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Heterogeneous Forecasters and Nonlinear Expectation Formation in the U.S. Stock Market

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Abstract: We use a Panel Smooth Transition Regression (STR) model to study nonlinearities in the expectation-formation process in the U.S. stock market. To this end, we use data from the Livingston survey to investigate how the importance of regressive and extrapolative expectations fluctuates over time as market conditions summarized by stock-market misalignments and recent returns change. We find that survey participants form stabilizing expectations in the long run. Short-run expectations, in contrast, are consistent with weak mean reversion of stock prices.

JEL-Classification: G17, E47, C53
Keywords: Non-linear expectation formation, Survey data, Stock market, Heterogeneous agents

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Nonlinear Expectation Formation in the U.S. Stock Market – Empirical Evidence from the Livingston Survey

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Abstract

This research applies data from the Livingston survey to study the time variation in the sentiment of U.S. stock-market forecasters. A Panel Smooth Transition Regression (STR) model is estimated to identify the importance of market conditions summarized by stock-market misalignments and recent returns for the formation of regressive and extrapolative expectations. We find that survey participants expect little mean reversion in times of large misalignments reflecting the observed substantial and persistent swings in stock prices. Recent returns are negatively extrapolated depending on the sign and the size of the return revealing a contrarian behavior of forecasters in the presence of market exuberance.

JEL classification: G17; E47; C53

Keywords: Non-linear expectation formation; Survey data; US Stock market; Heterogenous agents

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1 Introduction

The recent financial crisis has cast doubts on the usefulness of standard rational-expectations asset-pricing models for explaining large and persistent recurrent run-ups in stock prices. Evidence suggests that such run-ups in stock prices often seem to be unrelated to higher future cash flows or lower expected returns. Williams (2013), thus, suggests to relax the assumption of rational expectations and to take into account that potentially biased beliefs of future asset-price movements drive the decisions of market participants. Findings reported by Greenwood and Shleifer (2013) support this suggestion. Summarizing earlier and providing new empirical evidence based on survey data, they show that expected future returns are strongly positively correlated with past levels and returns of asset prices, a finding that they argue is at odds with the standard rational-expectations paradigm.

Against the background of such findings, Williams (2013) suggests a theoretical model that features pro-cyclical investor optimism and, at the same time, a mean-reverting mechanism that eventually guarantees that stock prices adjust to their fundamental values. These two features of his model build on a large and significant literature that has shown that incorporating heterogeneous agents into asset-pricing models is a powerful modeling strategy to replicate real-world properties of trading behavior in financial markets. The list of pioneering contributions to this literature includes the work by Frankel and Froot (1986), Cutler et al. (1990), and DeLong et al. (1990), to name just a few. In a more recent contribution to this literature, Barberis et al. (2013) study a consumption-based asset-pricing model that is populated by investors who form extrapolative expectations and other investors who form rational expectations. Such heterogeneous-expectation-formation models are consistent with survey evidence on how investors form their expectations (for the Livingston survey, see Prat 1994) and, accordingly, have been studied extensively in simulation-based studies of how agents switch between alternative forecasting techniques (Brock and Hommes, 1997; Dieci and Westerhoff, 2010, 2012; De Grauwe and Grimaldi, 2006; Bauer et al., 2009; Huang and Chen, 2014). Among the various forecasting techniques that have been extensively studied in simulation-based studies are techniques that assume some form of time-varying switching being extrapolative and regressive expectations formation. The Panel Smooth Transition Regression (STR) model that we use in this research to model the time variation in the sentiment of U.S. stock-market forecasters perfectly matches such switching mechanics and, thus, renders it possible to provide empirical evidence on a widely studied assumption in the theoretical asset-pricing literature.

Boswijk et al. (2007), Chiarella et al. (2014), Reitz and Slopek (2009), and Lof (2013) use nonlinear estimation techniques to confront variants of heterogeneous-expectations asset-pricing models to real-world data.[1] The results of their research shows that heterogeneity in expectations formation helps to explain asset-return dynamics. Specifically, the results of this research suggest that, reflecting the time-varying importance of regressive and extrapolative expectations, asset prices tend to be unstable within the neighborhood of their equilibrium values, but exhibit mean reversion in periods of substantial misalignments. In contrast to our research, however, earlier researchers typically have used data on observed asset-price fluctuations to test the predictions of heterogeneous-expectations asset-pricing models. For example, stock-price mean reversion is taken as evidence of expectations of asset prices reverting to their fundamental values. We, in contrast, study survey data of U.S. stock-market forecasts. Thereby, we are able to provide direct evidence on the kind of nonlinear switching between competing forms of expectations formation that forms the basis of much earlier theoretical and empirical research on agent-based asset-pricing models.

Heterogeneity in the way agents form expectations has also been documented in the literature studying survey data of forecasts of professional forecasters. For example, Taylor and Allen (1992) and Ito (1990) analyze short-run and long-run foreign exchange-rate forecasts. Their findings suggest that, while short-run forecasts typically feature extrapolative elements, long-run exchange-rate forecasts are consistent with a stabilizing regressive element. More recent evidence reported by Cheung and Chinn

[1]There is also an emerging strand of research testing agent-based models using lab experiments. This research is attractive because important questions such as to what extent positive feedback trading fuels asset-price bubbles can be analyzed in a low-noise environment (Huesler et al., 2013).

(2001) confirms this finding. As for the stock market, Prat (1994) shows that a combination of adaptive, extrapolative, and regressive models of expectations formation helps to some extent to explain how professional forecasters form stock-price forecasts. Survey data also are an important data source for studying social interactions among market participants. For example, Menkhoff et al. (2009) find that misalignments of the exchange rate and exchange-rate changes explain expectations heterogeneity in the foreign-exchange market. Lux (2009) reports strong evidence of social interactions as an important element in respondents' assessment of the German ZEW business climate index. More closely related to our research is the work by Reitz et al. (2012) and Goldbaum and Zwinkels (2014), who study the expectation formation in the oil and foreign-exchange markets. They find that fundamentalists form mean-reverting expectations whereas chartists form contrarian expectations.

In this research, we use stock-market forecasts as collected by the Livingston survey to analyze the formation of heterogeneous expectations in the U.S. stock market. We study six-months-ahead forecasts, where the data are available for a sample period of more than fifty years of time. Based on a fundamental value of stock prices constructed as suggested by Campbell and Shiller (1988), we model regressive and extrapolative expectation as a function of current market conditions as measured in terms of the misalignment of stock prices and stock-market returns. We estimate a Panel STR model to study the nonlinear expectation formation in the U.S. stock market. We show that survey participants' mean-reversion expectations become weaker as the observed misalignment increases. Moreover, survey participants' expectations are consistent with the view that recent returns are corrected depending on the size of the stock price change.

We organize the remainder of this research as follows. In Section 2, we describe our data and lay out how we construct the fundamental value of stock prices. In Section 3, we present our empirical model. In Section 4, we present our main empirical results. In Section 5, we provide further results from sub-sample estimations. In Section 6, we offer some concluding remarks.

2 The Data

In order to measure expectations, we use the semiannual Livingston survey maintained by the Federal Reserve Bank of Philadelphia. The sample period runs from 1958 to 2014. The Livingston survey is conducted in each year in June and December and covers forecasts of professional forecasters of several financial and macroeconomic variables, including the the inflation rate, the growth rate of output, and the stock price of the Standard & Poors (S&P) 500 stock market index. The stock-price forecasts that we study are for a forecast horizon of six months. Forecasts are available for various groups of forecasts. We study data for the following four groups: academics, forecasters working for commercial banks, forecasters working for investment banks, and forecasters working for non-financial firms. These four groups cover the majority of survey participants (294 out of the 362 forecasters). From the individual forecasts available for the forecasters who belong to the four groups, we form four times series of the arithmetic means of stock-price forecasts (that is, group-specific "consensus" forecasts). Because we analyze a more than 50-year long sample period covering semiannual data, we have available a total of 456 observations for our empirical analysis.[2]

In order to inspect the time-series dimension and the cross-sectional dimension of the data, Figure 1 shows the stock market-index (solid line), its fundamental value (dashed line), and the range of forecasts of the four groups of forecasters (shaded area). The general trend in stock-price forecasts tracks realized stock prices and the range of forecasts shows a generally moderate cross-sectional heterogeneity across groups of forecasters. The latter observation allows us to apply panel econometric techniques to estimate survey participants' forecasting functions.[3]

[Figure 1 about here]

We use the vector-autoregressive (VAR) approach proposed by Campbell and Shiller (1988) to construct the fundamental value of stock prices.

[2] The data and a detailed documentation are available at http://www.phil.frb.org/research-and-data/real-time-center/livingston-survey/.

[3] Cross-section fixed effects of the panel estimations do not significantly differ from each other.

Accordingly, we estimate a VAR(1) model on semi-annual data on the dividend-price ratio and dividends.[4] We then invoke restrictions on the estimated VAR model as described by Campbell and Shiller (1988) to compute a forecast of future growth of the dividend-price ratio, which we combine with the time-path of dividends to construct a semi-annual fundamental value of stock prices. The fundamental value closely tracks the actual stock-price index in the late 1950s and the first half of the 1960. The actual stock-price index falls short of the estimated fundamental value in the second half of the 1970 and the first half of the 1980. From approximately 1995 to 2008, the actual stock-price index is substantially larger than the estimated fundamental value. The financial and economic crisis of 2008 brought about a teymporary reversal of the actual stock-price index to its fundamental value. again exceeds its estimated fundamental value. Since then, however, the fundamental value again has increased at a higher pace than the actual stock-price index. In sum, we observe recurrent and persistent "misaligments" of stock prices, which may have important implications for the way forecasters form their forecasts.

3 The Empirical Model

We apply a Panel Smooth Transition Regression (STR) model to study the time-varying formation of expectations. The Panel STR model was introduced by Gonzalez et al. (2005) to model time series that are governed by a given number of different regimes. Switches between regimes are modeled in a smooth and continuous way and can be governed by the value of a particular variable or group of variables. Accordingly, the Panel STR model

[4]We use demeaned nominal data expressed in logs. Like Campbell and Shiller (1988), we use an annualized discount factor of 0.936, which is consistent with an annual real interest of 6.8%. Other calibrations of the discount factor yield similar results and are available upon request. Data source: http://www.econ.yale.edu/ shiller/data.htm. See Shiller (2005).

can be expressed as follows[5]

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

where $y_{t,i}$ is the forecast of the future semi-annual stock-price returns by the group of forecasters i at time t, and $x_{i,t}$ is the vector of information variables driving expectations. The transition parameters, q_t^j and ϕ_j, are slope parameters that determine the speed of transition between the two extreme regimes, with low absolute values resulting in a slower transition. Furthermore, θ_j is an asymmetry parameter. The term $\omega_j(q_t^j, \phi_j, \theta_j)$ represents one of r transition functions, each bounded between 0 and 1. The model also features q_t^j as threshold variables, ϕ_j to capture the transition speed, and θ_j as threshold parameters. Like Gonzalez et al. (2005), we assume that transitions between regimes can be captured by a logistic transition function of the following format:

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

Equations (1) and (2) constitute a general starting point for more specific empirical models. In line with the majority of contributions to the literature on asset-market expectations, we assume that the vector of regressors, $x_{i,t}$, contains the lagged forecasts to measure forecast persistence, the recent return on the stock-market index to allow for return extrapolation, and the current misalignment to consider the expected mean reversion in stock prices. Hence, the model allows both regressive and extrapolative expectations to be driven by two transition variables, namely the current misalignment and/or the recent stock returns.[6] In addition, we also test for the possibility that the two transition variables exert an influence on forecasting persistence.

[5]Our empirical model is a panel version of the STR model originally proposed by Ozaki (1985) and further developed and analyzed by Teräsvirta and Anderson (1992), Granger and Teräsvirta (1993) and Teräsvirta (1994). The Panel-STR model has been applied to oil price expectations by Reitz et al. (2012).

[6]The two types of expectation formation are at the center of most agent-based asset-pricing models, see, e.g., Day and Huang (1990). From a technical perspective, the transition variables determine the transition between the extreme parameter values β_0 and $\beta_0 + \beta_1$.

3.1 Model Specification

According to Gonzalez et al. (2005), building a Panel STR model can be done in three steps: (i) specification, (ii) estimation, and (iii) evaluation. The first step, model specification, requires identification of systematic changes in the relationship between the predicted future returns and the exogenous variables summarized in the vector of regressors, $x_{i,t}$. We, thus, test linearity against the Panel STR alternative using two threshold variables: $(s_t - f_t)$ and $(s_t - s_{t-1})$. The former reflects the current misalignment of the stock price, s_t, from the fundamental value, f_t, and the latter, $(s_t - s_{t-1})$, refers to the change in the stock price in the previous six-months period.

Testing the null hypothesis $H_0 : \phi_j = 0$ to identify the importance of a nonlinear component, however, is not straightforward. Under the null hypothesis, there are unidentified nuisance parameters implying that a simple t-test is not applicable. To circumvent this problem, Luukkonen et al. (1988) suggest to replace the transition function by its Taylor expansion approximation. In the resulting auxiliary regression

$$y_{t,i} = \alpha_i + \beta_0^{'*} x_{i,t} + \beta_1^{'*} x_{i,t} q_{i,t} + ... + \beta_m^{'*} x_{i,t} q_{i,t}^m + \epsilon_{i,t}, \tag{3}$$

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

– Insert Table 1 here –

The results summarized in Table 1 show that rejection of the linear model in favor of STR-type nonlinearity depends on the sample period being studied. When looking at the full sample period, we can reject the null hypothesis at the five-percent level for lagged returns influencing expected mean reversion, the current misalignment influencing returns and forecast persistence, and for past returns influencing current returns and forecast persistence. Obviously, statistically significant nonlinearities are more likely to be identified in long samples. However, nonlinear dynamics may also unfold in specific sub-samples. For example, against the backdrop of the recent financial and economic crisis, it is interesting to observe that the current misalignment seems to influence the expected mean reversion of stock prices (first line, last column). Hence, we report full-sample estimation results for all variable combinations and sub-sample estimation results for selected combinations.

As outlined by Gonzalez et al. (2005), the auxiliary regressions can also be used to determine the order of inhomogeneity, m, in Equation (2). The test results suggest that $m = 1$ is appropriate in case of the recent returns, and $m = 2$ in case of the current misalignment as the determining variable of the transition function.[7] The resulting specifications of the transition functions

$$\omega_t(mis_t, \phi_{mis}) = \frac{2}{1 + exp(-\phi_{mis} mis_t^2)} - 1 \tag{4}$$

and

$$\omega_t(return_t, \phi_{ret}) = \frac{1}{1 + exp(-\phi_{ret} return_t)} \tag{5}$$

ensure that ω_t remains in the interval between 0 and 1.[8]

3.2 Model Estimation

The second step consists of estimating the Panel STR model with fixed effects and predetermined regressors. Parameter estimates are obtained by applying nonlinear least squares after demeaning the data. It should be noticed that, unlike in standard linear models, the variable means depend on the parameters of the transition functions. Consequently, demeaned values are recomputed at each iteration of the estimation process (Gonzalez et al., 2005).

[7] Results of the inhomogeneity tests are available from the authors upon request.

[8] Location parameters, θ_j, have been set to zero to ensure convergence of the estimation routine.

The nonlinear mean reversion and extrapolation functions can each be reproduced with two different signed β_j/ϕ_j coefficient sets. This equivocality is typically covered by defining a non-zero starting value of the ϕ-parameters. We set each starting value to 0.5.[9] Moreover, we calculate robust standard errors to correct for arbitrary correlation patterns. To this end, we compute $\sum_i(\sum_t X_{it}u_{it})'(\sum_t X_{it}u_{it})$ as the center term in the sandwich estimator, where X_{it} and u_{it} are the observations and error terms for forecaster group i at time t.

When starting with the most general framework consisting of Equations (1),(4), and (5) convergence problems occur due to the small number of observations and the fact that different β_j/ϕ_j combinations produce similar transition functions leading to very little curvature of the objective function of the optimization routine. As a result we test for nonlinear dynamics of each variable separately.[10]

3.3 Model Evaluation

In a third and final step, we evaluate the estimated Panel STR model by applying two specification tests. As suggested by Gonzalez et al. (2005), an adaption of the tests of parameter constancy (PC) and of no remaining nonlinearity (NRNL) as developed by Eitrheim and Teräsvirta (1996) for univariate STAR models is employed. Both tests are performed in the way described in Section 3.1. First, the estimated model is augmented by a Taylor expansion representing additional nonlinearities (NRNL) or nonlinear time dependence of model coefficients (PC). The according LM-type test statistic has an asymptotic F-distribution. In the case of the NRNL-test, we consider the same transition variables as used in the Panel-STR model, while in the case of the parameter-constancy test powers of a time trend are included. Hence, the NRNL-test checks whether the Panel STR model fully captures the identified expectation nonlinearities and the parameter constancy test reveals any structural breaks in the sample.

[9]Starting with -0.5 leads to opposite-signed coefficients producing exactly the same transition function. Starting values of all other coefficients are set to zero.

[10]This strategy also helps us to isolate any nonlinear influence of the recent returns or the current misalignment on the expected mean reversion and the returns extrapolation.

4 Estimation Results

Given the three regressors, $y_{i,t-1}$, $(s_t - f_t)$, and $(s_t - s_{t-1})$, and the two transition variables, (s_t-f_t) and (s_t-s_{t-1}), we end up estimating six different models determined by each regressor/transition variable combination. In order to capture the persistence of forecasts, we add a second lag of the endogenous variable in each specification. The estimation results for the full sample are reported in Table 2. The R^2 statistics show that more than fifty percent of the forecast variation can be explained by the model. The tests for no remaining non-linearities and parameter constancy indicate that the non-linear model is superior to the linear specification and underpin our econometric specification.[11]

[Table 2 about here]

The total influence of a regressor on the expected percentage change of the S&P is measured by $\beta_0 + \beta_{1,trv}\omega_{j,t}$, where $\omega_{j,t}$ is a function of ϕ and the transition variable. The regular linear part is represented by β_0, while the nonlinear parts, $\beta_{1,trv}$ and ϕ, describe the time-variation with respect to the transition variable. For example, in case of the first column of Table 2 forecasts are driven by the current misalignment acting as both the regressor and transition variable. Also with regard to the first column of Table 2, it is important to note that the estimation routine exhibits convergence problems in an empirical environment characterized by a relatively small number of observations and moderate variation of a regressor. In our setting, such problems occur when the lagged return is used as the regressor and is used as a transition function for the persistence coefficient. In this, case we decided to skip the β_0 coefficient in favor of the nonlinear part.

The linear part represented by the β_0-coefficients reveals common features of forecasting behavior across all specifications. Moreover, given that the data set covers roughly fifty years of semi-annual observations the estimation results provide evidence on what has been called in the literature 'fundamentalist' expectations (Taylor and Allen, 1992). Forecasters forming

[11]Given a five percent threshold, only the NRNL test for the model with lagged returns influencing the forecasting persistence is significant at a marginal significance level of 0.048.

fundamentalist expectations believe that asset prices are mean reverting in the long run and expect negative future returns when stock prices are above their fundamental value. Our findings are consistent with this view because the misalignment coefficients are significantly negative. In line with time-series properties of stock prices well-documented in earlier literature, the expected mean reversion is quite small.

In contrast to pure fundamentalist expectations, much significant earlier research has shown that market participants also make use of 'chartist' techniques (Taylor and Allen, 1992). Market participants relying on this type of expectation formation extrapolate historical asset-price fluctuations, where researchers in the agent-based literature approximate the latter quite often by lagged returns. Because chartist techniques typically focus on short run price trends (that is, asset-price fluctuations that occur within a few trading days), while our data are available at a semi-annual frequency, it is not surprising that the estimated lagged-returns coefficient does not provide strong evidence of 'chartist' expectations. In general, the parameter estimates are significantly negative and of moderate magnitude, suggesting that observed returns are expected to be corrected in the long run.

In addition, we find strong evidence of forecast persistence. An aggregated autocorrelation coefficient of more than 60 percent suggests that information embedded in current forecasts significantly affects future forecasts.

The nonlinear part of the models consists of the $\beta_{1,trv}$ and the ϕ coefficient, which allows the respective regressor to exert a time-varying influence on the forecasters' predictions. The $\beta_{1,trv}$-coefficient and the ϕ-coefficient are statistically significant for all regressor/transition combinations, except for the last specification. For further interpretation of the estimation results it is convenient to graph the resulting parameter value against the values of the transition variable. This is done in Figure 2, where Panels a and b show the mean reversion coefficient against the current misalignment and returns, Panel c and d show returns extrapolation against the current misalignment and returns, and Panel e and f show forecast persistence against the current misalignment and returns.

[Figure 2 about here]

The findings summarized in Panel a Figure 2 show that large absolute misalignments as typically observed in bubble periods are perceived to have low potential for future correction. In contrast, small misalignments are expected to diminish more quickly as the mean reversion coefficient increases up to nine percent. Forecasters, hence, perceive relatively large real-world stock-market misalignments may be long-lasting. In contrast, the closer stock prices fluctuate around the fundamental value the higher is the speed of adjustment, which indicates that small deviations from a fundamental value trigger mean reversion expectations. This finding is in line with earlier empirical studies of heterogenous-expectations models. Boswijk et al. (2007) and Chiarella et al. (2014) show that the switching between forecasting techniques is significantly driven by recent realized profits. This implies that fundamentalist techniques will be substituted by chartist techniques when prices are moving away from their fundamental levels. Reitz and Taylor (2008) and Reitz et al. (2011) also report evidence that the mean reversion of exchange rates weakens as deviations from purchasing power grow. It has been argued that if the exchange rate is trending away from its fundamental value, then traders face a fundamental risk (Figlewski, 1979) and betting against the trend may lead to substantial losses. Market participants, thus, become increasingly reluctant to submit orders (Shleifer and Vishny, 1997). This is somewhat in contrast to theoretical contributions such as Dieci and Westerhoff (2010) and Huang and Chen (2014), where expected profits are supposed to increase in the absolute misalignment, leading more market participants to adapt a fundamentalist strategy. One way to reconcile their theoretical results with our empirical findings is to argue that, in our real-world data, a large increase in stock prices signals a "fundamental" change, implying that substantial and persistent misalignments force market participants to adjust their model of the fundamental value.

In order to graphically explore the time-variation in survey participants' mean reversion expectations, we focus on the influence of the current misalignment to calculate the expected error correction as $\psi_t = \beta_{0,mis} + \beta_{1,mis}\omega_t(mis_t, \phi_{mis})$. The time series of ψ_t together with the actual misalignment, $s_t - f_t$, is shown in Figure 3.

[Figure 3 about here]

Figure 3 confirms that a large absolute mean-reversion coefficients coincides with small misalignments. In contrast, small deviations of the actual stock price from its fundamental value are expected to diminish quickly. Interestingly, our estimates imply a very small expected error-correction term in the early 2000s, that is before the recent financial and economic crisis gathered steam. Hence, in line with Boswijk et al. (2007) forecasters seem to be well aware of the fact that bullish investors are reinforced by their recent investment performance leading to large and persistent swings in stock prices.

Recent returns also exhibit an interesting influence on the expected mean reversion of stock prices. As can been seen in Panel b of Figure 2, small observed returns lead to a mean reversion coefficient that coincides with the coefficient implied by the linear estimates of the other model specifications. As observed positive returns become larger, however, expected mean reversion increases, while the opposite is true for negative returns. Hence, in a stock-market environment characterized by repeated overvaluations strong positive returns tend to correlate with a stronger perception of market exaggerations to be corrected in the future. Negative returns, in turn, are perceived as a response to market exuberance and already constitute significant error correction leaving less room for further adjustments. However, narrow parameter variation suggests that these effects are not very pronounced.

Negative return extrapolation implies that panelists expect a reversion of previous returns and, therefore, act like contrarians. A negative extrapolation coefficient has also been documented by Reitz et al. (2012) and Goldberg and Zwinkels (2014). While a negative extrapolation coefficient is in contrast to a standard feature of agent-base asset-pricing models, where chartists are supposed to contribute a destabilizing component to the asset market by positively extrapolating recent trends, one should bear in mind that we study data available at a semi-annual frequency of the survey.

In our analysis, the time variation of return extrapolation may be driven by the observed returns and the current misalignment. Panel c of Figure 2 shows that the estimated parameters imply a steep symmetric transition function of return extrapolation with respect to the current misalignment. For small absolute misalignments, we find very little expected correction of observed returns, while misalignments of more than 30 percent trigger negative extrapolation of around 16 percent. [12] Large misalignments, thus, are perceived as exaggerations leading to lower persistence of returns (Shiller 1999). When examining the influence of the lagged return on the extrapolation coefficient in Panel d, we find the resulting this influence to be centered around its mean value of again -0.12. Positive returns are expected to correct at a slower pace than negative returns. Overall, it seems that forecasters believe that an overreaction of the stock market to positive news is smaller than to negative news of similar magnitude.

Panels e and f of Figure 2 summarize the results for the final two specifications of our empirical model, which allow for a systematic change of the persistence parameter of forecasts. Forecasting persistence decreases in times of positive misalignments and negative returns. Given that low persistence implies that forecasters put a relatively large weight on new information, the results also suggest that large negative misalignments and large positive returns are supposed to be less informative. However, it should be noted that the ϕ coefficient of the last specification of our model is statistically insignificant.

5 Sub-Sample Results

As indicated in Table 2, some of the regressor/transition variable combinations lead to rejections of linearities in specific sub-samples. The following Table 3 reports the estimation results for those two specifications for which we observe a rejection of linearity.

[Table 3 about here]

In the first specification, we look at the expected mean reversion in the time period around the financial crisis. The parameter estimates imply a transition function similar to the one shown in Panel a of Figure 2, confirming the

[12] The average return extrapolation of around 12 percent coincides with the linear terms of the other models (See the $\beta_{0,ret}$ coefficients in Table 2.

finding that large misalignments are expected to be corrected only in the long run. In contrast to the full sample estimates, however, forecasting persistence is substantially smaller. While the weight put on new information has been around 40 percent in the full-sample, it substantially increased at the end of the sample to roughly 70 percent. This increase is consistent with the view that during bubble periods market participants tend to believe that "this time is different".

In the second specification, which focuses on the 1960s and 1970s, we find, in contrast to the above results for the full sample, that news from positive returns were perceived to be more informative than negative returns. Although the interpretation of this "twist" in information processing should not be stretched too far, it illustrates that forecasting behavior is likely to change over time.

6 Conclusion

The recent financial and economic crisis has witnessed that boom and bust cycles on asset markets have the potential to seriously influence developments in the real sector of an economy. There is now an increasing consensus that time-variation in the sentiment of international investors is a major driving force of asset-price dynamics and, thus, asset-market cycles. We have estimated a Panel Smooth Transition Regression model on data from the Livingston survey to study the time-variation in forecaster sentiment in the U.S. stock market. Our results demonstrate that substantial nonlinearities characterize the formation of stock-price expectations. Expected mean reversion weakens as misalignments grow. This is consistent with the view that forecasters believe that market participants become more bullish if in the recent past bullish investments turned out to be successful. However, forecasts are also consistent with the view that recent returns will be corrected depending on the size and the sign of the stock-price change. We also find evidence of a strong and time-varying forecast persistence. Thus, our results lend strong support to the heterogeneous expectations approach of financial markets.

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Table 1: Nonlinearity tests

Variables		Samples			
Regressor	Transition	Full	1958 – 1978	1979 – 1998	1999 – 2014
mis	mis	1.934	2.472	1.457	9.377
		(0.123)	(0.064)	(0.229)	(0.000)
mis	ret	7.165	1.905	1.531	0.981
		(0.000)	(0.131)	(0.209)	(0.404)
ret	mis	3.043	0.922	1.401	0.513
		(0.029)	(0.374)	(0.245)	(0.674)
ret	ret	4.003	0.943	1.160	0.439
		(0.008)	(0.422)	(0.327)	(0.725)
pers	mis	3.828	2.397	0.962	1.569
		(0.010)	(0.070)	(0.413)	(0.201)
pers	ret	3.149	7.993	0.464	3.432
		(0.025)	(0.000)	(0.708)	(0.019)

Note: F-statistics of the linearity tests against STR-type nonlinearities. $P - Values$ in parenthesis represent marginal significance levels of the F-statistics. 'mis' indicate the current misalignment ($s_t - f_t$), 'ret' refers to the recent percentage change of the $S\&P$ index ($s_t - s_{t-1}$), and 'pers' denotes the lagged forecast. The sample contains semi-annually expectations of the Livingston S&P stock market survey from June 1958 to December 2014.

Table 2: Parameter estimates of the Panel STR model

Parameter	Model mis/mis	mis/ret	ret/mis	ret/ret	pers/mis	pers/ret
$\beta_{0,y(t-1)}$	0.392	0.398	0.419	0.418	0.420	–
	47.232	81.909	35.501	52.580	33.645	
$\beta_{0,y(t-2)}$	0.283	0.262	0.272	0.262	0.233	0.254
	14.835	15.415	14.191	14.085	12.593	12.867
$\beta_{0,mis}$	-0.090	0.076	-0.021	-0.022	-0.011	-0.024
	4.600	11.053	11.666	17.247	4.824	14.434
$\beta_{0,ret}$	-0.146	-0.222	–	–	-0.117	-0.157
	16.328	15.069			13.856	7.181
$\beta_{1,trv}$	0.084	-0.196	-0.161	-0.225	-0.089	0.823
	7.093	12.613	7.845	14.984	3.587	28.276
ϕ	9.232	3.465	51.862	4.375	10.007	1.861
	2.136	3.210	2.349	2.155	2.586	1.314
R^2	0.602	0.562	0.554	0.552	0.548	0.544
PC	0.999	0.745	0.120	0.102	0.963	0.835
NRNL	0.123	0.101	0.088	0.305	0.694	0.048

Notes: PC is the p-value for parameter constancy. $NRNL$ is the p-value for no remaining nonlinearity. The parameter $\beta_{1,trv}$ refers to the regressor with a time varying influence on the predicted return. t-statistics in parentheses are based on robust estimates of the covariance matrices of the parameter estimates. The sample contains semi-annually expectations of the Livingston S&P stock market survey from June 1958 to December 2014.

Table 3: Subsample estimates of the Panel STR model

	Model mis/mis 1999 - 2014	 pers/ret 1958 - 1978
$\beta_{0,y(t-1)}$	0.167	–
	3.990	
$\beta_{0,y(t-2)}$	0.136	0.213
	2.555	4.291
$\beta_{0,mis}$	-0.193	0.037
	2.810	3.246
$\beta_{0,ret}$	-0.198	0.345
	8.299	7.344
$\beta_{1,trv}$	0.165	1.298
	2.641	20.875
ϕ	13.738	10.835
	4.800	3.392
R^2	0.584	0.558
PC	0.525	0.315
NRNL	0.960	0.951

Notes: PC is the p-value for parameter constancy. $NRNL$ is the p-value for no remaining nonlinearity. The parameter $\beta_{1,trv}$ refers to the regressor with a time varying influence on the predicted return. t-statistics in parentheses are based on robust estimates of the covariance matrices of the parameter estimates. The sample contains semi-annually expectations of the Livingston S&P stock market survey as specified in the Table.

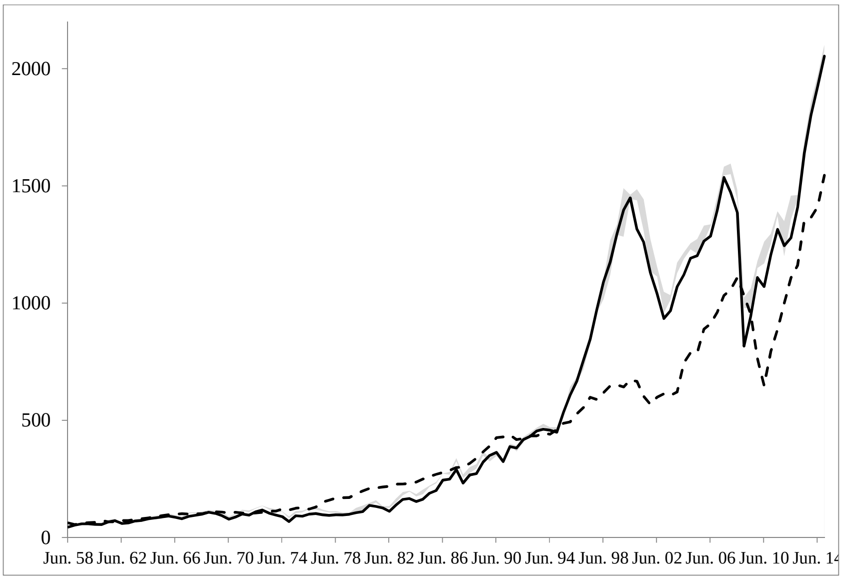

Figure 1: S& P Forecast Range, actual value and fundamental value
Notes: Figure 1 shows the stock market index (solid line), the fundamental value (dashed line), and the range of forecasts of the four groups (shaded area).

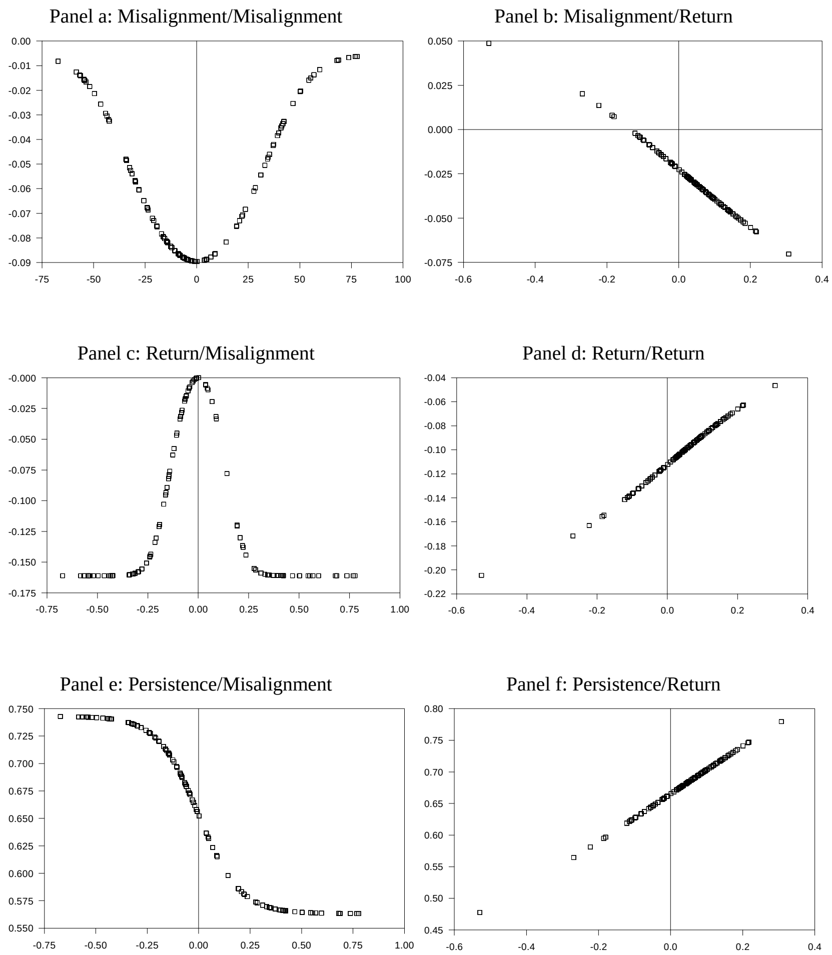

Figure 2: Transition functions

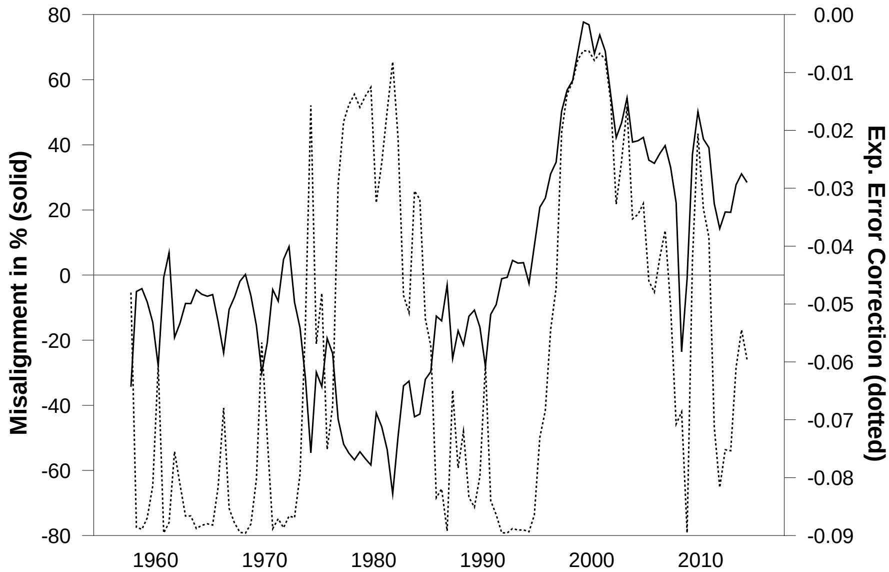

Figure 3: Time dynamics of expected mean reversion