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Speculation and nonlinear price dynamics in commodity futures markets

Abstract

In this article we present theoretical considerations and empirical evidence that the short-run autoregressive behavior of commodity markets is not only driven by market fundamentals but also by the trading of speculators. To empirically test this, we individually fit smooth transition autoregression models to commodity price series and find in many cases that the autoregressive behavior of price changes turns more positive as the relative size of speculative positions increases. This is especially pronounced for recent years. We propose as an explanation a growing fraction of speculators who engage in momentum trading.

Keywords: commodities, speculative positions, momentum, market dynamics, smooth transition autoregression.
JEL Classification: G13, G14.

Introduction

Influences of speculative activities on the formation of prices in commodity futures markets have been a relevant topic since a long time and were addressed in a number of studies. So far, most of these studies have aimed at detecting influences on the price or return volatility. Among them are Chang, Pinegar and Schacher (1997) who document that the coefficient on large speculator volume in the volume-volatility relationship in the gold, corn and soybeans market is much stronger than on volume of other traders. Studies which directly relate the level of speculation to volatility do generally not find any significant relationship. For example, Kocagil (1997) rejects the hypothesis that an increased intensity of futures speculation in metals markets tends to decrease spot price volatility. Irwin and Yoshimaru (1999) test the impact of commodity pool trading on volatility in 36 commodity markets and find no general evidence of an association between both. Only Chatrath and Song (1999) document, for five major agricultural commodities, a significant relationship between price jumps and the number of speculative contracts as well as the number of speculators, though a negative one.

Most of the academic work has so far focused on effects on the second moment of the return distribution. To the best of our knowledge, no study has been conducted to date which explicitly investigates price changes themselves in the light of speculation. A straight forward extension of existing research is therefore to ask whether a systematic shift in the dynamic behavior of price changes can be documented which is conditional on the varying degree of speculative activity in a market. The relevance of such research is obvious. It is of interest to scholars and policymakers to get a better understanding of commodity futures markets' dynamics as well as to sophisticated traders to arrive at superior trading strategies.

The idea that speculative activity could affect short-run price dynamics is based on two facts. One is that the objectives of the traders active in a market are substantially different from each other. The common notion is that speculators and hedgers are the two basic types of traders prevalent in a market. Hedgers participate in a market in order to reduce risk, which they cannot do or do not want to do by other means. Speculators, on the other side, engage in trading to explicitly take up risk in their quest for return.

The second one is an often reported stylized fact in many commodity markets: a persistent degree of autocorrelation. It has been documented, among many others, by Deaton and Laroque (1992). Reasons for its existence are manifold. Commodity markets are complex and differ substantially from capital markets. Tomek (1994) argues that inventory holding and transaction costs do both matter and are important factors for creating dynamic behavior but are not the only sources of dynamics. Williamson and Wright (1991) also refer to storage and additionally to transportation issues.

The presence of momentum may have consequences on the behavior of speculators. A straightforward way to benefit from correlated returns is to employ momentum or positive feedback strategies, i.e. buying when prices rise and selling when prices fall. Numerous studies have investigated the workability of such strategies. The general outcome is that these strategies have worked rather well in the past, especially over short horizons and even net transaction costs. Recent works include Shen, Szakmary and Sharma (2007) and Miffre and Rallis (2007). A pro-

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found overview can be found in Schneeweis, Kazemi and Spurgin (2007).

Though we have no direct evidence that speculators really trade on momentum, several studies point to that end. Sanders, Boris and Manfredo (2004) report a positive correlation between returns and speculative positions in the crude oil market. Röthig and Chiarella (2007) show for corn, live cattle and lean hogs that this relation is nonlinear and positive, and Sigl-Grüb and Schiereck (2008) document for a variety of markets that returns Granger cause speculative net positions but not vice versa.

Given these empirical results, theoretical considerations suggest furthermore that engaging in positive feedback trading is in this case a rational choice for an informed investor who does originally not trade on momentum caused by market fundamentals. De Long et al. (1990, p. 393) argue that in the presence of positive feedback traders it is rational for a speculator to "jump on the bandwagon and not to bug the trend". Because an informed rational speculator anticipates tomorrow's buying of positive feedback traders, he buys more on good news today than he would without their presence, driving prices up higher than the fundamental value. Hence, rational speculation will act destabilizing under these conditions, driving prices away from their actual equilibrium. Furthermore, a very recent empirical work by Guenster, Kole and Jacobsen (2008) documents in the case of U.S. industry return patterns that even in the obvious presence of a bubble the optimal response is to ride it than to avoid it. Validity of these results in the case of commodities may not be straightforward, but the occurrence of bubbles is not limited to capital markets and the results may be indicative for commodities, too.

The crucial point for our analysis is that if market participants indeed employ momentum or positive feedback strategies by and large, any eventual momentum already present in a market will be amplified further. This is because rising prices will trigger further purchases which again result in rising prices. Since momentum trading is not an original hedging activity, we expect that it is the speculators who mainly engage in it[1]. Therefore, when this is the case, we expect that the pattern of positively related price changes becomes stronger when the degree of speculative activities increases. Consequently, if significant dynamic behavior can be found in a market, only a part of it may be caused by market fundamentals, while another part is the consequence of speculators trading on it.

The above can be summarized in the research hypothesis of this paper: Under the presence of price momentum and rational speculation we expect that momentum increases as the relation between speculative and hedging positions enlarges. Therefore, we expect that the autocorrelation coefficients of an autoregressive model that we fit to price change series are significantly more positive in times when speculation is higher than in times where there is only low speculative activity.

To investigate this hypothesis we use the smooth transition autoregression (STAR) framework of Teräsvirta (1994). While using the varying degree of speculative positions as transition variable to switch smoothly between a hedgers-only and a speculators-only regime, we estimate the autoregressive coefficients for both regimes. We fit individual models to monthly returns of 19 different commodity markets and three different subsample periods. Although the fitted model is simple in that it only recognizes autoregressive behavior as the return generating process, we arrive at meaningful specifications in ten cases. In all these cases except one, the stronger positive coefficients of the speculators-only regime confirm our hypothesis. Additionally, the observation that we are better able to fit the model in the later subsamples may hint that speculators use momentum as a trading opportunity especially in the recent years.

The remainder of this paper is as follows. The next section introduces the dataset and Section 2 presents the STAR methodology. Empirical results to the hypothesis are then presented in Section 3. The last section contains the conclusion.

1. Data

A useful source for information regarding the degree of speculative activity in a market are the Commitment of Traders reports issued by the Commodity Futures Trading Commission, which contain a break down of the open interest of many major markets into different trader subcategories. Each market participant whose positions exceed a predefined limit has to report to the CFTC and classify himself either as being a commercial or a noncommercial trader. A commercial trader is one who is "commercially engaged in business activities hedged by use of the futures or option markets [.] This would include production, merchandising, or processing of a cash commodity, asset/liability risk management by depository institution, security portfolio risk management, etc." (CFTC Form 40). Reporting traders who

[1] Nevertheless we note that there are hedging strategies which result in the similar trading patterns like momentum strategies. Examples are the use of stop-loss orders or dynamic portfolio insurance strategies, which increase hedging activities as prices get worse. But, because commercials hedging needs exist in both directions, we believe that any overall effect is weak. In the crude oil market, an obvious example for this are explorers who appreciate a high selling price and refiners who favor a low purchasing price.

do not meet these criteria have to classify as noncommercials. Based on this collection procedure the Commitment of Traders reports break down total open interest into contracts held by commercials, noncommercials and contracts of traders who do not exceed the reporting level (nonreportables). A comprehensive treatment of the CoT data can be found in Sanders, Boris and Manfredo (2004).

The common notion, e.g. de Roon, Nijman, Veld (2000) or Bessembinder (1992), is that commercials engage in hedging, while positions of noncommercial traders are of a purely speculative nature and positions of nonreportables are some mixture of both. Although many studies use this classification, some care might be appropriate. Ederington and Lee (2002) demonstrate with a finer dataset for the oil market that it seems accurate to treat noncommercials as speculators but that commercial traders may not always be hedging. Sanders, Boris and Manfredo (2004) confirm these results for the whole energy complex. Based on these suggestions we treat noncommercials as purely speculative while we interpret results on hedgers with care, since hedgers might be seen as some subset of commercial traders.

Since October 1992, Commitment of Traders reports are released each Friday, containing a snapshot of past Tuesday's closing. Before that they were published biweekly, in most markets starting with January 1986.

From this we calculate the relative size of noncommercial positions in a market as

$$RSP_t = \frac{Number\ of\ noncommercial\ positions_t}{No.\ of\ noncommercial\ positions_t + No.\ of\ commercial\ positions_t}, \tag{1}$$

where the number of commercial positions is the sum of commercial long and short positions. The number of noncommercial positions is calculated as the sum of long and short positions plus two times the spread positions of noncommercials.

Prices of commodity futures contracts are taken from the Commodity Research Bureau InfoTech CD. The sample comprises data on 19 commodities from different sectors over the period January 1986 until March 2007. We use monthly data in order to be able to use CoT data from the pre-1992 period. This additionally reduces short-lived noise typically present in higher frequency time series. Monthly returns are calculated by cumulating daily changes of the log price in the nearby futures series. This nearby futures series is constructed using a rolling strategy: It contains settlement prices of the future with the shortest time to maturity. On the first day of the month of its expiry, the series switches to the futures contract with the second nearest maturity, and so on. This procedure circumvents problems with thin trading, which are likely to occur very shortly before maturity. To avoid any distortions, it is made sure that every absolute price change calculated across rolling days is computed from the same future contract. CoT numbers are averaged accordingly to arrive at monthly figures.

Summary statistics of commodity price changes are presented in Table 1. It also presents test statistics for autocorrelation, normality, and the presence of a unit root. We find evidence of autocorrelated returns in our monthly data. Returns are slightly fat tailed and positively skewed. As we would expect from returns, the presence of a unit root can be strongly rejected in all cases.

2. Methodology

The methodology we use for investigating the autoregressive behavior of returns is the smooth transition autoregression. Its roots lie in the switching regression model originally introduced by Quandt (1958). Recent advancements have been made by Teräsvirta and Anderson (1992), Granger and Teräsvirta (1993), Teräsvirta (1994, 1998), and Franses and van Dijk (2000). An introduction can be found in Teräsvirta (2004). It can have superior performance to ARMA specifications or models of the Markov switching type. The possibility to allow for a smooth transition between two extreme regimes is specially appealing in our context, since commercial and noncommercial traders interact at varying degrees.

The standard smooth transition autoregression model of lag order p has the form

$$y_t = (\varphi_1 + \varphi_2 y_{t-1} + ... + \varphi_p y_{t-p}) \cdot (1 - G(s_{t-d};\gamma,c)) + (\theta_1 + \theta_2 y_{t-1} + \ldots + \theta_p y_{t-p}) \cdot G(s_{t-d};\gamma,c) + \varepsilon_t, \tag{2}$$

with the autoregressive coefficients φ_i and θ_i, i=0,...p+1, the residuum $\varepsilon_t \sim$ iid$(0,\sigma^2)$ and the transition function $G(s_t; \gamma, c)$. $G(.)$ is bounded between 0 and 1 and is a function of the continuous transition variable s_{t-d} which can take on values from $-\infty$ to ∞. A popular choice for the transition function is the general logistic function of the form

$$G(s_t;\gamma,c) = \frac{1}{1 + \exp\left[-\gamma \prod_{k=1}^{K} (s_t - c_k)\right]}, \tag{3}$$

where the slope parameter γ controls the speed of the transition, and the location parameter(s) c_j the location of the transition function in s_{t-d}. $\gamma > 0$ is necessary for the model to be uniquely identified.

Table 1. Commodity sample and log return statistics

Commodity	Sector	Symbol	Market	Mean	Std. dev.	Skewness	Kurtosis	AR(1)	AR(2)	JB	ADF
Crude oil	Energy	CL	NYMEX	0.008	0.098	0.012	4.760	0.147*	-0.065**	32.91***	-13.95***
Heating oil	Energy	HO	NYMEX	0.006	0.094	0.201	3.782	0.057	-0.087	8.20**	-15.28***
Gasoline	Energy	HU	NYMEX	0.011	0.101	0.374	4.583	0.068	-0.217***	32.17***	-14.11***
Natural gas	Energy	NG	NYMEX	-0.007	0.152	0.048	3.322	0.068	-0.106	0.96	-13.11***
Orange juice	Foodstaff	JO	NYBOT	-0.001	0.082	0.286	4.375	-0.009	0.048	23.57***	-16.19***
Coffee	Foodstaff	KC	NYBOT	-0.008	0.111	0.520	4.320	-0.014	0.050	29.99***	-16.12***
Sugar	Foodstaff	SB	NYBOT	0.003	0.093	0.196	4.260	0.060	-0.059	18.49***	-14.96***
Soybean oil	Grains and Oilseeds	BO	CBOT	-0.004	0.069	0.004	4.325	-0.128**	0.127**	18.64***	-18.11***
Corn	Grains and Oilseeds	C_	CBOT	-0.006	0.068	0.507	6.815	0.044	0.082	165.52***	-15.19***
Oats	Grains and Oilseeds	O_	CBOT	-0.003	0.095	1.514	12.258	-0.110*	0.058	1,008.04***	-15.77***
Rough rice	Grains and Oilseeds	RR		-0.007	0.082	0.603	6.183	0.127**	0.151***	119.23***	-9.05***
Soybeans	Grains and Oilseeds	S_	CBOT	0.000	0.063	-0.296	5.227	-0.110	0.108**	56.45***	-17.71***
Soybean meal	Grains and Oilseeds	SM	CBOT	0.006	0.069	-0.014	4.950	-0.029	0.085	40.41***	-16.32***
Wheat	Grains and Oilseeds	W_	CBOT	-0.005	0.064	0.128	3.572	-0.016	-0.058	4.17	-16.15***
Cotton	Industrials	CT	NYBOT	-0.001	0.075	0.061	3.826	0.020	0.047	7.40**	-15.57***
Lumber	Industrials	LB	CME	0.000	0.089	0.251	3.837	0.009	0.044	10.12***	-15.75***
Feeder cattle	Livestock and Meats	FC	CME	0.005	0.039	-0.842	8.102	0.056	0.019	306.69***	-15.00***
Live cattle	Livestock and Meats	LC	CME	0.005	0.041	-0.801	7.845	-0.051	0.072	276.66***	-16.76***
Lean hogs	Livestock andMeats	LH	CME	0.003	0.076	-0.486	5.165	-0.038	0.005	59.85***	-16.48***
Pork bellies	Livestock and Meats	PB	CME	-0.003	0.113	0.061	4.154	-0.102	0.024	14.30***	-17.58***
Gold	Metals	GC	NYMEX	-0.001	0.038	0.374	3.682	-0.060	-0.119	10.89***	-16.89***
Copper	Metals	HG	NYMEX	0.010	0.077	0.526	5.527	0.039	-0.012	79.62***	-15.27***
Palladium	Metals	PA	NYMEX	0.004	0.087	0.156	4.846	0.013	0.045	37.24***	-15.70***
Platinum	Metals	PL	NYMEX	0.005	0.057	0.225	5.359	-0.084	0.004	61.28***	-17.29***
Silver	Metals	SI	NYMEX	-0.001	0.069	0.091	4.197	-0.121*	-0.104**	15.58***	-17.88***

Note: AR denotes autocorrelation coefficient of the returns. Significance is measured according to Ljung and Box (1979). JB is the Jarque-Bera (1980) test statistic, ADF is the Augmented version of the Dickey-Fuller (1979) test statistic. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

The choice of K determines the type of the actual transition. For K=1, G(.) changes monotonically from 0 to 1 with growing values of s_{t-d}. Hence, it can be used to model asymmetric behavior, for example, a given process in an economy whose dynamics differ at both turning points of the business cycle. For K = 2, G(.) becomes symmetric. In this case it has a global minimum at the point $s_{t-d} = (c_1 + c_2)/2$. For both, $s_t \to -\infty$ and $\to \infty$, it approaches 1. With this specification it is possible to model dynamic behavior which switches its behavior when the values of s_t become large or very small. In our framework we choose for obvious theoretical reasons $K = 1$.

This simple STAR model can be seen as a regime-switching model with two regimes, where the transition from one regime into the other is smooth and is controlled by the actual value of G(.). The model is very flexible and can be extended for different purposes, for example, to incorporate exogenous variables, see Teräsvirta (1998), or to a STAR model with time varying coefficients (TV-STAR), see Lundbergh et al. (2003). An extension which allows to incorporate more than two regimes, the MRSTAR model, was proposed by van Dijk and Franses (2000).

We individually fit STAR models to each of the commodity return series in our sample[1]. Teräsvirta / van Dijk and Medeiros (2005) demonstrate in their thorough forecasting exercise that a careful specification is crucial to successfully fitting nonlinear time series models. Granger (1993) strongly recommended a "specific-to-general" approach for that. It involves starting with a simple linear model and proceeding further to nonlinear models only if diagnostic tests suggest. For the case of STAR models this is specified further in the modelling cycle, a strategy for selecting appropriate STAR models according to Teräsvirta (1994) and van Dijk, Teräsvirta and Franses (2002). It entails three basic steps, specification, estimation and evaluation, and allows to make the necessary choices for the model in a systematic manner. The modelling cycle is data based. We will maintain it as far as it is viable in our context.

The first step is to select an adequate linear model. We use the Schwartz (1978) information criterion to select the appropriate lag length p. Based on this simple linear AR model linearity is then tested against the STAR alternative. The null hypothesis in (2) is $\theta_i = 0$, for each $i=0,\dots p+1$. When in this case the null hypothesis is valid and therefore $\theta_i = 0$ indeed, γ and c become unidentified nuisance parameters which are independent of the actual sample data. This affects the underlying distribution theory and renders any test invalid. Luukkonen, Saikkonen and Terasvirta (1988) and Teräsvirta (1994) suggest a Taylor expansion as approximation for the STAR model around $\gamma = 0$ which yields a linear model. We use a first order expansion because in our case $s_{t-d} \neq y_{t-p}$. This leads to

$$y_t = \beta_0 x_t + \beta_1 x_t s_t + e_t, \tag{4}$$

with $\beta_i = (\beta_{i,0}, \beta_{i,1}, \dots \beta_{i,p})$, $i = 0,1$, and $x_t = (1, y_{t-1}, \dots y_{t-p})'$. The null hypothesis then translates to H_0: $\beta_1 = 0$ in (4). It is tested with a standard variable addition test. Further details on the theory and computation are laid out by van Dijk, Teräsvirta and Franses (2002).

A subsequent choice which is also done by applying linearity tests is determining the appropriate lag order d of the transition variable in (2). For that purpose, linearity is tested for different values of d. Then the model is chosen which leads to the strongest rejection, i.e. the smallest p-value according to Teräsvirta (1994). We have theoretical reasons to set $d = 0$. Nevertheless, we apply the test for values $-2 < d < +2$. This will yield additional insights into the data. If our hypothesis is correct, we would expect that d will come out close to 0. If the optimal lag choice is ± 1 it would allow us to fit a better model while our hypothesis could still be maintained due to the very high and persistent autocorrelation which we find in speculative positions. But if the test is only significant for higher lag orders, the resulting model will become difficult to interpret in our context and we can not use it to evaluate our hypothesis. In pure time series applications also the type of the transition function (and hence a suitable value for K) needs to be determined. We abstain from it since our hypothesis suggests to set $K = 1$.

The second step in the modelling cycle is estimation of the parameters of the STAR model. We do that by using nonlinear least squares and the concentrated sum of squares function as in van Dijk, Teräsvirta and Franses (2002) and Leybourne, Newbold and Vougas (1998). The optimization algorithm we use for minimizing the sum of squared residuals is the downhill simplex algorithm of Nelder and Mead (1965). Appropriate starting values are taken from a grid search over γ and c, as is suggested.

Once the model is estimated, the evaluation stage follows and concludes the modelling cycle. Examining the model is necessary before making any infer-

[1] An alternative to the simple STAR would have been the panel STAR framework of Gonzalez, Teräsvirta and van Dijk (2005). We refrain from it since this would have implied that γ and c are equal over the whole cross-section. Since commodity markets differ from each other substantially, especially with regard to the average percentage of speculators active in a market, this is not desirable in our case.

ence. Following van Dijk, Teräsvirta and Franses (2002), it is done on the one hand by common sense diagnostics, and on the other hand by a number of misspecification tests developed for the STAR framework. The former, as Teräsvirta (1994) notes, is especially important when time series are relatively short. Therefore, we will only accept models in which the estimate of the location parameter c does not lie too far away from the actual values of the transition variable. We reject a model when c lies below the 0.15 percentile or above the 0.85 percentile of the sorted values of the relative size of speculative positions. This will mitigate the possibility of only having reached a local minimum and will make estimates more stable, since enough values are on both sides of c. Details and computation of the test procedures here applied are laid out by Eitrheim and Terasvirta (1996) and again van Dijk, Teräsvirta and Franses (2002). More specifically, we implement tests of parameter constancy, remaining nonlinearity and error autocorrelation. Parameter constancy is tested against the alternatives H1 of a smooth monotonic change in parameters, H2 of a symmetric nonmonotonic change in parameters, and H3 of a monotonical as well as non-monotonical change.

3. Empirical results

We carry out the sequences of the modelling procedure as laid out above. The left panel of Table 2 shows the number of lags selected by the Schwartz (1978) information criterion, as well as some details of the subsequently estimated linear AR models. The very low numbers for the R square and adjusted R square reveal their very low fit. The highest values are found for gasoline and soybean oil. Nevertheless, the explained variation hardly exceeds five percent. They are not of great use for modelling monthly price changes. Results of the linearity tests, the next step in building STAR models, are reported in the right panel of the table. At the ten percent level, linearity is rejected in roughly half of all cases, while at the five percent level it is still rejected in a third of all cases. The right panel also contains the suggested lag of the relative presence of speculators variable to be used as transition variable.

Table 2. Linear AR specifications and tests of linearity against STAR (full sample)

Commodity	No. of lags (BIC)	Linear AR model			Linearity test p-value	Suggested lag of RSP as transition variable
		No. of obs.	R^2	Adj. R^2		
Crude oil	3	252	0.020	0.008	0.091*	2
Heating oil	1	254	0.003	Na	0.581	
Gasoline	2	250	0.053	0.046	0.036**	1
Natural gas	1	203	0.005	na	0.548	
Orange juice	1	254	0.000	na	0.221	
Coffee	1	254	0.000	na	0.062*	0
Sugar	3	252	0.011	na	0.005***	0
Soybean oil	2	253	0.033	0.025	0.096*	-2
Corn	1	254	0.002	na	0.054*	0
Oats	1	254	0.000	na	0.084*	-1
Rough rice	4	239	0.028	0.012	0.232	
Soybeans	1	254	0.012	0.008	0.005***	0
Soybean meal	1	254	0.001	na	0.474	
Wheat	1	254	0.000	na	0.093*	2
Cotton	1	254	0.000	na	0.027**	-2
Lumber	1	254	0.000	na	0.004***	1
Feeder cattle	1	254	0.003	na	0.166	
Live cattle	1	254	0.003	na	0.143	
Lean hogs	1	254	0.001	na	0.130	
Pork bellies	1	254	0.010	0.006	0.439	
Gold	1	254	0.004	na	0.021**	1
Copper	1	254	0.002	na	0.004***	0
Palladium	1	254	0.000	na	0.652	
Platinum	1	254	0.007	0.003	0.000***	1
Silver	1	254	0.015	0.011	0.171	

Note: BIC is the Schwartz information criterion. RSP is the relative size of speculative positions as defined in the text. STAR models are selected as follows: first, for each commodity an AR model is determined using the BIC criterion. Then the Luukkonen, Saikkonen and Teräsvirta (1988) linearity test is applied for different lags of the relative size of speculative positions as potential transition variable. Reported is the lowest p-value together with its respective lag. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

We continue with fitting an individual STAR model for each commodity for which linearity was rejected at least at the ten percent level using the lag number and timely shift for the transition variable as determined before. The estimates of the coefficients together with the values of the R square and adjusted R square are reported in Table 3. The optimization algorithm converged in all cases. Nevertheless, we reject the models for crude oil, sugar, corn, oats and cotton because the estimate of the location parameter c is either above the 0.85 percentile (corn, cotton) or below the 0.15 percentile (all others) of the sorted values of the transition variable.

Before proceeding with making inference the models must pass a number of misspecification tests. Respective results are presented in Table 4. Although we arrive at estimates in nine different markets, we have to recognize that most models suffer from misspecification and hence can not be used further. Only soybeans and wheat look sufficiently are not rejected. Additionally, we consider platinum, too, since the only obvious rejection, residual autocorrelation, is made on a weak basis.

Based on these results the coefficient estimates of these remaining three models are examined with regard to our research hypothesis. We are particularly interested in the coefficients of the autoregressive parts. Statistically meaningful are only those of soybeans and platinum. In both raw materials we see a significantly negative coefficient in the hedgers-only regime while it is significantly positive in the speculators-only regime, thus lending support to our hypothesis.

Nevertheless, although this result confirms our hypothesis in at least these two cases, results look somewhat weak and we are particularly not satisfied with the frequent and strong rejection of parameter constancy often observed. We feel that the analysis needs further refinement. A natural respond to these rejections would be to allow parameters in each regime to change over time. This can be implemented by extending the models in place to the time varying smooth transition regression (TV-STAR) introduced by Lundbergh et al. (2003)[1].

Nevertheless, in order to keep the analysis simple we decided not to proceed in that direction but to divide our sample time-wise into three subsamples of equal length and re-estimate STARs for each subsample individually[2].

The modelling cycle is applied again for each susample. Table 5 shows details of the linear models as well as results of the linearity tests. In the first subsample, depicted in the left panel of the table, the Schwartz information criterion suggests for five materials lag orders of up to four, eight or even eleven lags. Since coefficients of such models can not be interpreted easily anymore we do not estimate models for these materials but simply leave them untouched.

Estimates of the STAR models are presented in Table 6 and statistics of the respective misspecification tests are depicted in Table 7. Overall, the models exhibit a much better fit. Adjusted R squares reach values of roughly 0.1. This is not much in absolute terms but considerably higher than using the full sample or even comparing to the linear design. It should also be seen with the fact in mind that price changes are modelled by using past values only. Most importantly, parameter constancy is now rejected much less often. After considering misspecification tests we accept 14 models. Out of these, ten models have significant estimates of their autoregressive coefficients. Out of these ten models in turn, all except wheat exhibit a positive coefficient in the speculators-only regime. Additionally, the coefficient of the hedgers-only regime is not only less positive but even negative and significant. From this it follows immediately that the coefficients in both regimes are statistically different from each other, since the both exhibit different signs and t-tests confirm that they are different from zero. Therefore, we find support for our hypothesis in 9 markets, although we have to note the only clear rejection in the case of wheat. We are not aware of any potential explanation for this observation.

[1] In short it can be described as a STAR model with a time trend as transition variable, which nests a further full STAR model in each of its regimes.

[2] As an additional note, the choice of three subsample periods is not arbitrary. We actually experimented with different forms of the TV-STAR model and found that in many models the regime representing time switched around the year 2000. By choosing three subperiods of equal length, the change from the second to the third period lays in the beginning of the year 2000.

Table 3. STAR specification (full sample)

Commodity	No. of obs.	R^2	R^2 adj.	γ	*c*	Coefficients Hedgers-only regime			Coefficients Speculators-only regime			Model accepted	Hypothesis
						$\varphi 1$	$\varphi 2$	$\varphi 3$	$\theta 1$	$\theta 2$	$\theta 3$		
Crude oil	c outside truncated range												
Gasoline	250	0.159	0.135	318,300.3	0.157	-0.016**	0.073	-0.103	0.046***	0.029	-0.349*		
Coffee	254	0.054	0.035	196,483.5	0.295	-0.026***	-0.182		0.012***	0.156*			
Sugar	c outside truncated range												
Soybean oil	253	0.085	0.059	275.9	0.351	-0.006	-0.119	0.278***	0.004	-0.172	-0.216***		
Corn	c outside truncated range												
Oats													
Soybeans	254	0.081	0.063	108.5	0.350	-0.013**	-0.400***		0.011***	0.126**		x	+
Wheat	252	0.052	0.033	1,157.8	0.388	0.008	0.028		-0.021***	-0.098		x	
Cotton	c outside truncated range												
Lumber	253	0.067	0.048	67.7	0.528	0.021***	-0.069		-0.031***	-0.044			
Gold	253	0.043	0.023	64.6	0.443	-0.005**	-0.080		0.018***	-0.124			
Copper	213	0.100	0.078	58.9	0.333	0.005	-0.249**		0.006	0.596***			
Platinum	253	0.078	0.059	19.3	0.360	-0.015**	-0.237***		0.032***	0.113*		x	+

Note: *, **, *** denote significance of the coefficient at the 10%, 5% and 1% levels, respectively.

Table 4. Misspecification tests for STAR (full sample)

Commodity	Parameter constancy			Remaining nonlinearity	Residual autocorrelation
	H1	H2	H3		
Crude oil					
Gasoline	2.164**	1.526	1.500*	2.550**	5.982***
Coffee	3.000**	2.832***	2.348***	2.082	2.258
Sugar					
Soybean oil	2.439**	1.647*	1.293	2.861**	3.045**
Corn					
Oats					
Soybeans	0.884	0.909	0.982	1.169	1.170
Wheat	0.651	0.866	0.788	1.476	0.359
Cotton					
Lumber	2.218*	1.630	1.655*	2.297*	1.643
Gold	0.554	0.860	0.790	1.449	5.997**
Copper	3.259**	2.921***	2.328***	3.109**	4.569**
Platinum	0.155	0.519	1.308	1.696	3.473*

Note: Parameter constancy is tested according to Lin and Terasvirta (1994) and Eitrheim and Teräsvirta (1996), where H1 is the alternative of 'smooth monotonic chances in parameters', H2 'nonmonotonic changes' and H3 'monotonic and nonmonotonic changes'. Tests of no remaining nonlinearity and no residual autocorrelation are calculated using Eitrheim and Teräsvirta (1996). *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

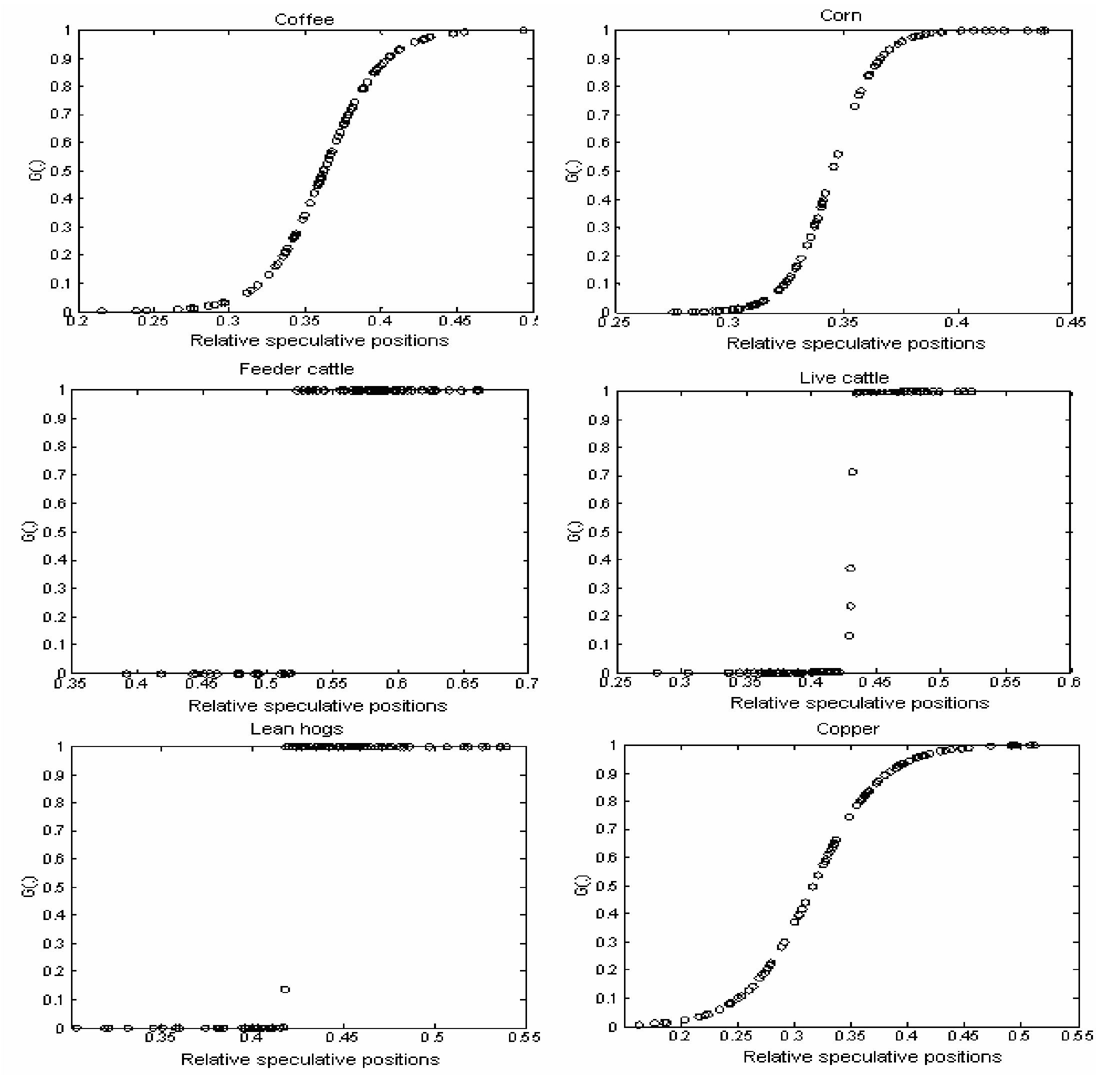

Fig. 1. Plot of relative speculative positions versus transition function values

Table 5. Linear AR specifications and tests of linearity against STAR (sub-samples)

Commodity	No. of lags (BIC)	Linear AR model			Linearity test p-value	Suggested lag of RSP as transition variable
		No. of obs.	R^2	Adj. R^2		
Subsample A: Jan. 1986 to Jan. 1993						
Crude oil	8					
Heating oil	1	84	0.011	na	0.507	
Gasoline	8					
Natural gas	11					
Orange juice	1	84	0.051	0.039	0.106	
Coffee	1	84	0.004	na	0.670	
Sugar	3	82	0.080	0.044	0.206	
Soybean oil	2	83	0.047	0.023	0.366	
Corn	1	84	0.020	0.008	0.200	
Oats	1	84	0.003	na	0.002***	-1
Rough rice	3	71	0.157	0.119	0.114	2
Soybeans	1	84	0.052	0.040	0.216	
Soybean meal	1	84	0.000	na	0.015**	2
Wheat	1	84	0.000	na	0.113	0
Cotton	1	84	0.044	0.032	0.281	
Lumber	1	84	0.016	0.004	0.029**	0
Feeder cattle	4					
Live cattle	1	84	0.013	0.001	0.456	
Lean hogs	2	83	0.057	0.033		No obs.
Pork bellies	1	84	0.003	na	0.339	
Gold	1	84	0.000	na	0.424	-2
Copper	1	84	0.001	na	0.688	
Palladium	1	84	0.000	na	0.702	
Platinum	8					
Silver	1	84	0.004	na	0.321	1
Subsample B: Feb. 1993 to Feb. 2000						
Crude oil	1	85	0.023	0.011	0.083*	-2
Heating oil	1	85	0.004	na	0.099*	0
Gasoline	1	85	0.004	na	0.038**	2
Natural gas	1	85	0.007	na	0.423	
Orange juice	1	85	0.044	0.032	0.344	
Coffee	1	85	0.000	na	0.015**	0
Sugar	1	85	0.010	na	0.182	
Soybean oil	1	85	0.011	na	0.086*	0
Corn	1	85	0.033	0.022	0.291	
Oats	1	85	0.010	na	0.092*	1
Rough rice	1	85	0.013	0.002	0.186	
Soybeans	1	85	0.003	na	0.093*	0
Soybean meal	1	85	0.003	na	0.150	
Wheat	1	85	0.005	na	0.357	
Cotton	1	85	0.010	na	0.210	
Lumber	1	85	0.002	na	0.003***	-1
Feeder cattle	1	85	0.013	0.001	0.093*	-1
Live cattle	1	85	0.007	na	0.464	
Lean hogs	1	85	0.003	na	0.137	
Pork bellies	1	85	0.039	0.027	0.490	
Gold	1	85	0.010	na	0.307	
Copper	1	85	0.000	na	0.594	
Palladium	1	85	0.002	na	0.697	
Platinum	1	85	0.037	0.025	0.039**	0
Silver	1	85	0.024	0.012	0.165	

Table 5 (cont.). Linear AR specifications and tests of linearity against STAR (sub-samples)

Commodity	No. of lags (BIC)	Linear AR model			Linearity test p-value	Suggested lag of RSP as transition variable
		No. of obs.	R^2	Adj. R^2		
Subsample C: March 2000 to March 2007						
Crude oil	1	85	0.020	na	0.243	
Heating oil	1	85	0.015	na	0.446	
Gasoline	2	85	0.083	0.060	0.010**	1
Natural gas	1	85	0.019	na	0.622	
Orange juice	1	85	0.001	na	0.115	
Coffee	1	85	0.012	na	0.004***	0
Sugar	1	85	0.021	na	0.091*	0
Soybean oil	1	85	0.080	0.064	0.062*	1
Corn	1	85	0.053	0.004	0.023**	0
Oats	1	85	0.000	na	0.063*	-1
Rough rice	1	85	0.062	0.014	0.246	
Soybeans	1	85	0.057	0.005	0.145	
Soybean meal	1	85	0.042	na	0.572	
Wheat	1	85	0.020	0.007	0.022**	1
Cotton	1	85	0.033	0.016	0.102	
Lumber	1	85	0.002	na	0.049**	1
Feeder cattle	1	85	0.019	na	0.018**	1
Live cattle	1	85	0.003	na	0.045**	0
Lean hogs	1	85	0.001	na	0.034**	1
Pork bellies	1	85	0.023	0.011		Missing obs.
Gold	1	85	0.056	0.005	0.250	
Copper	1	85	0.049	na	0.000***	0
Palladium	1	85	0.001	na	0.886	
Platinum	1	85	0.004	na	0.019**	1
Silver	1	85	0.057	0.016	0.277	

Note: BIC is the Schwartz information criterion. RSP is the relative size of speculative positions as defined in the text. STAR models are selected as follows: first, for each commodity an AR model is determined using the BIC criterion. Then the Luukkonen, Saikkonen and Teräsvirta (1988) linearity test is applied for different lags of the relative size of speculative positions as potential transition variable. Reported is the lowest p-value together with its respective lag. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

At that point, one may wish to further investigate the goodness of fit of the STAR models and conduct a test of its superior performance over the linear AR models. The elaborations made in the previous section on linearity tests illustrate that a direct test of superiority is not straightforward because of the problem of unidentified nuisance parameters in the STARs, in case the unknown underlying data generating process is linear in reality. Because an AR model only performs better when the data generating process is truly linear, linearity is the null hypothesis of such a test and hence relevant here. The truth is, however, that this issue is actually addressed by the linearity test.

Another interesting observation is that we find the highest number of accepted models and also the highest number of models which advocate our hypothesis in the latest subsample. While the number is less in middle subsample it is even zero in the first one. One possible interpretation is that speculators have become more aware of momentum as trading opportunity in recent years and can this way be easier modelled as a homogeneous group with regard to momentum, although they generally can be described as being very heterogeneous, see again, for example, Ederington and Lee (2002) for crude oil. This is in line with test results on parameter constancy.

As a last step, we print the values of the transition function against the transition variable for all six supporting models in the latest subsample. They are depicted in Figure 1. Each circle represents at least one data point. In the case of coffee, corn and copper, the transition from one to the other regime is indeed smoothly with a growing percentage of active speculators. This is differently in all three live stocks. Here, the switch is very abrupt, resembling a discrete regime switch. This corresponds to the large γ values of these models which we observe in Table 6. The reason may be, as discussed in the data section, that the behavior of commercial traders who proxy for hedgers is likely to extend beyond just hedging. Therefore, they may substantially add to momentum in times in which also speculators (i.e. noncommercials) are enticed to enter into a market. Furthermore, as Teräsvirta (2004) notes, estimates of γ may not be very accurate when the true γ is large because then many data points are necessary in the neighborhood of the location parameter c to arrive at a reliable estimate. Hence, our inference should not rely too much on the actual estimated value.

Table 6. STAR specification (sub-samples)

Commodity	No. of obs.	R^2	R^2 adj.	γ	c	Coefficients Hedgers-only regime			Coefficients Speculators-only regime			Model accepted	Hypothesis
						$\varphi 1$	$\varphi 2$	$\varphi 3$	$\theta 1$	$\theta 2$	$\theta 3$		
Subsample A: Jan. 1986 to Jan. 1993													
Oats	c outside truncated range												
Soybean meal	84	0.246	0.197	737,195.5	0.223	0.001	0.447**		0.003	-0.554***			
Lumber	84	0.109	0.051	78.5	0.370	0.002	0.228*		0.029**	-0.424***			
Subsample B: Feb. 1993 to Feb. 2000													
Crude oil	c outside truncated range												
Heating oil	85	0.158	0.105	49,649.5	0.122	0.018	-0.752***		-0.006	0.235***		x	+
Gasoline	85	0.117	0.061	209.8	0.148	-0.011	0.495*		0.030*	-0.224**			
Coffee	c outside truncated range												
Soybean oil	85	0.091	0.034	134.6	0.355	0.005	-0.111		-0.028**	0.248			+
Oats	85	0.106	0.049	156.5	0.200	-0.046**	-0.507		-0.004*	0.223***		x	+
Soybeans	c outside truncated range												
Lumber	85	0.157	0.103	57,571.9	0.641	0.027**	0.066		-0.059***	-0.245			
Feeder Cattle	85	0.112	0.056	114,492.3	0.433	0.006	0.251		-0.008**	-0.283		x	
Platinum	85	0.120	0.065	40.9	0.390	-0.006	-0.446***		0.023**	0.320***		x	+
Subsample C: March 2000 to March 2007													
Gasoline	82	0.253	0.182	118.0	0.171	-0.042**	0.129	-0.372***	0.063***	-0.164	-0.361		
Coffee	85	0.147	0.093	52.1	0.362	-0.076***	-0.436**		0.033***	0.114**		x	+
Sugar	85	0.070	0.011	41.3	0.232	0.001	-0.267		0.018	0.454**			
Soybean oil	84	0.182	0.130	4,243.1	0.357	0.036**	-0.238**		-0.017**	-0.336			
Corn	85	0.128	0.073	104.5	0.345	-0.021*	-0.164		0.013**	0.681**		x	+
Oats	85	0.142	0.088	2,478.8	0.294	-0.002	0.211**		0.053**	-0.527**		x	--
Wheat	84	0.133	0.078	59.9	0.408	0.022*	-0.139		-0.045***	-0.418		x	
Lumber	84	0.172	0.119	145.1	0.529	0.023*	-0.116		-0.071***	-0.332		x	
Feeder Cattle	84	0.186	0.134	14,076.4	0.520	-0.022*	-0.363**		0.011**	0.304***		x	+
Live cattle	85	0.145	0.091	1,228.5	0.431	0.001	-0.320***		0.008	0.445***		x	+
Lean hogs	84	0.154	0.100	45,377.3	0.418	0.013	-0.482***		-0.016	0.245***		x	+
Copper	85	0.214	0.165	33.5	0.317	0.004	-0.807***		0.015	0.591***		x	+
Platinum	84	0.119	0.063	101.8	0.301	-0.015	-0.002		0.027**	-0.005		x	

Note: *, **, *** denote significance of the coefficients at the 10%, 5% and 1% levels, respectively.

As an aside, we also note the following: At an earlier stage we presented results from other authors who found that speculators (or, more exactly non-commercials) choose their positions by reacting positively to past price changes. When price changes exhibit momentum we would expect that speculator presence tends to be stronger in times of high returns. Ceteris paribus, this bears as a consequence that the intercept of the speculators-only regime should be higher than that of the hedgers-only regime. Although we have no information on the actual behavior of commercials, this observation is indeed made in more than half of the models.

Table 7. Misspecification tests for STAR (sub-samples)

Commodity	Parameter constancy			Remaining nonlinearity	Residual autocorrelation
	H1	*H2*	*H3*		
Subsample A: Jan. 1986 to Jan. 1993					
Oats					
Soybean meal	0.637	1.787*	1.901*	2.434*	1.025
Lumber	0.616	2.396**	1.719*	4.758***	1.952
Subsample B: Feb. 1993 to Feb. 2000					
Crude oil					
Heating oil	0.195	0.234	1.101	0.469	1.243
Gasoline	1.538	2.356**	1.917**	0.858	0.597
Coffee					
Soybean oil	2.867**	1.546	1.224	0.315	1.090
Oats	0.975	1.388	1.505	1.453	0.913
Soybeans					
Lumber	2.018	1.752	1.577	5.599***	14.287***
Feeder cattle	1.130	0.775	0.811	1.164	1.027
Platinum	0.497	1.207	1.218	2.000	1.335
Subsample C: March 2000 to March 2007					
Gasoline	2.743**	2.053**	1.399	1.520	0.692
Coffee	0.183	0.755	0.624	0.553	0.956
Sugar	3.982***	2.470**	1.914**	3.753**	4.811**
Soybean oil	0.872	1.210	1.101	2.960**	5.060**
Corn	0.797	0.812	0.735	0.682	1.266
Oats	1.963	1.100	1.166	1.023	0.396
Wheat	0.367	0.552	0.807	1.272	0.387
Lumber	0.659	0.820	0.579	1.100	0.737
Feeder cattle	0.511	1.065	1.676*	1.605	1.644
Live cattle	0.366	0.810	1.408	1.960	0.212
Lean hogs	0.768	0.915	1.113	1.766	3.595*
Copper	1.791	1.759	1.269	0.901	4.875**
Platinum	0.909	0.574	0.958	1.050	0.655

Note: Parameter constancy is tested according to Lin and Teräsvirta (1994) and Eitrheim and Teräsvirta (1996), where H1 is the alternative of 'smooth monotonic chances in parameters', H2 'nonmonotonic changes' and H3 'monotonic and nonmonotonic changes'. Tests of no remaining nonlinearity and no residual autocorrelation are calculated using Eitrheim and Teräsvirta (1996). *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Conclusion

A well documented property of commodity markets is a persistent degree of momentum. This paper demonstrates that the short-term autoregressive behavior of commodity markets is not only determined by market fundamentals but also by the degree of speculative activity in a market.

Previous studies report that speculators' position taking positively depends on past price changes, which points to the end that they make use of market momentum by employing positive feedback trading strategies. According to De Long et al. (1990), this observation triggers further positive feedback trading of informed investors who do not trade on fundamental market momentum but on the presence of positive feedback traders.

Because a positive price change triggers further long engagements of speculators and further rising prices, a logical consequence from these considerations is that a higher percentage of speculative positions in a market will result in stronger momentum.

To investigate this hypothesis we individually fit smooth transition autoregression models to 19 different commodity return series. Using the relative size of speculative positions as transition variable we are able to measure the autoregressive behavior of a speculator-only regime and a hedger-only regime separately. We find support for our hypothesis in a variety of markets, while it is rejected in only one case.

The models employed here only recognize past price changes for explaining actual values. It is well possible that considering more sophisticated models with additional variables will improve the fit and allow a deeper insight into the matter. In future research it may therefore be promising to repeat this analysis with models which additionally consider fundamental variables as return driving factors. A possibility is to consider the suggestion of Reitz and Westerhoff (2007), who use the difference between actual prices and long-term average as determining factor for trader behavior.

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