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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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Non-technical Summary

The oil price dynamics between 2002 and 2008 have called researchers to look into the oil price development in more detail. So far, literature has either focused on the predictive power of oil price futures (Pagano and Pisani, 2009) or has analyzed the oil price dynamics within a micro-structural model based on heterogeneous agents (Reitz and Slopek, 2009). This paper analyzes the expectation formation process of oil price forecasters by the means of survey data. Since its expectations which drive the oil price, knowing how expectations are formed in the oil market is crucial to understand its functioning.

To this end, we compare the Consensus Economics forecasts with actual price developments in the oil market. We provide evidence that oil price forecasters form extrapolative as well as regressive expectations, i.e., forecasts are based on the recent oil price change and the misalignment to the fundamental oil price. The latter is calculated by assuming that it depends on excess capacity in oil production which has been eroded in recent years by remarkable growth for oil demand from emerging economies, especially China. This argument is frequently been put forward (Hamilton, 2008; Hicks and Kilian, 2009) and accounts for the fact that political events such as wars or embargoes are not the main forces driving the oil price (Barsky and Kilian, 2004; Kilian, 2008). Though, we find that the forecast error is systematically uncorrelated to the previous oil price change and the misalignment, our results indicate that oil forecasters produce a systematic oil price forecast since the oil price forecasts are significantly lower than the realized oil price. Additionally, we find that forecasters do not outperform a random walk forecast.

To provide an explanation for these results we, finally, analyze whether the

oil price development is subject to a peso-problem which arises if whenever the ex-post frequencies of regimes within a sample differ substantially from their ex-ante probabilities. We, indeed, find that oil price forecasts suffer from the peso problem, i.e. they believe to some extent that the oil price development will switch to another regime and converge to its equilibrium level. This provides 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. But if this regime shift does not occur, a systematic forecast error arises obviously not driven by irrational expectations.

The analysis has important consequences for market participants and policy makers alike. By analyzing and evaluating professional forecasts, we provide a rationale for the bias in forecasters' expectations. 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 is crucial for the conduct of monetary policy (Castro, 2008).

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 (Hamilton, 2009). 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. These sharp movements of the oil price were unforeseen by many economists (Brown et. al, 2008). As a consequence, some research institutes stopped forecasting the oil price as an ingredient of their macroeconomic models. 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 to the lack of predictability, there is evidence that the oil market is frequently subject to speculative bubbles driving 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 speculative trading is solely based on market participants' forecasts, the understanding of expectation formation is crucial to assess its role in price determination in the oil market.

A related strand of literature investigates whether futures prices are a useful measure of oil price expectations. Assuming rational expectations futures prices should be unbiased predictors of future spot prices. Empirical tests of the unbiasedness hypothesis have been inconclusive so far. While Moosa and Al-Loughani (1994) find that futures prices are neither unbiased nor

efficient predictors of future spot prices, Chernenko et al. (2004) and Chinn et al. (2005) are not able to reject the unbiasedness hypothesis. Coimbra and Esteves (2004) identify a downward bias which increases in the forecast horizon. To account for these mixed results Knetsch (2007) suggests that convenience yields should be considered in the present value model of oil prices. Alternatively, expectations can be directly measured by means of survey data which include oil price expectations. Since oil price expectations drive the actual oil price as well as the futures oil price, such an analysis is crucial to understand how the oil market functions.

This paper analyzes the expectation formation process of oil price forecasters using survey data. To this end, we compare the Consensus Economics forecasts with actual price developments in the oil market. Survey data have already been used to analyze the expectation formation process in financial markets. Taylor and Allen (1992), Ito (1990) and Menkhoff (1997) analyze 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 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. Analyzing and evaluating professional forecasts, we find that Peso problems may account for forecasters' biased expectations towards the oil price equilibrium value. This supports the finding of a rational bias in macroeconomic forecasts (Laster et al., 1999). 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).

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 apply various methods to shed some light on the forecast accuracy of oil price forecasts. Section 6 examines the oil price forecasts allowing for regime shifts 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.

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

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

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

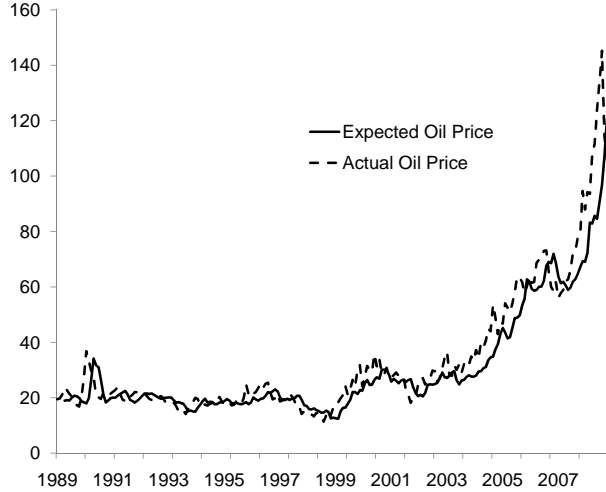
	Average
Actual Oil Price	33.8
Expected Oil Price	32.1
Standard Deviation	2.5
Time Period	Oct 1989 – Dec 2008
Number of Forecasters	75.2
Max	128
Min	45

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.

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 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

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

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.

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:

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

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*). 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.

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

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

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. Hamilton (2008) argues that the global demand for oil, especially from China, is the key determinant among others, like commodity price speculation, time delays or geological limitations on increasing production, OPEC monopoly pricing, and an increasingly important contribution of the scarcity rent. Hamilton (2008) 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/Kilian (2009) who find that news about global demand predict 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 GDP growth forecasts. In particular, Hicks/Kilian (2009) show that forecast revisions were associated with a hump-shaped response of the oil price.

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).

Although there is now little doubt that persistent shifts in the excess demand for oil is the major fundamental driving force of the last decade's oil prices, the important question remains, which variable should be used to capture demand dynamics. We tested the following oil market candidates. First, we divided global consumption of crude oil by non-OPEC crude oil production. The variable accounts for the fact that global demand has remained strong, but overall non-OPEC production growth has slowed. This imbalance increases reliance upon OPEC production and/or inventories to fill the gap (*OPECreliance*). A second variable as proxy for diminishing excess capacity or, more generally, market tightness is proposed by Andersen (2005). The author suggests that Chinese oil imports (IMP^{China}) accounts for a major part of world excess demand for oil and is strongly correlated with excess demand from other important emerging countries. exerting upward price pressure from increasing demand. Finally, a more forward looking measure of market tightness comprises the ratio of world oil reserves and 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 OECD Annual Statistical Bulletin (2008). Yearly data are interpolated to a quarterly frequency assuming an I(1)-process. Quarterly US dollar market prices of West Texas Intermediate (WTI) are taken from the IMF International Financial Statistics. The data set comprises the period from 1990 to 2008. Following the Engle-Granger methodology we separately regress oil prices on the fundamental variables.

$$s_t = \alpha + \beta f_t + \epsilon_t \quad (2)$$

The regression results are based on ordinary least squares. Standard errors

are adjusted for heteroskedasticity and serial correlation using Newey/West (1987) correction of the covariance matrix. Since the constant is statistically insignificant we re-estimated the model without intercept.

Table 3: Oil Price Fundamentals

Fundamental	<i>OPEC</i> reliance	<i>IMP</i> ^{China}	Reserves
β	1.75*** (0.03)	0.48*** (.005)	.23*** (.004)
Adj. R^2	0.29	0.65	0.25
ADF	-1.78	-3.04	-1.71

Note: Regression results for the equation $s_t = \beta f_t + \epsilon_t$; standard error in parentheses; *** (**) and * indicate significance on a 1 % (5 %) and 10 % significance level, respectively. ADF denotes the Dickey-Fuller test statistic of the regression residuals. The respective MacKinnon (1991) five percent critical value is -2.80 .

The Dickey-Fuller test statistics reveal stationarity of regression residuals only in case of *IMP*^{China}.³ Moreover, the adjusted R^2 statistics confirm the finding that only *IMP*^{China} explain a significant fraction of oil price variance. From these estimation results we conclude that empirically, the fundamental value f_t is sensibly approximated by China's oil imports.

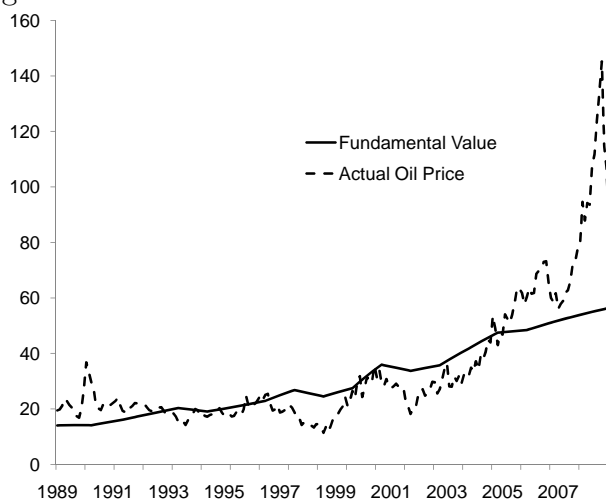
A graphical representation of the fundamental oil price series can be found in Figure 2. Although Figure 2 reports substantial deviations between the two series for the time period between 2005 and 2008, the actual oil price (s_t) tends to fluctuate around the fundamental value (f_t). We use the fundamental 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:

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

³The respective MacKinnon (1991) five percent critical value is -2.80 .

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.

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.

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.

Forecasters obviously rely on recent oil price changes and misalignments when building (stabilizing) oil price expectations. However, if the oil price time series follows the characteristics of a random walk, this forecasting behavior should translate into systematic forecast errors, which is in contrast to the efficient market hypothesis. 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:

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

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 4 – 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.

Table 4: 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 $H_0: \hat{\beta} = 1$.

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

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

Orthogonality implies that $\alpha = \beta = \gamma = 0$ so that neither the constant term nor any other available information explain the forecast error. Table 5 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.

Table 5: Test for Orthogonality

Specification	I	II	III
$\hat{\alpha}$.0652*** (.0213)	.0633*** (.0225)	.0675*** (.0236)
$\hat{\beta}$	-.0720 (.1240)	–	-.0836 (.1347)
$\hat{\gamma}$	–	-.0002 (.0474)	.0118 (.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.

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

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

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.

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

Table 6 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.

Table 6: Test for Forecasting Accuracy

$\hat{M}SER$	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 $\hat{M}SER$ 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.

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

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

regime

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

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. Though investigating low frequency data we allow the conditional variance to be time varying across regimes. 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).

Table 7: Markov Switching Model

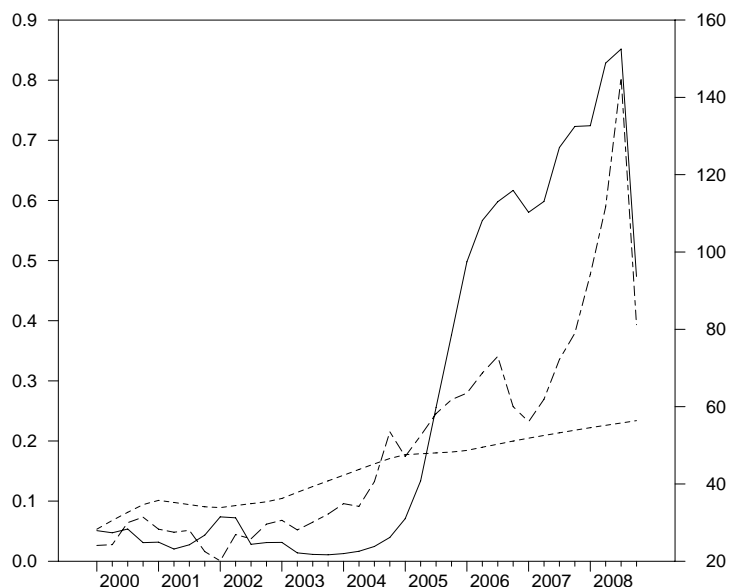
Regime	1	2
$\hat{\beta}$	-.1125*** (6.79)	-.0224 (0.17)
$\hat{\sigma}^2$.0017*** (5.20)	.0097*** (4.19)
P	.9383 (17.01)	.9366 (19.48)
Observations	73	

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.

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.

The smoothed probabilities for the mean reverting regime show that forecasters stuck to the no-change prediction as long as the actual oil price

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.

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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