



FINANCIAL ANALYSTS' FORECASTS
LESSONS FROM THE CRISIS

A DISSERTATION PRESENTED
BY

JAN PETER SCHMÜTSCH

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Contents

List of Tables	IV
List of Figures	V
List of Symbols and Abbreviations	VI
1 Introduction	1
2 Euro Stoxx 50 Forecasts and the Business Cycle:	
Revisiting Rationality	4
2.1 Introduction	4
2.2 Data	8
2.3 Methodology and Hypotheses	11
2.3.1 Modeling an Asymmetric Loss Function	11
2.3.2 Hypotheses and Underlying Theory	13
2.4 Results	15
2.4.1 EPS forecasts under asymmetric loss	15
2.4.2 Rationality Under Asymmetric Loss	16
2.4.3 Influence of Institute, Company, and Country Effects	17
2.4.4 Impact of Macroeconomic Cycles	19
2.4.5 Robustness Tests	22
2.5 Conclusion	26
2.6 Appendix	27
3 Are DAX EPS Forecasters Really Irrational?	35
3.1 Introduction	35
3.2 Data	36
3.3 Methodology and Hypotheses	38

3.3.1	Deriving a Forecaster’s Loss Function	38
3.3.2	Hypotheses and Underlying Theory	40
3.4	Results	42
3.4.1	Forecaster Sentiment	42
3.4.2	Rationality Under Asymmetric Loss	43
3.4.3	Impact of Institute and Company Effects	44
3.5	Conclusion	45
3.6	Appendix	46
4	EPS Forecasts: Herding, Optimism, and the Business Cycle	51
4.1	Introduction	51
4.2	Data	52
4.3	Methodology and Theory	54
4.3.1	Detecting Forecaster Optimism	54
4.3.2	Detecting Forecaster Herding	56
4.3.3	Assessing the Bias Impact	58
4.4	Results	60
4.4.1	Optimism and Forecast Accuracy	60
4.4.2	Herding Bias	64
4.4.3	Impact of Biases on Forecast Error	66
4.5	Conclusion	67
4.6	Appendix	68
5	Conclusion	74
	Bibliography	IX

List of Tables

2.1	Descriptive Statistics of Euro Stoxx 50 Forecasts	29
2.2	Asymmetry Parameter and Rationality Tests (Full Sample)	30
2.3	Asymmetry Parameter for Each Company (Quadratic)	31
2.4	Asymmetry Parameter for Each Industry (Quadratic)	32
2.5	Asymmetry Parameter for Each Country	33
2.6	Rationality Test for Each Country	34
3.1	Descriptive Statistics of DAX 30 Forecasts	37
3.2	Asymmetry Parameter and Rationality Test According to Forecast Horizon	48
3.3	Asymmetry Parameter and Rationality Test According to Business Cycle	49
3.4	Asymmetry Parameter for Each Company (Quadratic)	50
4.1	Descriptive Statistics of Dow Jones Industrial 30 and DAX 30 Forecasts	53
4.2	<i>S</i> -Statistic	65
4.3	Constituents and Descriptive Statistics (Dow Jones Industrial 30) . .	68
4.4	Constituents and Descriptive Statistics (DAX 30)	69
4.5	Prognoses and Forecast Errors by Year	72
4.6	Regression of Forecast Error Scaled to Stock Price	73

List of Figures

2.1	Cumulated share of total forecasts	8
2.2	Sample Illustration of Cross-Sectional Range of Euro Stoxx 50 Forecasts	10
2.3	Average Forecast Error by Release Date	11
2.4	Rationality Tests for Individual Forecasters	17
2.5	Linear and Quadratic Loss Function	20
2.6	Time-Varying Symmetry Parameter $\hat{\alpha}$ (Linear)	21
2.7	Time-Varying Symmetry Parameter $\hat{\alpha}$ (Quadratic)	22
2.8	Asymmetry Parameter per Forecaster (Linear)	27
2.9	Asymmetry Parameter per Forecaster (Quadratic)	28
3.1	Sample Illustration of Cross-Sectional Range of DAX 30 Forecasts . .	38
3.2	Rationality Test of Standard and Alternative Loss Parameters per Forecaster	44
3.3	Asymmetry Parameter per Forecaster (Linear)	46
3.4	Asymmetry Parameter per Forecaster (Quadratic)	47
3.5	Asymmetry Parameter and Times of Restored Rationality	47
4.1	Forecast Error Density Restricted to $<5\%$	55
4.2	Forecast Error by Year	61
4.3	Forecast Error by Month	62
4.4	Monthly S -Statistic for Dow Jones EPS Forecasts	70
4.5	Monthly S -Statistic for DAX EPS Forecasts	71

List of Symbols and Abbreviations

α	Asymmetry parameter
\bar{E}	Consensus prognosis
β	Regression coefficient
χ^2	Chi-squared distribution
ϵ	Regression error term
γ	Vector valued function
$\hat{\alpha}$	Estimated asymmetry parameter
$\hat{\beta}$	Estimated regression coefficient
\hat{E}	Prognosed value
$\hat{E}(\cdot)$	Expected value
\hat{h}	Auxiliary matrix
\hat{S}	Weighting matrix
$\mathbb{1}_{\{\cdot\}}$	Indicator function
$\mathcal{N}(\cdot)$	Normal distribution
τ	Time index
v	Vector of instruments
d	Number of instruments
DF	Degrees of freedom
E	Actual value

f Forecast
 F -value Hypothesis test statistic
 FE Forecast error
 FEK Kurtosis of forecast error
 FES Skewness of forecast error
 i Company index
 j Forecaster index
 $J(\cdot)$ Test for rationality
 L Loss function
 $LN(ANA)$ Natural logarithm of number of forecasts
 $LOSS$ Binary negative consensus forecast variable
 n Number of data points
 P Probability
 p Exponent of loss the function
 p -value Exceedance probability
 R^2 Coefficient of determination
 REC Binary recession variable
 S Herding statistic
 s Actual earnings
 SE Standard error
 T Number of forecasts
 t Time index
 t -statistic Hypothesis test value of t -distributed sample
 z Standard score
 cf. Confer
 DAX 30 Deutscher Aktien Index; German stock index

DJI Dow Jones Industrial index
e.g. Exempli gratia; for example
ECRI Economic Cycle Research Institute
EPS Earnings per share
et al. Et alii; and others
FYE Fiscal year end
GDP Gross Domestic Product
i.e. Id est; that is
IBES Institutional Broker Estimate System
IPO Initial public offering
M&A Mergers and acquisitions
NBER National Bureau of Economic Research
OLS Ordinary least squares
p. Page
pp. Pages
SIC Standard industrial classification
SP Stock price
U.S. United States

Chapter 1

Introduction

William Sharpe asserted us that “there is a relationship between expected returns and specific attributes of securities, where all such measures are *forward looking predictions*”.¹ Put differently, the stock market comprises predictions of analysts and investors, which if combined provide part of the information ultimately shaping the prices of single stocks.

Research on analyst output is extensive and mainly covers the rationality and the impact of forecasts.² The recent financial turmoil unveiled multi-faceted shortcomings in analyst output. Strikingly few analysts foresaw the hit that balance sheets on both sides of the Atlantic were to take. Even fewer adjusted their prognoses for the windfall profits companies made in the recovery that followed in time. Up until recently, forecasting researchers favored to explain the observed misjudgement through a *mélange* of analyst biases and irrationality (Shiller, 2000; Devenov and Welch, 1996).

One of the main biases discussed is forecaster herding. Several studies for a number of markets observe persevering anti-herding (Pierdzioch and Rülke, 2012; Naujoks et al., 2009). Yet there is no mutual consent on the impact the bias has on market efficiency or the quality of an individual forecast. Whilst Mewis (2000) highlight better dispersion of information and Ryan and Taffler (2004) point at the significance

¹Cf. Sharpe (1985), p. 438.

²For instance, Ramnath et al. (2008) distinguish between seven different streams of literature, i.e., “analysts’ decision processes, the nature of analyst expertise and the distributions of earnings forecasts, the information content of analyst research, analyst and market efficiency, analysts’ incentives and behavioral biases, the effects of the institutional and regulatory environment (including crosscountry comparisons), and research design issues”(p.34).

of analyst output for abnormal returns, Bhattacharya et al. (2012) question that there is any impact at all.

On a different note, there is a multitude of authors dealing with the rationality of forecasts. For instance, Laster et al. (1999) and Lamont (2002) describe what analysts truly seek to optimize. Far from delivering an unbiased estimate, their main goal is the optimization of a loss function that incorporates elements of accuracy, publicity gains, and financial remuneration. Here, positive and negative deviations yield the same loss. However, as Elliott et al. (2008) point out, taking such symmetric loss concepts as a starting point for assessments of rationality may be flawed as it might very well be that analysts seek to minimize an asymmetric loss function, i.e., do not attribute the same absolute loss to positive and negative digressions. This radical shift in perspective calls the long-reigning idea of irrational forecasts into question and initial empirical evidence in favor of this theory was provided in, e.g., Christodoulakis and Mamatzakis (2008) and Aretz et al. (2011).

Despite an increase in the number of studies, many relations and markets remain unaccounted for. Specifically, what is missing is the introduction of advanced econometric methods in order to detect biases in the forecasts for international companies and to assess the influence of crises on forecasters and the rationality of their forecasts. In other words, this thesis asks how economic crises and biases in financial analysts' forecasts interact over time and whether this can be attuned with standard and alternative concepts of rationality. In order to answer this overarching research question, the present thesis comprises three different chapters, that deal with the stated aspects as follows.

In a first step, we turn towards an assessment of forecasts for European companies. Using about 100,000 EPS forecasts for companies listed in the Euro Stoxx 50, we uncover the loss function of individual financial analysts by using the method presented in Elliott et al. (2005). Our results suggest that EPS forecasters on average have an asymmetric loss function and perceive underprojections of EPS to be more costly than overprojections. In addition, we report a strong degree of heterogeneity concerning the loss function among individual institutes, forecasted companies, and over time. In times of economic distress, EPS forecasters attribute an overestimation to a loss four times the size of a similarly dimensioned underprediction. This contributes to explain why forecasters prefer to submit pessimistic EPS projections in times of recession. In contrast to that, we report an almost symmetric loss function for the full sample reflecting the forecasters' general ambition to produce an accu-

rate forecast. Moreover, the number of rational forecasters doubles when assuming flexible loss compared to a standard symmetric loss function.

Allowing for an international comparison, we thereafter conduct a similar analysis with an exclusively German sample in order to recognize systemic characteristics. To this end, we rely on a sample of some 110,000 EPS forecasts for companies listed in the DAX 30 index, in order to estimate the loss function of individual financial analysts sticking to the Elliott et al. (2005) method as we want to ensure comparability. We conclude that forecasters have an asymmetric loss function and are on average too optimistic. In addition, we report that an asymmetric loss does attune rationality and empirical evidence for selected years. In comparison to a symmetric loss function, alternative loss concepts increase the number of rational forecasters threefold. Additionally, we can show that rationality is independent of the business-cycle and the targeted company but is formed on the institute level with the degree of asymmetry influenced by all three factors.

In a next chapter, we want to augment the analysis for a study of the most commonly discussed biases. Motivated by theories taken from the fields of monetary economics and forecasting research, we enquire into presence and impact of herding and optimism biases building on a data set of some 235,000 EPS forecasts covering companies listed in the Dow Jones Industrial Average and the DAX 30 indexes. Employing a recent detection method, we show that irrespective of the index anti-herding prevails and that it is more pronounced for longer forecast periods. On average, prognoses are overly optimistic and even more so during periods of economic distress. Additionally, we report that theories on seasonal accuracy do not per se hold true for DAX forecasts. Moreover, the median forecast error is consistently smaller for companies listed in the Dow Jones index, while estimate errors for German companies show a higher dispersion. Ultimately, we reveal that forecast accuracy is significantly driven by the state of the business cycle, the herding bias, and the consensus forecast.

At the end of the day, it is striking to what extent the business cycle determines the characteristics of EPS forecasts. The interaction of some of these biases and the state of the economy do not come as a full surprise. Rather, it is the persistence and reoccurrence in an international context that astonishes. Up to a certain extent, our findings are explorative, especially those that deal with cyclical asymmetry of forecasters' loss functions. Building hereupon, we provide some concluding remarks and recommend avenues for future research in the final chapter.

Chapter 2

Euro Stoxx 50 Forecasts and the Business Cycle: Revisiting Rationality¹

2.1 Introduction

The analysis of forecast rationality has long been determined based on symmetric loss functions that weight positive and negative deviations equally (Ito, 1990). Results based on such approaches regularly fail to find evidence of rationality. However, the recent literature has been augmented by alternative approaches that allow for asymmetric loss attributions and can potentially harmonize empirical data and concepts of rationality. Markedly, a well received model has been brought forward by Elliott et al. (2005). Thus far, the method has been chiefly employed in studies considering forecasts for macroeconomic variables (Pierdzioch and Rülke, 2012; Pierdzioch et al., 2013a). All of these papers rely on a finding by Elliott et al. (2008) that the use of symmetric rationality criteria is not appropriate when the loss function actually follows an asymmetric pattern. It has been well-known for quite a while that there are good reasons to argue that loss functions are asymmetric (Granger, 1969; Granger and Newbold, 1986; Zellner, 1986; Christoffersen and Diebold, 1997). Indeed, recent research provides ample evidence indicating that deviations from a

¹This chapter is based on the homonymous working paper co-authored by Markus Rudolf and Jan-Christoph Rülke (Schmütsch et al., 2013b).

symmetric loss function may be quite common (Elliott et al., 2005; Christodoulakis and Mamatzakis, 2008; Döpke et al., 2010; Sinclair et al., 2010).

One of the most prominent questions for investors and regulating bodies in the financial markets is therefore whether earnings per share (EPS) forecasts are rational and what loss concept best resembles the witnessed outcome. Since rationality can only be tested on a certain model specification (joint hypothesis), it is reasonable to use a model specification which allows a substantial amount of flexibility. Opposed to traditional rationality tests, which assume a symmetric loss function, we test rationality based on a flexible loss function, which might help to remedy the violation of forecast rationality. Additionally, we study how this flexibility can be exploited by analyzing the impact the macroeconomic cycle on the forecasting behavior.

The notion that analyst recommendations are potentially biased and irrational has long reigned the literature. Authors considered those forecasts efficient that promptly process novel information.² Rationality is traditionally tested through a Mincer-Zarnowitz regression, which minimizes a (symmetrical) mean squared error loss function. Accordingly, biases are referred to as systematic over- or underreaction to new information.³

We complement this stream of literature and build on the concept of asymmetric loss (Elliott et al., 2008). The idea has merit, as asymmetric loss functions have properties that might provide ways to attune the observed behavior and concepts of rationality. Most importantly, systematic forecast errors are not perceived as irrational behavior per se. While under traditional rationality criteria a forecast bias reflects irrational behavior, under an asymmetric loss function the forecast bias might look more rational. For instance, Patton and Timmermann (2007) report that the Federal Reserve Bank perceives overprojections of the growth rate to be more costly than underprojections which explains why the Fed issues conservative estimates of economic growth. They find non-optimal forecasts of the Federal Reserve under symmetric loss while allowing the loss function to depend on the forecast and the realization separately they found no evidence against optimality.⁴ Such a fore-

²Cf. Easterwood and Nutt (1999) for a sample definition.

³Cf. Abarbanell and Bernard (1992) for a discussion of motives for underreaction and DeBondt and Thaler (1990) for evidence on overreactions.

⁴Pierdzioch et al. (2012) report that the inflation forecasts published by the Bank of Canada are rational although the forecasts are systematically above the actual value. A reason for this finding might be that the Bank of Canada signals their willingness to fight inflation by providing to optimistic growth forecasts.

cast bias might be rational if the loss function does not solely depend on the forecast error. A number of studies explain why forecasters might have such rational bias. The line of reasoning include arguments such as reputation, financial compensation, incentives, product differentiation, or forecasting competition.

Explanations for why analysts have incentives to deviate from their best estimates are manifold. For instance, Batchelor and Dua (1990) find that it is rational for forecasters to differentiate their forecast product. Ottaviani and Sørensen (2006) argue that forecasters are subject to a forecasting tournament, which increases the forecast heterogeneity. An early attempt to show that optimism can be consistent with rationality has been provided by Easterwood and Nutt (1999), who find two potential explanations. Firstly, as the majority of analysts works for a brokerage house there is a catalyst for exaggerated prognoses that might drive trading volumes up. Secondly, they reason that negative prognoses for a company might trigger adverse reactions from the top management of this company and consecutively block access to prime information sources at the executive level.

Our findings may proof helpful for a number of agents in the financial forecasting process. Firstly, it is appealing to investors using EPS forecasts as a rational forecast bias might yield to undesired investment decisions. Identifying this bias and taking it into account might help to remedy the misinterpretation of financial forecasts. As a consequence, an underreaction to analyst forecasts might decrease excess volatility in the stock market. Secondly, the research directs itself at the regulating bodies, which might encounter innovative approaches to tackle the perceived problem of excess volatility in this paper. Policy makers currently discuss compensation schemes in the financial industry. Our study shed light on how analysts' compensation should be designed. In particular, we show that analysts' compensation should be decoupled from a company's overall success, which in turn is fueled by higher trading volumes and should rather be determined by forecast accuracy. Thirdly, financial analyst themselves can find the research encouraging in a way that they are willing to deviate stronger from the outstanding consensus forecast and hence generate more accurate prognoses. Eventually, the results are of interest for academia as we investigate the properties of EPS forecasts. Hence, to better understand the European financial market a deeper look into how EPS forecasts are made is warranted. Finally, our results are encouraging for academic scholars, who model financial markets' behavior based on the rational expectations hypothesis. While traditional tests of rational expectations tend to provide evidence of irrational expectations, we contribute to

this discussion by showing that biased EPS forecasts are not necessarily irrational.

Although our findings are relevant to a number of stakeholders in the forecasting process, investors are likely to benefit the most. As Ryan and Taffler (2004) show that trading volume and abnormal returns are driven by analyst output, it is well worth studying if and to what extent analysts submit their forecasts under an asymmetric loss function. If, for instance, analysts associate an underprojection of EPS with a higher loss than an overprojection, it is quite rational for an analysts to submit an optimistic, i.e., biased EPS forecast. Those forecasts in turn, might yield a misallocation of investors' money. If investors are not aware of asymmetric loss optimization nor its impact over the business cycle, such a misallocation in the financial market might be meaningful in macroeconomic terms as it hinders economic growth and shakes financial stability. Contrary to that, investors who are aware that EPS forecasts are made under asymmetric loss should be able to promote market efficiency. Therefore, one task of this study is to strengthen market efficiency by investigating whether EPS forecasts are made under asymmetric loss.

We rely on an approach disseminated in Elliott et al. (2005) in order to encounter evidence for asymmetric loss in a comparatively large panel of forecasts for earnings of companies in the Euro Stoxx 50 collected by the Institutional Brokers Estimate System (IBES) for the time span of 2000 until 2011. Our findings provide ample support for the notion that more forecasts are made optimizing an asymmetric than a symmetric loss function. In addition, we find that changes in asymmetry coincide with expansions and recessions in the sample. We conclude that periods of economic expansion favor optimistic forecasts while recessions lead to overly pessimistic ones.

This paper contributes to the research on analyst behavior through introducing the idea of cyclical asymmetry and employing a recent loss function analysis method to an exhaustive dataset of Euro Stoxx 50 EPS forecasts. To the best of our knowledge, this is the first time that cyclical asymmetry and European forecasts are analyzed in this respect. Previous research on potential asymmetry has either focused on U.S. data for shorter time horizons or relied on less advanced methods.⁵

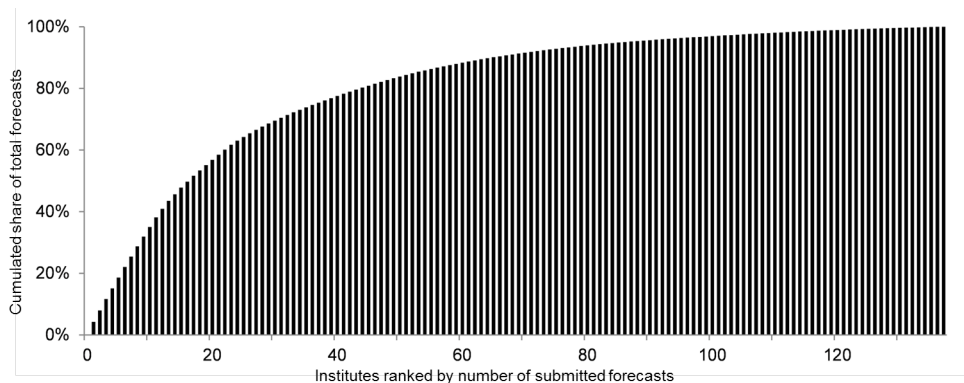
The remainder of the paper is organized as follows. While section 2.2 describes our data set, section 2.3 briefly outlines and motivates our hypotheses and presents our model. Thereafter, section 2.4 reports the empirical findings and some robustness tests. Finally, we offer some conclusions in section 2.5.

⁵Cf. inter alia Aretz et al. (2011) and Clatworthy et al. (2012).

2.2 Data

We use EPS forecasts provided by IBES to estimate the parameters of the analysts' loss function. The EPS forecasts refer to projections for companies that constitute the Euro Stoxx 50 index in the sample period January 2000 – December 2011. During this time period a total of $n = 105,052$ forecasts were submitted for a total of 76 companies listed in the index by 289 institutes.⁶ Each of the individual forecasting institutes, anonymously yet identifiable predicts a company's EPS for the respective fiscal year. Therefore, the forecasting horizon may vary between a maximum of 11 and a minimum of 1 month. Despite the large number of data points, our data set is unbalanced as neither all of the considered companies are included in the index for the full amount of years nor all forecasting institutes provided forecasts regularly.

Figure 2.1: Cumulated share of total forecasts



Note: The x-axis shows all institutes ranked by number of submitted forecasts while the y-axis shows the cumulated share of total forecasts.

Figure 2.1 is a histogram illustrating the unbalancedness of the panel. It contrast the forecasting institutes ranked by order with the cumulated share of total prognoses. Evidently, about half of all forecasts were contributed by the 20 largest institutes. On the other end of the distribution, a multitude of forecasting institutes delivered only a few dozens of prognoses. As no meaningful estimation of the shape of an asymmetric loss function can be made with only such a small amount of data points, we used only those forecasting institutes and those companies for which at least 40 EPS forecasts are available.⁷ This applies to 137 forecasting institutes and 64

⁶The number of companies excludes variations in spelling, rebranding, and changes of company's name that are included in the original IBES dataset.

⁷Of course, the threshold value is arbitrary but it enables us to keep a sufficiently large number of both forecasters and forecasts in the sample while estimating robust asymmetric loss functions. Results based on different participation rates are quantitatively similar and available upon request.

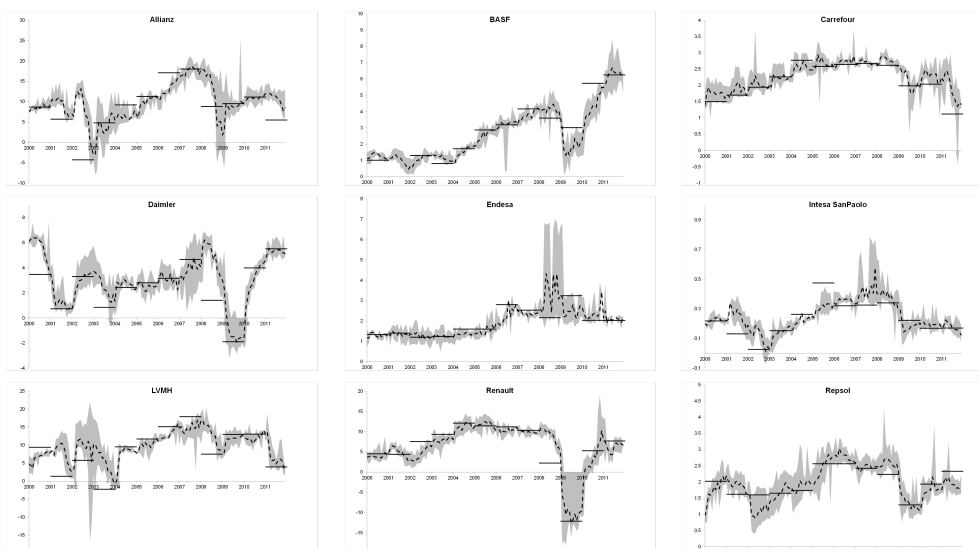
companies, which yields a total of 95,580 EPS forecasts. Additionally, we retrieved actuals from the IBES details database.

For assessing the impact of macroeconomic conditions on the symmetry of the loss function, we define periods of economic distress. As we think consistency in the recession definition is desirable, all recession peak and through dates are defined in accordance with Economic Cycle Research Institute (2012). The Economic Cycle Research Institute (ECRI) is a private data provider that resembles the NBER recession definition for a number of countries outside the U.S. that matches the official definitions remarkably well. Data provided by the ECRI has been used in a number of publications, *inter alia*, Sensier et al. (2002). Note that we distinguish between expansion and recession cycles on a country level basis rather than using a European aggregate definition. This renders it possible to account for country-specific effects.

Figure 2.2 plots the time series of (i) the cross-sectional range of EPS forecasts (shaded area), (ii) the consensus forecast (dotted line), and (iii) the actual EPS value (solid lines) for a sample of 9 companies. During the recession of 2008-2009 most companies experienced a substantial fall in EPS, while forecasters adjusted their predictions with a certain time lag which yield too optimistic EPS forecasts during that time period. Figure 2.2 reports, a strong degree of heterogeneity among the EPS forecaster. The cross-sectional average of EPS forecasts broadly moves in tandem with the actual EPS value. The scattering of forecasts around the cross-sectional average of forecasts, however, is substantial. The cross-sectional heterogeneity of forecasts is relatively small for, e.g., Repsol indicating that company specific characteristics may contribute to the forecasters disagreement on the future EPS. As we shall report in Section 2.4, the forecasters' heterogeneity of asymmetric loss may help to explain at least in part the cross-sectional heterogeneity of forecasts.

The vertical distance between actual value and the forecast can be interpreted as the forecast error defined as $s_{t+1} - f_{t+1}$ (where s_{t+1} is the the actual EPS in period $t + 1$ and f_{t+1} its prognosed value at time t), which is particularly large during the recent economic and financial crisis. For instance, in October 2008 the forecasts for Endesa range between 2.21 and 7.01 while the actual value was 2.16. This indicates a strong degree of disagreement among the forecasters which yield in substantial differences of individual forecast errors. Table 2.1 reports for each company the number of observations, the cross-sectional averaged forecast errors as well as its standard errors for the whole sample period and for the sample of expansion and recession periods.

Figure 2.2: Sample Illustration of Cross-Sectional Range of Euro Stoxx 50 Forecasts



Note: The selected charts illustrate the dispersion of forecasts given by month (shaded area), the average estimate (dotted line), and actual EPS values as of fiscal year end (solid line).

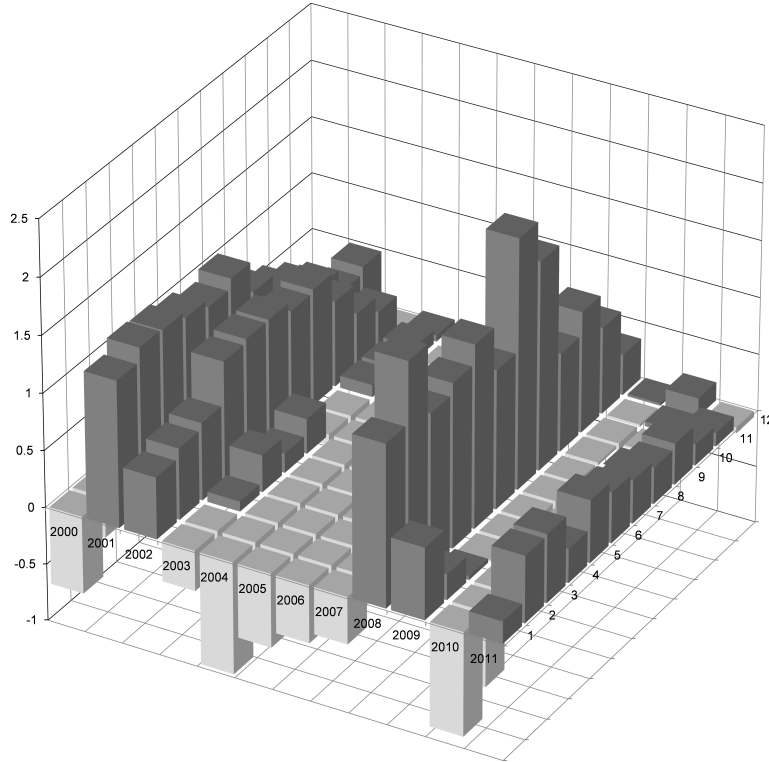
The table reports that for the full sample period as well as on a company level, EPS forecasts are significantly biased. More precisely, the forecasters overprojected the EPS over the whole sample period as indicated by the coefficient of -0.194 . Compared to this, in expansion periods the forecast error is not significantly different from zero and simultaneously positive and negative forecast errors are relatively balanced indicating that during expansion periods, forecasters try to target the actual value of EPS dynamics. In contrast, in times of economic recession the forecast error is negative by about -0.656 for all companies together as well as for 39 companies while only for 8 companies forecasters have overprojected EPS contraction periods. Also note that according to standard unit root tests all EPS series are stationary.

Moreover, Figure 2.3 illustrates the monthly forecast error. One can easily grasp two developments. Firstly, the forecast errors are positive, indicating the time lag leading to overly optimistic forecasts in crises years such as 2008. Secondly, the forecast errors tend to diminish in the course of each fiscal year, as more information is funneled into the forecasts elevating their prognostic power.

As of late, the IBES data have been reviewed critically, with a focus on three major deficiencies, i.e., deletions and additions, anonymizations, and alterations.⁸ We are

⁸Cf. Ljungquist and Marston (2009), pp. 1957-1959.

Figure 2.3: Average Forecast Error by Release Date



Note: The chart shows forecast errors defined as $s_{t+1} - f_{t+1}$ expressed in Euro, sorted by months of the respective year. Dark grey columns show positive, light grey ones negative deviations.

aware of the problems, that may result from such uncommon biases especially, when trying to gather information concerning the past state of mind. Notwithstanding the critique brought forward concerning data for the time period 2001-2007, we are confident that Thomson Financial as the current owner of the IBES panel has succeeded in rebuilding an “as-was” database.⁹

2.3 Methodology and Hypotheses

2.3.1 Modeling an Asymmetric Loss Function

To model the forecasters’ loss function we apply the approach developed by Elliott et al. (2005), who assume that the loss function, L , of a forecaster can be expressed

⁹Cf. Ljungquist and Marston (2009), pp. 1938-1939.

as:

$$L = [\alpha + (1 - 2\alpha)\mathbb{1}_{\{s_{t+1}-f_{t+1}<0\}}]|s_{t+1} - f_{s+t}|^p, \quad (2.1)$$

where s_{t+1} (f_{t+1}) reflects the (period t forecast of) the EPS in period $t + 1$ and $\mathbb{1}$ refers to an indicator function. The parameter p governs the functional form of the loss function, i.e., a linear loss function ($p = 1$) or a quadratic loss function ($p = 2$). The parameter $\alpha \in (0, 1)$ reflects the degree of asymmetry of the loss function, where a symmetric loss function is given if $\alpha = 0.5$.¹⁰

Elliott et al. (2005) show that, for a given parameter p the asymmetry parameter α can be consistently estimated by means of a generalized method of moments approach as expressed as:

$$\hat{\alpha} = \frac{\gamma_1' \hat{S}^{-1} \gamma_2}{\gamma_1' \hat{S}^{-1} \gamma_1} \quad (2.2)$$

where we define

$$\gamma_1 = \left[\frac{1}{T} \sum_{t=\tau}^{T+\tau-1} v_t |s_{t+1} - f_{t+1}|^{p-1} \right]$$

and

$$\gamma_2 = \left[\frac{1}{T} \sum_{t=\tau}^{T+\tau-1} v_t \mathbb{1}_{\{s_{t+1}-f_{t+1}<0\}} |s_{t+1} - f_{t+1}|^{p-1} \right]$$

and the vector of instruments v_t is used to estimate the weighting matrix given by $\hat{S} = \frac{1}{T} \sum_{t=\tau}^{T+\tau-1} v_t v_t' (\mathbb{1}_{\{s_{t+1}-f_{t+1}<0\}} - \hat{\alpha})^2 |s_{t+1} - f_{t+1}|^{2p-2}$. The number of forecasts starting at period $t = \tau + 1$ is given by T . We considered as instruments a constant (model 1), a constant and the lagged EPS value (model 2), a constant term and the lagged long-term government yield (model 3) and a constant term and the lagged redemption yield (model 4). These financial variables can be regarded to be economically meaningful EPS forecast errors and hence, are appropriate to estimate the EPS forecasters' loss function. When the weighting matrix depends on $\hat{\alpha}$, estimation is done iteratively.

Testing whether $\hat{\alpha}$ differs from α_0 ($=0.5$) is done by using the following z-test $\sqrt{T}(\hat{\alpha} - \alpha_0) \rightarrow \mathcal{N}(0, (\hat{h}' \hat{S}^{-1} \hat{h})^{-1})$, where $\hat{h} = \frac{1}{T} \sum_{t=\tau}^{T+\tau-1} v_t |s_{t+1} - f_{t+1}|^{p-1}$. Elliott et al. (2005)

¹⁰For $\alpha = 0.5$ and $p = 2$, the forecaster's loss increases in the squared forecast error. For $\alpha = 0.5$ and $p = 1$, the loss increases in the absolute forecast error. The binary values for p are an assumption made in Elliott et al. (2005). Indeed, other functional forms can be imagined but may be of arbitrary theoretical value and hard to combine with the envisioned methodology.

prove that testing for forecast rationality can be done by computing

$$J(\hat{\alpha}) = \hat{E} \frac{1}{T} \left(x'_t \hat{S}^{-1} x_t \right) \sim \chi_{d-1}^2, \quad (2.3)$$

where $x_t = \sum_{t=\tau}^{T+\tau-1} v_t [\mathbb{1}_{\{s_{t+1}-f_{t+1}<0\}} - \hat{\alpha}] |s_{t+1} - f_{t+1}|^{p-1}$ and d refers to the number of instruments. For a symmetric loss function, one can write $J(0.5) \sim \chi_d^2$ which provides a test whether forecasters under the assumption of a symmetric loss function form rational forecasts. For a linear or quadratic loss function, the test, $J(\hat{\alpha})$, shows whether forecasters form rational forecasts under an asymmetric loss function.

2.3.2 Hypotheses and Underlying Theory

Our conceptual framework builds on studies modeling forecasters' loss function (Laster et al., 1999; Elliott et al., 2008). Such models typically show how forecasters' efforts to simultaneously serve different segments of their addressees can lead to biased projections. Only if all forecasters have similar information and seek accuracy consistent with the demands of intensive users their best estimate will be an unbiased predictor of the future realization. More specifically, we assume that the loss L of an inaccurate forecast is a function of the forecast error: $L(f_{t+1}) = L |s_{t+1} - f_{t+1}|^p$ where p is the degree of nonlinearity, $f_{t+1}(s_{t+1})$ is the forecast (actual value) of the EPS of a specific company for period $t + 1$ and the term $|s_{t+1} - f_{t+1}|$ denotes the absolute forecast error. For $p = 1$ ($p = 2$) the loss of the forecaster increases linear (quadratic) in the forecast error. If the forecast turns out to be accurate the loss is zero ($L = 0$) while any inaccurate forecast yield a loss ($L > 0$).

Hypothesis 1 *The track record of financial forecasters in the Euro Stoxx 50 is based on an asymmetric loss function, which reflects that the loss not only depends on the size of the forecast error but also on its direction (i.e., over- and underprojection).*

Assuming forecasters minimize the loss of such a flexible loss function may help to explain the forecast bias among EPS forecasters. This in turn, helps to remedy the violation of the rational expectations hypothesis and we therefore assume:

Hypothesis 2 *Assuming that financial analysts optimize an asymmetric loss function, we cannot reject rationality as often as when assuming a symmetric one.*

The results would then be one piece of explaining the rational bias in the forecasting industry. An alternative approach roots in the assumption that forecasters are

compensated differently on the grounds of their forecasts. Laster et al. (1999) model two groups of customers, who demand forecasts. Members of the first group of customers use the forecasts on a regular basis and buy the forecasts regularly. These customers are interested in an accurate forecasts and choose to buy forecasts from a forecaster who has delivered the most accurate forecasts over a longer time period. Forecasters serving this group of customers might have a symmetric loss function since the forecasters target the actual realization. Members of the second group of customers only buy a forecast occasionally. As a consequence, they are not interested in a forecaster's forecast accuracy computed over a long period of time. Rather, these customer buy from the forecaster, who provided the best forecast in the last period. Translated into our setting, we argue that some forecasters might find it therefore rational to submit optimistic forecasts more often while others might submit conservative forecasts. Additionally, Keane and Runkle (1990) offer a number of forecaster characteristics such as age, education, and reputation that influence the likelihood of such extreme forecasts. These differences then translate into heterogeneity in the perceived losses of conservative/optimistic forecasts. This argument leads to the following hypothesis

Hypothesis 3 *There is a strong heterogeneity concerning the shape of the loss functions on the forecaster-level between forecasted companies, industries and countries.*

We incorporate this finding and account for forecaster characteristics' which might rationalize the forecast bias more properly than estimating loss function parameters on an aggregate level. Since forecaster characteristics such as age, education, and the information set might affect the forecasters' attitude to a higher extent than common shocks or industry and country characteristics, we expect to rationalize biased forecasts more often when estimating the loss function on an individual forecaster level. In contrast to this, we do not expect that the forecast bias can be better explained when accounting for industry or country effects and hypothesize:

Hypothesis 4 *Individual forecaster characteristics are more important in explaining the forecast bias than aggregate developments, country, and industry characteristics.*

Finally, we focus on the analysts' perceived losses of conservative/optimistic forecasts during economic cycles. As outlined before, we expect that the loss a forecaster incurs when submitting an inaccurate forecast depends on the state of the economy. This mainly results from the assumption that the arguments brought forward in

Easterwood and Nutt (1999), i.e., the influence on trading volumes and management benevolence are of pronounced importance during peaks in the business cycle. Hence, we hypothesize:

Hypothesis 5 *The degree of perceived losses of inaccurate forecasts varies with the business cycle, such that forecasters are overly optimistic in phases of economic expansion and too cautious/conservative during times of economic distress.*

We will further discuss the validity of these hypotheses in section 2.4 after we present our data and our theoretical framework in the next sections.

2.4 Results

In this section we present our baseline results concerning the degree of asymmetry in analysts forecasts before we focus on the rationalization of biased forecasts. Subsequently, we provide a number of robustness tests and relate our findings to our hypotheses derived above.

2.4.1 EPS forecasts under asymmetric loss

Table 2.2 reports the results for the whole sample period pooled across all forecasters. Given the linear specification ($p = 1$), the $\hat{\alpha}$ coefficient of about 0.476 indicates that forecasters experience a slightly higher loss when overestimating EPS compared to an underprediction of similar magnitude. In addition, this indicates that forecasters generally tend to have a linear symmetric loss function. This contrasts with the case of a quadratic specification, where the $\hat{\alpha}$ coefficient of about 0.62 indicates that the forecasters experience a higher loss when underpredicting the EPS compared to an overestimation of similar size. One can therefore conclude that forecasters optimizing a quadratic loss function on average submit too optimistic forecasts, which is in line with optimistic forecasting behavior in financial markets (Easterwood and Nutt, 1999). The results are surprisingly robust concerning the choice of sets of instruments.

To account for the heterogeneity among the 137 institutes which participated in the survey and provided EPS forecasts, Figures 3.3 and 3.4 plot the distribution of asymmetry parameters. When assuming a linear loss function the asymmetry

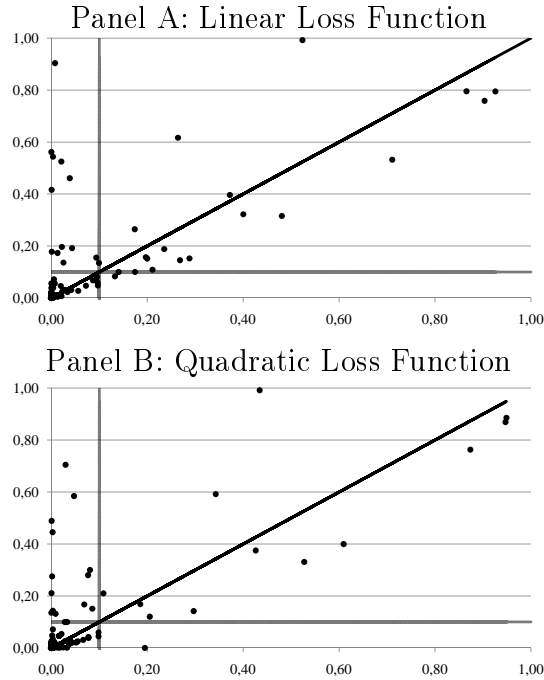
parameters are scattered around 0.5, whereas under a quadratic loss function the majority of EPS forecasters have an asymmetry coefficient larger than 0.5. This confirms our results based on the pooled data set but also highlights that there is a large heterogeneity among the EPS forecasters concerning their perception of forecast errors. While in model 3 a total of 47 forecasters have a symmetric quadratic loss function (marked grey), 14 (72) forecasters have an asymmetry coefficient which is lower (higher) than 0.5 (marked black) indicating that they associate a higher loss with overprojections (underprojections). This confirms hypothesis 1 which states that for most EPS forecasters the loss function is asymmetric. This heterogeneity, however, is not systematic since for both loss functions the results of a Wilcoxon test indicate that the asymmetry parameter are normally distributed.

2.4.2 Rationality Under Asymmetric Loss

Table 2.2 additionally reports the results of the rationality J -test based on a symmetric loss function, $J(0.5)$, and under asymmetric loss, $J(\hat{\alpha})$. The results indicate that rationality can be rejected under symmetric and under flexible loss when the asymmetry parameter $\hat{\alpha}$ is governed by the average coefficient of all forecasters. While the J -values under flexible loss are significantly lower than under symmetric loss, applying a flexible loss function does not make EPS forecasts rational per se.

In order to determine whether asymmetric loss functions have a better fit with observed behavior, we additionally plot the p -values of the rationality tests under symmetric and flexible loss against each other. Figure 2.4 shows for each individual forecaster (model 4) the p -values of the rationality test under symmetric (horizontal axis) and asymmetric loss (vertical axis). Under a linear loss function, we cannot reject the rationality condition at a ten percent level for 19 (31) forecasters when assuming symmetric (asymmetric) loss. This supports the notion that under asymmetric loss rationality can less strongly be rejected at the forecaster level. We find even more pronounced evidence when looking at the results under a quadratic specification where the number of rational forecasters for which we cannot reject rationality doubled from 13 (27) forecaster under symmetric (asymmetric) loss. This is confirmed by the fact that 79 (89) out of the 137 EPS forecasters are located above the solid 45 degree line indicating that asymmetric loss helps to a least in part remedy the violation of the rational expectations hypothesis. All in all, this provides us

Figure 2.4: Rationality Tests for Individual Forecasters



Note: The scatter diagram plots the p -values of the J-test on forecast rationality based on model 4. Other model specifications look similar and are available upon request. The upper (lower) panel reports the p -values based on the linear (quadratic) loss function under the null hypothesis of rationality for a symmetric loss function ($\alpha = 0.5$) on the horizontal axis and under a flexible loss function ($\hat{\alpha}_i$) on the vertical axis. Each dot represents an individual forecaster. The grey line reflects rationality on a ten percent level. The solid line is a 45 degree line.

with ample evidence confirming hypothesis 2, which claims that analysts' behavior appears more rational when assuming an asymmetric loss function.

2.4.3 Influence of Institute, Company, and Country Effects

To account for the heterogeneity of the asymmetric loss function, we estimated the loss function for each forecasting institute separately. Figures 2.8 and 2.9 report the results for the linear and quadratic specification. While we have to acknowledge a substantial degree of heterogeneity for the asymmetry parameters of individual forecasters, each and every estimate lies within the reasonable range between 0 and 1 indicating that our specifications are well behaved. The results for model 1 indicate that a total of 17 forecasters have an asymmetry parameter, which is significantly larger than 0.5 (z -test $> |2.56|$), while 81 forecasters show an asymmetry parameter not different from 0.5 and 39 forecasters have an asymmetry parameter significantly lower than 0.5. In the quadratic specification, the results for model 1 indicate that a total of 67 forecasters have an asymmetry parameter, which is larger

than 0.5, while 68 forecasters show an asymmetry parameter not different from 0.5 and 5 forecasters have an asymmetry parameter significantly lower than 0.5. The results are qualitatively similar for the other models. This indicates that on an individual level most forecasters exhibit a symmetric loss function under a linear loss function and put an equal weight on forecasting errors irrespective of their sign. However, some forecasters show an asymmetric loss function. To test whether the heterogeneity among the forecasters is systematic in statistical terms we tested the asymmetry parameters $\hat{\alpha}$ by means of a Wald test and a Wilcoxon test. While the null of the Wald test of equal coefficients can be rejected, the Wilcoxon test indicates that the asymmetry parameters are normally distributed. In essence, this supports the notion that the asymmetry parameter $\hat{\alpha}$ is influenced on the forecaster's level and confirms hypothesis 3.

In a next step, we analyze whether companies in the Euro Stoxx are exposed differently to asymmetric loss. The analysis of company-specific asymmetry parameters might be important since this reflects a systematic optimism or pessimism on a company level. Investors relying on EPS forecasts should be aware of those company-specific characteristics. If EPS forecaster weight over- and underprojections of EPS dynamics differently among companies in the Euro Stoxx an EPS forecasts should be biased and, hence, analysts might favor some companies over others. Table 2.3 reports the asymmetry parameter (linear loss function) for each company separately. Again, the results suggest a substantial degree of heterogeneity among the companies which exhibit asymmetry parameters between 0.105 (Sanofi-Aventis) and 0.941 (Alcatel-Lucent). The results for model 1 indicate that an asymmetry parameter which is larger than 0.5 (z-test $> |2.5|6$) is estimated for a total of 29 companies, while for 12 companies the asymmetry parameter is not different from 0.5 and for 23 companies the asymmetry parameter is significantly lower than 0.5. This displays a strong heterogeneity with respect to the asymmetry parameter on the company level. A secondary idea in this respect, would be to expect that the asymmetry parameter differs over branches. For instance, one could expect that EPS in the banking sector are more important than for technology companies, hence unexpected cuts of EPS are charged more costly, which in turn could be reflected through differences in the asymmetry parameter.

In order to confirm this idea, we clustered the sample into 9 different industries and calculated the asymmetry parameter accordingly. Indeed, the results outlined in table 2.4 suggest that some industries experience more others less optimistic forecasts.

Apparently, forecasters were most optimistic for the electronics, construction, and financial industries (with $\hat{\alpha}$ of 0.763, 0.717, and 0.653) and a bit more reserved for the chemical and energy business (0.350 and 0.417, respectively). This is indicative of the influence of the industry on the forecaster sentiment.

Furthermore, we tested for differences in rationality for individual company forecasts and find that for 1 (2) out of the 67 companies the rationality condition cannot be rejected on a ten percent level under symmetric (asymmetric) loss for model 3 and for 1 (3) for model 4. This reflects that asymmetric loss function estimated on a company level do not help to remedy the violation of the rational expectation hypothesis.

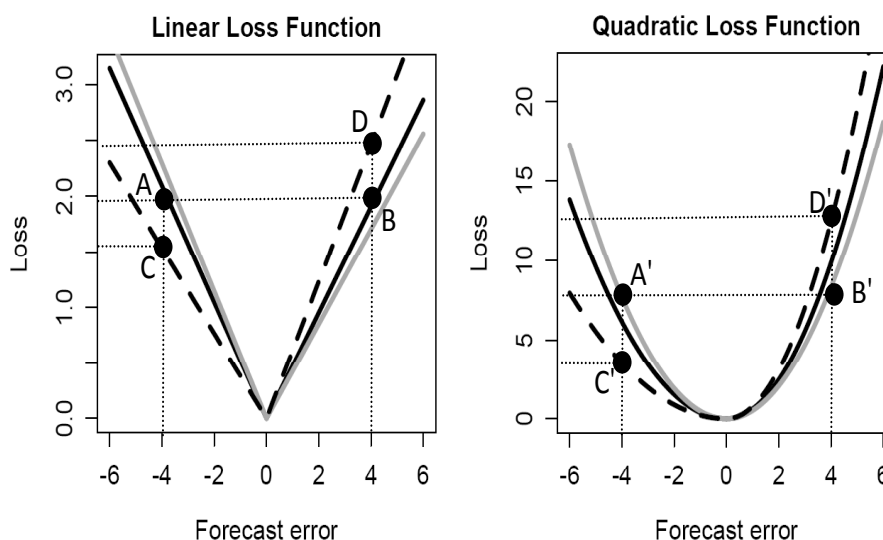
Ultimately, we tested for the influence the country where the company is headquartered has on the shape of forecasters' loss functions. For this purpose, Table 2.5 reports the results when pooling the companies with respect to countries. Remarkably, the asymmetry parameter is smaller than 0.5 for all countries except for Spain (Ireland) where $\hat{\alpha}$ is larger (not different) than (from) 0.5 under a linear loss function. Under a quadratic loss function, all asymmetry parameters are significantly larger than 0.5, except for Finland, indicating that in this specification EPS forecasters tend to suffer a higher loss when underpredicting EPS dynamics compared to an overestimation of similar size. Next, Table 2.6 reports the numerical results for the rationality tests in full. With the notable exception of an asymmetric loss function under model 3 for Ireland, we can reject rationality for all evaluated countries. All things considered, we can affirm hypothesis 4 as influences and information from the forecaster, company, industry, and country level impact the asymmetry parameter α .

2.4.4 Impact of Macroeconomic Cycles

In a next step, we determine the impact of macroeconomic cycles on the degree of the asymmetry parameter α . To this end, Table 2.2 reports the results for the full sample based on the three different models. When differentiating between expansion and recession periods both specifications show statistically significant differences. While in recession periods, the asymmetry parameter $\hat{\alpha}$ is the highest and of about 0.617 (0.780) under a linear (quadratic) loss function. This indicates that in times of recession, EPS forecaster endure a higher loss when underpredicting EPS compared to an overprojection of similar size. This result is again robust under different sets of

instruments and would potentially explain why forecasters show an optimistic bias especially during recession periods as witnessed by Table 2.1. Compared to that, during expansion periods the asymmetry parameter $\hat{\alpha}$ is significantly lower reflecting that in expansion periods EPS forecasters experience less fear to underpredict EPS dynamics. Under a quadratic loss function the asymmetry parameter of 0.520 is not statistically different from 0.5 indicating that EPS forecasters have a symmetric loss function. This underpins the finding that EPS forecasters in expansion periods target the actual value of EPS dynamics and perceive the same loss of under- and overprojections of EPS forecasts. Again these results are robust with respect to the choice of models.

Figure 2.5: Linear and Quadratic Loss Function



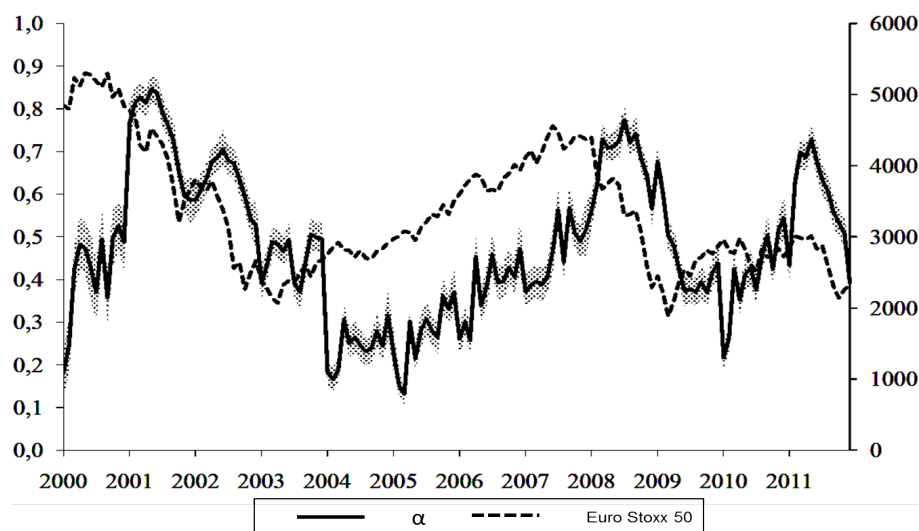
Note: The solid line (dotted line) reflects the loss function for the full sample (in times of crises) while the grey line reflects the loss function in times of economic expansion.

Figure 2.5 quantifies and visualizes the loss function for the full sample (black line), in times of recession (dotted line) and in times of expansion (grey line) for a linear and a quadratic loss function. The Figure shows that under the linear loss function EPS forecasters have an almost symmetric loss function for the full sample period. An overestimation of EPS by four Euros per share (point A) yields almost the same loss as an underprojection by four Euros per share (point B). By contrast, in times of recession (dotted line) an overassessment of EPS by four Euros (point C) is less costly for the average EPS forecaster than an underestimation of similar size (point D). This is opposed to the times of expansion where an overly pessimistic forecast is less costly than an optimistic forecast. Under a quadratic loss function,

an overestimation (point A') is as costly as an underprojection (point B') of similar size in times of expansion (grey line). This disparity is even more pronounced in times of recession, where an overestimation by four Euros (point C') is about three times as costly as an underprediction of four Euros (point D').

Moreover, we take advantage of the large number of EPS forecasts by estimating the asymmetry parameter $\hat{\alpha}$ for each month between January 2000 and December 2011, i.e., for 144 consecutive months. To this end, we only used those EPS forecasts, which had been submitted in the respective month. Figures 2.6 and 2.7 show the Euro Stoxx 50 index (dotted line, right-hand scale), the time-varying $\hat{\alpha}$ parameter (solid line, left-hand scale) as well as the 99% confidence interval (shaded area, left-hand scale) for model 1 based in the linear and the quadratic loss function. Specifications based in other models look similar and are available upon request. The figures show that the asymmetry coefficient always ranges between 0 and 1 indicating the robustness of our model. The figures also show a substantial variation of the asymmetry parameter.

Figure 2.6: Time-Varying Symmetry Parameter $\hat{\alpha}$ (Linear)

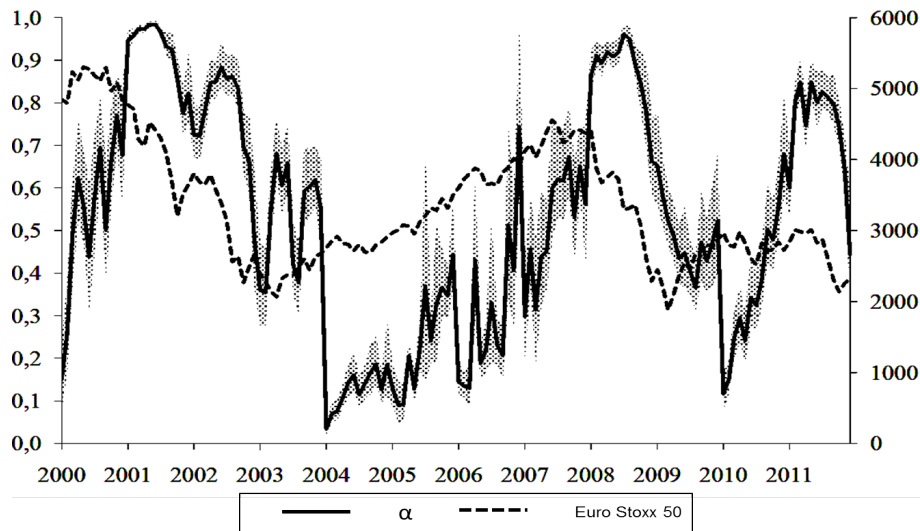


Note: The solid line shows the time-varying asymmetry parameter $\hat{\alpha}$ and its 99% confidence interval (shaded area). The dotted line reflects the the Euro Stoxx 50 index. The correlation coefficient of the asymmetry parameter $\hat{\alpha}$ and the Euro Stoxx 50 index is 0.16 and significantly positive.

Interestingly, the asymmetry parameter moves in tandem with the Euro Stoxx 50 (dotted line). This is supported by the significantly positive correlation coefficient between both developments. The asymmetry parameter is significantly lower than 0.5 between 2001-2003 and 2007-2009, which are recession periods in the develop-

ment of the Euro Stoxx. Compared to that, the asymmetry parameter is significantly higher than 0.5 for the periods 2004-2006 and 2009-2010, which represent growth periods in the Euro Stoxx development. This reflects that periods in which the Euro Stoxx increases are associated with periods in which forecasters perceive a higher loss when underestimating the EPS. This helps to explain why forecasters tend to overpredict the EPS in times of good stock market development, i.e., submit too optimistic forecasts while in times of recessions they perceive a higher loss when overestimating the EPS. This in turn clarifies, why forecasters tend to make too pessimistic forecasts when the stock index is decreasing. This supports hypothesis 5 and thus confirms overly cautious forecasts during recessions and excessively optimistic ones in periods of economic expansion.

Figure 2.7: Time-Varying Symmetry Parameter $\hat{\alpha}$ (Quadratic)



Note: The solid line shows the time-varying asymmetry parameter $\hat{\alpha}$ and its 99% confidence interval (shaded area). The dotted line reflects the the Euro Stoxx 50 index. The correlation coefficient of the asymmetry parameter $\hat{\alpha}$ and the Euro Stoxx 50 index is 0.21 and significantly positive.

2.4.5 Robustness Tests

Different Set of Instruments

In accordance with Aretz et al. (2011), we used different set of instruments to estimate the loss function. Alternatively to the four models presented in this study, we used the lagged dividend yield, the short term government bond yield, and a

combination thereof. Results show a surprisingly high degree of robustness of our results with respect to the choice of the sets of instruments and are available upon request. The most striking point from an instrumental point of view is that under model 2, which features a constant term and the forecast error as instruments, the rejection of forecast rationality is the strongest. This reflects that the rationality of EPS is more affected by systematic effects rather than by fundamental variables such as interest rate and yield spreads.

An Alternative Test for Asymmetric Loss

Patton and Timmermann (2007)'s proposition 3 shows that if the loss only depends on the forecast error (and the earnings per share has dynamics only in the conditional mean) or the loss function is homogenous in the forecast error (and the earnings per share has dynamics in the conditional mean and variance), a simple quantile test can be used to analyze the rationality of earnings per share forecasts. The quantile test stipulates that, under the null hypothesis of forecast rationality, it should not be possible to forecast the sign of the forecast error using data that are in the information set of forecasters at the time a forecast is made.

In order to implement the quantile test, we define $\mathbb{1}_{t+1} = 1$ if $s_{t+1} - f_{t+1} < 0$, and $\mathbb{1}_{t+1} = 0$ otherwise. As for the information set of forecasters at the time a forecast is made, we consider the wedge between the current earnings per share and the forecast, $s_t - f_{t+1}$, that is, the forecast of the relative change in earnings per share. The resulting quantile test can be implemented by estimating the following equation:

$$\mathbb{1}_{t+1} = \beta_0 + \beta_1(s_t - f_{t+1}) + \epsilon_{t+1}, \quad (2.4)$$

where β_0 and β_1 are coefficients to be estimated, and ϵ_{t+1} is a disturbance term. Estimation can be done by ordinary least squares.¹¹ If we estimate $\hat{\beta}_1 < 0$, then the model implies that the future EPS tends to fall short of (exceed) the forecast if the current EPS falls short of (exceeds) the forecast. Conversely, if we estimate $\hat{\beta}_1 > 0$, the future EPS tends to fall short of the forecast if the current EPS exceeds (falls short) the forecast.

¹¹Because of the limited number of observations per forecaster, we shall present estimation results for a model estimated by means of the ordinary least squares technique. Results for a qualitative response model, however, are similar to those we shall present in the vast majority of cases and are available upon request.

A Test for Market-Timing

An alternative interpretation of the quantile test of forecast rationality is obtained if recent research on forecaster (anti-)herding is being used to put Equation (2.4) into perspective. A test for forecaster (anti-)herding recently developed by Bernhardt et al. (2006) is particularly useful in this respect. We consider first a forecaster who forms an “efficient” (that is, median unbiased) private forecast of the future EPS value. In terms of Equation (2.4), such an unbiased private forecast implies that the forecast of the change in the EPS should have no explanatory power with respect to the ex-post forecast error, such that we should have $\hat{\beta}_1 = 0$. The probability that a forecast overshoots the future EPS should be equal to the probability that a forecast undershoots the future EPS, and the intercept coefficient should not be significantly different from $\hat{\beta}_0 = 0.5$. Conversely, a parameter $\hat{\beta}_1 \neq 0$ indicates forecast inefficiency. Such forecast inefficiency arises if the eventually published forecast differs from the unbiased private forecast. A wedge between the unbiased private forecast and the biased published forecast arises if the latter is influenced by public information, where the latter can be approximated by the current EPS (the naive random-walk-without-drift forecast). The intercept coefficient absorbs any time-invariant wedge between the current EPS and the set of public information available to a forecaster at the time a forecast has to be made, so that $\hat{\beta}_0 \neq 0.5$. If the usefulness of the current EPS as a sufficient statistic of public information changes over time, the model can be estimated by means of a recursive- or rolling-estimation window such that its parameters can change over time.

It is worth noting that, as compared to the test developed by Bernhardt et al. (2006), the model given in Equation (2.4) does not require computation of a consensus forecast to proxy public information. This is a useful feature of the test given in Equation (2.4) because we do not have to address issues concerning the implications of a potential bias in the consensus forecast for tests of forecaster herding (Jegadeesh and Kim, 2010). Also, the test does not depend on whether a consensus forecast exists in the first place (Kolb and Stekler, 1996).

In the case of forecaster herding, a forecaster publishes a forecast that “mimics” public information, implying that the published forecast is tilted towards the current EPS. If the private forecast exceeds the current EPS, the published forecast will be tilted towards the EPS from above. We have $s_t - f_{t+1} < 0$, but this difference is smaller than if the forecaster had published the unbiased private forecast. As a

result, the probability that the published forecast overshoots the future EPS gets smaller than in the benchmark case of an unbiased private forecast. The probability that we subsequently observe $s_{t+1} - f_{t+1} < 0$ decreases, requiring a coefficient $\hat{\beta}_1 > 0$. By the same token, if we have $s_t - f_{t+1} > 0$, such that the published forecast is smaller than the current EPS value, forecaster herding should imply that the published forecast is larger than the unbiased private forecast. The difference between s_t and the published forecast f_{t+1} , thus, is smaller than the difference between s_t and the unbiased private forecast. Hence, the probability that the published forecast undershoots the future EPS value gets smaller than in the case of an unbiased private forecast. The smaller undershooting probability, in turn, implies that it becomes more likely than in the case of an unbiased private forecast that we observe $s_{t+1} - f_{t+1} < 0$, requiring again a coefficient $\hat{\beta}_1 > 0$ if $s_t - f_{t+1} > 0$. Forecaster herding, thus, implies

$$P(s_{t+1} - f_{t+1} < 0 | s_t - f_{t+1} < 0) \downarrow \quad \text{and} \quad P(s_{t+1} - f_{t+1} < 0 | s_t - f_{t+1} > 0) \uparrow \quad \Rightarrow \beta_1 > 0, \quad (2.5)$$

where P = probability. Things are just the opposite round in case of forecaster anti-herding. Forecaster anti-herding implies that a published forecast is tilted farther away from the current EPS value than an unbiased private forecast. If $s_t - f_{t+1} < 0$, then the probability of overshooting of the forecast over the subsequent EPS value is larger than if a forecaster publishes an unbiased private forecast. Hence, if $s_t - f_{t+1} > 0$, the probability of $s_{t+1} - f_{t+1} < 0$ increases relative to the benchmark case of an unbiased private forecast, requiring a coefficient $\hat{\beta}_1 < 0$. If, in turn, $s_t - f_{t+1} > 0$, then the probability of undershooting of the forecast over the subsequent EPS value is larger than if a forecaster publishes an unbiased private forecast. Hence, if we have $s_t - f_{t+1} > 0$, the probability of $s_{t+1} - f_{t+1} < 0$ again increases relative to the benchmark case of an unbiased private forecast, requiring a coefficient $\hat{\beta}_1 < 0$. Forecaster anti-herding implies

$$P(s_{t+1} - f_{t+1} < 0 | s_t - f_{t+1} < 0) \uparrow \quad \text{and} \quad P(s_{t+1} - f_{t+1} < 0 | s_t - f_{t+1} > 0) \downarrow \quad \Rightarrow \beta_1 < 0. \quad (2.6)$$

The analogy between Equation (2.4) and the described test of forecaster (anti-) herding arises from the fact that Equation (2.4) resembles standard tests of market timing. Market timing tests are widely studied in the empirical finance literature to explore whether forecasts of excess returns predict the sign of future actual returns (Merton, 1981; Henriksson and Merton, 1981). It is also worth noting that Equation

(2.4) is reminiscent of a market-timing test developed by Cumby and Modest (1987). Their test requires estimation of a regression model of the realization of a variable, for example, actual excess real-estate returns on holdings in stocks, on a constant, and an indicator function that summarizes whether forecasts signal an investment in stocks, and zero else. Applications of market-timing tests to the macroeconomic context include Schnader and Stekler (1990), Stekler (1994) and Sinclair et al. (2010). In the context of our survey data of EPS forecasts, the test can be interpreted as a “test of forecast-error timing”. Because forecaster (anti-) herding implies that forecasters published biased forecasts, the bias in forecasts should immediately impact on the market-timing power of forecasts.

2.5 Conclusion

All things considered, we find that for Euro Stoxx 50 forecasts asymmetric loss functions better explain the behavior of analysts covered through the IBES dataset. Markedly, the alternative rationality concept is more important on the individual forecaster level than the company or country level. Furthermore, we can show that asymmetry is cyclical and additionally report a correlation with the stock market.

The implications of our findings are manifold. First, the possibility to attune the behavior of many analysts with the alternative concept of rationality allows us to shift the perspective on the forecasting industry. Research inquiring into additional factors shaping the loss function of analysts is likely to be fruitful. Second, both regulators and investors can build on our findings by incorporating the forecasts but discount them with attention to some exaggerations in the prognoses. Especially in times of higher volatility, regulators might find this a promising path to smooth market movements. Third, banks and brokers can take our results as a starting point for reshaping the remuneration schemes of analysts. Ignoring overall company success in the compensation of analysts, for example, is likely to ensure that no misaligned incentives result from increases in the trading volume.

2.6 Appendix

Figure 2.8: Asymmetry Parameter per Forecaster (Linear)

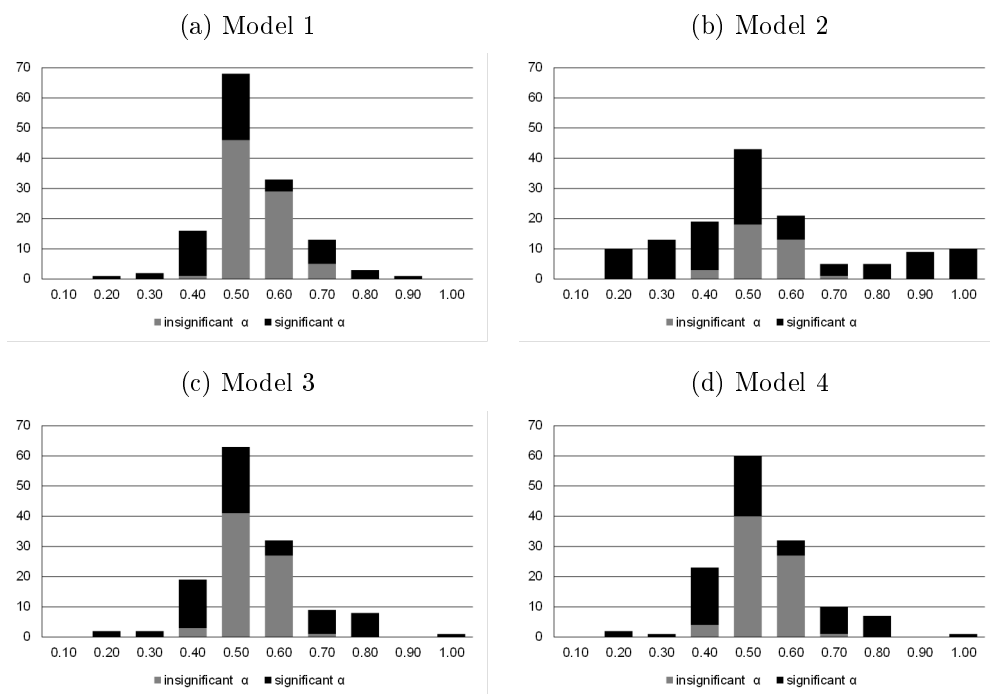


Figure 2.9: Asymmetry Parameter per Forecaster (Quadratic)

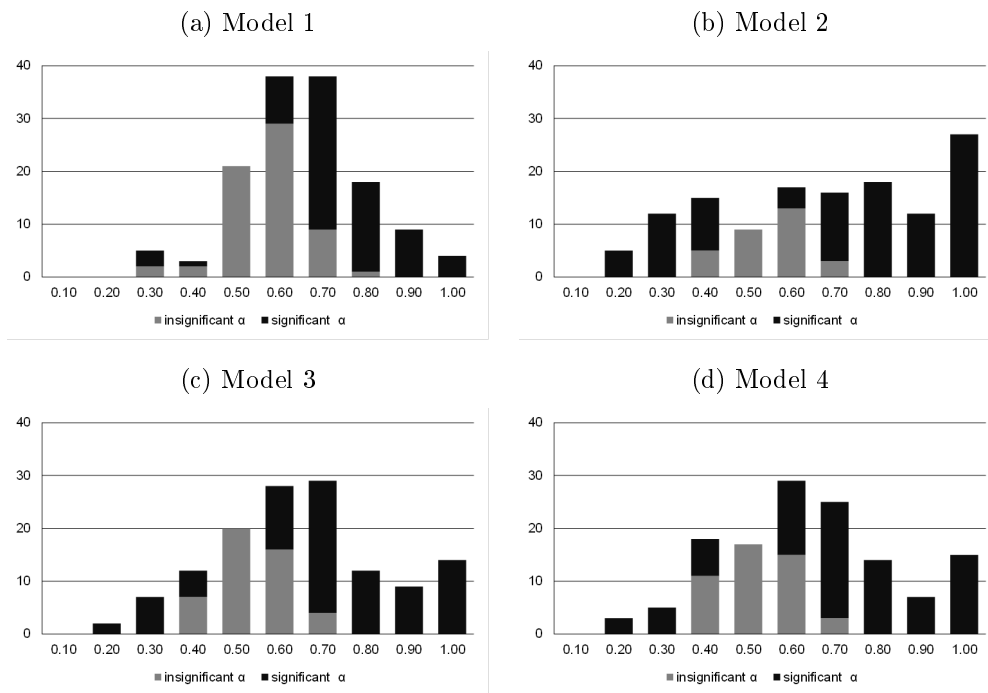


Table 2.1: Descriptive Statistics of Euro Stoxx 50 Forecasts

Company	Country	Expansion			Recession			Full Sample		
		<i>n</i>	FE	SE	<i>n</i>	FE	SE	<i>n</i>	FE	SE
AB INBEV	BEL	1,095	0.18 *	(0.01)	342	0.11 *	(0.02)	1,437	0.17 *	(0.01)
ABN-AMRO	NET	714	0.11 *	(0.02)	537	(0.04) *	(0.01)	1,251	0.05 *	(0.01)
AEGON	NET	1,102	0.16 *	(0.01)	548	(0.50) *	(0.03)	1,650	(0.06) *	(0.02)
AGEAS	BEL	1,157	(0.03)	(0.02)	504	(0.68) *	(0.04)	1,661	(0.22) *	(0.02)
AIR LIQUIDE	FRA	369	0.13 *	(0.02)	155	(0.01)	(0.02)	524	0.09 *	(0.01)
ALCATEL-LUCENT	FRA	1,491	(1.05) *	(0.05)	337	(0.51) *	(0.05)	1,828	(0.95) *	(0.04)
ALLIANZ	GER	1,431	0.01	(0.10)	657	(3.62) *	(0.28)	2,088	(1.13) *	(0.12)
ALSTOM	FRA	388	0.19 *	(0.05)	94	(0.68) *	(0.05)	482	0.02	(0.04)
ASS. GENERALI	ITA	1,032	(0.21) *	(0.01)	389	(0.57) *	(0.04)	1,421	(0.31) *	(0.02)
AVENTIS	FRA	470	(0.21) *	(0.02)	179	(0.41) *	(0.03)	649	(0.27) *	(0.02)
AXA	FRA	1,037	(0.01)	(0.02)	329	(0.51) *	(0.03)	1,366	(0.13) *	(0.02)
BANCA INTESA	ITA	1,131	(0.00)	(0.00)	397	(0.02) *	(0.01)	1,528	(0.01) *	(0.00)
BASF	GER	1,364	0.45 *	(0.02)	670	(0.52) *	(0.03)	2,034	0.13 *	(0.02)
BAYER	GER	1,423	0.25 *	(0.02)	651	(0.01)	(0.03)	2,074	0.17 *	(0.02)
BBVA	SPA	978	(0.02) *	(0.01)	627	(0.04) *	(0.01)	1,605	(0.03) *	(0.00)
BHV	GER	510	0.27 *	(0.05)	462	(0.76) *	(0.05)	972	(0.22) *	(0.04)
BMW	GER	1,199	0.50 *	(0.04)	548	(0.64) *	(0.06)	1,747	0.14 *	(0.03)
BNP-PARIBAS	FRA	1,369	0.24 *	(0.03)	335	(1.67) *	(0.15)	1,704	(0.14) *	(0.04)
CARREFOUR	FRA	1,556	(0.19) *	(0.01)	271	(0.11) *	(0.02)	1,827	(0.17) *	(0.01)
CREDIT AGRICOLE	FRA	1,159	0.06 *	(0.02)	237	(0.88) *	(0.05)	1,396	(0.10) *	(0.02)
CRH	IRE	114	(17.66) *	(5.61)	(-)	(-)	(-)	114	(17.66) *	(5.61)
DAIMLER	GER	1,628	(0.16) *	(0.04)	707	(1.37) *	(0.07)	2,335	(0.52) *	(0.04)
DT. BANK	GER	1,664	(0.31) *	(0.08)	785	(3.49) *	(0.19)	2,449	(1.33) *	(0.09)
DT. BOERSE	GER	943	0.27 *	(0.02)	247	(0.15) *	(0.03)	1,190	0.19 *	(0.02)
DT. TELEKOM	GER	1,445	0.11 *	(0.01)	685	(0.19) *	(0.05)	2,130	0.02	(0.02)
E.ON	GER	1,205	0.09 *	(0.02)	501	0.16 *	(0.02)	1,706	0.11 *	(0.01)
ENDESA	SPA	765	0.13 *	(0.01)	240	(0.13)	(0.08)	1,005	0.07 *	(0.02)
ENEL	ITA	901	0.04 *	(0.00)	295	0.08 *	(0.01)	1,196	0.05 *	(0.00)
ENI	ITA	1,622	0.05 *	(0.01)	583	(0.14) *	(0.02)	2,205	0.00	(0.01)
FRANCE TELECOM	FRA	1,964	(0.24) *	(0.04)	376	1.40 *	(0.17)	2,340	0.02	(0.04)
GAZ DE FRANCE	FRA	445	(0.06) *	(0.02)	83	0.10	(0.05)	528	(0.03)	(0.02)
GROUPE DANONE	FRA	509	0.01	(0.01)	170	(0.03) *	(0.01)	679	0.00	(0.01)
IBERDROLA	SPA	8	0.04	(0.04)	423	0.01 *	(0.00)	431	0.01 *	(0.00)
INDITEX	SPA	559	(0.20) *	(0.01)	394	(0.19) *	(0.02)	953	(0.20) *	(0.01)
ING GROEP	NET	1,211	0.10 *	(0.02)	425	(0.74) *	(0.06)	1,636	(0.12) *	(0.02)
KON. AHOLD	NET	1,499	0.01	(0.01)	709	(0.72) *	(0.02)	2,208	(0.22) *	(0.01)
KON. PHILIPS	NET	1,780	(0.27) *	(0.02)	796	(1.30) *	(0.05)	2,576	(0.59) *	(0.02)
KPN	NET	1,207	0.04 *	(0.00)	542	(0.11)	(0.04)	1,749	(0.00)	(0.01)
LAFARGE	FRA	1,430	(0.17) *	(0.03)	284	(1.72) *	(0.07)	1,714	(0.43) *	(0.03)
L'OREAL	FRA	1,271	0.05 *	(0.01)	274	(0.08) *	(0.01)	1,545	0.03 *	(0.01)
LVMH	FRA	1,263	0.36 *	(0.02)	292	(0.07) *	(0.02)	1,555	0.28 *	(0.02)
MITTAL STEEL	NET	835	(0.48) *	(0.05)	66	1.24	(0.61)	901	(0.36) *	(0.06)
MUNICH RE	GER	1,444	0.51 *	(0.10)	544	(5.53) *	(0.21)	1,988	(1.14) *	(0.11)
NOKIA	FIN	2,298	0.02 *	(0.00)	1,037	(0.02) *	(0.00)	3,335	0.00	(0.00)
PPR	FRA	1,425	(0.25) *	(0.04)	315	(1.42) *	(0.09)	1,740	(0.46) *	(0.04)
RENAULT	FRA	1,591	0.73 *	(0.07)	363	(3.72) *	(0.30)	1,954	(0.10)	(0.09)
REPSOL	SPA	1,519	0.02	(0.01)	807	0.05 *	(0.02)	2,326	0.03 *	(0.01)
RWE	GER	1,047	0.13 *	(0.02)	244	0.10	(0.05)	1,291	0.12 *	(0.02)
SAINT-GOBAIN	FRA	833	0.08 *	(0.02)	188	(0.66) *	(0.08)	1,021	(0.06)	(0.02)
SANOFI-AVENTIS	FRA	1,842	0.27 *	(0.01)	366	0.15 *	(0.02)	2,208	0.25 *	(0.01)
SANPAOLO-IMI	ITA	818	0.09 *	(0.01)	(-)	(-)	(-)	818	0.09 *	(0.01)
SAP	GER	1,341	0.09 *	(0.00)	616	(0.04) *	(0.01)	1,957	0.05 *	(0.00)
SCHNEIDER	FRA	1,489	0.22 *	(0.01)	286	0.09 *	(0.04)	1,775	0.20 *	(0.01)
SHELL	NET	849	0.17 *	(0.03)	345	0.87 *	(0.05)	1,194	0.37 *	(0.03)
SIEMENS	GER	1,681	(0.55) *	(0.03)	777	(0.54) *	(0.08)	2,458	(0.55) *	(0.03)
SOC. GENERALE	FRA	1,602	(0.49) *	(0.08)	373	(1.22) *	(0.12)	1,975	(0.63) *	(0.07)
SUEZ	FRA	662	0.10 *	(0.02)	200	(0.25) *	(0.03)	862	0.02	(0.02)
T.I.M	ITA	582	0.04 *	(0.00)	(-)	(-)	(-)	582	0.04 *	(0.00)
TELECOM ITALIA	ITA	1,208	0.04 *	(0.01)	252	0.00	(0.00)	1,460	0.03 *	(0.00)
TOTAL	SPA	211	0.06 *	(0.02)	846	(0.18) *	(0.02)	1,057	(0.13) *	(0.02)
UNIBAIL	FRA	481	(0.59)	(0.30)	105	1.32 *	(0.33)	586	(0.25)	(0.26)
UNILEVER	NET	713	0.02 *	(0.01)	136	0.04 *	(0.01)	849	0.02 *	(0.01)
VINCI	FRA	281	0.14 *	(0.01)	84	(0.13) *	(0.03)	365	0.08 *	(0.01)
VIVENDI	FRA	1,356	(0.44) *	(0.05)	304	0.62 *	(0.20)	1,660	(0.24) *	(0.06)
Full sample		70,516	(.029)	(.011)	25,334	-.656 *	(.015)	95,850	-.194 *	(.009)

Note: * indicates on the one percent level that FE is significantly different from 0. The forecast error defined as $s_{t+1} - f_{t+1}$ for the full sample period as well as for expansion and recession periods. To separate these periods we used the database provided by the Economic Cycle Research Institute (ECRI 2012).

Table 2.2: Asymmetry Parameter and Rationality Tests (Full Sample)

Specification	Sample	n	Asymmetry Parameter							
			Model 1		Model 2		Model 3		Model 4	
			$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE
Linear	Full sample	95,850	0.476 *	(0.002)	0.471 *	(0.002)	0.476 *	(0.002)	0.476 *	(0.002)
	Expansion	70,516	0.426 *	(0.002)	0.415 *	(0.002)	0.425 *	(0.002)	0.425 *	(0.002)
	Recession	25,334	0.617 *	(0.003)	0.710 *	(0.003)	0.628 *	(0.003)	0.628 *	(0.003)
Quadratic	Full sample	95,850	0.616 *	(0.005)	0.598 *	(0.003)	0.606 *	(0.003)	0.609 *	(0.003)
	Expansion	70,516	0.520	(0.007)	0.488	(0.004)	0.483 *	(0.005)	0.490	(0.005)
	Recession	25,334	0.780 *	(0.005)	0.889 *	(0.003)	0.824 *	(0.004)	0.837 *	(0.004)

Specification	Sample	n	Rationality tests											
			$J_2(0.5)$		$J_3(0.5)$		$J_4(0.5)$		$J_2(\hat{\alpha})$		$J_3(\hat{\alpha})$		$J_4(\hat{\alpha})$	
			p	$J_2(0.5)$	p	$J_3(0.5)$	p	$J_4(0.5)$	p	$J_2(\hat{\alpha})$	p	$J_3(\hat{\alpha})$	p	$J_4(\hat{\alpha})$
Linear	Recession	25,334	5,790	.00	2,381	.00	2,390	.00	5,648	.00	1,151	.00	1,173	.00
	Expansion	70,516	6,679	.00	1,978	.00	2,011	.00	4,622	.00	4,29.4	.00	462.4	.00
	Full sample	95,850	9,869	.00	2,018	.00	2,063	.00	9,170	.00	1,794	.00	1,839	.00
Quadratic	Recession	25,334	1,944	.00	1,992	.00	1,966	.00	608.1	.00	306.3	.00	375.7	.00
	Expansion	70,516	49.0	.00	350.0	.00	337.0	.00	40.0	.00	324.2	.00	325.3	.00
	Full sample	95,850	753.0	.00	1,635	.00	1,685	.00	92.5	.00	1,327	.00	1,355	.00

Note: SE = standard error, z-test = test of the null hypothesis that $\hat{\alpha} = 0.5$, * indicates on a one percent level that alpha is significantly different from 0.5. The instruments are a constant term (Model 1), a constant term and the lagged actual value (Model 2), a constant term and the lagged long-term government bond yield (Model 3) and a constant term and the lagged redemption yield (Model 4).

Table 2.3: Asymmetry Parameter for Each Company (Quadratic)

Name	Model 1		Model 2		Model 3		Model 4	
	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE
AB INBEV	0.165 *	(0.017)	0.066 *	(0.006)	0.114 *	(0.015)	0.094 *	(0.014)
ABN-AMRO	0.430 *	(0.020)	0.165 *	(0.011)	0.150 *	(0.016)	0.122 *	(0.015)
AEON	0.572 *	(0.018)	0.226 *	(0.013)	0.287 *	(0.018)	0.303 *	(0.019)
AGEAS	0.698 *	(0.015)	0.800 *	(0.011)	0.928 *	(0.008)	0.949 *	(0.007)
AIR LIQUIDE	0.273 *	(0.025)	0.084 *	(0.011)	0.269 *	(0.025)	0.266 *	(0.025)
ALCATEL-LUCENT	0.941 *	(0.005)	0.993 *	(0.001)	0.997 *	(0.001)	0.997 *	(0.001)
ALLIANZ	0.650 *	(0.014)	0.884 *	(0.007)	0.654 *	(0.014)	0.660 *	(0.014)
ALSTOM	0.487	(0.028)	0.074 *	(0.010)	0.954 *	(0.009)	0.956 *	(0.008)
ASS. GENERALI	0.843 *	(0.011)	0.940 *	(0.005)	0.912 *	(0.009)	0.900 *	(0.010)
AVENTIS	0.852 *	(0.016)	0.967 *	(0.005)	0.989 *	(0.007)	0.992 *	(0.007)
AXA	0.648 *	(0.016)	0.906 *	(0.007)	0.667 *	(0.016)	0.665 *	(0.016)
BANCA INTESA	0.555 *	(0.018)	0.859 *	(0.010)	0.695 *	(0.015)	0.714 *	(0.015)
BASF	0.401 *	(0.014)	0.104 *	(0.006)	0.226 *	(0.011)	0.251 *	(0.012)
BAYER	0.337 *	(0.014)	0.112 *	(0.007)	0.273 *	(0.013)	0.269 *	(0.013)
BBVA	0.606 *	(0.016)	0.843 *	(0.009)	0.810 *	(0.013)	0.842 *	(0.012)
BHV	0.640 *	(0.024)	0.892 *	(0.009)	0.908 *	(0.013)	0.910 *	(0.013)
BMW	0.417 *	(0.020)	0.100 *	(0.008)	0.252 *	(0.017)	0.255 *	(0.017)
BNP-PARIBAS	0.553 *	(0.016)	0.211 *	(0.011)	0.129 *	(0.010)	0.132 *	(0.010)
CARREFOUR	0.801 *	(0.011)	0.933 *	(0.005)	0.811 *	(0.011)	0.808 *	(0.011)
CREDIT AGRICOLE	0.600 *	(0.017)	0.830 *	(0.011)	0.572 *	(0.018)	0.553	(0.018)
CRH	0.838 *	(0.046)	0.996 *	(0.002)	0.993 *	(0.006)	0.995 *	(0.015)
DAIMLER	0.701 *	(0.013)	0.882 *	(0.006)	0.825 *	(0.009)	0.827 *	(0.009)
DT. BANK	0.734 *	(0.013)	0.878 *	(0.007)	0.856 *	(0.008)	0.849 *	(0.008)
DT. BOERSE	0.281 *	(0.019)	0.131 *	(0.010)	0.189 *	(0.014)	0.188 *	(0.014)
DT. TELEKOM	0.483	(0.020)	0.555	(0.019)	0.372 *	(0.017)	0.356 *	(0.017)
E.ON	0.363 *	(0.017)	0.202 *	(0.011)	0.358 *	(0.017)	0.358 *	(0.017)
ENDESA	0.409	(0.030)	0.246 *	(0.016)	0.237 *	(0.020)	0.235 *	(0.020)
ENEL	0.270 *	(0.018)	0.094 *	(0.008)	0.130 *	(0.012)	0.132 *	(0.012)
ENI	0.492	(0.015)	0.372 *	(0.013)	0.326 *	(0.013)	0.328 *	(0.013)
FRANCE TELECOM	0.489	(0.020)	0.602 *	(0.017)	0.230 *	(0.014)	0.214 *	(0.014)
GAZ DE FRANCE	0.562	(0.029)	0.518	(0.029)	0.628 *	(0.028)	0.665 *	(0.027)
GROUPE DANONE	0.499	(0.028)	0.412 *	(0.025)	0.507	(0.028)	0.508	(0.028)
IBERDROLA	0.326 *	(0.028)	0.113 *	(0.014)	0.211 *	(0.024)	0.213 *	(0.024)
INDITEX	0.925 *	(0.008)	0.984 *	(0.002)	0.978 *	(0.004)	0.979 *	(0.004)
ING GROEP	0.600 *	(0.017)	0.260 *	(0.013)	0.484	(0.017)	0.484	(0.017)
KON. AHOLD	0.827 *	(0.010)	0.960 *	(0.003)	0.946 *	(0.004)	0.945 *	(0.004)
KON. PHILIPS	0.851 *	(0.007)	0.976 *	(0.002)	0.890 *	(0.006)	0.908 *	(0.006)
KPN	0.507	(0.029)	0.679 *	(0.020)	0.379 *	(0.020)	0.383 *	(0.021)
LAFARGE	0.723 *	(0.013)	0.866 *	(0.008)	0.717 *	(0.013)	0.716 *	(0.013)
L'OREAL	0.414 *	(0.026)	0.277 *	(0.014)	0.429 *	(0.022)	0.428 *	(0.022)
LVMH	0.197 *	(0.011)	0.044 *	(0.004)	0.077 *	(0.007)	0.076 *	(0.007)
MITTAL STEEL	0.642 *	(0.025)	0.861 *	(0.013)	0.768 *	(0.018)	0.779 *	(0.018)
MUNICH RE	0.654 *	(0.013)	0.853 *	(0.008)	0.665 *	(0.013)	0.665 *	(0.013)
NOKIA	0.483	(0.012)	0.319 *	(0.010)	0.467	(0.012)	0.462 *	(0.012)
PPR	0.691 *	(0.014)	0.947 *	(0.004)	0.770 *	(0.013)	0.752 *	(0.013)
RENAULT	0.520	(0.018)	0.353 *	(0.016)	0.544	(0.017)	0.543	(0.017)
REPSOL	0.455 *	(0.013)	0.221 *	(0.009)	0.457 *	(0.013)	0.457 *	(0.013)
RWE	0.382 *	(0.020)	0.156 *	(0.011)	0.377 *	(0.020)	0.358 *	(0.019)
SAINT-GOBAIN	0.563	(0.023)	0.409 *	(0.020)	0.424 *	(0.021)	0.406 *	(0.021)
SANOFI-AVENTIS	0.105 *	(0.007)	0.050 *	(0.005)	0.070 *	(0.006)	0.068 *	(0.006)
SANPAOLO-IMI	0.295 *	(0.019)	0.030 *	(0.004)	0.020 *	(0.004)	0.021 *	(0.004)
SAP	0.302 *	(0.015)	0.071 *	(0.005)	0.106 *	(0.008)	0.105 *	(0.007)
SCHNEIDER	0.258 *	(0.014)	0.073 *	(0.006)	0.029 *	(0.006)	0.029 *	(0.006)
SHELL	0.226 *	(0.019)	0.079 *	(0.007)	0.079 *	(0.008)	0.078 *	(0.008)
SIEMENS	0.744 *	(0.011)	0.921 *	(0.005)	0.759 *	(0.010)	0.762 *	(0.010)
SOC. GENERALE	0.660 *	(0.014)	0.952 *	(0.004)	0.760 *	(0.012)	0.776 *	(0.011)
SUEZ	0.481	(0.022)	0.178 *	(0.014)	0.283 *	(0.019)	0.287 *	(0.019)
T.I.M	0.175 *	(0.017)	0.028 *	(0.004)	0.118 *	(0.013)	0.108 *	(0.013)
TELECOM ITALIA	0.338 *	(0.020)	0.145 *	(0.011)	0.194 *	(0.013)	0.194 *	(0.013)
TOTAL	0.667 *	(0.021)	0.928 *	(0.008)	0.711 *	(0.019)	0.710 *	(0.019)
UNIBAIL	0.546	(0.045)	0.203 *	(0.031)	0.518	(0.046)	0.501	(0.046)
UNILEVER	0.389 *	(0.021)	0.105 *	(0.009)	0.264 *	(0.018)	0.246 *	(0.018)
VINCI	0.302 *	(0.033)	0.140 *	(0.018)	0.179 *	(0.023)	0.173 *	(0.022)
VIVENDI	0.604 *	(0.024)	0.830 *	(0.013)	0.499	(0.020)	0.499	(0.020)

Note: SE = standard error, z-test = test of the null hypothesis that $\hat{\alpha} = 0.5$. * indicates on a one percent level that alpha is significantly different from 0.5. The instruments are a constant term (Model 1), a constant term and the lagged actual value (Model 2), a constant term and the lagged long-term government bond yield (Model 3) and a constant term and the lagged redemption yield (Model 4).

Table 2.4: Asymmetry Parameter for Each Industry (Quadratic)

Name	Model 1		Model 2		Model 3		Model 4	
	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE
Energy	0.417*	(.007)	0.294*	(.005)	0.401*	(.006)	0.402*	(.006)
Financial	0.653*	(.005)	0.771*	(.004)	0.667*	(.005)	0.656*	(.005)
Automobile	0.562*	(.010)	0.541*	(.010)	0.593*	(.010)	0.594*	(.010)
Telco	0.481	(.014)	0.557*	(.012)	0.304*	(.011)	0.287*	(.011)
Electronics	0.763*	(.006)	0.905*	(.003)	0.760*	(.005)	0.757*	(.005)
Others	0.595*	(.016)	0.775*	(.011)	0.556*	(.015)	0.561*	(.015)
Chemicals	0.350*	(.008)	0.147*	(.005)	0.283*	(.007)	0.284*	(.007)
Industrial Goods	0.605*	(.008)	0.586*	(.007)	0.583*	(.007)	0.586*	(.007)
Construction	0.717*	(.031)	0.566*	(.022)	0.616*	(.025)	0.625*	(.025)

Note: SE = standard error, z-test = test of the null hypothesis that $\hat{\alpha} = 0.5$. * indicates on a one percent level that alpha is significantly different from 0.5. The instruments are a constant term (Model 1), a constant term and the lagged actual value (Model 2), a constant term and the lagged long-term government bond yield (Model 3) and a constant term and the lagged redemption yield (Model 4).

Table 2.5: Asymmetry Parameter for Each Country

Country	n	Linear specification							
		Model 1		Model 2		Model 3		Model 4	
		$\hat{\alpha}_1$	SE	$\hat{\alpha}_2$	SE	$\hat{\alpha}_3$	SE	$\hat{\alpha}_4$	SE
Belgium	3,098	0.430 *	(0.009)	0.300 *	(0.008)	0.424 *	(0.009)	0.422 *	(0.009)
Finland	3,335	0.442 *	(0.009)	0.239 *	(0.007)	0.439 *	(0.009)	0.439 *	(0.009)
France	32,283	0.473 *	(0.003)	0.452 *	(0.003)	0.472 *	(0.003)	0.472 *	(0.003)
Germany	26,419	0.473 *	(0.003)	0.446 *	(0.003)	0.471 *	(0.003)	0.471 *	(0.003)
Ireland	114	0.404	(0.046)	0.248 *	(0.040)	0.398	(0.046)	0.393	(0.046)
Italy	9,210	0.471 *	(0.005)	0.426 *	(0.005)	0.466 *	(0.005)	0.466 *	(0.005)
Netherlands	14,014	0.475 *	(0.004)	0.437 *	(0.004)	0.475 *	(0.004)	0.475 *	(0.004)
Spain	7,377	0.551 *	(0.006)	0.702 *	(0.005)	0.552 *	(0.006)	0.553 *	(0.006)

Country	n	Quadratic specification							
		Model 1		Model 2		Model 3		Model 4	
		$\hat{\alpha}_1$	SE	$\hat{\alpha}_2$	SE	$\hat{\alpha}_3$	SE	$\hat{\alpha}_4$	SE
Belgium	3,098	0.551 *	(0.014)	0.419 *	(0.012)	0.476	(0.013)	0.443 *	(0.013)
Finland	3,335	0.483	(0.012)	0.319 *	(0.010)	0.467	(0.012)	0.462 *	(0.012)
France	32,283	0.584 *	(0.006)	0.560 *	(0.006)	0.597 *	(0.005)	0.596 *	(0.005)
Germany	26,419	0.628 *	(0.005)	0.703 *	(0.005)	0.617 *	(0.005)	0.615 *	(0.005)
Ireland	114	0.838 *	(0.046)	0.996 *	(0.002)	0.993 *	(0.006)	0.995 *	(0.015)
Italy	9,210	0.569 *	(0.008)	0.436 *	(0.008)	0.468 *	(0.008)	0.467 *	(0.008)
Netherlands	14,014	0.642 *	(0.007)	0.733 *	(0.005)	0.615 *	(0.006)	0.615 *	(0.006)
Spain	7,377	0.557 *	(0.009)	0.481	(0.008)	0.534 *	(0.009)	0.534 *	(0.009)

Note: SE = standard error, z-test = test of the null hypothesis that $\hat{\alpha} = 0.5$, * indicates on a one percent level that alpha is significantly different from 0.5 The instruments are a constant term (Model 1), a constant term and the lagged actual value (Model 2), a constant term and the lagged long-term government bond yield (Model 3) and a constant term and the lagged redemption yield (Model 4).

Table 2.6: Rationality Test for Each Country

Linear specification													
Country	n	$J_2(0.5)$	p	$J_3(0.5)$	p	$J_4(0.5)$	p	$J_2(\alpha)$	p	$J_3(\alpha)$	p	$J_4(\alpha)$	p
Belgium	3,098	1,380	.00	200.8	.00	219.5	.00	1,009	.00	135.4	.00	156.8	.00
Finland	3,335	1,770	.00	116.2	.00	124.1	.00	1,297	.00	71.55	.00	77.48	.00
France	32,283	7,648	.00	639.5	.00	643.6	.00	7,035	.00	539.1	.00	542.7	.00
Germany	26,419	7,184	.00	983.0	.00	938.5	.00	6,540	.00	899.7	.00	857.9	.00
Ireland	114	43.98	.00	7.10	.03	8.81	.03	35.15	.00	3.20	.07	5.42	.07
Italy	9,210	3,226	.00	664.7	.00	686.1	.00	2,809	.00	626.4	.00	647.0	.00
Netherlands	14,014	4,686	.00	135.1	.00	143.8	.00	4,255	.00	99.27	.00	108.0	.00
Spain	7,377	2,789	.00	201.0	.00	211.7	.00	2,762	.00	127.1	.00	137.5	.00

Quadratic-Specification													
Country	n	$J_2(0.5)$	p	$J_3(0.5)$	p	$J_4(0.5)$	p	$J_2(\alpha)$	p	$J_3(\alpha)$	p	$J_4(\alpha)$	p
Belgium	3,098	373.3	.00	410.7	.00	483.5	.00	356.3	.00	392.5	.00	431.5	.00
Finland	3,335	591.8	.00	76.53	.00	72.96	.00	512.7	.00	66.87	.00	60.14	.00
France	32,283	624.1	.00	914.4	.00	937.3	.00	652.1	.00	812.5	.00	857.1	.00
Germany	26,419	1634	.00	978.7	.00	942.1	.00	1788	.00	902.0	.00	869.2	.00
Ireland	114	28.98	.00	12.61	.00	11.70	.01	26.28	.00	26.29	.00	26.48	.00
Italy	9,210	759.5	.00	851.6	.00	893.2	.00	654.0	.00	802.7	.00	840.7	.00
Netherlands	14,014	1104	.00	430.0	.00	431.5	.00	842.1	.00	246.8	.00	250.4	.00
Spain	7,377	289.1	.00	96.11	.00	103.5	.00	268.9	.00	90.15	.00	97.64	.00

Note: SE = standard error, z-test = test of the null hypothesis that $\hat{\alpha} = 0.5$. The instruments are a constant term (Model 1), a constant term and the lagged actual value (Model 2), a constant term and the lagged long-term government bond yield (Model 3) and a constant term and the lagged redemption yield (Model 4).

Chapter 3

Are DAX EPS Forecasters Really Irrational?¹

3.1 Introduction

Traditionally, seminal papers assessing the rationality of forecasters came to the unanimous conclusion that financial forecasts are inefficient and thus irrational.² Most of these studies rely on a proposition by Ito (1990), who postulate that forecast errors are weighted in the analysts loss function irrespective of the direction of the forecast error. Accordingly, the traditional rationality measurement is performed through a Mincer-Zarnowitz regression that minimizes the mean squared error, i.e., a quadratic symmetric loss function. However, new methods and an advancement in theory put these results into question.

Elliott et al. (2005) propose a method that abandons the strict assumption of equally weighted forecast errors and flexibilize the loss function in as much as they allow different weights for positive and negative forecast errors. The outcome is a so called asymmetric loss function. In Elliott et al. (2008) the underlying assumption is most clearly framed: assessments of rationality based on symmetrical loss concepts are meaningless if the underlying loss function is actually (even only slightly) asymmet-

¹This chapter is based on the homonymous working paper co-authored by Markus Rudolf and Jan-Christoph Rülke (Schmütsch et al., 2013a).

²For instance, Chang and Osler (1999) and Takagi (1991) show that exchange rate forecasts are irrational. Here, the arguments rest on the acknowledged fact that information is processed untimely.

ric. The concept has been employed in a number of studies for different markets, where the authors were able to at least partially reverse the notion of irrational forecasts (Pierdzioch et al., 2012, 2013b).

We augment this new stream of literature for a study that applies the fresh concept to a dataset of EPS forecasts of DAX 30 listed companies. Our analysis emphasizes the appropriateness of the Elliott et al. (2005) approach. While rationality cannot be restored on an aggregate level but only for single years, the number of forecasting institutes that release rational forecasts increases by the factor of three. To the best of our knowledge, we are the first to analyze such a vast dataset of prognoses for German companies and therefore complement the growing literature on evidence of alternative loss functions.

On a different note, the analysis allows for additional insights. For instance, we harness the estimation of the asymmetry parameter as an alternative forecaster sentiment detection method. We show that analysts are overly optimistic and furthermore report considerable heterogeneity in the degree of asymmetry across the business cycle, the considered companies, and the respective institutes.

The remainder of the paper is organized as follows. At first, we provide some descriptive statistics of our data sample. Thereafter, section 3.3.1 introduces the methodology of Elliott et al. (2005) and the underlying hypotheses and present our results. Eventually, we offer some concluding remarks illustrating avenues for future research.

3.2 Data

We draw our conclusions from the analysis of a sample of EPS forecasts provided by the IBES database. The source has been employed in a series of studies (Keane and Runkle, 1998; Gu and Wu, 2003), although it recently has been critically reviewed.³ Table 4.4 offers an overview of the sample characteristics. The dataset covers forecasts from 1995 until 2012 and comprises 111,372 EPS forecasts for companies listed in the German DAX 30 stock index. We include both one and two year forecast horizons and find the number of respective forecasts to be fairly balanced. However,

³We are aware of the critical assessment of data quality brought forward in Ljungquist and Marston (2009). However, we trust the same authors' conclusion that the ex-post correction performed by the current provider Thomson-Reuters has re-established reliability.

it becomes clear that the remaining dimensions hint at a disproportionate dataset. This is due to at least three reasons.

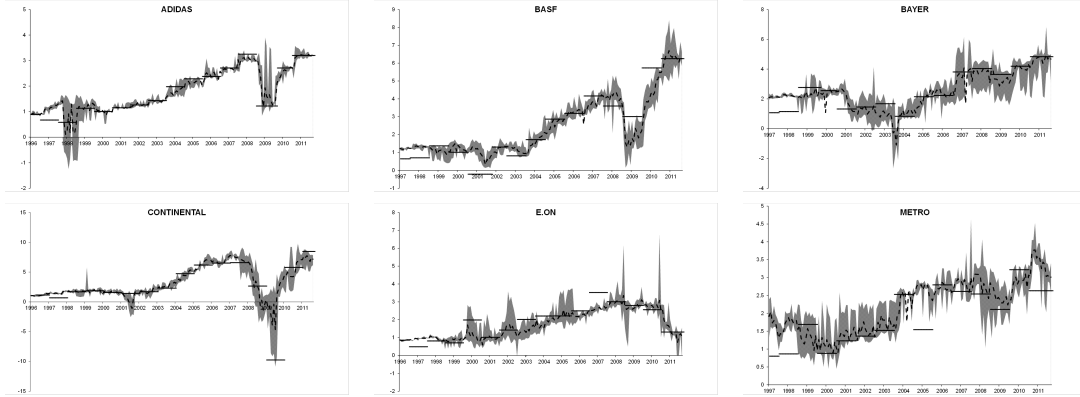
Table 3.1: Descriptive Statistics of DAX 30 Forecasts

Representation by	Total	Number of forecasts				
		Maximum	Minimum	Mean	Median	Std. Dev.
Company	41	4,882	61	2,716	2,811	1,419
Year	18	9,807	254	6,187	7,318	3,223
Institute	111	4,008	25	1,003	428	1,184
Forecasts <i>thereof</i>	111,372					
Recession	30,994					
Expansion	80,378					
1 yr forecast horizon	56,665					
2 yr forecast horizon	54,707					

Firstly, not all institutes continuously contributed to the sample. Secondly, the year 2012 only includes current forecasts as no assessment of the discrepancy of prognosis and realized value would have been possible at the time of writing. Thirdly, the dataset itself is unbalanced as evidently some companies are underrepresented. In order to account for this unbalancedness, we impose certain minimal criteria. After restricting the minimum number of forecasts per institute and company to 25, the sample comprises 41 single companies and 111 different institutes that contributed prognoses to the sample. As we seek to estimate asymmetry parameters for individual years, we only consider corporations if the particular calendar and fiscal years concur. Table 3.4 in the appendix provides the included companies and respective sample sizes in greater detail.

Figure 3.1 exemplarily illustrates the underlying dataset for six companies listed in the index. Here, the shaded area is the difference between the respective monthly maximum and minimum of forecasts, the dotted line represents the average of all current prognoses, and the bars show the realized variables. While the EPS forecasts tend to move with the realized value, a substantial degree of disagreement between the forecasters can be documented. For instance, in October 2009, for BASF (Bayer) the forecasts range between 1.42 and 3.80 (1.81 and 3.89) Euro per share. The disagreement among the forecasters can possibly be explained by the heterogeneity of the forecasters' loss functions (Pierdzioch et al. (2013a), p. 509.), which is studied in the next section.

Figure 3.1: Sample Illustration of Cross-Sectional Range of DAX 30 Forecasts



Note: The selected charts illustrate the dispersion of forecasts given by month (shaded area), the average estimate (dotted line), and realized EPS values as of fiscal year end (solid line). For the sake of legibility, extreme outliers were removed and previous month data was used if no fresh information was available.

3.3 Methodology and Hypotheses

3.3.1 Deriving a Forecaster's Loss Function

We rely on the loss function estimation and rationality test introduced in Elliott et al. (2005) and, among others, employed by Pierdzioch et al. (2013a). Adopting their notation the forecaster's loss function can be defined as:

$$L = [\alpha + (1 - 2\alpha)\mathbb{1}_{\{s_{t+1} - f_{t+1} < 0\}}] |s_{t+1} - f_{t+1}|^p \quad (3.1)$$

where s_{t+1} (f_{t+1}) is the (forecast of the) actual EPS value submitted by a forecaster in period t for period $t + 1$. Thus, The forecast error is given by $s_{t+1} - f_{t+1}$. The term $\mathbb{1}$ represents an indicator function, the parameter α determines the degree of asymmetry ($\alpha \in (0, 1)$), and the parameter defining the general shape of the function ($p \in [1; 2]$). If the asymmetry parameter $\hat{\alpha}$ is significantly lower (larger) than 0.5, it indicates that forecasters experience a higher loss when overpredicting the actual EPS value. This in turn, would rationalize overly pessimistic (optimistic) EPS forecasts. For $p=1$, the loss function takes on a linear shape, i.e., the loss increases proportionally with the forecast error. If p equals 2, the function has a quadratic, i.e., parabolic shape, for which the marginal loss increases with the forecast error. Equation (3.1) provides a general form of the function in full.

Elliott et al. (2005) show that, for a given parameter p , the asymmetry parameter,

α , can be consistently estimated by means of a generalized method of moments approach, and is given in equation (3.2).

$$\hat{\alpha} = \frac{\left[\frac{1}{T} \sum_{t=\tau}^{T+\tau-1} v_t |s_{t+1} - f_{t+1}|^{p-1} \right]' \hat{S}^{-1} \left[\frac{1}{T} \sum_{t=\tau}^{T+\tau-1} v_t \mathbb{1}_{\{s_{t+1} - f_{t+1} < 0\}} |s_{t+1} - f_{t+1}|^{p-1} \right]}{\left[\frac{1}{T} \sum_{t=\tau}^{T+\tau-1} v_t |s_{t+1} - f_{t+1}|^{p-1} \right]' \hat{S}^{-1} \left[\frac{1}{T} \sum_{t=\tau}^{T+\tau-1} v_t |s_{t+1} - f_{t+1}|^{p-1} \right]} \quad (3.2)$$

Here, T is the number of forecasts, where the lower limit is $t = \tau + 1$, and v_t is a vector of instruments. For our analysis we used four different sets of instruments which are known to have an impact on the dynamics in financial markets.⁴ Model 1 includes simply a constant term, Model 2 a constant term and the lagged realized value, Model 3 a constant term and the lagged long-term government bond yield, and Model 4 a constant term and the lagged redemption yield.

$$\hat{S} = \frac{1}{T} \sum_{t=\tau}^{T+\tau-1} v_t v_t' (\mathbb{1}_{\{s_{t+1} - f_{t+1} < 0\}} - \hat{\alpha})^2 |s_{t+1} - f_{t+1}|^{2p-2} \quad (3.3)$$

The use of lagged variables is of eminent importance as they are meant to resemble a set of information potentially available to the forecaster at the time of the estimate release. We obtain the yields from the Thompson Datastream database. Notably, the weighting matrix \hat{S} relies on $\hat{\alpha}$ and thus requires an iterative estimation process. The weighting matrix is given in equation (3.3).

$$J(\hat{\alpha}) = \frac{1}{T} \left(x_t' \hat{S}^{-1} x_t \right) \sim \chi_{d-1}^2 \quad (3.4)$$

As the classical Mincer-Zarnowitz regression cannot serve as an adequate measure for forecast rationality in a setting with asymmetric loss functions, Elliott et al. (2005) develop an alternative test outlined in equation (3.4), where x_t is given in equation (3.5) and d is the number of instruments.

$$x_t = \sum_{t=\tau}^{T+\tau-1} \left[\mathbb{1}_{\{s_{t+1} - f_{t+1} < 0\}} - \hat{\alpha} \right] |s_{t+1} - f_{t+1}|^{p-1} \quad (3.5)$$

⁴In this, we follow the procedure in Pierdzioch et al. (2013a), who give merit to Elliott et al. (2005) and Döpke et al. (2010).

One of the most useful properties of the J -test is that it allows us to test rationality for symmetric ($J(0.5)$) and asymmetric loss functions ($J(\hat{\alpha})$). Accordingly, our study shows whether the flexibility of the forecaster's loss function makes EPS forecasters more rational under an asymmetric loss compared to the standard symmetric loss.

3.3.2 Hypotheses and Underlying Theory

Having introduced the concept of alternative loss functions, it is worthwhile to explore whether this procedure can be meaningfully employed and to what extent formerly acknowledged biases hold true. At first, we steer our attention towards an assessment of analyst sentiment. Prior research confirmed consistent optimistic bias (Butler and Lang, 1991; Easterwood and Nutt, 1999), where optimism is usually defined as a positive forecast error and scaled to the stock price at the release of the actual value. Easterwood and Nutt (1999) name two plausible reasons for forecaster optimism that still hold true under asymmetric loss. Firstly, analysts are mainly working for brokerage houses and thus have an incentive to drive up trading volumes. This is easily done through releasing more optimistic forecasts and even if individual forecasters should not reap a direct financial gain, they still fare better as the company is less likely to lay off staff. Secondly, analysts might shy away from negative forecasts as through the release of pessimistic forecasts information channels into a company board might dry up. A different reasoning is presented in Richardson et al. (2004), who relates optimism to the "walk-down phenomenon". According to this study, forecasts, which are released at the beginning of a year are more optimistic for the time ahead and are only gradually revised to levels that are easier to beat for the respective companies. Irrespective, of the argumentation favored, we assume that optimism is on average prevalent in the forecasts and capture this with hypothesis 6.a.

Hypothesis 6.a *Forecasters on average release overly optimistic prognoses, which are even more pronounced for longer forecast horizons.*

The method proposed by Elliott et al. (2005), offers a clear alternative to former optimism detection methods, as the value of $\hat{\alpha}$ clearly allows a statement about the underlying bias. For instance, a value significantly below the threshold value of 0.5 points at pessimism, whereas values above this cut-off value suggests optimism.

Hypothesis 6.b *Optimism in forecasts depends on the business cycle.*

Additionally, we ask for the impact of the business cycle. Accordingly, hypothesis 6.b builds on the notion brought forward in Zhang (2006), who links times of increased uncertainty, e.g., times of recession, with positive overreaction to novel information.⁵

Hypothesis 7 *Instead of a symmetric loss function, forecasters optimize an asymmetric one.*

As we pointed out earlier, the meaningfulness of alternative loss functions is conditional upon the assumption that standard symmetric as presented in Mincer and Zarnowitz (1969) is inappropriate. Elliott et al. (2008) underscore this notion, as they show that all assessments of rationality are not to be trusted given that the underlying loss concept is only slightly asymmetrical. Although they empirically substantiate their reasoning with forecast data for the real GDP growth rate, they suggest that rationality can be remedied in quite a number of contexts with the suitable loss function prior estimated. Further evidence for the accuracy of this assumption is provided through a series of studies, e.g., Pierdzioch et al. (2013a), Clatworthy et al. (2012). Hypothesis 7 captures this reasoning and will be tested based on the procedure outlined in section 3.3.1.

Hypothesis 8 *Individual forecasters' loss functions and rationality are chiefly shaped through individual factors.*

Ultimately, we turn towards a preliminary assessment of the drivers behind the biases. We are eager to learn about the level at which the distortion evolves. Our working theorem is that rather than macroeconomic factors, i.e., the real growth rate, the inflation rate, institute or analyst bound factors such as remuneration scheme, age, time spent with the company, and work experience are crucial. Hypothesis 8 grasps this notion. Moreover, we will check this claim against the opposite reasoning, that the object of study, i.e., the listed companies and the respective industries they operate in, influence the bias magnitude.

⁵As Easterwood and Nutt (1999) rightly point at the differentiation of overreaction and optimism. However, they point out, that the subtle distinction is made through assessing the rationality next to the mere forecast error. Our approach inhibits such wrong-assessment as we do not look at mere forecast errors but rather go a step deeper and look at the underlying loss function and perform a rationality test on the estimated parameters.

3.4 Results

3.4.1 Forecaster Sentiment

At first, we avail ourselves of the estimated asymmetry parameters and the rationality tests as provided by Table 3.2 (in the appendix). The table lists the $\hat{\alpha}$ parameter and the corresponding $J(\hat{\alpha})$ tests for all four model specification according to the forecast horizon. When looking at the full sample, the $\hat{\alpha}$ coefficient oscillates between 0.518 and 0.535 (0.642 and 0.713) for the full sample in the linear (quadratic) specification. When looking exclusively at current year forecasts, the variable estimated for the linear (quadratic) specification ranges from 0.465 and 0.479 (0.620 and 0.649), i.e., the value drops slightly below the 0.5 threshold for $p=1$. The span is suspended upwards for two-year forecast horizons. Here, we find the estimated values to be between 0.559 and 0.627 (0.656 and 0.758, respectively). As pointed out earlier, the asymmetry parameter $\hat{\alpha}$ can serve as a reliable proxy for the assessment of the underlying forecaster behavior. If higher than 0.5, $\hat{\alpha}$ suggests that an overly positive estimate is connected to a smaller loss. Interestingly, the analysis reveals increased optimism for longer forecast horizons, which is in line with theories describing the “walk-down phenomenon” (Richardson et al., 2004). Accordingly, we consider the fact that the asymmetry parameter is continuously above the threshold value of 0.5 confirming hypothesis 6.a. However, it is well worth noting that the flexible loss concept does not restore rationality for the full sample since the rationality condition can be rejected under symmetric as well as asymmetric loss.

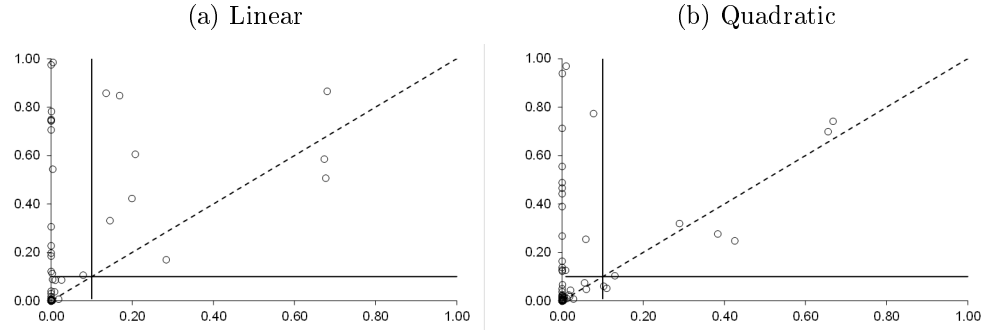
In a next step, we turn towards the impact of the business cycle on analysts’ sentiment. To this end, we clustered the EPS forecasts depending on the state of the economy at the time the forecast was released. Table 3.3 in the appendix outlines our results for the asymmetry parameter and the corresponding rationality tests. We use data from Economic Cycle Research Institute (2012) to determine the state of the business cycle. This dataset is unique as it resembles the considerably broad approach of the NBER to determine a recession and has been positively featured in various publications, inter alia in Grossarth-Maticek and Mayr (2008). For contractionary periods, the estimated $\hat{\alpha}$ values in a linear (quadratic) model range between 0.643 and 0.900 (0.868 and 0.939), whilst expansionary times the parameter is estimated to lie in between 0.444 and 0.470 (0.510 and 0.529). Notably, all estimated parameters are significantly different from 0.5 at a 99% confidence level. The results

in Table 3.3 indicate that DAX forecasters release more optimistic estimates in times of economic distress. Yet rationality cannot be remedied on the aggregate level, as the respective J -tests reveal. In order to allow for a more fine-grained analysis, we break the results of the rationality test down to single years. Figure 3.5 plots the values of $\hat{\alpha}$ on a yearly basis. Shaded areas show years for which the rationality tests' p -values are above one percent and thus do not allow to reject the assumption of rational forecasting. The chart allows two deductions. First, it provides further anecdotal evidence of a co-movement of sentiment and the economy. For example, the values of $\hat{\alpha}$ plummet in 2008 and 2009 for both specifications. Secondly, it reveals that despite rejected rationality on an aggregate level there are 10 years for the linear setting (5 for the quadratic specification) for which the alternative loss concept allows to reject irrationality. We therefore cannot accept hypothesis 6.b.

3.4.2 Rationality Under Asymmetric Loss

This relates to the research question posed in hypothesis 7, i.e., do more forecasters act rationally when assuming an asymmetric loss function if compared to standard loss concepts. Tables 3.2 and 3.3 clearly rejected the rationality for the full sample on the aggregate level. Nevertheless, Figure 3.5 shows that we cannot reject rationality for specific years. Now, for an assessment of individual forecaster rationality we need to compute the respective rationality tests under standard ($\alpha = 0.5$) and asymmetric ($\alpha = \hat{\alpha}$) loss. Figure 3.2 represents the results of our calculations. Here, the horizontal (vertical) axis shows the p -values for the J -tests on standard (alternative) loss. Values above 0.10 are considered as confirming rationality. For the linear (quadratic) specification, we cannot reject rationality for 9 (8) out of the 111 institutes in the sample under standard loss. When turning towards the outcome under the newly estimated asymmetry parameters, the number is elevated to 24 (22). In other words, the number of rational institutes is almost three times as high as under asymmetric loss. This suggests a considerably better fit of this model with empirical data and confirms the theory brought forward in Elliott et al. (2008). Accordingly, we cannot reject hypothesis 7.

Figure 3.2: Rationality Test of Standard and Alternative Loss Parameters per Forecaster



Note: The charts plot the p-values for the J-tests on rationality for Model 4. Comparable outcomes for other GMM-specifications are on hand and available upon request. The respective vertical axes provide the p-values for $J(\hat{\alpha})$, whilst the horizontal ones show the p-values for the results for the alternative $J(0.5)$. Each marker represents a single forecasting institute, the dotted line the bisector of an angle.

3.4.3 Impact of Institute and Company Effects

Ultimately, we use the prior stated findings to assess the heterogeneity of the asymmetric loss function. At first, we look into the dispersion of asymmetry parameters as illustrated in Figures 3.3 and 3.4. The bar diagrams show the number of $\hat{\alpha}$ parameters that are significantly different from 0.5 on a one percent level based on a z-test in black and those not significantly different in grey. For instance, the linear (quadratic) specification for model 3 reveals, that 72 (88) are significantly different from 0.5 and 39 (20) cannot be linked to z-values larger than 2.56. This underscores distinguished heterogeneity and thus confirms that the major factors influencing α are to be found on the institute level. Additionally, we looked into the asymmetry parameters as depending on the business cycle. Although we find the parameter to move with the state of the economy and show remarkable dispersion with values ranging from as little as 0.444 to as much as 0.939, the aggregate consideration does not help to restore rationality. In a final step, we looked at the impact of the company. One might safely assume parameters attached to single companies to significantly impact forecaster optimism or pessimism, e.g., a certain PR policy or the industry specific conditions. Table 3.4 shows for model 1 that the asymmetry parameter ranges between 0.13 and 0.87, thus covering almost the full scale of possible values. The extensive heterogeneity is reflected in the rationality tests, where rationality under asymmetric (standard) loss cannot be rejected for 4 (1) out of 41

companies in the most favorable scenario.⁶ All in all, we confirm hypothesis 8 and augment the list of asymmetry influencing factors for the business cycle and the object of study.

3.5 Conclusion

We enquired into the loss function of forecasters releasing EPS prognoses for DAX 30 listed companies during the last 18 years. We found ample evidence for asymmetric loss functions and confirmed that this alternative loss concept can remedy rationality for a number of years. Additionally, we use the loss function assessment as a starting point for an analysis of the forecasters' sentiment. We conclude that analysts are overly optimistic and that this attitude is aggravated for longer forecast horizons. In a next step we sought to answer the question what drives rationality. In the present paper, we looked into time, the company at which the forecast is directed, and the factors on the institute level as possible factors. Our analysis allows the exclusion of the first two and confirms that the driving force behind rationality is to be found at the institute level. This in turn points at numerous paths for future research. Event studies targeted at assessing the impact of M&A transactions, IPOs, spin-offs, and similar corporate finance actions promise to be insightful starting points to further illuminate the determinants of analyst rationality.

⁶The $J(\hat{\alpha})$ -tests are not included in full, though results for the remaining models and specification are quantitatively similar and available upon request.

3.6 Appendix

Figure 3.3: Asymmetry Parameter per Forecaster(Linear)

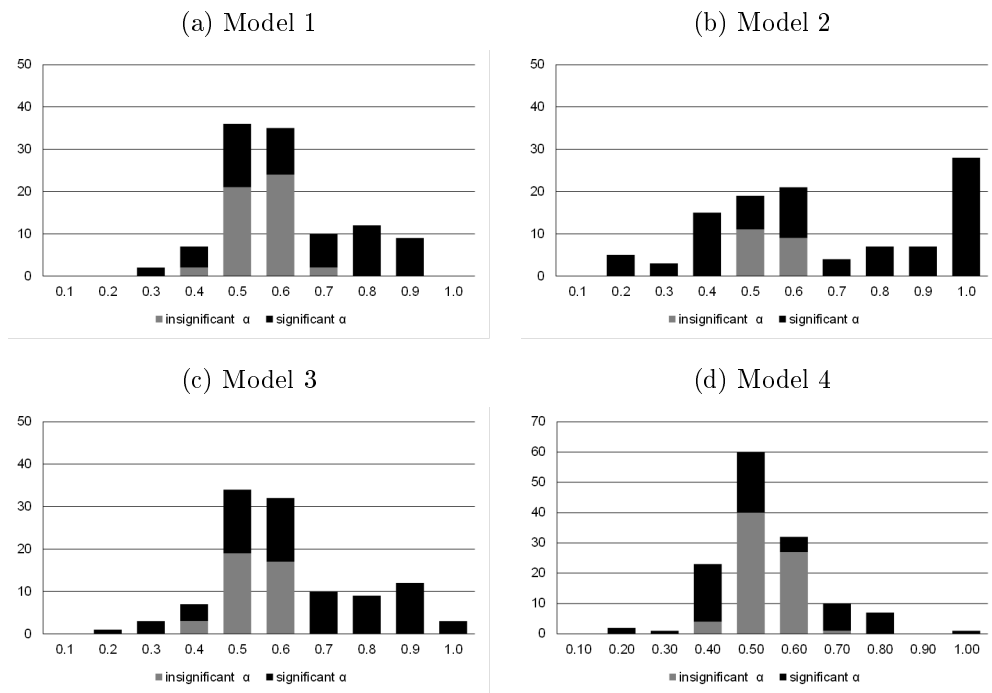


Figure 3.4: Asymmetry Parameter per Forecaster (Quadratic)

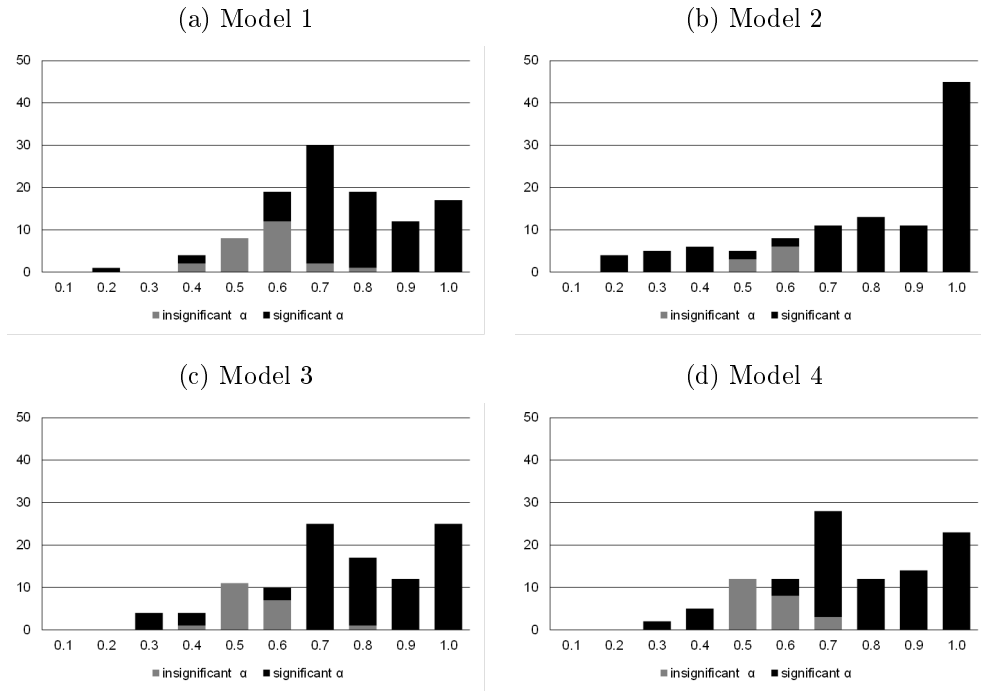
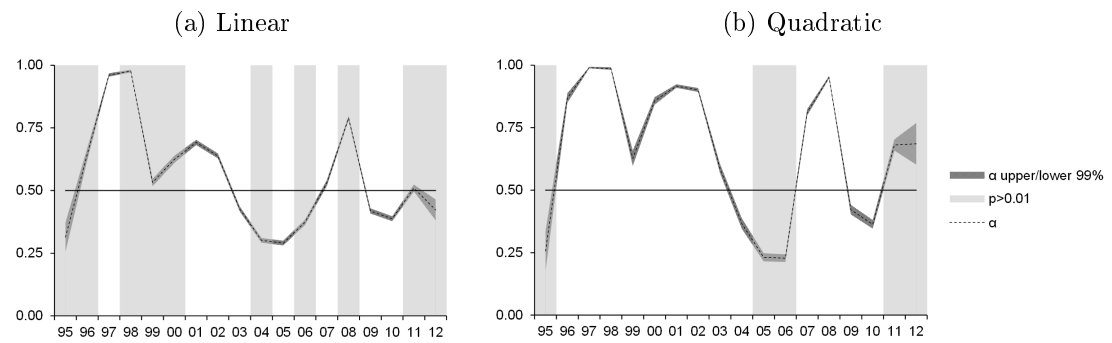


Figure 3.5: Asymmetry Parameter and Times of Restored Rationality



Note: The varying asymmetry parameter and periods of rationality under asymmetric loss (model 2).

Table 3.2: Asymmetry Parameter and Rationality Test According to Forecast Horizon

		Asymmetry parameter											
		Model 1			Model 2			Model 3			Model 4		
Specification	Sample	N	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	
Linear	Full	111,372	0.518 *	0.001	0.535 *	0.001	0.521 *	0.001	0.520 *	0.001	0.520 *	0.001	
	Current year	56,665	0.479 *	0.002	0.465 *	0.002	0.478 *	0.002	0.478 *	0.002	0.478 *	0.002	
	Next year	54,707	0.559 *	0.002	0.627 *	0.002	0.571 *	0.002	0.568 *	0.002	0.568 *	0.002	
Quadratic	Full	111,372	0.642 *	0.003	0.713 *	0.002	0.673 *	0.003	0.664 *	0.003	0.664 *	0.003	
	Current year	56,665	0.62 *	0.004	0.649 *	0.004	0.624 *	0.004	0.625 *	0.004	0.625 *	0.004	
	Next year	54,707	0.656 *	0.004	0.758 *	0.003	0.716 *	0.003	0.694 *	0.003	0.694 *	0.003	

		Rationality tests												
Specification	Sample	N	$J_2(0.5)$	p	$J_3(0.5)$	p	$J_4(0.5)$	p	$J_2(\hat{\alpha})$	p	$J_3(\hat{\alpha})$	p	$J_4(\hat{\alpha})$	p
Linear	Full	111,372	25,432	.00	5,974	.00	5,100	.00	26,223	.00	5,845	.00	4,999	.00
	Current year	56,665	12,199	.00	1,769	.00	1,781	.00	11,530	.00	1,675	.00	1,680	.00
	Next year	54,707	14,435	.00	5,329	.00	4,162	.00	14,729	.00	4,658	.00	3,575	.00
Quadratic	Full	111,372	5,498	.00	5,065	.00	5,027	.00	5,247	.00	4,215	.00	3,992	.00
	Current year	56,665	2,289	.00	1,423	.00	1,550	.00	2,451	.00	1,020	.00	1,188	.00
	Next year	54,707	3,546	.00	3,766	.00	3,595	.00	2,927	.00	3,171	.00	2,778	.00

Note: Horizon is the forecast horizon in years, SE = standard error, * = α significantly different from 0.5 at the 99% level. The instruments are a constant term (Model 1), a constant term and the lagged realized value (Model 2), a constant term and the lagged long-term government bond yield (Model 3) and a constant term and the lagged redemption yield (Model 4).

Table 3.3: Asymmetry Parameter and Rationality Test According to Business Cycle

Specification	Sample	N	Asymmetry parameter							
			Model 1		Model 2		Model 3		Model 4	
			$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE
Linear	Full	111,372	0.518 *	0.001	0.535 *	0.001	0.521 *	0.001	0.520 *	0.001
	Recession	30,994	0.643 *	0.003	0.900 *	0.002	0.671 *	0.003	0.661 *	0.003
	Expansion	80,378	0.470 *	0.002	0.444 *	0.002	0.468 *	0.002	0.468 *	0.002
Quadratic	Full	111,372	0.642 *	0.003	0.713 *	0.002	0.673 *	0.003	0.664 *	0.003
	Recession	30,994	0.868 *	0.003	0.939 *	0.001	0.903 *	0.002	0.883 *	0.002
	Expansion	80,378	0.529 *	0.004	0.510 *	0.003	0.522 *	0.003	0.527 *	0.003

Specification	Sample	N	Rationality tests												
			$J_2(0.5)$		$J_3(0.5)$		$J_4(0.5)$		$J_2(\hat{\alpha})$		$J_3(\hat{\alpha})$		$J_4(\hat{\alpha})$		
			p	$J_2(0.5)$	p	$J_3(0.5)$	p	$J_4(0.5)$	p	$J_2(\hat{\alpha})$	p	$J_3(\hat{\alpha})$	p	$J_4(\hat{\alpha})$	
Linear	Full	111,372	.00	25,432	.00	5,974	.00	5,100	.00	26,223	.00	5,845	.00	4,999	.00
	Recession	30,994	.00	7,418	.00	4,746	.00	3,936	.00	9,959	.00	2,528	.00	1,734	.00
	Expansion	80,378	.00	19,441	.00	3,231	.00	3,333	.00	18,821	.00	2,911	.00	2,970	.00
Quadratic	Full	111,372	.00	5,498	.00	5,065	.00	5,027	.00	5,247	.00	4,215	.00	3,992	.00
	Recession	30,994	.00	4,151	.00	3,936	.00	3,859	.00	1,665	.00	1,214	.00	685	.00
	Expansion	80,378	.00	3,490	.00	1,617	.00	1,797	.00	3,500	.00	1,634	.00	1,789	.00

Note: Horizon is the forecast horizon in years, SE = standard error, * = α significantly different from 0.5 at the 99% level. The instruments are a constant term (Model 1), a constant term and the lagged realized value (Model 2), a constant term and the lagged long-term government bond yield (Model 3) and a constant term and the lagged redemption yield (Model 4).

Table 3.4: Asymmetry Parameter for Each Company (Quadratic)

Name	N	Model 1		Model 2		Model 3		Model 4	
		$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE	$\hat{\alpha}$	SE
ADIDAS	3,730	0.51	0.01	0.67 *	0.01	0.52	0.01	0.52	0.01
ALLIANZ	4,533	0.57 *	0.01	0.90 *	0.00	0.57 *	0.01	0.57 *	0.01
ALTANA	2,336	0.40 *	0.01	0.35 *	0.01	0.39 *	0.01	0.39 *	0.01
BASF	4,805	0.53 *	0.01	0.65 *	0.01	0.56 *	0.01	0.57 *	0.01
BHV	2,811	0.66 *	0.01	0.91 *	0.01	0.77 *	0.01	0.70 *	0.01
BAYER	4,717	0.49	0.01	0.25 *	0.01	0.49	0.01	0.49	0.01
BEIERSDORF	3,212	0.50	0.01	0.46 *	0.01	0.50	0.01	0.50	0.01
BMW	3,416	0.40 *	0.01	0.25 *	0.01	0.38 *	0.01	0.38 *	0.01
CONTINENTAL	3,844	0.52	0.01	0.55 *	0.01	0.54 *	0.01	0.53 *	0.01
DAIMLER	4,721	0.63 *	0.01	0.93 *	0.00	0.66 *	0.01	0.67 *	0.01
DEGUSSA	942	0.78 *	0.01	0.99 *	0.00	0.87 *	0.01	0.89 *	0.01
DT. BANK	4,605	0.60 *	0.01	0.95 *	0.00	0.60 *	0.01	0.61 *	0.01
DT. BOERSE	2,366	0.41 *	0.01	0.27 *	0.01	0.40 *	0.01	0.41 *	0.01
DT. POST	2,751	0.48	0.01	0.33 *	0.01	0.48	0.01	0.48	0.01
DT. POSTBANK	1,318	0.59 *	0.01	0.99 *	0.00	0.61 *	0.01	0.61 *	0.01
DT. TELEKOM	4,399	0.51	0.01	0.53 *	0.01	0.51	0.01	0.51	0.01
DRESDNER BANK	349	0.58 *	0.03	1.00 *	0.00	1.00 *	0.00	1.00 *	0.00
E.ON	4,209	0.42 *	0.01	0.19 *	0.01	0.42 *	0.01	0.42 *	0.01
FRESENIUS	114	0.21 *	0.04	0.01 *	0.01	0.19 *	0.04	0.16 *	0.03
FRESENIUS MC	1,870	0.59 *	0.01	0.94 *	0.01	0.64 *	0.01	0.65 *	0.01
HANNOVER RE	2,481	0.42 *	0.01	0.27 *	0.01	0.39 *	0.01	0.36 *	0.01
HEIDEL. ZEMENT	2,752	0.58 *	0.01	0.81 *	0.01	0.58 *	0.01	0.58 *	0.01
HENKEL	3,772	0.39 *	0.01	0.25 *	0.01	0.37 *	0.01	0.37 *	0.01
HOECHST	793	0.87 *	0.01	1.00 *	0.00	0.99 *	0.00	1.00 *	0.00
HRE	882	0.50	0.02	0.96 *	0.01	0.30 *	0.02	0.29 *	0.02
KARSTADT	1,234	0.65 *	0.01	0.98 *	0.00	0.93 *	0.01	0.93 *	0.01
LANXESS	1,550	0.32 *	0.01	0.05 *	0.01	0.18 *	0.01	0.23 *	0.01
LINDE	2,981	0.43 *	0.01	0.15 *	0.01	0.38 *	0.01	0.37 *	0.01
LUFTHANSA	3,495	0.45 *	0.01	0.26 *	0.01	0.40 *	0.01	0.40 *	0.01
MAN	2,881	0.49	0.01	0.46 *	0.01	0.49	0.01	0.49	0.01
MANNESMANN	61	0.15 *	0.05	0.00 *	0.00	0.00 *	0.00	0.00 *	0.00
MERCK	3,840	0.49	0.01	0.25 *	0.01	0.48	0.01	0.49	0.01
METRO	3,906	0.74 *	0.01	0.97 *	0.00	0.83 *	0.01	0.84 *	0.01
MLP	1,376	0.69 *	0.01	0.91 *	0.01	0.69 *	0.01	0.69 *	0.01
MUNICH RE	3,809	0.54 *	0.01	0.92 *	0.00	0.54 *	0.01	0.55 *	0.01
PREUSSAG/TUI	1,566	0.69 *	0.01	0.97 *	0.00	0.75 *	0.01	0.75 *	0.01
RWE	2,570	0.49	0.01	0.33 *	0.01	0.48	0.01	0.48	0.01
SALZGITTER	1,594	0.58 *	0.01	0.76 *	0.01	0.59 *	0.01	0.59 *	0.01
SAP	4,882	0.48	0.01	0.32 *	0.01	0.47 *	0.01	0.47 *	0.01
SCHERING	3,178	0.48	0.01	0.21 *	0.01	0.47 *	0.01	0.47 *	0.01
VOLKSWAGEN	721	0.13 *	0.01	0.00 *	0.00	0.00 *	0.00	0.00 *	0.00

Note: SE = standard error, * = α significantly different from 0.5 at the 99% level. The instruments are a constant term (Model 1), a constant term and the lagged realized value (Model 2), a constant term and the lagged long-term government bond yield (Model 3) and a constant term and the lagged redemption yield (Model 4). Only companies with corresponding fiscal and calendar years included.

Chapter 4

EPS Forecasts: Herding, Optimism, and the Business Cycle¹

4.1 Introduction

In the vein of the most recent economic turmoil, criticism on the capability and the usefulness of the forecasting industry gained new momentum. Especially, prognoses on the earnings of private companies have come under close scrutiny as the estimated profits and the failures of, e.g., General Motors Inc. and AIG Inc. stood in glaring contrast and seemed to uncover a system torn by conflicts of interest and grossly overstated prognoses.

Research on biases in financial analysts' forecasts produced some remarkable studies in the past decades and covered a wide array of potential disruptions. To name a few, over- and underreaction to novel information (e.g., DeBondt and Thaler (1990)) and (anti-) herding (e.g., Grossman and Stiglitz (1976), Katz and Shapiro (1985)) formed a small yet significant part of this stream of literature. Moreover, the appropriate evaluation of the herding impact is still under dispute and oscillates between a positive connotation (as advocated by, e.g., Morris and Shin (2002)) and distinctly skeptical ones (e.g., Olsen (1996)). Moreover, the literature suggested a link between the business cycle and certain biases, e.g., that there is a link between herding and times of increased volatility (Ramnath et al., 2008) or optimism and

¹This chapter is based on the homonymous working paper co-authored by Markus Rudolf (Schmütsch and Rudolf, 2013).

times of uncertainty (Zhang, 2006). The link was confirmed in empirical studies with limited temporal or regional focus, e.g. by Ang and Ma (2001) for Indonesia, Korea, Malaysia, and Thailand for current year forecasts from 1997 and Chopra (1998) for a U.S. dataset. However, what has been missing thus far is a comparative study of the nexus of these biases and the economic cycle and its impact on forecast accuracy for international markets. We seek to close this gap through providing an exhaustive study that covers EPS forecasts for companies from the U.S. and Germany from almost a quarter of a century.

To this end, the present paper follows three steps. Firstly, we offer a survey of analyst optimism and its interaction with the business cycle. Secondly, we analyze the prevailing herding bias. Eventually, after dealing with the two most common contortions we ask about their impact on forecast accuracy. Based on the results generated with the innovative herding detection method of Bernhardt et al. (2006), we report prevailing anti-herding for forecasts on both sides of the Atlantic as well as enduring optimism that is aggravated in times of economic contraction. Additionally, we can show that both the state of the business cycle and the herding bias significantly influence the forecast error. This contrasts with the notion presented in Morris and Shin (2002), who deny adverse impacts through agent herding.

At first, we discuss our data sample and provide the reader with descriptive statistics. Section 3 introduces the blend of methodologies employed to work through the threefold research question. Thereafter, we present our results and offer a discussion of the study's findings highlighting avenues for future research.

4.2 Data

We work with data compiled by the Institutional Broker Estimate System (IBES). It is the primary source for a series for studies dealing with herding of financial analysts and biases in the forecasting process in general (Hong et al., 2000; Bernhardt et al., 2006). We select the companies in dependence on their listing in either the Dow Jones Industrial Average or the DAX 30 index. The basal constituents lists are drawn from the Compustat database. As we want to analyze optimism and herding biases for specific years and months, we need to harmonize the sample in terms of forecasting horizons. Therefore, we only include corporations whose fiscal years coincide with calendar years. The resulting lists of companies are provided in

greater detail in Tables 4.3 and 4.4 in the appendix. Additionally, we restrict the minimum number of forecasts per institute to 40 in order to exclude those that are not continuously contributing information and provide too few forecasts to deduct meaningful statements about their forecasting behavior. This procedure leaves us with a data sample of combined 235,715 data points. Table 4.1 illustrates the data sample for both indexes along the dimensions firm, institute, and year.

Table 4.1: Descriptive Statistics of Dow Jones Industrial 30 and DAX 30 Forecasts

Level	Total	Number of forecasts				Std. Dev.
		Maximum	Minimum	Mean	Median	
Dow Jones Industrial 30						
Firm	31	9,694	860	3,951.7	3,842	1,488.4
Institute	184	5,642	48	665.8	246	1,095.1
Year	24	6,962	4,091	5,104.3	4,765	796.2
DAX 30						
Firm	42	4,955	53	2,695.5	2,834	1,463.1
Institute	113	4,079	40	1,001.9	415	1,193.8
Year	17	9,845	493	6,659.5	7,661	2,916.1

Notes:

Representation by firm, institute, year, and analyst for both indices include current and two-year EPS forecasts.

The descriptive statistics show that the number of forecasts are fairly balanced over time, with a maximum of annual 6,962 forecasts for the U.S. sample and some 9,845 for its German counterpart. The number of forecasts per firm is more unbalanced and shows a significant standard deviation from the mean in both cases. Looking at the differences of mean and median is particularly revealing, when assessing how well balanced a dataset is. One can easily conceive that the largest deviations can be found at the institute level with standard deviations of 1,095.1 and 1,193.8, respectively, underlining the unbalancedness of the panel. The sample covers nearly a quarter of a century of Dow Jones forecast and 17 years of the DAX history. Whilst the DAX subsample includes 42 companies, there are only 31 represented in the Dow one. In part, this is due to more changes in the composition of the index and the exclusion of more companies with diverging fiscal and calendar years.

We deliberately refrain from restricting the forecast failures to 100% as argued in inter alia Clatworthy et al. (2012) for two reasons. Firstly, as we are eager to uncover the impact of the business cycle on forecast accuracy and sentiment we would need

to exclude an undue number of forecasts from recession periods. Secondly, we do not expect distortions in our analytical results as the employed test on forecaster herding is insensitive to outliers.² Moreover, while providing mean and median forecast errors, we check our reasoning against the latter.

4.3 Methodology and Theory

We split the overarching research question, i.e., how do economic downturns and biases in financial analysts' forecasts interact and what is the impact of such biases, into three parts. Firstly, we assess the interplay of optimism and the business cycle, then we deal with the existence of herding biases, and eventually turn to its impact on forecast accuracy. This section presents the underlying theories and the methods employed to answer these problems.

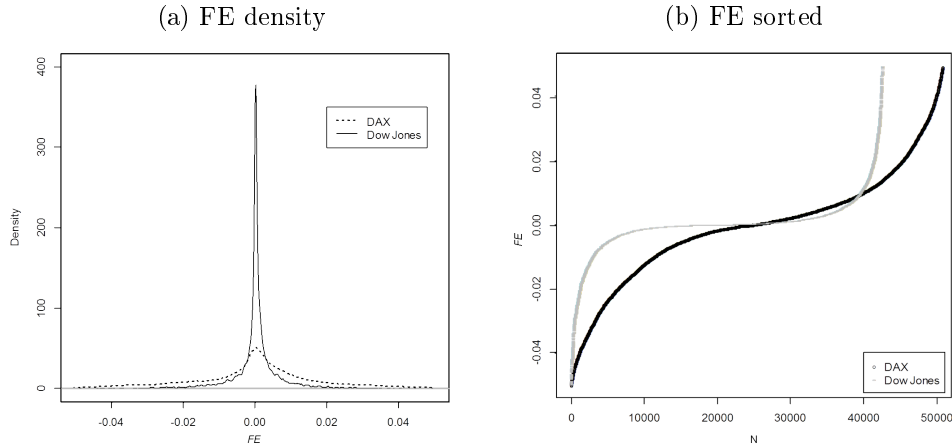
4.3.1 Detecting Forecaster Optimism

Optimistic biases in analyst forecasts have been explained by different approaches. For one thing, Easterwood and Nutt (1999) find two justifications for such behavior. They reason that the majority of analysts is employed by brokerage houses, which is eager to generate new business on the base of positive recommendations for certain stocks. Additionally, they argue that pessimistic forecasts might adversely affect the willingness of analysts' sources within companies to admit access to superior information in the future.

On a different note, Richardson et al. (2004) find the "walk-down" phenomenon to be a suitable explanation for the observed bias. Here, optimism occurs at the beginning of a fiscal period, only to gradually diminish, i.e., to walk down, to a level that the company actually can achieve. Additionally, the idea to research the interplay of crises and forecaster sentiment has merit as, e.g., Zhang (2006) argues that especially in times of increased uncertainty, analysts overreact to positive news. In a similar fashion DeBondt and Thaler (1990) discuss the over- and underreaction of financial analysts and they, too, find evidence for overreaction.

²Cf. Bernhardt et al. (2006) for proof of the insensitivity.

Figure 4.1: Forecast Error Density Restricted to <5%

*Notes:*

Forecast error (FE) as % of fiscal year end (FYE) stock price.

As part of our analysis focuses on the magnitude and sign of the forecast error, we provide descriptive statistics for the deviations in Table 4.5 in the appendix. In order to compare the forecast errors across companies and currencies, we scale them to the stock price corresponding to the forecast horizon. Hence, our definition of the forecast error FE looks as outlined in equation (4.1). Here, FE_{ijt} is the forecast error for company i at time t of forecaster j , E_{it} the respective realized value, \hat{E}_{ijt} the issued prognosis, and SP_{it} the stock price at fiscal year end corresponding to the forecast horizon.

$$FE_{ijt} = \frac{E_{it} - \hat{E}_{ijt}}{SP_{it}} \quad (4.1)$$

It is well worth noting, that mean and median forecast errors for both subsamples are negative, consistent with literature advocating analysts' optimism. Notably, there are some exceptions to the rule, especially during non-recession periods the error signs turn positive.³ Strikingly, while the median forecast error for the U.S. sample equals zero, it is slightly negative for the German forecasts still. Moreover, the highest absolute median deviations are encountered in the crisis year of 2008 with some -1.71% for Dow Jones estimates and -2.61% for DAX listed companies.⁴ Figure 4.1 depicts the density of average FE_{it} and captures the aforementioned

³Cf. Figures 4.4 and 4.5 in the appendix to see an illustration of boom and crisis periods.

⁴Cf. Table 4.5 in the appendix.

phenomenon graphically. In comparison to the forecast errors for Dow Jones listed corporations, which show a higher concentration around 0%, the density of average DAX FE_{it} exhibits a more leptokurtic distribution.

4.3.2 Detecting Forecaster Herding

Numerous economic explanations for herding are on hand. While the belief in irrational reasons for herding prevails, nourished by inter alia Shiller (2000) and Devenov and Welch (1996), rational explanations based on externalities are advocated by among others Katz and Shapiro (1985), Hirshleifer and Teoh (2003), Zwiebel (1995), or Scharfstein and Stein (1990). Next to reasoning about herd behavior, little has been said about its connection to the business cycle in the finance literature. For instance, Graham (1999) or Welch (2000) hypothesize that analysts tend to herd in times of greater uncertainty, whereas Ramnath et al. (2008) suggest that herding occurs when volatility is highest.

However, we find an analogous approach in the field of monetary economics. Theories of “self-fulfilling prophecies” would suggest that “market expectations coalesce” around a single opinion.⁵ Obstfeld (1996) points at a number of markets where this phenomenon might appear, among others he names public debt, banks, income distribution, and the real interest rate. There is little reason to assume the mechanism illuminated in his seminal paper to be any different when applied to the setting of the stock market. Put differently, one should assume a tendency to herd among financial forecasters at the outset of a recession.

In order to test this theory, we employ a recent (anti-)herding detection method by Bernhardt et al. (2006) and, for gaining insights into secondary research questions, use standard OLS regressions as well as measures taken from the field of accounting research.

The layout and interpretation of the test presented in Bernhardt et al. (2006) are without frills. To start with, an individual analyst’s i earnings per share (EPS) forecast is considered unbiased if the released estimate equals the mean of the assumed EPS distribution. This estimate is based on information incorporating private findings, company releases, and the research unveiled through posterior forecasts. Ac-

⁵Cf. Obstfeld (1996), p.1044.

cordingly, prior forecasts may gain a disproportionate weight in such informational cascades.⁶

Given that the analyst in question witnesses the mean of outstanding forecasts, she is prone to at least two types of biases. Firstly, she might (un-)consciously deviate her private estimate into the direction of the outstanding forecast, which is formally referred to as herding. Let E_{it}^p be the private estimate of the analyst i for period t , \hat{E}_{it} the published EPS forecast, and \bar{E}_{it} denote the outstanding consensus estimate at the time of analyst i 's estimate release. Hence, herding looks formally as the disparity of private and released estimate, i.e., $E_{it}^p > \hat{E}_{it} > \bar{E}_{it}$ and $E_{it}^p < \hat{E}_{it} < \bar{E}_{it}$, respectively.

Secondly, the analyst might willingly or unwillingly bias the published forecast away from the outstanding consensus – a behavior widely referred to as anti-herding. Similar to herding, the divergence of published and private estimates is key. Sticking to the notation used afore-mentioned, anti-herding looks like the following: $\hat{E}_{it} > E_{it}^p > \bar{E}_{it}$ and $\hat{E}_{it} < E_{it}^p < \bar{E}_{it}$. Analysts might strategically deviate their own forecast away from the consensus mainly for reputational reasons.⁷

Building on these basic ideas, the development of the test is straightforward. Assuming that forecasters' prognoses are unbiased, the probability that the EPS forecast is both above (below) actual earnings *and* the outstanding consensus has to equal 50%.⁸

$$\mathbb{E}(\mathbb{1}_{\{\hat{E}_{it} > E_{it}\}} | \hat{E}_{it} > \bar{E}_{it}) = 0.5 \quad (4.2)$$

$$\mathbb{E}(\mathbb{1}_{\{\hat{E}_{it} < E_{it}\}} | \hat{E}_{it} < \bar{E}_{it}) = 0.5 \quad (4.3)$$

Now, herding suggests that $E_{it}^p > \hat{E}_{it} > \bar{E}_{it}$ and thus the probability for a forecast exceeding actual EPS given that the prognosis already exceeded (fell short of) consensus estimates has to be below 50%. The probability of undershooting then looks like the following.

⁶The term “informational cascade” has been coined by Bikhchandani et al. (1992). They reason that in such settings, i.e., settings where the information released first is incorporated into any following, a type of externality appears that serves as a potential explanation for the herding phenomenon.

⁷Cf. Prendergast and Stole (1996) For a more elaborate discussion.

⁸Since $\mathbb{E}(\mathbb{1}_{\{A\}}) = P(A)$ the expected value of an indicator function is equal to the a probability of this event.

$$\mathbb{E}(\mathbb{1}_{\{\hat{E}_{it} > E_t\}} | \hat{E}_{it} > \bar{E}_{it}) < 0.5 \quad (4.4)$$

$$\mathbb{E}(\mathbb{1}_{\{\hat{E}_{it} < E_t\}} | \hat{E}_{it} < \bar{E}_{it}) < 0.5 \quad (4.5)$$

Looking at anti-herding, an analogous reasoning for overshooting applies:

$$\mathbb{E}(\mathbb{1}_{\{\hat{E}_{it} > E_t\}} | \hat{E}_{it} > \bar{E}_{it}) > 0.5 \quad (4.6)$$

$$\mathbb{E}(\mathbb{1}_{\{\hat{E}_{it} < E_t\}} | \hat{E}_{it} < \bar{E}_{it}) > 0.5 \quad (4.7)$$

Combining these insights, allows the calculation of a test statistic S , which basically is an average of probabilities for exceeding (undercutting) actual EPS given that the forecasts were already exceeding (undercutting) consensus estimates.

$$S_{it} = \frac{1}{2} \left[\frac{\sum_{i=1}^n \sum_{t=1}^T \mathbb{1}_{\{(\hat{E}_{it} > E_t) \cap (\hat{E}_{it} > \bar{E}_{it})\}}}{\sum_{i=1}^n \sum_{t=1}^T \mathbb{1}_{\{\hat{E}_{it} > \bar{E}_{it}\}}} + \frac{\sum_{i=1}^n \sum_{t=1}^T \mathbb{1}_{\{(\hat{E}_{it} < E_t) \cap (\hat{E}_{it} < \bar{E}_{it})\}}}{\sum_{i=1}^n \sum_{t=1}^T \mathbb{1}_{\{\hat{E}_{it} < \bar{E}_{it}\}}} \right] \quad (4.8)$$

The statistic unites some useful characteristics that make it a both robust and straightforward to read measure. Pierdzioch et al. (2013c) point at three major advantages. Firstly, it is robust to market-wide shocks, a feature especially valuable when inquiring into the impact of business cycle on the depicted bias. Secondly, the test results are insensitive to systematic forecast biases. Eventually, the S -statistic does not react to outliers in the sample.⁹

4.3.3 Assessing the Bias Impact

The motivation to look into the impact of forecasting biases is twofold. Firstly, one is curious whether analyst output has a meaningful impact on the market. There is ample literature supporting this view, e.g., Ryan and Taffler (2004) or Chen et al. (2013), who find evidence that links abnormal stock return to forecasts released by analysts. Secondly, the question remains whether the herding bias matters at all, especially when looking at forecast accuracy. Here, the literature is ambiguous. While seminal publications like Shiller (2000) suggest a negative impact of herding

⁹Cf. Bernhardt et al. (2006) for exhaustive proof of the test properties.

on market outcomes, more recent approaches, e.g., by Morris and Shin (2002) favor the view that herding spreads information wider and thus makes markets more efficient. Others, like Bhattacharya et al. (2012) deny even the chance of analysts to impact market outcomes.

Similar to a number of forecasting papers (e.g., Clatworthy et al. (2006), Easterwood and Nutt (1999), and Pierdzioch and Rülke (2012)), we analyze the impact of the herding bias on forecast accuracy through a standard multivariate regression system. In particular, we modify a model brought forward in Clatworthy et al. (2006) for factors of herding and recession. Equation (4.9) provides the amended model in greater detail.

$$FE_{it} = \alpha + \beta_1 S_{it} + \beta_2 REC_t + \beta_3 LOSS_{it} + \beta_4 LN(ANA)_{it} + \beta_5 FES_{it} + \beta_6 FEK_{it} \quad (4.9)$$

The dependent variable of the OLS regression is FE_{it} , which is the forecast error for company i at time t scaled to the stock price at the end of the fiscal year. Technically speaking, FE is defined as outlined in Equation (4.1), where SP_t is the stock price as of fiscal year end that corresponds to the forecast horizon of the estimate.

We expand the reasoning brought forward in Clatworthy et al. (2006) for components of (anti-)herding and the impact of contractionary periods. S_t is the value of the herding-statistic as defined in (4.8) calculated for the last six months prior to time t . We include this parameter as a series of papers (e.g., Shiller (2000), Morris and Shin (2002), Olsen (1996), and Bhattacharya et al. (2012)) discusses the significance of analyst herding and its impact on forecast accuracy and the market.¹⁰ The variable is logarithmically bound and has formerly been employed in a simple univariate regression model in Pierdzioch et al. (2010).

REC_t is a binary variable that is equal to 1 if the prognosis was released during a recession and 0 otherwise.¹¹ We include this variable for several reasons. Firstly, it appears straightforward to assume that crises are periods of altered uncertainty. Increased uncertainty in turn should decrease the forecast accuracy as less information

¹⁰Cf. Bikchandani and Sharma (2000) for a comprehensive revision of herding, its potential sources, and its impact.

¹¹We stick to the recession timeline released in Economic Cycle Research Institute (2012). The approach featured in this database closely resembles the NBER one and has been positively received in a series of papers, e.g, Grossarth-Maticek and Mayr (2008).

is at hand to estimate the variance in EPS. This view is supported by, e.g., Zhang (2006). Secondly, a multitude of essays deals with the nexus of recessions and their impact on forecast errors (e.g., Boschi (2007)).

$LOSS_{it}$ is defined as a binary variable, where a value of 1 indicates that the average of forecasts for company i at time t is negative (0 otherwise). Based on reasoning of Duru and Reeb (2002), the model of Clatworthy et al. (2006) already features this indicator to account for biased sentiment in such a case. In accordance with Clatworthy et al. (2006), we additionally account for the natural logarithm of the number of analysts issuing forecasts for company i at time t . This construct is grasped by $LN(ANA)_{it}$ and initially proposed by Gu and Wu (2003).

The idea to include higher moments of forecast errors originated in Gu and Wu (2003). The significant impact of higher moments on forecast errors is their starting point for assessing the rationality of forecasts. We adhere to their reasoning and include FES_{it} as the forecast error skewness of the last four monthly forecast errors. Additionally, we incorporate FEK_{it} defined as the kurtosis for the last four forecast errors.

4.4 Results

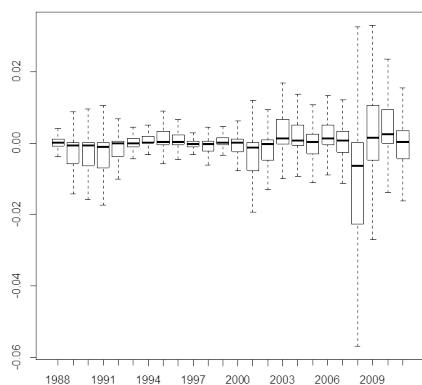
4.4.1 Optimism and Forecast Accuracy

At first, we look at the forecast error by year as given in Table 4.5 in the appendix and illustrated in Figure 4.2. Although the prognoses on average are fairly accurate (median forecast errors equal an astonishing 0.00% for Dow Jones forecasts and -0.08% of fiscal year end stock price for the DAX estimates), they show substantial dispersion over time. For instance, median forecast errors for current year forecasts oscillate between -1.71% and 0.31% (-2.61% and 0.82%) for the Dow (and DAX, respectively).

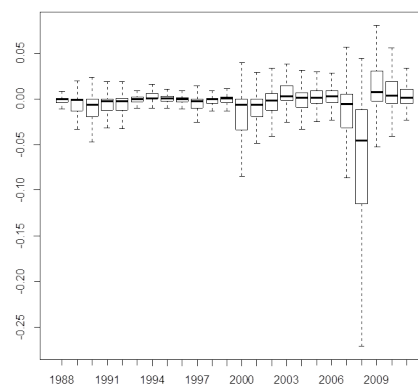
Given the negative mean forecast errors in most years, we find ample evidence for optimism among EPS forecasters. However, it is not as consistent as earlier research (e.g., Easterwood and Nutt (1999), Brown (1997)) suggests. A mere 3 out of 24 (5 out of 17) years of Dow (DAX) forecasts show positive deviations on average. Strikingly, this sentiment is less pronounced for the DAX, when looking at median forecast errors where we find 7 years with positive errors. Moreover, the

Figure 4.2: Forecast Error by Year

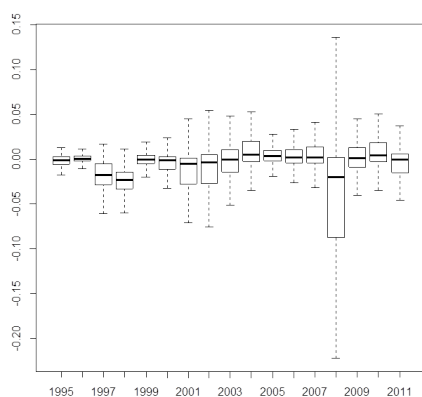
(a) DJI Current year FE boxplot



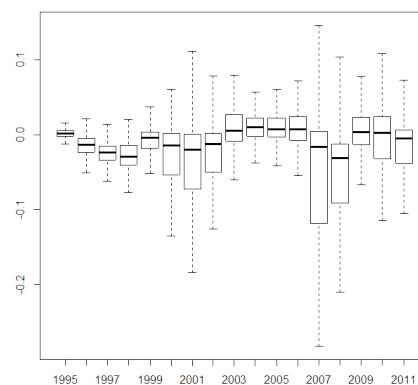
(b) DJI 2 year FE boxplot



(c) DAX Current year FE boxplot



(d) DAX 2 year FE boxplot

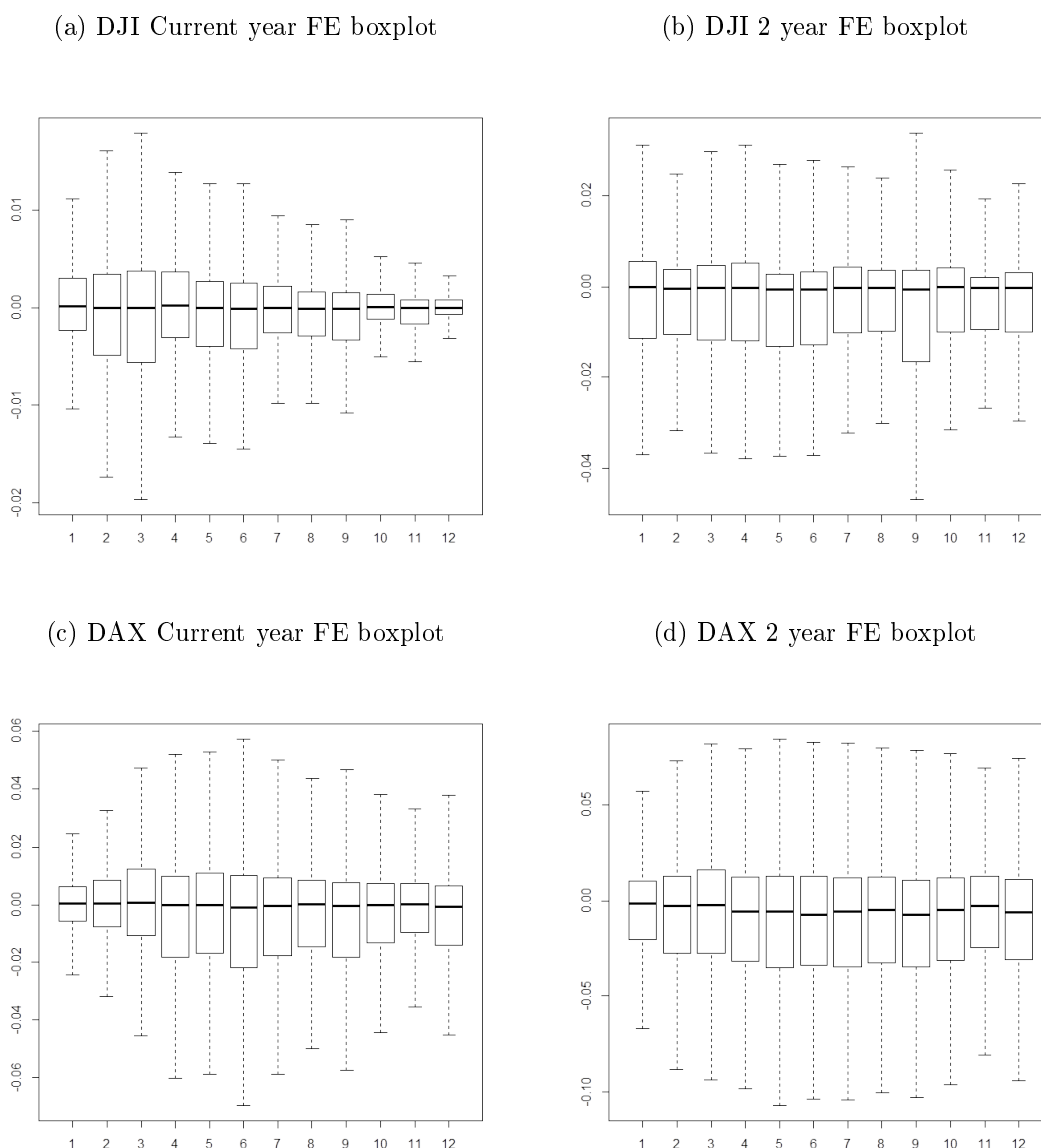


relationship is inverted for the Dow sample where only 11 years carry a negative sign. This indicates that extreme forecasts tend to be optimistic in the majority of cases.

It is particularly revealing to look at the years in contractionary periods, i.e., those periods shaded in Figures 4.4 and 4.5 in the appendix. These years show the largest absolute negative deviations and therefore the strongest optimism, with minimum values close to -6%. This is in line with findings and theories brought forward by Zhang (2006), who develops the notion that in periods of high uncertainty forecasters release overly optimistic estimates. Coinciding with our assumption of increased uncertainty during phases of economic distress, the dispersion is largest for the two

crises periods identified around the years 2000 and 2008. It is well worth noting, that there are no substantial differences between the two indexes, with the exception of forecast error magnitude. We deem this highly unusual and suggest this exploratory finding as a starting point for future research. Possible avenues might include company transparency, national reporting standards, and intensity of analyst coverage.

Figure 4.3: Forecast Error by Month



In a next step, we turn towards the monthly forecast error as illustrated in Figure 4.3. We do this for two reasons. Chiefly, we are eager to determine whether analyst optimism is shaped through seasonal elements. A full branch of literature (e.g.,

Brown and Rozeff (1978), Abarbanell and Bernard (1992), and Gu and Wu (2003)) provides analyses that demonstrate that forecasts show characteristics comparable to those of a seasonal random walk.¹² Though motivations for the employment of this method are manifold, most authors use it as a benchmark to discuss the superiority of analyst output compared to a naïve seasonal random walk.

On a different note, we might be able to determine differences between quarterly forecast errors resulting from the regulatory frame. Some authors take this as a starting point for research targeting regulatory impact. For instance, Bailey et al. (2003) show that apart from seasonality based on a pure monthly description, the introduction of Regulation Fair Disclosure led to patterns coinciding with the release of novel information through quarterly reporting.

The box-and-whisker plots of current year forecast errors reveal that for Dow Jones EPS estimates more than 50% of all deviations are below 1% of fiscal year end (FYE) stock prices, whilst for their German counterparts half the errors fall into a $\pm 2\%$ range. With regards to the direction of the forecast failure we, again, find a larger number of negative deviations underpinning analysts' tendency to publish optimistic forecasts. When turning to charts illustrating the two-year forecast horizon, both optimism and error dispersion augment. Roughly speaking, the bandwidth in which half the forecast errors can be found doubles for both indexes when compared to the one-year forecasts. Although the sample median error is close to zero, there are notable exceptions for single years. All in all, we confirm analyst optimism and find it to be two times as pronounced for the two-year forecast horizons.¹³

Interestingly, the seasonality aspect appears to shape forecast errors. The boxplot of current Dow forecast errors reveals two things. Firstly and in line with anticipation, the forecast errors gradually become smaller during the course of a year. This can easily be attributed to the dispersion of new information that is incorporated into later forecasts and diminished uncertainty. Secondly, the pattern of decrease is striking as the larger jumps of about 0.3% occur at the junctions of the respective quarters. We therefore consider this evidence for seasonality with respect to decreasing forecast errors and confirm Bailey et al. (2003)'s finding that the pattern of

¹²Gu and Wu (2003) in addition provide an ingenious approach to assessing forecast biases. Their focal point is the disparity of forecasting mean and median earnings, which is roughly caught through measuring higher moments of forecast errors. We employ this insight in section 4.4.3 and integrate variables accordingly.

¹³The number of one- and two-year forecasts is fairly balanced and thus not driving the difference. The numbers are provided in Table 4.2 and data in excess is available upon request.

information dispersion via quarterly earnings reports shapes the forecasting error.

Things look slightly different when looking at the deviations for DAX listed companies. Here, the bulk of forecast errors is increasing until June only to diminish thereafter in a pattern similar to the U.S. example. Notably, the error remains fairly large in December, with maximum values at 4%. More importantly, the quarterly pattern found for the Dow Jones listed corporations does not reappear. This could be evidence for less transparent information policies at companies. Another striking finding is the small forecast error in January. This might suggest that due to the lack of novel information, forecasts are built on last years earnings and therefore replicating a (very) simplistic time series model, in which analysts simply extrapolate last year's earnings.¹⁴ This contrasts with findings presented in Brown and Rozeff (1978), who show that it would be unsustainable if analyst output was inferior to such a model.¹⁵

4.4.2 Herding Bias

In this section we present the findings resulting from the herding test based on Bernhardt et al. (2006). Table 4.2 presents the full results for the complete dataset for both indexes. In line with the approach of Pierdzioch et al. (2010), we estimate a rolling S -statistic in order to account for distortions resulting especially from the most recent economic downturn. We accomplish this by calculating the overshooting and undershooting probabilities for the past 6 months, and thus diminish the impact of extreme months like September 2008, the month that Lehman Brothers Inc. collapsed. Table 4.2 additionally splits the sample according to the state of the business cycle, the forecast horizon, and the index.

In line with the theoretical reasoning presented in section 4.3.2, we find that with the exception of DAX forecasts from expansionary periods, anti-herding prevails for both indexes, with values ranging from 47.751 to 61.276. When looking at the values for the full data set, values that form the lower bottom of a 99% confidence band do not fall short of the cut-off value of 0.5. Moreover, anti-herding is slightly more pronounced for longer forecast horizons at any level (e.g., 56.072 vs. 55.755 for Dow Jones contractionary periods forecasts). A possible explanation for this

¹⁴This form of EPS estimation has been presented in inter alia Elgers and Lo (1994).

¹⁵Mainly, the authors rely on the factual argument that companies relying on forecasts would refrain from paying a premium for inferior results with such consistency.

phenomenon is that forecasters might incur smaller losses for extreme prognoses made under higher uncertainty, which is assumed to rise the less foreseeable a time span is.

Table 4.2: *S*-Statistic

Forecast Horizon	Contractionary Periods		Expansionary Periods		Total	
	1 Year	2 Years	1 Year	2 Years	1 Year	2 Years
Dow Jones Industrial 30						
<i>S</i>	55.755	56.072	55.295	59.090	55.582	57.924
Lower 99%	54.058	54.403	54.565	58.286	54.912	57.200
Upper 99%	57.452	57.740	56.024	59.894	56.251	58.647
Std. Dev.	0.006	0.006	0.003	0.003	0.003	0.003
<i>N</i>	9,602	8,688	57,526	46,688	67,128	55,376
DAX 30						
<i>S</i>	60.774	61.276	47.751	48.166	50.551	51.491
Lower 99%	59.707	60.227	47.115	47.501	50.007	50.931
Upper 99%	61.841	62.325	48.387	48.831	51.096	52.052
Std. Dev.	0.004	0.004	0.002	0.003	0.002	0.002
<i>N</i>	15,676	15,693	42,643	39,199	58,319	54,892

Notes:

The *S*-statistic is calculated according to equation (4.8). *N* is the number of forecasts in the indicated period. Business cycle peak and through dates in accordance with Economic Cycle Research Institute (2012).

In order to uncover the influence of the business cycle on the analysts' proneness to herd, we provide charts depicting the rolling herding statistic *S* for the two forecast horizons for the Dow Jones in Figur 4.4 (for the DAX in Figure 4.5) in the appendix. In accordance with the reasoning presented in section 4.3.2, one should expect the herding statistic *S* to drop at the outset of an economic downturn. Indeed, the eyeball's assessment of the charts seems inconclusive at first. Nevertheless, Figure 4.4 reveals that every crisis period is either preceded or starts with a significant downturn of the *S*-value. Figure 4.5 for current year forecasts shows the same pattern, although it is less pronounced for the 2008/09 recession. However, this movement regularly changes during the crisis with a countermotion of the *S*-value. We therefore consider this finding only as an indicative confirmation of the theory analogous to Obstfeld (1996). Moreover, our findings suggest, that such "coalescence" of market opinions only prevails for a relatively short period of time. Later in the the crisis, other factors appear to shape the prognostic behavior of analysts.

4.4.3 Impact of Biases on Forecast Error

The last part of our analysis strives to answer the question whether the confirmed herding bias has a meaningful impact on the forecast accuracy. To this end, we discuss the output of the multivariate regression models given in Table 4.6 in the appendix. We provide four different models, which include the variables as discussed in section 4.3.3. In order to assess the significance of our results, we provide two types of t -statistics. Firstly, we state the regular OLS t -statistics. Secondly, as the descriptive statistics reveal considerable variance in the forecast error variable and the respective error terms, we rely on White's heteroscedasticity-consistent standard errors. This approach has already been favored in, e.g., Clatworthy et al. (2006). We trust that this conservative approach will make our findings more reliable.

Irrespective of the model and the index considered, we confirm a significant influence of the herding statistic S_t . This finding holds true for all models and both indexes. However, and in line with the results presented in section 4.4.2, the direction of the impact is ambiguous. While an increase in herding of 10 points in the S -statistic leads to a 7% drop in forecast error for U.S. firms, the outcome inverts for the German sample. We therefore only can confirm that the herding bias significantly affects the accuracy of forecasts.

REC_t , our binary variable equal to 1 when the business cycle is in a recession, moves the forecast error in a clearer way. For instance, in Dow Jones model 1 its coefficient equals -0.212, i.e., it adds to (existing) optimism. This confirms the findings we presented before. Model 2 reveals, that $LOSS_{it}$ has the largest overall impact on the dependent variable, driving the forecasters' optimism. However, this variable should not be overstated as it does neither have a commensurable nor significant effect on the DAX sample.¹⁶

The remainder of our findings stand in contrast to the reported values in Gu and Wu (2003). Neither $LN(ANA)_{it}$, nor higher moments of the forecast error as grasped through the constructs FES_{it} and FEK_{it} exhibit a significant impact on the forecast error. This in part may be due to the fact, that the coverage through analysts is fairly balanced. As our dataset is more exhaustive in terms of time, absolute number of data points, and regions covered, we consider these results as a challenge to the concept favored in Clatworthy et al. (2006).

¹⁶We acknowledge that this observation might in part be driven through the extreme events in the course of the most recent economic downturn in the U.S..

4.5 Conclusion

Our results confirmed widespread optimism as suggested by inter alia Butler and Lang (1991), Easterwood and Nutt (1999), and Quian (2009) among financial analysts. In line with findings by Chopra (1998) we confirm that overoptimistic prognoses are more pronounced in times of recessions. Additionally, we showed that forecasters tend to anti-herd throughout all periods. Most importantly, we were able to render that the business cycle shapes the degree of optimism, co-determines the forecast error, and confirms the impact of the herding bias on forecast accuracy. All in all, these findings complement the theory presented in Zhang (2006), which establishes the relation of business cycle and forecaster sentiment, for a component of herding.

On a different note, we discovered that the median forecast accuracy for Dow listed companies is considerably above that of DAX listed ones. This is puzzling as the similar analyst coverage and information policy should inhibit big differences on the first glance. Therefore we suggest additional research in this field and recommend the regulatory framework and additional indexes as promising avenues for this purpose.

4.6 Appendix

Table 4.3: Constituents and Descriptive Statistics (Dow Jones Industrial 30)

	Company name	N	Months in sample	SIC	FE in %		
					Mean	Median	Std. Dev.
1	3M	3,115	288	2670	-0.04	-0.08	0.45
2	ALCOA	4,726	288	3350	-1.74	-0.31	7.22
3	AMERICAN EXPRESS	3,528	288	6199	-0.24	-0.01	2.42
4	AMERICAN INT. GROUP	3,495	288	6331	-415.50	-0.10	1962.03
5	AT&T	5,208	288	4813	-1.11	-0.17	5.39
6	BANK OF AMERICA	5,413	288	6020	-2.65	-0.06	9.21
7	BOEING	4,436	288	3721	-0.87	-0.05	3.07
8	CATERPILLAR	4,348	287	3531	-0.14	0.02	2.16
9	CHEVRON TEXACO	3,805	123	2911	0.86	0.68	3.02
10	CHRYSLER	2,319	121	3711	-1.24	0.15	5.16
11	CITIGROUP	3,375	216	6199	-52.98	-2.58	183.95
12	COCA COLA	3,348	288	2080	-0.02	0.00	0.13
13	DUPONT	3,842	288	2820	-0.38	-0.08	1.46
14	EXXON MOBIL	4,121	154	2911	0.72	0.50	2.19
15	GENERAL ELECTRIC	2,443	288	9997	-0.45	0.00	1.95
16	GENERAL MOTORS	4,634	254	3711	-6.41	-0.68	19.19
17	GOODYEAR TIRE	1,877	287	3011	-4.78	-0.94	12.29
18	HONEYWELL INT.	2,470	288	3728	-0.63	0.02	2.87
19	INT. BUSINESS MACHINES	5,310	288	7370	-0.16	-0.02	0.99
20	INT. PAPER	4,432	288	2631	-1.11	-0.25	3.87
21	INTEL	9,694	288	3674	-0.04	0.03	1.51
22	JOHNSON & JOHNSON	4,054	288	2834	0.03	0.01	0.14
23	JP MORGAN CHASE	4,580	288	6020	-1.32	-0.08	7.95
24	MCDONALDS	4,303	288	5812	0.16	0.04	0.56
25	MERCK	5,156	288	2834	-0.06	0.00	0.61
26	PFIZER	4,968	288	2834	-0.06	0.00	0.55
27	PHILIP MORRIS	3,075	288	2111	-0.30	-0.01	1.59
28	TRAVELERS	860	57	6331	-0.32	0.28	2.49
29	UNITED HEALTHCARE	3,253	243	6321	0.24	0.04	0.98
30	UNITED TECHNOLOGIES	2,958	288	3720	-0.07	0.03	0.48
31	VERIZON COMMUNICATIONS	3,358	143	4812	-0.32	-0.18	0.57

Notes:

Only those companies with coinciding fiscal and calendar years included. Forecast error defined as $FE = EPS_t - \hat{EPS}_t$, where EPS_t is the actual EPS at time t and \hat{EPS}_t is the expected EPS value.

Table 4.4: Constituents and Descriptive Statistics (DAX 30)

	Company name	N	Months in sample	SIC	FE in %		
					Mean	Median	Std. Dev.
1	ADIDAS	3,752	193	3021	-0.52	-0.02	2.69
2	ALLIANZ	4,535	176	6331	-6.64	-1.18	23.32
3	ALTANA	2,370	151	2800	-0.20	0.15	5.45
4	BASF	4,875	186	2800	0.44	-0.09	5.18
5	BAY. HYPO VEREINSBANK	2,889	144	6020	-2.38	-0.87	6.48
6	BAYER	4,753	187	2800	-0.32	0.02	4.18
7	BEIERSDORF	3,223	185	2844	-0.16	-0.01	1.73
8	BMW	3,461	150	3711	0.24	0.31	7.30
9	CONTINENTAL	3,873	197	3714	-3.27	-0.12	22.71
10	DAIMLERCHRYSLER	4,715	156	3711	-3.85	-0.95	12.20
11	DEGUSSA	953	66	2800	-4.95	-2.02	8.13
12	DEUTSCHE BANK	4,679	148	6020	-6.32	-1.46	22.67
13	DEUTSCHE BOERSE	2,385	130	6200	0.29	0.17	3.76
14	DEUTSCHE POST	2,757	132	4210	-0.57	0.00	2.72
15	DEUTSCHE POSTBANK	1,377	91	6020	-8.07	-0.73	22.39
16	DEUTSCHE TELEKOM	4,398	143	4813	0.12	-0.03	3.57
17	DRESDNER BANK	400	25	6020	-0.94	-0.43	5.87
18	E.ON	4,238	197	3670	0.21	0.16	2.95
19	FRESENIUS	109	11	8090	0.38	0.23	0.68
20	FRESENIUS MEDICAL CARE	1,887	180	3845	-0.63	-0.23	1.84
21	HANNOVER RE	2,478	135	6300	-1.22	0.30	10.42
22	HEIDELBERGER ZEMENT	2,761	184	3270	-2.09	-0.66	9.79
23	HENKEL	3,785	186	2840	0.26	0.09	1.95
24	HOECHST	880	63	2800	-2.51	-1.90	2.94
25	HYPO REAL ESTATE	900	67	6162	-16.51	-0.03	39.62
26	K+S	53	5	2870	0.14	-0.07	1.38
27	KARSTADT	1,291	88	4700	-6.64	-1.04	16.69
28	LANXESS	1,639	83	2820	2.50	1.08	9.34
29	LINDE	3,062	149	2810	0.58	0.34	5.00
30	LUFTHANSA	3,536	171	4512	-0.09	0.20	4.70
31	MAN	2,922	135	3711	-0.92	0.00	12.14
32	MANNESMANN	98	20	3500	32.57	14.25	46.60
33	MERCK	3,895	194	2834	0.08	0.01	7.78
34	METRO	3,954	185	5399	-1.77	-1.06	3.30
35	MLP	1,402	122	6211	-0.82	-0.25	1.73
36	MUNICH RE	3,933	159	6311	-7.49	-0.95	29.80
37	PREUSSAG/TUI	1,567	117	4700	-3.86	-1.50	8.31
38	RWE	2,779	132	4911	-0.56	-0.13	4.66
39	SALZGITTER	1,597	128	3312	-0.68	-1.09	33.28
40	SAP	4,955	197	7372	-0.05	0.00	0.98
41	SCHERING	3,298	143	2834	0.09	0.00	2.59
42	VOLKSWAGEN	797	32	3711	21.46	14.08	32.98

Notes:

Only those companies with coinciding fiscal and calendar years included. Forecast error defined as $FE = EPS_t - \hat{EPS}_t$, where EPS_t is the actual EPS at time t and \hat{EPS}_t is the expected EPS value.

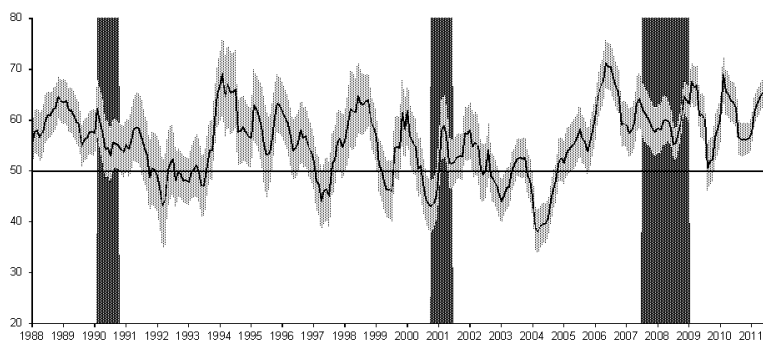
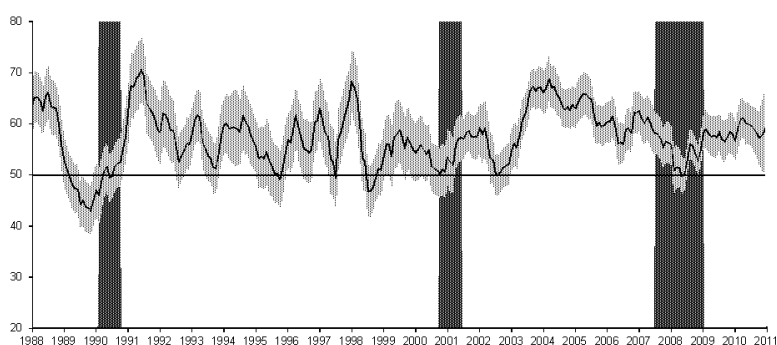
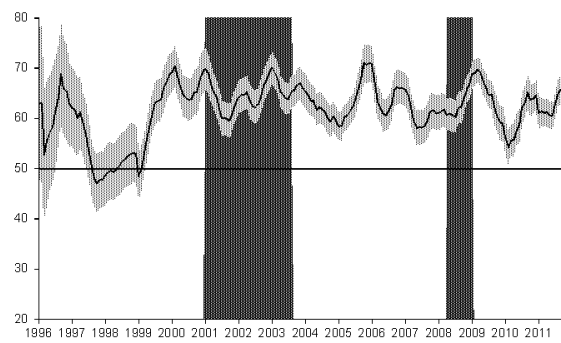
Figure 4.4: Monthly S -Statistic for Dow Jones EPS Forecasts(a) DJI current year S -statistic (recession periods shaded dark grey)(b) DJI 2 year S -statistic (recession periods shaded dark grey)

Figure 4.5: Monthly S -Statistic for DAX EPS Forecasts

(a) DAX current year S -statistic (recession periods shaded dark grey)



(b) DAX 2 year S -statistic (recession periods shaded dark grey)

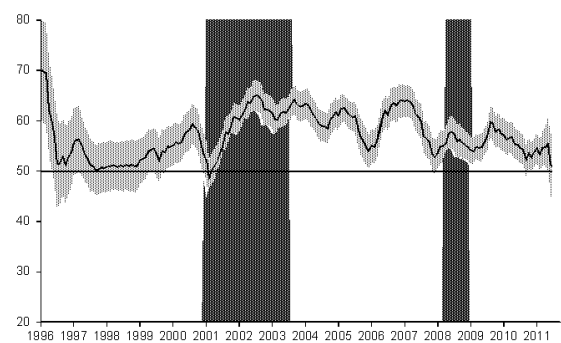


Table 4.5: Prognoses and Forecast Errors by Year

Year	Dow Jones Industrial 30					DAX 30				
	N	Mean	Median	Std. Dev.	t-Statistic on Mean	N	Mean	Median	Std. Dev.	t-Statistic on Mean
1988	4,674	-0.71	0.00	5.21	19.79	***	-	-	-	-
1989	4,565	-1.79	-0.06	6.03	22.53	***	-	-	-	-
1990	4,740	-2.15	-0.14	6.13	28.24	***	-	-	-	-
1991	5,119	-0.55	-0.13	3.02	32.24	***	-	-	-	-
1992	4,642	-0.12	-0.08	1.94	37.85	***	-	-	-	-
1993	5,235	0.17	-0.01	1.12	35.45	***	-	-	-	-
1994	4,423	0.02	0.04	1.26	33.60	***	-	-	-	-
1995	4,952	-0.19	0.04	2.08	30.08	***	0.11	0.05	0.96	2.56
1996	4,489	-0.35	0.02	2.14	26.91	***	-0.67	-0.22	1.49	-20.01
1997	4,145	-0.43	-0.05	1.71	32.69	***	-2.11	-2.00	1.62	-77.20
1998	4,738	-0.34	-0.02	1.74	33.39	***	-2.66	-2.48	2.03	-78.10
1999	4,091	0.11	0.03	2.61	24.92	***	-0.28	-0.05	3.19	-6.10
2000	4,593	-1.59	-0.06	5.30	24.01	***	-1.65	-0.34	4.35	-26.89
2001	4,790	-1.28	-0.29	3.54	32.15	***	-2.89	-0.97	6.34	-39.85
2002	4,708	-1.07	-0.04	5.94	23.79	***	-2.08	-0.68	6.10	-32.63
2003	5,481	0.52	0.20	2.31	38.60	***	-0.89	0.16	13.72	-6.46
2004	5,303	-0.73	0.08	7.33	23.09	***	-0.93	0.82	15.54	-5.80
2005	5,663	-1.12	0.06	8.04	24.23	***	0.22	0.51	6.34	3.36
2006	5,753	-1.35	0.19	11.09	18.78	***	0.11	0.34	5.39	1.87
2007	5,914	-23.84	0.02	118.07	16.04	***	-10.42	-0.11	64.12	-13.76
2008	6,962	-201.48	-1.71	1391.22	12.12	***	-15.59	-2.61	69.30	-21.29
2009	6,766	-15.47	0.31	219.34	8.74	***	0.12	0.25	18.78	0.64
2010	6,599	-0.44	0.30	41.04	6.37	***	0.27	0.42	4.68	5.74
2011	4,159	-0.88	0.04	15.37	7.10	***	-0.73	-0.03	3.00	-17.77
Overall	122,504	-14.02	0.00	339.99	-14.44	***	-2.62	-0.08	27.22	-32.36

Notes:

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ based on a two-sided t-test.

N is the number of current and two-year earnings per share (EPS) forecasts.

Forecast error defined as $FE = EPS_t - EPS_t$, where EPS_t is the actual EPS at time t and EPS_t is the expected EPS value.

Table 4.6: Regression of Forecast Error Scaled to Stock Price

Coefficients	Dow Jones Industrial Average 30				DAX 30			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Intercept	0.349 (3.801) [3.214]	0.328 (3.571) [3.107]	0.291 (3.165) [2.700]	** 0.292 (3.173) [2.707]	** -0.136 (-4.562) [-3.294]	*** -0.144 (-4.938) [-3.530]	*** -0.137 (-4.830) [-3.263]	*** -0.135 (-4.894) [-3.228]
S_t	-0.007 (-3.725) [-3.519]	*** -0.006 (-3.267) [-3.175]	*** -0.006 (-3.220) [-3.220]	*** -0.006 (-3.173) [-3.229]	*** 0.002 (4.317) [3.171]	*** 0.002 (4.766) [3.453]	*** 0.002 (4.766) [3.475]	*** 0.002 (4.833) [3.436]
REC	-0.212 (-3.286) [-5.709]	** -0.145 (-2.242) [-3.991]	* -0.147 (-2.277) [-4.051]	* -0.147 (-2.261) [-4.022]	*** -0.051 (-4.309) [-7.084]	*** -0.050 (-4.271) [-6.928]	*** -0.049 (-4.265) [-6.827]	*** -0.049 (-4.301) [-6.796]
$LOSS_{it}$	-	-1.952 (-3.284) [-20.876]	** -1.956 (-3.291) [-20.919]	** -1.957 (-3.292) [-20.921]	-	-0.135 (-1.650) [-5.766]	-0.135 (-1.651) [-5.771]	-0.134 (-1.648) [-5.745]
$LN(ANA)_{it}$	-	-	0.023 (1.682) [1.758]	0.024 (1.742) [1.817]	-	-	-0.005 (-1.798) [-1.193]	-0.004 (-1.776) [-1.177]
FES_{it}	-	-	-	0.014 (1.251) [1.360]	-	-	-	-0.002 (-0.904) [0.925]
FEK_{it}	-	-	-	-0.002 (-0.475) [-0.481]	-	-	-	-0.000 (-0.261) [-0.260]
Adj. R^2	0.006	0.061	0.062	0.062	0.010	0.016	0.016	0.016
F -value	23.7	162.0	122.3	81.9	26.5	28.9	22.0	14.8
DF	7403	7402	7401	7399	5063	5062	5061	5059

Notes:

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ based on a two-sided test using White's revised standard errors. The respective t -statistics are given in parentheses, while OLS t -values are provided in square brackets.

The dependent variable for all models is FE_{it} , which is defined as the actual EPS minus the current year forecast for company i in month t divided by FYE's stock price of the respective company.

S_{it} is the six month rolling herding statistic for every month.

REC is a binary variable equal to 1 when the forecast was issued during a month in a contractionary period.

$LOSS_{it}$ is a binary variable equal to 1 when the average forecast for a company i at time t is negative.

$LN(ANA)_{it}$ is the natural logarithm of the number of analysts contributing a prognosis for company i at time t .

FES_{it} is the skewness of FE_{it} of the last four months.

FEK_{it} is the kurtosis of FE_{it} of the last four months.

DF are the degrees of freedom per regression.

Chapter 5

Conclusion

In the present thesis, we analyzed datasets of EPS forecasts from various periods and regions. All in all, we juxtaposed forecasts for earnings of companies listed in the Euro Stoxx 50, the DAX 30, and the Dow Jones Industrial 30. Most importantly, our research establishes or substantiates, respectively, the following findings. Stock market analysts optimize an asymmetric loss function, they are on average too optimistic, they tend to anti-herd, and none of these phenomena can be seen as independent from the state of the economy. Moreover, it has become clear that forecaster sentiment and rationality are formed on the institute level. These concluding remarks provide the reader with a comprehensive survey of the results that were obtained in the single chapters. In addition, I would like to point at some potentially promising puzzles and future research questions that can be derived from the results presented above.

In chapter 2, we unveiled the loss function of forecasters of the Euro Stoxx 50 by applying the method proposed by Elliott et al. (2005). We were able to show that more forecasters behave rational under alternative than under symmetric loss. Therefore, we can show that this novel theoretic concept provides a better fit with the empiric data. This claim is all the more true, the more refined the level of clustering becomes. We looked at country, industry, company, and institute level and confirmed that the heterogeneity in the degree of asymmetry is vast on industry, company, and institute level. However, rationality is only restored for individual institutes, therefore suggesting that rationality is formed on this level. Notably, we proved a high degree of correlation between $\hat{\alpha}$ and the Euro Stoxx index. This correlation allows us to coin the term cyclical asymmetry. On a different note,

these findings feed the idea of procyclicality, i.e., that the forecasts the underlying sentiment driving the current direction of the stock market.

In chapter 3, we applied a commensurable reasoning to a sample of forecasts for companies included in the DAX 30 index. Again, we sought to determine the biases distorting the forecasts and its link to the business cycle. In a first step we determined the loss function for the full data set and when looking at the aggregate market, the $J(\hat{\alpha})$ -test confirms the restoration of rationality for individual but not the entire data set. In addition, we use the estimated $\hat{\alpha}$ parameters as a starting point for determining the sentiment. We find that forecasters were far too optimistic, using imagery, analysts were promising wealth beyond the dreams of avarice. Moreover, this attitude is more pronounced for longer periods of time. Similar to the preceding chapter, we looked at the drivers of rationality. The factors considered include time, company, and the institute and while heterogeneity is large over all these levels, rationality is only restored on the last.

Chapter 4 places in proximity biases in forecasts for companies in the largest North American economy and its European peer. We dived into an analysis of the optimism and the herding distortion for Dow Jones Industrial and DAX datasets. We confirm prevalent optimism and consistent with theories brought forward by Zhang (2006) find it to be aggravated in periods of economic contraction. With regards to herding, our analysis reveals that there is a distinct tendency to anti-herd in both samples. Through a regression analysis of forecast errors, we introduce the herding bias as a significant and driving force behind the accuracy of analyst output next to the state of the economy and various error properties discussed in earlier literature.

Future inquiries may find the present thesis a relevant and fruitful starting point for various puzzles that were either revealed through our explorations or come as natural extensions of the considered research question. Firstly, it might prove reasonable to consider how regulators could technically translate knowledge of exaggerated prognoses into a smoothing of the business cycle. Secondly, as contortions are inherent in human and therefore analysts' behavior, there is a need to design remuneration schemes that consciously counteract the discussed biases. Thirdly, we found out that rationality is determined at institute and even analyst level. This still calls for rendering the impact factors in greater detail. Ultimately, some differences in the accuracy of forecasts for earnings of German and American companies remain unaccounted for. Here, research into the impact of regulatory frames and differences in investor relations appear imperative.

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