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Working Paper

Heterogeneous forecasters and nonlinear expectation formation in the US stock market

Kiel Working Paper, No. 1947

Provided in Cooperation with:
Kiel Institute for the World Economy – Leibniz Center for Research on Global Economic Challenges

Suggested Citation: Pierdzioch, Christian; Reitz, Stefan; Ruelke, Jan-Christoph (2014) : Heterogeneous forecasters and nonlinear expectation formation in the US stock market, Kiel Working Paper, No. 1947, Kiel Institute for the World Economy (IfW), Kiel

This Version is available at:
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Working Papers

Kiel Institute for the World Economy

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No. 1947 | July 2014

Web: www.ifw-kiel.de

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

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

Christian Pierdzioch,[*] Stefan Reitz[†] and Jan-Christoph Ruelke[‡]

July 16, 2014

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.

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Note: This project has received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement no. 612955.

1 Introduction

The recent financial crisis has cast doubts that standard asset pricing models are useful to explain large and persistent recurrent run-ups in equity prices, which 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 stock-market participants. The 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 observed levels and returns of asset prices, a finding that is clearly at odds with the standard rational-expectation paradigm.

Based on these empirical 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 price adjust to their fundamental values. Basically, these two elements 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 extrapolative and regressive forecasting techniques (Brock and Hommes, 1997; De Grauwe and Grimaldi, 2006; Bauer et al., 2009). Upon using nonlinear estimation techniques to confront variants of such models to real-world data, Reitz and Slopek (2009), Boswijk et al. (2006), and Lof (2013)

show that allowing for heterogeneous expectations helps to explain asset return dynamics. Specifically, the results of this research suggest that, reflecting the time-varying importance of traders who form regressive and extrapolative expectations, asset prices tend to be unstable within the neighborhood of their equilibrium values, but exhibit mean reversion in the case of substantial misalignment.

Heterogeneity of expectation-formation processes has also been documented in the literature studying survey data of forecasts of professional forecasters. For example, Taylor and Allen (1992), Ito (1990), and Menkhoff (1997) 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 (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 expectation heterogeneity in the foreign exchange market, while Lux (2009) reports strong evidence of social interactions as an important element in respondents' assessment of the German ZEW business climate index. More recently, Greenwood and Shleifer (2013) stress the importance of extrapolative expectations as a potential driver of asset price bubbles.

In this research, we use stock-market forecasts as collected by the Livingston survey to analyze heterogeneous expectations in the U.S. stock market. The data comprise 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 functions of the current misalignment of stock prices and the recent stock-market returns returns as indicators of current market conditions. Upon estimating a Panel Smooth Transition Regression (STR) model, we show that survey

participants form stabilizing expectations in the long run. Short-run expectations, in contrast, are consistent with weak mean reversion of stock prices.

We organize the remainder of this paper 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 more detailed results on cross-sectionally differences of forecaster groups and the time variation of mean reversion expectations. 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 2011. 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, and the stock price of the Standard & Poors (S&P) 500 stock market index which we used to calculate the expected stock return. The forecast horizon of the forecast of the stock return is six months. Furthermore, the Livingston survey classifies forecasters into various groups, such as 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 (288 out of the 349 forecasters). For this reason, we use the forecasts of the forecasters who belong to these four groups to form four times series of the arithmetic means of stock-price forecasts. Because we analyze a more than 50-year time sample period based on semiannual data, we have available a total of 432 observations for our empirical analysis.[1]

In order to inspect the time-series dimension and the cross-sectional dimension of the Livingston data, Figure 1 shows the stock market index (solid

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

line), its fundamental value (dashed line), and the range of forecasts of the four groups (shaded area). While the general trend in stock-price forecasts tracks realized stock prices, the range of forecasts shows a substantial cross-sectional heterogeneity across groups of forecasters. For instance, in June 1980 (December 1999) the group of non-financial forecasters expected a decrease in stock prices to 115 (1,280), while the group of investment-banking forecasters expected the stock price to increase to 136 (1,490). This heterogeneity suggests that different group of forecasters use different economic models to form their forecasts.

[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. Accordingly, we estimate a VAR(1) model on yearly data on the dividend-price ratio and dividends.[2] We then invoke restrictions on the estimated VAR model 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 of stock prices 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. Since the financial and economic crisis of 2008, the actual stock-price index again exceeds its estimated fundamental value. In sum, we observe recurrent and persistent "misaligments", and these misalignments may have important implications for the way forecasters form their forecasts.

[2] We use demeaned nominal data expressed in logs. Like Campbell and Shiller (1988) we used a 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).

3 The Empirical Model

We apply a Panel Smooth Transition Regression (STR) model to study the time-varying formation of stock-market 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 fashion and can be governed by the value of a particular variable or group of variables. Accordingly, the Panel STR model can be expressed as follows[3]

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

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 slower transition. Furthermore, θ_j is an asymmetry parameter. The variable $\omega_j(q_t^j, \phi_j, \theta_j)$ represents one of r transition functions, each bounded between 0 and 1, q_t^j the threshold variable, ϕ_j the transition speed and θ_j the threshold parameter. Following Gonzalez et al. (2005), we assume that transitions between regimes can be captured by a logistic transition function of the following format:

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

Equation (1) together with equation (2) constitute a general starting point for more specific empirical models. In line with the majority of contributions dealing with 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 Standard & Poor's stock-market index to allow for return extrapolation, and the current misalignment to consider the expected mean reversion in U.S. stock prices. Therefore, the model

[3] 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).

allows for both regressive expectations and extrapolative expectations to be driven by the current misalignment and/or the recent stock return.[4] In addition, we also test for the possibility that these transition variables exert an influence on forecasting persistence.

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 the threshold variables $(s_t - f_t)$ and $(s_t - s_{t-1})$ where the former reflects the current misalignment of the stock price s_t from the fundamental value f_t and the term $(s_t - s_{t-1})$ 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 first-order Taylor expansion. 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.

[4] From a technical perspective, these market indicators determine the transition between the extreme parameter values β_0 and $\beta_0 + \beta_1$ and will be called "transition variables" in the following.

When looking at the full sample period, we can reject the null hypothesis at the five-percent level only for lagged returns influencing expected mean reversion and current misalignment influencing forecast persistence. For the sample starting in 1970, the last variable combination still yields a strong rejection of linearity, but any other variable combinations are statistically insignificant. In the same way, we find particular variable combinations to be statistically significant in other sub-samples, too. Since a clear picture regarding a specific set of variables or a specific sample does not emerge from these specification tests, we do not exclude variable combinations from the Panel STR estimation.

As outlined in Gonzalez et al. (2005) these 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 return and $m = 2$ in case of the current misalignment as the determining variable of the transition function.[5] 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.[6]

3.2 Model Estimation

The second step consists of estimating the Panel STR model. The Panel STR model is a fixed effects model with predetermined regressors. Parameter estimates are obtained by applying nonlinear least squares after demeaning the data. It should be noticed that unlike standard

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

[6] Location parameters θ_j have been set to zero due to convergence problems of the estimation routine.

linear models variable means depend on the parameters in the transition functions. Consequently, demeaned values are recomputed at each iteration of the estimation process (Gonzalez et al., 2005).

The prevailing 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.[7] Moreover, we calculate robust standard errors to correct for arbitrary correlation patterns by computing $\sum_i(\sum_t X_{it}u_{it})'(\sum_t X_{it}u_{it})$ 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 considering Equation (1) together with Equation (4) and Equation (5) convergence problems of the optimization routine occur due to the fact that β_j/ϕ_j combinations produce similar transition function. Because this was particularly the case for the recent return as a regressor or a transition variable we test for nonlinear dynamics of each variable separately.[8]

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 in 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

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

[8] This strategy also allows us to possibly isolate the linear influence of the recent returns on the predicted returns.

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. The latter is particularly important given that a significant fraction of our observations stems from a bubble-like episode.

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. The R^2 statistics show that around fifty percent of the forecast variation can be explained by the model. The test for no remaining non-linearities as well as parameter constancy indicate that the non-linear model is superior to the linear specification and underpins our econometric specification.[9] The results for all specifications are reported in Table 2.

[Table 2 about here]

The linear part of all models reveals common features of forecasting behavior. 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). In contrast to 'chartists' the fundamentalists believe that asset prices are mean reverting in the long run. Our findings are consistent with this view as the misalignment coefficients is significantly negative. Forecasters, thus, expect negative future returns when stock prices are above their fundamental value. In line with time-series properties of stock prices well documented in earlier literature, the expected mean reversion is quite small. The lagged-return coefficient confirms this finding. In general, the parameter estimates are significantly negative, but small in magnitude, suggesting that observed returns are expected to be corrected towards their fundamental value only in the long run. In addition, we find strong evidence of forecast persistence. An autocorrelation coefficient of around

[9] The only exception is the model with recent returns influencing the expected mean reversion with a marginal significans level of the no-remaining nonlinearity test statistic of $NRNL = 0.014$.

0.5 suggests that information embedded in current forecasts significantly affects future forecasts of the $S\&P$.

Turning to the nonlinear part of the models, we observe that the ϕ coefficient is statistically significant for all misalignment/return combinations, while insignificant for the persistence parameters. Starting with the time variation of the expected mean reversion in stock prices the estimated coefficients imply that small absolute misalignments are perceived to have low potential for future correction. In contrast, large misalignments as observed in bubble periods are expected to diminish more quickly as the mean reversion coefficient increases up to 20 percent. This reflects that financial market crashes drive asset prices quite quickly back to their fundamental value.[10] More generally, the closer stock prices fluctuate around the fundamental value the lower the speed of adjustment, which indicates that small deviations from a fundamental value trigger expectations of a random-walk-like behavior while larger deviations induce regressive expectations.

[Figure 2 about here]

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 estimations of the other model specifications. However, as lagged returns become larger expected mean reversion increases, while the opposite is true for negative returns. This suggests that in an asset market environment characterized by overvaluations occurring more often than undervaluations strong positive returns lead to expectations that large misalignments are corrected in the future, while negative returns already constitute substantial error correction leaving less room for further adjustments.

Compared to the findings for the expected misalignment the time variation of return extrapolation shows less pronounced dynamics. As Panel c of Figure 2 shows the estimated parameters define a steep transition function of return extrapolation with respect to the current misalignment. Only for small absolute misalignments do we find a decline of the standard return

[10] See the respective transition function in Figure 2.

correction coefficient of around -0.12.[11] When examining the influence of the lagged return on the extrapolation coefficient we find the resulting observation to be centered around its mean value of again -0.12. As a result, a nonlinear transition is hard identify leading to a lower t-statistic of ϕ. Nevertheless, there seems to be a tendency that bigger observed returns force survey participants to apply smaller return correction coefficients (Panel d in Figure 2).

The final two specifications allow for a systematic change of the persistence parameter of forecasts. Panel e and f of Figure 2 imply that forecasting persistence decreases in a market environment characterized by positive misalignments and negative returns. Suggesting that overvaluations outnumber undervaluations the above configuration just reflect the fact that inflating bubbles typically takes more time than a bust. However, it should be noted that neither of the ϕ coefficients is statistically significant.

5 Time Variation and Cross-Sectional Differences

Time-varying results

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 with the actual stock price misalignment $(s_t - f_t)$ is shown in Figure 3.

[Figure 3 about here]

The Figure reveals stabilizing expectations of survey participants in the sense that high absolute mean reversion coefficients coincide with large misalignments. However, small deviations of the actual stock price from its fundamental value are expected to diminish slowly. As a result, forecasters seem to be well aware of the fact that stock prices exhibit a unit root in the short run, but tend to be mean reverting over longer periods of time.

[11] This number coincides with the linear terms of the other models.

Individual groups

In order to account for differences among four groups of stock price forecasters, we estimate our linear model for each group separately. The results based on the fixed-effects estimator is reported in Table 3. The results suggest that the linear model is remarkable robust among the different groups. Interestingly academics seem to have the highest impact while they show the lowest auto-regressive component.

[Table 3 about here]

6 Conclusion

Based on the estimated fundamental value of U.S. stock prices we show that forecasts collected by the Livingston survey reveal substantial nonlinearities. For instance, expected mean reversion strengthens as misalignments grow, while recent returns are expected to be corrected depending on the size and the sign of the stock price change. Together with a strong forecast persistence the empirical results reflect so-called fundamentalist expectations typically observed for longer-run predictions. Our results clearly do not imply a violation of market efficiency, but they suggest that accounting for forecasts of macroeconomic data is an interesting avenue for future research on real-time stock return predictability.

In future research, it could be interesting to extend our empirical analysis in several directions. One direction would be to explore the cross-sectional dimension of survey data of forecasts of macroeconomic variables. We have focused in our empirical analysis on the predictive power of the cross-sectional mean of survey data to predict stock returns. Survey data, however, also feature a rich cross-sectional dimension, and it is interesting to study whether this cross-sectional dimension provides further insights that are useful for the real-time forecasting of stock returns. A link between stock returns and the cross-section dimension of survey data could arise if the latter captures disagreement and uncertainty among forecasters, which may impact on the equity risk premium.

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Table 1: Nonlinearity-Tests

Variables		Sample starting from ...				
Regressor	Transition	1958	1970	1980	1990	2000
mis	mis	1.949	1.958	5.586	2.316	3.693
		(0.121)	(0.120)	(0.001)	(0.077)	(0.015)
mis	return	5.132	1.804	2.283	9.680	1.397
		(0.002)	(0.146)	(0.080)	(0.000)	(0.250)
return	mis	2.396	0.796	0.669	2.599	3.445
		(0.068)	(0.497)	(0.572)	(0.054)	(0.020)
return	return	3.535	1.560	1.329	4.960	0.563
		(0.015)	(0.199)	(0.266)	(0.003)	(0.641)
pers	mis	3.098	5.654	1.263	1.564	0.872
		(0.027)	(0.001)	(0.288)	(0.200)	(0.459)
pers	return	2.282	0.988	2.186	2.933	1.356
		(0.079)	(0.399)	(0.090)	(0.035)	(0.262)

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 $(s_t - f_t)$, 'return' 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 semia-nnually expectations of the Livingston S&P stock market survey from June 1958 to December 2011.

Table 2: Parameter estimates of the Panel STR model

Parameter	Model					
	mis/mis	mis/ret	ret/mis	ret/ret	pers/mis	pers/ret
$\beta_{0,pers}$	0.515	0.540	0.537	0.535	0.491	0.430
	(25.569)	(36.399)	(23.374)	(27.289)	(15.811)	(2.875)
$\beta_{0,mis}$	-0.096	–	-0.034	-0.033	-0.025	-0.034
	(5.523)		(28.953)	(29.760)	(8.990)	(27.248)
$\beta_{0,ret}$	-0.113	-0.134	–	–	-0.120	0.184
	(9.409)	(11.112)			(10.320)	(0.609)
$\beta_{1,trv}$	0.078	-0.058	0.121	-0.220	-0.096	-0.155
	(8.741)	(13.649)	(9.856)	(9.430)	(3.395)	(11.650)
ϕ	5.854	-11.692	-396.578	-3.491	11.305	12.251
	(2.170)	(3.637)	(2.791)	(1.825)	(1.353)	(0.454)
R^2	0.517	0.515	0.507	0.515	0.512	0.510
PC	0.979	0.994	0.142	0.365	0.981	0.691
$NRNL$	0.226	0.014	0.101	0.189	0.673	0.074

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 2011.

Table 3: Parameter estimates of the linear model for different groups

Group	Full sample	Academics	Commercial Banks	Investment	Non-financial
y_{t-1}	0.1696*	0.1373*	0.1897*	0.1850*	0.1606*
	(.02)	(.04)	(.04)	(.04)	(.04)
w_t	0.7728*	0.8081*	0.7430*	0.7714*	0.7741*
	(.02)	(.03)	(.03)	(.04)	(.04)
Adj. R^2	0.9822	0.9854	0.9833	0.9797	0.9806
Observations	108	108	108	108	108

Notes: *LLh* is the log likelihood value. *NRNL* is the lowest p-value for no remaining nonlinearity up to ten lags. t-statistics in parentheses are based on robust estimates of the covariance matrices of the parameter estimates. $^{*}(^{+})$ denotes significance at the 1% (10%) level. The sample contains semi-annually expectations of the Livingston S&P stock market survey from June 1958 to December 2011.

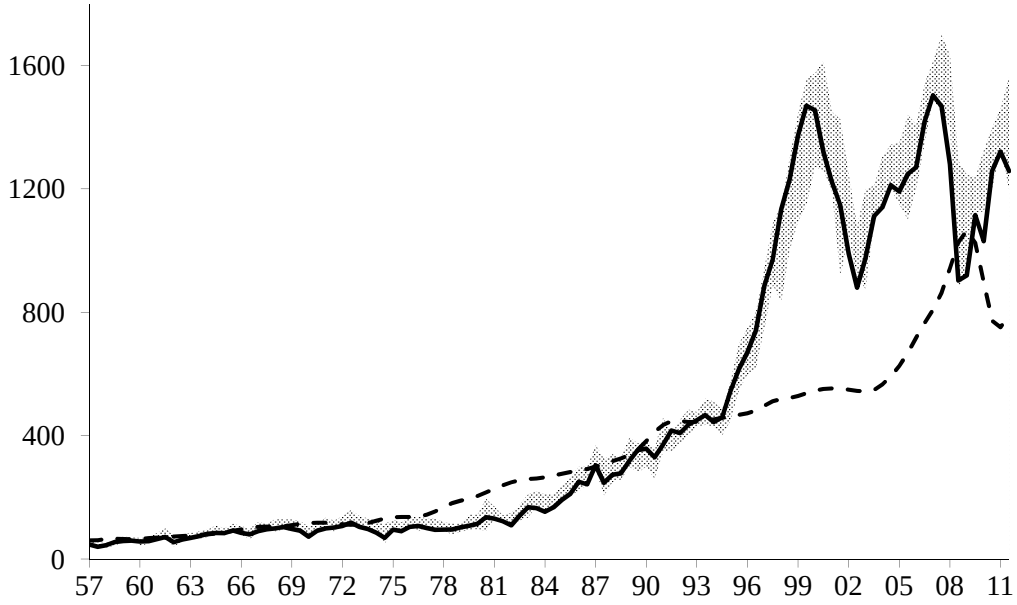

Figure 1: S& P Forecast Range, actual value and fundamental value
Notes: Figure 1 shows the stock market index (solid line), the fundamental value (dashed line), and the range of forecasts of the four groups (shaded area).

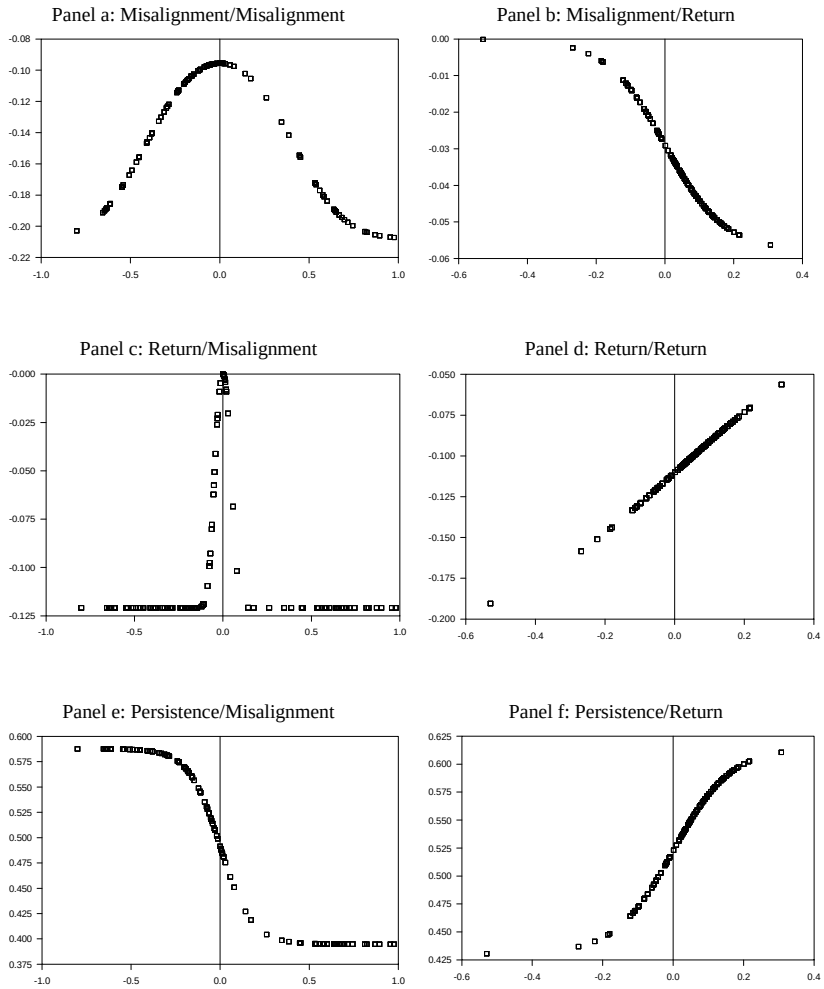

Figure 2: Transition functions

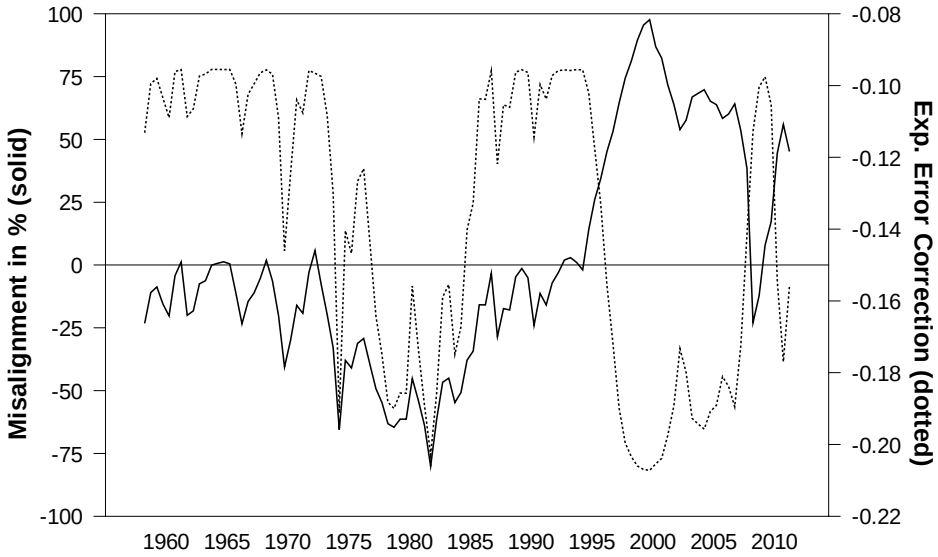

Figure 3: Time dynamics of Expected Mean Reversion