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Abhandlungen

Commodity Price Changes are Concentrated at the End of the Cycle

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Abstract

This paper introduces a new approach to the analysis of the cyclical behaviour of world commodity prices. Within booms and slumps, the behaviour of commodity prices seems to be quite similar, surprisingly even amongst different types of commodities (soft and hard), which are influenced by different shocks. The key result is that during commodity price booms, the faster growth occurs towards the end of the boom. Likewise, most of the collapse of prices occurs towards the end of slumps. This paper first establishes this behaviour as a new empirical regularity of commodity prices. Secondly, this paper introduces a novel way to conceptualise shocks to commodity prices as a cyclical occurrence, and on the basis of this newly established empirical regularity, the size of these cyclical shocks act as leading indicators of impending turnings points.

Keywords: Commodity prices, long term cycles, short term cycles, turning points.

JEL Classification: E32, E37, Q00.

Rohstoffpreisänderungen – Konzentration auf das Ende des Zyklus

Zusammenfassung

Diese Studie entwickelt eine neue Methode zur Analyse des zyklischen Verhaltens der Rohstoffpreise weltweit. Innerhalb von Auf- und Abschwüngen scheint die Entwicklung der Rohstoffpreise ähnlich zu sein. Überraschenderweise gilt dies für verschiedene Arten von Rohstoffen, die unterschiedlichen Schocks ausgesetzt sind. Das starke Wachstum gegen Ende des Rohstoffpreis-Booms stellt ein Schlüsselergebnis dar. Ähnliches gilt für Abschwünge, bei denen der größte Einbruch der Preise am Ende des jeweiligen Zyklus erfolgt. Dieser Artikel etabliert

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dieses Verhalten als empirische Regelmäßigkeit der zeitlichen Entwicklung von Rohstoffpreisen. Zudem stellt dieser Artikel einen neuartigen Weg vor, um Schocks von Rohstoffpreisen als zyklische Vorkommnisse zu konzeptionalisieren. Vor diesem Hintergrund ergibt sich der Befund, dass zyklische Schocks gut als vorlaufende Indikatoren von bevorstehenden Wendepunkten verwendet werden können.

I. Introduction

This paper distinguishes cycles of commodity prices into two categories; natural cycles which refer to generally rising and falling prices, and growth cycles which reflect periods of rapidly increasing and decreasing prices.

Natural cycles are the less frequent of the two as they reflect natural long run movements in commodity prices. Periods of generally rising prices are referred to as the boom phase; booms are typically brought upon by long periods of increasing demand and exacerbated by sluggish supply responses. Slumps are defined as periods of generally falling prices, which are typically caused by the accumulation of excess reserves and technological advancements making the extraction and production process more efficient as well as the substitution away from primary commodities easier (*Wright/Williams* (1982); *Gilbert* (1996)).

The key features of booms and slumps are their duration (how long they persist for), their amplitude (the net growth), and cumulative amplitude (trajectory). Utilising these concepts we apply an adaptation of *Sichel*'s (1993) test for cyclical asymmetry, to determine where, during booms and slumps, the growth is concentrated. We establish as an empirical regularity that on average, and across a wide range of different commodities, a significant proportion of the positive growth during booms and the negative growth during slumps are concentrated at the end of each respective phase. A corollary of this result is that, on average, during booms prices increase at an increasing rate until the peak, and during slumps, prices decrease at an increasing rate until the trough.

Commodity prices are frequently influenced by shocks emanating from real factors including adverse weather conditions, geopolitical conflict, recovering supply stocks, sudden demand shocks, as well as nominal factors such as the effect of an appreciating and depreciating USD[1]. This paper provides a novel method to identify these rapid movements and

[1] As these commodities are denominated in USD, changes in the exchange value of the dollar have inverse effects on the dollar prices of commodities. When the

conceptualise them as a short run cyclical phenomenon. Specifically, a Hamiltonian Markov-Switching (MS) state space model is developed and applied to isolate periods of rapidly rising prices (growth spurts) and periods of rapidly falling prices (growth plunges). The purpose for identifying these growth phases is that we can calculate their amplitude and determine what the relative size of their amplitude indicates about the likelihood of an impending turning point. Complementing this newly established regularity that most of the gain (fall) in prices occurs towards the end of the booms (slumps), we find that the largest shocks, in terms of their amplitude, do provide an indication that the peaks (troughs) are nearby. This paper explains how to distinguish between these extreme growth spurts and plunges and those of less considerable sizes. Interestingly, extreme growth spurts seem to be of a similar magnitude across different and unrelated commodities, where as the magnitude of extreme growth plunges varies significantly across different and unrelated commodities.

II. Review of Previous Studies

The economic literature on commodity price cycles begins with early microeconomic theories postulating that the disequilibrium of demand and actual supply creates seasonal fluctuations in prices (*Kaldor* (1934)). On the basis of this theory, evidence began to emerge that commodity prices exhibited cyclical behaviour in the early 2000s with papers from *Cashin et al.*/*Clements et al.* in 2002 and 2012, respectively. Both authors used turning point dating methodologies consistent with the original business cycle literature pioneered by *Burns*/*Mitchell* in 1946 and by *Bry*/*Boschan* in 1971. Other studies by *Labys et al.* in 2002 and *Jacks* in 2010 explore alternative methods to dating turning points in commodity price cycles.

Developments in the business cycle literature focused on analysing the behaviour of macroeconomic variables within cycle phases as a result of contributions by *Neftci* (1984) and *Sichel* (1993). Coinciding with these developments, new theories about commodity price dynamics, emphasising the role of storage and rational expectations began to emerge, explaining the existence of shocks and gradual mean reversion (*Grilli*/*Yang* (1988); *Deaton*/*Laroque* (1992); *Gilbert* (1996)).

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dollar appreciates (depreciates) vis-á-vis other major trading currencies, commodity prices are then reduced (raised) (*Dornbusch* (1976)).

These theories, aided with novel uses of newly established econometric techniques, are used as a mandate to explore the dynamics of commodity prices within their cyclical phases, with the intension of assessing to the extent that future price movements are predictable.

The benefits of doing so is simple, as many Governments of commodity exporting countries in developing and developed countries link their expenditure and savings to commodity prices, knowing when prices are going to start rising or falling can provide critical information to these Governments and help protect credit ratings and to aid in sensible economic policy formation.

In total, 28 commodities were selected, consisting of 19 renewable commodities (primarily agricultural products and a few industrial raw commodities) and 9 non-renewable commodities (base metals, oil and fertiliser inputs). The data extends from 1957 to 2013 in quarterly intervals. All data is obtained from the International Monetary Fund's International Financial Statistics database, and their details are displayed in Section A of the Appendix in Table A.1.

In forming real prices, the nominal prices are deflated by the 1990 base weighted manufacturing unit value index[2] (MUV), also supplied by the IMF. The MUV index is favoured over US CPI because of its ability to represent the price paid for manufactured exports from developing and emerging economies and hence is better at representing primary commodity prices than the latter.

III. Natural Cycles

Booms and slumps are the natural phases of commodity price cycles. A definition of a boom (slump) in commodity prices which is consistent with the business cycle literature, in particular the pioneering work of *Burns/Mitchell* (1946), would simply be a period of generally rising (falling) commodity prices. This definition is appealing because its flexibility allows enough time for longer durations and hence better reflect natural, long run up and down movements in commodity prices (*Cashin* et al.

[2] One potential drawback of the MUV index is that it may be overstated due to improvements in the quality of manufactured goods which dampens its ability to represent market prices (*Prebisch* (1950)). *Grilli/Yang* (1988) concur that the MUV index may not have been the best index to use during the 1970s, where large monetary and supply shocks in conjunction with exchange rate turmoil dominated the macroeconomic landscape.

(2002)). The point at which the slump (boom) transitions into the boom (slump) is named the cyclical trough (peak). A natural cycle must consist of a slump and a boom.

Despite the intellectual appeal of these boom and slump definitions, the ambiguity surrounding what exactly classifies as 'generally rising' and 'generally falling' leads to substantial debate over which models are best at locating the turning points as to separate periods of generally rising prices from generally falling prices. Structural time series (STS) models, developed by *Harvey* (1993) and favoured by *Labys et al.* (2000) and *Jacks* (2012), in the context of analysing commodity price cycles, provide a parametric approach for capturing the cyclical components of time series data. However, STS models are designed to replicate the cyclical process of an underlining process, and it is this conflict between model design and discovery which has prompted other researchers, notably *Cashin et al.* (2002) and *Clements* et al. to shift away from applying these parametric STS models and towards non-parametric algorithms, specifically the celebrated *Bry/Boschan* (1971) algorithm which is designed to isolate turning points based on a set of rules. The BBQ[3] algorithm provides a more appealing method to capture periods of generally increasing and decreasing prices because it incorporates minimum phase and cycle restrictions. This feature of the model is most appealing because it allows researchers to incorporate reasonable judgments, based on prior information, regarding the expected length of each boom and slump. Early insights into explaining why commodity prices cycle suggest that the cyclical behaviour is driven by the outcome of the independent production decision (which occurs several months prior to harvest) which tends to overcompensate the short-term imbalances between supply and demand, which inevitably leads to cyclical variations in quantity and therefore prices (*Kaldor* (1934)). On the basis of this theory, it is reasonable to impose a minimum phase length of 4 quarters, and the minimum cycle length to 8 quarters.

1. The Dynamics of Prices Within Booms and Slumps

Figure 1 shows the booms and slumps of four commonly encountered commodities, and the most striking and perhaps obvious feature of these cycles, as well as cycles of other commodities, is the fact that their booms and slumps are not symmetric. *Sichel* (1993) argued that asymmetric cy-

[3] BBQ is an acronym for Bry and Boschan Quarterly, details on how this algorithm works are disclosed in Section B of the Appendix.

cle phases can take two forms, a cycle can either be characterised as being 'steep' or 'deep'. Steep phases describe the situation where prices rapidly increase (decrease) at the beginning of the boom (slump), and then tend to plateau until the peak (trough). By contrast, deep phases describe phases where the growth is concentrated at the end of the boom (slump) and hence prices tend to meander at the beginning of the phase and then increase (decrease) rapidly until the peak (trough).

The question here is whether or not either form of asymmetry is systematic across a wide variety of different commodities. If commodities systematically exhibit either steep or deep cycle phases then this information is best used to help aid our understanding of how commodity prices move and hence may lead to a model that can explain commodity price behaviour, or for the purposes discussed in this paper, the forecastability of future movements.

To detect the presence of cycle phase asymmetry *Sichel* (1993), and to a certain extent *Neftai* (1984), compute the average growth rate for each phase and then test for steepness or deepness as evidence against cycle symmetry. However, detecting asymmetry is not necessarily sufficient, because given the broad range of commodities, it is more useful to know whether or not the extent to which cycle phases are asymmetric is consistent across different commodities. If this were the case then the turning points of some prices may be easier to predict than others. *Harding/Pagan* (2002) provide a more transparent and intuitive method for calculating the exact form and size of phase asymmetry. They begin by conceptualising each of the n_1 booms and n_0 slumps as a right-angled triangle and then comparing the actual trajectory to a stylised trajectory.

Each right-angle triangle provides information regarding the time spent in each phase, the growth, and the cumulative growth. Formally, these components are defined respectively as:

1. Duration
   The duration is the length of time spent in each phase. As the base of the triangle runs parallel to the time axis, the length of which (in quarters) measures the duration of each phase. Duration, for each phase, is denoted by T_j^i where $i = 1,\dots,n_j$ and $j = 0,1$[4]. The average duration is given by:

$$\bar{T}_j = \frac{1}{n_j}\sum_{i=1}^{n_j} T_j^i \quad i = 1,\dots,n_j \quad j = 0,1. \tag{1}$$

[4] Refer to Figure 2 for details regarding the notation.

2. Amplitude

   The amplitude of each phase is represented by the height of the adjacent side of the triangle. Point p^i_{Bj} is the log real price at the end of the i^{th} phase and point p^i_{Aj} is the log real price at the beginning of the i^{th} phase. The difference between the two provides an approximation of the percentage growth over the course of each phase[5] which henceforth will be referred to as the amplitude. Specifically, we define the amplitude of the i^{th} phase as:

$$A^i_j = \left(p^i_{Bj} - p^i_{Aj} \right) \cdot 100 \quad i = 1,\ldots,n_j \quad j = 0,1. \tag{2}$$

   hence the average amplitude of each phase simply becomes:

$$\bar{A}_j = \frac{1}{n_j} \sum_{i=1}^{n_j} A^i_j \quad i = 1,\ldots,n_j \quad j = 0,1. \tag{3}$$

   Figure 2 illustrates, using the price of tea as an example, how each boom and slump phase is conceptualised as a right-angled triangle, in panels (a) and (b) respectively.

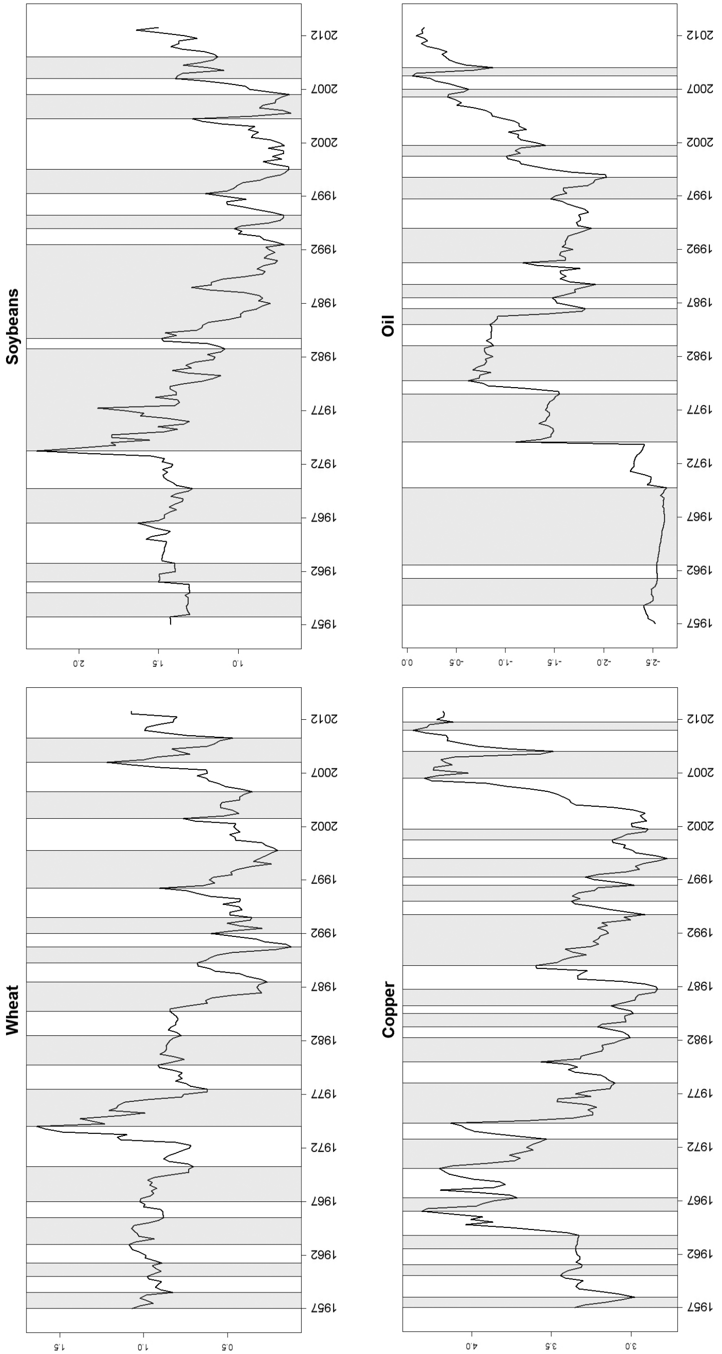
3. Cumulative amplitude

   The cumulative amplitude is the cumulative vertical distance between p^i_{Aj} and each subsequent price point until p^i_{Bj} *i.e.* the total area above the base, and below the price trajectory. *Harding/Pagan* (2002) devise a method to calculate this area by adding together the area of rectangles of unit length and height equal to $\left(p^i_{tj} - p^i_{Aj}\right)$[6]. This approximation, however, is too large because each rectangle will overstate or understate the actual area by approximately half the amplitude. In order to correct for this, half of the amplitude is subtracted from the height of these rectangles. Mathematically:

$$\begin{aligned} F^i_j &= \sum_{t=1}^{T^i_j} (p^i_{tj} - p^i_{Aj}) - \frac{\left(p^i_{tj} - p^i_{t-1j}\right)}{2} \\ &= \left(\sum_{t=1}^{T^i_j} (p^i_{tj} - p^i_{Aj}) \right) - \frac{A^i_j}{2} \quad i = 1,\ldots,n_j \quad j = 0,1. \end{aligned} \tag{4}$$

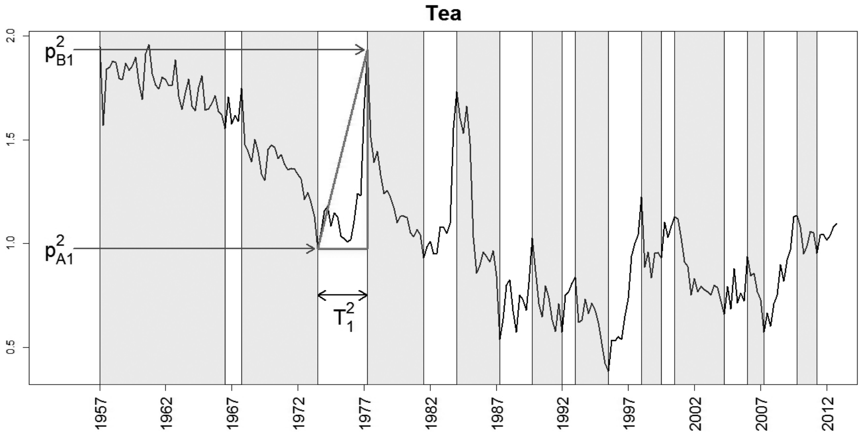
[5] The amplitude is the sum of the growth rates from trough to peak for booms and peak to trough for slumps, which is approximated by (2).

[6] $p^i_{Aj} \leq p^i_{tj} \leq p^i_{Bj}$ such that $p^i_{1j} = p^i_{Aj}$.

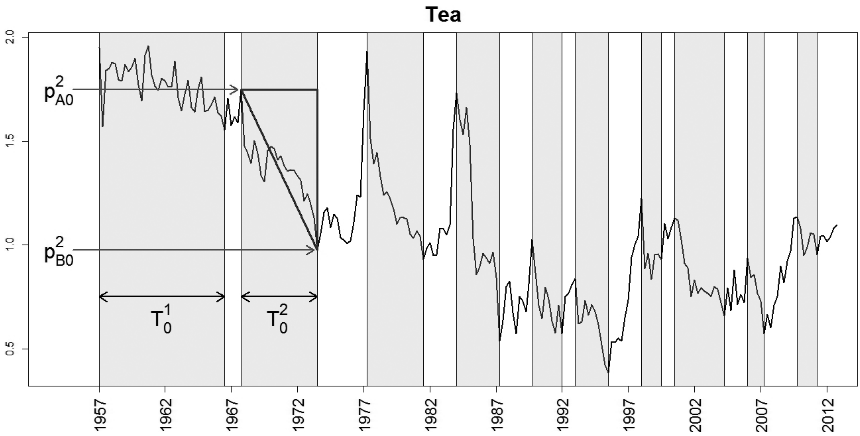


Notes: slumps are represented by the shaded regions and booms are left unshaded. The log of the real price is indicated along the y-axis.

Figure 1: Booms and Slumps of Commonly Encountered Commodities, as Dated by the BBQ Algorithm



(a) Representative slump phase



(b) Representative boom phase

Notes: the BBQ algorithm has detected 10 slumps (shaded regions) and 9 booms for tea from 1957Q1 to 2012Q4, hence n_0 = 10 and n_1 = 9. The superscript indexes the phase number (i = 1, …, n_j), and the subscript, takes the value of a 0 or a 1 to index a slump and boom, respectively. For example T_0^2 refers to the second slump and T_1^2 refers to the second boom.

Figure 2: Dissecting the Cycle

likewise the average cumulative amplitude is given by:

$$\bar{F}_j = \frac{1}{n_j}\sum_{i=1}^{n_j} F_j^i \quad i = 1,\ldots,n_j \quad j = 0,1. \tag{5}$$

Consider the case where a particular phase could not be characterised as being either steep or deep, in these unrealistic circumstances, the increase (decrease) in price is directly proportional to the phase's duration, and hence the price would follow the hypotenuse perfectly, therefore, the cumulative amplitude, defined by (4) would be equal to the area of the right-angled triangle. As the area of each right-angled triangle is given by:

$$AREA_j^i = \frac{T_j^i \cdot A_j^i}{2} \tag{6}$$

the difference between (4) and (6) would equal 0. If the difference between (4) and (6) is positive then the price trajectory must overshoot the hypotenuse, as depicted in Figure 3, panels (a) and (c); and if this difference were negative, then the price trajectory must undershoot the hypotenuse, as depicted in Figure 3, panels (b) and (d)[7].

This positive, neutral or negative difference is defined as the excess area, the excess area of each phase is then divided by its respective duration to form the excess index[8]:

$$E_j^i = \frac{F_j^i - AREA_j^i}{T_j^i} \quad i = 1,\ldots,n_j \quad j = 0,1. \tag{7}$$

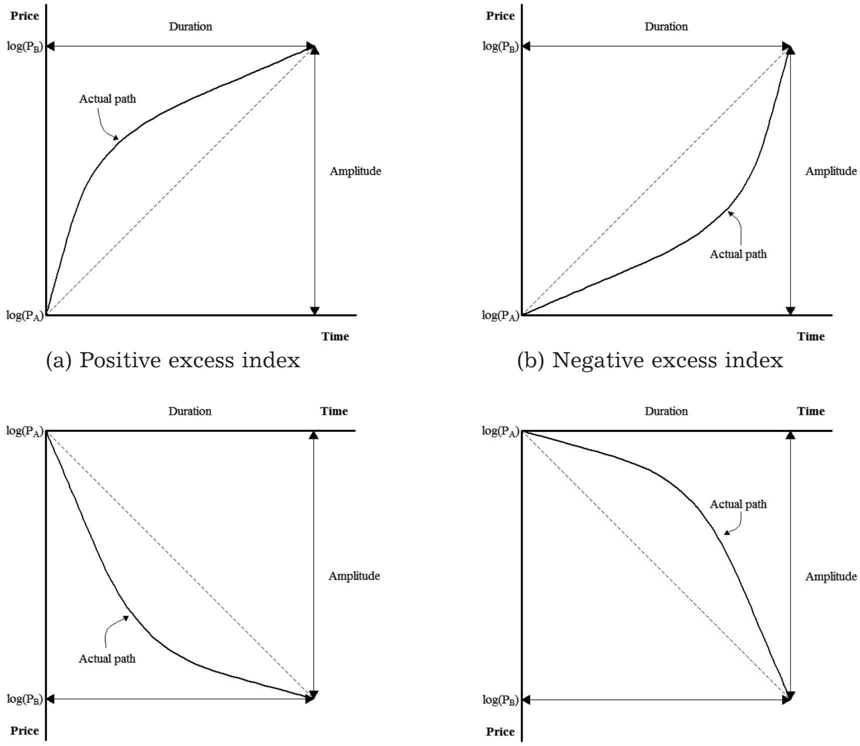
and the average excess index is given by:

$$\bar{E}_j = \frac{1}{n_j}\sum_{i=1}^{n_j} E_j^i \quad i = 1,\ldots,n_j \quad j = 0,1. \tag{8}$$

The type of phase asymmetry is then determined by the coefficient of the average excess index, which is calculated for each commodity's boom and slump phase. The results of which are displayed in Figure 4.

[7] This is only true for booms *i.e.* when $j = 1$ as the cumulative amplitude will always be positive, however, the same conclusion is reached if the absolute value of the cumulative amplitude is used when $j = 0$.

[8] If $E_j^i = 0$, then it may be the case that the price has either undershot and then overshot (or vice versa) the hypotenuse by the exact proportion, these events are extremely unlikely therefore this possibility can be ignored.



(a) Positive excess index

(b) Negative excess index

(c) Positive excess index

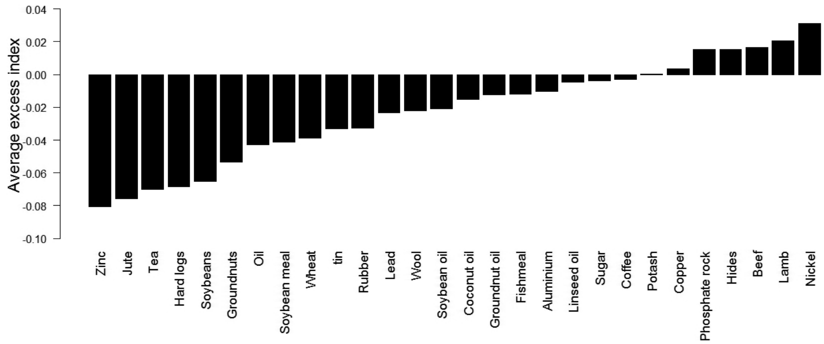
(d) Negative excess index

Notes: panel (a) depicts a price movement that is increasing at a decreasing rate until the peak, the alternative movement during booms is shown in Panel (b) which depicts a price movement that is increasing at an increasing rate until the peak. Likewise during slumps, Panel (c) depicts a price movement that is decreasing at a decreasing rate until the trough and Panel (d) depicts a price movement that is decreasing at an increasing rate until the trough.

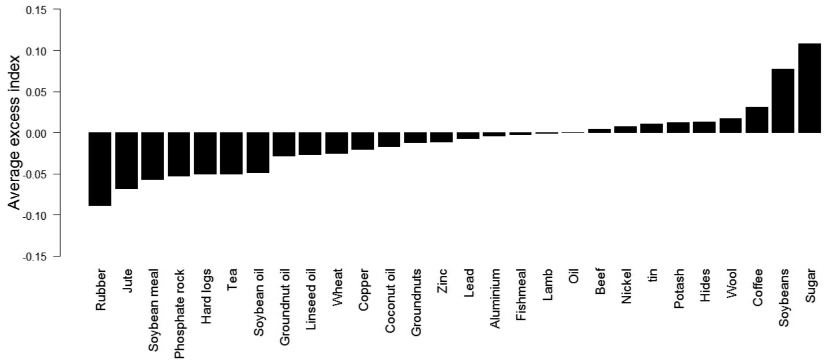
Figure 3: Stylised Movements of Prices During Booms and Slumps

Over two-thirds of the commodities have a negative excess index for both booms and slumps. This overwhelmingly suggests that panels (b) and (d) from Figure 3 best characterises the general behaviour of prices during booms and slumps, respectively. Moreover, whilst there is no obvious pattern regarding the size of the average excess index amongst the commodities[9], these results sympathise with *Deaton/Laroque's* (1992), conjecture that prices often spend long periods in the 'doldrums' before

[9] For example, zinc and jute share a similar average excess index value for their boom phases, and they are two completely unrelated commodities.



a) Boom phases



b) Slump phases

Notes: commodities are ranked from the smallest to the largest $\bar{E}_j$.

Figure 4: The Average Excess Index for Booms and Slumps

being punctuated by severe spikes, and when a high price is established, the possibility remains, that prices will remain high, particularly when inventories are low (*Deaton/Laroque* (1992)).

The next focus of this paper is to use this newly established regularity to provide a theoretical foundation to support the belief that large price changes can be used as leading indicators of impending turning points. Owing to the definition of booms (slumps), which stipulates the prices during booms (slumps) are generally rising (falling) there is substantial scope for falling (rising) prices to interrupt booms (slumps). Referring to Figure 1 for guidance, it is rather obvious that nested within both booms and slumps are short periods of rapidly increasing and decreasing prices. These rapid movements emanate from reoccurring shocks that commodities are frequently subject to, usually as a result of USD movements, geopolitical turmoil, sudden shortages and recovering supply World Bank (2009). Given this fundamental result, the largest shocks should signal an impending turning point.

The next focus of this paper is to identify these shocks, which is achieved by developing and applying a parametric model to detect periods of high and low growth, or positive and negative shocks.

IV. Growth Cycles

Here we define a positive shock as a growth spurt and a negative shock as a growth plunge, and a growth cycle must consist of one of each.

Growth cycle phases can be identified by isolating periods of high and low growth based on the probability that the commodity is experiencing either one. The most popular model used to achieve this is the Markov-Switching (MS) model introduced by *Goldfeldt/Quandt* (1973) and redesigned by *Hamilton* (1989).

Shumway/Stoffer (2010) show that Hamilton's MS model can be transformed into a state space model; the most appealing aspect of the state space model adaption is the ability to use the Kalman filter which provides time dependent estimates of the conditional probability that the commodity price, at any particular time, is in either the high or low growth state. The benefits of time varying conditional probability estimates are that the duration of the growth phases become dependent on the amount of time that the particular growth phase has been in that state (*Durland/McCurdy* (1994)). Growth phases may exhibit duration dependence that they have on the persistence of individual shocks because of the potential influence of weather patterns, the price of production inputs, and the state of economy.

The model stipulates that commodity prices y_t are generated by:

(9) $$y_t = z_t + n_t$$

such that

(10a) $$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + w_t \, Var(w_t) = \sigma_w^2$$

(10b) $$n_t = n_{t-1} + \alpha_0 + \alpha_1 S_t$$

Here (10a) is an AR(2)[10] process that governs the movement of commodity prices throughout time. The crux of the regime switching model comes from equation (10b), here n_t is a random walk with a drift component, where the drift component switches value from α_0 during a growth plunge to $\alpha_0 + \alpha_1$ during a growth spurt. This is because S_t switches between a value of 0 or 1 corresponding to plunges and spurts, respectively.

The unobserved parameters in (9) form the basis of the first component of the state space model, the state vector, $\mathbf{x_t}$:

$$\mathbf{x_t} = (z_t, z_{t-1}, \alpha_0, \alpha_1)'$$

The generation of the state vector $\mathbf{x_t}$ from the past state $\mathbf{x_{t-1}}$, for all time periods $t = 1,\ldots,n$, is given by the state space model, which in its simplest form, employs a first-order vector auto-regression[11]:

$$\mathbf{x_t} = \Phi \mathbf{x_{t-1}} + \mathbf{w_t} \quad Var(\mathbf{w_t}) = \mathbf{Q} \tag{11}$$

$$\begin{bmatrix} z_t \\ z_{t-1} \\ \alpha_0 \\ \alpha_1 \end{bmatrix} = \begin{bmatrix} \phi_1 & \phi_2 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} z_{t-1} \\ z_{t-0} \\ \alpha_0 \\ \alpha_1 \end{bmatrix} + \begin{bmatrix} w_{1t} \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

As the state vector is not directly observed, it needs to be estimated by the second component of the state space model, the observation equation[12]:

$$\Delta \mathbf{y_t} = \mathbf{A_t x_t} + \mathbf{v_t} \quad Var(\mathbf{v_t}) = \mathbf{R} \tag{12}$$

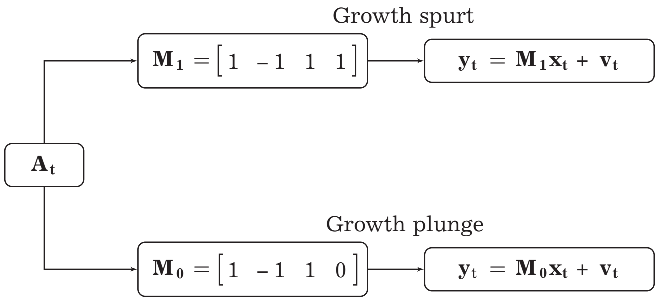
The observation equation is controlled by the observation matrix, $\mathbf{A_t}$, which can take two forms corresponding to the two different states. As shown in Figure 5 below, $\mathbf{A_t}$ takes the form of $\mathbf{M_0}$ during plunges and $\mathbf{M_1}$ during spurts and the observation equation is shown to adjust accordingly.

The parameters of the observation equation, which are specified below, are estimated by maximum likelihood estimation, and the estimated val-

[10] Unlike *Hamilton's* (1989) model, *Shumway/Stoffer* (2010) follow *Lam* (1990) by not restricting one of the autoregressive parameters to unity.

[11] It is assumed that w_{1t} is normally distributed, with variance Q.

[12] The observation noise $\mathbf{v_t}$ is assumed to be Gaussian white noise and uncorrelated with $\mathbf{w_t}$.



Notes: the difference between being in a high growth state and a low growth state is evident in equation (10b). When the commodity price is in a plunge, α_1 drops out of (10b) and therefore (12), in order for this to occur $\mathbf{A_t}$ must switch from $\mathbf{M_1}$ to $\mathbf{M_0}$. As seen above, the only difference between $\mathbf{M_1}$ and $\mathbf{M_0}$ is the fourth element (S_t), for example, when the commodity price is experiencing a plunge, $\mathbf{A_t} = \mathbf{M_0} = \begin{bmatrix} 1 & -1 & 1 & 0 \end{bmatrix}$, and hence (12) becomes $\mathbf{y_t} = \mathbf{M_0 x_t} + \mathbf{v_t} = \phi_1 z_{t-1} + \phi_2 z_{t-2} + \alpha_0 + w_t$.

Figure 5: The Switching Process

ues as well as their standard errors are reported in Section C of the Appendix in Table A.2.

$$\{\Theta\} : \{\phi_1, \phi_2, \sigma_w^2, \alpha_0, \alpha_1\}$$

Prior to estimation, each commodity's price observations are passed through a Kalman filter, the role of which is to calculate the individual densities of $\mathbf{y_t}$, given the past $\mathbf{y_1}, \dots, \mathbf{y_{t-1}}$, which is necessary for maximum likelihood estimation (*Kalman* (1960); *Kalman/Bucy* (1961)). These densities are denoted by $(f_t(t \mid t-1))$[13] in the log-likelihood function[14]:

$$\ln L_y \Theta = \sum_{t=1}^{n} \left(\sum_{j=0}^{m} \pi_j(t) f_j(t \mid t-1) \right) \quad j = 0,1 \quad m = 2 \tag{13}$$

Here π_j (t) is the unconditional time-varying probability that $\mathbf{A_t}$ takes the form of $\mathbf{M_j}$, specifically:

$$\pi_j(t) = P(\mathbf{A_t} = \mathbf{M_j})$$

as the conditional probability is equal to the product of the unconditional time-varying probability and the individual densities of $\mathbf{y_t}$, given the

[13] *Shumway/Stoffer* (1991) approximate the densities using a normal distribution.

[14] Optimisation of (13) was achieved by using a Broyden-Fletcher-Goldfarb-Shanno (BFGS) type algorithm.

past $\mathbf{y}_{\mathbf{t-1}}\cdots, \mathbf{y}_{\mathbf{t-1}}$, the term within the brackets of (13) is the sum of the conditional probabilities that $\mathbf{A_t}$ takes the form of $\mathbf{M_j}$, specifically:

$$\pi_j(t \mid t) = P(\mathbf{A_t} = \mathbf{M_j} \mid \mathbf{Y_t})$$

For filtering purposes the conditional transition probabilities are equal to:

$$\text{(14)} \qquad \pi_j(t \mid t) = \frac{\pi_j(t) f_j(t \mid t-1)}{\sum_{k=0}^{m} \pi_k(t) f_k(t \mid t-1)} \quad k = 0{,}1 \quad j = 0{,}1 \quad m = 2$$

The reason for this is because the conditional transitional probabilities must sum to unity to satisfy the Markov property. Hamilton (1989) uses these conditional transition probabilities to distinguish between high and low growth states on the basis that the series will only change state if the conditional transition probability is greater than 50 %. Following this rule, any commodity is said to be experiencing a growth plunge when the filtered conditional probability that $\mathbf{A_t}$ takes the form of $\mathbf{M_0}$ is greater than 50 %, and when this is the case, S_t takes the value of 0 and therefore, referring to Figure 5, $\mathbf{A_t}$ takes the form of $\mathbf{M_0}$.

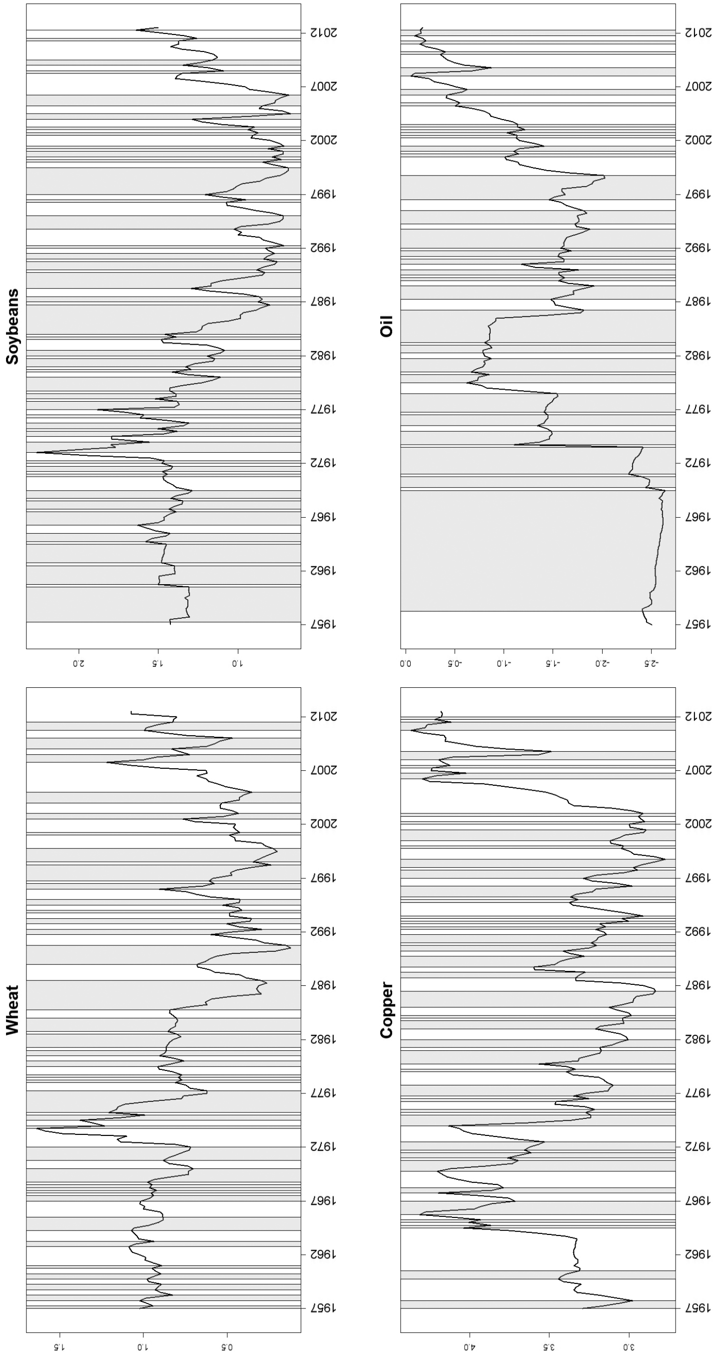
$$S_t = \begin{cases} 0 & \text{if } \pi_0(t \mid t) = 1 - P(\mathbf{A_t} = \mathbf{M_1} \mid \mathbf{Y_t}) > 0.5 \\ 1 & \text{otherwise} \end{cases}$$

A corollary of (14) when Hamilton's rule is adhered to is that S_t will equal 0 and hence the commodity will be experiencing a growth plunge if the conditional probability of this event occurring is greater than the conditional probability that the commodity is experiencing a growth spurt,

$$\pi_0(t) f_0(t \mid t-1) > \pi_1(t) f_1(t \mid t-1)$$

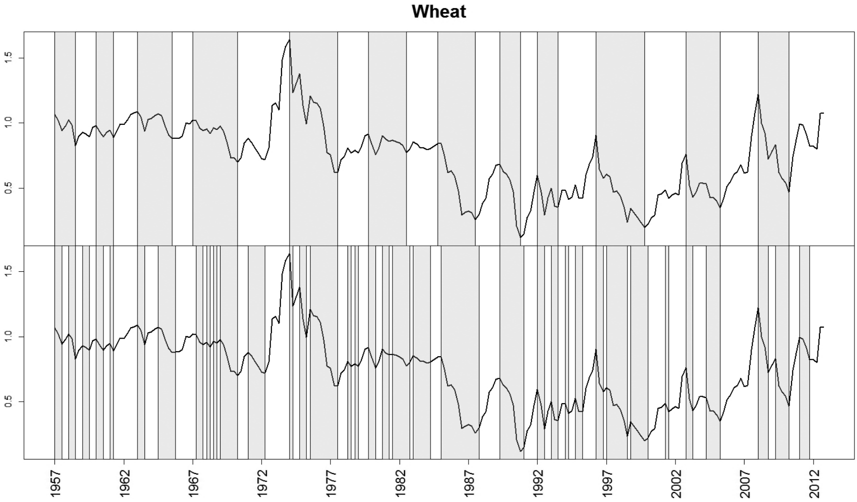
As depicted in Figure 6, whenever the shaded regions are observed, the above corollary holds.

Figure 7 compares the two types of cycles, using the price of wheat as an example, here the price of wheat is plotted twice on a single time axis, so that it can be seen exactly where during booms and slumps prices are experiencing either the high or low growth state, and the extent to which growth spurts and plunges interrupt slumps and booms, respectively.



Notes: growth plunges are represented by the shaded regions and growth spurts are left unshaded. The log of the real price is indicated along the y-axis.

Figure 6: Growth Spurts and Plunges of Commonly Encountered Commodities, as Dated by the Hamiltonian MS State Space Model



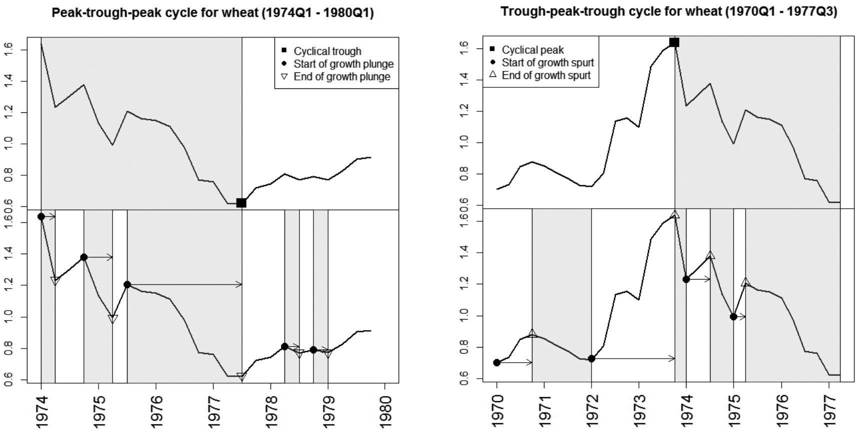
Notes: the log of the real price is indicated along the *y*-axis.

Figure 7: Growth Cycles are Nested Within Natural Cycles

Consider the periods from 1957Q1 to 1961Q3 and 1992Q1 to 1995Q3 as an example of when the price of wheat remained relatively stable. During these periods, the model seems to capture strictly increasing and falling prices of very short duration and low amplitude. What is important here is how the model identifies growth spurts and plunges during more definitive periods of increasing and decreasing prices, as the success of the model rests on its ability to capture long periods of rapidly increasing and decreasing prices. For example, consider the period from 1970Q1 to 1980Q1, here the model does not declare that the growth spurt or plunge is over simply because prices change direction briefly. The fact that the model ignores these very minor corrections is an attractive feature, emanating from its ability to incorporate duration dependence. Furthermore, since the model is able to capture these large, but not necessarily strictly increasing and decreasing prices, we have a better understanding of what constitutes as an extreme growth spurt and plunge as well as where they occur.

V. Are Extreme Shocks Good Leading Indicators of Impending Turning Points?

As the booms and slumps of commodity prices reflect long run up and down movements in commodity prices, it is inevitable that most will be interrupted by movements occurring in the opposite direction. This was certainly the case for commodity price booms and slumps during the 1970s where OPEC's decision to cut oil production forced prices to unprecedented heights. Prices during this boom and subsequent slump experienced a relatively high degree of volatility owing to the exchange rate turmoil brought upon by the collapse of the Bretton-Woods system (World Bank (2009)), resulting in numerous short-term cycles. Figure 8 illustrates how these factors shaped wheat's boom from 1970Q1 to 1973Q3 and subsequent slump from 1973Q4 to 1977Q2, in panel (a). Panel (b) repeats this slump, and shows the next boom phase from 1977Q3 to 1980Q1. Formally, the cycle depicted in panel (a) is referred to as a boom/slump cycle and that in panel (b) is a slump/boom cycle. The conjecture put forward in this paper is that the largest growth spurts (plunges) have predictive power as to when the peak (trough) of any particular boom/slump (slump/boom) cycle, is likely to occur. The important result displayed in panel (a) is the fact that the largest growth spurt ends at the peak, and



(a) Growth spurts nested within trough-peak-trough cycles

(b) Growth plunges nested within peak-trough-peak cycles

Notes: the log of the real price is indicated along the y-axis.

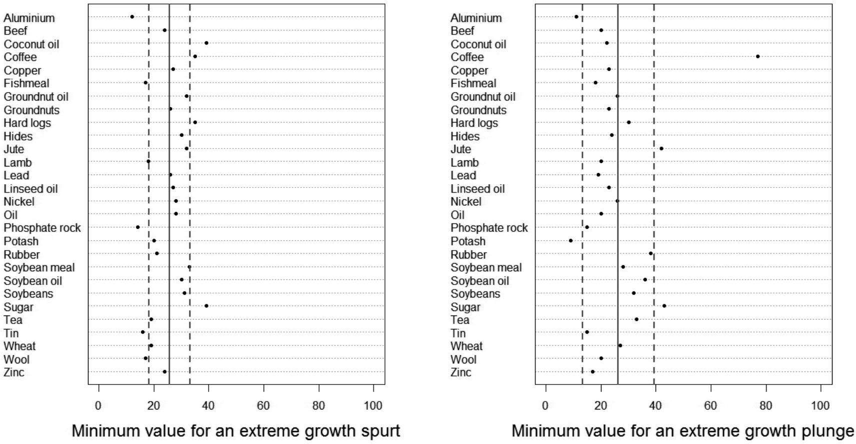
Figure 8: The Larger the Amplitude, the Smaller the Distance from the Turning Point

from panel (b) the largest plunge in prices ends at the trough; hence complementing the conjecture that prices increase (decrease) at an increasing rate until the cyclical peak (trough). To be able to infer that the largest growth spurts end at, or relatively close to the peak for all other cases, it needs to be emphasised that the amplitude of the growth spurts that end considerably prior to, or even interrupt the subsequent slump are not of a considerable size; and likewise with growth plunge amplitudes and the distance from the trough. Hence, the focus here is relating the distance between the end of the growth spurt from the peak of the boom/slump cycle, panel (a), to its corresponding amplitude; and relating the distance between the end of the growth plunge from the cyclical trough of the slump/boom cycle, panel (b), to its corresponding amplitude.

The idea is to find the minimum size of an extreme growth spurt and plunge for each commodity, and to examine as to whether or not periods of increasing (decreasing) prices of at least this magnitude can help predict future turning points. So that the question becomes if one observes a consistent[15] price increase (decrease) of this magnitude, how close is the cyclical peak (trough)? Here, an extreme growth spurt and plunge is defined in accordance with the empirical regularity that commodity prices increase (decrease) at an increasing rate during booms (slumps). As each natural cycle typically exhibits more than one growth spurt and plunge, only the extreme ones are informative, as these are more likely to be situated relatively close to the turning point. Therefore, if a commodity experiences n_1 boom/slump cycles (hence n_1 peaks) and n_0 slump/boom cycles (hence n_0 troughs) then that particular commodity should experience n_1 extreme growth spurts and n_0 growth plunges. On this basis, an extreme positive shock can be defined as an increase in price greater than the amplitude of the n_1^{th} largest growth spurt; and an extreme negative shock is defined as a decrease in price greater than the absolute value of the n_0^{th} largest growth plunge. These minimum values are disclosed in Column 6 of Tables 1 and 2 respectively.

The economic interpretation of these figures follows from how growth spurts and plunges are defined. The generally accepted reason as to why commodities experience large price increases in due to supply disruptions. For example, a drought in North America and/or Australia may cause wheat prices to increase suddenly by 19% or an outbreak of frost in conjunction with other tropical diseases may cause coffee prices to jump

[15] A consistent increase and decrease in price is determined by the average duration of growth spurts and plunges, see Column 2 of Tables 1 and 2, respectively.



(a) The average distance between the end of an extreme growth spurt and the cyclical peak

(b) The average distance between the end of an extreme growth plunge and the cyclical trough

Notes: in both panels, the prominent line indicates a distance of 0 between the end of a growth phase and the cyclical turning point, and the two dashed lines represent ±1 years.

Figure 9: At What Stage of the Cycle do Extreme Price Movements End?

by 35 % over a year. Likewise an over supply of wheat can cause prices to fall by 27 % and a fall in industrial output can cause copper prices to drop by 23 %. It is important to note that some extreme price events are caused solely by geopolitical events and civil unrest as it is the case for oil and other base metals, whereby industrial disputes have previously caused copper and nickel prices to increase. The extent to which these events influence prices varies and may be harder to quantify in the future.

Figure 9 plots the average distance[16] between the end of each extreme growth spurt and plunge from the closest cyclical peak and trough for each commodity, in panels (a) and (b) respectively. If these extreme price movements were able to predict exactly when the cyclical turning points occur, then this distance would be equal to 0. It is more informative and useful if these extreme price movements acted as leading indicators, instead of exact predictors, owing to the fact that many stake holders (such as those entities who would be vulnerable to depreciating prices) would benefit from prior warning in order to consider their hedging op-

[16] If this distance is positive then the growth phase ended prior to the cyclical turning point, and if this distance is negative then the growth phase was completed after the cyclical turning point.

Table 1

Summary Information Regarding the Predictive Power of Extreme Growth Spurts

Commodity	Average duration of booms (years)	Average duration of growth spurts	Number of peaks	Number of hits	Minimum value of an extreme growth spurt (%)	Average distance from the peak (years)	Standard deviation
Aluminium	1.7	2.7	12	9	12	0.25	1.03
Beef*	2.8	2.6	9	9	24	1.75	2.28
Coconut oil	2.1	3.7	12	10	39	0.42	0.81
Coffee	2.4	4.3	6	4	35	–2.38	4.34
Copper*	1.9	3.3	14	13	27	0.41	0.64
Fishmeal	2.0	2.7	13	13	17	0.38	0.70
Groundnut oil	3.0	2.8	10	10	32	1.35	3.00
Groundnuts	3.9	3.9	12	8	26	–0.40	0.87
Hard logs	3.5	3.6	8	5	35	0.59	0.98
Hides*	2.4	3.2	11	9	30	1.27	2.40
Jute	4.1	2.7	8	7	32	–0.59	1.29
Lamb*	2.0	2.1	9	8	18	–0.58	2.40
Lead	1.9	2.4	13	13	26	0.77	1.08
Linseed oil	2.1	3.2	12	11	27	0.60	0.91
Nickel*	2.5	2.7	8	8	28	1.03	1.37
Oil	2.2	2.5	10	7	28	0.60	1.21
Phosphate rock*	2.5	2.4	9	6	14	1.33	1.32
Potash*	3.0	5.7	10	6	20	0.25	1.55
Rubber	2.8	2.4	7	7	21	–0.50	1.32
Soybean meal	3.3	2.5	9	8	33	1.58	2.54
Soybean oil	1.9	2.6	11	10	30	–0.16	0.90
Soybeans	2.4	2.3	8	7	31	–0.97	1.94
Sugar	2.2	2.2	11	11	39	0.84	1.94
Tea	2.1	2.3	9	5	19	0.36	1.06
Tin	2.0	2.9	11	10	16	0.20	1.34
Wheat	2.2	3.1	11	9	19	0.05	0.88
Wool	2.0	3.1	11	9	17	–0.80	1.19
Zinc	1.8	2.3	14	14	24	0.59	1.09

Notes: commodities which are indexed by an asterisk are those commodities whose prices decrease at a decreasing rate and hence their growth is not concentrated at the end of the boom.

Table 2

Summary Information Regarding the Predictive Power of Extreme Growth Plunges

Commodity	Average duration of slumps (years)	Average duration of growth plunges	Number of troughs	Number of hits	Minimum value of an extreme growth plunge (%)	Average distance from the trough (years)	Standard deviation
Aluminium	2.5	2.7	13	11	11	0.94	1.09
Beef*	2.8	2.3	9	8	20	0.92	1.98
Coconut oil	1.9	3.1	13	6	22	0.10	0.72
Coffee*	5.6	4.7	6	5	77	4.75	6.06
Copper	1.9	2.4	13	11	23	0.85	1.38
Fishmeal	2.3	2.5	12	9	18	0.56	1.09
Groundnut oil	2.2	3.4	10	6	26	–0.68	2.21
Groundnuts	2.3	3.4	11	5	23	0.41	1.13
Hard logs	2.1	3.9	9	9	30	0.42	1.29
Hides*	2.0	3.5	11	9	24	–1.11	3.23
Jute	2.7	2.7	7	7	42	0.75	1.07
Lamb	3.1	2.7	9	8	20	1.31	2.79
Lead	2.1	2.8	12	11	19	0.75	1.25
Linseed oil	2.3	3.5	12	8	23	0.35	0.58
Nickel*	3.1	2.8	9	9	26	1.08	1.78
Oil	2.7	5.3	10	6	20	0.93	1.37
Phosphate rock	3.4	4.6	10	9	15	0.38	0.49
Potash*	2.2	3.1	9	5	9	–0.69	1.53
Rubber	3.9	2.1	7	7	38	1.39	4.52
Soybean meal	2.5	3.0	9	8	28	0.42	1.90
Soybean oil	2.8	2.9	10	9	36	1.00	1.76
Soybeans*	3.9	3.3	8	6	32	3.09	3.00
Sugar	2.4	2.5	11	11	43	1.18	1.80
Tea	2.9	2.2	8	6	33	1.91	1.79
Tin*	2.3	2.8	12	10	15	0.13	0.85
Wheat	2.5	3.1	10	5	27	1.23	1.35
Wool*	2.8	2.8	11	9	20	0.75	1.21
Zinc	2.1	2.5	13	11	17	0.63	0.90

Notes: commodities which are indexed by an asterisk are those commodities whose prices decrease at a decreasing rate and hence their growth is not concentrated at the end of the slump.

tions. This is particularly important for Governments of commodity exporting countries, as their spending patterns tend to increase pro-cyclically with commodity price booms (IMF (2012)) and developing countries who still derive approximately 60 % of their export revenue from non-fuel primary commodities (World Bank (2009)).

It is clear that, for most commodities, extreme price movements caused by said events end in the lead up to a cyclical turning point. Hence peaks and troughs are often preceded by price shocks. For some commodities such as tin and coconut oil there is almost no warning, where as for others including coffee and hides, extreme price movements are not helpful at indicating the arrival of turning points.[17]

VI. Robustness Checks

As previously discussed, the turning points of the natural cycles were located using the non-parametric BBQ algorithm. For consistency, all potential turning points were selected based on a two-quarter symmetric window (see Section B of the Appendix). Furthermore, it was specified that any boom or slump phase must persist for a minimum of a year. This minimum phase restriction was selected on the belief that it's the annual discrepancy between the investment decision and the actual supply that drives the cyclical behaviour.

Understandably, these parameters may not be appropriate for all commodities. In order to make the analysis more robust, several inputs to the BBQ algorithm were changed. Firstly, in order to capture more definitive turnings points, the symmetric window was increased to 5 quarters. Secondly, the minimum phase restrictions were increased to 8 quarters for perennial and non-renewable commodities. This increase in the minimum phase restriction makes economic sense because the supply lag tends to be significantly longer for these commodities.

As expected, the average duration of booms and slumps across all commodities has increased (see Column 1 of Tables 3 and 4, respectively). The first consideration is whether or not the longer boom and slump phases change the fundamental result that the growth is concentrated at the end of the phases, as indicated by a negative average excess index. When comparing the new results, depicted in Figure 10, with those from Fig-

[17] Growth is not concentrated at the end of these commodity's booms and slumps, see Figure 4.

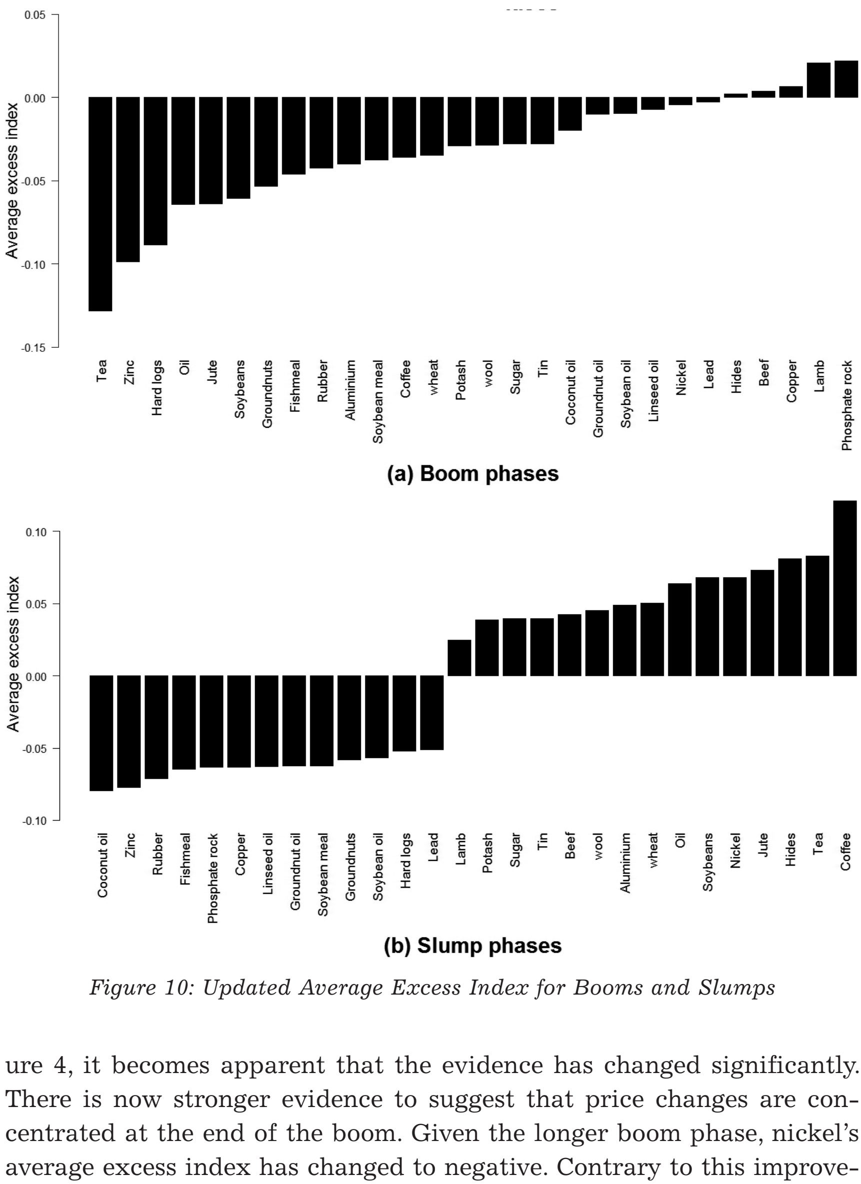


Figure 10: Updated Average Excess Index for Booms and Slumps

ure 4, it becomes apparent that the evidence has changed significantly. There is now stronger evidence to suggest that price changes are concentrated at the end of the boom. Given the longer boom phase, nickel's average excess index has changed to negative. Contrary to this improvement, the evidence that price changes are concentrated at the end of the slump has now become weaker.

After repeating the analysis outlined in Section 5, the results are in many cases more promising. Comparing Tables 1 and 3, in 26 cases the size of the sustained price increases which typically signals the cyclical

Table 3

Updated Summary Information Regarding the Predictive Power of Extreme Growth Spurts

Commodity	Average duration of booms (years)	Number of peaks	Number of hits	Minimum value of anextreme growth spurt (%)	Average distance from the peak (years)	Standard deviation
Aluminium	5.8	9	5	35	–0.15	0.34
Beef*	3.6	9	6	27	–2.33	2.58
Coconut oil	2.2	11	10	43	–0.45	0.84
Coffee	4.4	4	4	38	2.19	4.38
Copper*	3.4	12	7	47	–0.61	0.81
Fishmeal	4.5	9	6	45	–0.08	0.20
Groundnut oil	2.0	11	10	30	–1.77	3.18
Groundnuts	1.9	12	8	26	0.40	0.87
Hard logs	3.8	9	5	38	–0.63	1.12
Hides*	3.7	9	7	40	–0.57	1.51
Jute	3	8	7	32	0.59	1.29
Lamb*	2.2	9	8	18	0.58	2.40
Lead	1.9	13	10	31	–0.68	1.14
Linseed oil	2.5	11	10	28	–0.55	0.90
Nickel	4.0	8	4	49	–0.19	0.38
Oil	3.5	7	5	59	–0.15	0.34
Phosphate rock*	3.5	8	4	32	–1.06	0.75
Potash	4.3	6	5	36	–0.85	2.04
Rubber	3.5	7	7	21	0.50	1.32
Soybean meal	2.3	10	8	32	–1.43	2.45
Soybean oil	2.1	10	10	32	0.15	0.95
Soybeans	2.6	8	7	31	0.97	1.94
Sugar	3.4	11	8	53	–0.38	1.71
Tea	3.6	5	5	35	0.10	0.14
Tin	2.5	10	10	18	–0.23	1.41
Wheat	2.6	10	5	19	–0.50	1.09
Wool	1.9	11	9	19	–0.05	0.88
Zinc	3.4	10	10	62	0.00	0.00

Notes: commodities which are indexed by an asterisk are those commodities whose prices decrease at a decreasing rate and hence their growth is not concentrated at the end of the boom.

Table 4

Updated Summary Information Regarding the Predictive Power of Extreme Growth Plunges

Commodity	Average duration of slumps (years)	Number of troughs	Number of hits	Minimum value ofan extreme growth plunge (%)	Average distance from the trough (years)	Standard deviation
Aluminium*	3.5	10	5	39	–1.15	1.69
Beef*	3.75	8	6	23	–1.13	2.41
Coconut oil	2.2	12	6	22	–0.06	0.74
Coffee*	5.5	5	5	85	–3.50	5.85
Copper	3.0	11	8	34	–0.66	1.24
Fishmeal	2.8	9	7	33	–0.71	1.31
Groundnut oil	2.7	10	6	26	0.68	2.21
Groundnuts	2.3	11	5	23	–0.41	1.13
Hard logs	3.5	9	6	47	0.25	0.61
Hides*	3.0	9	7	28	–0.14	2.08
Jute*	2.7	9	7	32	–1.11	1.21
Lamb*	2.4	9	8	20	–1.31	2.79
Lead	2.6	12	10	32	–0.60	1.13
Linseed oil	2.4	10	8	32	–0.30	0.60
Nickel*	4.9	9	5	38	–0.70	1.57
Oil*	4.7	6	6	31	–0.96	1.59
Phosphate rock	6.5	9	5	21	–0.55	0.51
Potash*	3.8	6	5	17	0.08	0.52
Rubber	3.6	7	7	38	–1.39	4.52
Soybean meal	2.4	9	8	28	–0.42	1.90
Soybean oil	2.8	10	9	36	–1.00	1.76
Soybeans*	3.3	7	6	42	–4.32	3.16
Sugar*	2.6	11	8	64	–1.78	1.53
Tea*	5.6	6	5	35	–2.85	1.52
Tin*	2.0	11	10	18	–0.32	0.55
Wheat *	2.6	9	6	29	–1.69	1.79
Wool*	2.7	10	5	27	–1.23	1.35
Zinc	5	11	5	44	–0.50	0.87

Notes: commodities which are indexed by an asterisk are those commodities whose prices decrease at a decreasing rate and hence their growth is not concentrated at the end of the boom.

peak has stayed the same or increased. Groundnuts, jute, soybeans, and wheat are examples where this figure hasn't changed, and lamb, groundnut oil, rubber, and soybean meal, these figures have decreased. It was expected that this value would increase owing to the greater restrictions being placed on potential peaks. When considering the distance (in years) between the end of these rapid price spikes and the cyclical peak, these spikes have become better at predicting the peak in 15 cases. The most notable examples are: aluminium, (1 year to 0.15 years), soybean oil (1 year to 0.15 years), nickel (1.08 years to 0.55 years) and oil (0.93 years to 0.15 years).

Likewise, comparing Table 2 with Table 4, the size of the rapid fall in prices which should signal the end of the slump has increased, also consistent with expectations. However, the predictive power has fallen substantially. In a large amount of cases, once these price falls have been observed, the cyclical trough has been overshot by over a year in the cases of aluminium, beef, coffee, jute, lamb, rubber, soybeans, sugar, tea, wheat and wool. Whilst the predictive power has fallen, one can be confident that once a fall in prices of these magnitudes have been observed, their prices should be starting to recover, albeit, given the duration of booms (which can last several years) the recovery can be long.

VII. Conclusion

The research undertaken in this paper compliments the emerging trend in commodity price research. Over the past decade, the focus has shifted away from examining how stakeholders can benefit from appropriate intervention (if any), towards understanding patterns in world commodity prices and then creating inference about future movements.

Owing to the time between investment, production and eventual supply, commodity prices exhibit lengthy periods of generally rising prices (booms) and generally falling prices (slumps). By characterising these natural cycle phases in the form of a right-angled triangle and employing the excess index, we established as an empirical regularity, that for the vast majority of commodities, their growth is concentrated at the end of their booms and slumps.

Within these booms and slumps, commodities frequently experience periods of rapidly rising and falling prices, these shocks are typically caused by sudden shifts in demand, supply side influences, or geopoliti-

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cal events. By developing and utilising a Hamiltonian (MS) state space model we are able to capture and identify these shocks and conceptualise them as a cyclical phenomenon. Consistent with our findings that commodity prices increase at an increasing rate during booms and decrease at an increasing rate during slumps, we find that the largest of these shocks are situated at the end of the booms and slumps. The benefit from isolating these shocks is that we can measure their size in terms of amplitude (net growth) and assign a minimum value for them to be considered extreme. By quantifying these extreme price movements, one has a clearer understanding as to when the cyclical peak and trough is likely to occur.

Contingent on our theoretical understanding of how long booms and slumps should persist for, the size of these extreme prices movements which are nested within these booms and slumps can have varying predictive power for the arrival of cyclical turning points. When booms and slumps are allowed to persist for longer, it is found that peaks are easier to predict and troughs are largely unpredictable. However, once large price falls are observed, it's generally accepted that the boom phase has already begun. Moreover, with shorter booms and slumps, modest price increases and falls can signal the completion of the boom and slump phases, respectively.

Considering many Governments of commodity exporting countries link their expenditure to the prospect of high prices and that many producers undertake investment projects on the hope that prices will increase and/or remain high; this paper has provided some welcoming results as to suggest that large price movements are themselves effective leading indicators of future movements.

Appendices

A. Data

Table A.1
Commodities and Their Units

A. Renewables	
Coconut oil (Philippines/Indonesia), bulk, c.i.f. Rotterdam.	\$/Mt
Coffee New York cash price, ex-dock New York.	Cents/lb
Fishmeal Peru Fish meal/pellets 65 % protein, c.i.f.	\$/Mt
Groundnut oil (any origin), c.i.f. Rotterdam.	\$/Mt
Groundnuts 40/50 (40 to 50 count per ounce), c.i.f Argentina.	\$/Mt
Hard logs best quality Malaysian meranti, import price Japan.	\$/Mt
Hides heavy native steers, wholesale dealer's price, US, Chicago, f.o.b Shipping Point.	Cents/lb
Jute Bangladesh, BWD, f.o.b Mongolia.	Cents/lb
Lamb frozen carcass Smithfield London.	Cents/lb
Linseed oil crude, f.o.b Rotterdam.	\$/Mt
Rubber Singapore Commodity Exchange, No. 3 Rubber Smoked Sheets, 1st contract.	Cents/lb
Soybeans U.S. soybeans, Chicago Soybean futures contract.	\$/Mt
Soybean meal Chicago Soybean Meal Futures (first contract forward) Minimum 48.% protein	\$/Mt
Soybean oil Chicago Soybean Oil Futures (first contract forward) exchange approved grades.	\$/Mt
Sugar free market, Coffee Sugar and Cocoa Exchange (CSCE) contract no.11.	Cents/lb
Tea Mombasa, Kenya, Auction Price, US cents per Kilogram, c.i.f. U.K. warehouses.	Cents/Kg
Wheat no. 2, soft red winter, export price delivered at the US Gulf.	\$/Mt
Wool coarse, 23 micron, Australian Wool Exchange spot quote.	Cents/Kg
B. Non-renewables	
Aluminium 99.5 % minimum purity, LME spot price, c.i.f UK ports.	\$/Mt
Copper grade A cathode, LME spot price, c.i.f European ports.	\$/Mt
Lead 99.97 % pure, LME spot price, c.i.f European Ports.	\$/Mt

B. Non-renewables	
Nickel melting grade, LME spot price, c.i.f European ports.	$/Mt
Oil simple average of three spot prices; Dated Brent, West Texas Intermediate, and the Dubai Fateh.	$/bbl
Phosphate rock 70 % BPL, contract, f.a.s. Casablanca.	$/Mt
Potash standard size, bulk, spot, f.o.b. US Gulf.	$/Mt
Tin standard grade, LME spot price.	Cents/lb
Zinc high grade 98 % pure.	$/Mt

Notes: all currency values are expressed in USD at current exchange rates.

B. Bry and Boschan Type Algorithm

The *Bry/Boschan* (1971) algorithm (BBQ)[18] is essentially a non-parametric pattern recognition procedure that identifies where the turning points of natural cycles occur. Below is a brief description on how the algorithm works:

1. Identify the turning point.

   The lower bound of the boom phase is the trough and the upper bound is the peak. For slumps, the lower bound is the peak, and the upper bound is the trough. The BBQ algorithm uses the following rule to identify peaks and troughs.

   Peak: $$\Delta_t = 1(\Delta p_t > 0, \Delta p_{t-1} > 0, \Delta p_{t+1} < 0, \Delta_2 p_{t+2} < 0)$$

   Trough: $$\nabla_t = 1(\Delta p_t < 0, \Delta p_{t-1} < 0, \Delta p_{t+1} > 0, \Delta_2 p_{t+2} > 0)$$

2. Impose strict conditions on the turning points.

   The second step ensures that peaks and troughs must alternate. The Bry and Boschan algorithm ensures that once a peak is observed, the next turning point must be a trough. This is to ensure the existence of a slump. Likewise, for booms to exist, once a trough is observed, the next turning point must be a peak.

3. Restrict the number of phases.

   This step sets the minimum duration of each phase. The idea is that in order to capture natural movements that depict generally rising or falling commodity prices, we require phases to persist for a considerable amount of time before one can be confident that the commodity has entered a new phase.

[18] Versions of the BBQ program exist in GAUSS and MATLAB written by James Engel and are available from the NCER web page at *http://www.ncer.edu.au/data*. Based on the GAUSS code Sam Ouliaris (souliaris@imf.org) of the IMF Institute has produced a version of BBQ that is a macro for EXCEL, and this is what is used in this paper.

C. Hamiltonian Markov Switching State Space Model Parameter Estimates

Table A.2

Maximum Likelihood Estimates for the Observation Equation Using a BFGS Type Algorithm

Commodity	ϕ_1	SE (ϕ_1)	ϕ_2	SE (ϕ_2)	σ_w^2	SE (σ_w^2)	α_0	SE (α_0)	β_0	SE (β_0)
Beef	1.03	(0.07)	–0.07	(0.07)	0.08	(0.00)	–1.10	(0.32)	–0.64	(0.95)
Coconut oil	1.37	(0.06)	–0.48	(0.06)	0.12	(0.01)	–0.79	(1.20)	–0.44	(1.03)
Coffee	1.25	(0.07)	–0.29	(0.07)	0.11	(0.01)	0.97	(0.45)	0.54	(0.93)
Fishmeal	1.38	(0.06)	–0.41	(0.06)	0.09	(0.00)	0.69	(0.52)	0.32	(1.04)
Groundnut oil	1.23	(0.07)	–0.32	(0.07)	0.10	(0.01)	–0.22	(1.77)	–0.08	(1.44)
Groundnuts	1.15	(0.07)	–0.14	(0.07)	0.13	(0.01)	1.05	(0.51)	0.65	(0.93)
Hard logs	1.12	(0.06)	–0.28	(0.06)	–0.10	(0.00)	1.10	(0.33)	0.62	(0.94)
Hides	0.98	(0.09)	–0.20	(0.07)	0.12	(0.01)	0.84	(0.38)	0.19	(1.14)
Jute	1.24	(0.07)	–0.34	(0.07)	0.12	(0.01)	0.86	(0.43)	0.36	(1.01)
Lamb	1.09	(0.07)	–0.16	(0.07)	0.07	(0.00)	–0.35	(0.78)	–1.85	(0.72)
Linseed oil	1.20	(0.07)	–0.27	(0.07)	0.12	(0.01)	–0.19	(1.91)	–0.07	(1.51)
Rubber	1.21	(0.07)	–0.24	(0.07)	0.10	(0.01)	–0.07	(2.43)	–0.02	(1.81)
Soybean	1.06	(0.07)	–0.16	(0.07)	0.10	(0.01)	–1.08	(0.47)	–0.63	(0.94)

Commodity	ϕ_1	SE (ϕ_1)	ϕ_2	SE (ϕ_2)	σ_w^2	SE (σ_w^2)	α_0	SE (α_0)	β_0	SE (β_0)
Soybean Meal	1.11	(0.07)	–0.26	(0.07)	0.11	(0.01)	–1.03	(0.61)	–0.61	(0.94)
Soybean Oil	1.11	(0.07)	–0.20	(0.07)	0.11	(0.01)	1.00	(0.69)	0.62	(0.94)
Sugar*	1.21	(0.07)	–0.29	(0.07)	–0.17	(0.01)	0.51	(0.92)	0.21	(1.13)
Tea	0.92	(0.07)	–0.02	(0.07)	0.11	(0.01)	–0.40	(0.86)	–0.04	(1.23)
Wheat	1.09	(0.07)	–0.17	(0.07)	0.10	(0.00)	1.08	(0.35)	0.62	(0.95)
Wool	1.33	(0.06)	–0.36	(0.07)	0.08	(0.00)	0.98	(0.38)	0.49	(0.97)
Aluminium	1.19	(0.06)	–0.30	(0.06)	0.07	(0.00)	1.15	(0.35)	0.63	(0.95)
Copper	1.20	(0.07)	–0.22	(0.07)	0.11	(0.01)	0.99	(0.55)	0.57	(0.96)
Lead	1.26	(0.07)	–0.28	(0.07)	0.10	(0.01)	–1.12	(0.42)	–0.62	(0.93)
Nickel	1.24	(0.06)	–0.31	(0.06)	–0.11	(0.01)	1.05	(0.53)	0.59	(0.94)
Oil	1.02	(0.07)	–0.05	(0.07)	0.14	(0.01)	0.08	(3.62)	0.05	(2.52)
Phosphate Rock	1.23	(0.07)	–0.28	(0.07)	0.13	(0.01)	–1.00	(0.61)	–0.57	(0.94)
Potash	1.26	(0.07)	–0.31	(0.07)	0.10	(0.00)	–1.09	(0.31)	–0.59	(0.94)
Tin	1.31	(0.07)	–0.31	(0.07)	0.09	(0.00)	1.11	(0.33)	0.60	(0.95)
Zinc	1.30	(0.06)	–0.40	(0.06)	0.10	(0.00)	1.07	(0.38)	0.57	(0.98)

Notes: here $\beta_0 = \alpha_0 + \alpha_1$. All values are rounded to two decimal places.

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