification Codes: C22; C52; E3; Q2

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1 Introduction

Commodity prices are back in the news. And not just the price of oil. Or gold. In recent months international prices for cotton, maize, wheat, sugar, edible oils, coffee and many other basic goods and products have risen to near all–time record highs, if not record highs outright. Energy prices are also on the ascendancy, as are prices for a number of metals, both precious and otherwise. Moreover, these recent price run–ups appear in part to be a continuation of a trend started in the early–to–mid 2000s. To illustrate, the World Bank's food price index increased in nominal terms by nearly 170% from January 2000 through December 2010. Over the same period the World Bank's grain price index increased, again in nominal terms, by nearly 160%. Price increases for many commodities have been especially steep since 2006. And while commodity prices declined broadly during 2009 relative to their pre–recession highs, many prices have since rebounded in spectacular fashion.

High commodity prices have real and notable consequences for all consumers and end users, but especially for those in nations and regions that rely heavily on imports to augment domestic food, fibre, and energy production. For example, and as noted widely in the popular press, the spark igniting the widespread movement for democratic reforms throughout much of North Africa and the Middle East may have been escalating food prices (Gjelten, 2011). As well, in their 2011 winter meeting in Paris, G–20 finance ministers moved discussions regarding food price inflation to the top of their agenda after the World Bank Group's President Robert B. Zoellick declared that "...food prices are rising to dangerous levels and threaten tens of millions of poor people around the world" (World Bank, 2011a). Clearly, rising commodity prices have become a chief concern to consumers and policy makers alike. And while hard data in this regard do not exist, it seems reasonable to assert that the current focus on primary commodity price movements is rivaled only by the attention they received during the sharp price run–ups of the 1970s.

There are many plausible reasons for the recent surge in commodity prices, with most of these being well documented elsewhere. Even so, primary drivers for the recently observed price run–ups include first and foremost the rapid income growth of emerging economies, most notably in China and India. With rising purchasing power there appears to be concomitant "Westernization" of diets, with consumers in these countries increasingly demanding a richer, more varied diet, and oftentimes one more heavily tilted towards protein (Zhang and Law, 2010). Likewise, income growth in emerging economies has also corresponded with a rapidly increasing demand for oil and its derivatives. See, for example, Hamilton (2009) and Kilian (2009) for further discussion on these and related points.

The demands for energy and food are also increasingly linked in new ways (Abbott, Hurt, and Tyner, 2008). Since passage of the Energy Policy Act of 2005, the United States has established a renewable fuel standard (starting at four billion gallons in 2006) while simultaneously pursuing a policy of subsidizing ethanol production and restricting its import. Subsequently, the Energy Independence and Security Act of 2007 increased the volume of renewable fuel required to be blended into transportation fuel from nine billion gallons in 2008 to 36 billion gallons by 2022. According to USDA's National Agricultural Statistics Service, the result now is that effectively two out of every five bushels of corn produced in the United States are used directly in ethanol production (U.S. Department of Agriculture, 2011).

Tied to rising demands for food and energy, large weather shocks in various key producing regions have reduced supplies for many food commodities (World Bank, 2011b). The result is that in many instances global stock levels relative to overall use are small by historical standards. The implication is that, when combined with increasing (and inelastic) demands, commodity prices can be expected to rise sharply in response to even relatively small production shortfalls. There is also some belief that speculative activity has resulted in bubbles in the prices for a number of commodities in recent years. Even so, the evidence in favor of this hypothesis is mixed. See, for example, Sanders and Irwin (2010). Finally, some economists (see, e.g., Hamilton, 2010), assert that expansionary monetary policies (including but not limited to quantitative easing) pursued in recent years by the Federal Reserve and other central banks have stimulated inflationary pressures amongst prices for primary goods. While this later line of reasoning is certainly plausible, it is likely too soon to verify its true role in recent and on–going commodity price inflation. Whatever the reasons underlying their recent movements, two things seem unequivocal at this juncture: (1) prices for many commodities have increased sharply in nominal terms in recent times; and (2) these price movements are increasingly drawing the attention if not the ire of policy makers and consumers alike.

Surprisingly, what is missing in much of the current debate on commodity food price inflation is legitimate empirical analysis. Specifically, while recent commodity price moves have ventured into historically high levels in nominal terms, how does the picture change once general price inflation is taken into account? And once overall price inflation is considered, is it the case that underlying commodity price fundamentals have truly changed in recent years? As well, assume for the moment that underlying fundamentals for real commodity prices have changed, at least in a number of instances. In this event, a reasonable question is then to what extent is there coincidence in these observed changes? To our knowledge there has been no systematic examination of these and related issues. This observation is all the more surprising given the rather extensive literature that has evolved on examining long–term trends in primary commodity prices. See, for example, Kellard and Wohar (2006), Balagtas and Holt (2009), and Harvey et al. (2010).

In broad terms the overall goals of the present paper are: to examine fundamentals in real commodity price relationships; to determine if changes (or breaks) in these fundamentals have recently occurred; to determine the extent to which any such changes coincide; and to ascertain if there is any discernable pattern to the timing of such changes. We proceed by examining monthly primary commodity price data collected primarily 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 many others. In so doing we employ both a set of standard as well as new tools for examining shifts in price fundamentals. Specifically, we look for breaks by using a well–established procedure due to Bai and Perron (1998). We also implement a variant of the smooth shifting–mean autoregressive (SM–AR) process due to González and Teräsvirta (2008) to estimate changing fundamentals.[1] The later approach is of interest because it does not necessarily force structural change to be sharp but rather allows that it could be a gradual process over time. In this sense the SM–AR approach represents a reasonable alternative to that of Bai and Perron (1998), which forces structural change to be immediate and discrete. Finally, and as an alternative to the SM–AR methods of González and Teräsvirta (2008), we also present SM–AR results based on Gallant's (1984) flexible Fourier form. The Fourier form has been used recently by Becker, Enders and Hurn (2004, 2006) to model changing fundamentals in time series data, and is also useful for identifying smooth changes.

The outline of the paper is as follows. In the next section we present an overview of the methods employed to investigate changes in underlying price fundamentals. In section three we discuss in depth the implementation of the various methodologies. In section four we describe the data, while in section five we present results. In section six we discuss the implications of our analysis for the timing and causes of changing commodity price fundamentals. The final section concludes.

2 A Framework for Modelling Changing Fundamentals

Let cp_t denote a primary commodity price, and let p_t denote the produer price index. The fundamental building block for our investigation of changing commodity price fundamentals is a univariate autoregressive (AR) model. That is, we write a simple AR model 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 $\varepsilon_t \sim iid(0, \sigma^2)$. In the present context the variable Δy_t

denotes the monthly (real) inflation rate in a relevant commodity price. By examining real commodity prices we abstract from price movements caused by changes in the overall price level.[2]

Our focus here is on the time–varying intercept term, $\tilde{\delta}(t)$, and how it evolves over time. A now standard methodology for modelling $\tilde{\delta}(t)$, developed by Perron (1989) and Bai and Perron (1998), is to assume that the series of interest is stationary around a small set of discrete structural 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

$$\tilde{\delta}(t) \;=\; \delta_0 + \sum_{i=1}^{k} \delta_i I_{\tau_i}, \tag{2}$$

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.[3] Additionally, k denotes a finite and presumably small number of discrete breaks in the unconditional mean of the series in question and δ_i denotes additional parameters to be estimated.

A novel extension of the above approach is considered by González and Teräsvirta (2008). They assume that prices move around a deterministically shifting unconditional mean and that mean shifts can be either discrete or smooth. Specifically, they consider the case where

$$\tilde{\delta}(t) \;=\; \delta_0 + \sum_{i=1}^{k} \delta_i g(\eta_i, c_i, t^*), \tag{3}$$

where as before the δ_i are "mean–shift" parameters and $g(.)$ are logistic functions, defined as

$$g(\eta_i, c_i, t^*) \;=\; \big(1 + \exp(-\gamma(\eta_i)(t^* - c_i)/\hat{\sigma}_{t^*})\big)^{-1}, i = 1, \ldots, k, \tag{4}$$

where $\gamma(\eta_i) = \exp(\eta_i)$, $t^* = t/T, t = 1, \ldots, T$; $\hat{\sigma}_{t^*}$ denotes the standard deviation of t^*, $\hat{\sigma}_{t^*}$ is the estimated standard deviation of t^*, and is used to render $\gamma(\eta_i)$ unit free; and where η_i and c_i are parameters. Specifically, η_i is finite but is otherwise unrestricted in sign. As well, $c_i \in [0, 1]$ are centrality parameters, and $c_i T$ indicates points in the sample where mean shifts are centered.[4] From the point of view of statistical fit, the logistic function components in (4) are interchangeable. Identification may therefore be achieved by assuming that $c_1 < \ldots < c_k$. By construction each $g(\eta_i, c_i, t^*)$ component in (4) is bounded on the unit interval.

Given the specification in (4), it follows that the unconditional mean (fundamental) can, depending on the magnitude of η_i, experience either sharp or slowly evolving changes. Specifically, as the normalized value of $\eta_i \to 6$ the logistic function $g(\eta_i, c_i, t^*)$ effectively becomes a step function, with the step (mean break) occurring at date $c_i T$. In other words the logistic function component effectively becomes a Heaviside indicator function, I_{c_i} as defined in (2). Alternatively, for small values of η_i, say, $\eta_i = \text{-}1/2$, the function $g(\eta_i, c_i, t^*)$ approaches a linear trend. For values of η_i between these extremes, the corresponding logistic function will have the familiar sigmoidal shape. Moreover, by varying k additional flexibility can be built into the process. For example, the shifting mean could include a combination of discrete and smooth changes over time, as well as a linear trend. In this sense (3) and (4) represent a generalization of the Bai and Perron (1998) method in equation (2).

A related approach explored by Becker, Enders and Hurn (2004, 2006) is to model $\tilde{\delta}(t)$ by using low–order Fourier frequencies. Specifically, they define

$$\tilde{\delta}(t) \; = \; \delta_0 + \delta_1 t + \sum_{i=1}^{k} \left\{ \delta_{ci} \cos\left(2\pi f_i^* t/T\right) + \delta_{si} \sin\left(2\pi f_i^* t/T\right) \right\}, \tag{5}$$

where f_i^* are Fourier frequencies and where $k \leq T/2$. There are various ways of choosing the frequencies as well as k including, for example, model selection criteria. Similar to the logistic function approach outlined above, the Fourier approximation allows considerable flexibility in modelling shifting means. We include a linear trend in the estimating equation so that the starting and ending values of the approximation do not need to be equal.

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

$$E(y_t) \;=\; -\tilde{\delta}(t)/\rho, \tag{6}$$

where E denotes the expectation operator.

3 Estimation Strategies

The approach taken here focuses on models for commodity prices wherein $\tilde{\delta}(t)$ is estimated jointly with (1). In the present case the three types of mean–shift models are fully parametric. However, there are various specification issues to be resolved and, as well, an estimation strategy must be adopted. In all instances it is necessary to determine p, the order of the autoregressive model, and k, the number of "shifts." In general it is not clear which should be chosen first: the order of the process, p, or the number of shifts, k. We proceed here by obtaining the best fitting AR model (as measured by the Akaike information criterion, or AIC) in (1) by first assuming that $\tilde{\delta}(t) = \delta_0$, that is, by assuming that the unconditional mean is constant. We then attempt to determine if additional time–varying components are called for, that is, if the underlying commodity price fundamental has experienced breaks or shifts during the sample period. A similar approach is often adopted when specifying and estimating smooth transition autoregressive (STAR) models. See, for example, van Dijk, Teräsvirta and Franses (2002).

3.1 Bai–Perron Procedure

We begin with an examination of the popular Bai and Perron models that allow for discrete structural breaks in the underlying price fundamental. If the break dates are known, it is possible to set the Heaviside indicator in (2), estimate a model in the form of (1), and then test the null hypothesis that all values of δ_i in (2) equal zero by using a standard Chow test. Of course break dates are seldom known with certainty *a priori* so that a different methodology is required. Andrews and Ploberger (1994) develop a test that can be used to estimate a single sharp break occurring at an unknown date. The essence of the procedure involves searching for the break date by performing a Chow test for every possible break date. To ensure that there are an adequate number of observations in each regression, it is standard to use a 10% "trimming" such that breaks are assumed to occur only within the middle 80% of the sample. If a break is present, the value of t_i producing the best fit is a consistent estimate of the actual break date. The null hypothesis of structural stability is tested against the alternative of a one–time structural break using the Andrews and Ploberger (1994) supremum test. Simply put, Bai and Perron (1998, 2003) generalize this methodology to allow for k structural breaks.

3.2 Logistic Function Components

An approach to estimating the SM–AR's parameters when the shifting mean is identified with logistic function components is to use González and Teräsvirta's (2008) QuickShift procedure. Their approach is in turn an adaptation of the QuickNet framework for estimating artificial neural network (ANN) models described by White (2006). González and Teräsvirta (2008) noted that the specification for $\tilde{\delta}(t)$ is similar to a single hidden–layer ANN model. In order to implement the procedure it is necessary to choose an upper limit, $\overline{k}$, for the total number of mean shifts. A set of candidate transition functions is then obtained by evaluating the logistic function in (4) for a wide array of values for η and c, specifically, for a fixed grid. 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. The QuickShift procedure is explained in detail in González and Teräsvirta (2008).

In our applications we modified the QuickShift procedure as follows:

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

2. Determine the first smooth break as

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

   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

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

3. Repeat step 2 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). Determine the number of logistic function components to use in the final model as $\hat{k} = \operatorname{argmin}_{k \in \left(1, \ldots, \overline{k}\right)} \text{AIC}(k)$.

Simply put, we propose using a two–dimensional grid search to identify the logistic function parameters similar to that described by Leybourne, Newbold and Vougas (1998). As such this method involves $N_\eta \times N_c$ matrix inversions in step 2. For this reason we refer to our estimation strategy as SlowShift. The advantage of SlowShift, however, is that with a fine enough grid the in–sample mean square prediction error will be effectively minimized.[5]

As noted in step 3, we use the AIC to choose k, the number of logistic function components.[6] We determine the AIC for a model with k shifts as

$$\text{AIC}(k) = T \log \left(\sum_{t=1}^{T} \hat{\varepsilon}_{t,k}^2 \right) + 2\left(2 + p + 3k\right), \quad k = 1, \ldots, 10.$$

3.3 Fourier Series Approximation

Instead of modelling the breaks as being sharp or as logistic functions, an alternative is to use a modification of Gallant's (1984) flexible Fourier form. As shown in Becker, Enders and Hurn (2004, 2006), the essential characteristics of a series containing structural breaks can often be captured using the low frequency components of a Fourier approximation. The choice of a Fourier approximation to model the smoothly evolving time–varying intercept in (1) is driven by three important 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 though the actual function in question is not periodic. Second, unlike a Taylor series expansion using powers of $t, t^2, t^3 ...$, the sum of a small number of trigonometric components is bounded and projections into the future are necessarily finite. Although a Taylor series expansion 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 (5) 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 to every other *sine* and *cosine* function. Farley and Hinich (1970, 1975) originally explored the issue of testing for trigonometric functions and Gallant and Souza (1991) show that their joint distributions are multivariate normal.[7] To be consistent with our implementation of the SlowShift procedure, we select k, the number of frequencies in (5), by minimizing AIC. Since each frequency component entails the estimation of two additional parameters, the AIC for the Fourier model is calculated as

$$\text{AIC}(k) = T \log \left(\sum_{t=1}^{T} \hat{\varepsilon}_{t,k}^2 \right) + 2\left(2 + p + 2k\right), \quad k = 1, \ldots, 10.$$

4 Data

The commodity price data used in the empirical analysis were obtained from World Bank (various issues), from the IMF Financial Statistics Database, and in one instance (gold) from the Deutsche Bundesbank. We also examine the behavior of ocean freight rates for bulk products, a series collected by Lutz Kilian; see Kilian (2009) for details. Although a large array of commodity prices are available, we focus here on 24 prices and price indices These include: maize, soy, wheat, sorghum, palm oil, rice, cotton, coffee, cocoa, sugar, beef, logs, rubber, iron ore, copper, tin, lead, zinc, gold, silver, oil, coal, ocean freight rates, and food. The data are monthly, and in most instances span the period 1960–2010.[8] By design 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. Additionally, prices for metals used extensively in construction and manufacturing (iron ore, copper, tin, lead, and zinc) are also included, as well as prices for several precious metals (gold and silver) used for manufacturing and, at times, as an inflation hedge. The price of oil is included because of its universal importance as primary input in manufacturing, food production, and transportation, *et cetera*. Moreover, previous studies have focused exclusively on modelling breaks in oil prices over time (e.g., Perron 1989). And as noted in the introduction, there is the possibility that oil and maize have become more intertwined in recent years due to the rise of biofuel production. Oil, while important, is not the only relevant energy source, and for this reason we also include the price of coal. The price of ocean freight rates for dry cargo bulk products is included because it is thought to reflect general global economic activity and, moreover, to be an important consideration in the international transport of primary commodities. Finally, the price of food is a composite index that reflects the prices of cereal grains (11.3%), edible oils (16.3%) and other food (12.3%), the later of which includes oranges, bananas, beef, and poultry. As such, sharp changes in the food price index should be indicative of changes in the food sector in general. A detailed description of the data used including units, sample periods, and sources may be found in Appendix Table A1.

Prior to estimation all prices are deflated by the producer price index (PPI). Although the question of which deflator to use and for that matter whether or not to deflate at all is of importance when analyzing breaks in commodity prices (see, e.g., Wang and Tomek, 2007), we choose to work with real prices. We do so in an attempt to rule out identifying shifts that are simply the result of overall price inflation. We use the producer price index as opposed to the consumer price index in that essentially all of the commodities examined here can be regarded as intermediate inputs. Prior to estimation we transform each real price series by multiplying the real price by 100 and then by taking the natural logarithm.

As outlined previously, the building block for each shifting–mean model is one wherein the intercept $\tilde{\delta}(t)$ is constant over time. For this reason it is useful to have some idea of how well a linear AR model fits each series. In each case the order of the autoregressive process, p, was determined by minimizing AIC, where a maximum of twelve lags were allowed. Summary information on linear AR model estimates is reported in Appendix Table A2. In addition to the optimal lag order and various measures of fit and performance, an indication of general model misspecification (Ramesy's RESET test) and of structural change in the intercept (the Lin and Tersvirta, 1994, Lagrange Multiplier test for a shifting intercept) are also reported. Of interest is that for most commodities the results of these later tests imply that the linear AR model without a shifting mean is misspecified.

5 Estimation of Shifting Means

In this section we apply the methods described previously for estimating shifting means for commodity prices. For all models we set the upper limit for the number of autoregressive parameters, p, to twelve; we use AIC to determine the lag order of the autoregressive process by setting $\tilde{\delta}(t) = \delta_0$. The result is that we have $T = 599$ usable sample observations, from February, 1961 through December, 2010 for all commodities save silver ($T = 479$), coal

($T = 479$), and ocean freight ($T = 503$); see Appendix Table A1.

5.1 Bai–Perron Results

We employ the Bai and Perron (1998, 2003) methodology setting the maximum number of breaks at 9. With a 10% trim factor, in our sample the last of these breaks can occur no later than 2005:10. 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 two years (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 using the $UDmax$ critical values tabulated in Bai and Perron (1998).[9] 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 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 BIC. This procedure is recommended by Prodan (2008) and seems reasonable for a large number of commodities with varying numbers of potential breaks.

For each commodity, Table 1 reports the number of breaks, $\hat{k}$, selected by the BIC($\hat{k}$), the estimated value of ρ, the t–statistic for the null hypothesis $\rho = 0$, the value of R^2, the AIC, the sample value of $UD\max$ obtained by using all 9 breaks, the sup–F test for 1 and 9 breaks, respectively, and results for an LM test for remaining serial correlation up to lag four. Notice that for a 95% confidence interval, the $UD\max$ test allows us to reject the null hypothesis of no structural change for all commodities except for cocoa. However, for cocoa, we can reject the null hypothesis of no structural breaks if we use the 90% critical value. Moreover, for every commodity including cocoa, the sup–$F(9)$ test allows use to reject the null hypothesis of no breaks and accept the alternative of exactly nine breaks using a 95% confidence interval. Not surprisingly, for some commodities (i.e., cocoa, sugar, copper, tin, lead and zinc) we cannot reject the null of the sup–$F(1)$ test because of the presence of U–shaped breaks.

For our purposes, the key issue involves 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, the jumps in the prices of the other commodities. For each commodity, Figure 1 shows the time path of the estimated breaks superimposed over the actual price series. For clarity, the plots in Figure 1 focus only on the later part of the sample, beginning with 1985.[10] Table 2 reports the estimated date of the most recent upward shift along with the upper and lower boundaries of a 95% confidence interval. As should be clear from the results in Table 2, for oil, the *last* break occurs in December 2004 (2004:12). 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), cocoa (2008:11), copper (2005:09), tin (2006:06) and lead (2006:06). The oil price jump also precedes the jumps in the prices of wheat (2006:1), sorghum (2006:08) and zinc (2005:07) 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, beef, and overall food prices 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 (as shown in Table 2, the mean went from 20.48 to 40.50).

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 result from breaks being 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 1, 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. Note that similar problems occur in the end–of–sample run–ups in the prices of soy, rice, coffee, copper, and tin and in the secular decline in most commodity prices throughout the 1980s. 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. As such, the estimated break dates are not especially informative of the actual change points in the series.

5.2 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.[11] We restrict our search for c_i's to 100 equally spaced values in the $[0.05, 0.95]$ interval 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 $[0.368, 30]$.[12] The result is that 10,000 regressions are estimated for each iteration of the SlowShift procedure.

The estimation results obtained by using SlowShift are summarized in Table 3. Estimates for selected transition functions along with corresponding information on shift dates are reported in Table 4. As indicated in Table 3, for all commodities save palm oil, zinc, and ocean freight, the SlowShift procedure chooses at least two logistic function components; in the case of zinc AIC is minimized when $\hat{k} = 0$ while for palm and ocean freight $\hat{k} = 1$. Moreover, in sizteen instances four or more shifts are included in the final model specification (i.e., for maize, soy, wheat, sorghum, rice, coffee, cocoa, sugar, beef, iron ore, tin, gold, silver, oil, coal, and food). Also recorded in Table 3 are heteroskedasticity robust versions of diagnostic LM tests for remaining autocorrelation at lag four.[13] The results in Table 3 indicate that in most instances there is limited evidence of remaining autocorrelation.

Results in Table 4 indicate that in some (but not all) instances the shifts in underlying commodity price fundamentals 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 or slowly changing fundamentals is 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, iron ore, tin, gold, silver, oil, coal, and ocean freight.

Additional results of interest, as identified in Figure 1 (the dash–dot line), 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. As indicated by the plots in Figure 1, the SM–AR model with logistic function components does a reasonable job of identifying these periods and the resulting impacts on international coffee prices. In a similar situation the International Tin Agreement effectively collapsed in 1985, which again SlowShift picked up through the combination of several logistic function components. Finally, SlowShift identifies one long mean shift for the price of oil from the late 1950s through the middle of 1980, that is, through the period immediately following the second oil price shock of the late 1970s.

Of interest here, as with the Bai–Perron results, are the shifts that occurred in recent years, notably, since the early– or mid– 2000s. Results in Table 4 as well as in Figure 1 suggest that in many instances commodity price fundamentals did change rather sharply during this period. To illustrate, a rather abrupt increase in the underlying fundamental 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). See Table 4. Of additional interest is that similar distinct shifts occurred for most metals prices during approximately the same period, including iron ore (2007:07), copper (2003:06), tin (2006:03), lead (2003:06), gold (2008:06), and silver (2008:06).[14] 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), SM–AR models with logistic function components indicate that underlying price fundamentals for most industrial metals and, as well, for oil and coal apparently shifted upward about three–to–four years in advance of the corresponding rise in the fundamentals for grains and food commodities.

5.3 Fourier Results

Since breaks manifest themselves at the low end of the spectrum, Becker, Enders and Hurn (2004) recommend estimating (5) using a small number of low frequencies, k. As such we set $max(k) = 10$ and estimate each series in the form of (1) and (5). For each commodity, the second column of Table 5 reports the number of frequencies selected by the AIC. 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 k yielding the lowest AIC was $k = 6$ so that *sine* and *cosine* terms using frequencies f_1^* through f_6^* are included). Notice that the AIC does select a relatively large number of frequencies; in fact, for nine of the sixteen commodities frequencies are at the upper bound of 10. 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 layers or frequencies used in the estimating equation. Nevertheless, it seems that AIC might be overly generous in selecting the number of frequencies to use in estimation.

For present purposes, the key piece of information in Table 5 is in the third column 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.[15] 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 1, you can see that the last trough occurred in August of 2004 suggestive of an upward jump in the price of maize. Reading down the column, the last trough for oil occurred in July 2002. This clearly predates the last trough in all of the agricultural commodities (except rice and food). Interestingly, the last troughs in the means of copper, tin, and lead (but not zinc) occur prior to July 2002, which is when oil last changes.

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, as indicated by the summary results in Table 6, it seems unlikely that oil price jumps were the sole cause of subsequent shifts for other commodity prices. Specifically, this table combines results from Tables 2, 4, and 5 to indicate starting dates of the most recent price runs for each commodity and methodology. Unfortunately, it is not always straightforward to determine the beginning of a price movement. For example, for maize, the BP method selects a last upward break date of 2006:08, the ShowShift selects 2005:8 and the Fourier method 2004:09. Since this last shift in the price of maize is rather sharp, the BP 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.[16] However, in cases where the shift is gradual, the BP method seems to be the most problematic. For oil (see Panel 21 of Figure 1), the BP 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, zinc, 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 6, 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.

Based on the rankings, we can categorize each method in terms of which commodities began to rise early, which rose later in the sample, and those which are unclear (or have non–applicable last breaks: i.e., a last break occurring prior to 2000:01 so that it cannot be causal to the more recent price run ups). Notice that eight commodities, specifically, gold, rubber, lead, copper, tin, coal, iron ore, and oil seem to have the strongest evidence of early price shifts. Maize, sorghum, logs, palm oil, rice, and soybeans seem to increase somewhat later. Finally, some commodities have no breaks occurring after 2000:01 (e.g., food), run–ups which begin quite late in the sample period (e.g., cotton), or downward shifts following a previous upward shift (e.g., freight and zinc).

The key point is the timing of the various jumps seems somewhat out of synchronization if in fact oil is the primary causal factor. Specifically, we would expect that 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, all three methodologies generally indicate that the prices of most metals and building materials preceded the increase in the price of 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 (both on international markets as well as in commodity exchanges) commodities such as wheat and sugar.[17] A priori it is not clear why speculative activity would result in bubbles in the 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.

What, then, can we say? There are at least two plausible candidates for the recent shift in the fundamentals for a number of primary commodity prices. First, and as noted in the introduction, there is solid reason to believe that demand shifts for many energy and non–energy–related commodities may have occurred sometime in the mid 2000s and that, likewise, increases in supplies were not sufficient to offset these demand 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 (i.e., the demand for energy, industrial metals, and building materials seemingly increased first followed secondly by an increase in demand for many food–related commodities) are not inconsistent with this hypothesis; in this regard we concur with Hamilton (2009) and Kilian (2009). Secondly, and consistent with the conclusions of Abbott, Hurt, and Tyner (2008), we cannot rule out the possibility that for some commodities at least, 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 more–or–less permanent shift in underlying price fundamentals 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 price fundamentals.

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 fundamental 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, SlowShift and Fourier approximations. Interestingly, all three methods appear to tell a similar story: in recent years changes in the price of oil, the prices for most industrial metals, and the prices for several building materials pre–dated 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, the more plausible story seems to be that demand growth in emerging economies and the increasing utilization of certain crops for biofuels production have resulted in recent price runs.

Although this study has shed light on the timing and nature of recently observed commodity price movements, more work remains to be done. 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 the underlying fundamental? In this regard it may be possible to use the SlowShit or Fourier SM–AR modelling framework presented here in conjunction with methods advanced by, for example, Bierens (2000) to examine this important issue. This and related topics remain, however, as important future extensions of the analyses presented here.

Notes

[1]In turn, González and Teräsvirta (2008) base their framework on a variant of the time–varying autoregressive (TV–AR) model due originally to Lin and Tersvirta (1994).

[2]As Wang and Tomek (2007) note, it is important to deflate commodity prices in any study of long–term price movements.

[3]It is a simple matter as illustrated by Perron (1989) to extend the model so that $\tilde{\delta}(t)$ could include a linear trend term as well as breaks.

[4]Of course it is possible that one or more c_i lie outside the unit interval, although as a practical matter it may be difficult to accurately identify mean shifts that are centered beyond the range of the observed data.

[5]The framework described here for estimating the SM–AR model is similar to that often employed in estimating self–exciting threshold autoregressive (SETAR) models. See, for example, Hansen (1997) and Balke and Fomby (1997) for additional details.

[6]An alternative approach is to use the parameter constancy Lagrange Multiplier (LM) test introduced by Lin and Tersvirta (1994) and adopted by González and Teräsvirta (2008) in their implementation of QuickShift. In preliminary investigations we found that in most instances the model estimated by SlowShift when an LM test was used nested the model obtained when $\hat{k}$ is determined by minimizing AIC. For these reasons, and given that our goal is to describe changing commodity price fundamentals, we focus here on the results obtained by minimizing AIC.

[7]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, 2006) develop a sup–F test along the lines of Davies (1987).

[8]Exceptions are silver and coal (1970:01–2010:12) and ocean freight rates (1968:01–2010:12).

[9]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.

[10]Plots for the entire sample period are available upon request.

[11]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.

[12]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.

[13]LM tests for remaining autocorrelation are constructed in a manner similar to that described by González and Teräsvirta (2008) for testing for remaining mean shifts. Additional details are provided in Eitrheim and Teräsvirta (1996).

[14]It is of interest that the last shifts for gold and silver as identified by SlowShift, occurred simultaneously in June, 2008 and, moreover, just prior to the financial market collapse later that fall.

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

[16]Moreover, we do not want to simply average break dates since, as noted in the text, each method entails it own particular biases.

[17]Moreover, according to the Reuters webpage wheat and sugar continue to be 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).

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Table 1: Summary Results for Bai–Perron SM–AR Estimates.

Commodity	$\hat{k}$	$\hat{\rho}$	$t_\rho = 0$	R^2	AIC	UD_{max}	sup–$F(1)$	sup–$F(9)$	$\text{LM}_{SC}(4)$
Maize	6	-0.102	-7.837	0.168	216.46	13.748	13.748	9.450	0.826
Wheat	8	-0.093	-6.749	0.235	276.81	11.705	11.348	8.200	0.038
Soy	7	-0.164	-9.652	0.220	267.85	17.007	17.007	11.708	0.329
Sorghum	9	-0.170	-8.955	0.228	279.47	11.068	10.820	10.631	0.004
Palmoil	9	-0.134	-9.172	0.251	545.30	16.195	16.195	9.281	0.628
Rice	8	-0.189	-10.589	0.272	372.10	17.231	17.231	9.695	0.437
Cotton	6	-0.105	-7.024	0.346	-41.11	10.859	9.193	8.412	0.010
Coffee	9	-0.150	-10.216	0.234	522.63	12.203	9.450	11.813	0.145
Cocoa	9	-0.126	-8.819	0.154	528.99	9.830	6.385	9.830	0.078
Sugar	7	-0.051	-5.449	0.200	1048.46	10.815	6.272	8.710	0.034
Beef	9	-0.192	-10.649	0.285	-1.13	14.248	12.343	13.257	0.729
Logs	9	-0.153	-10.272	0.280	157.47	11.943	9.047	11.290	0.356
Rubber	6	-0.061	-6.380	0.147	395.45	17.665	17.665	8.783	0.002
Iron	7	-0.173	-9.659	0.233	413.92	25.132	18.144	14.548	0.021
Copper	8	-0.115	-8.567	0.229	505.18	11.886	8.324	9.143	0.476
Tin	9	-0.130	-9.544	0.223	111.40	13.713	5.780	10.882	0.087
Lead	9	-0.105	-7.982	0.167	538.24	10.573	7.489	7.846	0.892
Zinc	9	-0.136	-10.508	0.266	369.81	11.059	5.219	11.059	0.026
Gold	9	-0.093	-8.298	0.264	2.23	13.047	1.417	10.260	0.146
Silver	4	-0.006	-0.530	0.194	498.74	15.339	6.763	8.512	0.011
Oil	9	-0.219	-11.531	0.238	750.32	18.897	12.149	16.103	0.002
Coal	9	-0.269	-12.313	0.330	65.66	17.273	8.804	16.246	0.120
Freight	8	-0.223	-10.244	0.249	489.80	23.211	23.211	11.896	0.636
Food	4	-0.073	-6.604	0.150	194.23	19.150	12.644	10.893	0.212

Note: The column headed $\hat{k}$ denotes the number of structural breaks included in the final model. The column headed $\hat{\rho}$ denotes the estimates of the lagged level term in the SM–AR model. The column titled $t_\rho = 0$ reports the heteroskedasticity robust t–ratio for a test of the null hypothesis that $\rho = 0$. The column headed $\text{LM}_{SC}(4)$ includes p–values for a heteroskedasticity robust Lagrange Multiplier test for remaining autocorrelation up to lag four.

Table 2: Last Upward Break and Confidence Intervals for the Bai–Perron SM–AR Models.

Commodity	$\hat{k}$	Lower	Date	Upper	Commodity	$\hat{k}$	Lower	Date	Upper
Maize	6	2003:11	2006:08	2007:08	Rubber	6	2008:01	2008:12	2010:12
Soy	7	2006:06	2007:04	2008:05	Iron Ore	7	2007:02	2007:12	2008:02
Wheat	7	2003:11	2006:01	2006:07	Copper	8	2002:12	2005:09	2005:11
Sorghum	8	2006:03	2006:08	2006:09	Tin	8	2002:06	2003:09	2003:12
Palm Oil	9	2004:08	2006:06	2007:01	Lead	9	2003:08	2006:06	2007:01
Rice	8	2007:03	2008:01	2008:02	Zinc	8	2005:03	2005:07	2005:09
Cotton	6	2004:01	2008:11	2009:09	Gold	9	2008:07	2008:11	2009:08
Coffee	9	2007:09	2008:10	2009:08	Silver	4	2006:11	2008:11	2011:08
Cocoa	9	2007:12	2008:11	2010:05	Oil	9	2004:05	2004:12	2005:04
Sugar	7	1981:01	1985:06	1992:09	Coal	9	2006:11	2007:05	2007:07
Beef	9	1998:09	2003:06	2008:02	Ocean Freight	8	2002:07	2003:02	2003:07
Logs	9	2003:07	2005:11	2008:08	Food	4	1980:05	1980:10	1981:08

Note: Columns titled Lower (Upper) denote the lower (upper) limits for a 90% confidence interval for the identified break date. Columns headed Date reports point estimate for identified break dates.

Table 3: Summary Results for SlowShift SM–AR Estimates.

Commodity	$\hat{k}$	$\hat{\rho}$	$t_\rho = 0$	R^2	$\hat{\sigma}_{NL}$	$\hat{\sigma}_{NL}/\hat{\sigma}_L$	AIC	$LM_{SC}(4)$
Maize	6	-0.110	-5.906	0.148	0.049	0.965	250.75	0.418
Soy	5	-0.122	-4.307	0.170	0.052	0.964	315.06	0.381
Wheat	5	-0.107	-5.561	0.199	0.050	0.971	292.34	0.523
Sorghum	8	-0.136	-5.234	0.183	0.051	0.960	325.31	0.594
Palm Oil	1	-0.049	-3.812	0.162	0.066	0.990	590.68	0.968
Rice	6	-0.119	-4.760	0.219	0.056	0.956	410.29	0.942
Cotton	2	-0.038	-3.074	0.294	0.039	0.992	-27.43	0.076
Coffee	7	-0.083	-5.751	0.161	0.065	0.968	595.12	0.561
Cocoa	5	-0.072	-4.953	0.078	0.065	0.977	588.27	0.192
Sugar	5	-0.060	-4.827	0.161	0.099	0.975	1085.11	0.314
Beef	7	-0.184	-7.824	0.239	0.040	0.945	36.48	0.014
Logs	3	-0.078	-3.878	0.186	0.048	0.984	222.64	0.934
Rubber	2	-0.033	-3.251	0.080	0.058	0.991	436.63	0.786
Iron Ore	5	-0.124	-3.166	0.186	0.057	0.943	440.07	0.274
Copper	2	-0.038	-4.108	0.152	0.064	0.988	551.77	0.909
Tin	4	-0.060	-5.269	0.143	0.046	0.976	170.61	0.936
Lead	2	-0.042	-3.817	0.093	0.066	0.988	579.23	0.807
Zinc	0	-0.034	-2.819	0.140	0.058	1.000	434.23	0.878
Gold	5	-0.062	-5.700	0.205	0.041	0.969	36.06	0.539
Silver	5	-0.095	-4.813	0.170	0.075	0.969	505.27	0.871
Oil	7	-0.160	-4.752	0.150	0.079	0.950	825.49	0.079
Coal	9	-0.198	-5.551	0.251	0.049	0.933	125.63	0.704
Freight	1	-0.126	-4.625	0.145	0.072	0.975	505.22	0.656
Food	4	-0.072	-3.673	0.103	0.049	0.976	238.35	0.506

Note: The column headed $\hat{k}$ denotes the number of logistic function mean shifts included in the final model. The column headed $\hat{\rho}$ denotes the estimates of the lagged level term in the SM–AR model. The column titled $t_\rho = 0$ reports the heteroskedasticity robust t–ratio for a test of the null hypothesis that $\rho = 0$. The column headed $LM_{SC}(4)$ includes p–values for a heteroskedasticity robust Lagrange Multiplier test for remaining autocorrelation up to lag four.

Table 4: Selected Transitions and Shift Dates for SlowShift SM–AR Models.

Commodity	$\hat{\gamma}$	$\hat{c}$	10%	Center	90%	Commodity	$\hat{\gamma}$	$\hat{c}$	10%	Center	90%
Maize	30	0.91	2005:08	2006:08	2007:09	Rubber	9.87	0.95	2005:04	2008:06	2011:09
Soy	30	0.92	2006:01	2007:02	2008:02	Iron Ore	1.99	0.76	1983:01	1998:12	2014:10
							7.23	0.93	2003:03	2007:07	2011:12
Wheat	30	0.90	2005:02	2006:03	2007:03	Copper	30	0.85	2002:05	2003:06	2004:07
Sorghum	30	0.90	2005:02	2006:03	2007:03	Tin	30	0.90	2005:02	2006:03	2007:03
	3.55	0.95	1999:07	2008:06	2017:05						
Palm Oil	30	0.47	1983:05	1984:05	1985:06	Zinc	--	--	--	--	--
Rice	30	0.92	2006:01	2007:02	2008:02	Lead	30	0.85	2002:05	2003:06	2004:07
Cotton	2.97	0.55	1977:11	1988:06	1999:02	Gold	10.79	0.95	2005:07	2008:06	2011:05
Coffee	25.11	0.95	2007:03	2008:06	2009:09	Silver	8.26	0.95	2004:08	2008:06	2012:04
Cocoa	30	0.93	2006:06	2007:07	2008:08	Oil	30	0.86	2002:11	2003:12	2004:12
Sugar	30	0.40	1980:03	1981:03	1982:04	Coal	30	0.86	2002:11	2003:12	2004:12
							30	0.91	2005:08	2006:08	2007:09
Beef	30	0.67	1993:05	1994:05	1995:06	Freight	3.40	0.28	1965:07	1974:11	1984:03
Logs	30	0.73	1996:07	1997:07	1998:08	Food	30	0.40	1980:03	1981:03	1982:04

Note: 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 5: Summary Results for Fourier Frequency SM–AR Estimates.

Commodity	$\hat{k}$	Last	$\hat{\rho}$	$t_\rho = 0$	R^2	AIC	$\mathrm{LM}_{SC}(4)$
Maize	9	2004:09	-0.138	-7.371	0.164	241.354	0.295
Soy	10	2005:10	-0.176	-8.278	0.201	304.388	0.653
Wheat	10	2005:03	-0.285	-7.787	0.262	255.040	0.101
Sorghum	10	2005:03	-0.239	-7.052	0.207	301.543	0.023
Palm Oil	3	2002:11	-0.072	-5.641	0.180	585.242	0.783
Rice	10	2001:11	-0.232	-8.034	0.261	383.423	0.210
Cotton	9	2007:10	-0.178	-8.104	0.373	-66.468	0.014
Coffee	9	2007:05	-0.126	-7.411	0.181	576.398	0.472
Cocoa	10	2005:09	-0.152	-7.250	0.140	558.821	0.021
Sugar	10	2008:01	-0.145	-7.577	0.209	1062.034	0.049
Beef	10	2007:06	-0.307	-9.634	0.275	7.791	0.001
Logs	8	2002:12	-0.126	-7.383	0.220	212.897	0.450
Rubber	9	2007:12	-0.094	-5.919	0.135	425.649	0.254
Iron	8	2001:07	-0.237	-7.364	0.194	437.757	0.135
Copper	6	2000:12	-0.092	-5.877	0.186	541.518	0.081
Tin	3	2001:04	-0.077	-5.921	0.152	153.993	0.787
Lead	6	2008:04	-0.093	-6.094	0.131	567.722	0.302
Zinc	9	2002:11	-0.114	-7.359	0.210	421.429	0.114
Gold	10	2001:01	-0.251	-8.522	0.286	-15.901	0.023
Silver	10	2008:09	-0.182	-5.966	0.221	501.828	0.121
Oil	10	2002:07	-0.214	-7.776	0.168	812.993	0.009
Coal	9	2001:11	-0.289	-9.531	0.274	98.536	0.826
Freight	10	2006:09	-0.306	-9.445	0.233	500.678	0.015
Food	10	1999:11	-0.163	-7.868	0.156	219.410	0.069

Note: The column headed $\hat{k}$ denotes the number of Fourier frequencies included in the final model. The column titled Last indicates the date associated with the last change in direction in the unconditional mean. The column headed $\hat{\rho}$ denotes the estimates of the lagged level term. The column titled $t_\rho = 0$ records the heteroskedasticity robust t–ratio associated with the null hypothesis that $\rho = 0$.

Table 6: Last Upward Shift in Commodity Price Fundamentals.

Commodity	Bai-Perron	Commodity	SlowShift	Commodity	Fourier
		Commodities with Early Shifts			
Gold	2001:07	Copper	2002:05	Copper	2000:12
Rubber	2001:12	Lead	2002:05	Gold	2001:01
Soy	2007:04	Oil	2002:11	Tin	2001:04
Freight	2003:02	Coal	2002:11	Iron	2001:07
Beef	2003:06	Iron Ore	2003:03	Silver	2001:09
Lead	2003:08	Silver	2004:08	Rice	2001:11
Copper	2003:09			Coal	2001:11
Tin	2003:09			Rubber	2001:12
Coal	2003:10				
		Commodities with Intermediate Shifts			
Rice	2004:07	Wheat	2005:02	Oil	2002:07
Coffee	2004:08	Sorghum	2005:02	Palmoil	2002:11
Iron	2004:12	Tin	2005:02	Zinc	2002:11
Oil	2004:12	Rubber	2005:04	Logs	2002:12
		Gold	2005:07	Lead	2003:08
		Maize	2005:08		
		Commodities with Late or Non Applicable Shifts			
Zinc	2005:07	Soy	2006:01	Maize	2004:09
Logs	2005:11	Rice	2006:01	Wheat	2005:03
Wheat	2006:01	Cocoa	2006:06	Sorghum	2005:03
Palmoil	2006:06	Coffee	2007:03	Cocoa	2005:09
Maize	2006:08	Palm Oil	NA	Soy	2005:10
Sorghum	2006:08	Cotton	NA	Freight	2006:09
Cotton	2008:11	Sugar	NA	Coffee	2007:05
Cocoa	2008:11	Beef	NA	Beef	2007:06
Silver	2008:11	Logs	NA	Cotton	2007:10
Sugar	NA	Zinc	NA	Sugar	2008:01
Food	NA	Freight	NA		
		Food	NA		

Note: NA denotes "Non Applicable."

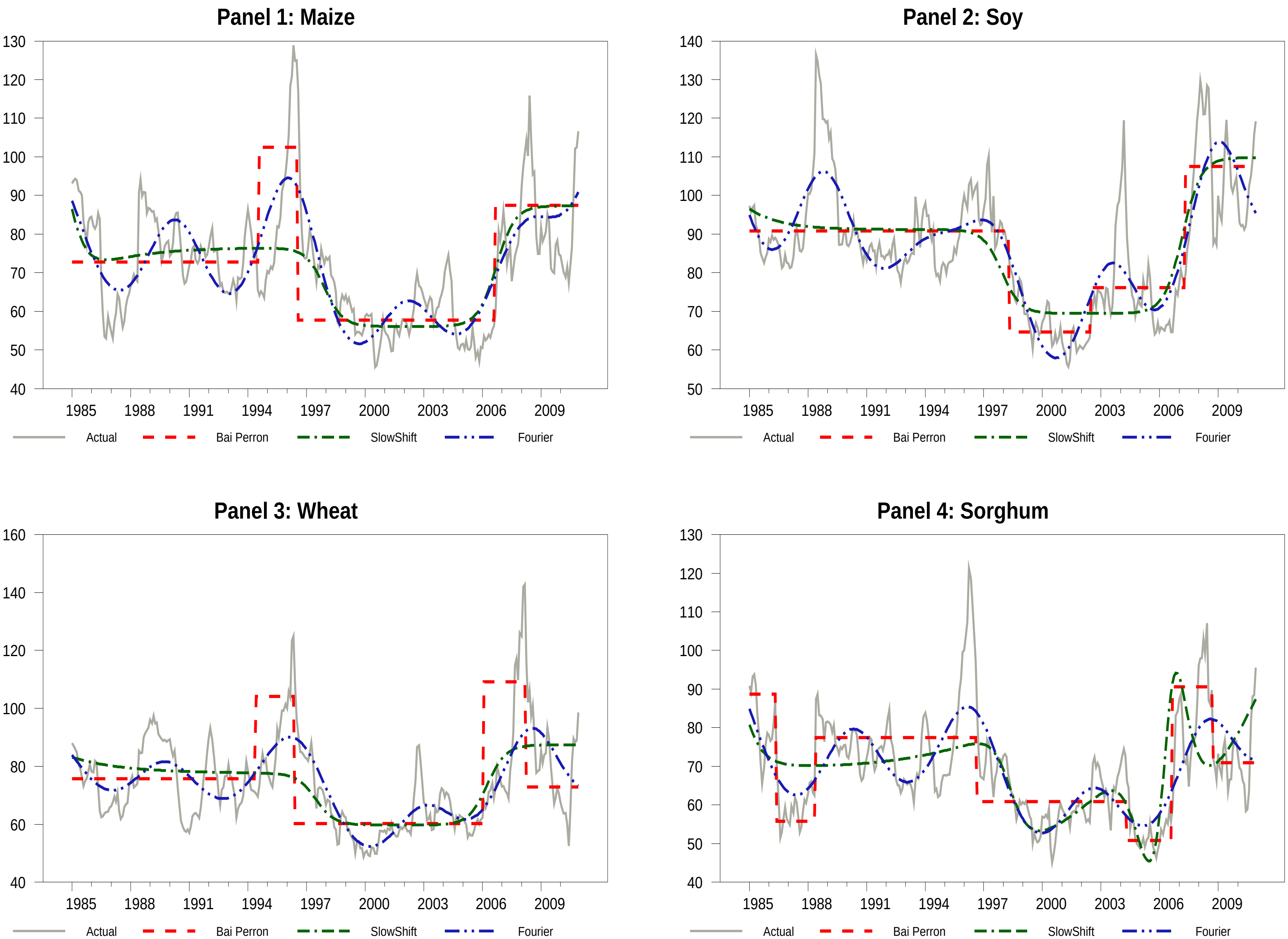

Figure 1: Commodity Prices, Actual Values and Shifting Means Obtained by Various Methods, 1985–2010.

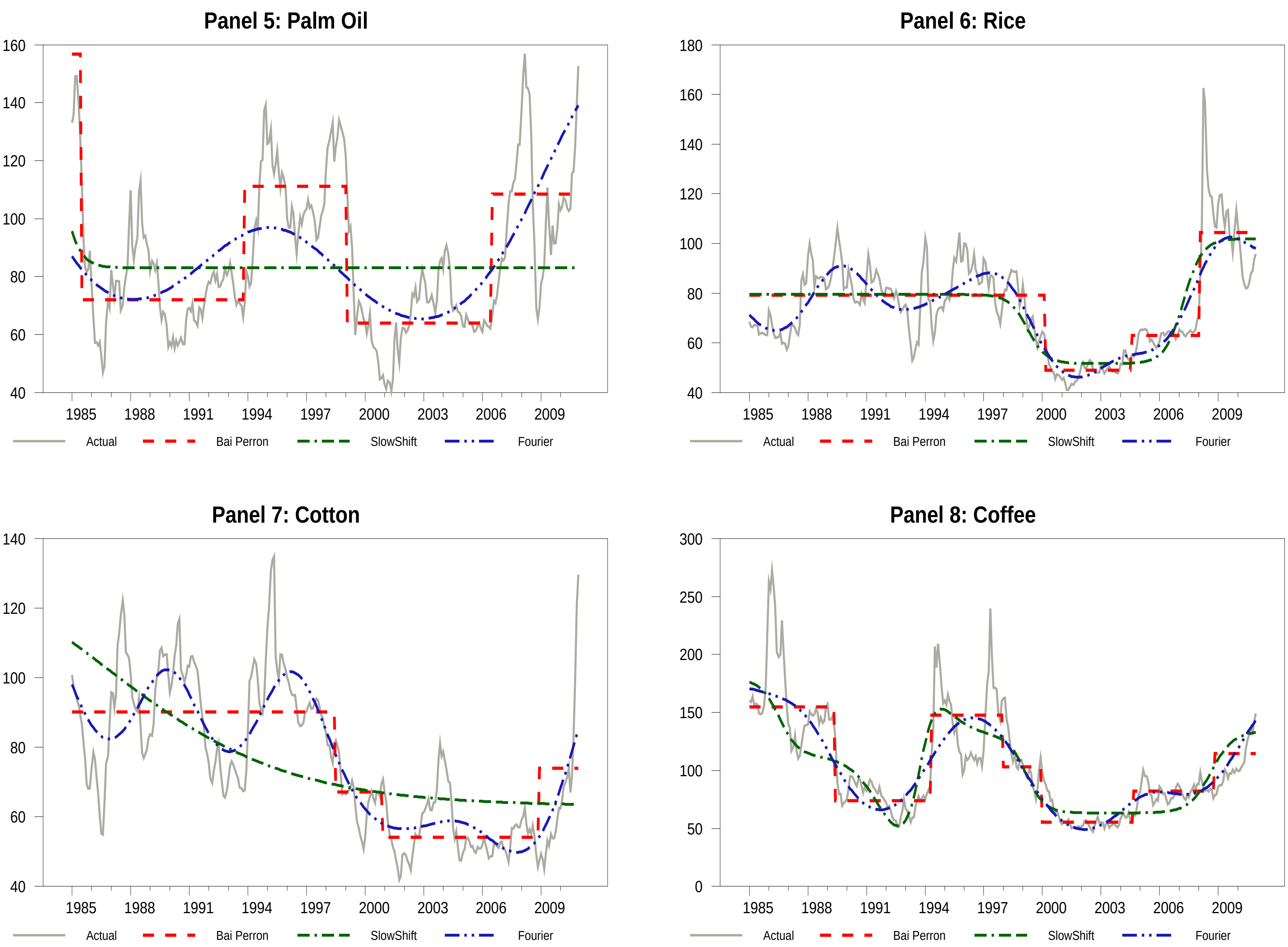

Figure 1: Commodity Prices, Actual Values and Shifting Means Obtained by Various Methods, 1985–2010 (Continued).

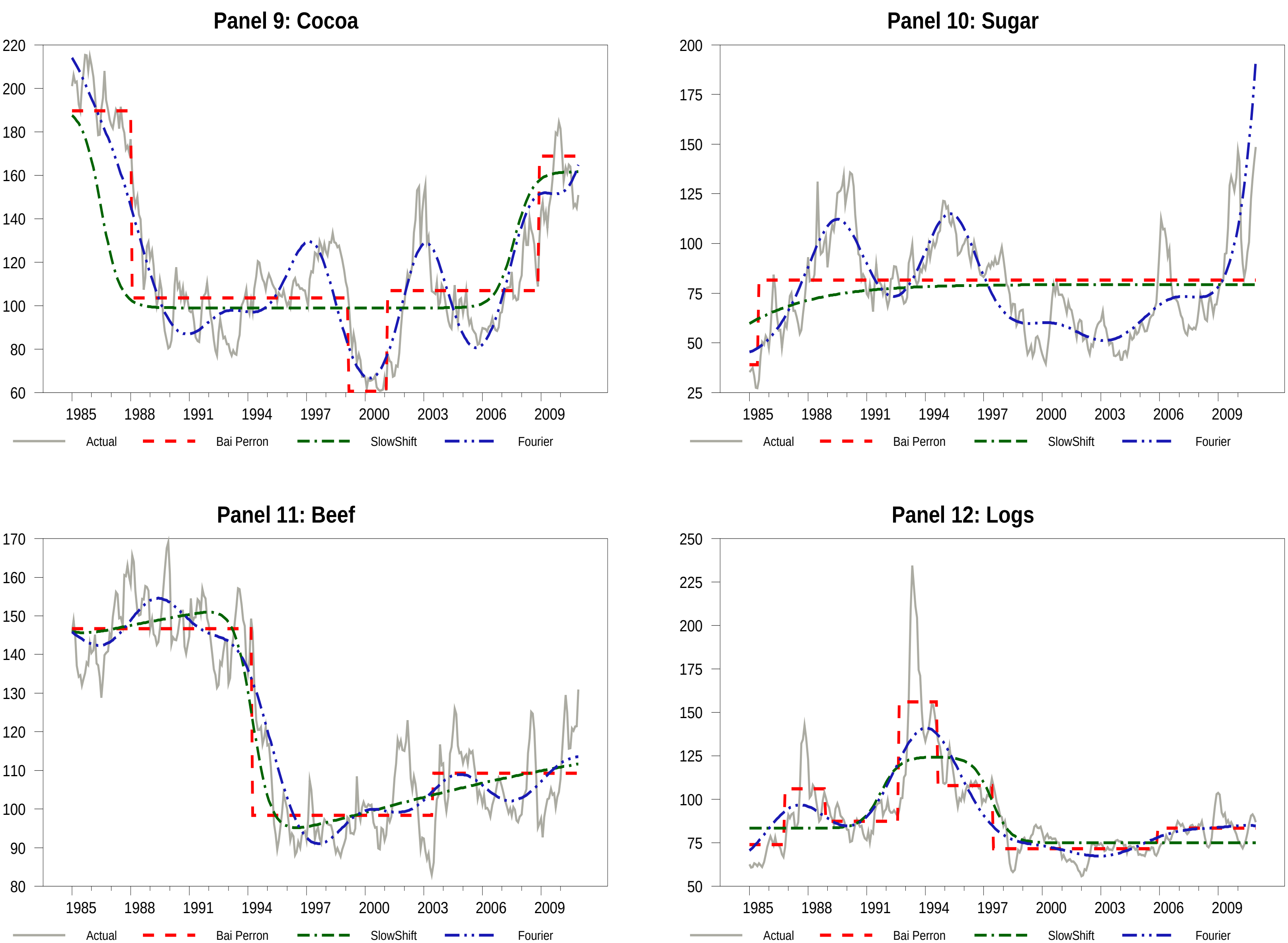

Figure 1: Commodity Prices, Actual Values and Shifting Means Obtained by Various Methods, 1985–2010 (Continued).

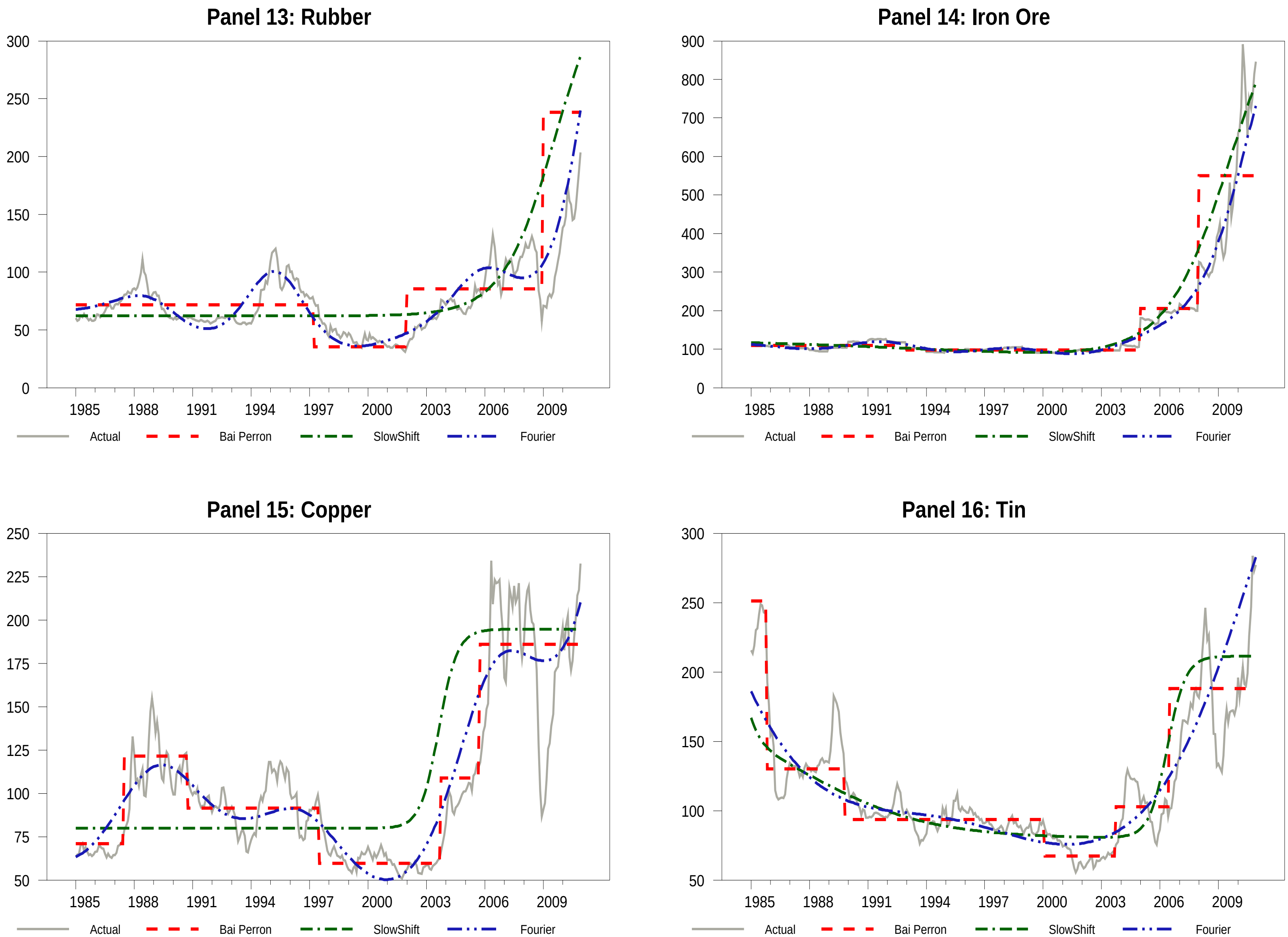

Figure 1: Commodity Prices, Actual Values and Shifting Means Obtained by Various Methods, 1985–2010 (Continued).

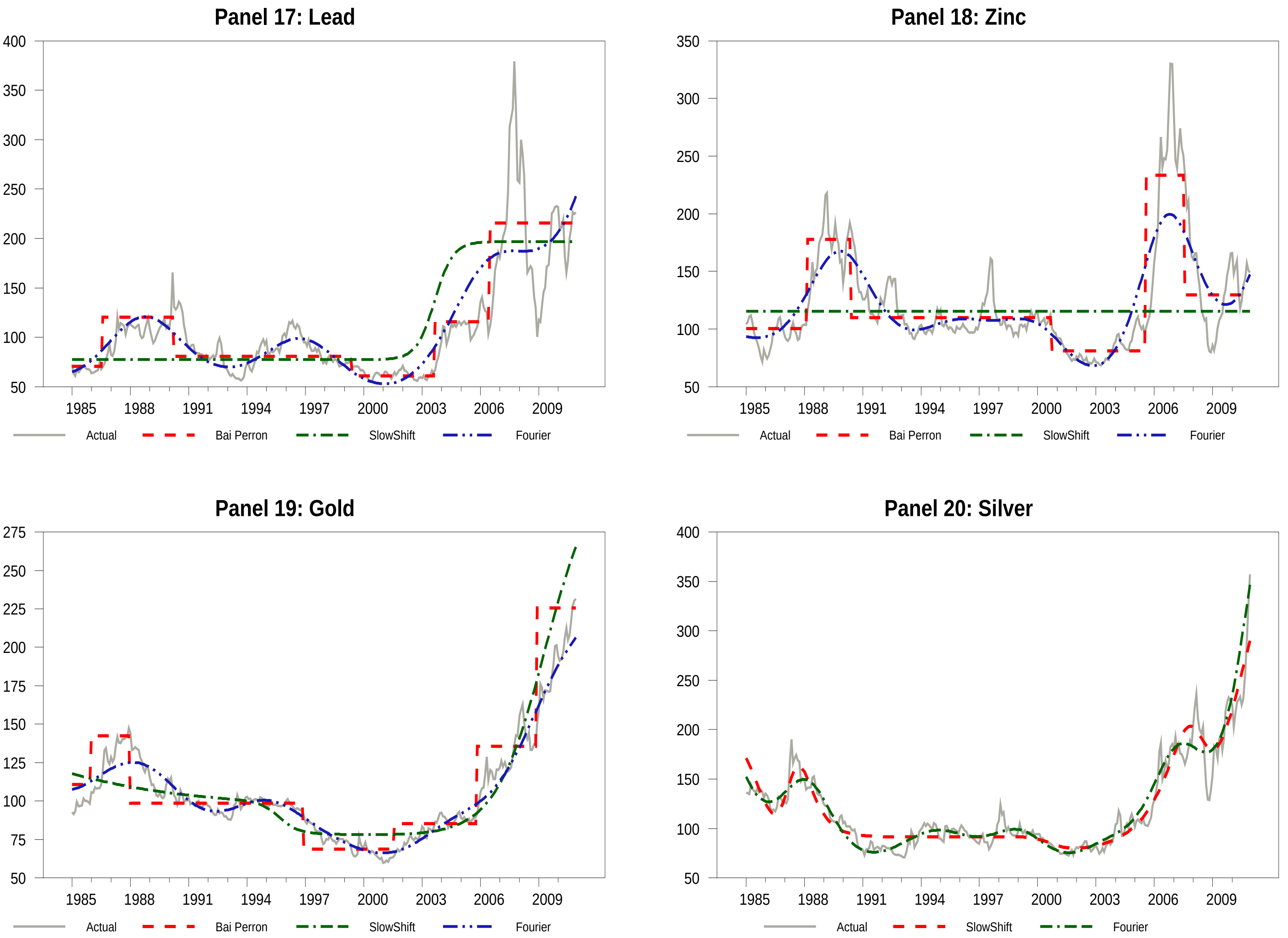

Figure 1: Commodity Prices, Actual Values and Shifting Means Obtained by Various Methods, 1985–2010 (Continued).

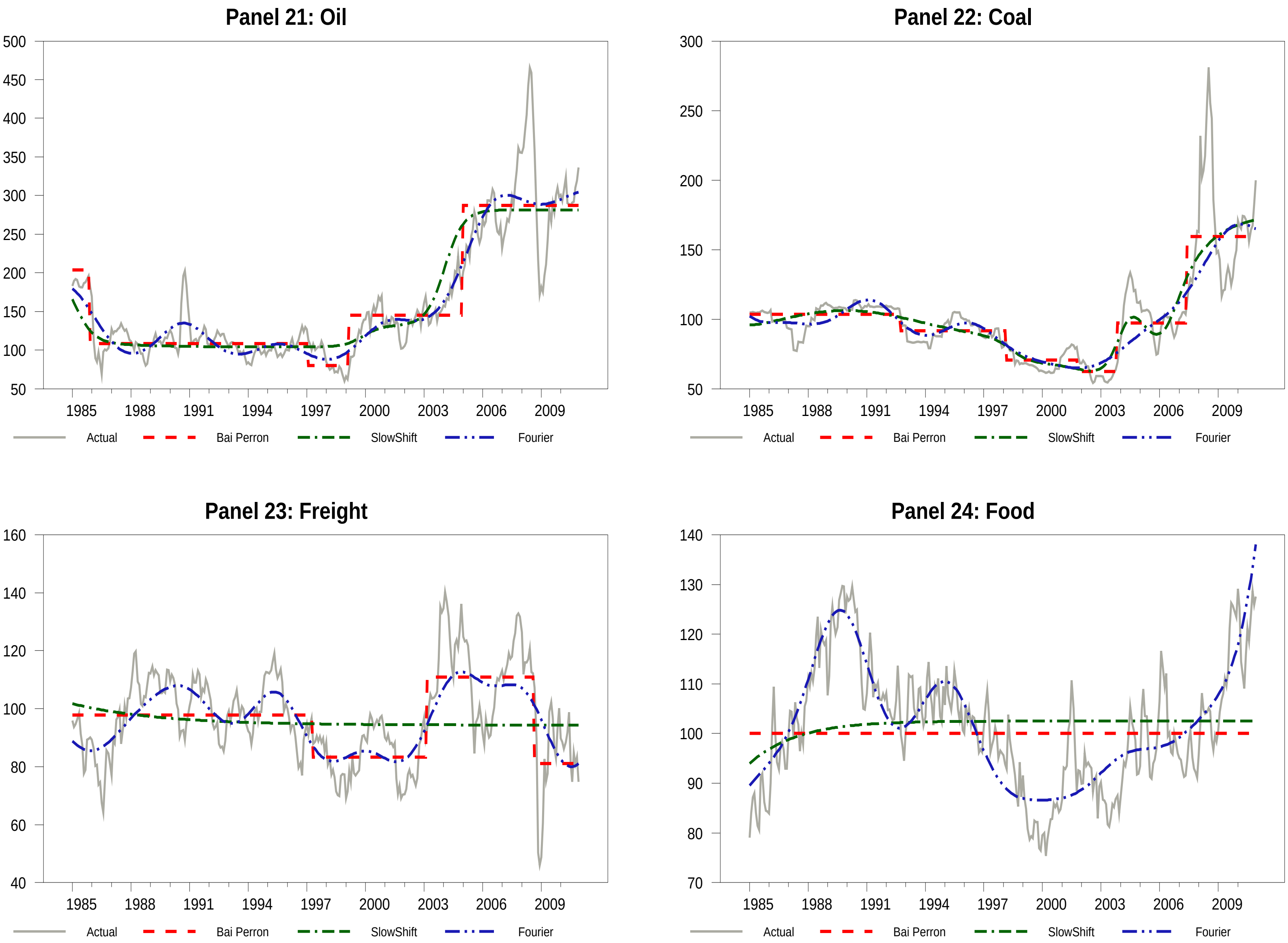

Figure 1: Commodity Prices, Actual Values and Shifting Means Obtained by Various Methods, 1985–2010 (Continued).

Data Description Appendix:

Table A1: Description of Monthly Commodity Price Data.

Commodity	Period	Units	Source	Description
1. Maize	1960:01-2010:12	dollars/mt	World Bank	U.S., No. 2 yellow, f.o.b., Gulf ports
2. Soy	1960:01-2010:12	dollars/mt	World Bank	U.S., c.i.f., Rotterdam
3. Wheat	1960:01-2010:12	dollars/mt	World Bank	U.S., No. 1, hard red winter, ordinary protein, export price delivered at the US Gulf port for prompt or 30 days shipment
4. Sorghum	1960:01-2010:12	dollars/mt	World Bank	U.S., no. 2 milo yellow, f.o.b. Gulf ports
5. Palm Oil	1960:01-2010:12	dollars/mt	World Bank	Malaysia, 5% bulk, c.i.f. North West Europe
6. Rice	1960:01-2010:12	dollars/mt	World Bank	Thailand, 5% broken, white rice (WR), milled, indicative price based on weekly surveys of export transactions, government standard, f.o.b. Bangkok
7. Cotton	1960:01-2010:12	cents/kg	World Bank	Cotton Outlook ”CotlookA index”, middling 1-3/32 inch, traded in Far East, C/F beginning 2006; previously Northern Europe, c.i.f.
8. Coffee	1960:01-2010:12	cents/kg	World Bank	International Coffee Organization indicator price, other mild Arabicas, average New York and Bremen/Hamburg markets, ex-dock
9. Cocoa	1960:01-2010:12	cents/kg	World Bank	International Cocoa Organization daily price, average of the first three positions on the terminal markets of New York and London, nearest three future trading months.
10. Sugar	1960:01-2010:12	cents/kg	World Bank	International Sugar Agreement (ISA) daily price, raw, f.o.b. and stowed at greater Caribbean ports
11. Beef	1960:01-2010:12	cents/kg	World Bank	Australia/New Zealand, chucks and cow forequarters, frozen boneless, 85% chemical lean, c.i.f. U.S. port (East Coast), ex-dock, beginning November 2002; previously cow forequarters
12. Logs	1960:01-2010:12	dollars/cm	World Bank	Malaysia, meranti, Sarawak, sale price charged by importers, Tokyo beginning February 1993; previously average of Sabah and Sarawak weighted by Japanese import volumes
13. Rubber	1960:01-2010:12	cents/kg	World Bank	Asia, RSS3 grade, Singapore Commodity Exchange Ltd (SICOM) nearby contract beginning 2004; during 2000 to 2003, Singapore RSS1; previously Malaysia RSS1

Table A1: Description of Monthly Commodity Price Data (continued).

Commodity	Period	Units	Source	Description
14. Iron Ore	1960:01-2010:12	cents/mt	IMF	67.55% iron content, fine, contract price to Europe, f.o.b. Ponta da Madeira
15. Copper	1960:01-2010:12	dollars/mt	World Bank	LME, grade A, minimum 99.9935% purity, cathodes and wire bar shapes, settlement price
16. Tin	1960:01-2010:12	cents/kg	World Bank	LME, refined, 99.85% purity, settlement price
17. Lead	1960:01-2010:12	cents/kg	World Bank	LME, refined, 99.97% purity, settlement price
18. Zinc	1960:01-2010:12	cents/kg	World Bank	LME, high grade, minimum 99.95% purity, settlement price beginning April 1990; previously special high grade, minimum 99.995%, cash prices
19. Gold	1960:01-2010:12	dollars/troy oz	Bundesbank	London Afternoon Fixing, last day of the month
20. Silver	1970:01-2010:12	cents/troy oz	IMF	New York
21. Oil	1960:01-2010:12	dollars/bbl		average spot price of Brent, Dubai and West Texas Intermediate, equally weighted
22. Coal	1970:01-2010:12	dollars/mt	World Bank	Australia, thermal, f.o.b. piers, Newcastle/Port Kembla, 6,300 kcal/kg (11,340 btu/lb), less than 0.8%, sulfur 13% ash beginning January 2002; previously 6,667 kcal/kg (12,000 btu/lb), less than 1.0% sulfur, 14% ash
23. Ocean Freight	1968:01-2010:12	index	Lutz Killian	Collected from *Drewrys Shipping Monthly*, various issues since 1970, 1966:01 = 1
24. Food	1960:01-2010:12	Index	Word Bank	Includes fats and oils, grains and other food items, 2000 = 100
25. PPI	1960:01-2010:12	Index		U.S. Producer Price Index, All Commodities, 1982 = 100

Note: mt denotes metric ton; kg kilogram; bbl barrel; and LME denotes the London Metal Exchange. All World Bank data were obtained from World Bank pink sheets, and may be obtained from http://blogs.worldbank.org/prospects/category/tags/historical-data. All IMF data were obtained from the International Monetary Fund's Financial Statistics database. Gold prices were obtained from the Deutsche Bundesbank, and may be obtained from http://www.bundesbank.de. Current and historical values for Lutz Killian's ocean freight rate index may be obtained from http://www.umich.edu/ lkilian.

Table A2: Summary Results for Linear AR Model Estimates.

Commodity	Lags	$\hat{\rho}$	$t_\rho = 0$	R^2	AIC	$\text{LM}_{SC}(4)$	RESET	$\text{LM}_t(6)$
Maize	1	-0.014	-2.370	0.075	264.06	0.897	0.000	0.007
Soybeans	2	-0.018	-1.635	0.100	334.17	0.641	0.002	0.013
Wheat	12	-0.018	-2.404	0.142	303.21	0.904	0.007	0.021
Sorghum	8	-0.012	-1.639	0.100	334.93	0.743	0.624	0.013
Palm Oil	4	-0.019	-2.634	0.144	597.37	0.971	0.114	0.002
Rice	11	-0.014	-2.808	0.137	433.94	0.910	0.000	0.020
Cotton	12	-0.009	-1.871	0.281	-22.31	0.048	0.000	0.000
Coffee	2	-0.017	-2.455	0.095	598.50	0.428	0.005	0.061
Cocoa	1	-0.012	-2.006	0.026	591.07	0.105	0.000	0.159
Sugar	3	-0.023	-2.267	0.109	1090.79	0.603	0.736	0.078
Beef	11	-0.013	-2.130	0.137	69.46	0.036	0.008	0.001
Logs	3	-0.028	-2.679	0.154	227.41	0.880	0.003	0.035
Rubber	1	-0.014	-2.069	0.060	437.65	0.698	0.101	0.127
Iron	12	-0.002	-0.400	0.076	485.46	0.248	0.001	0.010
Copper	2	-0.015	-1.937	0.129	556.27	0.870	0.528	0.026
Tin	2	-0.006	-1.598	0.094	179.97	0.909	0.027	0.000
Lead	1	-0.016	-2.065	0.067	584.28	0.867	0.000	0.151
Zinc	5	-0.034	-2.819	0.140	434.23	0.881	0.169	0.460
Gold	11	-0.005	-1.677	0.146	49.15	0.562	0.031	0.000
Silver	6	-0.012	-0.891	0.104	528.62	0.501	0.000	0.011
Oil	6	-0.005	-1.459	0.048	851.50	0.683	0.014	0.004
Coal	12	-0.024	-2.610	0.120	155.15	0.001	0.161	0.000
Freight	12	-0.047	-3.749	0.095	543.94	0.234	0.141	0.010
Food	1	-0.025	-1.732	0.051	247.90	0.384	0.015	0.110

Note: Lags denotes value of p in (1), selected by AIC. Column $\hat{\rho}$ reports estimates of the lagged level term and $t_\rho = 0$ reports the heteroskedasticity robust t–ratio for the null hypothesis that $\rho = 0$. The $\text{LM}_{SC}(4)$ column includes p–values for a heteroskedasticity robust Lagrange Multiplier test for remaining autocorrelation up to lag four. RESET denotes the p–value associated with a Ramsey RESET test where $h = 4$. The column headed $\text{LM}_t(6)$ records p–values for a Lin and Tersvirta (1994) sixth–order Lagrange Multiplier test for intercept non–constancy.