Non Linear Oil Price Dynamics - A Tale of Heterogeneous Speculators? *

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Abstract

While some of the recent surge of oil prices can be attributed to robust global demand at a time of tight production capacities, commentators occasionally also blame the impact of speculators for part of the price pressure. We propose an empirical oil market model with heterogeneous speculators. Whereas trend-extrapolating chartists may tend to destabilize the market, fundamentalists exercise a stabilizing effect on the price dynamics. Using monthly data for WTI oil prices, our STR-GARCH estimates indicate that oil price cycles may indeed emerge due to the nonlinear interplay between different trader types.

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1 Introduction

Recent years witnessed a drastic rise in crude oil prices. Having been as low as 20 US dollars at the start of 2002, the price of West Texas Intermediate (WTI) exceeded 70 US dollars per barrel in mid-2006. To some extent this sharp price increase reflected market tightness driven by robust demand growth and dwindling spare production capacities, as global economic activity recovered briskly from its last downturn and energy consumption expanded rapidly in developing countries, especially in China (Sommer et al., 2005). However, commentators have also occasionally blamed the impact of speculators for part of the upward pressure on oil prices (e.g. Greenspan, 2004), with some analysts hinting at a speculative bubble in oil prices. Empirical investigations in this direction have primarily focused on data on the composition of open interest in crude oil futures markets published by the US Commodity Futures Trading Commission (CFTC) and have produced rather cautious results so far. Haigh et al. (2005) find that managed money traders (otherwise known as hedge funds) provide liquidity to large commercial traders (hedgers), not vice versa, altering their positions in response to price innovations and position changes by hedging participants. Consistently, IMF staff (Dao et al., 2005) observe that speculative activity follows changes in spot prices, which may imply that speculators consider a price trend to be lasting.

More generally, there exists widespread evidence that both private and professional speculators rely on simple trading strategies to determine their investment positions. For instance, Smidt (1965) reports that a large fraction of the speculators applies price charts to render trading decisions in commodity markets. Similar results are obtained by Draper (1985) and Canoles (1998). Furthermore, Sanders et al. (2000) discerns evidence of positive feedback trading in several commodity markets and Weiner (2002) detects evidence of herding behavior in the petroleum market. Overall, these studies indicate that speculative trading based on technical and fundamental analysis is a major factor of price variation in many commodity markets.

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

While the fundamentally justified price of oil has clearly risen in recent years - probably owing to the erosion of spare capacity in oil production - the impact of chartists may have aggravated the upward price movement at times. We use China's oil imports as proxy for diminishing excess capacity to determine the fundamental oil price.[1] Applying a STR-GARCH estimation procedure to monthly WTI prices in the period from 1986 to 2006 we find strong support for our setup. All coefficients are statistically significant and of the correct sign. Remember that the family of smooth transition autoregressive (STAR) models, developed by Teräsvirta and Anderson (1992), Granger and Teräsvirta (1993) and Teräsvirta (1994), implies the

[1]One might argue that this is a fairly crude way of modelling the fundamental price of oil. However, the aim of this paper is not to develop a sophisticated model of the fundamental oil price, but rather to analyze the interplay between different trader types. Thus, we restrict our fundamental price model to a simple and intuitively appealing approach that is able to replicate the stylized development of the fundamental oil price in recent years.

existence of two distinct regimes, with potentially different dynamic properties. The transition between the regimes is smooth. In our setup, the market impact of fundamentalists is low in one regime but high in the other. Since the market impact of the fundamentalists increases when prices run away from their long-run equilibrium values, booms and slumps are eventually countered. However, a (too) low market impact of fundamental traders in periods where prices are close to fundamental values and the presence of technical traders may be a crucial reason for cyclical price fluctuations, as observed in many commodity markets. Clearly, destabilizing chartists may then drive prices away from fundamental values.

The remainder of the paper is organized as follows. In section 2, we present our stylized model of the oil market with heterogeneous interacting traders. In section 3, the STR GARCH framework is applied to the chartist and fundamentalist model followed by a description of our data set. Section 5 contains the estimation results, before the final section concludes the paper.

2 A Stylized Model

Our model is inspired by the chartist-fundamentalist approach, which has proven to be quite successful in replicating some important stylized facts of stock and foreign exchange markets (Boswijk et al., 2006, DeGrauwe and Grimaldi, 2006; Brock and Hommes 1998; LeBaron et al., 1999). While the behavior of chartists is likely to be destabilizing, fundamentalists exercise a stabilizing effect on the price dynamics. However, the influence of the two trader types is typically not constant over time. In periods in which technical traders dominate the market, booms and slumps may emerge. When fundamental analysis gains in popularity, prices are pushed back to more moderate values. Within these models a larger part of the dynamics is driven by the interactions of the speculators. A central lesson of this branch of research is that the dynamics of asset prices is not completely determined by exogenous random shocks, such as new information, but has a substantial endogenous component. The core assumptions of the chartist-fundamentalist approach are backed up by many empirical studies. For instance, laboratory experiments indicate that agents are boundedly rational. They tend to apply simple rules of thumb which have proven to be useful in the past (Kahneman, Slovic and Tversky, 1986). Asset pricing experiments conducted by Smith (1991) or Sonnemans et al. (2004) furthermore indicate that financial market participants use simple forms of forecast rules such as extrapolative or regressive predictors. In the asset pricing experiments, bubbles and crashes are frequently observed. Survey studies by Taylor and Allen (1992) or Menkhoff (1997) reveal that professional foreign exchange dealers rely on both technical and fundamental analysis to determine their investment positions. As already mentioned in the previous section, similar results are observed for commodity market traders. In general, one may conclude that speculators use a mix of adaptive and regressive expectation formation rules to predict prices, regardless of the market in which they are trading.

Guided by these observations, we seek to develop a simple model that may help us to explain the strong cyclical motion of oil prices. Of course, many aspects influence the evolution of commodity prices. However, the role of speculators for oil price dynamics seems to be under-researched until now, which is why we will explicitly concentrate on them. In brief, the key elements of our oil market model may be outlined as follows: We consider two types of traders. Chartists extrapolate past price trends into the future and therefore add a positive feedback to the dynamics. Fundamentalists expect prices to return towards their fundamental value. While the market impact of chartists is constant, the market impact of fundamentalists depends on their confidence in mean reversion. For example, the larger the mispricing of oil, the more fundamentalists are convinced that a price correction towards the fundamental price will occur. After all active speculators have submitted their orders, the new oil price is announced. If buying orders exceed selling orders, the price of oil increases and vice versa. Then the next trading round starts.

Assuming that oil prices are determined in an order-driven market governed by heterogeneous agents (DeGrauwe and Grimaldi, 2005, 2006), the oil price change at time $t+1$ can be expressed as a function of excess demand from chartist and fundamentalist traders plus a noise term:

$$p_{t+1} = p_t + a^M(D_t^F + D_t^C) + \epsilon_{t+1}, \tag{1}$$

where p_t is the logarithm of the spot oil price at time t, and a^M is a positive reaction coefficient determined by the market maker. D_t^F and D_t^C denote the excess demand from fundamentalist and chartist speculators, respectively. The oil price change depends on the excess demand from both fundamentalist and chartist speculators, because the market maker does not observe them individually.

Orders are submitted by risk neutral speculators and depend on the expected excess returns which consists of the expected change in the oil price. We follow Reitz and Westerhoff (2007) and model the chartist trader's order as a positive function of the recent return:

$$D_t^C = a^C(p_t - p_{t-1}), \tag{2}$$

whereas the parameter a^C is expected to be positive. This modelling strategy is motivated by Dao et al. (2005) finding that speculative activity follows changes in spot prices, which implies that speculators consider a price trend to be lasting.

Compared to chartist traders, fundamentalist traders base their expectations considering the future oil price development on an analysis of oil price fundamentals, leading to a time-varying long-run equilibrium value, denoted with f_t. While the oil price is expected to revert over time, the weight attached to the deviation from the fundamentals in determining orders may vary over time. Thus, fundamentalist traders' orders may be expressed as

$$D_t^F = a^F w_t(f_t - p_t), \tag{3}$$

where a^F is a positive reaction function coefficient. As usual, we assume that the agents know the time varying long-run equilibrium value f_t of the oil price (Day and Huang, 1990; Brock and Hommes, 1998). Fundamental analysis then suggests buying (selling) undervalued (overvalued) oil. Note that selling oil either corresponds to reducing an open position or going short. The effective demand of the fundamentalists depends on their market impact w_t, i.e. the total orders submitted by fundamental traders are given as $a^F w_t(f_t - p_t)$. We assume that there exists a pool of latent fundamental traders who may become active if market circumstances look appealing to them. The market impact of the fundamentalists is defined as

$$w_t = \frac{1}{1 + exp(-\phi|f_t - p_t|)}. \tag{4}$$

Note first that w_t is restricted to the interval [0.5, 1]. Hence, at least 50 percent of the fundamentalists are active, regardless of the condition of the market.[2] The second term in the denominator captures the agents' confidence in fundamental analysis. The larger the deviation between the price of oil and its fundamental value, the stronger the confidence in mean reversion. As a result, the market impact of fundamental analysis increases. The parameter ϕ captures the curvature of (4). The larger ϕ, the more quickly fundamental traders will enter the market as the boom or slump increases.[3] Combining equations (1) - (4), the solution for the oil price can be derived as

$$p_{t+1} = p_t + \alpha(p_t - p_{t-1}) + \delta w_t(f_t - p_t) + \epsilon_{t+1}, \tag{5}$$

with $\alpha = a^M a^C > 0$ and $\delta = a^M a^F > 0$.

[2]The basic impact of the fundamentalists may also be interpreted as the impact of the real economy, i.e. the orders triggered by imbalances between the demand of the consumers and the supply of the producers in a given period. For instance, if the price is below its equilibrium value, then consumers will demand more than is offered by the producers in that period. As a result, their net demand is positive.

[3]With the logistic form of eq. (4) we follow the switching mechanism of Brock and Hommes (1997) and Lux (1998) and is the spirit of recent work by De Grauwe and Grimaldi (2005, 2006), who develop a similar switching function in their model of chartist-fundamentalist interaction.

From equation (5) we can see that, for a given value of δ , fundamentalist traders' stabilizing impact on the oil price increases nonlinearly with their confidence in fundamental analysis. As the oil price becomes increasingly misaligned, fundamentalist traders increase their orders and mean reversion strengthens. If the oil price is far from its fundamental equilibrium value, fundamentalist traders provide maximum mean reversion, since w_t will be close to unity. We now turn to the empirical implementation of the model.

3 The empirical model

Our aim is to investigate empirically the role of heterogeneous speculators through an investigation of the nonlinear theoretical oil price model outlined in the previous section. Our empirical model belongs to the STAR (Smooth Transition Autoregressive) family of models originally proposed by Ozaki (1985) and further developed and analyzed by Teräsvirta and Anderson (1992), Granger and Teräsvirta (1993) and Teräsvirta (1994). STAR models allow an economic variable to follow a given number of regimes with switches between regimes achieved in a smooth and continuous fashion and governed by the value of a particular variable or group of variables. The STAR framework has previously proved successful in applications to commodity prices (Reitz and Westerhoff 2007) and exchange rate behaviour (Taylor and Peel, 2000; Taylor et al. 2001; Kilian and Taylor, 2003).[4]

In order to examine the empirical evidence of our market microstructure model we use monthly data, implying that the conditional variance of oil price returns may not be constant over time. To cope with the heteroskedastic properties of monthly returns, we, therefore, apply the STR-GARCH procedure originally developed by Lundbergh and Teräsvirta (1998) and applied by Gallagher and Taylor (2001), Reitz and Taylor (2008) and Reitz and Westerhoff (2007). The STR-GARCH model

[4]De Grauwe and Grimaldi (2001) apply a quadratic specification to model deviations of the exchange rate from fundamental equilibrium, which can be interpreted as an approximation to a STAR specification.

consists of a mean equation containing a smooth transition function and a standard GARCH(1,1) volatility equation. In the present context, given the theoretical model outlined above, this suggests an empirical model of the form:

$$\Delta p_t = \alpha \Delta p_{t-1} + \delta w_t (f_{t-1} - p_{t-1}) + \epsilon_t \tag{6}$$

$$w_t(\phi, f_{t-d} - p_{t-d}) = \frac{1}{1 + exp(-\phi |f_{t-d} - p_{t-d}|)} \tag{7}$$

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

where Δ is the first-difference operator and $\epsilon = \nu_t \sqrt{h_t}$ and ν_t^{iid} is N(0,1). The transition parameter ϕ is a slope parameter that determines the speed of transition between the two extreme regimes, with low absolute values resulting in slower transition. The major differences between the empirical model (6)-(8) and the theoretical model set out in the previous section are twofold. The first difference lies in our introduction of a GARCH process to model the variance of oil price returns. When estimating the model it turns out, however, that the simpler ARCH(1) specifications sufficiently capture the conditional standard variance of the error term. Second, we allow in our empirical model for a value of the delay parameter, d, different from one since the importance of searching for an appropriate value of the delay parameter in empirical applications of STAR models has been stressed by Teräsvirta and others (e.g. Teräsvirta and Anderson, 1992; Granger and Teräsvirta, 1993: Teräsvirta, 1994).

4 The data

Our data sample contains monthly US dollar market prices of WTI crude oil derived from the IMF International Financial Statistics database over the period from 1986:1 to 2006:12. Hence, the time series consists of 252 observations. The use of nominal prices, as represented in Figure 1, is motivated by the fact that we are interested in explaining cycles in nominal oil prices and, of course, speculators are primarily concerned with expected nominal price changes. As a technical byproduct, this avoids the need to select an appropriate deflator, which is a non trivial issue (Deaton, 1999). In order to calculate a fundamental value of the oil price we assume that it depends on excess capacity in oil production, which has been eroded in recent years by strong demand growth from emerging economies, especially China.

It is commonly believed that there is a tight relationship between political events such as wars or embargoes and oil price changes. However, Barsky and Kilian (2004) argue that this type of exogenous shocks are but one of a number of different driving forces of oil prices and their impact may differ greatly from one episode to another in an unsystematic way. The authors stress that political disturbances do not necessarily cause surging oil prices and major oil price increases may occur in the absence of such shocks. The minor long-run impact of oil production shortfalls on oil prices is confirmed in great detail in Kilian (2008). Generating a counterfactual production level by extrapolating its pre-event level, Kilian is able to quantify the aggregated shortfall of OPEC countries' oil production. The change over time in this series expressed as a share of world oil production may be viewed as a measure of exogenous oil supply shocks. They range from minus 7 percent to plus 3 percent of world crude oil production and account for only 6 percent of the variability in world crude oil production changes. Obviously, exogenous oil production shortfalls are of limited importance in explaining oil price changes. Thus, Kilian (2008) concludes that these results highlight the dominance of alternative driving forces such as persistent shifts in demand for oil.

The relationship between oil prices and Chinese oil imports was originally proposed by Anderson (2005). As a result, we use China's imports of crude oil as proxy for diminishing excess capacity or, more generally, market tightness. Yearly data on Chinese imports of oil are interpolated to a monthly frequency assuming an

I(1)-process.

$$log(WTI_t) = \underset{(2.73)}{0.83} + \underset{(7.43)}{0.35} \cdot log(IMP_t^{China}) + u_t$$

The regression results are based on Hansen's (1982) Generalized Method of Moments.[5] Standard errors are adjusted for heteroskedasticity and serial correlation using Newey and West (1987) correction of the covariance matrix. The Dickey-Fuller test statistic ($ADF = -25.50$) confirms stationarity of regression residuals implying a cointegration relationship between the two variables. The adjusted R^2 statistic exceeds 60 percent, implying that our simple model explains a significant fraction of oil price variance. Moreover, the Durbin Watson test statistic ($DW = 0.1$) reveals serial correlation of standard errors, which we interpret as the outcome of persistent oil price misalignments. These estimation results allow for the approximation of the fundamental value f_t as linear function of China's oil imports.

[Figure 1 about here]

Already simple visible inspection confirms the strong cyclical behavior of oil prices around the fundamental value. Since we try to model nonlinear mean reversion of the oil price, percentage returns are calculated as $100\Delta log(P_t)$. Table 1 provides some descriptive statistics revealing standard properties of oil market returns.

[Table 1 about here]

In contrast to most financial market time series, oil price returns exhibit strong autocorrelation at various lags (Deaton and Laroque, 1992). The distribution of returns is slighty skewed and large absolute returns occur more frequently than normal. For further stylized facts of commodity price dynamics in general consult Borenzstein et al. (1994) or Cashin et al. (2002).

[5]We choose GMM because it does not require the usual normality assumption, and because standard errors can be adjusted to take account of both heteroscedasticity and serial correlation. In the regression, the set of instruments equals the set of regressors implying that parameter estimates parallel OLS parameter estimates (Bjønnes and Rime, 2005).

5 Estimation results

The modeling procedure for building STAR models was carried out as suggested by Granger and Teräsvirta (1993) and Teräsvirta (1994). First, linear autoregressive models were estimated to choose the lag order of the autoregressive term on the basis of the Bayes Information Criterion criterion. We found that first-order autocorrelation seemed to be appropriate for oil price returns in our data set. Second, we tested linearity against the STAR model for different values of the delay parameter d, using the linear model ($w_t = 1$, for all t) as the null hypothesis. To perform this test we estimate the auxiliary regression

$$\Delta p_t = \theta_0 + \theta_1 \Delta p_{t-1} + \theta_2 x_{t-1} + \theta_3 x_{t-1} x_{t-d} + \theta_4 x_{t-1} x_{t-d}^2 + \theta_5 x_{t-1} x_{t-d}^3 + \epsilon_t, \qquad (9)$$

for a wide range of values of d , i.e. $1 \leq d \leq 24$.[6] We chose $d = 3$, which gives the smallest marginal significance level. Third, we decided to apply the logistic STAR model on the basis of a sequence of tests as described in Granger and Teräsvirta, (1993).

Since (7) is a linear transformation of the standard logistic transition function as proposed by Teräsvirta and Anderson (1992), robust standard errors may be derived. This is important because conditional normality cannot be maintained. Under fairly weak regularity conditions, however, the resulting robust estimates are consistent even when the conditional distribution of the residuals is non-normal (Bollerslev and Wooldridge, 1992). Table 2 contains our final estimation results.

[Table 2 about here]

The estimation results displayed in Table 2 reveal that the STR GARCH model is able to capture nonlinear dynamics in oil prices. The Ljung-Box Q statistics AR(p) and ARCH(p) indicate that standardized residuals and squared standardized

[6] Note that $x_t \equiv f_t - p_t$.

residuals do not exhibit serial dependence. In order to check for remaining nonlinearities we re-estimate the auxiliary equation (9) using the standardized residuals instead of oil price returns. On the basis of a LM-type test the null hypothesis $H_0 : \theta_3 = \theta_4 = \theta_5 = 0$ is tested against the alternative of additional nonlinear structure (Eitrheim and Teräsvirta, 1996; Lundbergh and Teräsvirta, 1998). The reported p-values of the test statistic reveal that the null of no remaining nonlinearity ($NRNL$) cannot be rejected at standard levels of significance.

We now turn to the central question as to whether there is evidence in favor of chartist- and fundamentalist-driven oil price dynamics. The answer is given by the likelihood ratio test statistic and the t-statistics of the respective parameter estimates. To provide a likelihood ratio test statistic we compare the above model with a simpler AR(1)-ARCH(1) specification so that the parameters δ and ϕ are restricted to zero. The resulting test statistics show that the introduction of STR-type dynamics increases the log likelihood with a significance level of one percent. The chartist and fundamentalist coefficients are of the correct sign and are statistically significant at the one percent level. Statistically significant estimates of ϕ point to moderate transitions between regimes. In Figure 2 we have plotted the estimated transition function against lagged values of deviations of the oil price from its fundamental value.

[Figure 2 about here]

There seems to be a reasonable number of observations above and below the equilibrium value, so that we can be confident in our symmetric specification of the transition function. The transition function attains values up to 0.83 over the sample period, but only for quite large misalignments. Considerable mean reversion is triggered by fundamentalist speculation only for relatively strong misalignments. For deviations from the fundamental value of the order of plus or minus 40 percent - the range in which most of the observations are clustered - the transition function value is around 0.65. Overall, the relatively weak mean reversion seems to allow for destabilizing speculation resulting in persistent oil price bubbles.

6 Conclusions

In this paper we develop an empirical oil market model with heterogeneous interacting agents relying on technical and fundamental analysis to determine their orders. Technical analysis is a trading method that aims at identifying trading signals out of past price movements. Fundamental analysis predicts a convergence between prices and fundamental values and thus tends to stabilize the price process. However, the relative market impact of the two trading strategies is not constant over time but depends on the degree of the oil price misalignment. Our STR-GARCH model reveals that the more the price deviates from its long-run equilibrium value, the more fundamentalists will become active. Their orders then drive prices back to more moderate values. However, if the price is close to its fundamental value, the market impact of fundamentalists is relatively low. In such a situation, the presence of destabilizing chartists and/or random shocks may cause a new (temporary) bull or bear market. Our model suggests that heterogeneous agents and their nonlinear trading impact may be responsible for pronounced swings in oil prices, as witnessed in recent years.

References

Anderson, J. (2005), 'Oil Prices and China', *The Economist* 374 (8414), February 19th, 2005, 64.

Barsky, R. and L. Kilian (2004), 'Oil and the Macroeconomy since the 1970s', *Journal of Economic Perspectives*, 115-134.

Bjønnes, G. and D. Rime (2005), 'Dealer Behavior and Trading Systems in Foreign Exchange Markets', *Journal of Financial Economics* 75, 571-605.

Bollerslev, T. and J. Wooldrigde (1992), 'Quasi Maximum Likelihood Estimation and Inference in Dynamic Models with Time Varying Covariances', *Econometric Review* 11, 143-172.

Borenzstein, E., M. Khan, C. Reinhart and P. Wickham (1994), 'The Behavior of Non-Oil Commodity Prices', *IMF Occasional Paper* 112, IMF, Washington.

Boswijk, H., C. Hommes and S. Manzan (2006), 'Behavioral Heterogeneity in Stock Prices', *Journal of Economic Dynamics and Control* special issue WEHIA workshop, Essex, 2005, forthcoming.

Brock, W. and C. Hommes (1997), 'Heterogeneous Beliefs and Routes to Chaos in a Simple Asset Pricing Model', *Journal of Economic Dynamics Control* 22, 1235-1274.

Canoles, B., S. Thompson, S. Irwin and V. France (1998), 'An Analysis of the Profiles and Motivations of Habitual Commodity Speculators', *Journal of Futures Markets* 18, 765-801.

Cashin, P., J. McDermott and A. Scott (2002), 'Booms and Slumps in World Commodity Prices', *Journal of Development Economics* 69, 277-296.

Dao, T., P. Nicholson, S. Ouliaris and H. Samiei (2005), 'Recent Developments in Commodity Markets', IMF World Economic Outlook September 2005, 57-65.

Day, R. and W. Huang (1990), 'Bulls, Bears and Market Sheep', *Journal of Economic Behavior and Organization* 14, 299-329.

Deaton, A. (1999), 'Commodity Prices and Growth in Africa', *Journal of Economic Perspectives* 13, 23-40.

Deaton, A., and G. Laroque (1992), 'On the Behavior of Commodity Prices', *Review of Economic Studies* 59, 1-24.

DeGrauwe, P., H. Dewachter and M. Embrechts (1993), Exchange Rate Theory: Chaotic Models of Foreign Exchange Markets. Blackwell, Oxford.

DeGrauwe, P. and M. Grimaldi (2001), 'Exchange Rates, Process and Money: A Long-Run Perspective', *International Journal of Finance and Economics* 6 (4), 289-314.

DeGrauwe, P. and M. Grimaldi (2005), 'Heterogeneity of Agents and the Exchange Rate: A Nonlinear Approach', in P. De Grauwe (ed.), Exchange Rate Economics: Where Do We Stand?, Cambridge and London: MIT Press, 125-167.

DeGrauwe, P. and M. Grimaldi (2006), 'Exchange Rate Puzzles: A Tale of Switching Attractors', *European Economic Review* 50, 1-33.

Eitrheim, O. and T. Teräsvirta (1996), 'Testing the Adequacy of Smooth Transition Autoregressive Models', *Journal of Econometrics* 74 (11), 59-75.

Draper, D. (1985), 'The Small Public Trader in Futures Markets' in: A. Peck (Ed.) Futures Markets: Regulatory Issues. American Enterprise Institute for Public Policy Research, Washington: 211-269.

Fabozzi, F. (2001), Handbook of Portfolio Management, New York: John Wiley and Sons.

Farmer, D. and S. Joshi (2002), 'The Price Dynamics of Common Trading Strategies', *Journal of Economic Behavior and Organization*, 49, 149 – 171.

Gallagher, L. and Taylor, M.P. (2001), 'Risky Arbitrage, Limits of Arbitrage and Nonlinear Adjustment in the Dividend-Price Ratio', *Economic Inquiry* 39, 524-36.

Granger, C. and T. Teräsvirta (1993), Modeling Nonlinear Economic Relationships, Oxford University Press, Oxford.

Greenspan, A. (2004), Testimony Before the US House of Representatives' Budget Committee September 8th, 2004, see www.federalreserve.gov/boarddocs/testimony/2004/.

Haigh, M., J. Hranaiova and J. Overdahl (2005), 'Price Dynamics, Price Discovery and Large Futures Trader Interactions in the Energy Complex', US Commodity Futures Trading Commission, Staff Research Report.

Hommes, C. (2006), 'Heterogeneous Agent Models in Economics and Finance' in: L. Tesfatsion and K. Judd (eds.), Handbook of Computational Economics, Volume 2: Agent-Based Computational Economics, Elsevier Science B.V., 1109-1186.

Kahneman, D., P. Slovic and A. Tversky (1986), Judgment under Uncertainty: Heuristics and biases, Cambridge University Press, Cambridge.

Kilian, L. (2008), 'Exogenous Oil Supply Shocks: How Big Are They and How Much Do They Matter for the U.S. Economy?' *Review of Economics and Statistics*, forthcoming.

Kilian, L. and M. Taylor (2003), 'Why Is It So Difficult to Beat the Random Walk Forecast of Exchange Rates?', *Journal of International Economics* 60, 85-107.

LeBaron, B. (2006), 'Agent Based Computational Finance' in: K. Judd and L. Tesfatsion (eds.), Handbook of Computational Economics, Volume 2: Agent-Based Computational Economics, Elsevier Science B.V.

LeBaron, B., B. Arthur and R. Palmer (1999), 'Time Series Properties of an Artificial Stock Market', *Journal of Economic Dynamics and Control* 23, 1487-1516.

Lundbergh, S. and T. Teräsvirta (1998), 'Modeling Economic High Frequency Time Series with STAR GARCH Models', Stockholm School of Economics, Working Paper No. 291.

Lux, T. (1998), 'The Socio-Economic Dynamics of Speculative Markets: Interacting Agents, Chaos and Fat Tails of Return', *Journal of Economic Behavior and Organization* 33, 143-165.

Menkhoff, L. (1997), 'Examining the Use of Technical Currency Analysis', *International Journal of Finance and Economics* 2, 307-318.

Ozaki, T. (1985), 'Nonlinear Time Series Models and Dynamic Systems' in: E. Hannan, P. Krishnaiah and M. Rao (eds.), Handbook of statistics, Volume 5, 25-83, Amsterdam, Elsevier.

Reitz, S. and M.P. Taylor (2008), 'The Coordination Channel of Foreign Exchange Intervention: A Nonlinear Microstructural Analysis', *European Economic Review* 52, 55-76.

Reitz, S. and F. Westerhoff (2007), 'Commodity Price Cycles and Heterogeneous Speculators: A STAR-GARCH Model', *Empirical Economics* 33, 231-244.

Sanders, D., S. Irwin and R. Leuthold (2000), 'Noise Trader Sentiment in Futures Markets' in: B. Goss (ed.) Models of futures markets. Routledge, London: 86-116.

Smidt, S. (1965), 'Amateur Speculators: A Survey of Trading Strategies, Information Sources and Patterns of Entry and Exit from Commodity Futures Markets by Non-Professional Speculators', Cornell Studies in Policy and Administration, Cornell University.

Smith, V. (1991), Papers in Experimental Economics. Cambridge University Press, Cambridge.

Sommer, M., D. Gately and P. Atang (2005), 'Will the Oil Market Continue to Be Tight?', IMF World Economic Outlook April 2005, 157-183.

Sonnemans, J., C. Hommes, J. Tuinstra and H. van de Velden (2004), 'The Instability of a Heterogeneous Cobweb Economy: A Strategy Experiment on Expectation Formation', *Journal of Economic Behavior and Organization* 54, 453-481.

Taylor, M. and H. Allen (1992), 'The Use of Technical Analysis in the Foreign Exchange Market', *Journal of International Money and Finance* 11, 304-314.

Taylor, M. and D. Peel (2000), 'Nonlinear Adjustment, Long-Run Equilibrium and Exchange Rate Fundamentals', *Journal of International Money and Finance* 19, 33-53.

Taylor, M., D. Peel, and L. Sarno (2001), 'Nonlinear Mean Reversion in Real Exchange Rates: Toward a Solution to the Purchasing Power Parity Puzzles', *International Economic Review* 42, 1015-1042.

Teräsvirta, T. and H. Anderson (1992), 'Characterizing Nonlinearities in Business Cycles Using Smooth Transition Autoregressive Models', *Journal of Applied Econometrics* 7, 119-139.

Teräsvirta, T. (1994), 'Specification, Estimation, and Evaluation of Smooth Transition Autoregressive Models', *Journal of American Statistical Association* 89, 208-218.

Weiner, R. (2002), 'Sheep in Wolves Clothing? Speculators and Price Volatility in Petroleum Futures', *Quarterly Review of Economics and Finance* 42, 391-400.

Table 1: Summary statistics of WTI oil price returns

January 1986 - December 2006 (252 observations)

$Mean$	0.40
$Std.deviation$	8.38
$Skew$	-0.05
$ExcessKurt.$	3.31
JB	114.53^{***}
$AR(1)$	0.22^{***}
$AR(6)$	-0.15^{***}
$AR(12)$	0.002^{***}
$ARCH(1)$	0.22^{***}
$ARCH(6)$	0.26^{***}
$ARCH(12)$	-0.04^{***}

Notes: The sample contains monthly observations of the WTI spot oil price from January 1986 to December 2006. AR(L) denote autocorrelation coefficients for returns with Ljung Box-Q statistics in parentheses. ARCH(L) denote autocorrelation coefficients for squared returns with Ljung Box-Q statistics in parentheses. JB is the Jarque Bera test statistic.
$^{*}(^{**},^{***})$ denotes significance at the 10% (5%, 1%) level.

Table 2: Parameter estimates of the STR GARCH model

January 1986 - December 2006

α	$0.23(3.17)^{***}$
δ	$0.09(2.87)^{***}$
ϕ	$1.94(2.23)^{**}$
β_0	$0.004(9.81)^{***}$
β_1	$0.30(1.91)^{*}$
β_2	$--$
LLh	523.07
LRT	9.90^{***}
$AR(1)$	0.98
$AR(6)$	0.61
$ARCH(1)$	0.57
$ARCH(6)$	0.57
$NRNL$	0.21

Notes: The sample contains monthly observations of the WTI spot oil price from January 1986 to December 2006. α, δ, ϕ indicate the estimated parameters of the mean equations, β_0, β_1, and β_2 are the estimated GARCH(1,1) parameters, LLh is the log likelihood value, LRT is the likelihood ratio test statistic with restrictions $\delta = \phi = 0$. $AR(p)$ denotes the p-value for the Ljung-Box statistic for serial correlation of the residuals up to p lags. $ARCH(q)$ denotes the p-value for the Ljung-Box statistic for serial correlation of the standardized squared residuals up to q lags. $NRNL$ is the lowest p-value for no remaining nonlinearity up to 12 lags. t-statistics in parentheses are based on robust estimates of the covariance matrices of the covariance matrices of the parameter estimates. $^{*}(^{**},^{***})$ denotes significance at the 10% (5%, 1%) level.

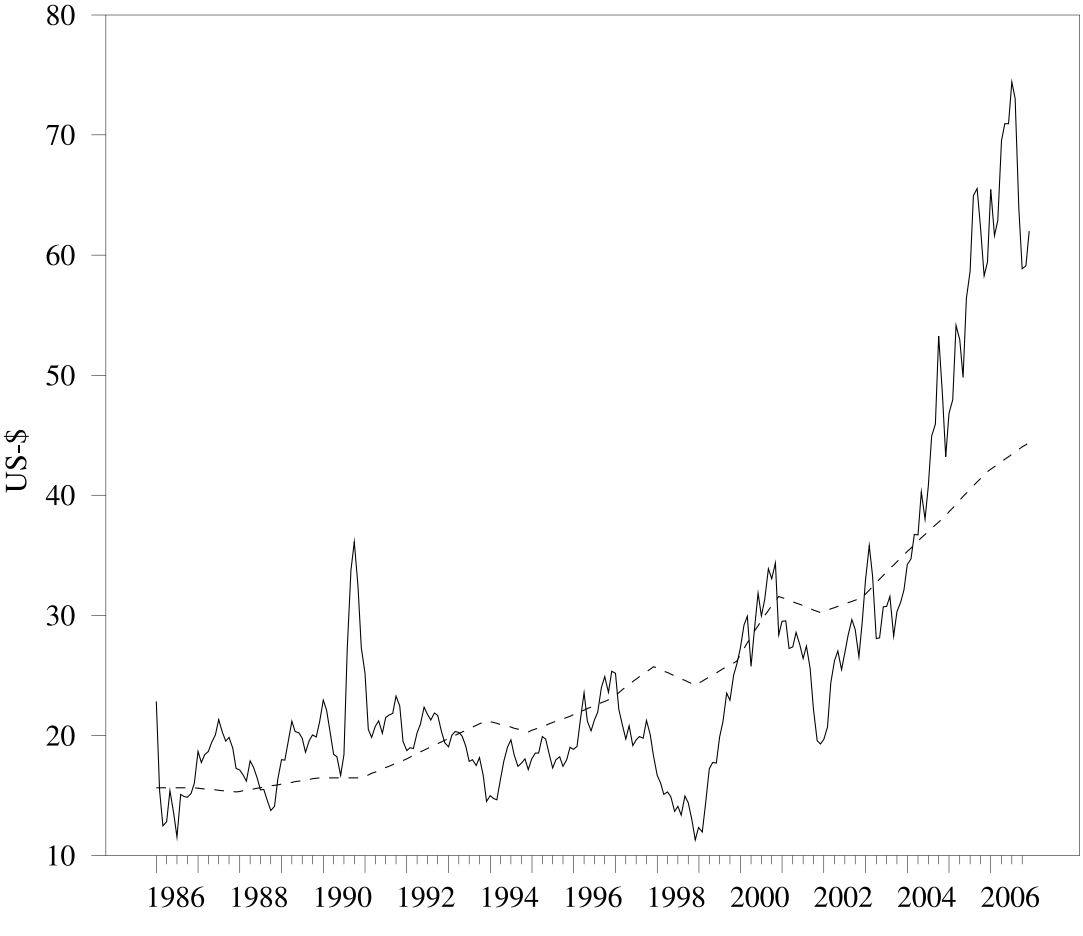

Figure 1: WTI spot oil price (solid line) and China's oil imports (dashed line)

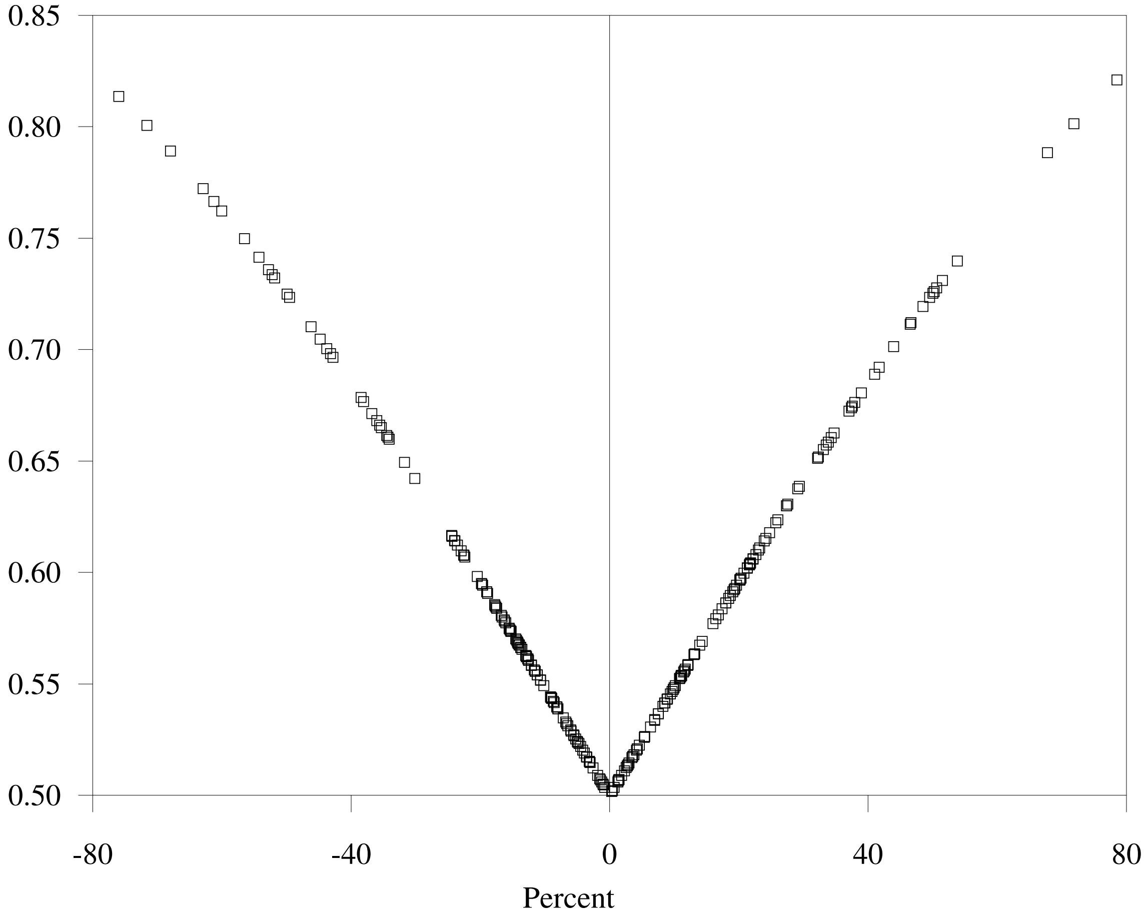

Figure 2: Empirical transition function of fundamentalist speculation