

# **SAFEGUARDING** FOOD SECURITY IN VOLATILE **GLOBAL MARKETS**



EDITED BY  
**ADAM PRAKASH**



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# Safeguarding food security in volatile global markets

Edited by Adam Prakash

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## Chapter 2

# Commodity prices: theoretical and empirical properties

Matthieu Stigler<sup>1</sup>

*Though there has been progress, the understanding of commodity prices and the ability to forecast them remains seriously inadequate. Without such understanding, it is difficult to construct good policy rules. (Deaton, 1999, p. 24)*

*It is sometimes argued that if economists really understand something, they should be able to predict what will happen next. But [commodity] prices are an interesting example (stock prices are another) of an economic variable which, if our theory is correct, we should be completely unable to predict. (Hamilton, 2009, p. 184)*

This chapter aims to provide a thorough description of time series properties of commodity prices. A comprehensive understanding of these properties plays a key role in shaping agricultural and trade policy, as well as guiding the decision-making process of economic agents.

I focus on four indicators of a price distribution- its mean, volatility, asymmetry and kurtosis. For each of these indicators, I briefly outline relevant theoretical models and extract their respective predictions. I then review a few key findings from empirical studies associated with each indicator, and test them on a sample of 24 commodities.

## Background

Periods of crisis and extreme volatility highlight the difficulty of predicting agricultural commodity price movements and has reinforced the need to understand their behaviour. Clarifying the characteristics of commodity prices - especially trends - is crucial for developing countries that rely on commodity exports or that import significant amounts of food. As [Deaton \(1999\)](#) emphasizes, a better understanding of commodity prices is necessary to construct good policy: it will help governments and development agencies shape policies and decide on which products require focus, and at the level of the producer, understanding commodity prices helps individuals make key decisions about which crops to plant.

The need to understand the complexity of commodity price dynamics has become more urgent against the backdrop of current tendencies to remove traditional governmental stabilization schemes (i.e. price bands and market intervention) in favour of transactions on globalized markets. By contrast to earlier years, when agents focused on the spot price only,

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<sup>1</sup> Statistics Division (FAO).

they must now grapple with a wide range of complex factors including derivatives markets, futures and options, phenomena of normal backwardation, maturity effects, and the link between futures and spot prices.

It is beyond the scope for this chapter to do justice to the vast body literature dedicated to the various aspects of price commodities; instead I endeavour to review some stylized facts about commodity price dynamics. I describe the key features of a price distribution, namely what are known as its “moments” such as the mean, volatility, asymmetry and the presence of large values.

For each feature of the commodity price series under investigation, I begin by briefly discussing the predictions of mainstream price formation theories. I then review the body of empirical literature that analyses the empirical relevance of the prediction to each feature, and, when possible, I test the prediction on a sample of 24 commodities. The data are based on the efforts of Grilli & Yang (1988) to build an informative data set, which has been used widely in previous studies on commodity price trends. I use the disaggregated set as prepared by Pfaffenzeller et al. (2007). The sample contains commodities that differ significantly in terms of production typology: crops (rice, maize, wheat), livestock products (wool, lamb, beef, hides), plantation and forestry products (tobacco, cotton, tea, jute, banana, sugar, cocoa, coffee, rubber, palm oil, timber) and metals (lead, copper, tin, aluminium, zinc and silver).

## Economic theories for commodity prices

The term “commodity” can refer to a variety of goods that may differ greatly in production (or extraction), use (as inputs or final goods for the consumer), or storability (from a few days for the banana to centuries for metals). Thus it seems logical to conclude that explanations for the behaviour of markedly different commodities will require different theories. Here, I give an overview of three theories of commodity prices: the storage model, the scarcity rent model and the cobweb model.

### *The storage model*

There is one theory about commodity price behaviour that tends to dominate: the storage model. The storage model has a long history, beginning with writings of Gustafson (1958) and later exhaustively presented by Williams & Wright (1991). As Chapter 15 of this book discusses this model in detail, it is sufficient here to provide a brief description with an emphasis on the time series price properties that the model predicts.

The storage model studies how speculators will engage in commodity transactions based on their expectations of future price changes. Typically, when the actual price is below the level speculators expect to prevail in the next period (namely, the long-term mean of the price adjusted for storage and interest rate costs), speculators will store the commodity in order to sell it at a higher price during the next period. By contrast, when the current price is *above* the next period’s expected value, speculators will not store the commodity. In the case when there are no incentives to store (the so-called stock-out case), price dynamics simply follow the path of the underlying supply shocks.

Clearly, the storage model theory is best suited for commodities which are easily stored and whose production is unpredictable (such as those dependent on weather conditions). In regard to the commodity groups analysed for the current study, the storage model is best suited to describe staple commodities and non-perishable plantation crops.

### Scarcity rent

Although the storage model has also been applied to metals, specific features of the metal industry set it apart from other agricultural commodities. Firstly, metal production (actually extraction) is less influenced by weather uncertainties than most agricultural commodities are. Secondly, the best way to store metal is actually not to extract the product at all. Thus, the key economic decision to be made regarding metals concerns the rate of extraction rather than at the level of storage.

One of the first theories to address metals pricing is the theory of scarcity rent. This theory, which dates back to [Hotelling \(1931\)](#), states that because resources are non-renewable, owners will charge a higher price and thus receive a “scarcity rent”. From the theory emerged the so-called Hotelling rule: a decision to extract resources based on an intertemporal arbitrage will lead to price changes corresponding to interest rate changes.

However, the Hotelling prediction does not seem sufficient to explain today’s observed price movements, partly because its underlying assumption of finite resource availability has been undermined by constant new discoveries and technological change which allow for better extraction and use of lower quality ores ([Krautkraemer, 1998](#)).

### The “Cobweb” model

Finally, mention should be made of a compelling model for predicting the prices of livestock products known as the “cobweb model.” This model, which was introduced by [Ezekiel \(1938\)](#), considers price fluctuations as endogenous, rather than exogenous (as in the storage model). The storage model asks how exogenous shocks in the supply will be transmitted into price movements. By contrast, the cobweb theory explains that price variations are the results of the behaviour of market participants.

Agent’s price expectations play a crucial role in the livestock industry, where the lag between producing decision and effective production can be up to 3 years. While both the cobweb and storage theories model how agents form their expectations, they are based on two fundamentally different assumptions: while the storage model assumes that agents have rational expectations, adherents of the cobweb model assume that producers have naive expectations. Thus, according to the cobweb model, agents will base their production decision on the prevailing price, even if they know that the next period’s price will likely diverge (this explains the term “naive expectations”). By doing so, agents’ expectations can create variations in price: when prices are low (high), they will reduce (increase) their production, so that the next period will see opposite high (low) prices.

Even though the model of naive expectations has been deemed improbable and has received little attention in the mainstream literature, it has not been altogether disregarded in the study of agricultural commodity pricing (see, for example [Mitra & Boussard, 2008](#)). A reason for continued interest is its ability to generate oscillatory prices, which are considered applicable in describing cattle dynamics. For example [Aadland \(2004, p. 1977\)](#) writes,

*Aggregate cattle stocks are a peculiar economic time series. To the best of my knowledge, no other series displays such regular and lengthy economic cycles. The regularity of the cattle cycle, [...] is unmistakable—spanning approximately 10 years from peak to peak. (Aadland, 2004)*

As the other theories mentioned above do not account for such cyclical behaviour, this makes the cobweb model an interesting candidate to help predict cattle prices.

Firstly, it should be noted that the theories elucidated thus far consider markets free from government intervention. However, it is clear that price stabilization (especially minimum



price programmes, see Chapter 1) and trade policies (see Chapter 17) may have important impacts on commodity price behaviour. Moreover, there are theories that emphasize the importance of the macroeconomic environment, such as the “overshooting” model of (Frankel, 1986, 2006), in which monetary expansion induces commodity price inflation in the short-run (see Chapter 3).

## Properties of commodity prices

To describe the properties of commodity prices, I will look at four indicators – the “moments” – of a price distribution: its mean, volatility (variance), skewness, and kurtosis. Because the focus of this chapter is on time series dynamics, a key point of interest is whether these moments vary over time. Thus, I give special emphasis to the time persistence of the first two moments, namely the hypothesis of mean reversion and volatility clustering.

In the section that follows, I define the properties of commodity prices by investigating mean reversion and persistence, volatility, skewness, and kurtosis.

### *Mean: non-stationary or reverting? A debate*

#### *Price persistence: an explanation*

One of the central characteristics of a price series is its *persistence*, i.e. its degree of auto-correlation. Persistence has a fundamental impact on the behaviour of a series, as it indicates, loosely speaking, how past changes will influence the course of future changes. Typically, series with high persistence will have a long memory, which means that past shocks continue to play an important role in determining the commodity’s future price trajectory, and that returning to the series “attractor” will take a long time.

In Figure 2.1, the series shown in blue is simulated with an auto-correlation coefficient of 0.3, 0.6, 0.95 and 1, respectively. The clear pattern that emerges here is that the closer the coefficient is to 1, the more variation the series displays and the more unstable it appears to be.

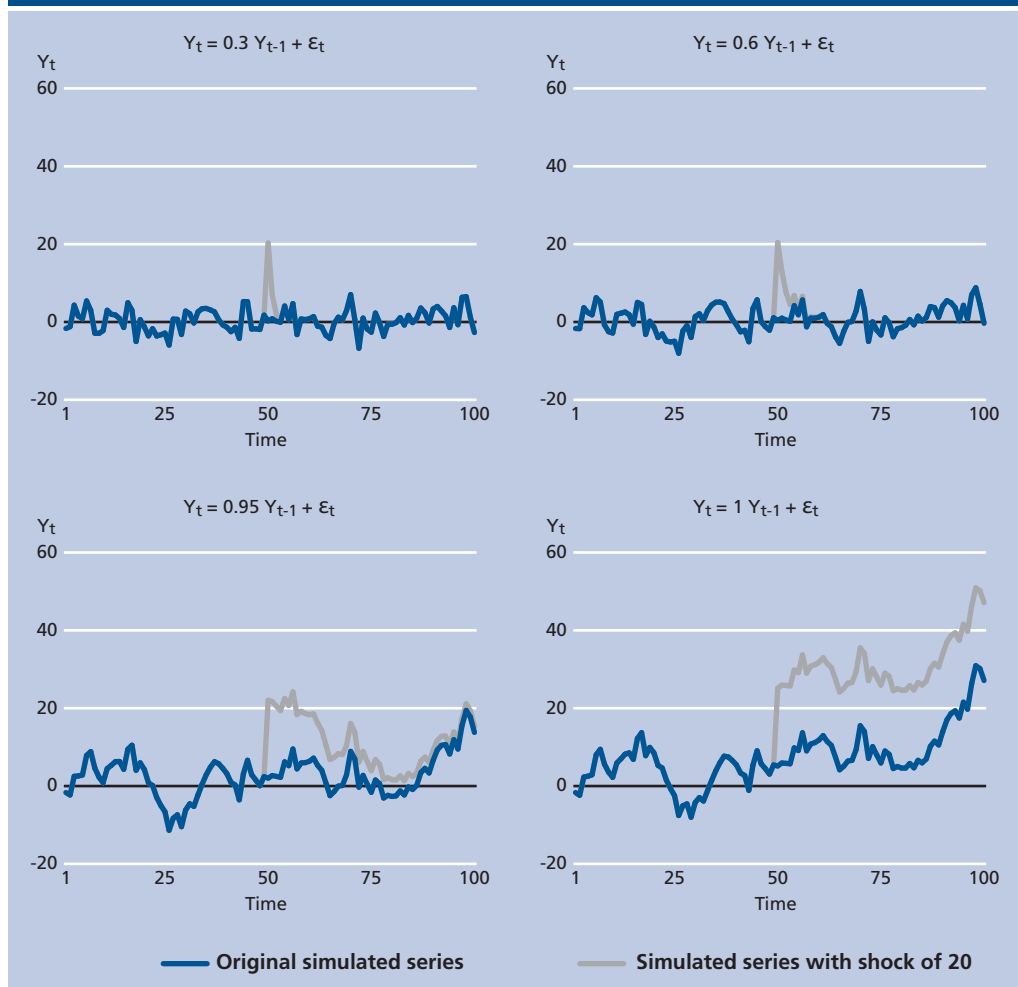
The second series (in grey) shows the same series but with a one-period shock of 20 units occurring at time 50. Interestingly, in the case of low auto-correlation coefficients, the shock dissipates rapidly, i.e. the grey shocked series returns to the black after a few periods only. Alternatively, for series with high persistence values, the same shock has a much more pronounced effect; many more periods are required for the variable to return to “normal” levels. In the case of an auto-correlation coefficient of 1, the shock has a permanent impact, and the series exhibit infinite memory.

In this case, the series is said to be non-stationary (equivalently: containing a unit root), which means that its mean or variance will change over time. Alternatively, a series with a coefficient smaller than 1 have fixed mean and variance.

The degree of persistence also impacts series predictability. Series with a coefficient lower than 1 exhibit stable forecast intervals, while series with a coefficient of 1 show forecast intervals that expand over time. This means that they are impossible to predict, and that the probability of an increase at any given time is as likely as a decrease. Thus, no price trends can be inferred from the data.

In summary, the question of series persistence plays a crucial role and has very practical implications for the market participant. If a series is found to be non-stationary, there is little that can be done to forecast it; a sharp decline is as likely as a sharp increase. Finally, the question of a series’ persistence is also relevant for modelling strategy, as non-stationary variables require non-standard statistical techniques.

Figure 2.1: The implications of series persistence for a simple AR(1) process



Source: Own simulations.

### *Price persistence: theoretical considerations*

Storage model theorists tend to agree that agricultural prices should be stationary. The storage model seeks to show how, in the presence of an i.i.d. (independent and identically distributed) supply and a deterministic demand function, commodity storage induces price auto-correlation. But whether this auto-correlation leads to stationarity or non-stationarity (random walk) is not directly predicted by the theory.

In an influential article, [Deaton & Laroque \(1992\)](#) investigate how the storage model can replicate the relatively high, but still stationary, auto-correlation found in annual prices of more than 10 commodities. That the prices were found to be stationary appeared justified to the authors:

*The random walk hypothesis seems very implausible, at least for commodities where the weather plays a major role in price fluctuations; a random walk requires that all fluctuations in price be permanent. (Deaton & Laroque, 1992, p. 3)*

The many studies employing competitive storage models that followed Deaton and Laroque's seminal 1992 paper (for example [Deaton & Laroque, 1995, 1996](#) and [Chambers & Bailey, 1996](#)) seemed to adopt the same belief in price stationarity. Indeed, they sought to replicate high auto-correlation without asking whether or not the auto-correlation is generated by stationary or non-stationary series. But even Deaton and Laroque themselves challenged the storage model, as it appeared rather unable to replicate this phenomenon in empirical commodity prices. This discrepancy was recently resolved by [Cafiero et al. \(forthcoming\)](#) (see also Chapter 15), who found that after a small modification of Deaton and Laroque's approach, the storage model was indeed able to replicate high-correlations. However, none of [Cafiero et al. \(forthcoming\)](#) results predict values close to non-stationarity (see Figures 15.2, 15.3, 15.4 and 15.5), which casts doubt on the ability of the storage model to generate non-stationary series.

By contrast the theory of financial market efficiency considers non-stationarity to be a given. This theory, popularized by Fama in 1960, argues that for a market to be efficient, prices should not be predictable and will thus follow a non-stationary random-walk<sup>2</sup> (more precisely, a martingale, of which the random walk is one model). The rationale is that price predictability can only be temporary because predictability reveals unexploited patterns in prices that attract investors. It is the activity of investors trading in predictable patterns that will ultimately result in the cancellation of predictable pattern. Even though the efficient market theory has been challenged in recent years by results of behavioural finance studies (see [Shiller 2003](#) for a survey) and also Chapter 14), findings nevertheless indicate that in most financial markets prices exhibit at least near non-stationary behaviour.

While both theories are based on rational expectations, one predicts stationarity while the other predicts non-stationarity.

### *Price persistence: empirical results*

Empirical results of price persistence analyses differ greatly and depend on the frequency and type of price (whether spot or future) analysed. For example, scholars analysing price transmission generally use cointegration tools, as virtually all studies report non-stationarity in agricultural prices. By contrast, studies testing the Prebisch-Singer hypothesis find more nuanced cases of stationarity, as will be seen below.

Indeed, an important body of literature has dealt with price stationarity in the context of the Prebisch-Singer (PS) hypothesis. The PS hypothesis states that as the price of commodities decreases relative to that of manufactured goods (and services), the terms of trade of commodity-exporting countries deteriorates. The first causes cited for this phenomenon were the low income elasticity of commodity demand and the high prices caused by manufacturers' market power. These explanations have recently been disregarded in favour of those relating the deterioration of the term of trade to the quasi-infinite supply of labour in developing countries ([Deaton & Laroque, 2003](#)).

While the initial empirical tests of the PS hypothesis focused on detecting a significant negative trend, later studies, beginning with [Cuddington & Urzua \(1989\)](#), pointed out the importance of precursory testing for the presence of stationarity. Indeed, it is important to disentangle deterministic trends generated by almost stationary processes from stochastic trends generated by random-walks.

<sup>2</sup> Although this is formally not a necessary condition – see [Lucas \(1978\)](#).

This observation gave rise to a flood of new studies applying various stationarity and unit root tests to the standard data of Grilli and Yang, which have been revisited each time new econometric tests have become available.<sup>3</sup>

While an exhaustive review of all the results testing the PS hypothesis is impossible, one can at best mention a few key developments. Recent studies have progressively modelled the trend component more realistically by allowing for a structural break (Leon & Soto, 1997), two structural breaks (Zanias 2005 and Kellard & Wohar 2006), a smooth break (Persson & Terasvirta 2003, Balagtas & Holt 2009), or by modelling the break with smooth components (Gilbert, 2006).

However, a complication that arises when testing the null hypothesis of a linear unit root against the alternative of stationarity with breaks is that the alternative is actually composed of two hypotheses, namely that of stationarity and that of structural break. Thus, rejection of the linear unit root test does not imply necessarily rejection of the unit root, but can be owing to rejection of the hypothesis that there is no break. The papers cited above use tests that are not immune to this problem. More accurate tests are provided by Lee & Strazicich (2003, 2004), who allow trends to be present both under the null and the alternative.

The long excursion on the methodological issues of testing for downward trends predicted by the PS hypothesis leads one back to the initial question of commodity price stationarity. While researchers have tended to rely heavily on Grilli and Yang's aggregated data, it has since been acknowledged that aggregate data may hide important disparities that exist within commodities. Thus, testing for each commodity separately is also useful.

A number of influential studies have tested the PS hypothesis on separate commodities. Kellard & Wohar (2006) applied unit root tests to 24 commodities and found that 14 appear to be trend stationary once structural breaks are taken into account. Ghoshray (forthcoming) argues that the rejection of unit roots tests in favour of stationary alternatives with structural breaks might be owing to the presence of a break in the null hypothesis as mentioned above. He applied Lee & Strazicich (2003)'s test, along with a battery of others, to the deflated prices of 24 commodities (including 18 agricultural commodities). When using standard unit root tests, Ghoshray found that 17 of the 24 series were non-stationary. Applying linear unit root tests against stationary series with one structural break, only 7 series appeared to be non-stationary. Finally, the number of series found to be non-stationary increased to 11 once the more appropriate test of Lee and Strazicich was used. Kellard & Wohar (2006) reached similar results finding 10 non-stationary series.

It is difficult to summarize the conclusions of these various studies, as the results are highly sensitive to the test used, and inference appears to be less than robust. It is even quite probable that these results will be challenged in the future with the arrival of new testing procedures.

### *Price stationarity: policy implications*

Having concluded the academic debate I now briefly discuss the policy implications of price stationarity. The first point to highlight is that there is significant uncertainty regarding the presence of trends in agricultural commodities. Furthermore, if trends do exist, they do not appear to last very long (with the possible exception of rice which is declining steadily). As Ghoshray (forthcoming) notes:

<sup>3</sup> To paraphrase Maddala & Kim (1998), the Grilli and Yang data set has become the "guinea pig" of agricultural economists, much like what Nelson and Plosser's data set is for mainstream economists.

*Forecasting of commodity prices proves to be difficult. The evidence suggests that policy recommendations would be difficult to implement given the mixed and varying trend results.*  
Ghoshray (forthcoming, p. 9)

Because there is uncertainty as to whether or not prices trend at all, and whether or not price shocks are persistent, the best solution at the national and producer level may be to diversify commodity production, which would hopefully reduce the risks associated with the persistence of shocks and price unpredictability .

### *Nonlinearities*

**The storage and TAR models** Up to this point in the discussion, almost all of the unit root tests discussed were based on linear representation such as:

$$\Delta y_t = \alpha y_{t-1} + \beta_1 \Delta y_{t-1} + \dots + \beta_p \Delta y_{t-p} + \epsilon_t \quad (1)$$

Such formulations, however, are not satisfactory on theoretical grounds. In fact, various theories conclude that commodity prices exhibit nonlinear behaviour.

In the storage model, for instance, the constraint that inventories cannot be negative induces a nonlinear feature, i.e. that there are two distinct price dynamic regimes. The first regime corresponds to the usual regime of positive stocks, with speculator activity introducing auto-correlation of price between i.i.d. harvests. But when there is a stock-out, a different price regime emerges in which price dynamics simply replicate the harvest dynamics.

This phenomenon of regime switching between periods can be captured using the so-called threshold auto-regressive model (TAR), which aims to estimate two regimes that are split according to a “threshold variable”. When estimating the storage model, the threshold variable chosen is simply the price:

$$\Delta y_t = \begin{cases} \alpha_L + \beta_{1L} \Delta y_{t-1} + \dots + \beta_{1L} \Delta y_{t-p} + \epsilon_t & y_{t-1} \leq \gamma \\ \alpha_H + \beta_{2H} \Delta y_{t-1} + \dots + \beta_{2H} \Delta y_{t-p} + \epsilon_t & y_{t-1} > \gamma \end{cases} \quad (2)$$

The estimated “threshold value”  $\gamma$  can be interpreted in this context as the value above which stock-outs will occur. Thus, the TAR model estimates both the “critical level” as well as the dynamics specific to each regime. For instance, according to storage theory, the coefficient  $\alpha_H$  in the second regime should be close to 0, and thus reveal the low auto-correlation of stock-outs.

Ng (1996) applied the TAR model to the original series used by Deaton & Laroque (1992) and detected nonlinearity in 5 of the 13 series. Her estimated threshold values were in line with Deaton and Laroque’s results, and indicated relatively short periods of stock-outs (ranging from 3-25 percent of the sample). Whether or not there is low auto-correlation in stock-outs is difficult to establish owing to the small number of observations in these regimes. Arguing that the large standard errors may be owing to the small number of observations, Ng simply compared the values of the coefficients. She concluded that there was important auto-correlation in the stock-out regime which contradicted the storage model prediction. Ng’s methodology of relying on estimates without taking into account their standard errors is certainly questionable (see Cafiero & Wright, 2006), but there are to date no other approaches to assess the auto-correlation in regimes that have such a small number of observations.

It should be emphasized that the storage model, which primarily helps describe commodities linked to seasons, is essentially a theory that helps understand price variations

between crop years. This implies that using monthly instead of annual data cannot help us determine the validity of this model, and conversely, that the theory cannot help us determine price variations within a given year. Interestingly, other theories, which use daily or monthly time series instead of annual data do predict nonlinear behaviour.

**Nonlinearity and financial theories** The issue of price nonlinearity has also been considered by finance theorists. For example, some have investigated the connection between herding behaviour and price bubbles. The first statistical investigations of this sort looked at the multivariate relationships between prices and their fundamentals (Diba & Grossman, 1987). But because the validity of such multivariate analysis rests on the accurate choice of fundamental variables, other approaches that use price series only (Haas et al., 2004) have emerged.

The underlying idea of these univariate analyses is that the presence of an economic bubble translates statistically into auto-regressive coefficient values higher than 1, i.e. it causes *explosive* behaviour. Clearly, because the bubble is a temporary phenomenon, these theories also predict regime-switching behaviour. In these cases, regimes are said to exhibit *explosive* behaviour. As illustrated in Box 14.3 in Chapter 14, two different tests of explosive roots run on a daily price series indicated the presence of a price bubble during the 2006-08 turmoil in global agricultural markets.

Another theory in finance, also discussed in Chapter 14, finds nonlinearity by taking into account trading behaviour on financial markets by distinguishing between noise and informed trades.

**Nonlinearity and livestock products** Theories of nonlinearity have also been applied to the case of livestock products. As mentioned above, a prominent feature of cattle prices is their cyclical behaviour. Holt & Craig (2006) applied nonlinear models to hog-corn price series by highlighting the asymmetry in the supply response to prices. They pointed out that on-farm quantities can be reduced almost instantaneously (by slaughtering), while rebuilding animal herds takes significant time. Holt and Craig thus applied the so-called smooth transition model and found evidence of significant nonlinearities.

## Volatility

As highlighted in the previous section, agricultural commodity prices tend to be characterized by a high rate of persistence that is difficult to distinguish from a random-walk, leading to uncertainty in future price movements. Another important factor that adds to this uncertainty is the high price volatility that characterizes agricultural markets.

Volatility can be defined in many ways (see Chapter 1 for a complete overview). Traditionally, volatility refers to unexpected price movements. There is indeed a part of price movement that can be expected, such as seasonality or trends (though the discussion above casts doubts on this fact). The notion of volatility refers rather to the *unexpected* price movements. Typically, volatility measures involve two phases: a filtering phase followed by an estimating phase. Evidently, the second phase will depend on the first, and misspecification of what is termed the “mean specification” will induce misspecification of the nature of volatility.

Theoretically speaking, the presence of volatility can easily be explained by the inherent configuration of supply and demand in agriculture. Supply cannot adjust easily in the short run, and is subject to significant weather uncertainty, while demand is also relatively low in the short run. According to these configurations, a simple weather shock can result in a significantly higher price shock.

*Volatility: ARCH and GARCH models*

Volatility has been extensively analysed in the field of finance, and the tools developed in this research have in turn been applied to commodity prices. I review here the main developments in the financial literature, discuss their application for agricultural markets, and question whether the dynamics of agricultural prices differ from those of financial asset series.

The simplest measure of volatility is the average of the variations of the logarithmic transformed series, which has the advantage of being easily interpreted as the mean percentage change<sup>4</sup>:

$$\hat{\sigma}^2 = \frac{1}{T} \sum (\log(y_t) - \log(y_{t-1})) \tag{3}$$

This equation nevertheless assumes a constant variance over time. It is often stated that the variance tends to “cluster” during certain periods: periods of low volatility tend to follow low volatility, and high volatility tends to follow high volatility. Engle (1982) introduced a model to take this phenomenon into account by writing the conditional variance as an auto-correlated process. From this arose the Auto-Regressive Conditional Heteroskedastic model (ARCH):

$$\begin{aligned} y_t &= f(y_{t-1}) + u_t \\ u_t &= \epsilon_t \sigma_t \\ \epsilon_t &\overset{iid}{\rightarrow} \mathcal{D}(0,1) \\ \sigma_t^2 &= \omega + \alpha u_{t-1}^2 \end{aligned} \tag{4}$$

where  $\mathcal{D}(0,1)$  is an arbitrary i.i.d. distribution with mean 0 and variance 1. Typical choices for the distribution include the normal (as in Chapter 8) or the Student distributions (as in Chapter 6 and 16).

In (4) the conditional variance  $\sigma_t^2$  is assumed to depend only on the values of the previous shocks. The ARCH model was generalized by Bollerslev (1986) who made the conditional variance depend also on its past values. This led to the GARCH model:

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{5}$$

In the GARCH model, while the conditional variance  $\sigma_t^2$  is time-varying, the process has an unconditional variance (given by  $\omega/(1 - \alpha - \beta)$ ) as long as the sum of the coefficients  $\alpha + \beta$  does not equal 1 or above.

*ARCH and GARCH models applied to agricultural commodities*

When applied to agricultural markets, the presence of GARCH effects will depend on the type of series considered, as well as the frequency of the data. But interestingly, GARCH effects are not limited to high frequency future prices. Indeed, when modelling the quarterly prices of soybean, sorghum and wheat, Ramirez & Fadiga (2003) found evidence of volatility clustering.

Though volatility clustering has been widely observed empirically, there is a paucity of theoretical explanations for this phenomenon (Shiller, 1989). In the case of agricultural

<sup>4</sup> This stems from the fact that for small changes, the difference of the log of a series is approximately the percentage change – see Hamilton (1994, p. 438).

commodities, Beck (1993) showed that the storage model can induce ARCH(1) effects in prices. Her empirical investigation of the annual prices of diverse agricultural commodities confirmed this prediction as ARCH effects were present in storable commodity prices, but not in non-storable ones.

It is beyond the scope of this chapter to provide a detailed survey of the numerous studies that have used GARCH models to study the volatility of commodity prices. Therefore, I have chosen to highlight a few that address specific features of agricultural price volatility. I will discuss asymmetric responses of volatility, micro determinants of asymmetry, as well as the influence of macro-variables.

### *Asymmetric effects on volatility*

Equation (1) shows that coefficient  $\alpha$  estimates the effect of a “shock” on conditional variance. However, this effect does not need to be symmetric; it is possible that either positive or negative shocks impact the market in different ways. Such an asymmetric effect can be measured using the EGARCH models of Nelson (1991), or the GJR-GARCH model of Glosten et al. (1993). Using these models on financial data, it has frequently been observed that negative shocks cause greater volatility than positive shocks do. This asymmetry has been explained in finance by the fact that negative shocks represent “bad news” owing to the so-called leverage effect.

Interestingly, the situation tends to be reversed in the case of commodity prices: a price increase generates a higher volatility. This phenomenon can be explained by the storage model, where price increases show the tendency to deplete stocks and hence increase volatility. Beck (2001), for example, has found such asymmetry by studying annual prices of 13 commodities. In addition, Carpentier (2010)’s systematic investigation showed asymmetry to be robust across a sample of more than 10 daily commodity prices and across different sub-periods. A more thorough investigation is discussed in Chapter 16, where it is found that the asymmetric effect increases as the volatility level itself increases.

### *Micro effects on volatility: the Samuelson effect*

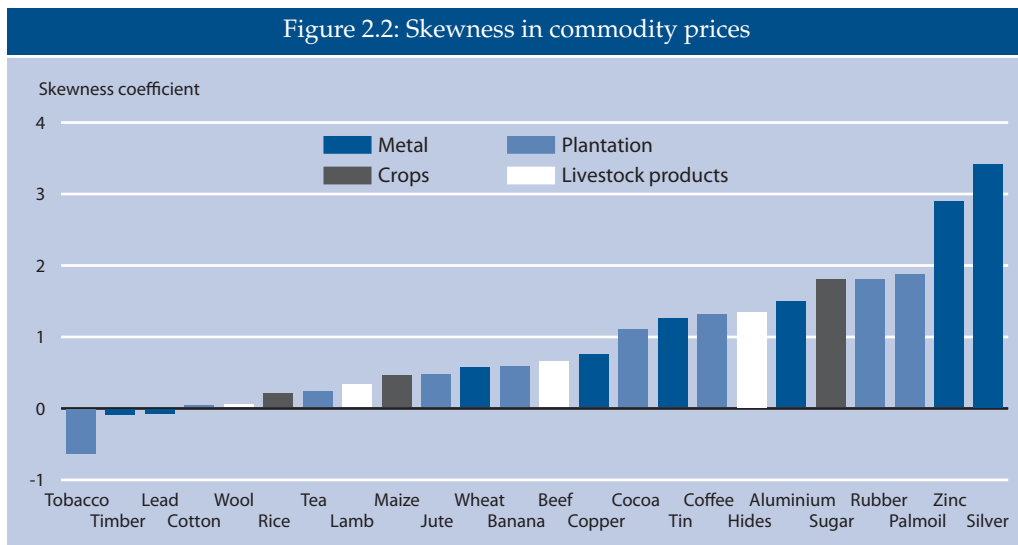
Using future prices instead of spot prices creates additional difficulties in modelling volatility. The first feature that emerges is seasonality, where, for example, volatility is higher at certain times of the year, typically at pre-harvest periods. More important is the so-called Samuelson effect, which states that volatility tends to increase as the maturity date of the futures contract approaches. This implies that futures contracts with the closest maturity (or even the spot price) exhibit a greater volatility than contracts at later maturities.

The Samuelson effect implies that by choosing to analyse a price series with the nearest maturity future, one introduces artificial volatility. The presence of the maturity effect for agricultural commodities has been confirmed by many studies, among others Milonas (1986), Kalev & Duong (2008) and Karali & Thurman (2010). Interestingly, Karali & Thurman find that the maturity effect significantly impacts the daily volatility of wheat prices, which is estimated to increase on average by 30 percent between the farthest and closest day to maturity. Using a synthetically constructed futures series with a constant maturity of 100 days rather than the nearby maturity can avoid the issue of maturity effects.

### *Volatility: macro determinants*

Up to this point in the study, only conditional volatility is discussed, i.e. the volatility at time  $t$  given values at  $t - 1$ . It is important to keep in mind that according to the GARCH model,





Source: Own calculation based on Pfaffenzeller et al. (2007) data.

while the conditional variance is time dependant, the unconditional variance (the average volatility given all values) is assumed to be a constant, and is given by:

$$\frac{\omega}{1 - \alpha - \beta} \tag{6}$$

It may also be fruitful to discuss whether the unconditional volatility varies with time. For example, it is generally claimed that while volatility in the 1990s was low, it increased significantly during the turmoil of 2006-2008. In an influential article, Schwert (1989) observed that indeed the stock-return volatility was evolving over time, and tried to determine whether this evolution was dependent on macro-economic variables.

A similar question has been asked by Roache (2010) in the context of agricultural commodities. Roache uses the spline-GARCH model of Engle & Rangel (2008) which decomposes volatility into two factors: short and long-run volatilities. Roache measured how the extracted long-run component of volatility was influenced by a set of 16 macroeconomic variables. Among these variables, inflation volatility and market volumes had a positive effect on volatility, while exchange rate and activity levels were found to have a negative impact.

### Skewness

The skewness coefficient provides information about the asymmetry of a distribution. A value of 0 will indicate a symmetric distribution while a positive (negative) value will indicate a distribution skewed to the right (left).

Are there any theoretical arguments that predict commodity price symmetry? Once again one can look to the storage theory. Because inventories can only be positive (one can store now what will be consumed later, but one cannot consume now what will be produced later), the smoothing effect of storage will be effective to prevent decreases, but not increases.

How does this prediction translate into reality? Figure 2.2 shows the skewness coefficient computed on raw deflated prices. It indicates that commodities generally tend to exhibit a positive skewness, and thus conform to the storage model's prediction.

Because the storage model attributes price skewness to the action of storage, one would expect that a commodity's storability will impact its degree of asymmetry. But Figure 2.2 above does not confirm this hypothesis definitively. While one can find an overall positive skewness (except for the case of tobacco, which might depend on the very different dynamics of tobacco demand), the commodities that appear very similar in terms of storability do not seem to share the same skewness properties. For instance, easily storable commodities like metals can have either the highest (zinc, silver) or lowest (lead) skewness. Similarly, banana is a commodity that practically cannot be stored or in any case its storability is much less than wheat or maize, yet it has a higher skewness than either of these two commodities.

When discussing these conflicting findings, one should keep in mind that price asymmetry can also be owing to price stabilization policies. Indeed, the introduction of a floor price will introduce positive skewness in the prices. Conversely, a ceiling price can reduce positive skewness. It is, however, unclear how this helps explain the conflicting results above.

One might ask how skewness in a series will affect the estimation procedure, as usual models are based on the assumption of an underlying symmetric distribution. There are various ways to deal with this question. If the intent is to estimate the conditional mean equation, a simple method to use is the quasi-maximum likelihood (ML) approach. Specifying a wrong distribution for the maximum likelihood does not in fact greatly affect the estimation of the parameters (the estimator is still consistent in most cases), but it affects its standard errors. Thus, the quasi-ML proceeds to the estimation as if the errors were normal, but corrects for the variables' standard errors.

An alternative approach would be to specify the distribution errors directly by using an asymmetric rather than the standard normal distribution. This is more frequently done in the context of GARCH models, where the error distribution is nonetheless modelled specifically. Ramirez & Fadiga (2003) provided an example of such approach applied to commodity prices (wheat, soybean and sorghum), and found that taking skewness into account through an asymmetric distribution reduced the model's forecast errors.

From a practical perspective, the presence of positive skewness can help policy design. Indeed, positive price asymmetry implies that one can be quite confident in establishing a minimum price level<sup>5</sup> under which prices are unlikely to fall. On the other side, an upper bound is much more difficult to establish. That is, consumers or importing countries must be prepared for virtually any increase in price.

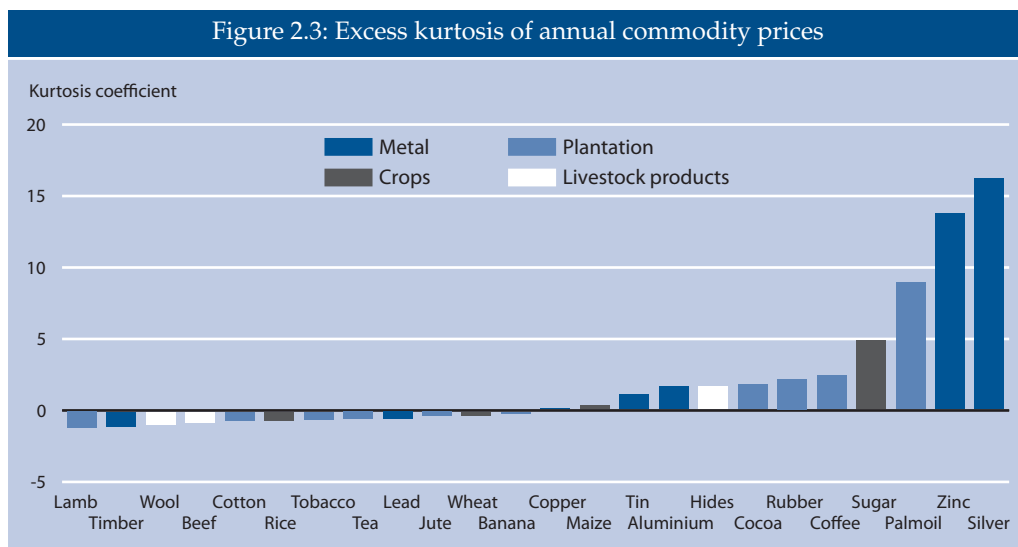
### *Kurtosis*

The excess kurtosis of a distribution conveys the thickness of its tails, i.e. the preponderance of extreme values. A positive (negative) excess kurtosis will imply a distribution that is fat (thin) tailed, while a value close to zero will indicate a distribution with tails similar to those of the normal distribution.

Excess kurtosis is usually found in equity markets, which can exhibit high or extreme values. This is also the case for commodity markets. The storage commodity model again helps explain this phenomenon. Indeed, when inventory levels are extremely low or even zero, prices can spike very high. Thus, it is the alternation of frequent periods of low prices with rare periods of turbulence that leads to a significant price kurtosis.

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<sup>5</sup> Say a 2.5 percent quantile



Source: Own calculations based on Pfaffenzeller et al. (2007) data.

Figure 2.3 shows the excess kurtosis of commodities sample. Positive excess kurtosis is found in half of the sample, while the second half exhibits negative excess kurtosis.

## Conclusion

The aim of this chapter was to provide a description of the time series properties of commodity prices. For this purpose, focus was made on the key indicators of a price distribution – mean, volatility, skewness and kurtosis – both empirically and theoretically.

Regarding the first indicator – the mean – I focused mainly on how price series evolve around their means. The key issue here is whether prices tend to be stationary and revert to their mean, or instead follow an unpredictable random walk. I found that in theoretical studies, this issue remains ambiguous as there are arguments both in favour and against the random-walk hypothesis. This uncertainty is also present in empirical studies which produce contradictory findings. The results of empirical tests depend not only on the type of commodity investigated, but also on price frequency and even on the type of test used. Thus, I conclude that this uncertainty is a significant concern, as one cannot establish whether apparent trending behaviour is a permanent trend generated by a deterministic component, or rather an artifact owing to a stochastic trend. This implies that there is uncertainty about the persistence of shocks, and scholars cannot confidently predict whether shocks will be permanent or transitory.

Secondly, I discussed the importance of volatility and its persistence in commodity prices. I looked at studies using the GARCH model which is widely used in the context of financial markets. However, there are important features that distinguish agricultural from financial markets. A striking difference is that in agricultural markets, unexpected price increases tend to increase the variance, while in financial markets this leads to decreases. I further highlighted a few issues when constructing a price series to test for volatility, problems owing to the so-called Samuelson effect.

Thirdly, it was seen that commodity prices have an asymmetric distribution. While asymmetry is theoretically consistent with the storage model, the distribution of the asymmetry coefficient among commodities seems to contradict the model's predictions. In fact, while asymmetry is theoretically linked to the storability of a commodity, there was no clear link between asymmetry and storability in the sample. I also found contradictory results when examining price kurtosis. Indeed, the storage model predicts a positive kurtosis, which is found, however, in only half of the sample, the second half exhibiting negative kurtosis. These two results show that standard methods for modelling should be slightly modified as they are based on the assumption of normal errors. Secondly they indicate that causes of both asymmetry and kurtosis of prices, though commonly encountered, are still not fully understood.

The analysis presented and the literature surveyed in this chapter suggests that a fundamental understanding of commodity prices – especially between theory and empiricism – is lacking, which should be kept in mind in policy-design.

Firstly, one can see that many of the empirical results do not align themselves with the predictions of the storage model. Furthermore, it has been challenging to find common time series properties even among commodity groups that share many production features. The second issue concerns price persistence. It can indeed be seen that many prices appear to be non-stationary, or at least highly persistent, a fact that seems to be at odds with the mainstream storage model. This makes policy-making a difficult task, as predicting persistent prices lead to wide forecast error intervals that are of little use in practice. This suggests that Deaton's statement about the inadequacy of understanding of commodity prices, made almost a decade ago, remains valid.

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