Darmstadt Discussion Papers in Economics

Investigating nonlinear speculation in cattle, corn, and hog futures markets using logistic smooth transition regression models

Andreas Röthig and Carl Chiarella

Nr. 167

Arbeitspapiere
des Instituts für Volkswirtschaftslehre
Technische Universität Darmstadt

ISSN: 1438-2733

Economic Theory

Investigating nonlinear speculation in cattle, corn, and hog futures markets using logistic smooth transition regression models*

Andreas Röthig** and Carl Chiarella†

February 2006

Abstract

This article explores nonlinearities in the response of speculators' trading activity to price changes in live cattle, corn, and lean hog futures markets. Analyzing weekly data from March 4, 1997 to December 27, 2005, we reject linearity in all of these markets. Using smooth transition regression models, we find a similar structure of nonlinearities with regard to the number of different regimes, the choice of the transition variable, and the value at which the transition occurs.

Keywords: Futures markets, speculation, nonlinear dynamics, smooth transition regression model.

JEL Classification: **G10, G11, C22, C53.**

---

*This paper was written while the first author was visiting the School of Finance and Economics, University of Technology, Sydney. The hospitality and stimulating research environment provided are gratefully acknowledged. The first author also wishes to thank Ingo Barens and Willi Semmler for their support and advice.

**Institute of Economics, Darmstadt University of Technology, and Center for Empirical Macroeconomics, University of Bielefeld, Germany.

†School of Finance and Economics, University of Technology, Sydney, Australia.

1 Introduction

The primary objective of this study is to provide initial empirical evidence on the patterns of nonlinear speculative behavior in live cattle, corn, and lean hog futures markets. Understanding traders' behavior is important to understanding the impact of trades on asset prices and on stability in the respective markets. Although a large body of empirical research on modelling traders' behavior has emerged, empirical studies for futures markets are scarce (for a recent survey see Wang, 2003).

This study adds to the literature by focusing on nonlinearities in speculative behavior. We apply the logistic smooth transition regression (LSTR) model to analyze the impact of price changes on long speculative positions. Therefore this investigation also relates to other studies using this model class. LSTR models have been used in a range of different fields of macroeconomic research including monetary economics (Lütkepohl et al., 1999; Sarno, 1999), GDP growth (Mejia-Reyes et al., 2004), and business cycles (Skalin and Teräsvirta, 1999; van Dijk and Franses, 1999), as well as for modelling phenomena like El Niño (Hall et al., 2001). A feature of the LSTR methodology is that it is possible to test for linearity and estimate a nonlinear model without having to make a priori assumptions about the structure of the nonlinearities. By allowing for distinct regimes, the model is suitable for analyzing regime dependent mean behavior.

We follow the modelling cycle proposed by Teräsvirta (1994, 1997, 1998, 2004) and van Dijk et al. (2002). Our findings reject linearity in the reaction of speculation to price changes in all markets researched. Moreover there appears to be a similar structure of nonlinearity in these markets with regard to the number of different regimes, the choice of the transition variable, and the value at which the transition occurs.

The remainder of this article is organized as follows. Section 2 describes the data and presents summary statistics. Section 3 presents some first insights into the relationship between speculators' and hedgers' trading activity and changes in settlement prices using vector autoregressions, and in particular Granger causality tests and impulse response analysis. Section 4 provides evidence on nonlinearities in speculators' trading activity using LSTR models. A brief summary and concluding remarks are presented in the final section.

2 Data

This article investigates nonlinearities in the relationship between weekly settlement price changes and weekly data on trader positions of live cattle, corn, and lean hog futures contracts from March 4, 1997 to December 27, 2005. The live cattle and lean hog futures contracts are traded at the CME while the corn futures contract is traded at the CBT. Our sample begins after the CME changed the hog contract from live hog to lean hog, starting with the February 1997 contract (see Liu, 2005). The sample consists of 460 observations. Data on futures prices come from Datastream. The returns Δp_t are measured as one hundred times the natural logarithm of the first differences of weekly futures settlement prices. The trader position data are obtained from the CFTC's Commitments of Traders (COT) report. The COT reports provide information on trader positions on each Tuesday for markets with at least 20 trader positions.[1] The two groups of traders contained are commercial (i.e., hedgers) and noncommercial traders (i.e., speculators). We focus our analysis on commercial and noncommercial long positions. Changes in hedgers' and speculators' long positions (Δh_t, and Δs_t) are defined as one hundred times the natural logarithm of the first differences of the respective positions.

Table 1 presents summary statistics, ARCH-LM, and Unit Root test results for the data set. The results of the ARCH-LM test indicate that there is no conditional heteroskedasticity in all but the lean hog Δs_t series. For all series, both the augmented Dickey-Fuller (ADF) test and the KPSS test reject nonstationarity.

[1]For more information on the COT reports, see the CFTC's Web site at www.cftc.gov.

Table 1: Summary Statistics, ARCH-LM, and Unit Root Tests

Series		Sample	Obs.	Mean	Min.	Max.	Std. Dev.	Skewness	Kurtosis	ARCH-LM	ADF	KPSS
Live Cattle	Δh_t	03/04/1997-12/27/2005	460	0.1397	-25.7708	20.9704	5.4307	-0.3686	5.2635	0.4922	-18.4539	0.0514
	Δp_t	03/04/1997-12/27/2005	460	-0.0058	-7.7450	8.7024	2.1298	0.1229	4.8417	0.7411	-20.2289	0.0867
	Δs_t	03/04/1997-12/27/2005	460	0.1188	-68.1434	56.1031	14.2812	-0.2970	6.2459	0.8620	-18.6241	0.0198
Corn	Δh_t	03/04/1997-12/27/2005	460	-0.2491	-157.758	18.3309	8.5985	-12.3902	228.7774	0.9405	-17.5469	0.1070
	Δp_t	03/04/1997-12/27/2005	460	-0.0041	-14.8675	13.5109	3.2386	0.0716	5.1203	0.9265	-18.4231	0.0698
	Δs_t	03/04/1997-12/27/2005	460	0.2374	-160.658	62.8754	16.2698	-1.5285	22.8011	0.9783	-17.4505	0.1063
Lean Hog	Δh_t	03/04/1997-12/27/2005	460	0.4505	-29.2175	31.7947	6.0022	-0.0011	7.7806	0.0683	-14.1823	0.0949
	Δp_t	03/04/1997-12/27/2005	460	-0.0259	-29.2544	29.0083	5.4339	0.2819	9.0509	0.1727	-15.5453	0.0949
	Δs_t	03/04/1997-12/27/2005	460	0.2583	-103.621	57.7630	17.8609	-0.2509	5.9736	0.0103	-15.3788	0.0284

Note: Δh_t and Δs_t are defined as 100*ln of first differences of long positions of hedgers and speculators on the basis of CFTC's COT reports. The Δp_t series is measured as 100*ln of first differences of weekly futures settlement prices. The price data is obtained from Datastream. The ARCH-LM test is used for testing the null hypothesis of no conditional heteroskedasticity. ARCH-LM results are in p-values. ADF and KPSS are the test statistics of the augmented Dickey Fuller and the Kwiatkowski, Phillips, Schmidt, and Shin test. The ADF test rejects the null hypothesis of nonstationarity if the test statistic is negative and the absolute value of the test statistic exceeds the critical value of the respective significance level: 1%: -2.56; 5%: -1.94; 10%: -1.62. The KPSS test rejects the null hypothesis of stationarity if the test statistic exceeds the critical value of the respective significance level: 1%: 0.739; 5%: 0.463; 10%: 0.347. For more information on the tests applied here, see Lütkepohl and Krätzig (2004).

3 VAR analysis

Our empirical investigation starts with the analysis of Granger causality and impulse response functions generated through vector autoregressions (VAR). The main idea is to get some first insights into the data using a linear model before testing for nonlinearities. If the Granger causality tests point to causal relations between the variables, impulse response analysis is used to check whether there is a certain direction of causality. Based on this preliminary analysis, the data set will be checked for nonlinearities in the next section in order to test this direction of causality in different regimes.

The number of lags of the VARs are determined from the Akaike, Hannan-Quinn, and Schwartz information criteria which suggest the use of one lag in the regressions.

Table 2: Granger causality test

	Effect of price changes (Δp_t) on ...			
	... speculation (Δs_t)		... hedging (Δh_t)	
	Test value	p-value	Test value	p-value
Live Cattle	11.0590	0.0009	0.8808	0.3482
Corn	4.9100	0.0269	0.0061	0.9376
Lean Hog	1.5770	0.2095	1.3601	0.2438

The results of the Granger causality test are presented in Table 2. The noncausality null hypothesis can only be rejected for the live cattle speculation (Δs_t) and the corn speculation (Δs_t) series, using a 5% significance level. On the basis of these tests no causal relation can be diagnosed for the lean hog speculation and all hedging series. These results support the theory that hedgers hold futures positions in conjunction with spot positions. Changes in futures prices therefore do not affect hedging strategies.

The impulse response functions presented in Figure 1 confirm the Granger causality results. The responses of the hedging series to a price shock are small and negative for live cattle and lean hog futures contracts and close to zero for the corn futures contract. Contrariwise, the responses of live cattle, corn, and lean hog speculation are significantly positive.

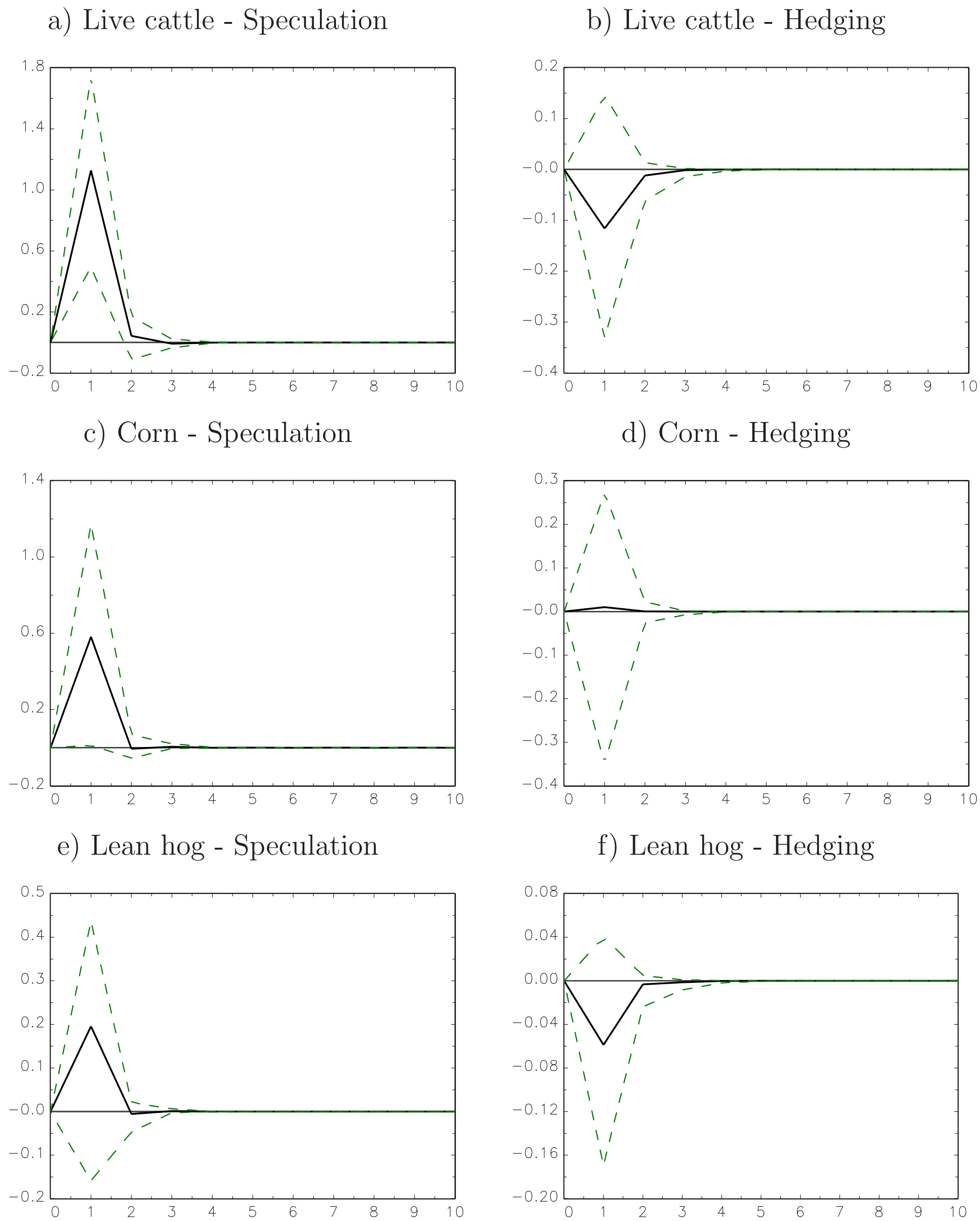

Figure 1: Impulse responses: Effect of price shocks (Δp_t) on speculation (Δs_t) and hedging (Δh_t).

Table 3: Residual analysis

		Tests for autocorrelation		LJB test for nonnormality	Multivariate ARCH-LM
		Portmanteau test	LM test		
Cattle	Δh_t	0.0230	0.4496	0.0000	0.6784
	Δs_t	0.0770	0.3091	0.0000	0.0009
Corn	Δh_t	0.5852	0.6464	0.0000	0.0797
	Δs_t	0.3064	0.0357	0.0000	0.9225
Hog	Δh_t	0.6913	0.6657	0.0000	0.1996
	Δs_t	0.0619	0.0296	0.0000	0.0000

Table 3 presents the p-values of a range of diagnostic tests. Portmanteau and Breusch-Godfrey LM tests for autocorrelation, Lomnicki-Jarque-Bera (LJB) test for nonnormality, and the multivariate ARCH-LM test are considered. The tests for autocorrelation yield mixed results. The null hypothesis of no autocorrelation is rejected for live cattle Δh_t (Portmanteau test), as well as corn Δs_t and lean hog Δs_t (LM test), using a 5% significance level. However, for no series do both Portmanteau and Breusch-Godfrey LM tests jointly reject the null hypothesis of no autocorrelation. The results of the Lomnicki-Jarque-Bera (LJB) tests unequivocally point to nonnormality. Lütkepohl (2004, p. 46) argues that nonnormal residuals may signal neglected nonlinearities. We will analyze potential nonlinearities in the next section. Finally, the H_0 of no ARCH is rejected for the live cattle Δs_t and the lean hog Δs_t series. This result is in particular interesting since the univariate ARCH test results presented in Table 1 reject conditional heteroskedasticity for all except the lean hog Δs_t series. Although the results of the residual analysis are not fully satisfactory we will not follow this up but move on to the nonlinear modelling.

4 LSTR analysis

4.1 The model

In the last section we found positive impulse responses of speculation to price shocks. In this section we will analyze whether this reaction is regime-independent as suggested by the linear VAR model or, whether the speculation series react differently to price movements, depending on different price regimes. In order to obtain a useful characterization of the dynamics which, however, allows for a simple interpretation of the results, we chose the logistic smooth transition regression (LSTR) model for the following investigation. Moreover, a modelling cycle and evaluation stages as well as freely available software already exist (see Teräsvirta, 1994, 1998, 2004, van Dijk et al., 2002, and Lütkepohl and Krätzig, 2004).

The standard LSTR model is defined as

$$y_t = \phi' z_t + \theta' z_t G(\gamma, c, \tau_t) + u_t, \quad u_t \sim iid(0, \sigma^2) \tag{1}$$

where $z_t = (w_t', x_t')'$ is a vector of explanatory variables with $w_t' = (1, y_{t-1}, ..., y_{t-n})'$ and $x_t' = (x_{1t}, ..., x_{kt})'$ which is a vector of exogenous variables. $\phi = (\phi_1, ..., \phi_m)$ and $\theta = (\theta_1, ..., \theta_m)$ are parameter vectors.

The general logistic transition function

$$G(\gamma, c, \tau_t) = \left(1 + exp\{-\frac{\gamma}{\hat{\sigma}_{\tau_t}^K} \prod_{k=1}^{K} (\tau_t - c_k)\}\right)^{-1}, \quad \gamma > 0 \tag{2}$$

is a bounded function in the interval [0, 1], where γ is the slope parameter which indicates how rapid the transition from zero to unity is, c is the vector of location parameters that determines where the transition occurs, and τ_t is the transition variable. The sample standard deviation of τ_t, labelled $\hat{\sigma}_{\tau_t}^K$, is used to make γ approximately scale-free. Depending on the choice of K, equations (1) and (2) jointly define the LSTR1 ($K = 1$) or LSTR2 ($K = 2$) model, respectively. For $K = 1$, we have two regimes where the parameters $(\phi + \theta G(\gamma, c, \tau_t))$ change monotonically as a function of the transition variable from ϕ (if $G(\gamma, c, \tau_t) = 0$) to $\phi + \theta$ (if $G(\gamma, c, \tau_t) = 1$). For $K = 2$, we have three regimes where the two outside regimes are identical but different to the middle one. In our approach, we will not choose K explicitly but leave the decision to the linearity tests described in the next section.

4.2 Testing linearity against LSTR

To test linearity against LSTR is the first step of the LSTR modelling cycle as proposed by Teräsvirta (1994, 1998, 2004). The linearity tests were conducted for up to eight lags. The variables with the smallest p-values are chosen as transition variables. For the live cattle, corn, and lean hog series the variable Δp_t rejects the null hypothesis of linearity most strongly. The p-values are presented in Table 4.

Table 4: Testing linearity against LSTR

	Suggested transition variable	p-value	Suggested model
Live Cattle	Δp_t	0.0055	LSTR1
Corn	Δp_t	0.0083	LSTR1
Lean Hog	Δp_t	0.0000	LSTR1

The choice between the LSTR1 and LSTR2 model is based on a series of F-tests as discussed in Teräsvirta (1994, 1998, 2004). The test results (not reported here) suggest to use a LSTR1 model for all series investigated. These results obtained, concerning the choice of the transition variable and the model for the series analyzed in this investigation, point to a similar structure of the interrelation of speculative activity and futures prices in these markets. First, the choice of Δp_t as the transition variable stresses the key role of futures prices and therefore supports the results of the impulse responses and Granger causality tests obtained through the VAR investigation. Second, the choice of the LSTR1 model indicates that there is a transition between two different regimes. Since the linear VAR model is not capable of catching these dynamics we can expect to gain additional insights from the LSTR1 model.

4.3 Live cattle - speculation dynamics

The next step in the modelling cycle is to specify the parameter structure of the model. A number of LSTR models with a variety of different lags were estimated for the live cattle speculation series and variables with poor explanatory power were excluded from the final specification using p-values as a guidance. The final regression results in equation (3) are reported together with a number of statistics.

$$\begin{aligned}\Delta s_t \quad = \quad & -\underset{(0.00)}{5.27} - \underset{(0.17)}{0.08}\,\Delta s_{t-1} - \underset{(0.00)}{0.31}\,\Delta s_{t-7} - \underset{(0.00)}{0.18}\,\Delta s_{t-8} + \underset{(0.69)}{0.30}\,\Delta p_t \\ & + \underset{(0.01)}{1.12}\,\Delta p_{t-1} - \underset{(0.59)}{0.25}\,\Delta p_{t-3} - \underset{(0.01)}{1.30}\,\Delta p_{t-4} \\ & +[\underset{(0.00)}{6.92} + \underset{(0.00)}{0.24}\,\Delta s_{t-1} + \underset{(0.00)}{0.33}\,\Delta s_{t-7} + \underset{(0.02)}{0.21}\,\Delta s_{t-8} + \underset{(0.07)}{1.66}\,\Delta p_t \\ & - \underset{(0.64)}{0.30}\,\Delta p_{t-1} + \underset{(0.16)}{0.85}\,\Delta p_{t-3} + \underset{(0.02)}{1.47}\,\Delta p_{t-4}] \\ & [1 + exp\{-(\underset{(NaN)}{33.47}\,/\hat{\sigma}^1_{\Delta p})(\Delta p_t + \underset{(NaN)}{0.46})\}]^{-1}\end{aligned} \tag{3}$$

$$T = 452,\ \ \hat{\sigma} = 12.88,\ \ R^2 = 0.24,\ \ AIC = 5.15,\ \ pLM_{ARCH}(1) = 0.80,$$
$$pLM_{ARCH}(4) = 0.00,\ \ pLJB = 0.00,\ \ pLM_{AR}(1) = 0.69,\ \ pLM_{AR}(4) = 0.00$$

The p-values of the coefficients appear in parentheses. T is the sample size; $\hat{\sigma}$ is the estimated standard deviation of the residuals; R^2 is the coefficient of determination; AIC is the Akaike information criterion; $pLM_{ARCH}(q)$ is the p-value of the LM test of no ARCH up to order q; $pLJB$ is the p-value of the Lomnicki-Jarque-Bera normality test; and $pLM_{AR}(q)$ is the p-value of the LM test of no error autocorrelation up to order q. The assumption of normality as well as the hypotheses of no ARCH and of no error autocorrelation are rejected up to order four. However there is no evidence of ARCH and autocorrelation at one lag.

Before analyzing the estimated coefficients it is useful to take a look at Figure 2. Figure 2 presents the transition function plotted against its argument (Δp_t) and against time. When the transition function equals zero (i.e., the last row of equation (3) equals zero) only the linear part of the model (i.e., the first two rows of equation (3)) enter the regression. Contrariwise, when the transition function equals one, the complete model is necessary to capture the features of Δs_t.

a) Transition function plotted against Δp_t

b) Transition function plotted against time

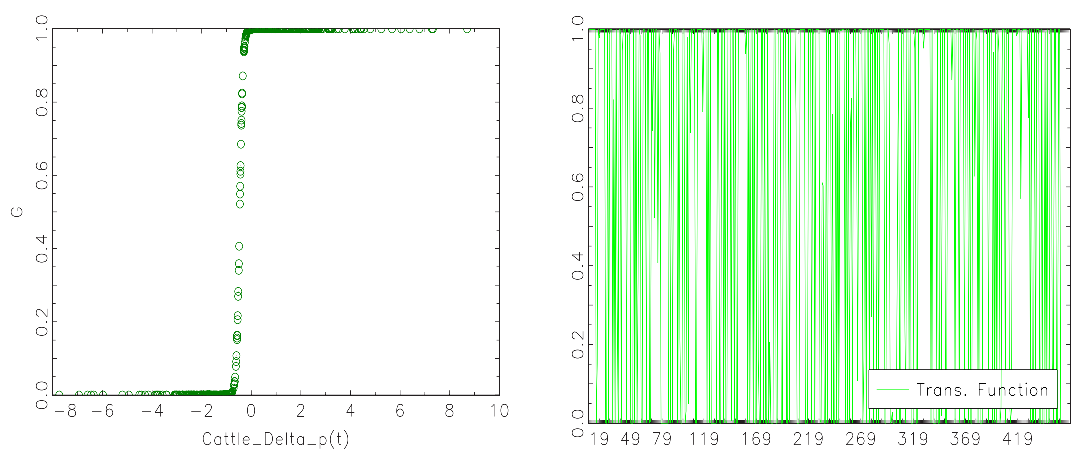

Figure 2: Live cattle transition function.

Note that, the transition variable Δp_t is the natural logarithm of the difference between the futures settlement price at time t and the settlement price at t minus one week, since we analyze weekly data. Positive values of Δp_t therefore represent an increase in futures prices while negative values of Δp_t represent a fall in futures prices. Interestingly, the transition shown in Figure 2a) occurs when Δp_t is close to zero ($c = -0.46$). Hence, we have different regimes, depending on wether futures prices are rising or falling. That means, in the case of falling futures prices where the transition function equals zero, the linear component of equation (3) fully describes the data generating process, while in the case of increasing prices where the transition function equals one, the entire model (linear plus nonlinear) is used for the regression.

The transition from one regime to the other is rather rapid ($\gamma = 33.47$). Since every point in Figure 2a) represents an observation, one can easily retrace the realizations of the transition function. Most observations are close to the two extremes ($G = 0$ or $G = 1$) while only a few observations are in the intermediate range. This supports the finding of a fast transition from one state to the other. Figure 2b) shows that the transition function varies between zero and unity over the entire time frame. Hence, there seems to be no 'normal regime' of $G = 0$ or $G = 1$ but there is a continuous alternation between these two regimes. The structure of the observations in Figure 2a) is supportive of this finding since the realizations of the transition function appear to be subdivided into approximately equal parts.

Now we take a closer look at how futures prices affect speculation in the live cattle futures market. Therefore we focus on the coefficient estimates presented in equation (3). The effect of Δp_t on Δs_t is positive and much larger in expansions ($0.3 + 1.66 = 1.96$) than in the regime with falling prices (0.3). Moreover, in regard to the p-values presented in parentheses, Δp_t has only a significant impact on Δs_t in the former case, using a 10% significance level. In addition, former speculative activity seems to play an important role in the regime with rising prices. The sign of Δs_{t-1} changes from slightly negative to positive during the transition to the regime where $G = 1$. Moreover, the estimate is significant at the 1% level in the latter case. These findings are indicative of herding and feedback trading during booms, with positive price movements acting as a signal to traders.[2]

4.4 Corn - speculation dynamics

We proceed with the estimation of an LSTR1 model with transition variable Δp_t for the corn speculation series. After excluding some variables with poor explanatory power, the final regression equation reads as follows:

[2]Nofsinger and Sias (1999) define herding as investors following a common signal. Feedback trading is a special case of herding, where lagged returns act as the common signal.

$$
\begin{aligned}
\Delta s_t \;=\;& -\underset{(0.01)}{9.57} - \underset{(0.99)}{0.00}\,\Delta s_{t-1} - \underset{(0.96)}{0.00}\,\Delta s_{t-7} + \underset{(0.14)}{0.13}\,\Delta s_{t-8} \\
& + \underset{(0.74)}{0.22}\,\Delta p_t + \underset{(0.90)}{0.04}\,\Delta p_{t-2} + \underset{(0.79)}{0.09}\,\Delta p_{t-7} - \underset{(0.32)}{0.37}\,\Delta p_{t-8} \\
& +[\underset{(0.00)}{17.90} + \underset{(0.06)}{0.20}\,\Delta s_{t-1} + \underset{(0.45)}{0.09}\,\Delta s_{t-7} - \underset{(0.09)}{0.20}\,\Delta s_{t-8} \\
& + \underset{(0.57)}{0.51}\,\Delta p_t + \underset{(0.99)}{0.00}\,\Delta p_{t-2} - \underset{(0.03)}{1.43}\,\Delta p_{t-7} + \underset{(0.23)}{0.73}\,\Delta p_{t-8}] \\
& [1 + exp\{-(\underset{(NaN)}{4.02}\,/\hat{\sigma}^1_{\Delta p})(\Delta p_t + \underset{(NaN)}{0.20})\}]^{-1}
\end{aligned} \tag{4}
$$

$$T = 452,\ \ \hat{\sigma} = 14.13,\ \ R^2 = 0.28,\ \ AIC = 5.33,\ \ pLM_{ARCH}(1) = 0.43,$$
$$pLM_{ARCH}(4) = 0.95,\ \ pLJB = 0.00,\ \ pLM_{AR}(1) = 0.00,\ \ pLM_{AR}(4) = 0.00$$

The assumption of normality is, again, rejected as well as the null hypothesis of no autocorrelation. However, there seems to be no ARCH.

Figure 3a) and 3b) present the transition function plotted against Δp_t and against time. Compared to the speculation dynamics in the cattle futures markets, here, the transition between the two states is much smoother ($\gamma = 4.02$). However, the transition, again, occurs close to $\Delta p_t = 0$ ($c = -0.20$) indicating an expansion and contraction regime. Another similarity is that the observations seem to be subdivided into equally sized parts, and the transitions occur steadily over the entire time frame although there is a much larger number of observations in the intermediate range of G.

The estimates presented in equation (4) are supportive of the assumption of similarity between cattle and corn speculation dynamics. Here, again, the effect of Δp_t on Δs_t is positive and much larger in expansions ($0.22 + 0.51 = 0.73$) than in contractions (0.22), pointing to herding behavior in the corn futures market during price expansions. However, the estimates are not significant at any level. Additionally, there is some similarity concerning Δs_{t-1}. In the contraction regime, Δs_{t-1} does not have any influence on Δs_t, whereas in the expansion state, there is a significant positive impact, using a 10% significance level.

a) Transition function plotted against Δp_t

b) Transition function plotted against time

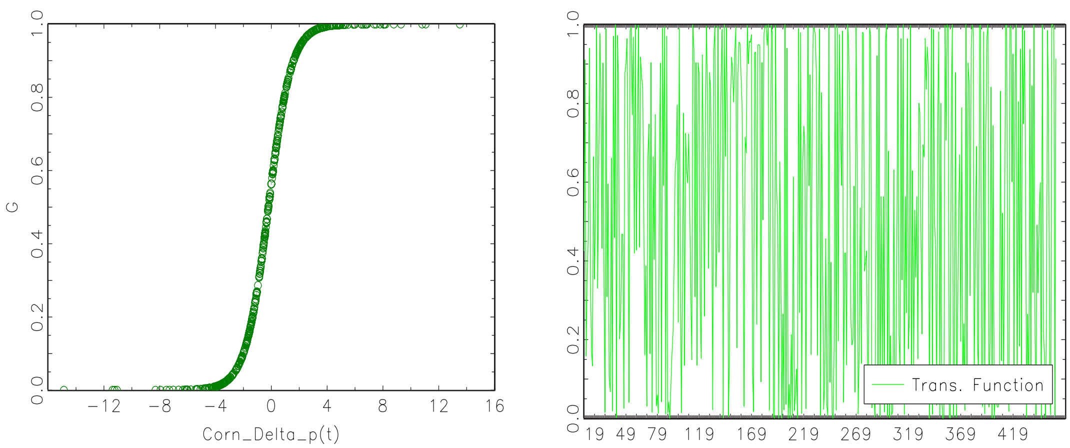

Figure 3: Corn transition function.

4.5 Lean hog - speculation dynamics

Finally, we estimate an LSTR1 model with transition variable Δp_t for the lean hog speculation series.

$$
\begin{aligned}
\Delta s_t \;=\;& -\underset{(0.00)}{17.66} + \underset{(0.16)}{0.18}\,\Delta s_{t-1} - \underset{(0.00)}{0.50}\,\Delta s_{t-2} + \underset{(0.04)}{0.22}\,\Delta s_{t-8} \\
& - \underset{(0.02)}{1.13}\,\Delta p_t - \underset{(0.02)}{0.68}\,\Delta p_{t-1} - \underset{(0.00)}{1.36}\,\Delta p_{t-6} - \underset{(0.06)}{0.54}\,\Delta p_{t-7} \\
& + [\underset{(0.00)}{21.66} - \underset{(0.34)}{0.15}\,\Delta s_{t-1} + \underset{(0.00)}{0.63}\,\Delta s_{t-2} - \underset{(0.12)}{0.21}\,\Delta s_{t-8} \\
& + \underset{(0.00)}{1.47}\,\Delta p_t + \underset{(0.00)}{1.38}\,\Delta p_{t-1} + \underset{(0.00)}{1.74}\,\Delta p_{t-6} + \underset{(0.07)}{0.69}\,\Delta p_{t-7}] \\
& [1 + exp\{-(\underset{(NaN)}{3.63}\,/\hat{\sigma}^1_{\Delta p})(\Delta p_t + \underset{(NaN)}{2.89})\}]^{-1}
\end{aligned}
\qquad (5)
$$

$$T = 452,\;\; \hat{\sigma} = 16.46,\;\; R^2 = 0.18,\;\; AIC = 5.64,\;\; pLM_{ARCH}(1) = 0.00,$$

$$pLM_{ARCH}(4) = 0.03,\;\; pLJB = 0.00,\;\; pLM_{AR}(1) = 0.01,\;\; pLM_{AR}(4) = 0.11$$

The null hypotheses of normality and no ARCH are rejected whereas the null hypothesis of no error autocorrelation cannot be rejected up to order four.

The transition function presented in Figure 4a) displays a smooth transition ($\gamma = 3.63$) from the contraction to the expansion regime. The transition, however, does not take place as close to zero as in the former investigations ($c = -2.89$). In addition, unlike the observations of cattle and corn futures speculation, here, the observations are not split into two equally sized regimes. There seem to be more observations for the expansion regime $G = 1$ than for $G = 0$. The results presented in Figure 4b) confirm this finding.

a) Transition function plotted against Δp_t

b) Transition function plotted against time

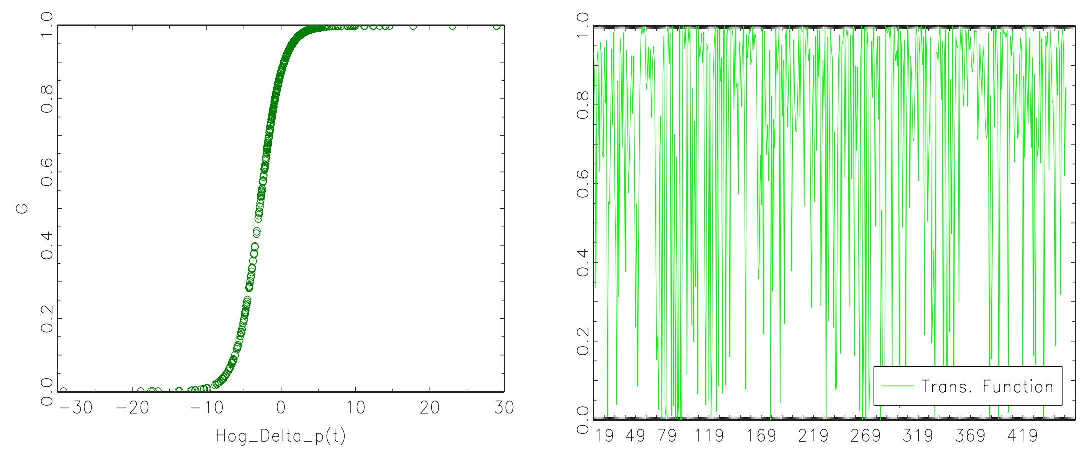

Figure 4: Lean hog transition function.

The regression results presented in equation (5) reveal a clear structural break in the effects of past price changes from negative in the contraction regime ($-1.13\ \Delta p_t$ $-0.68\ \Delta p_{t-1}$ $-1.36\ \Delta p_{t-6}$ $-0.54\ \Delta p_{t-7}$) to positive during price expansions ((-1.13 $+\ 1.47$) Δp_t + ($-0.68 + 1.38$) Δp_{t-1} + ($-1.36 + 1.74$) Δp_{t-6} + ($-0.54 + 0.69$) $\Delta p_{t-7} = 0.34\ \Delta p_t + 0.70\ \Delta p_{t-1} + 0.38\ \Delta p_{t-6} + 0.15\ \Delta p_{t-7}$). Moreover, these effects are highly significant. Hence, the tendency from a moderate impact of price changes on speculation during contractions to significantly positive effects during booms in the cattle and corn futures markets is even more obvious in the lean hog futures market where the signs of the coefficients change from negative to positive. However, in contrast to the cattle and corn futures, former speculative activity does not seem to play a role here. The estimated coefficients for s_{t-1} are not significant and do not support former findings of a stronger impact of s_{t-1} on s_t during price expansions.

4.6 Misspecification testing

We conclude the modelling cycle by checking the quality of the estimated LSTR1 models. The tests discussed here are LM-type tests of no additive nonlinearity and parameter constancy.

The results presented in Table 5 indicate that the LSTR1 models are adequate with regard to parameter constancy and no remaining nonlinearity, at least for the live cattle and lean hog series. The results for the corn series point to remaining nonlinearities. Although the chosen LSTR1 model does not seem to explain all nonlinearity found in the corn data, the test results do not point to an LSTR2 model. Because of this, together with the fact that linearity is most strongly rejected if Δp_t is the transition variable, we do not change the structure of the model. Moreover, parameter constancy is not rejected for the corn series.

Table 5: Test for no remaining nonlinearity and parameter constancy

	Linearity				Parameter constancy		
	F	F4	F3	F2	$K=1$	$K=2$	$K=3$
Cattle	0.8695	0.5797	0.4693	0.9765	0.8188	0.9423	0.7346
Corn	0.0169	0.1379	0.4750	0.0067	0.8936	0.5442	0.5877
Hog	0.1649	0.3308	0.1591	0.2816	0.5396	0.5997	0.7061

Note: The table contains p-values of F-variants of LM diagnostic tests of no remaining nonlinearity and parameter constancy. With regard to the test for no remaining nonlinearity, the following decision rules apply: F represents the general test for no remaining nonlinearity. If the null hypothesis of no remaining nonlinearity is rejected, a sequence of null hypotheses (corresponding to F4, F3, and F2) is tested. If the rejection of F3 is the strongest, select an LSTR2 model, otherwise an LSTR1 model is appropriate (see Teräsvirta, 1998). The results of the parameter constancy test are given for three different transition functions with $K = 1, 2, 3$.

5 Conclusions

After a first introductory look at speculators' and hedgers' reactions to price shocks using vector autoregressions, nonlinear dynamics of speculators' long positions in live cattle, corn, and lean hog futures markets were studied. Nonlinearities were found in all markets. Speculators react differently to price changes, depending on the price regime. The transition from one regime to the other occurs when price changes are close to zero, indicating different behavior during price expansions and contractions. Trading activity induced by price changes appears to be much more intense during price expansions. In addition, at least for the live cattle and corn futures markets, former speculative activity plays a significant role in expansions. Our findings therefore suggest herding behavior and positive feedback trading of speculators in booms.

The contribution of this study is that it uncovers a similar pattern of nonlinearities in three different agricultural futures markets. While the choice of LSTR1 models for all series indicates that there are not more than two different regimes apparent, the choice of the transition variables emphasizes the key role of recent price changes in this investigation. Moreover, the value at which the transition takes place is close to zero for all series, indicating that the different regimes represent contractions and expansions. The similar pattern therefore concerns the type of model suggested to accurately catch the nonlinear dynamics as well as the choice of the transition variable, and the actual occurrence of the transition. The nonlinearities found in the present study may also hold in other futures markets like financial, commodity, and foreign currency futures markets. However, this remains to be confirmed in future research.

References

Hall, A.D., J. Skalin and T. Teräsvirta (2001). *A nonlinear time series model of El Niño.* Environmental Modelling & Software, 139-146.

Liu, Q. (2005). *Price relations among hog, corn, and soybean meal futures.* The Journal of Futures Markets, Vol. 25, No. 5, 491-514.

Lütkepohl, H. (2004). *Univariate time series analysis.* In: H. Lütkepohl and M. Krätzig, eds. *Applied Time Series Econometrics*, 222-242, Cambridge University Press, Cambridge.

Lütkepohl, H. and M. Krätzig (2004). *Applied Time Series Econometrics.* Cambridge University Press, Cambridge.

Lütkepohl, H., T. Teräsvirta and J. Wolters (1999). *Investigating stability and linearity of a German M1 money demand function.* Journal of Applied Econometrics 14, 511-525.

Mejia-Reyes, P., D.R. Osborn and M. Sensier (2004). *Modelling real exchange rate effects on output performance in Latin America.* The University of Manchester, Discussion Paper Series, Number 035.

Nofsinger, J.R. and R.W. Sias (1999). *Herding and feedback trading by institutional and individual investors.* The Journal of Finance, Vol. LIV, No. 6, 2263-2295.

Sarno, L. (1999). *Adjustment costs and nonlinear dynamics in the demand for money: Italy, 1861-1991.* International Journal of Finance and Economics, 4, 155-177.

Skalin, J. and T. Teräsvirta (1999). *Another look at swedish business cycles.* Journal of Applied Econometrics, 14, 359-378.

Teräsvirta, T. (1994). *Specification, estimation, and evaluation of smooth transition autoregressive models.* Journal of the American Statistical Association 89, 208-218.

Teräsvirta, T. (1997). *Smooth transition models.* In: C. Heij, H. Schumacher, B. Hanzon and K. Praagman, eds. *System Dynamics in Economic and Financial Models*, 109-136, John Wiley and Sons, Chichester.

Teräsvirta, T. (1998). *Modeling economic relationships with smooth transition regression.* In: A. Ullah and D.E.A. Giles, eds. *Handbook of Applied Economic Statistics*, 507-552, Marcel Dekker, New York.

Teräsvirta, T. (2004). *Smooth transition regression modeling.* In: H. Lütkepohl and M. Krätzig, eds. *Applied Time Series Econometrics*, 222-242, Cambridge University Press, Cambridge.

van Dijk, D. and P.H. Franses (1999). *Modeling multiple regimes in the business cycle.* Macroeconomic Dynamics 3, 311-340.

van Dijk, D., T. Teräsvirta and P.H. Franses (2002). *Smooth transition autoregressive models - a survey of recent developments.* Econometric Reviews, 21(1), 1-47.

Wang, C. (2003). *The behavior and performance of major types of futures traders.* The Journal of Futures Markets, Vol. 23, No. 1, 1-31.