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Abstract

We use oil price forecasts from the Consensus Economic Forecast poll to analyze how forecaster build their expectations. Our findings point into the direction that the extrapolative as well as the regressive expectation formation hypothesis play a role. Standard measures of forecast accuracy reveal forecasters' underperformance relative to the random-walk benchmark. However, it seems that this result might be biased due to peso problems.

JEL classification: F31, D84, C33
Keywords: Oil price, survey data, forecast bias, peso problem

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1 Introduction

During the time period 2002 to mid 2008 the oil price increased tremendously from a level of 20 US dollar per barrel to an all time high of 145 US dollar per barrel in July 2008. This oil price shock hit the oil importing nations heavily and some economists view this development as one cause for the current worldwide recession. In turn, the sharp drop of the oil price down to 30 US dollar per barrel in December 2008 implies a heavy burden for exporting nations such as Russia or Dubai suffering from the dramatic deterioration of their terms of trade. This sharp drop of the oil price was unforeseen by many economists. (Brown et. al, 2008). As a consequence, some research institutes do not forecast the oil price in their large macroeconomic models anymore. Instead, it is assumed that the oil price follows a random walk so that the current oil price level serves as the best predictor for the oil price in the future (Fricke, 2009).

In addition, there is evidence that the oil market is frequently subject to bubbles which drive the oil price away from its equilibrium level. For instance, Reitz/Slopek (2009) find that the interaction of chartists and fundamentalists on oil markets account for substantial and enduring oil price misalignments. Since trades on this market are solely based on participants' expectations, it is important to understand how expectations are formed in the oil market.

This paper analyzes the expectation formation process of oil price forecasters. To this end, we compare the Consensus Economics forecasts with actual price developments in the oil market. The analysis has important consequences for market participants and policy makers alike. By analyzing and evaluating professional forecasts, we provide a rationale for forecasters' biased expectations towards the oil price equilibrium value. This supports the finding of rational bias in macroeconomic forecasts (Laster et al., 1999). Moreover, since major central banks respond to expected future inflation developments, the analysis of expectations in the oil market may be crucial for the conduct of monetary policy (Castro, 2008).

Survey data has already been used to analyze the expectation formation process is financial markets. Ito (1990) analyzes short-term and long-term foreign exchange rate forecasts for the time period between May 1985 and June 1987. While the former show bandwagon behavior, medium-term exchange rate forecasts forecasts exhibit a stabilizing feature. MacDonald/Marsh (1993) examine the efficiency of oil market expectations published in the Consensus Economics 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 only, while our analysis nearly covers a twenty year period.

The remainder of the paper is structured as follows. In the next section, we describe the data set while section 3 examines the expectation formation process of oil price forecasters. In section 4, we examine the question whether expectations are formed rationally. Particularly, we test whether forecasts fulfill the rationality conditions of unbiasedness and orthogonality. In section 5, we shed some light on the forecast accuracy of oil price forecasts and apply various methods to check whether the forecasts are significantly better or worse compared to a random walk forecast. Section 6 examines the oil price forecasts under a regime shift and analyzes the so called ‘peso problem’. Finally, section 7 concludes.

2 The data set

In this paper we use the mean of the three months oil price forecasts published in the Consensus Economic Forecast poll. The poll started in October 1989 and our sample period ends in December 2008. Table 1 shows the main features of the data set. On average 75 forecasters participated in the poll while the number of participants in the poll varies between 45 and 128 forecasters. The participants of the Consensus Economic Forecast poll work for investment banks, commercial banks and consultancies.[1] The Consensus Economics Forecast poll has been used by other studies. Analyzing GDP and inflation forecasts, Blix et. al (2001) and Batchelor (2001) have found that Consensus Economic forecasts are less biased and more accurate in terms of mean absolute error and root mean squared error compared to OECD and IMF forecasts.

– Insert Table 1 here –

The analysis of oil price expectations is especially appealing since the oil market recently shows persistent dynamics. Figure 1 shows the actual oil price (dotted line) and the oil price forecast (solid line) for the time period under consideration. The vertical distance between the two series reflects the forecast error. At a first glance, Figure 1 shows that oil price forecasts in the 1990s seem to be a good indicator of the future oil price. But since the beginning of the increase in the oil price in 2002, oil price forecasts were on average lower than the actual oil price indicating that the oil forecasters underestimated the oil price development. In the subsequent analysis we analyze oil price forecasts in more detail. We thereby only use forecasts made in January, April, July, and October for the period between 1989 and 2008. In doing so, we avoid the problem of serial correlated forecast errors

[1] A complete list of the participating institutions is available upon request.

since the forecast horizon is three months. Hence, the forecast horizon has already expired when the next forecast is made and subsequent forecasts should be independent from each other.[2]

– Insert Figure 1 here –

3 Examination of the expectation formation process

3.1 Extrapolative expectation formation hypothesis

This section examines the expectation formation process. We begin by investigating whether the data supports the hypothesis that market participants have extrapolative expectations. Given the structure of the survey, this would be the case if the expected change of the oil price is a function of the oil price development of the past. More specifically, we estimate the following expectation formation process:

$$E_t[s_{t+1}] - s_t = \alpha + \beta(s_t - s_{t-1}) + \epsilon_t. \tag{1}$$

Here, s_t ($E_t[s_{t+1}]$) denotes the log of the (expectation of future) oil price at time t. Since we use non-overlapping forecasts the time frequency $t+1$ refers to a three-month period. In addition, ϵ_t symbolizes the error term. If we find that β is positive this would indicate that whenever the oil price increased during the previous three months, forecasters expect a further increase for the future. In this case, expectations would show *bandwagon behavior*. However, if β is negative this would indicate that an increase during the past makes forecaster to expect a decrease during the next period *(contrarian behavior)*.

[2] We also used different forecast frequencies (e.g., February, May, August and November). However, the results do not change qualitatively and are available upon request.

The estimates of equation (1) – shown in Table 2 (Specification I)– imply that forecasters form contrarian expectations. The slope coefficient is significantly negative and takes a value of about $-.20$. This means that, for example, a ten percent increase of the oil price during the last three months lead forecasters to expect a 2.0 percent decrease for the next three months. The constant term ($\hat{\alpha}$) takes a value of $-.01$ and is also highly significant. Obviously, the forecaster expect – on average – the oil price to decrease by one percent each quarter.

– Insert Table 2 here –

3.2 Regressive expectation hypothesis

In order to investigate the regressive expectation hypothesis one could test whether deviations from the equilibrium level also influence the oil price expectations. Of course, this incurs the nontrivial problem of specifying an equilibrium oil price level. We calculate a fundamental value of the oil price by assuming 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. To some extent, this is in contrast to the common belief that particularly political events such as wars or embargoes are the main forces driving the oil price. However, Barsky/Kilian (2004) argue that this type of exogenous shocks are but one of a number of different determinants of oil prices and their impact may differ greatly 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 surging oil prices 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.

The relationship between oil prices and Chinese oil imports was originally proposed by Anderson (2005). 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 quarterly frequency assuming an I(1)-process.

$$\underset{}{s_t} = \underset{(0.49)}{-0.29} + \underset{(6.03)}{0.51} \cdot log(IMP_t^{China}) + \epsilon_t \qquad (2)$$

The regression results are based on Hansen's (1982) Generalized Method of Moments. Standard errors are adjusted for heteroskedasticity and serial correlation using Newey/West (1987) correction of the covariance matrix. The Dickey-Fuller test statistic ($t - value = -2.80$)[3] 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. These estimation results allow for the approximation of the fundamental value f_t as linear function of China's oil imports.

A graphical representation of the fundamental oil price series can be found in Figure 2. Although Figure 2 reports substantial deviations between the two series for the time period between 2005 and 2008, the actual oil price (s_t) tends to fluctuate around the fundamental value (f_t). We use the fundamental oil price series as a measure for the equilibrium oil price. Hence, the deviation of the actual oil price from its equilibrium value is a second explanatory variable. We, therefore, estimate the following equation:

$$E_t[s_{t+1}] - s_t = \alpha + \beta(s_t - s_{t-1}) + \gamma(s_t - f_t) + \epsilon_t. \qquad (3)$$

[3]The five percent critical value is -2.77 (Phillips and Ouliaris, 1990).

where $(s_t - f_t)$ is the log difference between the current oil price and the equilibrium level. The γ-coefficient measures to which extent forecasters expect the oil price to return to its equilibrium level. If γ turns out to be negative (positive) forecasters do (not) expect the oil price to move to the equilibrium which is referred to as *(de)stabilizing behavior*. However, if γ is not different from zero, forecasters do not respond in their expectations to deviations from the equilibrium oil price level.

As can be inferred from Table 2 (Specification II), the estimated regressive coefficient is indeed significantly negative and takes a value of $\hat{\gamma} = -.049$. This implies that forecasters expect that a gap between the actual oil price and its equilibrium value is closed by 4.9 percent each quarter. As a robustness check we estimate β and γ simultaneously (Table 2, Specification III). The estimated $\hat{\beta}$ and $\hat{\gamma}$ coefficients are still in the same range as before and multi-collinearity between both independent variables does not seem to be an issue given the small and insignificant correlation coefficient of about .25.

– Insert Figure 2 here –

The tests on extrapolative as well as regressive expectation hypothesis reveal stabilizing oil price expectations. Forecasters obviously rely on recent oil price changes and misalignments when building oil price expectations for the future. This seems to be somewhat at odds with the efficient market hypothesis. If the oil price time series follows the characteristics of a random walk, this forecasting behavior should translate into significant forecast errors. Tests should reject the hypothesis that forecasters build their expectations in a rational way. As a consequence, the following section applies an unbiasedness test and also deals with the orthogonality condition to test the rational expectation hypothesis.

4 Tests for rationality of expectations

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

4.1 Unbiasedness

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

$$s_{t+1} - s_t = \alpha + \beta(E_t[s_{t+1}] - s_t) + \epsilon_{t+1} \tag{4}$$

Unbiasedness prevails if $\alpha = 0$ and $\beta = 1$. 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 estimate equation (4) by using an OLS model. The results – summarized in Table 3 – indicate that the constant (i.e., $\hat{\alpha}$) is significantly different from zero. However, it can be inferred from the standard errors that $\hat{\beta}$ is not different from unity. The significant $\hat{\alpha}$-coefficient implies that expectations are not an unbiased predictor of the future development.

– Insert Table 3 here –

4.2 Orthogonality

We now turn to the test for orthogonality. It examines whether forecast errors are unrelated 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 of the actual oil price level from its fundamental value $(s_t - f_t)$.

Hence, we estimate

$$s_{t+1} - E_t[s_{t+1}] = \alpha + \beta(s_t - s_{t-1}) + \gamma(s_t - f_t) + \epsilon_{t+1} \tag{5}$$

Orthogonality implies that $\alpha = \beta = \gamma = 0$ so that neither the constant term nor any other available information explain the forecast error. Table 4 reports that $\hat{\alpha}$ takes a positive value of about .065. This implies that the forecast error is on average positive. Forecasters – on average – expected that the oil price is by 6.5 percent smaller than it actually was. This finding is also in line with the information given in Table 1: While the actual average oil price is 33.8 US dollar per barrel, the average of the expected oil price takes the value of at 32.1 US dollar per barrel. Hence, the expected oil price level was by 5.3 percent lower than the actual oil price.

– Insert Table 4 here –

Interestingly, the estimated $\hat{\beta}$ and $\hat{\gamma}$-coefficients are not significantly different from zero. This implies that forecasters 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 forecasters use the full information set consisting of the previous development and the misalignment. However, we also document that forecasters produce a significant forecast error since the oil price forecasts are – on average – significantly lower than the realized oil price. In order to solve this puzzling feature, the next section analyzes the forecast accuracy in more detail comparing the price forecasts with a naive random walk model.

5 Expectations and forecast accuracy

In order to assess the accuracy of forecasters' predictions we employ two types of tests. The first test is based on the forecasts' mean squared error-ratio (MSER) relative to a naive random walk forecast as done in Mark (1995) and Faust et al. (2003). The related P-value tests whether the MSER is significantly different from unity using the framework of Diebold/Mariano (1995). The advantage of this approach results from its applicability for a variety of accuracy measures and their distributions.[4] As done in Mark (1995), the truncation lag is calculated by using the data-dependent formula provided by Andrews (1991).

The second test employed here is the projection statistic introduced by Evans/Lyons (2005). The forecasters' predictions are regressed on realized changes in (log) spot oil price

$$E_t[s_{t+1}] - s_t = \alpha + \beta(s_{t+1} - s_t) + \epsilon_{t+1} \tag{6}$$

where ϵ_{t+1} is a white-noise disturbance term. Forecasters' performance against a driftless random walk can be examined by simply testing for statistical significance of the β-coefficient. Obviously, to generate meaningful forecasts, it should possess a positive sign. If, otherwise, the forecasters had no predictive power for future changes of the oil price or if the latter does follow a random walk, it is only ϵ_{t+1} that drives $E_t[s_{t+1}] - s_t$. Note that if the oil price indeed follows a random walk, it cannot be correlated with $s_{t+1} - s_t$, since the forecasts are calculated using data up to period t. As in Evans/Lyons (2005), equation (6) is estimated using Newey/West (1987) estimators to deal with potentially remaining serial correlation in the residuals.

[4] Earlier test, for example the one introduced by Christiano (1989), primarily suffer from non-normal asymptotic distributions when analyzing nested models.

Table 5 reports results of both the Diebold and Mariano test and the Evans and Lyons projection statistic. The estimated figures suggest that the accuracy of forecasters' predictions is negligible. The mean squared error of forecasters' predictions significantly exceeds the mean squared error of the no-change forecast. Moreover, the β-coefficient of the Evans/Lyons (2005) regression is positive but small.

– Insert Table 5 here –

In summary, we find that forecasters – on average – do not outperform a random walk forecast. However, the puzzling feature remains that the forecasts fully include information on the previous oil price development and the misalignment but the forecasts are biased in the sense that forecasters expect a lower oil price than actually occurred. An explanation which might have caused this puzzling feature is the so called 'peso problem' which is analyzed in the next section.

6 Does forecasting accuracy suffer from peso problems?

Peso problems are sometimes defined to arise when the distribution of the asset price includes a low probability but major impact regime that generates extreme asset price returns (Krasker, 1980). Because this regime has low probability, it is unlikely to be observed in small samples. Thus, peso problems may be defined as arising whenever the ex-post frequencies of regimes within a sample differ substantially from their ex-ante probabilities. When a peso problem is present, the sample moments do not match the population moments agents use when forming expectations (Bekaert et al., 2001). However, the possibility that this regime shift may occur definitely affects forecasters expectations. Regarding the oil market, we may interpret the lack of forecasting accuracy and negative bias in forecasters' prediction – particularly in the period between 2005 and mid 2008 – as the result of the incorporated possibility of a sudden return of the oil price to its fundamental value.

In order to assess the relevance of a peso problem inherent in forecasters expectations we conduct the following experiment. As in Froot and Thaler (1990) we assume that forecasters have in mind two possible states of the future oil price. One state or regime consists of the idea that the oil price further follows its bubble path and the second state implies the return to its fundamental value. Estimating a two-state Markov regime-switching model then provides us with a time-varying (smoothed) probability, which forecasters have assigned to the bubble-bursting regime.[5]

The conditional mean reflects both the bubble and the bubble-bursting regime

$$E_t[s_{t+1}] - s_t = \beta_1(1-S_t)(s_t - f_t) + \beta_2(S_t)(s_{t+1} - s_t) + \sigma_1(1-S_t)\epsilon_t + \sigma_2(S_t)\epsilon_t, \quad (7)$$

where regime indicator $S_t = \{0, 1\}$ is parameterized as a first-order Markov process and the switching or transition probabilities are P and Q, respectively. The conditional variance is restricted to be constant within both regimes implying that the only source of heteroskedasticity is due to regime changes.[6] Under the assumption of conditional normality for each regime, the conditional distribution of the forecasted oil price change is a mixture of normal distributions (Hamilton, 1994).

– Insert Table 6 here –

[5]Regime-switching models have been applied to Peso-type problems by – among others – Evans (1996), Kaminsky (1993), Gray (1996) and Bekaert et al. (2001).

[6]Because this study is not about forecasting second moments, such a simplification seems to be reasonable.

The estimated regression coefficients of the first regime reveal statistically significant expectations of oil price mean reversion. The second regime indicates random walk expectations of forecasters as the estimated coefficient occurs to be statistically insignificant. Although forecasters lack ability to predict price changes even in a two regime framework, they seem to include a no-change scenario when forming oil price expectations. The weighting of the regimes is represented in Figure 3.

– Insert Figure 3 here –

The smoothed probabilities for the mean reverting regime show that forecasters stuck to the no-change prediction as long as the actual oil price remained within a reasonable range around the fundamental value. Since the spot price started to increase dramatically in 2005 the implied weight on mean reverting expectations picked up as well. Consequently, oil price predictions exhibited a persistent (negative) bias during this period. In the end, however, the oil price dropped substantially thereby confirming the inclusion of a mean reverting regime.

In summary, we find that oil price forecasts suffer from the peso problem providing an explanation for why forecasters show a significant forecast error, i.e., they expect a lower oil price than actually occurred, although they use the full set of information. Apparently, the forecast error is not due to irrational expectations in the sense that the forecasters neglect relevant information. The forecast error can rather be attributed to the existence of different regimes in the actual oil price development. Forecasters believe to some extent that the oil price development will switch to another regime and converge to its equilibrium level. But if this regime shift did not occur this yields a forecast error which is not driven by irrational expectations.

7 Conclusion

The recent roller-coaster in the international oil market has revealed forecasters' inability to predict major trends in the spot oil price. Using data from Consensus Economic Forecast poll we show that three-month oil price forecasts are inferior relative to the random walk benchmark by standard measures of forecast accuracy. Predictions tend to exhibit extrapolative (contrarian) as well as regressive properties leading to a downward bias of expectations in the recent period when the oil price dramatically surged. However, smoothed probabilities estimated from a two-stage regime-switching model interprets the bias as the outcome of a peso problem underlying the statistical inference. In fact, the fast decrease in the oil price in the second half of 2008 finally provided a rationale for the downward bias.

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Table 1: Summary Statistics of the Expected and Actual Oil Price

	Average
Actual Oil Price	33.8
Expected Oil Price	32.1
Standard Deviation	2.5
Time Period	Oct 1989 – Dec 2008
Number of Forecasters	75.2
Max	128
Min	45

Note: 'Standard Deviation' is the average standard deviation of the aggregated forecasts as published in the Consensus forecast poll; 'Max' ('Min') is the maximum (minimum) number of participants.

Table 2: Regression Results for the Extrapolative and Regressive Expectation Hypothesis

Specification	I	II	III
$\hat{\alpha}$	-.0103***	-.0515***	-.0454***
	(.0054)	(.0066)	(.0055)
$\hat{\beta}$	-.1977***	–	-.1777***
	(.0292)		(.0291)
$\hat{\gamma}$	–	-.0496***	-.0311***
		(.0138)	(.0117)
Adj. R^2	.3737	.1371	.4215
Various Test	F(1,74) = 45.75	F(1,74) = 12.92	F(2,73) = 28.32
Statistics	Prob > .0000	Prob > .0006	Prob > .0000
Observations	76	76	76

Note: Regression results for the equation (3) $E_t[s_{t+1}] - s_t = \alpha + \beta(s_t - s_{t-1}) + \gamma(s_t - f_t) + \epsilon_t$; standard error in parentheses; *** (**) and * indicate significance on a 1 % (5 %) and 10 % significance level, respectively; correlation coefficient between $(s_t - s_{t-1})$ and $(s_t - f_t)$ is .2577 and not significantly different from zero.

Table 3: Test for Unbiasedness

$\hat{\alpha}$	.0490*
	(.0268)
$\hat{\beta}$	.6645
	(.3697)
Adj. R^2	.0289
Observations	76

Note: Regression results for the equation $s_{t+1}-s_t = \alpha+\beta(E_t[s_{t+1}]-s_t)+\epsilon_{t+1}$; standard error in parentheses; *** (**) and * indicate significance on a 1 % (5 %) and 10 % significance level, respectively; for $\hat{\beta}$ this applies for H_0: $\hat{\beta} = 1$.

Table 4: Test for Orthogonality

Specification	I	II	III
$\hat{\alpha}$	.0652***	.0633***	.0675***
	(.0213)	(.0225)	(.0236)
$\hat{\beta}$	-.0720	–	-.0836
	(.1240)		(.1347)
$\hat{\gamma}$	–	-.0002	.0118
		(.0474)	(.0513)
Adj. R^2	.5633	-.0137	-.0223
Observations	75	75	75

Note: Regression results for the equation $s_{t+1} - E_t[s_{t+1}] = \alpha + \beta(s_t - s_{t-1}) + \gamma(s_{t-1} - f_t) + \epsilon_{t+1}$; standard error in parentheses; *** (**) and * indicate significance on a 1 % (5 %) and 10 % significance level, respectively.

Table 5: Test for Forecasting Accuracy

$\hat{MSER}$	1.132
	(.8896)
$\hat{E}L-\alpha$	-.0471***
	(.0064)
$\hat{E}L-\beta$	.0630**
	(.0311)
Adj. R^2	.0418
Observations	76

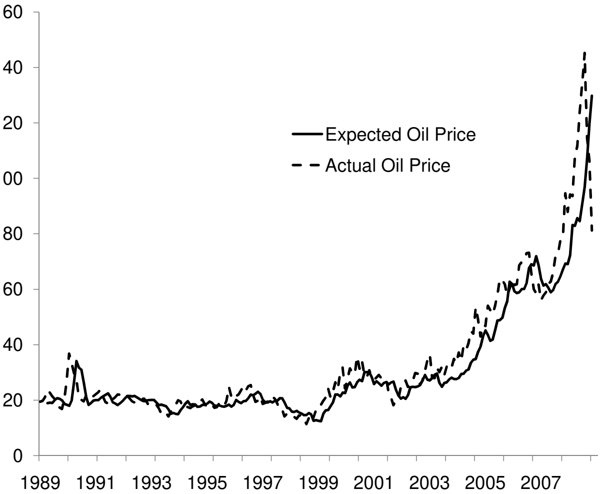
Note: The P-value of the $\hat{MSER}$ indicated the significance value for H_0: forecasters' performance equal random walk versus forecasters' performance better than random walk; $EL-\alpha$ and $EL-\beta$ refer to the estimated coefficients of the Evans and Lyons (2005) regression; standard error in parentheses; *** (**) and * indicate significance on a 1 % (5 %) and 10 % significance level, respectively.

Table 6: Markov Switching Model

Regime	1	2
$\hat{\beta}$	-.1125***	-.0224
	(6.79)	(0.17)
$\hat{\sigma}^2$	.0017***	.0097***
	(5.20)	(4.19)
P	.9383	.9366
	(17.01)	(19.48)
Observations	73	

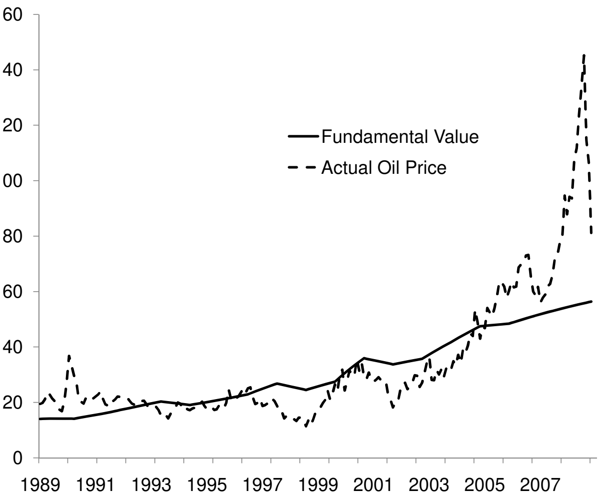
Note: The sample contains quarterly observations from 1990 to 2008; t-statistics in parentheses are based on heteroskedastic-consistent standard errors; *** (**) and * indicate significance on a 1 % (5 %) and 10 % significance level, respectively.

Figure 1: Actual Oil Price and Mean Forecast



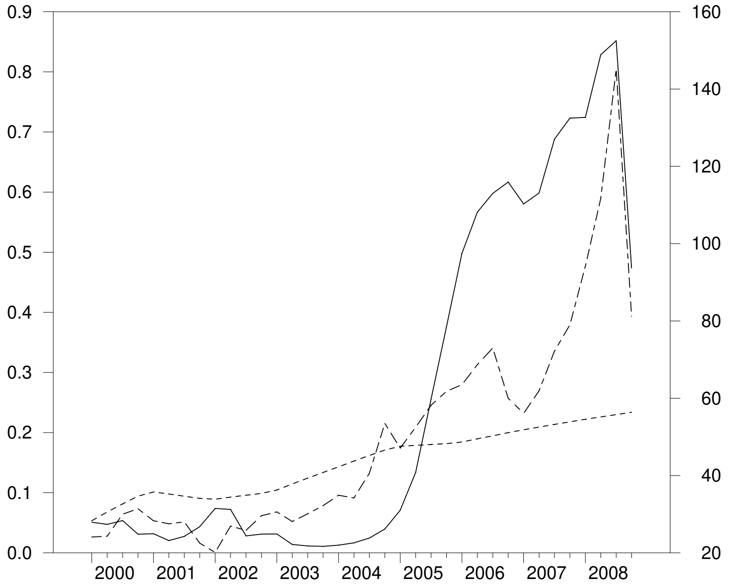
Notes: The solid shows the mean of the oil price forecast for the time of the forecast while the dotted line reflects the actual oil price.

Figure 2: Actual Oil Price and Fundamental Value



Notes: The fundamental value (solid line) of the oil price is calculated as described in subsection 3.2.

Figure 3: Smoothed Probabilities of the Bubble-Bursting Regime



Notes: The solid line shows the smoothed probabilities of the bubble-bursting regime, the dashed line shows the actual oil price, and the dotted line reflects the fundamental value of the oil price.