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# The Relation Between Overreaction in Forecasts and Uncertainty: A Nonlinear Approach

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**Abstract** This paper examines if overreaction of oil price forecasters is related to uncertainty. Furthermore, it takes into account impacts from oil price return and oil price volatility on forecast changes. The panel smooth transition regression model from González et al. (2005) is applied with different specifications of the transition functions to account for nonlinear relations. Data on oil price expectations for different time horizons are taken from the European Central Bank Survey of Professional Forecasters. The results show that forecast changes are governed by overreaction. However, overreaction is markedly reduced when high levels of uncertainty prevail. On the other hand, noisy signals and positive oil price returns tend to cause higher overreaction.

**Keywords:** Overreaction, Uncertainty, Panel Smooth Transition Regression

**JEL Classification:** G14; C33; E37

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# 1 Introduction

The forecasts of professional forecasters (e.g. on commodity prices, exchange rates, earnings etc.) are often found to be biased. The behavior of analysts and the formation of their expectations are addressed by different parts of the literature. When forecasters revise their predictions, a frequently observed bias is overreaction. They are found to underreact to some information or at some point in time and overreact on other occasions. De Bondt and Thaler (1990) and Abarbanell and Bernard (1992) examine this topic for security analysts and Easterwood and Nutt (1999) for earning forecasts. The topic is analyzed most recently by Pancotto et al. (2013) for exchange rate forecasts. Aside from overreaction, other biases of forecasters are known. For example, they are overconfident (Hilary and Menzly, 2006; Deaves et al., 2010) or show herding behavior (De Bondt and Forbes, 1999; Hong et al., 2000; Welch, 2000; Clement and Tse, 2005; Pierdzioch et al., 2010).

In case of overreaction, the idea is that forecasters tend to form expectations that are too extreme given the available type of information. More precisely, expected values are higher than the realized values if positive information are processed and lower than the realized values if negative information are processed. Theoretical foundations from heuristics for forecasters' overreaction are discussed in Amir and Ganzach (1998). They identify the heuristics of "representativeness", "anchoring and adjustment", and "leniency (optimism)" as the main forces that drive overreaction. The representativeness heuristic states that the probability of an event is judged based on the perceived similarity of the evidence to the event. Thus, forecasters base their predictions on some intuitive estimation of the dispersion of the predictor and the dispersion of the outcome, ignoring the validity. In this case, low values of predictors leads to excessively low predictions and high values of predictors leads to excessively high predictions. Anchoring causes forecasters to anchor at a certain value which is related to the prediction, e.g. their own previous forecasts. Since they are unwilling to depart, their forecast adjustment is insufficient. Evidence for anchoring is found by Campbell and Sharpe (2009) for the group of macroeconomic forecasters. Leniency, the third heuristic, depicts optimism. While the representativeness heuristic is assumed to cause overreaction, anchoring and adjustment causes underreaction and leniency leads to overly optimistic forecasts.<sup>1</sup> However, different regimes and circumstances might lead to different weights of representativeness and anchoring and adjustment. Forecasters might overreact at some occasions and underreact at others.

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<sup>1</sup>Hirshleifer (2001) provides a more detailed description of different heuristics.

A promising candidate for interactions with heuristics is the market uncertainty. As Hirshleifer (2001) points out, a misspecification effect should be strongest with high uncertainty because the absence of reliable information about fundamentals leaves more room for psychological biases. For example, Ganzach and Krantz (1991) discuss the positive influence of high uncertainty on optimism. With regard to overreaction and underreaction, however, it is not obvious which psychological bias prevails with uncertainty (if any). The patterns of behavioral biases are supposed to be the outcome of different heuristics, thus it depends which prevail in order to observe overreaction or underreaction with high uncertainty. Even changes in forecasters' behavior might be possible, e.g. overreaction in periods with low uncertainty and underreaction in periods with high uncertainty. Thus, it's not surprising to find mixed empirical evidence. Gu and Xue (2007) find that forecasters seem to be overly optimistic after extreme good news, which they justify with high uncertainty. Likewise, the results from De Bondt and Thaler (1990) support this finding. However, Jacowitz and Kahneman (1995) express a different view of the relation between overreaction and uncertainty. They examined in a study on anchoring effects that persons will refer more closely to their anchors the more uncertain they are about the future. This should result in underreaction (or at least less overreaction) in the case of higher uncertainty. Evidence for this hypothesis is found by Zhang (2006) for earning forecasts.

Apart from uncertainty, overreaction or underreaction in forecast changes can be triggered by other variables as well. In particular, the return of the underlying asset is relevant (e.g. Abarbanell (1991); De Bondt (1993); Glaser et al. (2007)). For earning forecasts, van Dijk and Huibers (2002) find that strong price momentum of the corresponding stock cause underestimation of future earnings. Reitz et al. (2012) find that oil price forecasters expect a reversion of oil price increases given that the increases are below a certain threshold. Otherwise no reversion is expected. However, the usefulness of the underlying return as a signal to forecasters depends on its quality. If forecasters receive only a noisy signal, the information might be misleading.

This paper analyzes overreaction in oil price forecast changes using the framework from Amir and Ganzach (1998) and examines if forecast changes are affected by uncertainty, the return of the underlying asset and the noise of the asset. Data are taken from the Survey of Professional Forecasters (SPF) provided by the European Central Bank. Furthermore, this paper contributes to the literature by testing in a direct way for a (nonlinear) relation between uncertainty and analysts' forecast changes. Uncertainty is measured by the EURO STOXX 50 volatility index of

implied volatility. It is examined if forecasters show nonlinear adjustment of their behavior with rising levels of uncertainty. The panel smooth transition regression (PSTR) model from González et al. (2005) could be used in this way. Typically, the model is applied with a univariate transition function allowing for a single transition variable. Additionally, a multivariate transition function will be considered in this paper, as suggested by Lof (2012) in the context of time series. Multivariate transition functions allow to estimate nonlinear influences of different variables simultaneously. Therefore, the joint relations of uncertainty, the oil price return and the noise of the oil price as a signal are tested. The simultaneous use of three variables in a multivariate transition function might help to separate influences of uncertainty from oil price movements.

The remainder of the paper is as follows. Section 2 describes the data. Section 3 outlines the estimation approach with the PSTR. Section 4 provide the empirical results for different model specifications. The paper concludes with section 5.

## 2 Data

To study the behavior of forecasters, data on the one- until four-quarter-ahead crude oil price forecasts (in USD) from the Survey of Professional Forecasters (SPF) are used. The SPF is collected by the European Central Bank among professional forecasters. The survey asks for short- until medium-term expectations on different macroeconomic variables. The respondents are spread geographically over the European Union and are divided almost equally into financial and non-financial institutions.<sup>2</sup> Four times a year in the first month of each quarter, participants are asked to report their expectations about macroeconomic variables for different forecast horizons.

The study at hand uses an unbalanced panel of 88 forecasters over the period 2002Q2-2013Q1 with 44 different quarters. In each quarter, forecasters provide their expectations on oil prices movements for five different forecast horizons. However, only the one- until four-quarter-ahead forecasts are used due to the low response rate for the five quarter horizon.

The price per barrel of Brent crude oil from the first trading day of the respective quarter is taken from Macrobond. Uncertainty is proxied by the VStoxx implied volatility (taken from Macrobond). The noise of the oil price movement is measured by the oil price volatility calculated as the mean of squared daily returns. Both variables are calculated at the day of questionnaire as the average of the previous

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<sup>2</sup>Garcia (2003) and Bowles et al. (2007) provides a detailed description of the SPF.

126 trading days. The return of the oil price is defined as the change in a 126 trading day window ending at the day of the questionnaire.

Summary statistics of all variables are reported in table 4. The forecast errors are on average negative and increasing for longer time spans which denotes (growing) underprediction of the oil price.

### 3 The Model

Let  $s_t$  denote the oil price at time  $t$  and  $E_i[s_{t+1}|I_t]$  the expectation of forecaster  $i$  at time  $t$  concerning the oil price in period  $t + 1$  ( $i = 1, 2, \dots, N$ ,  $t = 1, \dots, T$ ), where  $N$  is the number of forecasters and  $T$  is the number of time periods (i.e: total number of quarters). As suggested by Amir and Ganzach (1998), the following regression functions are defined for the different forecast horizons:

$$E_i[s_{t+1}|I_t] - s_{t+1} = \beta(E_i[s_{t+1}|I_t] - E_i[s_{t+2}|I_{t-1}]) + u \quad (1)$$

$$E_i[s_{t+2}|I_t] - s_{t+2} = \beta(E_i[s_{t+2}|I_t] - E_i[s_{t+3}|I_{t-1}]) + u \quad (2)$$

$$E_i[s_{t+3}|I_t] - s_{t+3} = \beta(E_i[s_{t+3}|I_t] - E_i[s_{t+4}|I_{t-1}]) + u \quad (3)$$

where  $E_i[s_{t+1}|I_t] - s_{t+1}$  is the forecast error for the one quarter ahead oil price forecast from forecaster  $i$ ,  $E_i[s_{t+2}|I_t] - s_{t+2}$  is the forecast error for the two quarter ahead forecast and  $E_i[s_{t+3}|I_t] - s_{t+3}$  is the forecast error for the three quarter ahead forecast. The right hand side of equations (1)-(3) consist of the forecast updates between the period  $t - 1$  and  $t$ . To give an example, lets say the quarter of interest is the third quarter 2012. In this case  $E_i[s_{t+1}|I_t]$  in equation (1) is the forecast for the third quarter 2012 issued in the second quarter 2012, i.e.  $E_i[s_{2012Q2+1}|I_{Q2}]$ . The term  $E_i[s_{t+2}|I_{t-1}]$  is the forecast for the third quarter 2012 issued in the first quarter 2012, i.e.  $E_i[s_{2012Q2+2}|I_{Q1}]$ . The difference between the two terms, written on the right hand side, depicts the change over time in oil price forecasts concerning the third quarter 2012. The left side of the equation contains the realized error of the oil price forecast (issued in the second quarter 2012) concerning the price in the third quarter 2012.

Forecast changes incorporate all new information about the expected oil price movement, evaluated from the viewpoint of the individual forecaster at a given point in time. If forecasters do not overreact or underreact, changes in their forecasts should be without influence on the observed forecast errors. Thus, unbiased forecast changes implies insignificant  $\beta$ . On the other hand, a positive  $\beta$  implies overreaction and a negative  $\beta$  underreaction of forecasters.

To test for nonlinear relations between uncertainty and forecast changes, the panel smooth transition regression (PSTR) model from González et al. (2005) is applied. It allows for changing forecasting behavior in different regimes, depending on the prevailing level of uncertainty. The transition between different regimes is allowed but not restricted to occur in a smooth way. The panel smooth transition model converges for high values of the estimated transition speed towards the threshold panel model of Hansen (1999). Furthermore, the observations are allowed to change (gradually) between regimes according to changes in the transition variable. In the current setting, the PSTR is used to analyze whether forecasters exhibit different behavior of overreaction/underreaction with respect to growing uncertainty.

Of course, the use of the panel smooth transition model is not restricted to nonlinear overreaction. Amongst others, López-Villavicencio and Mignon (2011) use the approach to investigate the relation between inflation and growth while Reitz et al. (2012) analyse nonlinear expectations in the context of chartist and fundamentalist models.

The PSTR model is defined as:

$$y_{i,t} = \mu_i + \beta_0' X_{i,t} + \sum_{j=1}^J \beta_j' X_{i,t} g_{j,t}(q_t; \gamma_j, c_j) + u_{i,t}, \quad (4)$$

where  $\mu_i$  captures individual effects and  $g_{j,t}(q_t; \gamma_j, c_j)$  is one of  $j$  transition functions which determine regime switches. The model is combined with each of the equations (1)-(3). Thus,  $y_{i,t}$  denotes the forecast error of forecaster  $i$  at different quarters and  $x_{i,t}$  is the corresponding forecast change. The logistic transition function is defined as

$$g_{j,t}(q_t; \gamma_j, c_j) = \left( 1 + \exp \left( -\gamma_j \prod_{r=1}^R (q_t - c_{j,r}) \right) \right)^{-1}, \quad (5)$$

where  $c_{j,r}$  is one of  $r$  location parameters,  $\gamma_j$  is the speed of transition between the regimes and  $q_t$  is the threshold variable. In the univariate case,  $q_t$  consists solely of the uncertainty. In case of a multivariate transition variable  $q_t = Q_t \lambda_j$  includes up to  $p$  different variables  $Q = [q_1 \dots q_p]$ . The weights  $\lambda_j$  of variables in the transition function are unknown and are estimated alongside with  $c_{j,r}$  and  $\gamma_j$ . However, not all parameters can be identified simultaneously. Following Lof (2012), the elements of the vector  $\lambda$  are restricted to sum up to one which implies that  $Q_t \lambda_j$  is a weighted sum of the specified transition variables.

The transition function  $g_{j,t}(q_t; \gamma_j, c_j)$  is bounded between 0 and 1 which are



associated with regression coefficients  $\beta_0$  and  $\beta_0 + \beta_1$ , respectively. If  $r = 1$ , the model has two regimes associated with high and low values of the threshold variable. For  $r = 2$ , the model has three regimes where the outer ones are equal. The parameter  $\gamma_j$  determines the speed of transition and for  $\gamma_j \rightarrow \infty$  the model approaches Hansen (1999) threshold model. For  $\gamma_j \rightarrow 0$  the model collapses to a standard fixed effects model.

The PSTR model allows to investigate the forecasting behavior as a function of prevailing uncertainty taking into account possible non-linear relations. According to González et al. (2005) the implementation of the model is carried out in three steps: (i) specification, (ii) estimation, and (iii) evaluation.

### *Specification*

The first step involves testing of linearity against the PSTR alternative. The same test which allows testing for linearity could be used to select the appropriate order  $r$  of the transition function if linearity is rejected. Testing for linearity is important since the PSTR model is not identified under the null hypothesis of  $H_0 : \gamma_j = 0$ . This, however, complicates the test procedure since the test statistic contains unidentified nuisance parameters under the null hypothesis. This is solved by using a first-order Taylor expansion around  $\gamma_j = 0$  to derive the auxiliary regression

$$y_{i,t} = \mu_i + \beta_0^{l*} x_{i,t} + \beta_1^{l*} x_{i,t} q_t + \dots + \beta_m^{l*} x_{i,t} q_{j,t}^m + u_{i,t}^* \quad (6)$$

where  $\beta_1^{l*} \dots \beta_m^{l*}$  are multiples of  $\gamma_j$ . Testing  $H_0^* : \beta_1^{l*} = \dots = \beta_m^{l*} = 0$  in the auxiliary regression is equivalent to testing  $H_0 : \gamma_j = 0$ . The test is carried out by applying the robust LM-test derived by González et al. (2005).

The test procedure is easily applied if the transition function is univariate. However, in case of a multivariate transition function equation (6) cannot be estimated if the weights  $\lambda_j$  are unknown. Therefore, the weights are derived first by substituting  $q_{j,t} = Q_t \lambda_j$  into a first-order version of equation (6)

$$y_{i,t} = \mu_i + \beta_0^{l*} x_{i,t} + \beta_1^{l*} x_{i,t} (Q_t \lambda_1) + u_{i,t}^*. \quad (7)$$

Rewriting equation (7) yields

$$y_{i,t} = \mu_i + \beta_{0,k}^{l*} x_{i,t} + \sum_{l=1}^p \phi_l x_{i,t} q_{l,t} + u_{i,t}^* \quad (8)$$

with  $\phi_l = \beta_1^{l*} \lambda_l$ . The parameters  $\lambda_j$  can be identified with the use of the restriction

$\sum_{l=1}^p \lambda_{k,l} = 1$ . To see this, note that

$$\sum_{l=1}^p \phi_l = \beta_1'^* \sum_{l=1}^p \lambda_l = \beta_1'^* \Rightarrow \lambda_m = \left( \sum_{l=1}^p \hat{\phi}_l \right)^{-1} \hat{\phi}_m. \quad (9)$$

The estimated weights  $\lambda_j$  of equation (9) are used to test for nonlinearity.

Irrespectively if a univariate or multivariate transition function is present, the test procedure against nonlinearity can be used to select the appropriate order  $r$  of the transition function by testing  $H_{03}^* : \beta_3^* = 0$ ,  $H_{02}^* : \beta_2^* = 0 | \beta_3^* = 0$  and  $H_{01}^* : \beta_1^* = 0 | \beta_3^* = \beta_2^* = 0$ . Following Teräsvirta (1994),  $R = 2$  is chosen if the rejection of  $H_{02}^*$  is the strongest, otherwise  $R=1$  is chosen.

### *Estimation*

The estimation of the parameters in the PSTR consists of applying alternately fixed effects and nonlinear least squares. If  $\gamma_j, c_j$  and  $\lambda_j$  are given, equation (4) is a linear function of  $\beta$  and the parameters are estimated by ordinary least squares after mean demeaning the data. However, estimated means depend on  $\gamma_j, c_j$  and  $\lambda_j$ . Therefore, the means have to be re-estimated at each iteration. The parameter  $\gamma_j, c_j$  and  $\lambda_j$  of the transition function are estimated for given  $\beta$  by nonlinear least squares. This procedure is carried out until convergence occur. However, choosing appropriate starting values for  $\gamma_j$  and  $c_j$  is important in order to ensure the convergence of the model. Starting vales are selected by an extensive grid search across the parameters in the transition function. If required, starting values for  $\lambda_j$ 's are provided by equation (9) after the nonlinearity tests.

### *Evaluation*

After estimation, the results are evaluated by testing for parameter constancy and no remaining nonlinearity. Both tests are conceptual similar to the previous test for linearity. Thus, a Taylor expansion around  $\gamma_j = 0$  is used. The test for parameter constancy evaluates the null hypothesis of the PSTR against the alternative of a time varying panel smooth transition model (TV-PSTR). Under the alternative, the parameters are assumed to change smoothly over time by a transition function similar to (5) with time as the transition variable. The test for no remaining nonlinearity is used to evaluate if the PSTR is able to capture the present nonlinearity in the data.

## 4 Results

The PSTR is applied to three different horizons. The one, two and three quarter ahead forecast errors are regressed on the corresponding forecast changes and time dummies. Table 1 shows the result for the  $\chi^2$ -tests against nonlinearity. The upper part of table 1 lists the results for the univariate transition function with uncertainty (measured by implied volatility) as the only transition variable. The test results show that linearity of forecast changes with respect to uncertainty is rejected for each forecast horizon. A PSTR with two regimes ( $r=1$ ) is the preferred specification for all horizons.

The lower part of table 1 lists the linearity tests for the multivariate specification of the transition functions. In addition to uncertainty, the two variables on oil price return and oil price volatility are included. The weights are calculated according to equations (7)-(9). They are required for the estimation of  $\beta_1^*$  in equation (7) and the subsequent test against nonlinearity. Unsurprisingly, rejection of linearity tend to be slightly stronger by incorporating the additional variables. Again, a specification with two regimes ( $r=1$ ) is preferred for all forecast horizons.

Table 1: Nonlinearity tests

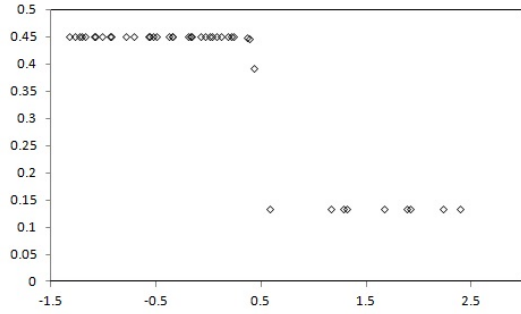
	1 Quarter	2 Quarter	3 Quarter
<i>Univariate PSTR</i>			
Nonlinearity test	16.987	9.649	15.8196
Order of r	1	1	1
<i>Multivariate PSTR</i>			
Nonlinearity test	19.431	12.761	17.770
$\lambda_1$	-15.014	-1.096	-1.322
$\lambda_2$	6.848	0.690	0.850
$\lambda_3$	9.166	1.405	1.472
Order of r	1	1	1

Note:  $\chi^2$ -statistics of nonlinearity test. The 5% critical value is 3.84.

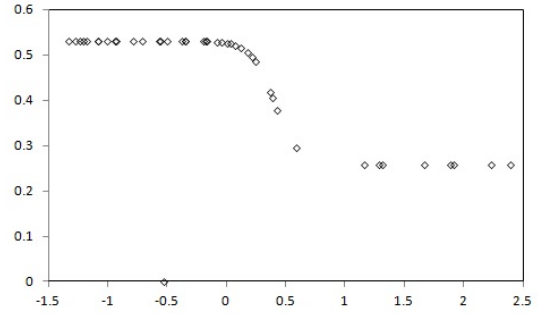
The estimated weights  $\lambda_1$  (= implied volatility),  $\lambda_2$  (= oil price volatility) and  $\lambda_3$  (= oil price return) show different signs and give a first hint of their opposite influences on forecast changes. The weights are used as starting values for the PSTR model in the subsequent regressions.

The univariate PSTR models with uncertainty as the only transition variable are discussed first. Table 2 lists the estimated parameters for the different forecast horizons. Together, parameters  $\beta_0$  and  $\beta_1$  allow to illustrate the behavior of forecasters. For all forecast horizons,  $\beta_0$  and  $\beta_1$  are significant, indicating that forecasts

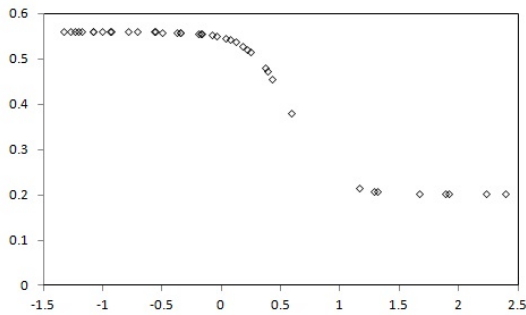
Figure 1: Univariate transition function



(a) One quarter horizon



(b) Two quarter horizon



(c) Three quarter horizon

Note: Transition variable  $q_{1,t}$  (uncertainty) on the horizontal axis; estimated parameters  $(\beta_0 + \beta_1 g_1)$  on the vertical axis.

are governed by some kind of misreaction.  $\beta_0 + \beta_1 g_{1,t}$  captures the effects of forecast changes on forecast errors if the transition function approaches unity while  $\beta_0$  is the prevailing effect of forecast changes on forecast errors if the transition function approaches zero. The joint effects of  $\beta_0$  and  $\beta_1$  are presented graphically in figure 1. The figure shows the estimated transition function as a plot of  $(\beta_0 + \beta_1 g_j(q_t; \gamma_j, c_j))$  against the transition variable (uncertainty). The estimated  $\beta_0$ 's are positive for all forecast horizons with 0.45 for the first, 0.53 for the second and 0.56 for the third quarter ahead prediction which means that forecasters tend to overreact for low values of the transition variable. Furthermore, overreaction increases with longer forecast horizons as the estimated  $\beta_0$  grow in magnitude for longer horizons.

On the other hand, the estimated  $\beta_1$ 's are negative for all horizons. Decreasing levels of overreaction are found for higher levels of uncertainty. Therefore, forecasters overreact less when high levels of uncertainty prevails compared to times with low levels of uncertainty. The higher uncertainty about the future state of the economy cause forecasters to issue more careful predictions in the sense that the predictions are located somewhat closer to their old forecasts from the previous quarter. Differences in the estimated speed of transition ( $\gamma$ ) are directly visible in the figures. For

the first quarter ahead forecasts, the high  $\gamma$  lead to a sharp transition between the regimes while a smoother transition prevail for the second and third quarter.

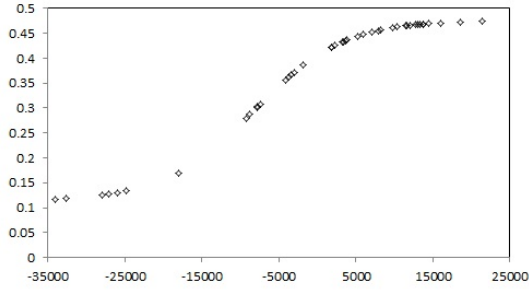
The diagnostic checks for the univariate specification of the PSTR are listed at the bottom of table 2. The test for no remaining nonlinearity evaluates if the PSTR is able to account entirely for the nonlinearity in the data. For all forecast horizons, the hypothesis of no remaining nonlinearity cannot be rejected. The test for parameter constancy reveals no structural breaks or time trends for the one and two quarter horizon. Only the third quarter horizons shows some signs of changing parameters over time.

The overall finding from the first specification is that forecasters overreact frequently. This, however, does not mean that forecasters make ever increasing (decreasing) forecast errors for clear upward (downward) trending oil prices. In fact, parts of the forecasters show some sort of fluctuation around the realized value on the individual level. In one quarter, they adjust their forecasts in positive direction and overshoot the realized value whereas they adjust downward in the following quarter and undershoot the oil price. This fluctuation takes place irrespectively from trends in oil prices.

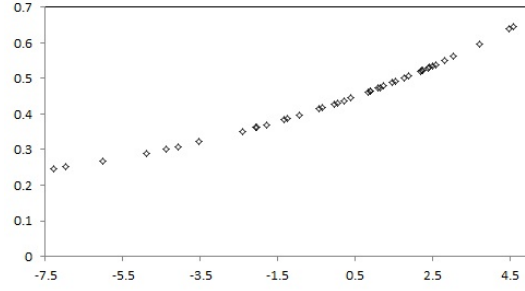
The second specification of the transition function includes the oil price return alongside with the implied volatility and the oil price volatility. Forecasters might react different for positive or negative oil price returns. Furthermore, small changes of oil prices might be regarded of less importance while greater changes could be taken into account. The volatility of the oil price is supposed to measure the quality of the signal extracted from the return. Noisy signals are harder to interpret and might lead to inferior decisions. To account for such behavior, the return, the oil price volatility and market uncertainty are used jointly as transition variables in a multivariate PSTR model. The transition variables are standardized which allows a direct interpretation of their weights ( $\lambda$ ) in the transition function. Note that standardization of the transition variables does not change the outcome.

As mentioned earlier, tests for linearity are rejected for each forecast horizon (see table 1).  $\beta_0$  in table 3 represents the effects of forecast changes on the forecast errors if the transition function approaches zero. This in turn is determined by the weights  $\lambda$  for uncertainty, oil price return and noise. For the one quarter ahead forecasts,  $\lambda_1 = -12590$  corresponds to the weight of uncertainty which enters negatively in the transition function. The oil price return  $\lambda_3 = 6816$  and the noise in the oil price information  $\lambda_3 = 5775$  enter positively. The same pattern is observed for the second and third quarter horizons with  $\lambda_1 = -2.088$ ,  $\lambda_2 = 1.105$ ,  $\lambda_3 = 1.983$  and  $\lambda_1 = -1.905$ ,  $\lambda_2 = 0.986$ ,  $\lambda_3 = 1.919$ , respectively. Therefore, the first regime prevails c.p. with

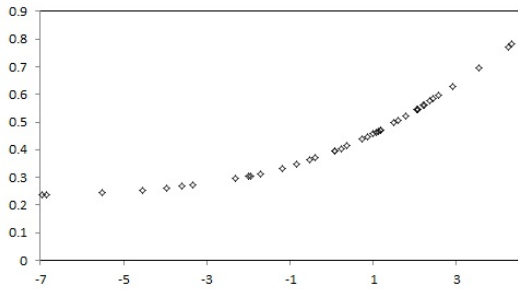
Figure 2: Multivariate transition function



(a) One quarter horizon



(b) Two quarter horizon



(c) Three quarter horizon

Note: Transition variable  $\lambda_1 q_{1,t} + \lambda_2 q_{2,t} + \lambda_3 q_{3,t}$  on the horizontal axis; estimated parameters  $(\beta_0 + \beta_1 g_1)$  on the vertical axis.

high uncertainty, little noise and negative returns. Estimated  $\beta_0$ 's in the first regime are 0.113 for the first, 0.120 for the second and 0.226 for the third forecast horizon. Therefore, all forecast horizons are characterized by overreaction in the first regime.

The  $\beta_1$ 's have positive signs for all forecast horizons indicating even stronger overreaction in the second regime. Therefore, a moderate overreaction in the first regime is followed by stronger overreaction in the second regime. At first sight, the results seem to be inconsistent with the finding of the univariate PSTR where higher overreaction prevails in the first regime followed by moderate degrees of overreaction in the second regime. However, the different order of the regimes are caused by different signs of the estimated weights for uncertainty in the multivariate specification. While uncertainty enters positively for the univariate model, table 3 shows negative weights of implied volatility for the multivariate specification with  $\lambda_1 = -12590.49$  in the first quarter,  $\lambda_2 = -2.088$  in the second and  $\lambda_3 = -1.905$  in the third quarter horizon.

The results of the transition between the regimes are presented graphically in figure 4. For all forecast horizons, forecasters change smoothly from moderate overreaction to higher degrees of overreaction if c.p. uncertainty decreases, the return increases and the noise increases. Similar to the first specification, forecasters tend

to anchor more at old forecasts for rising uncertainty in the market. Stronger noise in the oil price signal leads to stronger overreaction. A lower quality of oil price movements as a signal cause forecasters to overstate trends. If (c.p.) the quality of the signal increases, the magnitudes of oil price changes are observed better and less overreaction occurs. The results for the oil price return indicate that overreaction is stronger for positive returns than for negative returns.

The most important factor for the transition between the regimes is uncertainty in case of the one and two quarter forecast horizons. For the third quarter horizon, the return turns out to be slightly more important. The corresponding weight is estimated with 1.919 while the weight for uncertainty is -1.905. The volatility of the oil price receives the lowest weights in all forecast horizons.

The evaluation of the PSTR models with implied volatility, the oil price volatility and oil price return is presented in the bottom of table 3. For all forecast horizons, the test of no remaining nonlinearity cannot be rejected. The same holds for the test of parameter constancy.

## 5 Conclusion

This paper examines the nonlinear influence of uncertainty on overreaction of oil price forecasters by using the (multivariate) panel smooth transition model from González et al. (2005). Furthermore, a second specification analyzes a joint transition function with uncertainty, oil price return and oil price volatility. The PSTR model is able to fully account for nonlinearity with respect to variables in both specification. The transition between the two regimes occur slower in the multivariate specification compared to the univariate specification. For the one quarter horizon, near threshold-type transition is observed in the univariate PSTR model.

In general forecasters tend to overreact. However, forecasters are more cautious in their forecast changes and form expectations which are closer to their previous forecasts when market uncertainty is high. This indicates that uncertainty is negatively related to overreaction. The multivariate specification of the transition function which includes the oil price return and the oil price volatility confirms this result. Regarding oil price returns, asymmetric behavior is observed. Results indicate that positive returns tend to cause stronger overreaction than negative returns. The noise in the oil prices movement increases overreaction. A Lower quality of oil price movements as a signal cause forecasters to overstate observed or assumed trends.

Table 2: Results of the univariate PSTR

	1 Quarter	2 Quarter	3 Quarter
$\beta_0$	0.449 (0.028)	0.530 (0.024)	0.559 (0.022)
$\beta_1$	-0.317 (0.057)	-0.273 (0.082)	-0.358 (0.046)
Year dummies	included	included	included
<i>Transition parameters</i>			
$\gamma$	74.985	10.000	5.792
$c_1$	0.450	0.405	0.585
<i>Model evaluation</i>			
$R^2$	0.938	0.956	0.954
Remaining nonlinearity	0.584	1.008	1.753
Parameter constancy	3.558	2.332	8.163

Note: Robust standard errors in parentheses;  $\chi^2$ -statistics for test of remaining remaining nonlinearity and parameter constancy; critical values are 5.02 and 7.38, respectively.

Table 3: Results of the multivariate PSTR

	1 Quarter	2 Quarter	3 Quarter
$\beta_0$	0.113 (0.057)	0.120 (0.109)	0.226 (0.066)
$\beta_1$	0.363 (0.070)	3.351 (0.966)	1.047 (0.269)
Year dummies	included	included	included
<i>Transition parameters</i>			
$\lambda_1$	-12590.49	-2.088	-1.905
$\lambda_2$	5775.379	1.105	0.986
$\lambda_3$	6816.111	1.983	1.919
$\gamma$	0.0002	0.131	0.416
$c_1$	-8229.925	17.397	4.018
<i>Model evaluation</i>			
$R^2$	0.954	0.956	0.954
Remaining nonlinearity	0.068	0.003	0.634
Parameter constancy	2.367	1.349	2.599

Note: Robust standard errors in parentheses;  $\chi^2$ -statistics for test for remaining nonlinearity and parameter constancy; critical values are 5.02 and 7.38, respectively.



Table 4: Summary statistics

	Obs.	Mean	Std.	Min.	Max.
1Q ahead forecast error	1721	-2.912	14.573	-51.710	62.470
2Q ahead forecast error	1676	-5.759	21.849	-67.710	119.970
3Q ahead forecast error	1628	-8.699	23.302	-76.710	106.160
Forecast change $2Q_{t-1}$ to $1Q_t$	1721	3.066	14.445	-80.000	59.000
Forecast change $3Q_{t-1}$ to $2Q_t$	1624	2.768	13.851	-77.000	73.000
Forecast change $4Q_{t-1}$ to $3Q_t$	1628	2.073	13.355	-77.000	68.000
Implied volatility	1721	-0.036	0.994	-1.328	2.398
Oil price volatility	1721	-0.012	0.984	-1.037	3.613
Oil price return	1721	-0.003	0.981	-3.547	1.656

Note: Summary statistics of variables for the period 2002Q2-2013Q1.

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