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by

Stefan Reitz,

Jan-Christoph Rülke

and

Georg Stadtmann

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FURTHER INFORMATION
Department of Business and Economics
Faculty of Social Sciences
University of Southern Denmark
Campusvej 55
DK-5230 Odense M
Denmark

Tel.: +45 6550 3271
Fax: +45 6550 3237
E-mail: lho@sam.sdu.dk
http://www.sdu.dk/ivoe

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Nonlinear Expectations in Speculative Markets – Evidence from the ECB Survey of Professional Forecasters

Stefan Reitz[a*,b], Jan-Christoph Rülke[c] and Georg Stadtmann[d]

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Abstract

Chartist and fundamentalist models have proven to be capable of replicating stylized facts on speculative markets. In general, this is achieved by specifying nonlinear interactions of otherwise linear asset price expectations of the respective trader groups. This paper investigates whether or not regressive and extrapolative expectations themselves exhibit significant nonlinear dynamics. The empirical results are based on a new data set from the European Central Bank Survey of Professional Forecasters on oil price expectations. In particular, we find that forecasters form destabilizing expectations in the neighborhood of the fundamental value, whereas expectations tend to be stabilizing in the presence of substantial oil price misalignment.

JEL classification: F31, D84, C33
Keywords: agent based models, nonlinear expectations, survey data

Address:
[*] Corresponding author: Stefan Reitz
[a] Institute for Quantitative Business and Economics Research, University of Kiel, Heinrich-Hecht-Platz 8, D-24118 Kiel, Germany, Tel.:+49-431-8814-284, Email: stefan.reitz@qber.uni-kiel.de
[b] Kiel Institute for the World Economy, Germany.
[c] Department of Economics, WHU – Otto Beisheim School of Management
[d] University of Southern Denmark, Department of Business and Economics, Campusvej 55, 5230 Odense M, Denmark, and Europa Universität Viadrina, Frankfurt (Oder), Germany.

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1 Introduction

Understanding how agents form expectations is at the center of an ongoing discussion in the literature whether or not the trading behavior in speculative markets destabilizes market prices. Based on the perception that models with representative agents frequently failed to predict or even to explain market behavior, researchers increasingly depart from the underlying assumption of rational expectations. Motivated by the seminal survey study of Taylor and Allen (1992), the introduction of heterogenous expectations has proven to be a powerful tool to replicate properties of trading behavior in financial markets (Hommes, 2009; Hommes and Wagener, 2009; Westerhoff, 2009). The bulk of heterogeneous expectation approaches introduces a nonlinear law of motion governing agents' *switching* between otherwise linear forecasting techniques (Brock and Hommes, 1997; De Grauwe and Grimaldi, 2006; Lux, 1998; Westerhoff, 2003). Of course, the introduction of a nonlinear switching function in an otherwise standard linear framework is a promising strategy as it enhances the model's explanatory power and generality (Hommes, 2006; LeBaron, 2006; Lux, 2006). From an empirical perspective, however, it might be the case that in real world speculative markets forecasters' expectations themselves exhibit substantial nonlinearities: Market participants most likely observe that asset prices are inherently nonlinear. For example, it is often found that asset prices tend to be unstable within the neighborhood of its equilibrium value, but exhibit mean reversion in the case of substantial misalignment (Reitz and Slopek, 2009). As a result, asset price forecasts cannot be modeled in a standard unconditional fashion.[1]

Given that state dependence of traders' expectations could be an important aspect of asset price dynamics, we provide empirical evidence of nonlinear

[1] For example, Bauer et al. (2009) show that in the presence of a target zone, traders' conditional forecasts introduce an additional stabilizing nonlinear component into exchange rate dynamics.

expectation dynamics using survey data from the European Central Bank (ECB).[2] Survey data constitute an important data source for observing expectation heterogeneity and social interaction among market participants. For example, Menkhoff et al. (2009) find that misalignments of the exchange rate and exchange rate changes explain expectation heterogeneity in the foreign exchange market. Lux (2009) reports strong indication of social interaction as an important element in respondents' assessment of the German ZEW business climate index. Traditionally, survey data has been used to analyze how market participants form expectations in financial markets. Taylor and Allen (1992), Ito (1990) and Menkhoff (1997) analyze short-run and long-run foreign exchange rate forecasts. While short-run expectations show bandwagon behavior, long-run exchange rate forecasts exhibit a stabilizing feature.

The empirical analysis is based on a recently released disaggregated data set of the *Survey of Professional Forecasters* (SPF) on oil prices conducted on a quarterly basis by the ECB. To investigate possible expectation non-linearities, we look at oil price forecasts' state dependent reaction to recent oil price changes and current oil price misalignments. Estimating a panel smooth transition regression (Panel STR) model proposed by González et al. (2005), we find that, in the neighborhood of the fundamental value, oil price forecasters expect the prevailing misalignment to grow in the future. However, the expected change of the oil price is a (nonlinear) decreasing function of the difference between the current oil price and its fundamental value. Above a certain threshold of the misalignment, the oil price is expected to revert substantially. By revealing forecasters' perception of locally unstable but globally stable price dynamics, the analysis establishes

[2] Earlier contribution such as Taylor and Allen (1992) and Cheung and Chinn (2001) provide strong motivation for the development of heterogeneous expectation models, but did not investigate possible expectation nonlinearities.

the existence of a complex and realistic expectation formation process. This is an important (and encouraging) result for the chartist and fundamentalist modeling approach.

The remainder of the paper is structured as follows. In the next section, we discuss the oil market and the related literature. Section 3 describes the data set while section 4 examines various ways to determine a fundamental value of the oil price. In section 5, we attempt to determine whether expectations are formed rationally. Specifically, we test whether forecasts fulfill the rationality conditions of unbiasedness and orthogonality. While section 6 examines oil price forecasts applying a non-linear Panel-STR framework, section 7 reports the estimation results. Finally, section 8 concludes.

2 The Oil Market and Related Literature

Between 2002 and mid-2008, the oil price increased tremendously from US$ 20 per barrel to an all-time high of US$ 145 per barrel in July 2008. This oil price shock hit the oil importing nations heavily, and some economists regard this as one cause for the current worldwide recession. In turn, the sharp drop of the oil price down to US$ 30 per barrel in December 2008 has implied a heavy burden on oil exporting nations such as Russia or Saudi Arabia, which have experienced a severe deterioration in their terms of trade. These oil price movements were unforeseen by many economists (Brown et al., 2008). However, recently the oil price recovered to a level of about US$ 98 per barrel (December 2011).

The upward pressure on oil prices has occasionally been blamed in part on the influence of speculation (e.g. Greenspan, 2004) with some analysts believing that the all-time high was the direct result of a speculative bubble.

Based on data on the composition of open interest in crude oil markets published by the US Commodity Futures Trading Commission (CFTC) speculative activity would be expected to occur mainly in futures markets such as the Chicago Mercantile Exchange or New York Mercantile Exchange. In fact, recently published data from the CFTC suggest that swap traders, hedge funds, and commodity trading advisors account for a major share of open positions. In addition, there is evidence from empirical studies that the oil market is frequently subject to bubbles which drive the oil price away from its equilibrium level. One such study by Reitz and Slopek (2009) finds that the interaction of chartists and fundamentalists on oil markets may account for substantial and persistent misalignments in oil prices. However, the nonlinear dynamics of oil price expectations necessary for price dynamics such as those recently observed have been taken for granted or are inferred from oil prices themselves. Since speculative trading is based solely on market participants' forecasts, an understanding of expectation formation is crucial for assessing its role in price determination in the oil market.

Regarding oil price expectations, MacDonald and Marsh (1993) examine the efficiency of forecasts published in the Consensus Economic Forecast poll. For the sample period between October 1989 and March 1991, they show that oil price forecasters form stabilizing expectations, but provide biased and inefficient projections. However, their analysis is limited to 18 months whereas our analysis covers a period of nearly eight years. Prat and Uctum (2011) also use oil price expectations of the Consensus Economic Forecast poll for a three-month and a twelve-month horizon over the period November 1989 – December 2008. They find that the rational expectations hypothesis is rejected and that none of the extrapolative, regressive, or adaptive processes fits the data. Instead, they rather suggest a mixed expectations model, defined as a linear combination of these traditional processes which was interpreted as the aggregation of individual mixing behavior and of heterogenous groups of agents using simple processes. However, their analysis is restricted to the time dimension, because they only have access to the mean forecast of the aggregated survey data and not to person-specific forecasts. This yields only a number of 75 forecasts for the three-month forecast and 18 observations for the twelve-month forecast. In contrast, our analysis uses disaggregated data covering about 800 observations which allows for a detailed analysis of the time *and* cross-section dimension among the forecasters.

Another strand of the literature on oil price forecasts uses oil price futures to analyze the expectation forming process in the oil market. Abosedraa and Baghestani (2004) evaluate the predictive accuracy of crude oil futures prices for different time horizons over the time period 1991 to 2001. They construct a naive forecasting model to generate comparable forecasts as benchmarks. However, only the one-month and twelve-months ahead futures prices outperform the naive random walk suggesting their limited usefulness as predictors for future realizations. Knetsch (2007) supports this view and shows that an oil price forecasting technique which is based on the present value model of rational commodity pricing outperforms futures prices. The author proposes a forecasting technique which is based on the marginal convenience yield derived by the cost-of-carry relationship. However, this technique was also unable to improve forecast accuracy compared to the random walk.

3 The Data Set

We use the disaggregated data set of the SPF conducted by the ECB on a quarterly basis.[3] Since the ECB has released the SPF just recently, only

[3]Garcia (2003) describes the SPF data set which is accessible and explained in more detail on the webpage: www.ecb.int/stats/spf.

very few studies have used the SPF and none of these studies used the oil price forecasts. Garcia and Manzanares (2007) and Bowles et al. (2009) analyze the forecast accuracy of the forecasters in the SPF. They find that individual point predictions for the inflation rate and the real growth rate tend to be biased towards favorable outcomes, i.e. forecasters overpredict growth and underpredict inflation rates, which is in line with the study of Elliott et al. (2008).

The SPF poll started in 2002Q1 and we have access to survey data until 2010Q4. Data to construct the fundamental value of the oil price is limited to 2009Q4. As a consequence the main part of our study will cover the time span 2002Q1 – 2009Q4, covering a total of 32 quarters. While a total of 94 forecasters participated in the survey who provide about $1,400$ oil price forecasts, we only included forecasters who have participated in all polls. This applies to 25 forecasters and yields 800 oil price forecasts.[4] The participants are professional economists working with financial institutions such as international economic research institutes, investment and commercial banks. The ECB asks professional economists in the euro area at the beginning of each quarter to forecast the oil price and publishes the results within the next two weeks. A great advantage of the SPF is that it provides oil price forecasts for the end of the consecutive five quarters ahead. Hence, forecasters are requested to predict the oil price for five different forecast horizons, which allows us to analyze the expectation formation process in an detailed fashion. Crude oil prices (West Texas Intermediate) from the first trading day of the respective quarter are provided by Thomson Datastream.

[4]The unbalanced and the balanced data set show a similar mean, standard deviation and forecast performance which might be due to the fact that the ECB does not select the forecasters based in their track record. Hence, an occasion when a participant does not respond to the survey is actually random which should mitigate the selection bias of the balanced data set. More information on the unbalanced data as well as for each forecaster is available upon request.

Table 1 reports the main features of the data set. While the actual oil price over the sample period is US$ 58 per barrel, the forecasters expect the oil price to decrease with the lowest value of the average four-quarter-ahead forecast.

– Insert Table 1 here –

The analysis of oil price expectations is especially appealing since the oil market has recently shown substantial swings. Figure 1 compares the actual oil price (solid line) to the mean of the lagged oil price forecasts (dotted lines). Hence, the vertical difference between the actual oil price and the one- (five-) quarter-ahead forecast is the forecast error. Figure 1 shows that the forecast error is positive for the period before 2008Q3, which implies that forecasters – on average – expected a lower oil price than the actual oil price. The next section investigates how various measures of the fundamental oil price are constructed.

– Insert Figure 1 here –

4 Fundamental Value of the Oil Price

When building expectations about future changes of the oil price forecasters consider some kind of fair value to which the market price is believed to converge over time. Of course, there is little reason to believe that an easily observable fundamental value exists in which every forecaster agrees upon. Since the estimation results may be driven by the choice of the fundamental value we run the subsequent regressions on the basis of a simple and a more sophisticated fundamental variable. The simple fundamental value boils down to the calculation of a sixteen quarters moving average and reflects the fact that most traders on speculative markets use it as a benchmark (Ito, 1990). Particularly in real world financial markets, where buy or sell decision often have to be made within seconds traders often adhere to a set of moving averages in order to derive their trading rules.[5]

In contrast to simple moving averages forecasters may consider a fundamental value, which is more closely related to oil market variables. In fact, there exists a large number of potential candidates to explain persistent swings in the evolution of the oil price. Hamilton (2009), however, argues that the global demand for oil, especially from China, is the key determinant among a host of others, such as commodity price speculation, time delays or geological limitations on increasing production, OPEC monopoly pricing, and an increasingly important contribution of the scarcity rent. He therefore concludes that the strong growth in demand from China has substantially driven the oil price in the last decade. This view is supported by Hicks and Kilian (2009), who find that news about global demand presages much of the surge in the oil prices from mid-2003 until mid-2008 and much of its subsequent decline. Their measure of global demand shocks is based on revisions of professional real growth forecasts. In particular, Hicks and Kilian (2009) show that forecast revisions were associated with a hump-shaped response of the oil price.

Using oil demand to approximate the fundamental value of the oil price is, to some extent, in contrast to the common belief that political events such as wars or embargoes are the main forces driving the oil price. However, Barsky and Kilian (2004) argue that such exogenous shocks are only one of a number of different determinants of oil prices and their impact may

[5]Ter Ellen and Zwinkels (2010) made use of moving averages to approximate traders' perception of the fundamental value in an agent based model of the oil market.

differ substantially from one episode to another in an unsystematic way. Beyond the fact that orthogonal oil supply shocks may not distort oil price regressions, the authors stress that political disturbances do not necessarily cause oil prices to surge and major oil price increases may occur in the absence of such shocks. The small impact of oil production shortfalls on oil prices is confirmed in great detail in Kilian (2008) highlighting the dominance of alternative driving forces such as persistent shifts in the demand for oil.

Although there is now little doubt that persistent shifts in the excess demand for oil are the major fundamental driving force of the past decade's oil prices, the important question remains as to which variable should be used to capture demand dynamics. We include the following oil market candidates as long-run driving forces of the fundamental value. First, we divided global consumption of crude oil by non-OPEC crude oil production. Yet, the variable accounts for the fact that global demand has remained strong overall non-OPEC production growth has slowed. This imbalance increases reliance upon OPEC production and/or inventories to fill the gap ($OPEC^{reliance}$). A second variable as a proxy for diminishing excess capacity or, more generally, market tightness is proposed by Andersen (2005). The author suggests that Chinese oil imports (IMP^{China}) account for a major share of world excess demand for oil and is strongly correlated with excess demand from other important emerging countries, thereby exerting upward price pressure due to increasing demand. Finally, a more forward-looking measure of market tightness comprises the ratio of world oil reserves to daily world oil consumption ($Reserves$) and gives the number of remaining days before oil resources are expected to be depleted.

World oil consumption, production and reserves were provided by the Energy Information Administration, while Chinese imports of oil are taken from the

OECD Annual Statistical Bulletin (2009). Yearly data are interpolated to a quarterly frequency assuming an I(1)-process. Crude oil prices (WTI) from the first trading day of the respective quarter are provided by Thomson Financial, Datastream. The data set comprises the period from 1986 to 2009. The results of the Augmented Dickey-Fuller tests represented in Table 2 suggest non-stationarity of the oil price and the above excess demand fundamentals.

– Insert Table 2 –

We follow the Johansen procedure (Johansen, 1991; Johansen and Juselius, 1994) to test for cointegration of the oil price and the different demand variables. First, the unrestricted VAR models are estimated including two lags as suggested by the Schwarz information criteria. Second, trace statistics are calculated to test the null hypothesis of no cointegration. When investigating the relationships between $OPEC^{reliance}$, IMP^{China}, and $Reserves$ we find that the null hypothesis of no cointegration cannot be rejected at standard levels. The trace statistic of $TR = 30.20$ does not exceed its 5 percent critical value of $TR^{*} = 35.19$. This implies that potential cointegration relationships among fundamental can be ruled out. Adding the spot oil price to the system leads to the rejection of the null in favor of one cointegrating equation.[6] Based on the results of these cointegration tests we assume that forecasters calculate the fundamental value regressing the spot oil price on the demand variables:

$$s_t = \alpha_0 + \alpha_1 OPEC_t^{reliance} + \alpha_2 IMP_t^{China} + \alpha_3 Reserves_t + u_t. \qquad (1)$$

Given that forecasters can only rely on data available at time t the regression is updated every quarter and estimated coefficients are used to calculate the time t fundamental value.[7] The first regression uses data ranging from 1986

[6] Trace statistic $TR = 48.03$ exceeds its critical value of $TR^{*} = 47.86$.

[7] Note that the indices refer to the forecasters' information set. In fact, since forecasts are made at the beginning of a quarter data on fundamentals are used up to the preceding quarter.

to 2001.

Figure 2 shows the demand fundamental (dotted line), the moving average fundamental (dashed line) and the actual oil price (solid line). Until 2006 the oil price fluctuated around the fundamental value before subsequently starting to increase substantially. For the period between 2006 and 2008, Figure 2 provides anecdotal evidence that the oil price tends to move back to the fundamental value after its sharp rise. Hence, the application of the fundamental value based demand variables as suggested by Hamilton (2009) seems to fit the actual behavior of the oil price quite well.

– Insert Table 2 and Figure 2 here –

5 Tests for Rationality of Expectations

To examine the question of whether expectations are formed rationally, we follow Ito (1990), MacDonald and Marsh (1996), and Elliot and Ito (1999) in applying two criteria: unbiasedness and orthogonality.

5.1 Unbiasedness

To investigate whether oil price forecasts represent unbiased predictors of future oil price changes, we estimate the following relationship:

$$s_{t+h} - s_t = \alpha_h + \beta_h(E_{t,i}[s_{t+h}] - s_t) + \epsilon_{t+h,i} \tag{2}$$

where $s_{t+h} - s_t$ is the change in the oil price and $E_{t,i}[s_{t+h}] - s_t$ is the expected change by forecaster i at time t. Unbiasedness prevails if $\alpha_h = 0$ and $\beta_h = 1$. Note that in this case oil price changes are not necessarily forecasted accurately but the forecast errors do not show any systematic pattern.

In a first step, we estimated equation (2) by OLS (results not presented) but realized that cross-section autocorrelation is a serious problem. Market wide shocks and new information that occur between the expectations were set in period t and the oil price materialize in period $t+h$ will influence the forecasting success of all forecasters in the same direction. As a consequence standard errors would be biased downwards. As a consequence, we corrected for the cross-section autocorrelation and standard errors increased by a factor of about 3. This indicates the severeness of this bias in variability when estimating just with OLS.

The results – summarized in Table 3 – indicate that the $\hat{\beta}_h$ coefficient decreases as the forecast horizon increases. Since the constant (i.e., $\hat{\alpha}_h$) is significantly different from zero and, except for the one-quarter-ahead forecast, the $\hat{\beta}_h$ coefficient is different from unity, the oil price expectations are not an unbiased predictor of the future development.

– Insert Table 3 here –

5.2 Orthogonality

We now turn to the test of orthogonality. It stipulates the question whether or not forecast errors are related to information on oil price changes available at the time of the forecast. As a representation for the latter we use two arguments, namely the previous oil price change $(s_t - s_{t-1})$ as well as the difference between the actual oil price level and its demand-based fundamental value $(s_t - f_t)$. To test the orthogonality condition of oil price forecasts, we estimate:

$$s_{t+h} - E_{t,i}[s_{t+h}] = \alpha_h + \beta_h(s_t - s_{t-1}) + \gamma_h(s_t - f_t) + \epsilon_{t+h,i} \qquad (3)$$

Orthogonality implies that $\alpha_h = \beta_h = \gamma_h = 0$ so that neither the constant term nor any other available information explains the forecast error. We used time fixed effects to control for systematic cross-section autocorrelation due to market wide shocks. Table 4 reports that $\hat{\alpha}_h$ takes a significant negative value in all but one regressions.

– Insert Table 4 here –

While the estimated $\hat{\beta}_h$ coefficient is significant for the three forecasts with the longest forecast horizon, it becomes insignificant for the shorter forecast horizons. Furthermore, the estimated γ_h-coefficient is significantly negative for all but one forecast horizons. This implies that forecasters do not take all the information regarding the previous oil price change and the misalignment into account when predicting the oil price. In summary, we find that oil price forecasts are biased and hence not rational.

6 A Nonlinear Model of Oil Price Expectations

The literature on the chartist and fundamentalist approach extensively showed that time series properties of financial market prices can be reproduced by the nonlinear interaction of linear forecasting techniques.[8] To ensure global stability of the price path, it is generally assumed that market participants increasingly switch to stabilizing expectations as the misalignments grow. This is motivated by the finding in survey studies (Taylor and Allen, 1992; Menkhoff, 1997) that the fraction of forecasters building regressive expectations goes up as the forecast horizon increases. If market participants observe that asset prices tend to be unstable within the neighborhood of its equilibrium value and exhibit stronger mean reversion in the case of substantial misalignment they may adjust their forecasts accordingly. This state dependence of expectations is not necessarily

[8] See the surveys by LeBaron (2006) and Hommes (2006).

confined to regressive expectations, but may also appear within the category of extrapolative expectations. Thus, it seems reasonable to presume that traders' expectations, regressive or extrapolative, exhibit substantial nonlinearities.

6.1 The Panel-STR model

In the following we apply the Panel-STR methodology to provide empirical evidence on the potentially nonlinear behavior of oil price expectations. The Panel-STR model was introduced by González et al. (2005) to account for smooth and gradual transition of a system between two or more regimes:[9]

$$y_{t,i} = \alpha_i + \beta_0' x_{i,t} + \sum_{j=1}^{r} \beta_j' x_{i,t} \omega_j(q_t^j, \phi_j, \theta_j) + \epsilon_{t,i} \tag{4}$$

where $y_{t,i}$ is the endogeneous variable, $x_{i,t}$ is the vector of exogenous variables and $\omega_j(q_t^j, \phi_j, \theta_j)$ is one of r transition functions, each bounded between 0 and 1, q_t^j the threshold variable, ϕ_j the transition speed and θ_j the threshold parameter. We follow González et al. (2005) and use a logistic specification to model the transition function:

$$\omega_t(q_t^j, \phi_j, \theta_j) = \frac{1}{1 + exp(-\phi_j \prod_{k=1}^{m}(q_t^j - \theta_j))}. \tag{5}$$

Equation (4) together with equation (5) constitute a quite flexible generalization of the standard two-regime Panel-STR model. Since the vector of regressors contains both the current misalignment as well as the recent change of the oil price the model simultaneously deals with regressive and extrapolative expectations. As argued earlier each forecasting strategy may be performed conditional on a set of threshold variables. Although there is

[9]The Panel-STR model has been applied to exchange rates by Béreau et al. (2008).

a wide range of possible candidates influencing the current stance of forecasters' expectations,[10] we restrict our choice to the current misalignment and the recent return. This reflects the fact that in contrast to speculators forecasters may be less concerned about the performance of particular trading strategies, but try to identify whether or not current trends are lasting. This boils down to investigating whether forecasters have learned how oil prices behave in different market environments. Thus, our model should allow for both regressive expectations and extrapolative expectations to be driven by the current misalignment and the recent price return. The modeling procedure for building Panel-STR models is carried out in three steps according to González et al. (2005): (i) specification, (ii) estimation, and (iii) evaluation.

6.2 Model Specification

The important task in the specification step is the identification of a possible nonlinear relationship between the endogenous and exogenous variables. To this end, we test linearity against the STR model using the threshold variables $(s_t - f_t)$ and $(s_t - s_{t-1})$.[11] Testing the null hypothesis $H_0 : \phi_j = 0$ to identify the role of a nonlinear component, however, is not straightforward. Under the null, there are unidentified nuisance parameters implying that a simple t-test is not applicable. To circumvent this problem we follow Luukkonen et al. (1988) and replace the transition function by its first-order Taylor expansion. In the resulting auxiliary regression:

$$y_{t,i} = \alpha_i + \beta_0^{'*} x_{i,t} + \beta_1^{'*} x_{i,t} q_{i,t} + ... + \beta_m^{'*} x_{i,t} q_{i,t}^m + \epsilon_{i,t} \tag{6}$$

[10] Empirical agent based models such as Boswijk et al. (2007) and Ter Ellen and Zwinkels (2010) rely on recent profits or mean squared errors of the respective trading strategy to map the switching of speculators.

[11] Using these two terms to analyze the actual law of motion of the oil price yields evidence of regressive as well as extrapolative features in the actual oil price development. The results are available upon request.

the vectors of parameters $\beta_1'^*, ..., \beta_m'^*$ are multiples of ϕ implying that rejection of $\beta_1'^* = ... = \beta_m'^* = 0$ is taken as evidence in favor of nonlinearity. The related LM-test statistic is derived in González et al. (2005).

– Insert Table 5 here –

The results represented in Table 5 show that, in general, the linear model is strongly rejected in favor of STR-type nonlinearity. When looking at the results of the full sample regressions the following details are worth mentioning: *First*, the highest χ^2-statistics occur when the regressor variable is combined with the same transition variable. This suggests that extrapolative expectations exhibit nonlinearities with respect to recent returns, while regressive expectation are influenced by the current value of misalignment. Of course, regressive expectations also seem to be driven by the latest observable return, which points to a cross combination of regressor and transition variable. Extensive experimentation, however, revealed that additional consideration of cross variable specifications quite often led to non-convergence of the estimation routine. This might be due to the fact that higher order terms in the Taylor expansion are strongly correlated. In order to ensure comparability among the different combinations of forecasting horizon and fundamental variable, we opt for a specification without any cross variable terms.

Second, when considering the fundamental value based on our proxy variables for oil demand the identification tests produce comparable results.[12] *Third*, it might be suspected that the revealed nonlinearities are due to the oil price bubble starting in 2007. Although bubble episodes should not ex ante be excluded from the regressions, the relatively short sample available for estimation might lead to an over-representation of bubble-observations

[12] Cross variable combinations of misalignment and recent return produce higher test statistics only for short-run forecasts of one month.

and biased test results. Consequently, we performed sub-sample robustness checks to assess the impact of the post-2007 oil price bubble. The results in Table 5 confirm that linearity is rejected in favor of STR-type nonlinearities even in off-bubble periods.

6.3 Model Estimation

As outlined in González et al. (2005) these regressions can be used to determine the order of inhomogeneity m in equation (5). The test results suggest no common order of inhomogeneity over the entire range of forecasting horizons and different fundamental values. Moreover, the recommended functional forms do not necessarily ensure convergence of the estimation routine. As a result of extensive experimentation we find that a robust solution to this problem is a logistic transformation of the absolute value of the transition variable. The specification of the transition function:

$$\omega_t(q_t^j, \phi_j, \theta_j) = \frac{2}{1 + exp(-\phi_j |q_t^j - \theta_j|)} - 1. \tag{7}$$

ensures that ω_t remains in the interval between 0 and 1.[13]

The PSTR model is a fixed effects model with exogenous regressors. Parameter estimates are obtained applying nonlinear least squares after demeaning the data. It should be noticed that unlike standard linear models, variable means depend on the parameters in the transition functions. Consequently, demeaned values are recomputed at each iteration of the estimation routine (González et al., 2005). The prevailing nonlinear mean reversion and extrapolation functions can each be reproduced with two different sets of coefficients. Thus, the nonlinear estimation routine is sensitive to the sign of the start-

[13] An exponential transition function of the form $1 - exp(-\phi_j |q_t^j - \theta_j|)$ produces comparable results.

ing value of ϕ-parameters. We set each starting value to 0.5.[14] Moreover, we calculate robust errors to correct for arbitrary correlation patterns by computing $\sum_i(\sum_t X_{it}u_{it})'(\sum_t X_{it}u_{it})$ as the center term in the sandwich estimator where X_{it} and u_{it} are the observations and error terms for forecaster i at time t.

6.4 Model Evaluation

To evaluate the estimated P-STR model we consider two specification tests. Specifically, González et al. (2005) suggest an adaption of the tests of parameter constancy (PC) over time and of no remaining nonlinearity (NRNL) as developed in Eitrheim and Teräsvirta (1996) for univariate STAR models. Both tests are performed in the way described in section 6.2. First, the estimated model is extended by the terms of a Taylor expansion representing additional nonlinearities (NRNL) or nonlinear time dependence of model coefficients (PC). The according LM-type test statistic has an asymptotic F-distribution. In the case of the NRNL-test we consider the same transition variables as used in the Panel-STR model, while in the case of the parameter constancy test powers of a time trend are included. By doing so the NRNL-test checks whether the Panel-STR model has fully captured the identified expectation nonlinearities and the parameter constancy test reveals any structural breaks in the sample. The latter is particularly important given that a significant fraction of our observations stem from a bubble episode.

7 Empirical Results

The empirical model of oil price expectations has been applied to five different forecasting horizons using two different fundamental values. As outlined before the simple moving average as well as the more sophisticated excess

[14] Starting values of all other coefficients are set to zero.

demand variable are calculated to specify regressive expectations. Extrapolative expectations refer to the recent oil price return.

7.1 Underlying Fundamental: Excess Oil Demand

Table 6 contains our final estimation results applying the excess demand variable as the fundamental value. The estimated coefficients are statistically significant in all cases. When looking at the shift parameters θ in the transition function we find that, in the case of extrapolative expectations, the estimated values remain largely unchanged over different forecasting horizons. The estimation routine investigating four and five quarters ahead forecasts did not converge, so we decided to set the θ parameter to the estimated value of the preceding models. In the case of regressive expectations the shift parameter increases in absolute terms indicating that longer run forecasts may reflect fundamentals to a lower extent than the current value suggests. The coefficient ϕ determining the curvature of the transition function increases for both regressive expectations and extrapolative expectations pointing to a faster transition between 0 and 1 as the forecasting horizon increases. The estimated β_0s and β_1s suggest the following interesting interpretations.

First, in the case of extrapolative expectations, the previous results are confirmed. The forecasts in the ECB survey seem to exhibit contrarian behavior as an observed oil price increase is expected to be reverted in the future. The extent to which this return reversion is expected to occur depends on the absolute value of the oil price return. As can be observed in Figure 3 smaller returns are expected to be unwinded quite immediately, whereas larger returns are expected to be more persistent. Returns exceeding a threshold of about twenty percent are not expected to be reverted at all. Obviously, the nature of extrapolative expectations switches from contrarian to bandwagon behavior.

– Insert Table 6 and Figure 3 here –

Second, in the case of regressive expectations the linear term β_0 is significantly positive. This implies that, in general, forecasters' expectations tend to be destabilizing as a given misalignment is expected to be inflated by future increases of the oil price. The negative coefficient β_1 together with the specified transition function, however, shows that the expected destabilization is reduced with rising misalignment. Forecasters using the excess demand variable seem to interpret small deviations of the actual oil price from its fundamental value as a signal for a stronger misalignment in the future, while large deviations are expected to be reverted. This type of nonlinearity in expectations is robust with respect to the entire set of forecasting horizons.

– Insert Figure 4 –

When comparing the expected mean reversions in Figure 4 we find that the transition function is shifted downwards slightly as the forecasting horizon increases. Short-run forecasts exhibit stabilizing expectations only in the presence of larger misalignments, while long-run forecasts imply significant mean reversion also for smaller deviation of the oil price from its fundamental value. Put differently, market participants seem to believe that misalignments are inflated in the short run, but will be eliminated thereafter. Of course, very small (negative) misalignments are not expected to be corrected at all. All in all these results are consistent with the view that forecasters believe oil prices to exhibit enduring misalignments, but remain globally stable.

If we interpret the above setup as a representative agent model where the average respondent has a nonlinear forecasting function that is explosive close to the fundamental value and mean-reverting in the case of substantial misalignment, we may compare the reported dynamics in expectations with empirical results of heterogeneous agents models (HAM). For example, in the HAM of Boswijk et al. (2007) dealing with the U.S. stock market one trader type has stable mean reverting expectations while the other has unstable trend extrapolation expectations. The switching between trader types depends on the profitability of the respective trading techniques in the recent past. The authors find that in the case of a rapid increase of stock prices not accompanied by improvements in the fundamentals losses for fundamentalists and profits for trend followers cause evolutionary pressure towards trend followers, thus reenforcing the trend in prices. In a similar HAM of the oil market Ter Ellen and Zwinkels (2010) assume prices to be determined by both fundamentalist expectations exerting a stabilizing effect and chartist expectations introducing a destabilizing influence on oil price dynamics. Because the switching mechanism in this model is based on squared forecasting errors trends resulting in misalignments tend to be reinforced as chartist expectations gain weight in the market. Respondents in the survey of professional forecasters expect large oil price returns to be followed by returns of the same sign, implying that the nonlinear return dynamics identified in empirical HAMs seem to be perceived by market participants. Complementing the above studies, the empirical HAM of Reitz and Slopek (2009) explicitly focusses on the stabilizing influence of fundamentalist trading. While the number of chartist is assumed to be constant over time, the number of fundamentalists may change in accordance to the recent misalignment. The empirical results reported in Reitz and Slopek (2009) suggest that fundamentalists gain weight in the oil market as misalignments grow thereby providing necessary mean reversion to ensure global stability. This is compatible with the forecasters' view that large misalignments will finally be eliminated during the course of future trading. While empirical HAMs show a considerable variety of switching mechanisms, their results regarding the time varying stability of asset price dynamics seem to be reflected in the expectations of the ECB oil price forecasters.

7.2 Underlying Fundamental: Moving Average

The fundamental value of the preceding section is based on quite complex calculations and it might be argued that market participants tend to apply much simpler measures to approximate an asset price's equilibrium value. This is emphasized by the fact that standard fundamental models fail to explain a substantial fraction of asset price variation. In real world financial markets, where buy or sell decision often have to be made within seconds, traders often adhere to a set of moving averages in order to derive their trading rules. Consequently, researchers in agent based modeling made use of moving averages to approximate traders's perception of the fundamental value (Ter Ellen and Zwinkels, 2010). Table 7 contains our final estimation results applying a sixteen quarters moving average as the fundamental value.[15]

– Insert Table 7 here –

Like in the previous section, the estimated coefficients are statistically significant in all cases and the model fit increases in terms of $\overline{R}^2$ as the forecasting horizon increases. When looking at the shift parameters θ in the transition function we find that the estimated values remain in the same range over different forecasting horizons. The coefficient ϕ determining the curvature of the transition function also remains in the same range for the regressive expectations. In the case of extrapolative expectations a substantial increase of this parameter points to a faster transition between 0 and 1 as the forecasting horizon increases. The estimated β_0s and β_1s

[15] As a robustness check, we also experimented with a twelve quarters moving average. The estimation results remain qualitatively unchanged and are available from the authors on request.

suggest the following interpretations.

First, in the case of extrapolative expectations, the linear term β_0 is significantly negative. The forecasts in the ECB survey seem to exhibit contrarian behavior. A given observed oil price increase is expected to be reverted in the future. The extent to which this return reversion is expected to occur depends on the absolute value of the oil price return. While smaller returns are expected to be unwound immediately, larger returns are expected to be more persistent. *Second*, in the case of regressive expectations the linear term β_0 is significantly negative. This implies that, in general, forecasters' expectations tend to be stabilizing as a given misalignment is expected to be diminished by future decreases of the oil price. The positive coefficient β_1 together with the specified transition function reveals that the expected mean reversion declines with a rising misalignment. Forecasters using a moving average fundamental obviously view strong misalignments to be more persistent than smaller deviations from the equilibrium value. This somewhat surprising finding is robust with respect to the entire set of forecasting horizons and may be interpreted as a result of forecasters' increased precaution regarding the speed of future mean reversion as misalignments become substantial. A more technical interpretation of the estimation results is based on the fact that moving averages are correlated with the actual oil price. An upswing of the oil price also increases its moving average. The more the moving average adjusts to current price developments the smaller is the need for future price changes to close the gap.

7.3 Sub-Sample Results

Due to the fact that the ECB survey of professional forecasters started in 2002 the fraction of forecasts made in the presence of the oil price bubble is quite large. As a consequence, the results of the paper might be driven solely by the huge run-up in oil prices. In particular, the finding that expectations only become stabilizing in the presence of a substantial mispricing is suspected to be bubble-driven. As a further robustness check we perform a sub-sample exercise excluding the bubble period starting in 2007. The remaining 500 observations are used to estimate a slightly modified Panel-STR model.[16] First, the shift parameters θ in the transition functions turned out be statistically insignificant, so we skipped these coefficients from the final estimations. Second, squared transition variables dominated absolute values in terms of convergence of the estimation routine and model fit. In the case of the longer-run forecasts the estimation of coefficient ϕ in the transition functions of extrapolative expectations obviated convergence. We decided to set $\phi = 153.61$ as resulted from two quarters ahead forecasts. Table 8 contains our estimation results.

– Insert Table 8 here –

The coefficients of regressive expectations are statistically significant and exhibit the same signs as in the full-sample estimation, while the parameters of extrapolative expectations switched signs. Obviously, the nonlinear properties of regressive expectations remain qualitatively the same. Regarding extrapolative expectations, however, we conclude that in off-bubble periods small returns provoke bandwagon expectations, while large returns result in contrarian expectations. This is consistent with the idea that in general, expectations behave globally stable, while in the presence of potential asset price bubbles forecasters seem to consider a shift in the fundamental value implying oil price returns to be of permanent nature.

7.4 Model Evaluation

The model explains an increasing fraction of forecasting variability in terms of $\overline{R}^2$ as the forecasting horizon increases. Most likely, the influence of short-

[16]The excess demand variables are used to calculate the fundamental value.

run oil price dynamics due to the impact of new information diminishes as forecasters have to deal with long-run fluctuations. In order to assess to what extent the nonlinear part in the panel regressions improve the models explanatory power, we calculate the χ^2-statistic of the likelihood ratio test by setting $\beta_1 = \phi = \theta = 0$ in the restricted (linear) model. The one percent critical value of the $\chi^2(6)$-statistic is 16.81. Of course, under the null hypothesis of $\phi = 0$ there are unidentified nuisance parameters ruling out this procedure as a rigorous statistical test. The NRNL-test statistics indicate some remaining nonlinearities.[17] Compared to the initial tests against linearity presented in section 6.2, however, the Panel-STR models catch a great deal of STR-type nonlinearity. Regarding the parameter constancy tests we find little room for structural breaks. Although the F-statistics are often statistically significant, particularly in case of the moving average fundamental, no single higher order trend component in the test regression is significantly different from zero at the five percent level. Given that the same specification is applied across all forecast horizons/fundamental value combinations ensuring comparability among the respective alternatives, the Panel-STR model fits the data reasonably well.

8 Conclusion

This paper investigates oil price expectations of the Survey of Professional Forecasters (SPF) conducted by the European Central Bank. The data set allows for disaggregating oil price expectations over a period spanning eight years. In contrast to earlier linear studies of survey data, we are able to identify important nonlinear properties of forecasters' expectations. Applying a Panel-STR model developed by González et al. (2005), we find that the expected mean reversion of oil prices depends on its current misalignment.

[17]Re-estimation of the model including higher order terms of the transition variables did not improve the results.

The expectations reflect the perception of destabilizing oil price dynamics in neighborhood of the fundamental calculated by means of oil demand variables, while mean reversion of oil prices is expected to become stabilizing where substantial misalignments exist. Extrapolative expectations are nonlinear in the sense that smaller returns are expected to be unwinded immediately, while larger returns are perceived to be more persistent. These expectation dynamics are prevalent regardless of the forecasting horizon investigated. A sub-sample exercise excluding the oil-price bubble reveals that the nonlinear dynamics of regressive expectations remain the same. Extrapolative expectations exhibit a different type of nonlinearity as small returns seem to provoke bandwagon expectations, while large returns result in contrarian forecasts. This clearly indicates that the scope for detailed sub-sample estimation of nonlinear STR-models in the presence of comparatively short data sets is limited. In general, however, we are confident that the SPF forecasters' perception of locally unstable but globally stable price dynamics provides evidence for the existence of a complex expectation formation process encouraging the introduction of nonlinear expectation in asset price models. In fact, it would be interesting to see whether forecasters at times switch between regressive and extrapolative expectations in a predictable fashion. This is left for future research.

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Table 1: Summary Statistics of the Expected Oil Price

Forecast Horizon	1Q Ahead	2Q Ahead	3Q Ahead	4Q Ahead	5Q Ahead	Actual
mean	57.01	55.98	55.27	55.08	55.16	58.29
standard deviation	25.83	25.61	25.46	25.47	25.67	26.77
skewness	0.69	0.60	0.51	0.42	0.38	0.65
kurtosis	3.56	3.29	2.99	2.68	2.48	3.51
forecasters	25	25	25	25	25	–
observations	900	900	900	900	900	37

Note: Table 1 shows the average oil price forecast for the end of the respective quarter as well as the descriptive statistics for the sample period between 2002Q1 and 2010Q4.

Table 2: Unit Root Tests

Fundamental	$SpotOilPrice$	$OPEC^{reliance}$	IMP^{China}	$Reserves$
ADF	-1.53	-1.86	0.33	-1.99

Note: ADF denotes the adjusted Dickey-Fuller test statistic of the unit root test(intercept included). The respective MacKinnon (1991) five percent critical value is $ADF_{crit} = -2.89$.

Table 3: Test of Unbiasedness

	1Q Ahead	2Q Ahead	3Q Ahead	4Q Ahead	5Q Ahead
$\hat{\alpha}^{unb}$	.0822**	.1079**	.1480**	.1926***	.2169***
	(.0330)	(.0544)	(.0641)	(.0686)	(.07184)
$\hat{\beta}^{unb}$	0.8793	0.4912*	.4203*	.4884*	.3926**
	(.2503)	(.3008)	(.3031)	(.2888)	(.2780)
R^2	.1433	.0339	.0286	.0452	.0331
Obs	875	850	825	800	775

Note: The table represents the regression results for the equation $s_{t+h} - s_t = \alpha_h + \beta_h(E_{t,i}[s_{t+h}] - s_t) + \epsilon_{t+h,i}$. Standard error in parentheses; *** (**) and * indicate significance at the 1% (5%) and 10% levels of the null hypothesis that $\hat{\alpha} = 0$ and $\hat{\beta} = 1$, respectively.

Table 4: Test of Orthogonality

	1Q Ahead	2Q Ahead	3Q Ahead	4Q Ahead	5Q Ahead
$\hat{\alpha}^{ortho}$	-.0592***	.0320	-.2343***	-.0945**	-.1703***
	(.0155)	(.0237)	(.0338)	(.0405)	(.0503)
$\hat{\beta}^{ortho}$	-.0056	.0656	-.5406***	-.2384***	-.1951***
	(.0318)	(.0468)	(.0552)	(.0638)	(.0574)
$\hat{\gamma}^{ortho}$	-.6434***	-.4819***	-.9483***	-.8633***	-.1698
	(.0375)	(.0523)	(.0772)	(.0887)	(.1232)
R^2	.8986	.9252	.9251	.9137	.9056
Obs	800	800	800	800	775
Forecasters	25	25	25	25	25

Note: Regression results for the equation $s_{t+h} - E_{t,i}[s_{t+h}] = \alpha_h + \beta_h(s_t - s_{t-1}) + \gamma_h(s_t - f_t) + \epsilon_{t+h,i}$ by means of the Newey/West panel estimator; robust autocorrelation and heteroskedastic standard error in parentheses; *** (**) and * indicate significance at the 1% (5%) and 10% levels, respectively.

Table 5: Nonlinearity-Tests

			Full sample		up to 2006:4	
Forecast	Regressor	Transition	MA16	Demand	MA16	Demand
1Q	mis	mis	51.18	12.09	81.55	31.93
	mis	return	18.57	23.18	14.58	24.29
	return	mis	2.68	25.29	46.66	32.09
	return	return	59.29	67.29	15.87	12.69
2Q	mis	mis	68.43	15.59	80.23	66.58
	mis	return	16.81	26.13	14.69	49.3
	return	mis	0.63	6.65	87.89	98.01
	return	return	37.82	45.9	27.57	18.93
3Q	mis	mis	82.93	26.94	106.51	95.83
	mis	return	10.04	21.15	3.48	55.59
	return	mis	0.37	8.23	124.81	121.7
	return	return	36.56	43.09	30.63	21.77
4Q	mis	mis	87.41	36.53	93.59	94.87
	mis	return	9.44	22.53	3.75	44.77
	return	mis	1.49	7.46	110.71	114.12
	return	return	31.62	36.71	40.57	31.09
5Q	mis	mis	80.9	39.09	90.32	96.49
	mis	return	10.49	23.69	4.92	47.11
	return	mis	2.33	7.72	106.05	108.19
	return	return	23.32	27.95	37.22	28.63

Note: χ^2-statistics of the linearity tests against STR-type nonlinearities. The one percent critical value is $\chi^2_{crit} = 11.34$. 'mis' indicated the current misalignment $(s_t - f_t)$, and 'return' refers to the recent percentage change of the oil price $(s_t - s_{t-1})$. Data from 1Q2002 to 4Q2009.

Table 6: Panel-STR Model with the Demand Fundamental

Expectation	Coefficient	1Q	2Q	3Q	4Q	5Q
Regressive	β_0	2.17	2.16	1.92	2.26	2.35
		(0.31)	(0.27)	(0.15)	(0.19)	(0.18)
	β_1	-2.24	-2.30	-2.12	-2.53	-2.65
		(0.31)	(0.27)	(0.15)	(0.19)	(0.18)
	ϕ	16.65	16.07	30.84	31.07	31.02
		(1.14)	(1.04)	(2.45)	(2.58)	(2.45)
	θ	-0.06	-0.09	-0.17	-0.16	-0.16
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Extrapolative	β_0	-0.51	-0.78	-1.00	-1.13	-1.08
		(0.06)	(0.08)	(0.11)	(0.11)	(0.11)
	β_1	0.63	0.93	1.15	1.25	1.16
		(0.07)	(0.09)	(0.11)	(0.12)	(0.12)
	ϕ	9.90	13.11	13.84	15.66	15.59
		(1.04)	(1.35)	(1.79)	(1.90)	(2.22)
	θ	0.20	0.21	0.21	0.21	0.21
		(0.01)	(0.01)	(0.01)	(–)	(–)
$\overline{R}^2$		0.19	0.24	0.35	0.38	0.40
LRT		133.90	156.10	230.76	217.18	189.18
$NRNL$	regressive	9.96	5.62	7.93	7.55	8.32
	extrap.	28.09	12.06	11.07	7.34	5.99
PC	F(12,763)	2.98	2.16	3.58	2.88	2.68

Note: Regression results for the equation (4) and equation (5); robust standard error in parentheses; LRT indicates the χ^2-statistic of the likelihood ratio test setting $\beta_1 = \phi = \theta = 0$ in the restricted (linear) model. The one percent critical value of the $\chi^2(6)$-statistic is 16.81. $NRNL$ is the F-value for no remaining nonlinearity as described in section 6.4; PC reflects the F-statistic of parameter constancy against STR-type time variation. Data from 1Q2002 to 4Q2009.

Table 7: Panel-STR Model with the MA Fundamental

Expectation	Coefficient	1Q	2Q	3Q	4Q	5Q
Regressive	β_0	-1.07	-2.04	-2.84	-3.27	-3.44
		(0.27)	(0.29)	(0.38)	(0.48)	(0.50)
	β_1	1.14	2.06	2.84	3.21	3.35
		(0.27)	(0.30)	(0.39)	(0.49)	(0.51)
	ϕ	7.45	8.84	9.01	9.10	9.08
		(1.12)	(0.68)	(0.58)	(0.67)	(0.70)
	θ	-0.14	-0.11	-0.12	-0.11	-0.11
		(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Extrapolative	β_0	-0.40	-0.55	-0.82	-1.01	-0.91
		(0.06)	(0.08)	(0.12)	(0.16)	(0.17)
	β_1	0.46	0.60	0.84	0.99	0.85
		(0.06)	(0.09)	(0.12)	(0.15)	(0.16)
	ϕ	8.03	13.14	18.63	25.17	27.17
		(1.30)	(2.22)	(2.92)	(4.68)	(6.48)
	θ	0.22	0.22	0.22	0.23	0.23
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\overline{R}^2$		0.16	0.23	0.32	0.37	0.40
LRT		112.30	146.66	190.46	197.18	188.36
$NRNL$	regressive	2.64	2.85	3.50	5.11	5.05
	extrapol.	20.85	10.97	9.52	6.54	5.34
PC	F(12,763)	1.38	1.42	2.08	1.71	1.57

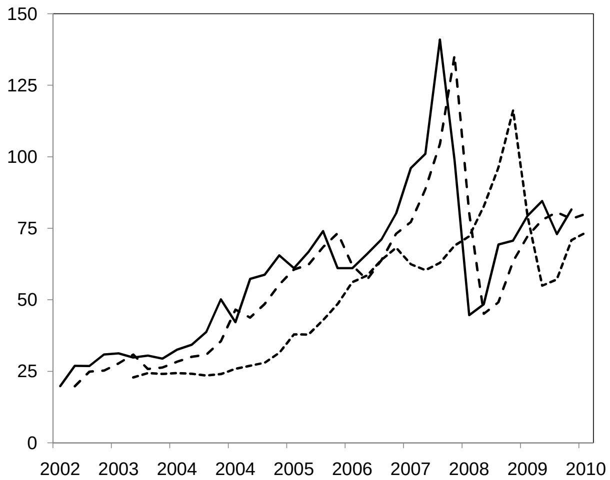
Note: Regression results for the equation (4) and equation (5); robust standard error in parentheses; LRT indicates the χ^2-statistic of the likelihood ratio test setting $\beta_1 = \phi = \theta = 0$ in the restricted (linear) model. The one percent critical value of the $\chi^2(6)$-statistic is 16.81. $NRNL$ is the F-value for no remaining nonlinearity as described in section 6.4; PC reflects the F-statistic of parameter constancy against STR-type time variation. Data from 1Q2002 to 4Q2009.

Table 8: Sub-Sample Estimation Using the Demand Fundamental

Expectation	Coefficient	1Q	2Q	3Q	4Q	5Q
Regressive	β_0	0.84	1.39	1.38	1.54	1.61
		(0.08)	(0.22)	(0.15)	(0.18)	(0.24)
	β_1	-0.97	-1.49	-1.51	-1.70	-1.80
		(0.19)	(0.20)	(0.15)	(0.16)	(0.21)
	ϕ	17.28	28.49	25.17	27.45	28.60
		(9.35)	(8.50)	(7.46)	(8.70)	(9.49)
Extrapolative	β_0	0.53	1.05	0.79	0.73	0.79
		(0.29)	(0.31)	(0.21)	(0.18)	(0.27)
	β_1	-0.81	-1.38	-1.18	-1.14	-1.23
		(0.28)	(0.31)	(0.22)	(0.19)	(0.27)
	ϕ	142.41	153.61	153.61	153.61	153.61
		(57.80)	(35.65)	(–)	(–)	(–)
$\overline{R}^2$		0.33	0.33	0.31	0.32	0.34
LRT		41.18	57.96	45.24	43.42	41.80
$NRNL$	regressive	0.11	5.79	12.34	15.67	16.63
	extrapol.	0.09	1.46	5.45	8.17	7.00
PC	F(12,763)	0.77	1.12	2.56	3.30	3.54

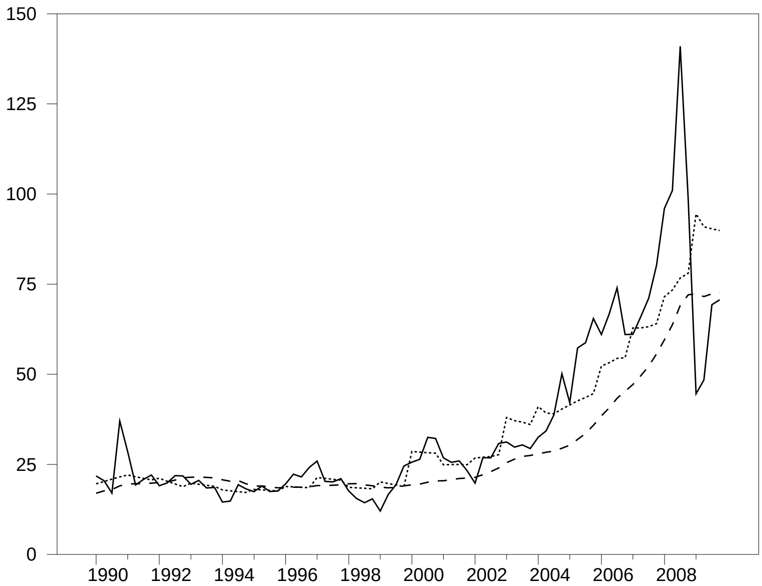
Note: Regression results for the equation (4) and equation (5); robust standard error in parentheses; LRT indicates the χ^2-statistic of the likelihood ratio test setting $\beta_1 = \phi = 0$ in the restricted (linear) model. The one percent critical value of the $\chi^2(6)$-statistic is 16.81. $NRNL$ is the F-value for no remaining nonlinearity as described in section 6.4; PC reflects F-statistic of parameter constancy against STR-type time variation. Data from 1Q2002 to 4Q2006.

Figure 1: Actual Oil Price and Mean Forecast (in US dollar)



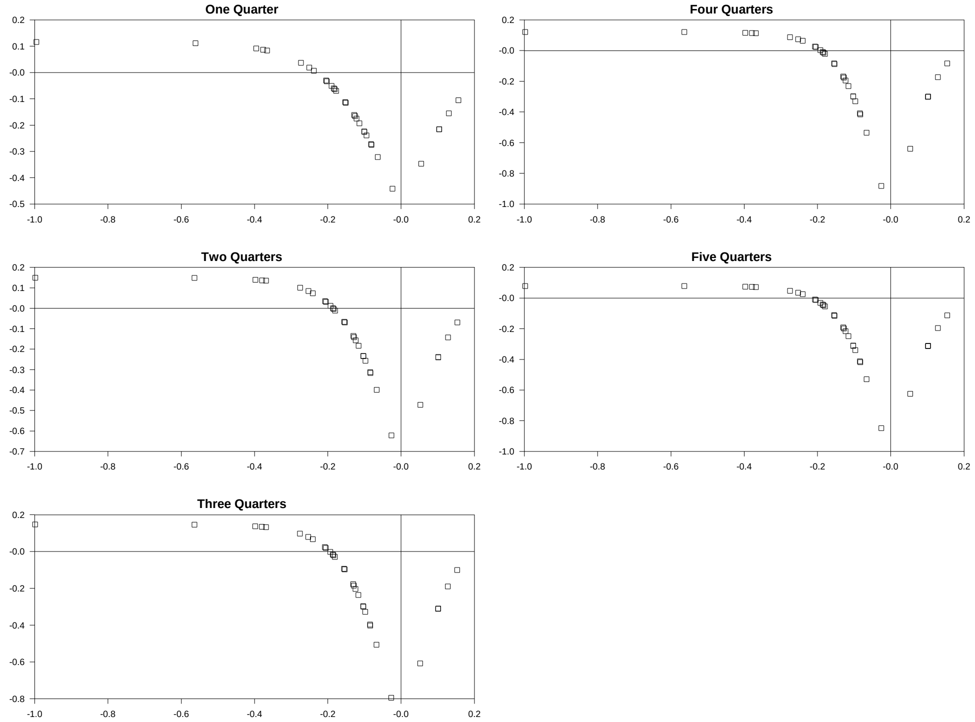
Notes: The (fine) dotted line reflects the mean of the one- (five-) quarter-ahead oil price forecast at the time of its realization while the solid line shows the actual oil price. The vertical difference between the actual oil price and the oil price forecast is therefore the forecast error.

Figure 2: Actual and Fundamental Values of the Oil Price (in US dollar)



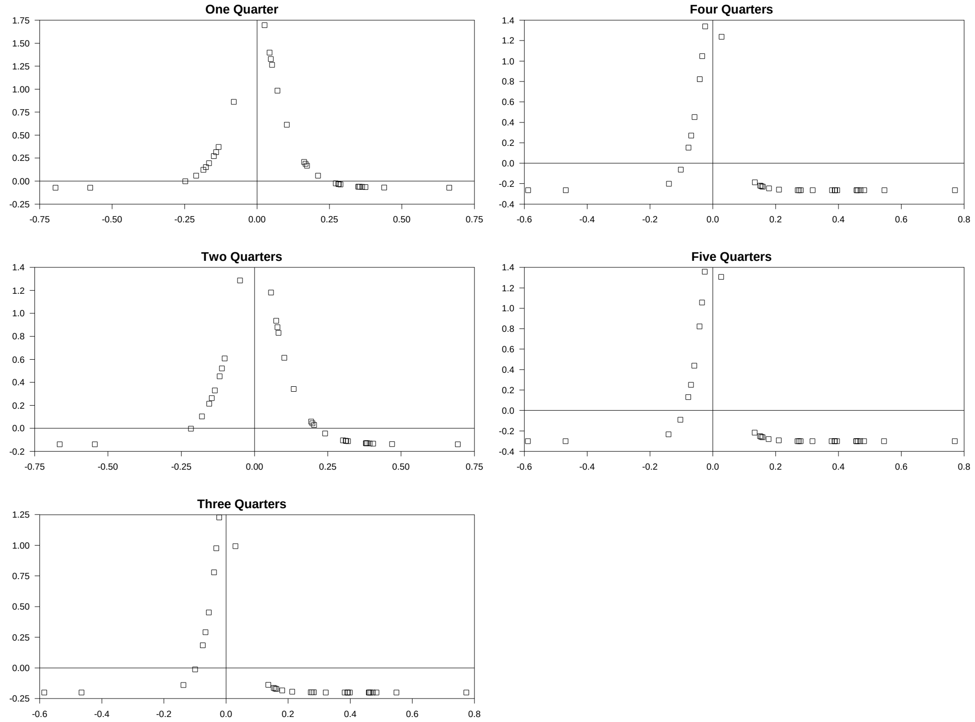
Notes: Solid line – actual oil price, dotted line – excess demand fundamental,
dashed line – moving average 16 quarters. Data from 1990 to 2009.

Figure 3: Transition Functions for Extrapolative Expectations



Notes: The figures show the expected mean reversion ($\beta_0 + \beta_1\omega_t$) on the vertical axis and the lagged return $s_t - s_{t-1}$ on the horizontal axis.

Figure 4: Transition Functions for Regressive Expectations



Notes: The figures show the expected mean reversion ($\beta_0 + \beta_1\omega_t$) on the vertical axis and the misalignment $s_t - f_t$ on the horizontal axis.