Commodity price cycles and heterogeneous speculators: A STAR-GARCH model

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Abstract

We propose an empirical commodity market model with heterogeneous speculators. While the power of trend-extrapolating chartists is constant over time, the symmetric impact of stabilizing fundamentalists adjusts endogenously according to market circumstances: Using monthly data for various commodities such as cotton, sugar or zinc, our STAR-GARCH model indicates that their influence positively depends on the distance between the commodity price and its long-run equilibrium value. Fundamentalists seem to become more and more convinced that mean reversion will set in as the mispricing enlarges. Commodity price cycles may thus emerge due to the nonlinear interplay between different trader types.

Keywords

commodity markets, chartists and fundamentalists, nonlinearities, STAR-GARCH model

JEL classification

C51, D84, Q11

1 Introduction

One salient feature of commodity prices is their strong cyclical behavior. Exploring the price dynamics of 36 commodities in the period from 1957 to 1999, Cashin et al. (2002) report that the average length of a commodity price cycle, defined as a peak-through-peak movement, is about 68 months. Price slumps seem to last somewhat longer than price booms, i.e. around 39 months versus 29 months. Moreover, the amplitude of commodity price fluctuations may be quite dramatic. The average price fall across all commodities was 46 percent during slumps, while the average price rise across all commodities was 42 percent during booms. Such price swings are, of course, challenging issues for policy makers. Especially for the design of counter-cyclical stabilization policies it is essential to have a comprehensive understanding of commodity price dynamics.

The goal of this paper is to develop a model that may help us to explain cyclical commodity price motion. As is well known, speculators have a marked influence on the evolution of commodity prices. In addition, there exists widespread evidence that both private and professional speculators rely on simple trading strategies to determine their investment positions. For instance, Smidt (1965) reports that a large fraction of the speculators applies price charts to render trading decisions in commodity markets. Similar results are obtained by Draper (1985) and Canoles (1998). Furthermore, Sanders et al. (2000) discerns evidence of positive feedback trading in several commodity markets and Weiner (2002) detects evidence of herding behavior in the petroleum market. Overall, these studies indicate that speculative trading based on technical and fundamental analysis is a major factor for price variation in many commodity markets.

Consequently, we seek to develop a simple commodity market model with technical and fundamental traders. Technical analysts form price predictions by extrapolating historical price trends. Most importantly, if prices increase (decrease), technical analysis suggests buying (selling) the commodity. Such behavior tends to destabilize the markets. Fundamental analysis is based on the assumption that prices converge towards their long-run equilibrium value. For example, if the price is below its fundamental value, fundamental analysis triggers buying signals. Within our setup, the market impact of stabilizing fundamental traders is determined endogenously: The greater the distance between the price of the commodity and its long-run equilibrium value, the more fundamentalists enter the market. In fact, the degree of under- or overvaluation indicates both the mean reversion potential and the chance that a price correction will set in. Since our fundamentalists do not distinguish between under- and overvaluation the structure of the model is entirely symmetric. As a result we are dealing with strong and persistent misalignments in commodity markets but do not address asymmetries like differing durations of booms and slumps.

Using a STAR-GARCH estimation procedure and monthly data for cotton, soybeans, lead, sugar, rice and zinc in the period from 1973-2003, we find strong support for our setup. All coefficients are statistically significant and of the correct sign. Remember that the family of smooth transition autoregressive (STAR) models, developed by Teräsvirta and Anderson (1992), Granger and Teräsvirta (1993) and Teräsvirta (1994), implies the existence of two distinct regimes, with potentially different dynamic properties. The transition between the regimes is smooth. In our setup, the market impact of fundamentalists is low in one regime but high in the other. Since the market impact of the fundamentalists increases when prices run away from their long-run equilibrium values, booms and slumps are eventually countered. However, a (too) low market impact of fundamental traders in periods where prices are close to fundamental values and the presence of technical traders may be a crucial reason for cyclical price fluctuations, as observed in many commodity markets. Clearly, destabilizing chartists may then drive prices away from fundamental values.

The remainder of the paper is organized as follows. In section 2, we present our commodity market model with heterogeneous interacting traders. In section 3, we discuss our estimation results. The final section concludes the paper.

2 Commodity markets and heterogeneous speculators

2.1 Background and motivation

Our model is inspired by the chartist-fundamentalist approach, which has proven to be quite successful in replicating some important stylized facts of stock and foreign exchange markets (Day and Huang 1990, Kirman 1991, de Grauwe et al. 1993, Brock and Hommes 1998, LeBaron et al. 1999, Lux and Marchesi 2000, Farmer and Joshi 2002, Chiarella, Dieci and Gardini 2003, Rosser et al. 2003). While the behavior of chartists is likely to be destabilizing, fundamentalists exercise a stabilizing effect on the price dynamics. However, the influence of the two trader types is typically not constant over time. In periods in which technical traders dominate the market, booms and slumps may emerge. When fundamental analysis gains in popularity, prices are pushed back to more moderate values. Within these models a larger part of the dynamics is driven by the interactions of the speculators. A central lesson of this branch of research is that the dynamics of asset prices is not completely determined by exogenous random shocks, such as new information, but has a substantial endogenous component.

The core assumptions of the chartist-fundamentalist approach are backed up by many empirical studies. For instance, laboratory experiments indicate that agents are boundedly rational. They tend to apply simple rules of thumb which have proven to be useful in the past (Kahneman, Slovic and Tversky 1986). Asset pricing experiments conducted by Smith (1991) or Sonnemans et al. (2004) furthermore indicate that financial market participants use simple forms of forecast rules such as extrapolative or regressive predictors. In the asset pricing experiments, bubbles and crashes are frequently observed. Survey studies by Taylor and Allen

(1992) or Menkhoff (1997) reveal that professional foreign exchange dealers rely on both technical and fundamental analysis to determine their investment positions. As already mentioned in the previous section, similar results are observed for commodity market traders. In general, one may conclude that speculators use a mix of adaptive and regressive expectation formation rules to predict prices, regardless of the market in which they are trading.

Guided by these observations, we seek to develop a simple model that may help us to explain the strong cyclical motion of commodity prices. Of course, many aspects influence the evolution of commodity prices. Most notably, nonlinear cobweb models have the potential to produce endogenous (complex) price dynamics. For instance, Day (1994) and Hommes (1998) investigate potential nonlinearities in the demand and supply functions of consumers and producers, and Brock and Hommes (1997) explore the case in which producers have heterogeneous expectations. However, the role of speculators for commodity price dynamics seems to be under-researched until now, which is why we will explicitly concentrate on them. Another important goal of the current paper is to confront our model with real data. Instead of calibrating the model by hand, we try to estimate the parameters of the model.

2.2 Setup

In brief, the key elements of our commodity market model may be outlined as follows: We consider two types of traders. Chartists extrapolate past price trends into the future and therefore add a positive feedback to the dynamics. Fundamentalists expect prices to return towards their fundamental value. While the market impact of chartists is constant, the market impact of fundamentalists depends on their confidence in mean reversion. For example, the larger the mispricing of the commodity, the more fundamentalists are convinced that a price correction towards the fundamental price will occur. After all active speculators have submitted their orders, the new price of the commodity is announced. If buying orders exceed selling orders, the price of the commodity increases and vice versa. Then the next trading round starts.

Let us now turn to the equations of the model. The main principle of technical analysis is to go with the current price trend (Murphy 1999). The orders of technical traders in period *t* may be formalized as

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

where *a* denotes a positive reaction coefficient and *P* stands for the price of the commodity. Hence, if the price change of the commodity between period *t* and *t*-1 is positive, chartists are willing to buy the commodity, otherwise they sell it.

The orders generated by fundamental trading rules may be written as

$$D_t^F = b(F - P_t), \tag{2}$$

where *b* is a positive reaction parameter. As usual, we assume that the agents know the constant long-run equilibrium value *F* of the commodity (Day and Huang 1990, Brock and Hommes 1998). Fundamental analysis then suggests buying (selling) undervalued (overvalued) commodities. Note that selling the commodity either corresponds to reducing an open position or going short.

The effective demand of the fundamentalists depends on their market impact *W*, i.e. the total orders submitted by fundamental traders are given as $W_t D_t^F$. We assume that there exists a pool of latent fundamental traders who may become active if market circumstances look appealing to them. The market impact of the fundamentalists is defined as

$$W_t = \frac{1}{1 + \exp\left(-c\frac{|F - P_t|}{\sigma_t}\right)}. \tag{3}$$

Note first that W is restricted to the interval [0.5, 1]. Hence, at least 50 percent of the fundamentalists are active, regardless of the condition of the market.[1] The second term in the denominator captures the agents´ confidence in fundamental analysis. The larger the deviation between the price of the commodity and its fundamental value, the stronger the confidence in mean reversion. As a result, the market impact of fundamental analysis increases. The parameter c captures the curvature of (3). The larger c, the more quickly fundamental traders will enter the market as the boom or slump increases. Finally, the perceived mispricing is conditioned on the volatility, measured by the conditional standard deviation of the commodity price. Since the risk of trading increases with volatility, the agents are more cautious in turbulent periods. The updating process of the volatility measure is formalized in section 3.

The price adjustment of the commodity depends on the excess demand, i.e. on the net order size of the speculators. The price for period t+1 is quoted as

$$P_{t+1} = P_t + d\,(D_t^C + W_t D_t^F) + \varepsilon_t\,, \tag{4}$$

where d is a positive price adjustment coefficient. Accordingly, if buying exceeds selling the price of the commodity goes up, and if selling exceeds buying the price of the commodity goes down. One may interpret (4) as the stylized behavior of a market maker or as the result of an electronic limit order book (e.g. Farmer and Joshi 2002 or Chiarella and Iori 2002). The noise term ε captures all remaining perturbations that may affect the price evolution.

Inserting (1)-(3) into (4) yields the law of motion of the commodity price

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[1] The basic impact of the fundamentalists may also be interpreted as the impact of the real economy, i.e. the orders triggered by imbalances between the demand of the consumers and the supply of the producers in a given period. For instance, if the price is below its equilibrium value, then consumers will demand more than is offered by the producers in that period. As a result, their net demand is positive. For econometric reasons, we did not explicitly model the behavior of the real economy. It is, however, at least partially embedded in (3) and (4).

$$P_{t+1} = P_t + ad\,(P_t - P_{t-1}) + \frac{bd(F - P_t)}{1 + \exp\left(-c\,\frac{|F - P_t|}{\sigma_t}\right)} + \varepsilon_t\,. \qquad (5)$$

Due to the time-varying impact of the fundamentalists, (5) is a nonlinear map. Price changes obviously depend on the time-invariant orders of chartists, on the time-varying impact of fundamentalists and on random shocks. In the next section, we explore whether the mechanism offered in this paper is supported by the data.

3 Specification and estimation of the model

3.1 Specification of the model

The aim of this section is to investigate nonlinearities in monthly commodity prices on the basis of the above theoretical approach. Our setup belongs to the STAR (smooth transition autoregressive) model family, originally proposed by Teräsvirta and Anderson (1992) and developed further by Granger and Teräsvirta (1993) and Teräsvirta (1994). These models have been applied to quarterly and monthly exchange rates by Sarantis (1999), Kilian and Taylor (2003), and to stock market indexes by Nam et al. (2001, 2002). These papers reveal that the STAR approach is capable of modeling nonlinear mean reversion of asset prices. It can also provide superior performance compared to simple ARIMA specifications and other competing approaches such as the Markov switching model.

In order to examine the empirical evidence of the chartist-fundamentalist model outlined in section 2, we use monthly data, implying that the conditional variance of commodity price returns may not be constant over time. To cope with heteroskedasticity in monthly returns, we apply the STAR-GARCH procedure developed by Lundbergh and Teräsvirta (1998).

To be precise, our empirical model consists of a mean equation containing a smooth transition variable and a standard GARCH(1,1) volatility equation:

$$\Delta P_t = \alpha \Delta P_{t-1} + [\delta(F_{t-1} - P_{t-1})] W(c; F_{t-\lambda} - P_{t-\lambda}; h_{t-\lambda}) + \varepsilon_t , \tag{6}$$

$$W(c; F_{t-\lambda} - P_{t-\lambda}; h_{t-\lambda}) = \left[1 + \exp\left(-c \frac{|F_{t-\lambda} - P_{t-\lambda}|}{\sqrt{h_{t-\lambda}}} \right) \right]^{-1} \tag{7}$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} , \tag{8}$$

where $\varepsilon_t = \nu_t \cdot \sqrt{h_t}$ and $\nu_t \overset{iid}{\sim}$ N(0,1). The parameter $\alpha = ad$ stands for the time-invariant price impact of the chartists and the parameter $\delta = bd$ denotes the potential price impact of fundamental analysis. The relative number of fundamental traders who are active $W(c; F_{t-\lambda} - P_{t-\lambda}; h_{t-\lambda})$ is restricted to 0.5 – 1 and depends on the standardized absolute deviation of the commodity price from its fundamental value $|F_{t-\lambda} - P_{t-\lambda}| / \sqrt{h_{t-\lambda}}$. The transition parameter *c* is a slope parameter and determines the speed of transition between the two extreme regimes, with low absolute values of *c* resulting in slower transition.

To determine the appropriate delay λ of the transition variable, the modeling procedure for building STAR models is carried out as suggested in Granger and Teräsvirta (1993) and Teräsvirta (1994). First, linear AR(*k*) models are estimated to choose the lag order *k* on the basis of the AIC and BIC criterion. We find that the BIC value indicates an AR(1) process for all commodity returns, while in some cases the AIC value suggests a higher lag order. For the sake of parsimony, however, we decided to set $k = 1$. Second, we test linearity against STAR models, for different values of the delay parameter λ, using the AR(1) linear model as the null. To perform this test we estimate the auxiliary regression

$$\Delta P_t = \theta_0 + \theta_1 \Delta P_{t-1} + \theta_2 X_{t-1} + \theta_3 X_{t-1} X_{t-\lambda} + \theta_4 X_{t-1} X_{t-\lambda}^2 + \theta_5 X_{t-1} X_{t-\lambda}^3 + \varepsilon_t , \tag{9}$$

where $X_t \equiv F_t - P_t$. The linearity hypothesis is H_0: $\theta_3 = \theta_4 = \theta_5 = 0$. To specify the value of the delay parameter λ, (9) is estimated for a wide range of values, $1 \leq \lambda \leq 24$. In cases where linearity is rejected for more than one λ, we select the one for which the null has the smallest p-value (Lundbergh and Teräsvirta, 1998). In pure times series applications a third test is performed to decide whether a logistic or an exponential function is the appropriate specification of the transition function. However, for the above theoretical reasons we make use of a modified logistic transition function. To capture heteroskedasticity in monthly returns, we specify the conditional volatility as a standard GARCH(1,1) process.

3.2. Data description

Our data sample contains monthly US-dollar market prices of cotton, lead, rice, soybeans, sugar, and zinc, derived from the *IMF International Financial Statistics database* over the period from 1973:1 to 2003:5. Hence, each time series consists of 365 observations. The use of nominal prices, as represented in Figure 1, is motivated by the fact that we are interested in explaining cycles in nominal commodity prices and, of course, speculators are primarily concerned with expected nominal price changes. As a technical byproduct, this avoids the need to select an appropriate deflator, which is a non trivial issue (Deaton, 1999). Already simple visible inspection reveals the strong cyclical behavior of commodity prices. Especially for developing countries relying on export revenues, such price fluctuations may be quite serious.

[Figure 1]

Since we try to model nonlinear mean reversion of the aforementioned commodity prices, percentage returns are calculated as $100 \cdot \Delta\log(P_t)$. Table 1 provides some descriptive statistics revealing standard properties of commodity market returns. The mean of returns is not significantly different from zero, reflecting the fact that commodity prices are generally trendless (Deaton 1999). The Dickey-Fuller test statistics in Table 1 confirm mean stationarity of commodity prices except for zinc.[2] The property of commodity prices to revert to a long-run unchanging average provides us with a simple and convenient approximation for the fundamental value. We compute the fundamental value F as $\sum \log(P_t)/(N-1)$. In contrast to most financial market time series, commodity returns exhibit strong autocorrelation at various lags (Deaton and Laroque 1992). The distribution of returns is significantly skewed, and large absolute returns occur more frequently than normal. For further stylized facts of commodity price dynamics consult Borenzstein et al. (1994) or Cashin et al (2002).

[Table 1]

3.3 Estimation results and interpretation

We use RATS 5.0 programming for the quasi maximum likelihood estimation method. Since the assumption of conditional normality cannot be maintained, robust estimates of the covariance matrices of the parameter estimates are calculated using the BFGS algorithm. Under fairly weak conditions, the resulting estimates are even consistent when the conditional distribution of the residuals is non-normal (Bollerslev and Wooldridge 1992). Teräsvirta (1994) points out that estimating the transition parameter c may cause particular problems such as slow convergence of the estimation routine or overestimation. However, the recommended rescaling of the transition variable by means of the conditional standard deviation is already introduced using the standardized deviation of the market price from its fundamental value. On the basis of this standardization, we set $c = 1$ as a starting value for the estimation routine.[3] Table 2 shows the estimation results.

[2] The Dickey-Fuller test statistic for the time series of zinc shows that non stationarity cannot be rejected. In order to detrend the time series we calculated real zinc prices using the unit value index as provided by the IMF's International Financial Statistics. However, re-estimation of the model reveals no significant parameter changes so that we continue to report results of nominal prices for the sake of comparability. Estimation results of the model using real zinc price data are available from the authors upon request.

[3] Experimentation showed that the results reported in Table 2 are robust with respect to various starting values.

[Table 2]

The estimation results displayed in Table 2 are quite similar to each other, indicating that the specified model is robust when applied to different commodity prices. The Ljung-Box Q statistics[4] AR(p) and ARCH(p) indicate that the model is able to capture the serial dependence of the conditional mean and variance process. In order to check for no remaining nonlinearities (NRNL) we re-estimate the auxiliary equation (9) using standardized residuals instead of commodity price returns. On the basis of a LM-type test the null hypothesis H_0: $\theta_3 = \theta_4 = \theta_5 = 0$ is tested against the alternative of additional nonlinear structure (Eitrheim and Teräsvirta, 1996; Lundbergh and Teräsvirta, 1998). The reported p-values of the NRNL test statistic reveal that the null of no remaining nonlinearity cannot be rejected at standard levels of significance. However, there seems to remain some weak nonlinearities in the case of soybeans.

We now turn to the central question as to whether there is evidence in favor of chartist- and fundamentalist-driven commodity price dynamics. The answer is given by the likelihood ratio test statistics and the t-statistics of the respective parameter estimates. To provide likelihood ratio test statistics we compare the above model with a simple AR(1)-GARCH(1,1) specification so that the parameter δ is restricted to zero. The resulting test statistics show that the introduction of chartist and fundamentalist parameters increases the log likelihood with significance levels of one percent in case of cotton, soybeans, sugar, and zinc, and at the five percent level in the case of rice and lead.

The chartist and fundamentalist coefficients are of the correct sign and are statistically significant at the one percent level, except for the fundamentalists who trade in the lead

[4] See Ljung and Box (1978).

market.[5] Statistically significant estimates of c point to moderate transitions between the outer and the middle regimes. In Figure 2 we have plotted the estimated transition function against lagged values of standardized deviations of the commodity price from its fundamental value.

[Figure 2]

In every case there seems to be a reasonable number of observations above and below the equilibrium value, so that we can be confident in our symmetric specification of the transition function. The transition function attains values up to unity over the sample period, but only for quite large standardized deviations. However, due to the nonlinearity of the transition function considerable mean reversion is already triggered by fundamentalist speculation for relatively moderate misalignments. For deviations from the fundamental value of the order of plus or minus 5 percent – the range in which many of the observations are clustered – the transition function value is around 0.75. This implies that a substantial fraction of the mean reversion potential is realized quite quickly when bubbles start.

4 Conclusions

An ongoing evolutionary competition between heterogeneous trading strategies seems to be a major engine for the strong fluctuations observed in financial markets; see, for example, the surveys of Hommes (2001) and Lux (2004) on models with interacting technical and fundamental traders. Note that financial assets and commodities are related in the sense that they are traded at stock exchanges. So what drives the cyclical motion of commodity prices? In this paper we try to develop an empirical commodity market model with heterogeneous interacting agents who rely on technical and fundamental analysis to determine their orders.

[5] Our results reveal that fundamentalists may wait some time until they start to exploit the mispricing in the market (in the rice, sugar and lead market λ is equal to 10). One reason might be that fundamentalists need some time to figure out the mispricing (e.g. lack of information). Another reason might be that it is not optimal to enter the market too quickly but wait until the mispricing (bubble) has more strongly evolved.

Technical analysis is a trading method that aims at identifying trading signals out of past price movements. Fundamental analysis predicts a convergence between prices and fundamental values and thus tends to stabilize the price process. However, the relative market impact of the two trading strategies is not constant over time but depends on market circumstances.

Our STAR-GARCH model indicates that the more the price deviates from its long-run equilibrium value, the more fundamentalists will become active. Their orders then drive prices back to more moderate values. However, the dynamics are characterized by two regimes. If the price is close to its fundamental value, the market impact of fundamentalists is relatively low. In such a situation, the presence of destabilizing chartists and/or random shocks may cause a new (temporary) bull or bear market. Our model suggest that heterogeneous agents and their nonlinear trading impact may be responsible for pronounced swings in commodity prices. Since the structure of the model is entirely symmetric we are dealing with strong and persistent misalignments in commodity markets but do not address asymmetries like differing durations of booms and slumps. This is left for future research.

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Table 1
Summary statistics of commodity price returns (in percent)
Data from 1973:05 to 2003:5 (361 observations)

	Cotton	Soybeans	Rice	Sugar	Lead	Zinc
Mean	0.099	-0.015	0.150	0.069	0.085	0.169
Standard deviation	5.197	6.252	8.512	10.62	6.546	6.439
Skewness	0.582	0.187	0.865	0.25	0.212	0.014
Excess Kurtosis	1.12	7.00	6.04	1.03	1.99	2.99
AR(1)	0.567 (117.49)	0.199 (14.47)	-0.130 (6.17)	0.290 (30.78)	0.200 (14.64)	0.316 (36.43)
AR(6)	-0.076 (139.22)	-0.028 (34.44)	0.004 (15.94)	0.000 (32.93)	0.044 (18.18)	-0.014 (49.83)
AR(12)	-0.075 (141.46)	-0.091 (42.36)	-0.010 (12.63)	-0.068 (40.61)	-0.033 (22.67)	-0.106 (60.06)
$Lbq^2(1)$	57.83	47.06	26.50	19.81	32.75	22.26
$Lbq^2(6)$	77.33	103.13	45.69	42.63	33.14	98.93
$Lbq^2(12)$	99.99	118.65	49.06	72.93	34.22	200.11
JB	39.58	743.94	665.31	19.98	62.77	135.17
DF	-3.45***	-3.46***	-3.51***	-3.44**	-3.01**	-2.42

Notes: AR denote autocorrelation coefficients for the returns with Ljung Box-Q statistics in parentheses (Ljung and Box, 1978). $Lbq^2(L)$ denote the Ljung Box-Q statistics for the squared returns. JB is the Jarque Bera test statistic, while DF is the Dickey-Fuller test statistic with 12 lags. * (**, ***) denotes significance at the 10% (5%, 1%) level.

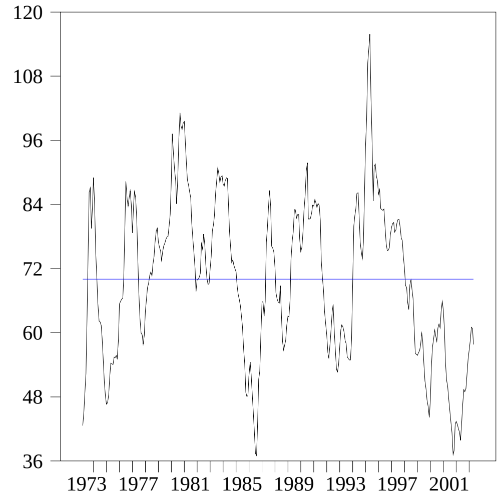
Table 2

Parameter estimates of STAR GARCH models for commodity price returns (1973 – 2003)

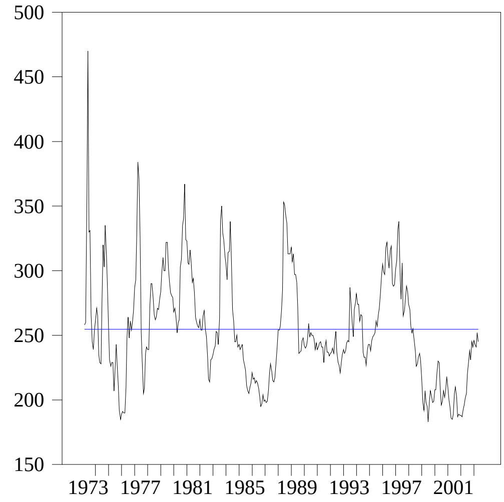
	Cotton λ=*1*	**Soybeans** λ=*1*	**Rice** λ=*10*	**Sugar** λ=*10*	**Lead** λ=*10*	**Zinc** λ=*1*
α	0.56 (12.48)***	0.34 (3.78)***	-0.19 (3.37)***	0.30 (5.81)***	0.26 (4.30)***	0.26 (5.07)***
δ	0.06 (5.86)***	0.09 (3.13)***	0.06 (2.63)***	0.05 (3.09)***	0.04 (1.73)*	0.07 (3.91)***
c	0.17 (3.14)***	0.23 (2.25)**	0.36 (5.33)***	0.30 (2.79)***	0.47 (2.51)***	0.23 (4.12)***
β_0	4.62 (2.30)**	9.84 (2.57)**	29.67 (2.53)**	4.89 (2.16)**	27.19 (10.44)***	5.63 (2.89)***
β_1	0.24 (2.85)***	0.30 (3.06)***	0.25 (2.17)**	0.17 (3.10)***	0.32 (2.72)***	0.22 (3.26)***
β_2	0.51 (3.86)***	0.43 (3.88)***	0.31 (1.67)*	0.79 (13.52)***	–	0.62 (7.42)***
LLh	986.10	879.55	746.55	678.53	837.36	866.22
LRT	24.16***	17.02***	7.18**	82.68***	7.16**	30.06***
AR(12)	0.24	0.86	0.38	0.29	0.87	0.11
ARCH(12)	0.70	0.17	0.68	0.84	0.85	0.64
NRNL	0.19	0.09	0.74	0.52	0.67	0.74

Notes: The sample contains monthly observations of log commodity prices from May 1973 to May 2003. λ denotes the delay of the smooth transition variable. α, δ, c indicate the estimated parameters of the mean equations (in percent), β_0, β_1, and β_2 are the estimated GARCH(1,1) parameters (in percent), LLh is the log likelihood value and LRT the likelihood ratio test statistic with restriction δ = 0. t-statistics in parentheses are based on robust estimates of the covariance matrices of the parameter estimates. * (**, ***) denotes significance at the 10% (5%, 1%) level. AR(12) denotes the p-value of the Ljung Box-Q statistic for 12th order autocorrelation of standardized residuals (Ljung and Box, 1978). ARCH(12) is the p-value of the Ljung Box-Q statistic for 12th order autocorrelation of squared standardized residuals. NRNL is the lowest p-value for no remaining nonlinearity with up to 24 lags (Eitrheim and Teräsvirta, 1996).

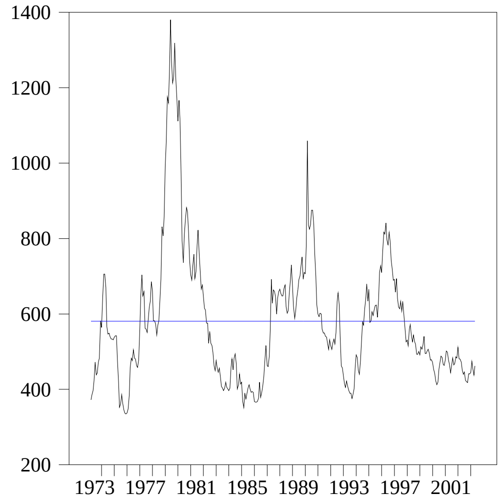
Figure 1: Nominal US-Dollar Commodity Prices
Monthly Data from 1973:5 to 2003:5



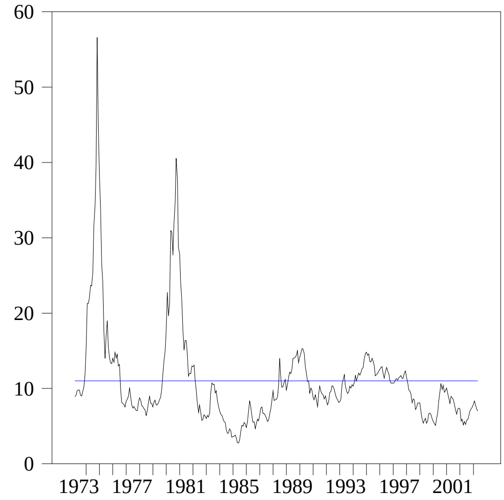
Cotton *(US cents per Pound)*



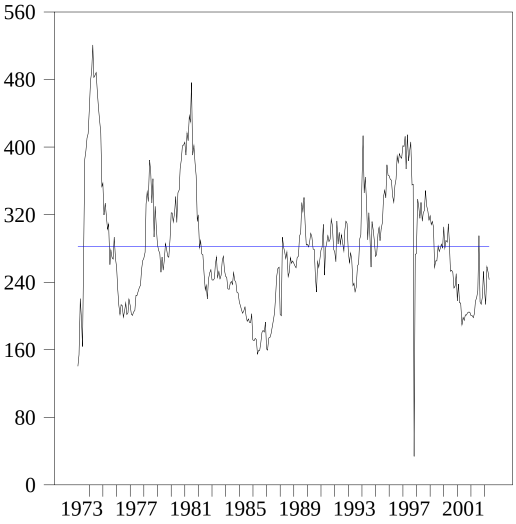
Soybeans *(US Dollar per Metric Ton)*



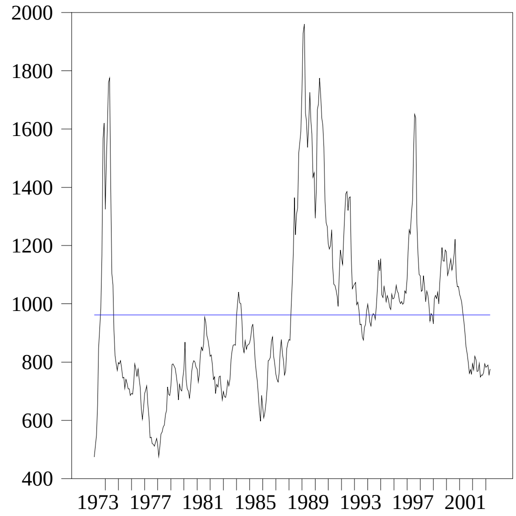
Lead *(US Dollar per Metric Ton)*



Sugar *(US cents per Pound)*

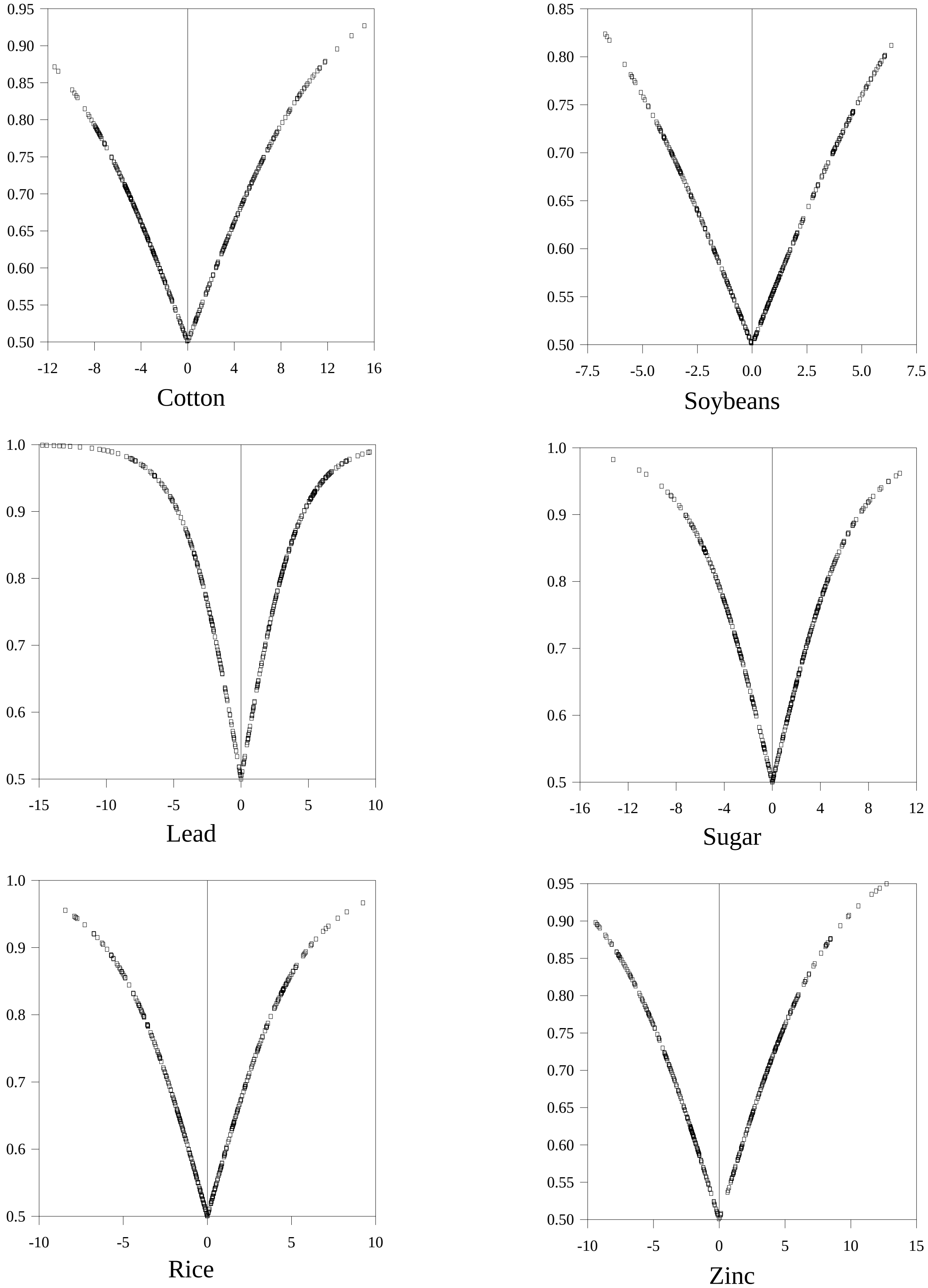


Rice *(US Dollar per Metric Ton)*



Zinc *(US Dollar per Metric Ton)*

Figure 2: Empirical Transition Functions of Fundamentalist Speculation
Monthly Data from 1973:5 to 2003:5



Notes: The x - axis gives the standardized misalignment and the y - axis gives the relative number of fundamentalists