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Commodity price dynamics and the nonlinear market impact of technical traders: empirical evidence for the US corn market

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Abstract

We develop a simple model with technical and fundamental traders to explain the cyclical motion of commodity prices. The crucial element of our model is a nonlinear market impact of technical traders: Estimation of our STAR-GARCH model using monthly US corn price data reveals that technical traders increasingly enter the market as booms or slumps enlarge. One reason may be that they only gradually learn about the emergence of persistent price trends. The behavior of trend-extrapolating speculators obviously enforces mispricings and thus contributes to cyclical motion as observed in actual commodity markets.

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1. Introduction

Models with heterogeneous interacting traders [1–6] have proven to be quite successful in replicating the stylized facts of financial markets [7–10], i.e., the models generate time series which display intricate price dynamics, bubbles and crashes, fat tails for the distribution of the returns and volatility clustering. This branch of research is quite important since it may help us to devise better models of risk management [11], trading strategies [12] or regulation of financial markets [13–15]. So far, most of these models have been designed for asset markets.

Although commodity markets differ in several aspects to asset markets they also share some similarities. On the one hand, they roughly display the same stylized facts [16]. On the other hand, most commodities are traded at stock exchanges and are thus also influenced by the activity of speculators. The goal of this paper is to develop a simple commodity market model which explicitly focuses on the trading behavior of heterogeneous agents. A second goal is to confront our model with actual data. Instead of calibrating the model by hand such that it produces realistic price dynamics we seek to estimate our model. Surprisingly, only few attempts exist where parameters of multi-agent models are directly derived from the data. One reason may be that one has to sacrifice certain real-life market details: If the setup is too complicated, econometric analysis is precluded. However, we think that empirical evidence for a model is valuable, even if some interesting model elements have to be excluded.

The structure of our model is roughly as follows: We consider two types of agents: fundamentalists and chartists [17–20]. Fundamentalists are convinced that prices will return toward their long-run equilibrium values. Hence, if the price is below (above) its fundamental value, they will buy (sell) the commodity. Such a trading strategy tends to stabilize the market since prices are pushed toward their equilibrium values. Technical traders aim to identify price signals from past price trends. The basic principle of technical analysis is that prices move in trends. Technical traders thus buy the commodity when prices increase and sell the commodity when prices decrease. While the market impact of fundamental traders is constant over time, the market impact of technical traders is time varying and depends on market circumstances.

We test our model for the US corn market. A STAR-GARCH estimation setup indicates that the further the corn price deviates from its long-run equilibrium value, the more technical traders enter the market. As a result, bubbles may become self-fulfilling since they attract an increasing number of destabilizing trend-extrapolating agents (and the power of fundamental traders simultaneously remains constant). Our mechanism may be explained by the fact that agents only gradually learn about the emergence of a new bubble process. For instance, it may take some time for the agents to recognize the price trend or for them to meet someone already trading in that market. In a broader sense, our view of a slow, yet persistent process of information dissemination has recently also been proposed to explain irrational exuberance in stock markets [21].

The remainder of the paper is organized as follows: In Section 2, we present our commodity market model, in Section 3, we present empirical evidence for the US corn market, and in Section 4, we conclude.

2. A commodity market model

The price of the commodity is determined on an order-driven market in which two types of traders are active: fundamentalists and chartists.[1] Assuming a log-linear price impact function [1], the log of the price p of the commodity in period $t+1$ is quoted as

$$p_{t+1} = p_t + (d_t^F + w_t^C d_t^C) + \varepsilon_t \,, \tag{1}$$

where d^F and d^C denote the net orders (i.e., the difference between buy and sell orders) generated by fundamental and technical trading rules, respectively. The market impact of technical traders w^C adjusts endogenously over time. All additional price perturbations that are not explained by our model are captured by the noise term ε. According to (1), excess buying tends to drive the commodity price up and excess selling tends to drive it down.

Fundamental analysis is built on the premise that prices revert towards their long-run equilibrium value. A typical specification of a fundamental trading rule is

$$d_t^F = \alpha(f - p_t) \,. \tag{2}$$

The log of the fundamental value f is set constant (see Section 3). Since α is a positive reaction coefficient, the fundamental trading rule (2) suggests buying the commodity when the price is below its fundamental value and selling the commodity when the price is above its fundamental value.[2]

Technical analysis favors going with the current price trend. Orders triggered by technical analysis rules may be formalized as

$$d_t^C = \delta(p_t - p_{t-1}) \,, \tag{3}$$

where δ is a positive reaction coefficient. As long as the price increases, technical traders take a long position, otherwise they go short.

Within our model, the market impact of technical traders is time-varying and thus their effective demand $w_t^C d_t^C$ is nonlinear. We assume that there exists a pool of latent technical traders who may enter the market if market circumstances look appealing to them. To be precise, the relative number of technical traders is

[1] The model we present here is quite stylized and may thus also be used to describe stock and currency markets. All these markets have in common that their price dynamics is influenced, if not driven, by heterogeneous interacting speculators.

[2] Note that (2) may also be interpreted as the orders which result from the real economy, i.e., the demand of the consumers and the supply of the producers in a given time step. For example, if the price of the commodity is below its long-run equilibrium value, the consumers demand more than is offered by the producers in that period. As a result, their net demand is positive, as indicated by (2). Moreover, (2) combined with random noise is an Ornstein–Uhlenbeck process.

expressed as

$$w_t^C = \frac{1}{1 + \exp(-\phi|f - p_t|/\sigma_t)} \, . \tag{4}$$

Note that at least 50% of the potential technical traders are active ($f = p$). Their impact may increase up to 100% if the mispricing in the market goes to infinity. The idea behind (4) is that the larger the bubble becomes, the more attention it receives by the chartists. They become increasingly aware that "something is going on" in the market and thus they want to participate in the "money-making process". The parameter φ captures the curvature of (4). The larger φ, the more quickly the agents enter the market as the boom or slump evolves. Finally, the perceived mispricing is conditioned on volatility σ, measured as the standard deviation. A high volatility period makes trading more risky and technical traders are consequently less eager to enter the market. The updating process of the volatility will be explained in the next section.

Combining (1)–(4), one obtains

$$r_t = p_t - p_{t-1} = a(f - p_{t-1}) + \frac{\delta(p_{t-1} - p_{t-2})}{1 + \exp(-\phi|f - p_{t-1}|/\sigma_t)} + \varepsilon_t \, . \tag{5}$$

Returns, i.e., log price changes, depend on time-invariant mean-reversion orders of fundamentalists, time-varying trend-extrapolating orders of chartists, and random shocks. In the next section, we investigate whether our setup is supported by the data.

3. Empirical evidence

Smooth transition autoregressive (STAR) models [22–24] imply the existence of two distinct regimes with potentially different dynamic properties, where the transition between regimes, however, is smooth. In order to examine the empirical evidence of our model we apply a STAR-GARCH approach [25]. Accordingly, the empirical model consists of a mean equation containing a smooth transition variable and a standard GARCH(1,1) volatility equation:

$$r_t = \alpha(f - p_{t-1}) + \delta r_{t-1} w(\phi; f - p_{t-d}; h_{t-d}) + \varepsilon_t \, , \tag{6}$$

$$w(\phi; f - p_{t-d}; h_{t-d}) = \left(1 + \exp\left[-\phi \frac{|f - p_{t-d}|}{\sqrt{h_{t-d}}}\right]\right)^{-1} \, , \tag{7}$$

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

where $\varepsilon_t = v_t \cdot \sqrt{h_t}$ and $v_t \overset{iid}{\sim} \mathrm{N}(0,1)$. The relative number of active technical traders $w(\phi; f - p_{t-d}; h_{t-d})$ depends on the standardized absolute deviation of the commodity price from its fundamental value $|f - p_{t-d}|/\sqrt{h_{t-d}}$. Due to the heteroskedasticity of the returns, we specify the conditional volatility as a standard GARCH(1,1) process. To determine the appropriate delay d of the transition

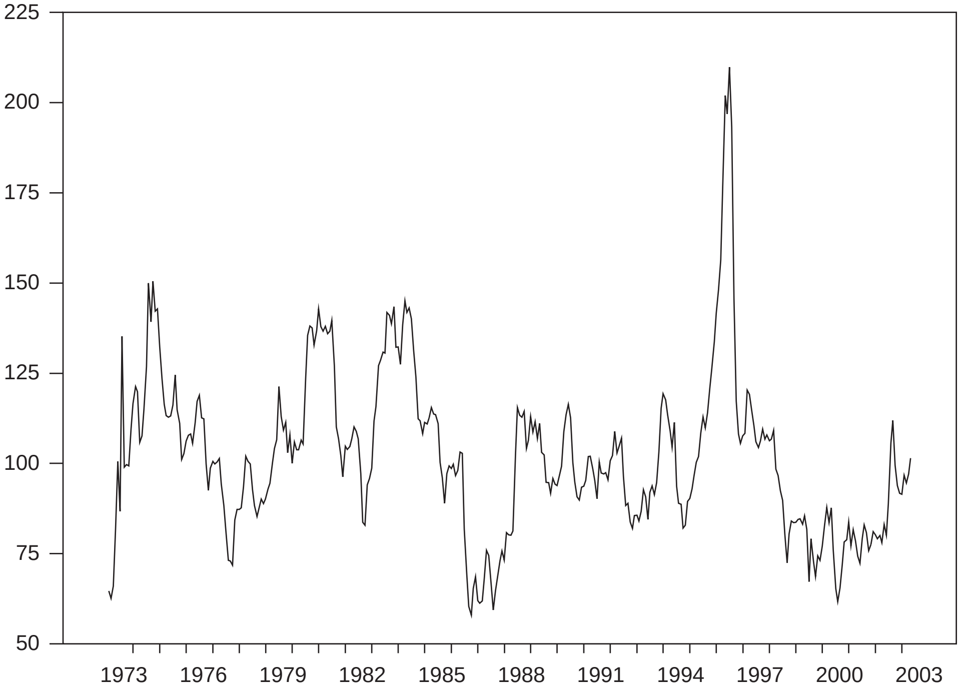

Fig. 1. The US corn price index from 1973:5 to 2003:5 (1982 = 100). The 360 monthly observations are provided by the US Department of Labor, Bureau of Labor Statistics and are available at http://www.bls.gov/ppi/home.htm.

variable, the modeling procedure for building STAR models is carried out as suggested in Refs. [23,24]. First, linear AR models are estimated to choose the lag order k on the basis of the BIC criterion [26]. We find that a simple AR(1) process seems to be appropriate for corn price returns. Second, we test linearity against the STAR model for different values of the delay parameter d, using the AR(1) linear model as the null. Since linearity is rejected for more than one d, we select $d = 2$ for which the null has the smallest p-value [25].

Fig. 1 presents the evolution of the US corn price index (1982 = 100) over the period 1973:5–2003:5. The time series consists of 360 monthly observations and is provided by the US Department of Labor, Bureau of Labor Statistics.[3] The mean of log price changes is not significantly different from zero, reflecting the fact that commodity prices are generally trendless [27]. 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 log fundamental value f as $\sum p_t/(N-1)$. As for most commodities, corn returns exhibit strong autocorrelation, their distribution is significantly skewed and large absolute returns occur more frequently than normal.

[3]The data are available at http://www.bls.gov/ppi/home.htm.

Table 1
Parameter estimates of the STAR-GARCH model for the US corn market

$$r_t = \underset{(3.84)}{0.072}(f - p_{t-1}) + \underset{(6.12)}{0.446}\, r_{t-1} \times (1 + \exp[-\underset{(2.22)}{0.199}|f - p_{t-2}|/\sqrt{h_{t-2}}])^{-1}$$

$$h_t = 0.00\underset{(3.83)}{2524} + \underset{(3.33)}{0.316}\,\varepsilon_{t-1}^2 + \underset{(1.13)}{0.149}\,h_{t-1}$$

$\mathrm{LRT} = 14.86, \mathrm{AR}(12) = 0.15, \mathrm{ARCH}(12) = 0.29, \mathrm{NRNL} = 0.71$

Notes: t-statistics in parentheses are based on robust estimates of the covariance matrices of the parameter estimates. LRT is the likelihood ratio test statistic with restrictions $\delta = \varphi = 0$. AR(12) denotes the p-value of the Ljung–Box Q-statistic for 12th-order autocorrelation. ARCH(12) is the p-value of the Ljung–Box Q-statistic for 12th-order autoregressive conditional heteroscedasticity. NRNL is the p-value for no remaining nonlinearity.

We use RATS[4] 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 numerical algorithm proposed by Broyden, Fletcher, Goldfarb, and Shanno (BFGS) as described in Ref. [28]. Under fairly weak conditions, the resulting estimates are even consistent when the conditional distribution of the residuals is non-normal [29]. Table 1 shows the estimation results.

The Ljung–Box Q-statistics AR(p) and ARCH(p) as suggested by Ljung and Box [30] indicate that the model is able to capture the serial dependence of the conditional mean and variance process.[5] Moreover, according to the reported p-value for the NRNL test, we cannot reject the null of no remaining nonlinearity at standard levels of significance. To provide likelihood ratio test statistics we compare the above model with a simple AR(1)-GARCH(1,1) specification so that the parameters α and φ are restricted to zero. The resulting test statistic shows that the introduction of technical and fundamental traders increase the log likelihood with 1% significance level. The chartist and fundamentalist coefficients are of the correct sign and are statistically significant, providing evidence in favor of speculative corn price dynamics.

Remember that STAR models imply the existence of two distinct regimes, whereby the transition between regimes is smooth. In our model, the market impact of technical traders is low in one regime but high in the other. Fig. 2 depicts the relative number of technical traders entering the US corn market as predicted by our model and the relative mispricing in that market. As can be seen, the market impact of chartists increases when prices run away from their fundamental values. Since the market impact of fundamentalists remains constant, the market may temporarily stop tracking its fundamental value. In fact, the corn market displays huge distortions. For instance, the price deviated from its fundamental value by about 75% in 1996, a situation in which almost all potential chartists have been active.

[4]RATS is a standard statistical software package and a trademark of Estima, Evanston, IL 60201. For more details see http://www.estima.com.

[5]And indeed, both simulated and actual corn time series display excess kurtosis and significant autocorrelation coefficients for absolute returns.

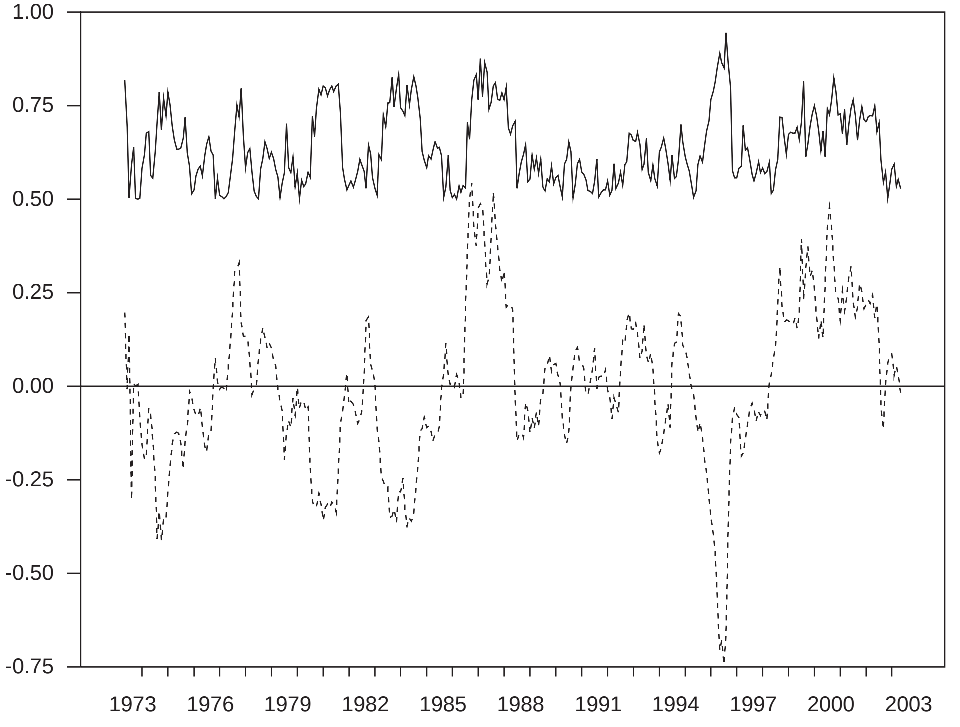

Fig. 2. Corn price dynamics and market impact of technical traders in the time domain. The solid line denotes the relative number of technical traders and the broken line stands for the relative mispricing, i.e., *f*–*p*.

From a policy perspective, our model suggests that regulators should already employ counter-cyclical stabilization policies in the early stages of a bubble. The longer they wait, i.e., the more the bull or bear market evolves, the more destabilizing agents they have to fight.

4. Conclusions

Models with heterogeneous interacting agents have considerably improved our knowledge of speculative markets. While some of these models focus on simple settings which are still analytically tractable [1,17,20], other models are more computationally oriented and aim at matching the statistical properties of asset prices [2,3,5,6]. The goal of the current paper is to develop a stylized commodity market model. As it turns out, there is significant empirical evidence for technical and fundamental speculation in the US corn market. Since technical traders increasingly enter the market as the price deviates from its long-run equilibrium value, lasting and pronounced bull and bear markets may emerge. Of course, further analysis is needed to sharpen our understanding of commodity markets. We hope that our paper will stimulate more (empirical) work in this exciting and important research direction.

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