

SAFEGUARDING FOOD SECURITY IN VOLATILE **GLOBAL MARKETS**



EDITED BY
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Safeguarding food security in volatile global markets

Edited by Adam Prakash

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Chapter 14

The economics of information and behaviour in explaining excess volatility

Adam Prakash and Matthieu Stigler¹

So long as economists were content to regard the economic system in a static fashion, it was reasonable to treat it as a self-righting mechanism... As soon as we take expectations into account, the stability of the system is seriously weakened... it is henceforth not at all surprising that the economic system of reality should be subject to large fluctuations. (Hicks, 1939)

Economic agents are continuously required to make decisions in the face of a future that is not yet known. Therefore, expectations play an essential role in the determination of current economic variables. On the other hand, the expectations that agents hold at any time are determined by the information they have at that date on the economic system, in particular on its current and past states. Observed economic processes are thus the result of a strong and complex interaction between expectations of agents involved and the actual realizations of economic variables (Grandmont, 1977). Consequently, the evolution and stability of the price system will depend upon the rules and processes of expectations formation and revision used by agents (Radner, 1991).

The notion of the price system as an information entity was alluded to in Chapter 1. In this chapter, the behavioural dimensions of markets are explored with respect to how expectations are formed when agents possess diverse information and how this might generate excess volatility. There is a host of competing theories of how expectations and trading behaviour influence prices and volatility. Even though many may possess intuitive appeal, the data that would support theoretical mechanisms underpinning behaviour are by and large unobservable, such as expectational processes. Similarly, the notion of "fair" or "fundamental value" which is needed to assess how excessively volatile prices are cannot be deduced. Finally, the electronic marketplace produces instantaneous audit trails of order flow and transactions that are segregated by types of traders, but these are not furnished (FAO, 2010: *special feature*).

As a consequence, measurement issues have thus largely confined the testing of theory to the experimental realm rather than the empirical realm. While these theories show that active trading allows markets to efficiently incorporate information about demand and supply fundamentals, if fundamentals-based trading does not take place, futures markets can act as a distorting lens; they can distort agricultural prices and lead to bubble-type phenomena.

Moreover, traders rely on information about current market fundamentals and on forecasts of future market conditions, but, as Chapters 3 and 4 have shown, there is considerable uncertainty in the sources of shocks, which encumbers signal extraction in

¹ Statistics Division (FAO).

a noisy environment. Traders are required to formulate their expectations about price movements based on partial signals and uncertain data. By focusing on a limited number of available signals, there is a plausible risk of herding by following the behaviour of others, or simply basing trading decisions on trend extrapolation.

Efficient markets, excess volatility and bubbles

The efficient market hypothesis (EMH) has been one of the cornerstones of modern economic theory. EMH has widely been applied in finance and commodity models to explain prices dynamics in competitive markets. Basically, the theory requires agents to form expectations rationally, and whenever new information emerges (e.g. new harvests or stock forecasts) they update their expectations appropriately. Importantly, all agents need not be correct in forming expectations, some may overreact and some may under-react, but as a whole the market is always "right". On average, responses are randomly normally distributed with the result that market prices cannot be readily exploited to earn excess profits. This implies that expected price movements $E[P_{t+1}]$ are governed purely by new information I_t with prices following a random walk:

$$E[P_{t+1}|I_t] = P_t E[P_{t+1}|I_t] = P_t \quad (1)$$

In a series of seminal papers, Grossman (1976, 1995) and Grossman & Stiglitz (1976, 1980) identify a paradox within the rational expectations framework and its notion of "fully revealing information equilibria". The authors emphasize the conflict between the efficiency with which markets embody information and the incentives to acquire information: prices cannot perfectly reflect all available information, because if this was so, agents who expend resources in collecting information would receive no return for their efforts, rendering trade redundant.

To resolve this paradox without loosening the tenet of the EMH, Grossman and Stiglitz introduce agents who possess different information traits: those who are informed and those who are uninformed, together with the addition of "noise" to produce "partially" rather than fully revealing equilibria.

As illustrated in Box 14.1, Grossman (1995) theorizes that there are incentives to directly collect information, to help forecast the dynamic feasibility of people's plans, and to attempt to profit from their inability to realize their plans. The attempts to profit from collecting information about such feasibility enhances the informativeness of the price system and helps the plans cohere by the transmittal and aggregation of information. In this setting, the rational-expectations equilibrium price aggregates disperse private information, while avoiding perfect revelation due to unobservable supply shocks.

Box 14.1: Informational dimensions of the price system

The Transmission of information by prices: Consider the price p_t of a commodity X , which possesses a random *ex post* return, r_t where $r_t = p_t - p_{t-1}$. The level of r_t depends on a random variable, η_t which can be observed at a cost at $t-1$, and another unobservable random variable ε_t :

$$r_t = \eta_t + \varepsilon_t \quad (2)$$

Where η_t and ε_t are independent normally distributed variables. The quantity η_t can be regarded as a measurement of r_t with error, so that knowledge of η_t does not eliminate the risk associated with the

commodity. The demand for X by agents with information on η_t , $X_{D,t}^i$ will depend both on p_t and the value of η_t :

$$X_{D,t}^i = X^i(p_t, \eta_t) \quad (3)$$

Given $\partial X_{D,t}^i / \partial \eta_t > 0$ and $\partial X_{D,t}^i / \partial p_t < 0$ and introducing the demand by uninformed agents denoted as $X_{D,t}^u = X^u(p_t)$, equilibrium requires:

$$\lambda X_{D,t}^i(p_t, \eta_t) + (1 - \lambda) X_{D,t}^u(p_t) = X_{S,t} \quad (4)$$

where $X_{S,t}$ is the supply of the commodity and γ represents the fraction of informed agents trading in the particular market. Uninformed traders observe only p_t , but from p_t they may be able to infer η_t . To see this, assume that $X_{S,t}$ is fixed. Uninformed traders can infer that a higher p_t is associated with a higher η_t , as an increase in η_t increases $X_{D,t}^i$ and hence p_t . In the absence of any other stochastic elements in the model, the conditional distribution of r_t given p_t is the same as the conditional distribution of r_t knowing η_t . Consequently, the price system conveys all the information from the informed to the uninformed.

The Aggregation of information by prices: Consider a market for a commodity, in which the price at period $t + 1$, p_{t+1} depends on the information received by n informed traders ($n > 1$). Assume that the i th trader observes some signal, ϑ_i where $\vartheta_i = p_{t+1} + \varepsilon_i$. The stochastic term ε_i prevents any single trader from ascertaining the true signal from p_{t+1} . The current price p_t is a function of the observed information of the different traders, $p_t(\vartheta_1, \vartheta_2, \dots, \vartheta_n)$ and reveals more information to each trader than each is initially endowed with. That is, the price system aggregates all the market's information in such a manner that p_t is a sufficient statistic for the unknown value of p_{t+1} . A trader who divests no resources in gathering information can achieve a similar return to those traders who pay for ϑ_i . In a similar vein, a trader who purchases ϑ_i and then observes $p_t(\vartheta)$ where $\vartheta = \vartheta_1, \vartheta_2, \dots, \vartheta_n$, finds that ϑ_i is redundant; $p_t(\vartheta)$ is superior to ϑ_i , reflecting all necessary information, and can be obtained without cost.

Noise: The above asserts that the price system aggregates and transmits information perfectly, and equilibrium is in this instance fully revealing: price reveals to each trader the information acquired by all traders. However, under conditions in which either the demand or supply is stochastic, a rise in price might again be owing to a higher η_t , but a higher p_t might also arise from an increase in $X_{D,t}^i$ or a fall in $X_{S,t}$. Hence, for any observed p_t there is a distribution of possible values of η_t

Source: Grossman & Stiglitz (1980).

Yet another controversy was also identified with the EMH, but this time the issue concerned empirical observation. Shiller (1981) and Shiller (1990) provided statistical evidence showing volatility in the equities market to be "excessive" over and above that which is predicted by efficient market theorists. Despite their claim that the EMH can explain sudden and unexpected price movements as a result of new information (e.g. expected earnings), Shiller's argument is that fluctuations are far too large - some five to thirteen times higher - to be attributable to mere changes in information. He postulates that the observed excess volatility is a result of psychological beliefs that exert a greater influence on the market than do economic fundamentals.

There is now substantial evidence that stock prices are more volatile than should be expected if they were equal to the present value of a rational expectation of future dividends (Gilles & LeRoy, 1991; Bulkeley & Harris, 1997). However, there is little consensus about why prices appear to be excessively volatile. In addition to Shiller's thesis, Bulkeley and Harris survey a number of competing explanations: one explanation, consistent with the EMH, is the argument that there may be rational bubbles in stock prices (West, 1988; Flood,

1990) or that price movements may be explained by market frictions (Weil, 1989). The authors hypothesize that somewhere in between these two extremes is the possibility that markets may incorporate new information into prices, but not in expectations of future returns as agents simply use irrational and inappropriate mechanisms to forecast returns by overreacting to current information (see deBondt & Thaler, 1985).

If expectations, rational or otherwise, are driving departures from fundamental values, a major problem in testing competing hypotheses concerns the fact that expectations cannot be observed, as discussed in Box 14.2.

Box 14.2: Limitations in identifying bubbles

At this stage in the development of economic theory, the rational bubble hypothesis can be regarded as devoid of empirical content. The main reasons are that we do not observe expectations, and we cannot exclude other, entirely rational, non-bubble alternative explanations of prices. The theory "provides no clue" about the conditions initiating or terminating bubbles. One reason that a bubble hypothesis is difficult, if not impossible, to test is that expectations are measured relative to some maintained hypothesis and, with rational expectations, exploit all of the information that is relevant according to the maintained hypothesis. Bubble phenomena are what remains unexplained by the hypothesis. In this sense, bubbles are a name assigned to phenomena that may be explained by an alternative hypothesis.

There are other ways of modelling expectations that remain consistent with rational expectations and full use of available information but do not involve bubbles. Suppose that the process governing asset prices or other variables is:

$$x_t = A_t e^{\alpha t} u_t \quad (5)$$

where t is time, A , α and u are random walks with zero mean and constant variance.

Instead of a single random shock with zero mean and constant variance, let's assume that asset prices (or other variables) are subject to three types of shocks, each with zero mean. First, there are transitory, random deviations around a fixed trend or stationary value (u_t). This is the familiar random walk. Second are permanent changes in level, ΔA_t , and third are permanent changes in growth rates, $\Delta \alpha_t$. Investors cannot observe the errors directly, and cannot separate them initially and for some time after. They can only infer from a series of observations whether the level has changed permanently, thereby temporarily altering the measured growth path. A single observation does not permit the investor to know whether a current change is a temporary deviation that will revert to the prior mean, a persistent change that permanently changes the mean level but not the growth rate, or a permanent change in the growth rate.

If the variance of the transitory component is relatively large, several observations are required for modest confidence that a change in the mean is permanent. And additional observations may be needed to decide whether the mean will continue to change, i.e. that the observed change is a change in growth rate and not a permanent change in level. Series like profits, stock prices and productivity are examples of relatively noisy series. After five years of productivity growth above the average or trend of the previous twenty years, we can only guess whether there has been a permanent change in trend productivity growth and profits, in one but not the other, or in neither. The length of time needed to gain confidence about the permanence of the change depends on relative variances of transitory and permanent shocks.

As a model of asset prices, this model differs from the bubble model. It views the investor as using incomplete and noisy information to infer the future path of profits and asset prices. Investors or speculators do not trade mainly on noise. They try to infer future patterns or trends and they pay for the services of professional letter writers and advisers, or the services of professional investors, who use different types of models and procedures to reduce not just risk but uncertainty. They hire economists to forecast the future because, despite the mediocre record of such forecasts, they are the best forecasts available.

Unlike the rational bubble model, in this model expectations are based on imperfect knowledge of future fundamentals such as profits. Unlike the irrational exuberance model, systematic changes in fundamentals are critical. Investors and speculators may grossly overestimate (or underestimate) future profits and dividends, but they rely on their imprecise knowledge of the future and correct, or perhaps over-correct, when new information becomes available.

Source: Adapted from Meltzer (2002).

Rational bubble models assume that in spite of the market's full cognizance of an asset's fundamental worth, investors may be willing to pay more than this value. If the rational expectation of future price growth is large enough to assure a normal rate of return, a rational bubble may be perpetuated. However, in order for the bubble to be sustained, price must grow at a rate faster than perpetual returns.

Shiller (2003) also depicts a simple and intuitive feedback mechanism that permits (irrational) bubbles. His "irrational exuberance" model of behaviour posits that if prices of an asset begin to rise, positive returns by incumbent investors fuels the spread of over-enthusiasm in the market, attracting public attention. New (uninformed) investors then enter the market and start to bid up prices. As investors extrapolate price rallies into the future, it feeds the expectation of further price increases, drawing in new players. In describing Shiller's bubble model, Lansing (2007) states "the market's meteoric rise is typically justified in the popular culture by some superficially plausible 'new era' theory that validates the abandonment of traditional valuation metrics". However, just as upward price motion can be set forth, the onset of pessimism and can lead to a collapse in Shiller's bubble.

At the heart of Shiller's feedback model is the prediction that investors chose naive price extrapolation rules over above fundamental-based rules. In a similar vein, Lansing (2006) shows that by "locking-in"² to an extrapolative forecast rule will likely follow if other investors are following the same approach. From the viewpoint of an individual investor observing an upward sustained trend, switching to a fundamentals-based forecast would appear to reduce forecast accuracy, so there would be no incentive to do so.

In addition to positive feedback trading and trend extrapolating, there is a host of other behavioural theories that support the rejection of the EMH in explaining excess volatility. Most concentrate on irrationality on the part of uninformed traders who base trade on current and past price movements *vis-à-vis* their informed counterparts who are more cognisant of fundamentals in their transactions.

Uninformed traders observe price movements but cannot distinguish whether signals relate to noise or changing fundamentals. Hence, without acquiring information, they run the risk of incorporating noise signals into their trading strategy and perpetuating the broadcast across the market. Uninformed traders are prone to following "momentum strategies"³ of buying commodities that have experienced rising prices and selling those that have underperformed.

If one can detect momentum trading, changes in positions can be anticipated offering arbitrage possibilities. De Long et al. (1990) report that traders employed by financial institutions will engage in momentum trading to meet their institutions' short-term

² Lansing (2006) uses the concept of "locking-in" as an irrational choice among competing technologies, as chance events or "historical accidents" may cause people to initially choose, and then stick with, an inferior technology. Extrapolative rules can be viewed as an inferior technology because market predictions would improve if all investors could be induced to switch to a fundamentals-based approach.

³ However, subsequent research by Crombez (2001) that by augmenting factor pricing models with additional factors, momentum can be observed even with perfectly rational traders.

performance targets, even if doing so implies going against signals from long-term fundamental supply and demand factors.

Barberis et al. (1998) demonstrate that current good (bad) news has power in predicting positive (negative) returns in the future. Evidence shows that over longer horizons, equity prices overreact to consistent patterns of news pointing in the same direction. This is in support of Kahneman and Tversky's (Kahneman & Tversky, 1979) over-reaction hypothesis that individuals tend to overweigh recent information and underweigh past information, which is in violation of the Bayesian principle that predictions must be moderated by consideration of their probability of occurrence.

Daniel et al. (1998) propose a unified theory of "overconfidence, self-attribution, and security market under- and over-reactions" based on investor psychology to explain anomalous departures from the EMH. Their theory is premised on two behavioural attributes. The first is that traders are overconfident about their ability to evaluate sentiment by overestimating the importance of their private information signals. The second is that confidence changes in a biased fashion as a function of their decision outcomes. The authors show that the first premise implies overreaction to private information arrival and under-reaction to public information arrival, giving rise to excess volatility in prices, while the second premise leads to momentum-type effects.

Relevance to agricultural commodity markets

It may appear confounding in relating the relevance of the foregoing discussion with price behaviour in agricultural markets. Traditionally, agricultural commodities have been looked upon as a poor investment because, owing to the tendency of their prices to fall historically in real terms - as a result of productivity growth and falling marginal costs - they have a negative rate of return. Consequently, prices of commodities have not had the propensity to keep up with overall inflation.

However, as discussed in Chapter 3, agricultural commodities (including food products) have recently attracted investment as a store of wealth that potentially varies inversely with the inflation/deflation effects on monetary assets. In other words, as equity and bond returns decrease, there is a tendency for commodity returns to rise as inflation increases. Investors have thus identified commodities as an "asset class" and see portfolio diversification advantages in adding a proportion of commodity futures to equity and bond portfolios. They set out to replicate an index or a sub-index of one of these as shown in Table 14.1.

The influx of money towards tracking these indices has experienced enormous growth: in the period from the end of 2003 to March 2008, investments in commodity index funds increased from USD 13 billion to USD 260 billion, and the prices of the 25 commodities that compose popular indices (the Standard & Poor's Goldman Sachs Commodity Index and the Dow Jones - AIG Commodity Index) had risen by an average of 183 percent in those five years.⁴ However, such investment in commodity derivatives does not pay interest, rents, dividends, or entitle the holder to a share of a company's future cash flow. Therefore, the only return that can be expected is a favourable change in the price of the contract⁵ and for this reason, buying commodities futures is considered speculation and not investment (Masters & White, 2008).

⁴ See Shedlock: "Quantifying Commodities Speculation, MISH'S Global Economic Trend Analysis" <<http://globeconomicanalysis.blogspot.com/2008/05/quantifyingcommodities-speculation.html>>.

⁵ After the cost of carry is deducted.

Table 14.1: Traded commodity indices

	Reuters/ Jefferies CRB Index (RJ/CRB)	Rogers International Commodity Index (RICI)	Dow-Jones- AIG Commodity Index (DJAIG)	S&P Goldman Sachs Commodity Index (SPGSCI)	Deutsche Bank Liquid Commodity Index (DBLCI)
Launch date	1957, rev. 2005	1998	1998	1991	2003
New York Board of Trade (NYBOT)				Chicago Mercantile Exchange (CME)	
No. Components	19	36	19	24	6
Agriculture	8	18	6	8	2
Livestock	2	2	2	3	0
Agriculture weights (%)					
2005				11.16	
2007		31.9	30.2	13.1	22.5
2008	34	31.9	28.43	12.58	22.5
2009	34	31.9	29.23	17.65	22.5
2010			29.5	13.7	
Livestock weights (%)					
2005				4.66	
2007		3	9.2	5	
2008	7	3	8.5	4.16	
2009	7	3	6.65	6.37	
2010			7.4	5.24	

Source: Zawojka (2010).

As investment interest in commodities rises, it is natural to ask whether shocks from conventional asset markets rather than underlying commodity market fundamentals may weaken the diversification value of commodities (Silvennoinen & Thorp, 2010). The authors assert that macroeconomic fundamentals may increase commodity futures correlations with other assets via common drivers such as interest rates and spreads, and expectations of future world growth. Interestingly, Tang & Xiong (2010) have shown that agricultural commodities have begun to behave more and more like the energy commodities they are indexed with.

Indeed, index traders behave like noise traders: they change their total positions in commodities based on information signals relating to other asset markets of no relevance for

commodity markets which can give rise to momentum trading strategies. In addition, index traders, though maintaining a commodity's predetermined weight in the index, may change the composition of their positions in response to price changes for different commodities. This makes it difficult for other traders to judge whether market prices are changing because of the position changes of the noise traders or as a response to new information about market fundamentals (UNCTAD, 2009).

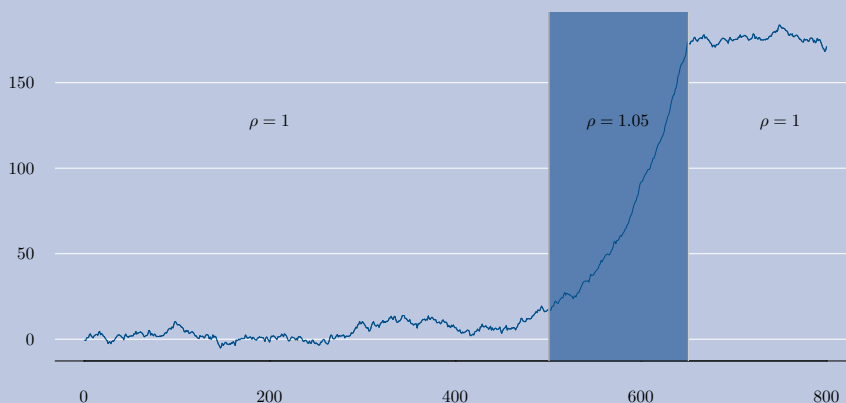
Index traders may also take position changes that are so large relative to the size of the market that they move prices. This is commonly referred to as the "weight-of-money" effect. Again, by assuming index-weighted positions across commodity portfolios, large positions can present weight-of-money risks.

In the face of short-run price inelasticity in both production and consumption, physical adjustment mechanisms of markets are weak and can magnify weight-of-money risks. This is particularly true when physical inventory levels fall, in which case the relevance and determinacy of expectations based on longer-term fundamental factors sharply declines (UNCTAD, 2009). "This indeterminacy allows weight of the speculative money to determine the level of prices" (Gilbert, 2008). As a consequence, the traditional mechanisms - efficient absorption of information and physical adjustment of markets - that have normally prevented prices from moving away from levels determined by fundamental supply and demand factors have become weak in the short term, thus heightening the risk of speculative bubbles occurring.

Box 14.3: A bubble in the wheat market?

Statistically, the notion of a bubble is based on the properties of explosive time series. This necessarily implies the root of an autoregressive (AR) process being higher than the value of one, which reflect compounded over-reaction in past values. This can be seen from Figure 14.1, which shows the path of a series where the AR(1) coefficient is unity in the first period, 1.05 in the second and unity again in the third period. A very small change in the AR(1) coefficient is shown to induce a very large change in the dynamics of the data generating process.

Figure 14.1 Simulated series with explosive root



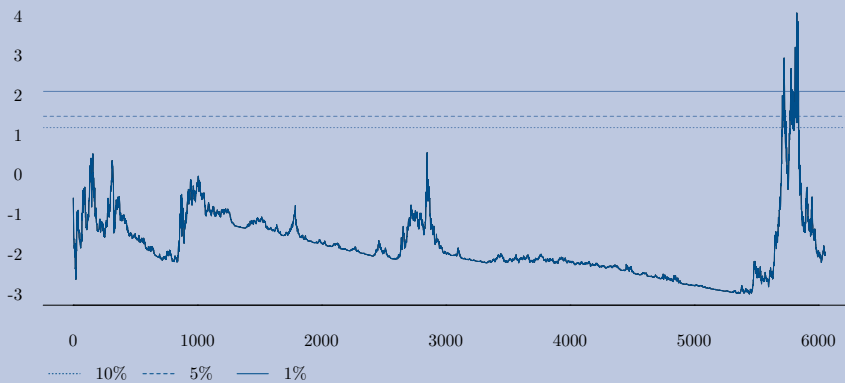
An influential study linking bubbles and statistically explosive behaviour is provided by Diba & Grossman (1987) who investigated bubble formation in asset prices by applying unit root tests to differenced prices and dividends, as well as in cointegration tests. The rationale of applying these tests on differenced values is that according to the authors, if a series is explosive, a unit root test

would not be rejected: not only for the levels of the series, but also for the differenced series. Those results, however, were challenged by Evans (1991), who showed by simulation that this procedure had very low power in the case of a periodically collapsing bubble.

To address Evan’s criticism, the literature has now focused on models with AR dynamics that change over time. Different models are available for this purpose. Waters (2008) for instance uses a stochastic explosive root framework, while Hall et al. (1999) employ Markov-Switching unit root tests. Furthermore, Phillips et al. (2009) propose a simple recursive unit root test.

We focus on wheat futures prices from CME with a constant maturity of 100 days. The data are shown in Figure 14.2 and are derived on the methodology discussed in Chapter 2 for constructing synthetic futures series. We then perform the recursive ADF test as well as the Markov-Switching test. Turning to the former, we employed the procedure outlined in Phillips et al. (2009) who provide a test based on the recursive ADF test statistic, denoted sup-ADF. Results are shown in the Figure 14.2 below, where it is seen that the null of a random walk is strongly rejected towards explosive behaviour. Interestingly, the period of explosive behaviour corresponded quite closely to the 2006-08 event (starting end of August 2007, finishing 3-4 April 2008).

Figure 14.2 Moving DF test on wheat futures prices



To ensure the robustness of these results, we employ a second method advocated by Hall et al. (1999). These researchers used Markov-Switching AR processes, allowing a distinction between different regimes (for more information see Chapter 16). Again, there appears evidence in favour of explosive behaviour as shown in the following table:

Table 14.2 Markov-switching AR model

	Estimate	Std. Error	t value	Pr(> t)
$const_1$	11.01	0.38	28.67	< 2.2e-16
$const_2$	-10.85	0.39	-28.11	< 2.2e-16
ρ_1	0.97	0.00	940.37	< 2.2e-16
ρ_2	1.03	0.00	1003.96	< 2.2e-16
σ	5.83	0.06	101.68	< 2.2e-16
p11	0.55	0.03	17.37	< 2.2e-16
p22	0.49	0.03	17.54	< 2.2e-16

It is seen that the AR coefficient in the second high regime (ρ_2) has a value of 1.03 and there is a high probability (49 percent, see parameter p22) of remaining in that regime.

Econometric evidence the role of non-commercial speculation

One of the main reasons that opinions are so divergent about the role of commodity investment in generating excess volatility and prices departing from fundamental value has to do with the econometric methods used to substantiate claims. The primary tool at the econometrician's disposal, which has been applied prolifically in the debate, is the Granger causality test (see Box 14.4). For instance Gilbert (2009) found evidence of a significant relationship between index fund trading activity and returns in several commodity markets. By contrast, Irwin & Sanders (2010) applied the test framework and concluded that there is "mild evidence of a negative relationship between index fund positions and the volatility of commodity futures prices, consistent with the traditional view that speculators reduce risk in futures market and therefore lower the cost of hedging".

Because the Granger causality test is prone to model selection bias as well as small sample bias, it is not surprising that results from these tests can be used to reject competing hypotheses. In addition, Pagan & Schwert (1990) and Phillips & Loretan (1990) have shown that transaction data on commodity exchanges are far too volatile for Granger-type tests to be meaningful.

Box 14.4: Testing the influence of variables - Granger causality

In a seminal paper, Granger (1969) developed a time-series data based approach to assess the directional influence of one variable to another, which has since become known as Granger (non-)causality. The approach is simply the following: x is a cause of y if it is useful in forecasting y . "Useful" here means that x is able to increase the accuracy of the prediction of y with respect to a forecast, considering only past values of y . Formally, given an information set Ω_t with the form $(x_t, \dots, x_{t-j}, y_t, \dots, y_{t-1})$, one can say that x_t is Granger causal for y_t with respect to Ω_t if the variance of the optimal linear predictor of y_{t+h} , based on t , has smaller variance than the optimal linear predictor of y_{t+h} based only on lagged values of y_t , for any h . Thus, x Granger-causes y if and only if $\sigma_1^2(y_t: y_{t-j}, x_{t-i}) < \sigma_2^2(y_t: y_{t-j})$, with j and $i = 1, 2, 3, \dots, n$ and σ^2 representing the variance of the forecast error.

In spite of its name, true causality cannot be inferred from Granger causality testing. If both x and y are driven by a common third process with a different dynamic order, inference from bi-directional tests could be reversed.

An enquiry into the destabilizing impact of momentum traders

In technical analysis, a charted price trend resembles a cup with a handle. It occurs when the price of a security reaches a high and then takes a U-shaped downtrend and uptrend. This is the cup. When the price approaches its previous high, investors who bought at or near the previous high tend to sell their shares, which causes the price to drop slightly. This is the handle. After the handle "completes", the price of the security tends to increase significantly. Technical analysts view cups and handles as buy signals under the correct circumstances.⁶

As discussed above, the causal link between speculative activity and price movements has been criticized on grounds that causation might be subject to reversal. However, the traditional view that increased speculation should bring about price stability might be questioned given the influx of new types of traders on organized markets. In this section,

⁶ Definition on Internet <http://financial-dictionary.thefreedictionary.com/Cup+and+Handle>.

we investigate the issue more closely, examining how the interplay between so called technical/chartist and fundamental traders can potentially have a role in influencing prices.

It is important to clarify the different connotations typically associated with the term “speculation”. A distinction that is usually made is based on the United States’ Commitment of Traders (COT) report, in which commercial and non-commercial traders are separated out. This distinction has potentially important implications for price discovery and underpins the theoretical literature on price determination, namely the competitive storage model (Williams & Wright, 1991 and Deaton & Laroque, 1992). The underlying notion of this model is that storage decisions by commercial traders smooth prices by taking quantities off markets when harvests are abundant. In such instances, speculation is found to have a stabilizing effect. Price spikes occur when speculation has ceased and there are stock-outs.⁷

A further distinction that was made at the beginning of this chapter and in Chapter 3 concerns fundamental and technical (or momentum) traders. Fundamental traders are defined as traders with a deep knowledge of the market, which allows them to form an informed judgment on fundamental value. Hence, when traded prices depart from perceived fundamental value, fundamental traders expect that the price will revert to its fundamental value and hence will sell (buy) when the price is too high (low). In contrast, technical traders by definition trade according to rules that mostly amount to inferring statistical tendencies and anomalies from the data. Typically, they tend to reinforce prevailing market trends.

There is a large amount of evidence that confirms the active participation of technical traders on markets and an equally sizeable body of theoretical literature on their influence (see Easley et al., 2008). As early as 1950s Working (1953) developed a model in which traders are divided into two groups: those who are well-informed and skilful and those who are ill-informed and unskilled. Zeeman (1974) presented a model of catastrophe, theorizing how volatility could occur in an environment with fundamentalist and trend-following technical traders when the latter are sufficiently influential to impact markets. Day & Huang (1990) and De Grauwe et al. (1993) have shown that chaotic dynamics can arise in models with fundamentalists and chartists when the latter exercise sufficient influence. Farmer & Joshi (2002) find that technical traders can amplify incoming noisy information, alter its distribution, and induce temporal correlations in volatility and volume. Others, such as Chiarella et al. (2008), Taylor & Allen (1992) and Nofsinger & Sias (1999) show similar influence of technical analysis.

De Long et al. (1990) and De Long et al. (1990) demonstrate that noise traders occasionally out-perform fundamentalist traders. Du et al. (2009) employ a sophisticated stochastic volatility model to show that speculation, as measured by the ratio of non-commercial positions to commercial positions, has important impacts on the volatility of oil, and incidentally that there are significant volatility spillovers from oil into maize.

Models

An empirical test of the hypothesis of fundamental versus technical traders applied on commodity markets can be found in the work of Reitz & Westerhoff (2007) and Reitz & Slopek (2009). They model explicitly the two types of agents, under the notion that fundamental traders become more active when the deviation of price from its fundamental value is large.

⁷ This is contrary to the idea of hoarding, which through storing the commodity in expectation of a price increase, may contribute to price upswings.

The demand by the momentum traders, D^C is modelled as following:

$$D_t^C = a(P_t - P_{t-1}) \quad (6)$$

where the coefficient a indicates how much the momentum traders believe the trend will continue. On the other hand, the demand of fundamental traders, D^F , is assumed as:

$$D_t^F = b(F - P_{t-1}) \quad (7)$$

where F is the fundamental value of the commodity. Fundamental traders are assumed to know the intrinsic value of the commodity, and to intervene on the market when the price is drifting too far from this value, i.e. selling an over-valued commodity, buying an undervalued one. Contrary to momentum traders, their behaviour will have a stabilizing impact on the prices.

Reitz & Westerhoff (2007) add an interesting feature to the model by assuming that the effect of fundamental traders will not be fixed, but will increase when the spread between the fundamental and actual value of the commodity increases. In other words, the more the price departs from its fundamental value, the more traders will follow a fundamental strategy. To model the fact that the variable's impact increases depending on its own level, they use the Smooth Transition Autoregressive (STAR) model (Terasvirta & Anderson, 1992), with the transition function W_t , indicating the impact of fundamental traders in the market⁸, that evolves accordingly to the logistic function:

$$W_t = \frac{1}{1 + \exp\left(-c \frac{|F - P_t|}{h_t}\right)} \quad (8)$$

W_t takes values between 0.5 and 1. c is the so-called slope parameter of the logistic function, which indicates how smooth the transition from 0.5 to 1 is. Figure 14.3 shows the value the value of W_t for different values of c .

The value h_t corresponds to the conditional volatility measure obtained from a GARCH model:

$$h_t = \beta_0 + \beta_1 \epsilon_{t-1}^2 + \beta_2 h_{t-1} \quad (9)$$

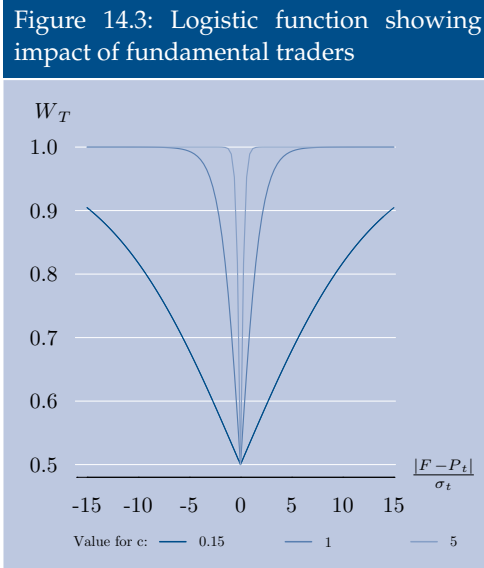
With the addition of the GARCH equation, the model is now a STAR-GARCH model, introduced by Lundbergh & Terasvirta (1998). An important difference, nevertheless, is that Reitz & Westerhoff (2007) introduce the GARCH term in the mean equation, which makes it a generalization of the ARCH-in-mean (ARCH-M) model of Engle (1982). This can be interpreted as the effect of volatility on perceptions of the fundamental gap. Indeed, in times of high volatility the spread is reduced, and this can be viewed as the difficulty in distinguishing fundamental signals in periods of high volatility.

The final version of the model is obtained by assuming that the evolution of the price is given by⁹:

$$P_{t+1} = P_t + d(D_t^C + W_t D_t^F) + \epsilon_{t+1} \quad (10)$$

⁸ This cannot be properly interpreted as a percentage of fundamental traders, as the ratio of momentum traders is constant in their model.

⁹ Note that the authors use ϵ_t instead of ϵ_{t+1} , which is obviously a mistake.



where d is interpreted as a price adjustment coefficient. Inserting the previous equations into (10) leads to:

$$P_{t+1} = P_t + ad(P_t - P_{t-1}) + \frac{bd(F - P_t)}{1 + \exp\left(-c\frac{|F - P_t|}{\sigma_t}\right)} + \epsilon_{t+1} \tag{11}$$

For the fundamental value F , [Reitz & Westerhoff \(2007\)](#) use the mean of the price series, based on the fact that the series appear to be stationary, while [Reitz & Slopek \(2009\)](#) use Mainland China’s oil imports as a fundamental value in their analysis. The authors apply the model for six commodities, including cotton, soybeans, sugar and rice, and find that the linearity tests in all are rejected and that the coefficient corresponding to bd is significant. They interpret this result as evidence for the presence of fundamental traders, leading them to the conclusion "our model suggest that heterogeneous agents and their nonlinear trading impact may be responsible for pronounced swings in commodity prices".

While innovative, this approach suffers from several drawbacks. Indeed, rewriting equation (11) slightly differently, we obtain:

$$\Delta P_{t+1} = W_t \delta + W_t \beta P_t + \alpha \Delta(P_t) + \epsilon_{t+1} \tag{12}$$

which now corresponds to a STAR version of the usual ADF formulation of the unit root tests, with the smooth effect on the mean reversion and intercept coefficient. Such STAR unit root models have been formally addressed in [Kapetanios et al. \(2003\)](#) and [Sollis et al. \(2002\)](#).

STAR reverting models have been widely applied in different contexts such as testing the purchasing power parity (PPP) hypothesis ([Chortareas & Kapetanios 2004](#), [Cerrato & Sarantis 2006](#)), and for hysteresis in unemployment ([Yilanci, 2008](#)). Modifications where the transition is abrupt (as in threshold models) have also been applied to similar hypotheses ([Bec et al., 2004](#)) and for the interest rate spread ([Bec et al., 2008](#)). In the field of agricultural commodities, the STAR model has been employed in the commodity terms-of-trade debate

Figure 14.4: Prices used in modelling momentum

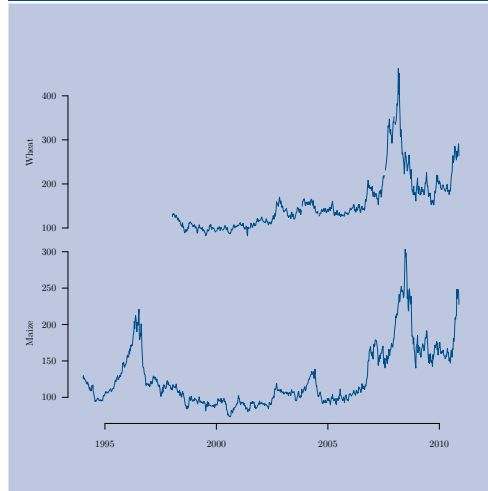


Table 14.3: Summary statistics of wheat and maize price series

	Wheat	Maize	Diff Wheat	Diff maize
Length	662.00	879.00	661.00	878.00
Mean	155.57	126.09	0.21	0.12
Sd	61.69	40.81	9.28	5.71
Kurtosis	1.73	1.44	-0.27	-0.41
Skewness	3.45	1.87	13.88	9.88
AR(1) value	0.99	0.99	-0.09	
DF test stat	-1.35	-1.25	-16.72	-20.33

(Persson & Terasvirta 2003, Balagtas & Holt 2009) and also in the context of spatial price transmission (Goodwin et al., 2008).

It should be noted as early as here that while the results can be interpreted as contributing to the debate on the behavioural dimensions of markets, they may also constitute just a depiction of the nonlinear behaviour of commodity prices. We therefore have concurrent explanations that cannot be disentangled by the present econometric framework.

Data and results

Proceeding nevertheless, we examine behaviour in the CME wheat and maize market. The data, shown in Figure 14.4, are weekly and are taken from FAO. The series start in January 1998 for wheat and January 1994 for maize, and both end in November 2010. Summary statistics of each series are provided in Table 14.3.

Stationarity of the series is examined by applying different unit root tests, including the classical ADF (Dickey & Fuller, 1981), the PP (Phillips & Perron, 1998) as well as the DF-GLS (Elliott et al., 1996), the third test being more efficient in the presence of trends. None of these

tests reject the null hypothesis of a unit root in each series at the 10 percent level, although the PP test statistic has values close to this level. In caution, the ADF and PP tests have known low power in the presence of GARCH effects, and this is highly probable in the weekly data. It could be circumvented by simply using a unit root test that accounts for known GARCH effects, such as by Seo (1999), but testing the null against the true alternative of a stationary but nonlinear process, as identified in Pippenger & Goering (1993), would likely improve inference.

We hence use the unit root of Kapetanios et al. (2003), which has the alternative model very similar to (11):

$$\Delta y_t = \rho y_{t-1} \{1 - \exp(-\theta y_{t-1}^2)\} + \sum_{i=1}^p \gamma_i \Delta y_{t-i} + \epsilon_t \tag{13}$$

There are several issues in applying this test to models of the type (11). These mostly concern the treatment of GARCH effects, the nature of the transition function applied (exponential instead of a symmetric logistic), and the treatment of the deterministic term.¹⁰ Leaving them aside, we conjecture that this test is valid for the case in (11).

Employing different combinations of lag orders and deterministic components, we fail to reject a unit root in the maize series, but find a rejection at the 5 percent level for wheat, giving relevance to (11) for this commodity. As highlighted above, the inclusion of h_t (the GARCH component) into the transition function adds a non-trivial complication, as the traditional two-step estimators (mean and then variance) cannot be applied. By resorting to a joint maximum likelihood method, which combines the STAR and the GARCH attributes, estimation of the so-called hyper parameters of the STAR model (the slope component of the transition function), however, was found difficult to implement, as the likelihood function is potentially flat around the slope estimate.

Results for estimating the full model were unsatisfactory, revealing potentially local maxima. We then attempted a simpler version, where the scaling in (11) is achieved by using long-term variance without estimating the GARCH equation. The results using this method are shown in Table (14.4).

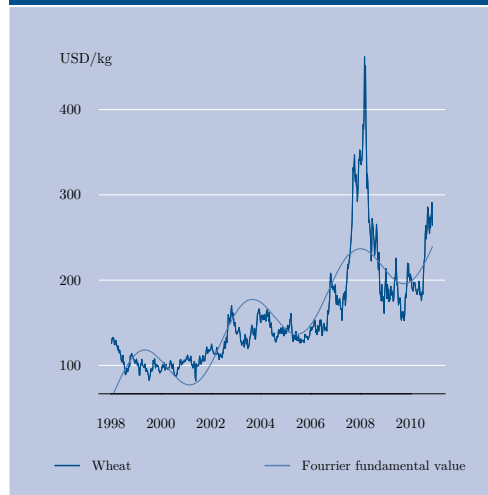
Table 14.4: Parameter estimates from model (11)

	Estimate	Std. Error	t value	Pr(> t)
ρ	0.0085	0.0069	1.23	0.2173
γ_1	-0.0816	0.0393	-2.08	0.0381

It is seen that the coefficient on y_{t-1} is very low, and does not appear to be significantly different from zero. This leads us to question the specification of the fundamental value. The notion of the static mean to represent fundamental value is highly questionable, as this presupposes that the fundamental price of wheat has remained constant throughout the period, and ignores the strong likelihood for disequilibria to be present in a weekly series. However, this in turn then raises an important conundrum, namely what is the “fair value” or “fundamental price” of the commodity? One approach would be to resort to theoretical forms underlying price determination as in Reitz & Slopek (2009). Instead, we assume the

¹⁰ Here, the constant corresponding to the fundamental value is subtracted before, leading to a demeaned version of the test, with $y_t = Y_t - \bar{Y}_t$.

Figure 14.5: Fourier fundamental value in wheat price series



fundamental value can be measured by a moving average. By doing so, we acknowledge that fundamentals evolve, but avoid the risk of using a mis-specified proxy for fundamental value.

The estimation of the moving fundamental value could be done in different ways, for instance by using a simple moving average process or through nonparametric methods. We use a Fourier approximation, retaining the low frequency component. This is motivated by the fact that through a Fourier approximation, one can model multiple smooth breaks as well as a slowly moving deterministic component. In addition, [Enders & Lee \(2009\)](#) provide unit root tests that explicitly take these attributes into account. Therefore, the equation to test for fundamental mean reversion is:

$$\Delta y_t = \alpha(t) + \rho y_{t-1} + \sum_{i=1}^p \gamma_i \Delta y_{t-i} + \epsilon_t \quad (14)$$

with the deterministic component $\alpha(t)$ modelled as follows:

$$\alpha(t) = \alpha_0 + \sum_{k=1}^n \alpha_k \sin(2\pi kt/T) + \sum_{k=1}^n \beta_k \cos(2\pi kt/T) \quad (15)$$

There are two versions of the test, one with a single low frequency (between 1 to 5 say) and another that uses the sum of frequencies. We apply the first test to both the wheat and maize series, and confirm the previous results. Figure 14.5 shows the wheat series with its estimated long-term component that we assume as the fundamental value.

We now estimate the model (11) using the fundamental component from the Fourier approximation.

It is now observed that the parameter corresponding to y_{t-1} is significantly higher than what was obtained in the previous model, where the fundamental value simply represented the mean of the series. The t -value is also definitively higher, indicating significance. Being

Table 14.5: Parameter estimates from model (14) with slow moving average

	Estimate	Std. Error	t value	Pr(> t)
y_{t-1}	0.0723	0.0207	3.49	0.0005
Δy_{t-1}	-0.0696	0.0391	-1.78	0.0754

very close to zero, the smoothness coefficient, however, is surprisingly low, indicating that that the “fundamental spread” tends to be corrected very slowly.

To come back to the main objective of the analysis, that of identifying the impact of fundamental traders on prices, we find that when including nonlinearities to how agents perceive mispricing, “fundamental reversion” cannot be rejected. This phenomenon is likely to come about from the interplay of both types of traders, indicating that fundamental traders have a stabilizing impact, whereas technical traders do not. This conclusion should be taken with caution, as the findings are potentially consistent with competing theories that deal either with real factors or with behavioural dimensions.

Conclusions

This chapter explored the theory and evidence of the behavioural dimensions of markets, especially how expectations are formed when traders possess diverse information and how these expectations might generate excess volatility. It demonstrated that a multitude of competing and conflicting theories of trading behaviour can potentially influence prices and volatility.

Much of what is conjectured has intuitive appeal, but given that data supporting theoretical mechanisms and underpinning behaviour are unobservable, robust empirical evidence is by and large absent. An important, though fairly self-evident point, is that if “fair price” or “fundamental value” could be observed, it would be straightforward to measure the excess volatility in prices.

Nevertheless, the analysis presented in the chapter employed the notion of fundamental value to show how technical traders can shift prices away from equilibrium, underscoring the importance of fundamentals based trading in stabilizing markets. While this “evidence” may contribute to the debate on the behavioural dimensions of markets, the evidence may equally just confirm the nonlinear statistical properties of commodity prices that other theories have a role in explaining, such as the competitive storage model presented in the next chapter.

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