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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 affected by uncertainty. Furthermore, it takes into account joint effects of uncertainty and oil price returns on forecast changes. The panel smooth transition regression model from González et al. (2005) is applied with univariate and multivariate 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 forecasters overreact for low levels of uncertainty and underreact for increasing uncertainty. Furthermore, returns are found to be more relevant for forecast changes in short time horizons while uncertainty dominates for longer ones.

Keywords: Overreaction, Underreaction, Uncertainty, Nonlinear relation

JEL Classification: G14, G29, C33.

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1 Introduction

The forecasts of professional forecasters on commodity prices, exchange rates, earnings and other topics are used by economic agents to form decisions. However, even professionals are not immune to biases and non-rational behavior. The behavior of analysts and the formation of their expectations are addressed by different parts of the literature. Just to mention a few, forecasters are found to be overconfident (e.g. Hilary and Menzly (2006), Deaves et al. (2010)), show patterns of herding behavior (e.g. De Bondt and Forbes (1999), Hong et al. (2000), Welch (2000), Clement and Tse (2005), Pierdzioch et al. (2010)) and overreaction. This paper, however, will only examine the topic of overreaction in forecast changes.

Forecasters are found to underreact to some information or at some point in time and overreact on other occasions. The idea, in case of overreaction, is the tendency to form expectations that are too extreme given the available type of information. More precisely, expected values are higher than the realized value if positive information are processed and lower than the realized value if negative information are processed. De Bondt and Thaler (1990) and Abarbanell and Bernard (1992) examine this topic for security analysts and Easterwood and Nutt (1999) for earning forecasts. Most recently, the topic is analyzed by Pancotto et al. (2013) for exchange rate forecasts.

Theoretical foundations from heuristics why forecaster may overreact 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 means that the probability of an event is judged based on the perceived similarity of the evidence to the event. Thus, people 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, a low value of a predictor leads to excessively low predictions and a high value of a predictor 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 will be insufficient. Evidence for anchoring is found by Campbell and Sharpe (2009) for the group of macroeconomic forecaster. Leniency, the third heuristic, means optimism. While the representativeness heuristic is assumed to cause overreaction, anchoring and adjustment causes underreaction and leniency leads to overly optimistic forecasts¹. However, it is not a priori known if either representativeness or anchoring

¹Hirshleifer (2001) provides a more detailed description of different heuristics.

and adjustment dominates the forecasting behavior and under which circumstances.

A promising candidate for interactions with the heuristics is the uncertainty about fundamental values. As Hirshleifer (2001) points out, a misspecification effect should be strongest with high uncertainty because the absence of reliable knowledge 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 clear which psychological bias prevails with uncertainty (if any). The pattern of behavioral biases are supposed to be the outcome of different heuristics, thus it depends which are the predominant ones in order to observe overreaction or underreaction with high uncertainty. Even changes in the analysts behavior might be possible, e.g. overreaction in periods with low uncertainty and underreaction in periods with high uncertainty. Thus, it is 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 the 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 heuristics and the interaction with uncertainty, other effects can possibly cause overreaction and underreaction in forecast changes as well. In particular, the return of the underlying asset is found to be relevant (e.g. Abarbanell (1991); De Bondt (1993); Glaser et al. (2007)). Theissen (2007) points out that this is especially true for the most recent returns of one or two weeks. For earning forecasts, van Dijk and Huibers (2002) find strong price momentum of the corresponding stock to 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. Therefore, it might be important to control not only for uncertainty but also for the recent return when analyzing the over- or underreaction of forecasters.

This paper uses forecast changes of oil price forecasters to examine if they are in general governed by overreaction or underreaction. For this purpose, the regression-based test for overreaction from Amir and Ganzach (1998) is used. Furthermore, this paper contributes to the literature by testing in a direct way for a (nonlinear) relation between uncertainty and analyst forecast changes. Uncertainty means in

this context the fundamental uncertainty about the future state of the economy, 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. The multivariate transition function allows to estimate the nonlinear influences of different variables simultaneously. Therefore, the joint relations of uncertainty and recent returns on forecast changes are tested. The simultaneous use of both variables in a multivariate transition function might help to identify effects which are not driven by the uncertainty but rather the underlying oil price movement. In this paper, the data on the one- until four-quarter-ahead crude oil price forecast from the European Central Bank Survey of Professional Forecasters (SPF) are used.

The reminder 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 and 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 institutions². Four times a year in the first month of each quarter, participants are asked to deliver their expectations about macroeconomic variable for different points in time in the future.

The study at hand uses an unbalanced panel of 66 forecasters over the period 2002Q2-2013Q1 with 44 different quarters, resulting in a maximum of 1,624 observations. In each quarter, forecasters provide their expectations on oil prices 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

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

from Macrobond. Uncertainty is measured by the EURO STOXX 50 volatility index of implied volatilities for the day of the questionnaire, provided from Macrobond. The recent return of the oil price is defined in USD and captures the period from the beginning of the quarter until the questionnaire. It is therefore designed to model short term trends in oil prices.

The summary statistics for the variables are reported in table 5. 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:

$$E_i[s_{t+1}|I_t] - s_{t+1} = \alpha_1 + \beta_1(E_i[s_{t+1}|I_t] - E_i[s_{t+2}|I_{t-1}]) + u_1 \quad (1)$$

$$E_i[s_{t+2}|I_t] - s_{t+2} = \alpha_2 + \beta_2(E_i[s_{t+2}|I_t] - E_i[s_{t+3}|I_{t-1}]) + u_2 \quad (2)$$

$$E_i[s_{t+3}|I_t] - s_{t+3} = \alpha_3 + \beta_3(E_i[s_{t+3}|I_t] - E_i[s_{t+4}|I_{t-1}]) + u_3 \quad (3)$$

where $E_i[s_{t+1}|I_t] - s_{t+1}$ is the forecast error of the one quarter ahead forecast from forecaster i . $E_i[s_{t+1}|I_t] - E_i[s_{t+2}|I_{t-1}]$ is the change in the individual forecast between time $t - 1$ and t for a certain point in the future, in this case the now one quarter ahead period. Thus, $E_i[s_{t+2}|I_{t-1}]$ is the expected two quarter ahead oil price from the past quarter $t - 1$. Accordingly, $E_i[s_{t+3}|I_{t-1}]$ is the three quarter ahead forecast, issued one quarter ago etc.

The forecast changes incorporate all new informations 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, the change in their forecasts should have no influence on the observed forecast error. Thus, unbiasedness with respect to forecast changes implies an insignificant β . On the other hand, a positive β implies overreaction and a negative β underreaction of the forecaster.

To incorporate the effects from uncertainty, the panel smooth transition regression (PSTR) model from González et al. (2005) is used. 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.

The PSTR model is defined as:

$$y_{it} = \mu_i + \beta_0' x_{it} + \sum_{j=1}^r \beta_j' x_{it} g_j(q_t; \gamma_j, c_j) + u_{it} \quad (4)$$

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

$$g_j(q_t; \gamma_j, c_j) = \left(1 + \exp \left(-\gamma \prod_{j=1}^m (q_t - c_j) \right) \right)^{-1} \quad (5)$$

where c_j is one of r location parameters, γ 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, measured by the EURO STOXX 50 volatility index of implied volatilities. In case of a multivariate transition variable $q_t = Q_t \kappa$ includes the uncertainty and the recent return but might contain up to p different variables $Q = [q_1 \dots q_p]$. The weights κ of variables in the transition function are unknown and are estimated alongside with c_j and γ . However, not all parameters can be identified simultaneously. Following Lof (2012), the elements of the vector κ are restricted to sum up to one which implies that $Q_t \kappa$ is a weighted sum of the specified transition variables.

The transition function $g_j(q_t; \gamma_j, c_j)$ is bounded between 0 and 1 with are associated with regression coefficients β_0 and $\beta_0 + \beta_1$, respectively. If $m = 1$, the model has two regimes associated with high and low values of the threshold variable. For $m = 2$, the model has three regimes where the outer ones are equal. The parameter γ determines the speed of transition and for $\gamma \rightarrow \infty$ the model approaches Hansen (1999) threshold model. For $\gamma \rightarrow 0$ 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 linearity against the PSTR alternative. The same test which allows testing for linearity could be used to select the appropriate order m 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 $H_0 : \gamma = 0$. 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 $\gamma = 0$ to derive the auxiliary regression

$$y_{it} = \mu_i + \beta_0'^* x_{it} + \beta_1'^* x_{it} q_t + \dots + \beta_m'^* x_{it} q_t^m + u_{it}^* \quad (6)$$

where $\beta_1'^* \dots \beta_m'^*$ are multiples of γ . Testing $H_0^* : \beta_1'^* = \dots = \beta_m'^* = 0$ in the auxiliary regression is equivalent to testing $H_0 : \gamma = 0$. 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 κ are unknown. Therefore, the weights are derived first by substituting $q_t = Q_t \kappa$ into a first-order version of equation (6)

$$y_{it} = \mu_i + \beta_0'^* x_{it} + \beta_1'^* x_{it} (Q_t \kappa) + u_{it}^* \quad (7)$$

and rewriting equation (7) to

$$y_{it} = \mu_i + \beta_0'^* x_{it} + \sum_{l=1}^p \phi_l x_{it} q_{l,t} + u_{it}^* \quad (8)$$

with $\phi_k = \beta_1'^* \kappa_k$. The parameters κ can be identified with the use of the restriction $\sum_{k=1}^p \kappa_k = 1$. To see this, note that

$$\sum_{k=1}^p \phi_k = \beta_1'^* \sum_{l=1}^p \kappa_l = \beta_1'^* \Rightarrow \kappa_m = \left(\sum_{l=1}^p \hat{\phi}_l \right)^{-1} \hat{\phi}_m. \quad (9)$$

The estimated weights κ 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 m 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), $m = 2$ is chosen if the rejection of H_{02}^* is the strongest, otherwise $m=1$ is chosen.

Estimation

The estimation of the parameters in the PSTR consists of applying alternately fixed effects and nonlinear least squares. If γ, c_j and κ_m are given, equation (4) is a linear function of β and the parameters are estimated by ordinary least squares after mean demeaning the data. However, the estimated means depend on γ, c_j and κ_m . Therefore, the means have to be re-estimated at each iteration. The parameter γ, c_j and κ_m of the transition function are estimated for given β by nonlinear least squares. This procedure is carried out until convergence occur. However, choosing appropriate starting values for γ and c_j is important in order to ensure the convergence of the model. Starting vales are selected by estimating the PSTR for different possible values. The most appropriate values in terms of the tests for no remaining nonlinearity and parameter constancy are used for the final regression. For κ_m , the estimated weights from equation (9) are used as starting values.

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 $\gamma = 0$ is used. The test for parameter constancy evaluate the null hypothesis of the PSTR against the alternative of a time varying panel smooth transition model (TV-PSTR). Under the alternative, the parameter are assumed to change smoothly over time by a transition function similar to (5) with time as the transition variable. The test for 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. Table 1 shows the result for the χ^2 -tests against nonlinearity. The upper part of table 1 contains the results for univariate transition functions with uncertainty as the only transition variable. Furthermore, a model with a multivariate transition function,

containing uncertainty alongside with the oil price return, is tested. For the second model, the required weights for testing against linearity are presented in table 1 as well.

For univariate PSTR models with uncertainty as the only transition variable, the tests for linearity are rejected at the 5%-level for all forecast horizons. This implies that the PSTR model is the preferred estimation approach over the standard fixed effects model. The sequence of linearity tests to select the order of the transition function, described in the model part, opt for a specification with $m = 2$ for all forecast horizons. Therefore, the transition function is supposed to approach unity at both low and high levels of uncertainty and approach zero for intermediate levels of uncertainty.

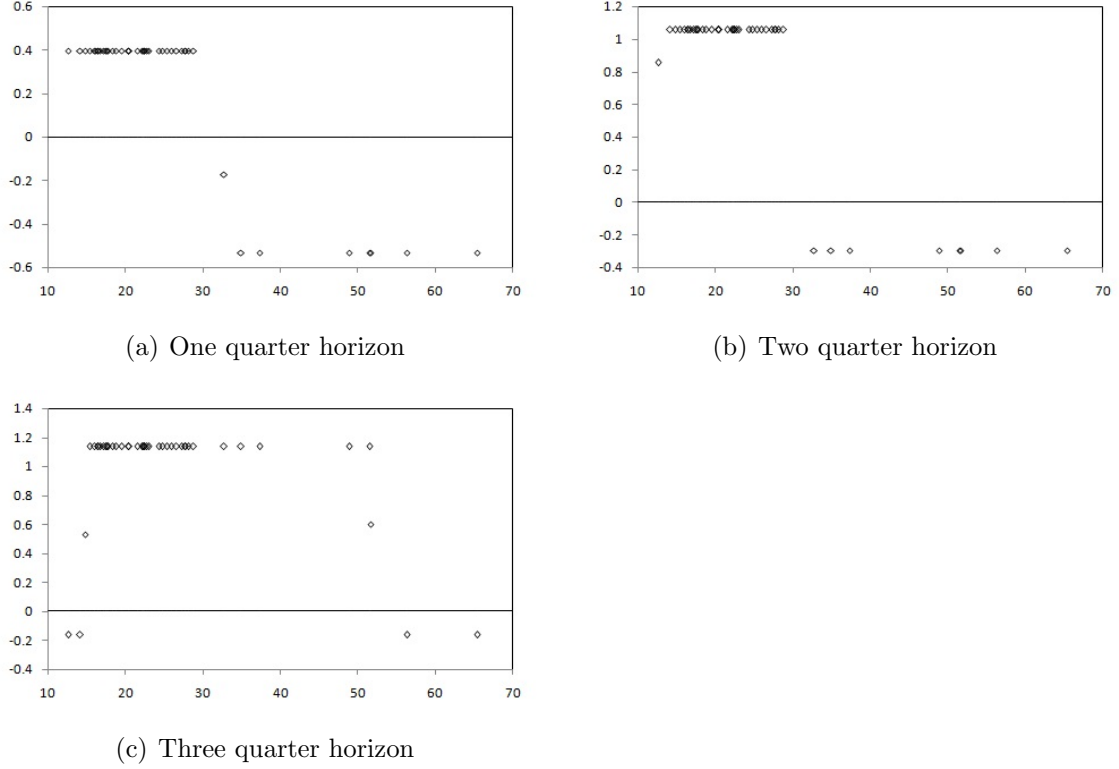
Table 1: Nonlinearity tests

	1 Quarter	2 Quarter	3 Quarter
<i>Univariate transition</i>			
Nonlinearity test	76.119	55.45	67.734
Order of m	m=2	m=2	m=2
<i>Multivariate transition</i>			
Nonlinearity test	65.584	59.015	61.9
κ_1	177.305	-0.493	-89.013
κ_2	-176.305	1.493	90.013
Order of m	m=2	m=1	m=1

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

The lower part of table 1 lists the results of the test against nonlinearity for the multivariate transition function. The weights are calculated according to equations (7)-(9). They are required for the estimation of β_1^* in equation (7) and the subsequent test against nonlinearity. In order to avoid overfitted models, a simple t-test on each component of the weights is conducted which reveal no insignificant parameters. As in the univariate case, the null hypothesis of linearity is always rejected at the 5%-level but the order of the transition function is mixed. For the one quarter horizon m=2 is selected while for the two and three quarter horizons m=1 is preferred. The estimated weights κ_1 for uncertainty and κ_2 for the oil price return from the test against nonlinearity in table 1 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 rejection of the null hypothesis of linearity for different specifications of the transition variable allows the estimation of the PSTR model.

Figure 1: Univariate transition function



Note: Implied volatility on the horizontal axis; forecast overreaction and underreaction ($\beta_0 + \beta_1 g_t$) on the vertical axis.

The first estimated model is the PSTR model with a univariate transition function where uncertainty is used as the only transition variable. Table 3 shows the estimated parameters for the different forecast horizons. Together, β_0 and β_1 allow to characterize the behavior of forecasters with respect to uncertainty. First thing to notice is that all β_0 s and β_1 s for all forecast horizons are significantly different from zero which indicate that forecasters show some pattern of misreaction. The parameter β_0 is the prevailing effect of forecast changes on forecast errors if the transition function approaches zero. The estimated parameters are positive for all horizons with 0.4 for the first, 1.06 for the second and 1.14 for the third quarter ahead prediction. In the absence of uncertainty, forecasters tend to overreact irrespectively which horizon is analyzed. Furthermore, overreaction in the absence of uncertainty tends to increase for longer forecast horizons as the estimated β_0 grow in magnitude for longer horizons.

The β_1 s captures the effects of uncertainty on the relation between forecast changes and forecast errors. The joint magnitude of $\beta_0 + \beta_1$ for different levels of uncertainty are presented graphically in figure 1. Values below zero indicate underreaction of forecasters while values above stand for overreaction. 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 implied volatility. In case of the one and two quarter horizon, forecasters switch from overreaction for low and medium values of uncertainty to underreaction for high values of uncertainty. The relatively high estimated speed of transition (γ) leads to sharp transitions between the regimes. Forecasters tend to overreact for low uncertainty and shorter horizons when they adjust their predictions. The picture changes for growing uncertainty as they underreact, on average, in their forecast changes. 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 close to their old forecasts from the previous quarter. For the three quarter horizon, underreaction is present for both low and high levels of uncertainty while overreaction dominates for intermediate levels. Therefore, forecasters show the same behavior for high uncertainty than in the other two horizons but they seem to react different to very low levels of uncertainty.

The transition functions for the one and two quarter ahead forecast errors in figure 1 occur with a single monotonic transition between two extreme regimes of either overreaction or underreaction. Thus, even if $m=2$ is chosen for transition functions, $m=1$ -shaped functions are estimated. The minimum of the transition functions in case of $m=2$ is defined as $(c_1 + c_2)/2$ and therefore two equal regimes for low and high values of the transition variable are defined alongside with a different regime in the middle. However, the one and two quarter ahead regressions locate the minimum of the transition functions at the lower bound of the numerical range of the implied volatility. Therefore, the second outer regime is not part of the regression. For the one and two quarter horizons, the only maximum of the transition function is located near the upper bound of the numerical range of implied volatility. The three quarter horizon contains both extreme regimes for high and low values of the transition variable

Overall, forecasters are found to 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 diagnostic checks for the univariate PSTR are listed in the bottom of table 3. The test of no remaining nonlinearity evaluates if the PSTR is able to account entirely for the nonlinearity in the data. For all forecast horizons, the hypothe-

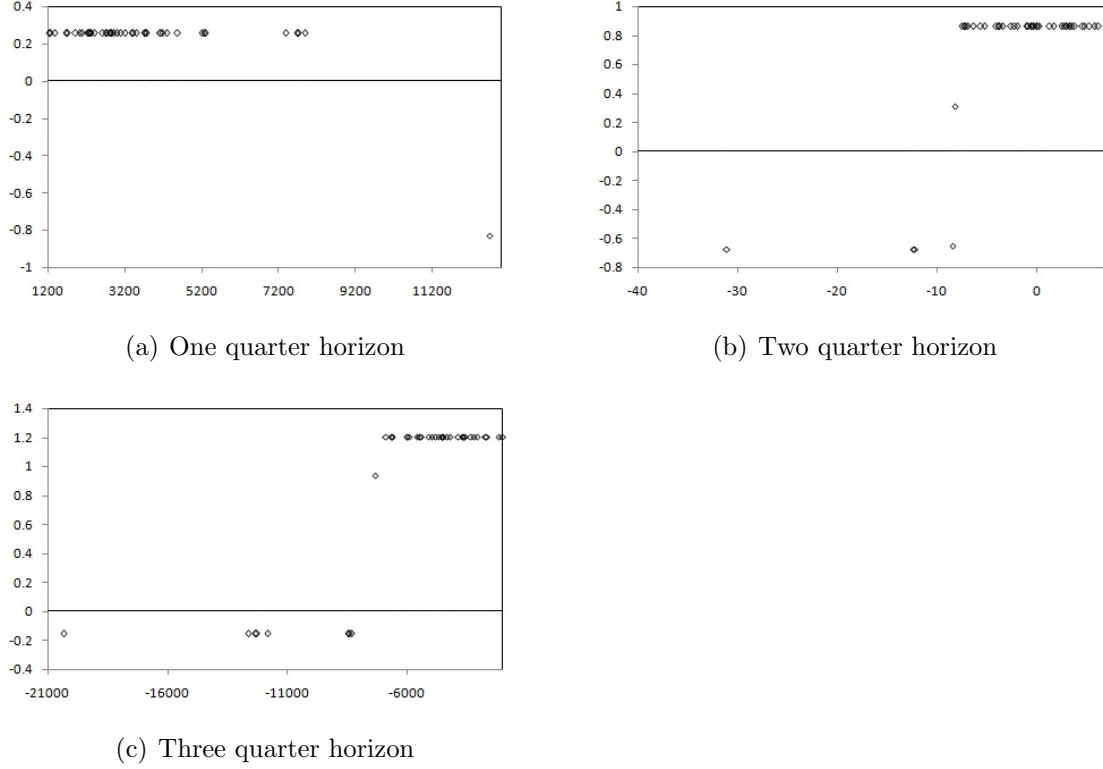
sis of no remaining nonlinearity cannot be rejected at the 2.5%-level. Following González et al. (2005), the test of no remaining nonlinearity uses the half of the previously defined significance level in order to ensure parsimonious models. The test of parameter constancy reveals no structural breaks or time trends in the estimated parameters. The only exception is the three quarter horizon which shows some evidence of changing parameters. However, no TV-PSTR is estimated in order to ensure comparability with the other models. The estimated R^2 from the PSTR with univariate transition functions show that the models are able to explain between 18-20% of the variation in the data. This results are encouraging, however the question arises if overreaction in forecasts is only driven by uncertainty. Instead, other influences are possible.

The return of the oil price is supposed to play a role since forecasters might adjust their behavior in the presence of strong upward or downward trends. Small changes in the recent oil prices might be regarded of less importance while greater changes could be taken into account. Furthermore, if trends are not driven by fundamentals forecasters might expect a reversion of the oil price which could cause them to underreact with respect to their forecast change. To account for such behavior, the recent return and uncertainty are specified together as transition variables in a multivariate PSTR model.

Again, the hypothesis of linearity is tested first. The test is rejected for all forecast horizons which allows an application of the PSTR. Regarding the order m of the transition functions, the results are mixed. For the first quarter horizon, a specification with $m = 2$ is suggested while $m = 1$ is preferred for the second and third quarter. However, the multivariate PSTR model did not converged for a specification with $m = 2$ so the order is set to $m = 1$ for the first quarter.

The required weights κ for the tests against nonlinearity point in opposite directions and indicate contrary influences of the return and uncertainty for all forecast horizons. The estimated weights for the final model, listed in table 4, confirm this results as they are of opposite sign for every forecast horizon. Regarding the interpretation of the estimated betas, more caution is needed for PSTR models with multivariate transition variables. The weights for uncertainty κ_1 and the recent return κ_2 are estimated dynamically at each iteration. They are not restricted in their sign but only in their sum which has to equal unity. For the one quarter horizon at the one hand and the two and three quarter horizon on the other hand, table 4 show changing signs of the estimated weights. That is, uncertainty enters positive into the transition function for the one quarter horizon but negative for the two and three quarter horizon.

Figure 2: Multivariate transition function



Note: Transition variable with implied volatility and oil price returns $(\kappa_1 q_{1t} + \kappa_2 q_{2t})$ on the horizontal axis; forecast overreaction and underreaction $(\beta_0 + \beta_1 g_t)$ on the vertical axis.

The β_0 in table 4 lists the effects of forecast changes on the forecast error if the transition function approaches zero. This is the case for low values of the new synthetic transition variable (i.e. the joint effect of uncertainty and recent return). For the first quarter horizon, β_0 is estimated with 0.257. Therefore, forecasters tend to overreact in an environment of low uncertainty and high (positive) recent return. For higher uncertainty and lower (or negative) return, they switch to underreaction as β_1 is estimated with -1.086. However, figure 4a reveals that the estimated effect is driven by an outlier. Underreaction of forecasters with respect to their forecast changes is only present in a single time period.

The two quarter horizon has an estimated β_0 of -0.679. Therefore, forecaster do not adjust their expectations sufficiently if the transition function approaches zero. The weights κ reveal that this happens for high uncertainty and flat or negative changes of the oil price. For the two quarter horizon, β_1 is 1.54 which implies overreaction for low uncertainty and higher returns. This relation is presented graphically in figure 4b. The transition occur sharply again and in a threshold-style. Altogether, the findings are similar to the one quarter horizon (overreaction for low uncertainty and high returns, underreaction in the other case) but the reversed signs

of the weights cause reversed signs of the parameters as well.

The third quarter horizon is no exception from the overall picture. The negative β_0 of -0.155 and the positive β_1 of 1.359 mean overreaction for low uncertainty and positive returns and underreaction in case of high uncertainty and negative returns. Figure 4c displays a rather sharp transition between the two regimes as only one period is located between the extreme regimes.

Altogether, forecasters tend to overreact for high positive returns and low uncertainty and underreact for high negative returns and high uncertainty for all forecast horizons. However, the estimated weights for the influence of uncertainty and the return on the transition function change over the horizons. In order to derive a rough measure which variable is driving mainly the transition from overreaction to underreaction, an auxiliary regression is carried out. The recent return and uncertainty are regressed separately on the synthetic transition variable. The comparison of the attained R^2 serves as a measure of influence. Of course, specifying both variables together as control variables would result in perfect prediction with weights κ as estimated coefficients. Results for the auxiliary regression are listed in table 2.

Table 2: Auxiliary regressions

	1 Quarter	2 Quarter	3 Quarter
Uncertainty	0.897	0.335	0.895
Return	0.404	0.936	0.406

Note: R^2 of auxiliary regressions.

Uncertainty is found to be the predominant influence on the transition variable for the one and three quarter horizon while the return dominates for the second quarter. Leaving apart the first quarter which is driven by a single outlier, this implies that the recent return of the oil price is more important for shorter horizons while uncertainty, which depicts uncertainty about fundamentals, dominates the transition between over- and underreaction for longer horizons. Similarly to the univariate case, forecasters tend to anchor at their old forecasts for rising uncertainty about fundamentals. By controlling for the return it becomes clear that uncertainty matter most for longer forecast when fundamentals are supposed to play a major role in forecasting. The direct comparison of this results with the univariate transition model reveal likewise influences of uncertainty.

The evaluation of the PSTR models with multivariate transition functions is presented in the bottom of table 4. For all forecast horizons, the test of no remaining nonlinearity cannot be rejected. The same holds for the test of parameter constancy. Compared to the univariate models, the R^2 of the PSTR model is higher for every

forecast horizon. Therefore, the PSTR with multivariate transition function provides a better fit to the data.

5 Conclusion

This paper examines the nonlinear influence of uncertainty on overreaction in oil price forecasts by the use of the univariate panel smooth transition model from González et al. (2005). Furthermore, the interaction of uncertainty with the oil price return is analyzed in a multivariate version of the estimator. The second model performs superior compared to the univariate PSTR model. Both types of models show high estimated speeds of transitions and therefore a quick transition between the extreme regimes.

In general, forecasters are found to underreact when the economy is governed by high uncertainty about the future. Forecasters are more cautious in their forecast changes and form expectations which are closer to their previous forecasts when they are uncertain. On the other hand, forecasters overreact when the uncertainty is low. These results from the univariate PSTR model are confirmed when the return is used as an additional transition variable. Overreaction and the return have opposing influences on overreactions. This lead to the conclusion that forecasters tend to overreact for low uncertainty and positive returns and underreact in case of high uncertainty and negative returns. The results reveal that oil price forecasters give greater weights to the return for shorter horizon and to uncertainty for longer horizons when making their forecast changes. This could be interpreted as the greater weight of expected fundamental trends on the long-term oil price forecasts.

Table 3: PSTR with univariate transition function

	1 Quarter	2 Quarter	3 Quarter
β_0	0.401 (0.035)	1.057 (0.054)	1.137 (0.06)
β_1	-0.932 (0.051)	-1.354 (0.0794)	-1.3 (0.088)
<i>Transition parameters</i>			
γ	0.23	6.874	2.09
c_1	-1.373	30.839	14.798
c_2	32.702	12.656	51.645
<i>Model evaluation</i>			
R^2	0.18	0.209	0.196
Remaining nonlinearity	0.123	1.878	2.605
Parameter constancy	2.729	1.363	11.891

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

Table 4: PSTR with multivariate transition function

	1 Quarter	2 Quarter	3 Quarter
β_0	0.257 (0.027)	-0.679 (0.065)	-0.155 (0.058)
β_1	-1.086 (0.052)	1.54 (0.079)	1.359 (0.087)
<i>Transition parameters</i>			
κ_1	151.395	-0.149	-241.856
κ_2	-150.395	1.149	242.856
γ	0.047	21.854	0.015
c_1	9600	-8.241	-7426.03
<i>Model evaluation</i>			
R^2	0.226	0.244	0.209
Remaining nonlinearity	0.871	0.1792	0.634
Parameter constancy	0.533	2.258	3.735

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

Table 5: Summary statistics

	Obs.	Mean	Std.	Min.	Max.
1Q Ahead Forecast Error	1624	-3.119	14.445	-51.710	62.470
2Q Ahead Forecast Error	1592	-5.996	21.744	-67.710	119.970
3Q Ahead Forecast Error	1561	-8.878	23.312	-76.710	106.160
Forecast Change $2Q_{t-1}$ to $1Q_t$	1624	3.114	14.329	-80.000	59.000
Forecast Change $3Q_{t-1}$ to $2Q_t$	1624	2.718	13.655	-77.000	73.000
Forecast Change $4Q_{t-1}$ to $3Q_t$	1624	2.131	13.110	-77.000	68.000
Implied Volatility	1624	25.175	11.734	12.670	65.450
Recent Return	1624	1.608	4.913	-18.550	8.010

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

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