What Determines Forecasters' Forecasting Errors?

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Abstract

This paper contributes to the growing literature in macroeconomics and finance on expectation formation and information processing by analyzing the relationship between expectation formation at the individual level and the prediction of macroeconomic aggregates. Using information from business tendency surveys we present a new approach of analyzing qualitative forecasting errors made by forecasters. Based on a quantal response approach with misclassification we define qualitative mispredictions of forecasters in terms of deviations from the qualitative rational expectation forecast and relate them to individual and macro factors driving these mispredictions. Our approach permits a detailed analysis of individual forecasting decisions allowing for the introduction of individual and economy wide determinants that affect the individual forecasting error process.

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1 Introduction

Expectation formation by economic agents is a key element of models in macroeconomics and finance. Although the rational expectations assumption has served as the dominant work horse in most models, the critique on this behavioral assumption is as old as the rational expectations hypothesis itself. The recent literature in macroeconomics and finance emphasizes information rigidities and heterogeneity in information processing by economic agents to explain observed deviations from theoretical predictions based on models with homogeneous agents with rational expectations. In particular models with partial (individuals only observe a noisy information signal, Woodford (2002), Sims (2010)) and delayed (only a share of individuals receives up-to-date information, c.f. Calvo (1983), Mankiw & Reis (2002), Reis (2006a, b) and Lorenzoni (2010)) information have been developed and provide more realistic mechanisms for information processing. This paper takes a closer look on individual expectation formation and information processing by exploiting the informational content of rich business tendency survey data on the basis of a novel approach of dynamic misclassification.

The use of survey tendency data to analyze expectation formation has also a rather long tradition in economics due to their relative simplicity and discreteness. Business tendency surveys not only represent a timely source of information (Lui, Mitchell & Weale (2010)) and perform reasonably well in predicting stock returns (Barberis, Greenwood, Jin & Shleifer (2015)), or macro variables like inflation (Ang, Bekaert & Wei (2007)), but also provide a good opportunity for empirical work on imperfect information models (Mankiw & Reis (2010)). While pure time series approaches require some functional form assumptions on the expectation formation process, tests of individual expectation formation on the basis of tendency survey data take the directional forecasts of individuals for the comparison of predictions with realizations. Therefore, no behavioral hypothesis on the expectation formation process has to be imposed ex-ante. Moreover, the heterogeneity in beliefs and information sets can, in principle, be accounted for due to the richness of the data in terms of their high cross-sectional and time series dimension.

Traditionally, quantification methods like the probability method tracing back to Anderson (1951) and Carlson & Parkin (1975) or regression methods (e.g. Pesaran 1984, 1985, 1987) were used to measure aggregate expectations on a continuous macro variable at one point in time using j qualitative responses at the individual level. These approaches depend heavily on the aggregation rule (the quantification method), implicit homogeneity assumptions and identifying restrictions (e.g. assumptions on the threshold parameters), so that a rejection of a certain expectation formation hypothesis may always be the result of the underlying identification restrictions and aggregation rules.

Our new approach is based on a dynamic quantal response model with misclassification. We use a generalized linear model with logistic link function with an ARMA mean function (GLARMA) to model the individual misclassification probabilities. Thus our approach generalizes previous cross-sectional misclassification approaches for qualitative dependent variables (Hausman, Abreyava & Scott-Morton (1998), Hausman (2001), and Dustmann & van Soest (2004)) to a dynamic framework. The estimate of this dynamic misclassification matrix allows us to interpret individual qualitative mispredictions in terms of deviations from the qualitative rational expectations forecast and relate them to individual and macro factors driving these individual mispredictions.

Although looking at qualitative forecasts at the individual level we compare in our approach j qualitative predictions with the corresponding qualitative macro outcome at a given point in time. Through the introduction of a dynamic Markov type misclassification matrix our approach accounts for individual heterogeneity in forecasting behavior. As such, our approach permits a detailed analysis of individual forecasting decisions allowing for the introduction of individual and economy wide determinants affecting the individual forecasting error process.

Like the early studies on expectation formation using tendency data our approach is consistent with the rather general definition of expectations as subjectively held beliefs by individuals. Special behavioral assumptions like rational expectations are reflected in a special form of the misclassification matrix (see Gourieroux & Pradel (1986)). Our model allows for the estimation of individual specific misclassification matrices and due to the linearity between forecasts at the aggregate level and individual forecasts we can also aggregate the misclassification matrix to obtain a measure for aggregate expectation errors in the sense of Pesaran & Weale (2006).

Our model is estimated with data from the Financial Markets Survey of the Centre for European Economic Research (ZEW), a monthly qualitative survey of around 330 financial experts, giving six-month-ahead predictions of major macroeconomic aggregates and financial indicators observed over 16 years. Contrary to the approaches relying on aggregation rules, our discrete response approach allows us to exploit the information on individual forecasting errors effectively. For N_t participants in the survey at time t the discretization of the macro series leaves us with $\sum_{t=1}^{T} N_t$ forecast comparisons at the micro level, while exploiting the continuous macro variable with an aggregated continuous forecast (e.g. in the tradition of Carlson-Parkin) leaves us with only T comparisons at the macro level. More concretely, in our empirical study this leads to $300 \times 242 = 72600$ individual forecasts comparisons compared to 242 at the macro level and allows us to relate the individual forecast errors to the individual characteristics of the forecasters. By using external survey information on the value of thresholds separating the outcome space at the macro level implies a certain information loss compared to the information contained in the continuous macro variable. However, the identifying restrictions imposed are by far less severe compared to the ones imposed by traditional quantification techniques relying e.g. on distributional assumptions and symmetry, besides obtaining an easy to interpret matrix of misclassification errors.

Our findings show that professional forecasters in our dataset are able to correct/revise their mis-predictions in the long run but not in the short run. In this sense, this paper also contributes to the literature on delayed information processing or the theory of "*inattentiveness*" proposed by Reis (2006a, b), highlighting that individual forecasters need time to process new information. New information is only progressively incorporated in their predictions. Moreover, this paper also contributes to the literature on heterogeneity of expectations related to the dispersion of information, leading to the so called "*rational inattention*" concept proposed by Sims (2003).

The outline of the paper is as follows: In Section 2 we describe the data and the ZEW financial market survey. In Section 3 we present the general modelling framework, its econometric implementation and its estimation procedure. Section 4 discusses the empirical findings. Section 5 presents a number of robustness checks, while Section 6 concludes and gives an outlook on further research.

2 Data

2.1 ZEW Financial Market Survey

Our empirical analysis is based on the ZEW Financial Market Survey which has been conducted since December 1991 on a monthly basis and focuses on international financial market series. Those include the financial markets in Germany, USA, Japan, Great Britain, France, Italy, and since January 1999, the Euro-Area. Each month representatives of the German financial sector employed in banks, insurance companies or at finance departments or economic research departments in large industrial corporations - therefore called experts - are polled on their expectations regarding the developments in important international financial markets. From December 1991 to January 2012, e.g. 242 months, 1086 experts responded at least once on the survey. Since 1993 the number of participants is relatively stable, with around 300 experts responding to the questionnaire each month.

Participants are asked to give their six-months-ahead predictions for the economic activity, the inflation rate, the short and the long term interest rates, the exchange rates, and the profits of 13 German industries (banking, insurance, vehicles construction, chemicals and pharmaceutical, steel/non-ferrous metals, electrical engineering, mechanical engineering, consumer goods and retailing, construction, utilities, service providers, telecommunications, information technology), as well as the oil price. Up to November 1998, the exchange rate question relates to US-Dollar, Yen, UK-Pound and Swiss Franc per Deutsche Mark (DM) and since December 1998 per Euro.

The ZEW Financial Markets Survey is a purely qualitative survey, meaning that the respondents are asked to predict, whether in the next six months the price of the corresponding "financial market series" will go up, stay the same, or go down. The qualitative nature of the answers guarantees low costs of information collection and a timeliness of the data. As the survey responses are first provided to the participants attrition rates are low and missing values occur completely at random. A fourth possibility is to choose "no assessment", if forecasters do not want or are unable to make a prediction. Responses' probabilities for this category are rather small (on average less than 3 percent) and show no systematic correlations with the state of the macro economy. This category will therefore be ignored. At the beginning each questionnaire had to be returned on the third Friday of a month, but since October 2001 it changed to the second Friday of a month. The results of the questionnaire are published each month in the ZEW Financial Market Report. It includes a detailed listing of the changes in the percentages of the different response categories, as well as their standard deviations, for the inflation rate, the short and long term interest rates, the stock indices, the exchange rates, and the oil price. The ZEW Financial market report receives a lot of attention in German and European media and is closely observed by stock market investors.

Here we concentrate on 5 series asked with respect to Germany namely the inflation rate, the short and long term interest rates, DAX30, and the USD/EUR exchange rate. We decide to focus on 3 macro variables and 2 financial series in order to highlight whether forecasters form their expectations differently for different economic variables.

The ZEW asked survey participants in a separate survey conducted in August 1997 about their up and down threshold values of their no-change interval for every financial market series. The median threshold values are available to us and given by $(-0.002, 0.002)$ for inflation rate changes, $(-0.2, 0.2)$ for both short and long term interest rates changes, $(-0.03, 0.035)$ for DAX30 returns and $(-0.015, 0.015)$ for USD/EUR exchange rate returns. Given that this additional survey was only carried out once, we assume in the following that these thresholds are constant across time and used by all survey participants.

2.2 Descriptive Figures

From the set of 1086 forecasters having responded during the life-time of the survey (242 months) at least once, we have selected those who have answered the questionnaire at least 12 times and thus shown a minimum regular interest in the survey. Altogether we end up with roughly 300 participants per month, from which about 10% each are experts from industry firms and insurance companies. The share of managers returning the survey amounts to 15%. All of these figures remain relatively stable over the lifetime of the survey. Despite the length of the sample period, the response rates of the questionnaires are very high (see Figure 2 in Appendix A.1)

Figure 1 presents for the 5 variables under consideration the graphs of the shares for up/same/down answered by the survey participants (sample probabilities) and the graphs of the 6 months changes (inflation and interest rates) or the 6 months returns (DAX 30 and USD/EUR), in the first two rows. In these graphs the "up" probability share is always drawn in blue, the "same" probability share is always drawn in grey and the "down" probability share is always drawn in yellow.

From a pure inspection of the (up/same/down) sample probabilities of the survey participants (row 2), we see that for the inflation and the interest rate series the group of experts seems to anticipate the changes of the underlying series very well. For the DAX 30 and the USD/EUR series, however, this intuition is much less clear.

3 Modelling Framework

3.1 General Model Specification

The basic idea for our model set-up relies on the definition of forecasts for the discrete counterparts of a continuous macro variable based on different information sets at the macro and at the micro level. We restrict our model set-up to models of expectation formation which have a straightforward statistical formulation. However, the framework can be easily generalized to models based on other behavioral assumptions.

Let Y_t^* be a continuous time series process at the macro level with $t = 1, \ldots, T$ and define $\{\mathcal{S}_k, k = 1, \ldots, K\}$ and $\{\mathcal{G}_l, l = 1, \ldots, L\}$ as two given partitions (for the macro and micro level, respectively) of the outcome space of Y_t^*. Let Y_t be the discrete counterpart of Y_t^* within a threshold crossing ordinal response model taking on the form of the k^{th} unit-vector for $Y_t^* \in \mathcal{S}_k$, i.e., if $Y_t^* \in \mathcal{S}_k$ the k^{th} component of Y_t, $Y_{k,t}$, is equal to one, while all other components are equal to zero. Correspondingly define for the second partition, $\tilde{Y}_t$ as the l^{th} unit-vector of dimension L indicating that $Y_t^* \in \mathcal{G}_l$. For example, if Y_t^* denotes a first difference or a return rate series possible partitions could be a two states partition (growth vs. no growth) or a three states world (large growth rate above some positive threshold, weak growth around zero called the "no-change" state, large negative growth rate below some negative threshold). The distinction between two different partitions is reasonable for many tendency data if the survey contains a no-change interval, while at the macro level a reasonable partition could also be a binary one. Assume a forecasting horizon of length h and a partition $\{\mathcal{S}_k\}$ and let $\mathcal{F}_t$ be the information set given at time t, then for Y_{t+h} there exists a K dimensional vector $\mathbf{P}_{t+h}$ with the typical element

$$\Pr[Y_{t+h}^* \in \mathcal{S}_k | \mathcal{F}_t] = \Pr[Y_{k,t+h} = 1 | \mathcal{F}_t], \tag{1}$$

that given the information set $\mathcal{F}_t$ the outcome Y_{t+h}^* at time $t + h$ lies in $\mathcal{S}_k$. Since $\mathrm{E}[Y_{k,t+h}|\mathcal{F}_t] = \Pr[Y_{k,t+h} = 1|\mathcal{F}_t]$ the k-th element of $\mathbf{P}_{t+h}$ is the continuous rational expectations forecast of state k in the sense of Gourieroux & Pradel (1986).

Consider now the same process forecasted by an individual forecaster i, $i = 1, \ldots, N_t$, where N_t denotes the number of participants in the survey at time t. Each forecaster is assumed to make a qualitative assessment at time t about the development of the macro variable Y_{t+h}^*. $\mathbf{P}_{i,t+h}$ denotes the L dimensional vector of probabilities

$$\Pr[Y_{t+h}^* \in \mathcal{G}_l | \mathcal{F}_{it}] = \Pr[\tilde{Y}_{l,t+h} = 1 | \mathcal{F}_{it}], \tag{2}$$

that state l occurs in $t+h$ given individual i-th information set $\mathcal{F}_{it}$.

The forecasts at the micro level may differ because of different information sets $\mathcal{F}_{it}$ (information disparity) but also because of different individual probability measures (belief disparity). In principle, our setup allows for both kinds of disparities, but for the ease of notation to cover the standard case of information disparity at the micro level, we stick to the assumption of belief homogeneity.[1]

Expectations at the macro level, $\mathbf{P}_{t+h}$, and expectations for forecaster i, $\mathbf{P}_{i,t+h}$, are related through the $K \times L$-dimensional, individual misclassification matrix $\Pi_{i,t+h}$ by:

$$\mathbf{P}_{i,t+h} = \Pi'_{i,t+h}\mathbf{P}_{t+h}, \tag{3}$$

where the components of $\Pi_{i,t+h}$ are given by $\pi^{kl}_{i,t+h} = \Pr\left[\tilde{Y}_{l,t+h|\mathcal{F}_{it}} = 1 \middle| Y_{k,t+h|\mathcal{F}_t} = 1\right]$.

The individual misclassification matrix, $\Pi'_{i,t+h}$, defined in (3) relates the objective expectation formation process at the macro level[2] to the individual (possibly subjective) expectation formation process at the micro level. If $\mathbf{P}_{t+h}$ denotes the predictions of the state indicator vector under rational expectations, the misclassification matrix measures the deviation of a forecaster's beliefs from the true data generating process. For identical partitions $\mathcal{S}_k = \mathcal{G}_k, K = L$, the forecaster's expectations are rational in the sense of Muth (1961), if the misclassification matrix is the identity matrix, $\Pi_{i,t+h} = \mathrm{I}_K$. Moreover, at the macro level specific expectation formation schemes such as static expectations, adaptive or error learning expectations can be imposed. In this case the misclassification matrix can be used to measure deviations of the individual forecaster's beliefs from a given macroeconomic model world. For instance let $\mathbf{P}_{t+h}$ be the probability forecasts for the exchange rate changes based on a purchasing power parity model. In this case $\Pi_{i,t+h}$ measures the extent to which the beliefs of forecaster i differ from the purchasing power parity hypothesis.

3.2 Average Expectations

Our approach allows for heterogeneous expectations, i.e. in the general set-up developed above $\Pi_{i,t+h}$ is individual specific (e.g. reflecting ability or experience of

[1]For both, informational disparity and disparity in beliefs $\Pr[\tilde{Y}_{l,t+h} = 1|\mathcal{F}_{it}] = \mathrm{E}_{it}[\tilde{Y}_{l,t+h}|\mathcal{F}_{it}]$, where $\mathrm{E}_{it}[\cdot]$ indicates that the expectation is taken under the i-th forecasters (subjective) probability measure at t.

[2]We refer to objective expectations and objective probabilities as those implied by the (theoretical) model on the macro level, see Muth (1961).

forecaster i) as well as time specific (e.g. evolvement of macroeconomic uncertainty over time). Pesaran & Weale (2006) propose the concept of average rational expectations in a model with heterogeneous expectations. This concept relies on the weighted average of the individual conditional densities of the continuous macro variable to be forecasted. Average expectations are consistent with the existence of heterogeneity in beliefs and allow for systematic deviations from rational expectations at the individual level. Let $\bar{\mathbf{P}}_{t+h}$ be the average expectation over the state vector Y_{t+h} defined as

$$\bar{\mathbf{P}}_{t+h} = \sum_{i=1}^{N_t} w_{it}\mathbf{P}_{i,t+h} = \sum_{i=1}^{N_t} w_{it}\mathrm{E}[Y_{t+h}|\mathcal{F}_{it}] \tag{4}$$

where the non-negative weights satisfy the conditions $\sum_{i=1}^{N_t} w_{it} = 1$ and $\sum_{i=1}^{N_t} w_{it}^2 = O\big(\frac{1}{N_t}\big), \forall t$. Inserting (3) gives

$$\bar{\mathbf{P}}_{t+h} = \sum_{i=1}^{N_t} w_{it}\Pi'_{i,t+h}\mathbf{P}_{t+h} = \bar{\Pi}'_{t+h}\mathbf{P}_{t+h}, \tag{5}$$

where $\bar{\Pi}'_{t+h} = \sum_{i=1}^{N_t} w_{it}\Pi'_{i,t+h}$. Let $u_{t+h} = Y_{t+h} - \mathbf{P}_{t+h}$ and $u_{i,t+h} = Y_{t+h} - \mathbf{P}_{i,t+h}$ be the expectation error vector for the macro and the individual level respectively. The two expectations errors are related by

$$u_{i,t+h} = \big(\mathrm{I}_K - \Pi'_{i,t+h}\big)\mathbf{P}_{t+h} + u_{t+h}. \tag{6}$$

Aggregating over the number of forecasters in survey wave t gives the average expectation error $\bar{u}_{t+h} = \sum_{i=1}^{N_t} w_{it}u_{i,t+h}$

$$\bar{u}_{t+h} = \big(\mathrm{I}_K - \bar{\Pi}'_{t+h}\big)\mathbf{P}_{t+h} + u_{t+h}. \tag{7}$$

Under a set of sufficient conditions stated in Pesaran & Weale (2006), $\bar{u}_{t+h} \xrightarrow{\text{q.m.}} u_{t+h}$ for $N_t \to \infty$, this implies $\mathrm{I}_K = \bar{\Pi}'_{t+h}$, so that average expectations equal rational expectations. Using the average misclassification matrix $\bar{\Pi}'_{t+h}$ we are able to test the expectation formation in terms of a 'consensus' or market concept. Note that $\Pi'_{i,t+h}$ can be used to test for a specific expectation hypothesis at the individual level for each forecaster separately in the sample. In this case $\bar{\Pi}'_{t+h}$ can simply be regarded as a summary statistic.

3.3 Estimation

Our model is estimated within a standard panel framework based on the individual discrete forecasts for the change (return) of a given macro or financial series. We treat the discrete forecasts at the individual level as misclassified values (mispredictions) of the macro forecasts. The outcome probabilities at the individual level can be expressed as the sum of the misclassification matrix and the macro outcome probabilities. This leads to a log likelihood function, $\ln \mathcal{L}$, of the form

$$\ln \mathcal{L} = \sum_{t=1}^{T} \sum_{i=1}^{N_t} \sum_{l=1}^{L} \mathbb{1}_{\{\tilde{Y}_{l,t+h|\mathcal{F}_{it}}=1\}} \ln \mathbf{P}_{i,t+h,l}, \tag{8}$$

where $\mathbf{P}_{i,t+h,l} = \sum_{k=1}^{K} \pi_{it+h}^{kl} \cdot \mathbf{P}_{t+h,k}$ and $\mathbf{P}_{t+h,k}$ is the k-th element of $\mathbf{P}_{t+h}$. In order to facilitate the computation of the likelihood $\mathbf{P}_{t+h,k}$ is estimated in a first step. For the elements of the misclassification matrix we choose a multinomial logistic form, where the log-odds ratios of the misclassification probabilities follow a generalized Autoregressive Conditional Moving Average (ARMA) type process, detailed below.

For the Maximum Likelihood (ML) estimation of our model as outlined in (8), we need to specify a model for the macro probability vector $\mathbf{P}_{t+h}$ for the discrete outcomes of the macro series and a specification for the misclassification matrix Π_{it+h}.

In the following we will concentrate on the case $L = K = 3$, i.e. a macro world with $K = 3$ states (up/same/down) that matches the $L = 3$ answer categories asked for in the ZEW survey. We set $h = 6$ which corresponds to the 6 months forecasting horizon asked for in the ZEW survey.

3.4 Macro World Probabilities

We rely on a dynamic quantal response strategy to derive $\mathbf{P}_{t+h}$ at time t. We assume the following time series specification for Y_{t+h}^*:

$$Y_{t+h}^* = \mu_{t+h} + \varepsilon_{t+h}, \tag{9}$$

where $\mu_{t+h} = \mathrm{E}[Y_{t+h}^*|\mathcal{F}_t]$ denotes the conditional expectation of Y_{t+h}^* given $\mathcal{F}_t$. This model is sufficiently general to incorporate standard expectation formation models, such as static, adaptive or error learning specifications and also standard time series specifications such as ARMA models by choosing μ_{t+h} appropriately. The k^{th} component of $\mathbf{P}_{t+h}$ can then be obtained by

$$\mathbf{P}_{t+h,k} = F_{t+h}\big(\tau_{t+h}^{k} - \mu_{t+h}\big) - F_{t+h}\big(\tau_{t+h}^{k-1} - \mu_{t+h}\big), \text{ for } k = 1, 2, 3, \tag{10}$$

where F_{t+h} denotes the conditional cumulative density function (c.d.f.) of ε_{t+h} given $\mathcal{F}_t$ and τ_{t+h}^k the k^{th} threshold, where we set for convenience $\tau_{t+h}^K = \infty$ and $\tau_{t+h}^0 = -\infty$

for all t. Assuming an ordered probit model we obtain:

$$\mathbf{P}_{t+h,k} = \Phi\left(\frac{\tau_{t+h}^{k} - \mu_{t+h}}{\sigma_{t+h}}\right) - \Phi\left(\frac{\tau_{t+h}^{k-1} - \mu_{t+h}}{\sigma_{t+h}}\right), \text{ for } k = 1, 2, 3, \tag{11}$$

where Φ denotes the standard normal c.d.f. and $\sigma_{t+h} = \mathrm{E}[\sigma_{t+h}|\mathcal{F}_t]$, with σ_t the standard deviation of ε_t.

h-Step Ahead Forecast In our empirical study we obtain the forecasts $\hat{\mathbf{P}}_{t+h}$ by estimating σ_t on the grounds of a six month realized volatility estimator using weekly observations and we use, following the definition of Marcellino, Stock & Watson (2006), a direct AR(4) forecasting models for σ_{t+h} and Y_{t+h}^* to obtain the forecasted variables $\hat{\sigma}_{t+h}$ and $\hat{Y}_{t+h}^*$ at time t. We use expanding window regression with data dating back to January 1974 to obtain the parameter estimates for the direct AR(4) models.

The Perfect Forecast Case For comparison reasons and to rule out forecasting model uncertainty caused by the use of a potentially misspecified forecasting model we also consider the following perfect forecast case under which we assume that we know the realizations of σ_{t+h} and Y_{t+h}^* already at time t. Hence, we obtain $\hat{\mathbf{P}}_{t+h}$ by setting $\hat{\sigma}_{t+h} = \sigma_{t+h}$ and $\hat{Y}_{t+h}^* = Y_{t+h}^*$. Also in this cas,e σ_t is obtained by a six month realized volatility estimator using weekly observations.

For both cases and for each series analyzed, we use the ZEW's constant median up and down threshold values detailed in section 2 in (11) to determine the (up/same/down) partition of the respective macro series. This dynamic quantal response forecasting strategy should be understood as a starting point for the prediction of $\hat{\mathbf{P}}_{t+h}$. An alternative strategy consist of deriving the probability vector $\hat{\mathbf{P}}_{t+h}$ by dynamic quantile regression based forecasts of Y_{t+h}^*, in which the respective quantiles, which then yield $\hat{\mathbf{P}}_{t+h}$, are chosen to match the up and down thresholds. A further possibility consists of transforming Y_t^* with the help of the threshold series into their discrete counterparts Y_t and to forecast $\hat{\mathbf{P}}_{t+h}$ directly with the discrete information using for example an Autoregressive Conditional Multinomial (ACM) model of Russell & Engle (2005).

3.5 Misclassification Matrix

Recall the misclassification matrix Π_{it+h}, whose components are given by

$$\pi_{i,t+h}^{kl} \quad = \quad \Pr\left[\tilde{Y}_{l,t+h|\mathcal{F}_{i,t}} = 1 \middle| Y_{k,t+h|\mathcal{F}_t} = 1\right]. \tag{12}$$

Thus $\pi_{i,t+h}^{kl}$ is the probability that a participant i gives the assessment l although the true assessment should have been k, for $k, l = 1, 2, 3,\ l \neq k$. The probability that the assessment of the participant is correct, i.e., that no misclassification occurs, is then given by $\pi^{kk}_{i,t+h}$ and the sum over l of $\sum_l \pi^{kl}_{i,t+h}$ is equal to one by definition (adding-up constraint).

Similar to Russell & Engle (2005) for their autoregressive multinomial model (ACM) we use with a logistic link function of the form:

$$\pi^{kl}_{i,t+h} = \frac{\exp\{\Lambda^{kl}_{i,t+h}\}}{\sum_{l=1}^{3} \exp\{\Lambda^{kl}_{i,t+h}\}} \ , \qquad k,l = 1,2,3, \tag{13}$$

where the log-odds ratio $\Lambda^{kl}_{i,t+h}$ will be specified in terms of an autoregressive form as given below. As normalization constraint, we use as the reference category the corresponding correct macro outcome category, i.e. $\Lambda^{kk}_{i,t+h} = 0$ for $k = l$, such that the odds ratios are defined as the quotient of a given misclassification probability to the probability of a correct classification. The resulting vector of log-odds ratios given by

$$\begin{aligned} \Lambda^{k}_{i,t+h} &= \left(\Lambda^{kl}_{i,t+h}, \Lambda^{kl'}_{i,t+h}\right)' \\ &= \left(\ln\left[\frac{\pi^{kl}_{i,t+h}}{\pi^{kk}_{i,t+h}}\right], \ln\left[\frac{\pi^{kl'}_{i,t+h}}{\pi^{kk}_{i,t+h}}\right]\right)' , \text{for } k,l,l' = 1,2,3, \text{ and } k \neq l \neq l' \ , \end{aligned} \tag{14}$$

is specified as a multivariate ARMA type process, including explanatory variables. All in all the log odds ratios in (14) define nine misclassification probabilities for the three true states of the world. Due to the three adding-up constraints there are two log-odds ratio to be estimated for each of the true states of the world. For the vector log-odds ratios we assume the following linear autoregressive form:

$$\Lambda^{k}_{i,t+h} = c^k + GZ_{i,t+h} + A^k \xi_{i,t+h-1} \quad \forall k = 1,2,3, \tag{15}$$

with A^k being a matrix of dimension (2×3) with the elements $\{a^k_{ll'}\}$, for $l, l' = 1,2,3$ with $l \neq k$. c^k denotes the (2×1) vector of constants $c^k = (c^k_l, c^k_{l'})'$, for $l, l' \neq k$. $Z_{i,t+h}$ denotes the g-dimensional vector of explanatory variables which are time and/or individual specific and are included statically with G as the corresponding coefficient matrix of dimension $(2 \times g)$. The misclassification indicator vector driving the ARMA type model is specified as

$$\begin{aligned} \xi_{i,t+h} &= (\xi^1_{i,t+h}, \xi^2_{i,t+h}, \xi^3_{i,t+h})' \\ &= \begin{pmatrix} \left(\mathbb{1}_{\{\tilde{Y}_{2,t+h|\mathcal{F}_{it}}=1\}} + \mathbb{1}_{\{\tilde{Y}_{3,t+h|\mathcal{F}_{it}}=1\}}\right) \cdot \mathbb{1}_{\{Y_{1,t+h}=1\}} \\ \left(\mathbb{1}_{\{\tilde{Y}_{1,t+h|\mathcal{F}_{it}}=1\}} + \mathbb{1}_{\{\tilde{Y}_{3,t+h|\mathcal{F}_{it}}=1\}}\right) \cdot \mathbb{1}_{\{Y_{2,t+h}=1\}} \\ \left(\mathbb{1}_{\{\tilde{Y}_{1,t+h|\mathcal{F}_{it}}=1\}} + \mathbb{1}_{\{\tilde{Y}_{2,t+h|\mathcal{F}_{it}}=1\}}\right) \cdot \mathbb{1}_{\{Y_{3,t+h}=1\}} \end{pmatrix} , \end{aligned} \tag{16}$$

which is the three-dimensional state vector of individual i at time $t+h$ representing whether that individual misclassified at time t the true change of the underlying variable. For example, if $\xi_{i,t+h} = (1,0,0)'$ then individual i predicted either a no change or a negative change of the variable at time t, although in reality the variable went up in the period from t to $t+h$. Hence, negative coefficients in A^k imply lower values in the corresponding log-odds ratio vector $\Lambda^k_{i,t+h}$ and thus a learning effect, positive coefficients imply a more pronounced degree of misclassification, while mixed sign patterns of the coefficients do not allow for a clear statement about the learning effect just by examination of the signs of the coefficients.

Note that in our empirical study we employ ACM specifications with one lag, and use the same set of explanatory variables for each state k and assume that the coefficient matrices are equal across states, i.e. $G = G^1 = G^2 = G^3$, so that the corresponding coefficients reflect the general impact of the explanatory variables on misclassification. The specification can be easily generalized to include more lags and different coefficient matrices for the explanatory variables for each state.

3.6 Definition of Explanatory Variables

Our set of explanatory variables can be divided in two classes: purely individual specific and both, time and individual specific variables. We specify four individual specific explanatory variables, namely Insurance_i, Industry_i, Manager_i and Reliability_i. Since our group of experts consists of experts from banks, insurance and industry companies we include dummy variables to figure out whether experts from particular groups have different abilities in forecasting the underlying series. Thus, we generate the dummy variables Insurance_i and Industry_i to be equal to 1 if individual i is a representative of an insurance or industry firm, respectively, and 0 otherwise. Hence, the group of bankers forms the basis category. The dummy variable Manager_i is equal to 1 if individual i belongs to the management board and 0 otherwise and thus measures the forecasting ability of managers over the other groups of experts working in economic, security analysts, asset management or financial accounting divisions. Reliability_i is defined as the share of the number of questionnaires returned in time over the overall returned number of questionnaires for each individual i. This explanatory variable allows us to characterize the general degree of punctuality or reliability of each participant, which we assume to be an overall characteristic of a forecaster and time independent.

In contrast Performance_{it} is a time and individual specific variable defined as the share of correct predictions over the last 12 months of individual i. More specifically

$$\begin{aligned} Performance_{it} &= \frac{1}{12}\sum_{\tau=0}^{11}\mathbb{1}_{\{\tilde{Y}_t|F_{t-h-\tau}=Y_t|F_{t-h-\tau}\}} \\ &= \frac{1}{12}\sum_{\tau=0}^{11}\sum_{k=1}^{3}\mathbb{1}_{\{\mathbb{1}_{\{\tilde{Y}_{k,t-\tau}|F_{it-h-\tau}=1\}}=\mathbb{1}_{\{Y_{k,t-\tau}|F_{t-h-\tau}=1\}}\}}. \end{aligned}$$

This variable captures the effect of the historical forecasting performance of each participant on their future assessments. This variable allows us to examine a general individual specific long term learning process, while the misclassification indicator parameters $\xi^k_{i,t+h}$ reflect a short term error learning process with respect to specific states of the world, here $k = 1, 2, 3$ (up/same/down).

Note, that all explanatory variables have positive domains so that their influence on the vector of log-odds ratios and thus on the degree of misclassification can be interpreted in a straightforward way. A positive coefficient implies higher values for the components in the vector of log-odds ratios and hence reflects a higher degree of misclassification, since by construction for every state k the basis category corresponds to the "correct prediction" category.

4 Empirical Findings

4.1 Descriptive Figures

In Figure 1 below we present for the 5 variables under consideration the 6 months standard deviation estimated with a realized volatility estimator (row 3), as well as the objective probabilities of up/same/down for both the perfect forecast (row 4) and the 6 months ahead forecasting scenarios (row 5). In these graphs the up probability share is always drawn in blue, the same probability share is always drawn in grey and the down probability share is always drawn in yellow.

Whereas the perfect forecast case objective probabilities mimic the behavior of the series very closely (row 3), the objective probabilities from the 6 months ahead forecasting scenario (row 4) do anticipate their general behavior also quite well but to a less amplified extent and with variations only in a narrow band above stable baseline shares. This is of course due to the specific forecasting setup for probabilities that adds additional forecasting uncertainty and thus cloaked the true changes of the underlying series. The perfect forecast probabilities, in contrast, rule out any forecasting model uncertainty and constitute the limiting case in that respect that we assume that at time t we already know the return (and its standard deviation) of the particular series from t to $t+6$.

Under the assumption of (average) rational expectations these sample probabilities should correspond on average to the above discussed forecasted objective probabilities. However, we observe a certain degree of discrepancies between the sample and the objective probabilities yielding a specific amount of misclassification that we analyze within the proposed modeling framework.

4.2 Estimation Results

In Table 1 we present for both macro probability scenarios the estimation results for the explanatory variables included in the ACM misclassification regressions for the 5 variables under consideration. The detailed estimation outputs (Tables 5 and 6) can be found in Appendix A.2.

A first important finding is that for the perfect forecast and the 6 months ahead forecasting scenarios we find no general qualitative differences in the effects of the explanatory variables on the degree of misclassification which implies a certain robustness of the results with regard to the choice of the specific forecasting model for the 6 months ahead prediction of the macro up/same/down probabilities.

Our first main results show that individuals learn in the long term but not necessarily in the short term. Except for the long term interest rates in the perfect forecast scenario, where the coefficient is positively significant, we find that for all 5 series the effect of past prediction performance, which measures the degree of correct forecasts over the last 12 months, has a significant negative impact in both scenarios on the degree of misclassification implying a significant link between better historical prediction performance and more accurate future forecasting ability of individual i. Hence, we observe that those forecasters who have given a better assessment in the past do continue to do so also in the future. They reveal a sharpened understanding of the data generating process, may be better informed or may have access to better resources in making their predictions especially in the long run. This finding also allows an interpretation as a general long term learning of individual i through the performance variable, in the sense that the individual forecaster learns from his past long run mistakes how to make more accurate forecasts which then imply increasing shares of correct predictions and thus less misclassification of future forecasts.

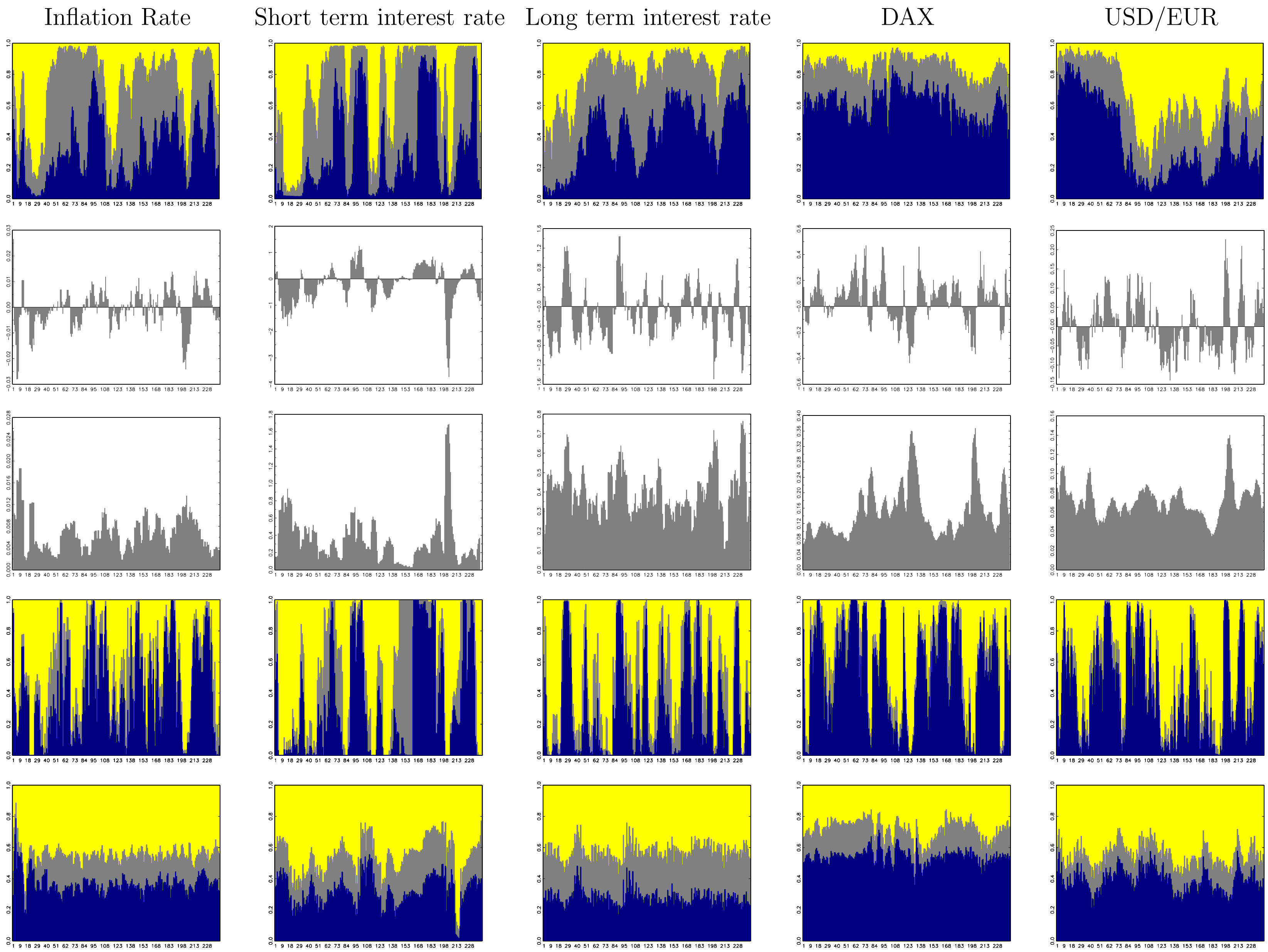

Figure 1: The first row displays the shares for up/same/down (in blue/grey/yellow) answered by the survey participants (sample probabilities) for the inflation and interest rates as well as the DAX 30 and USD/EUR, the second row displays the graphs of the 6 months changes (inflation and interest rates) or the 6 months returns (DAX 30 and USD/EUR) of the actual series. The third row shows the 6 months standard deviation estimated with a realized volatility estimator. The objective probabilities of up/same/down for the perfect forecast, resp. for the 6 months ahead forecasting scenarios can be found in the fourth and the fifth rows (resp.).

Short-term Learning

The effect of only the last mis-prediction and short term learning can be examined by looking at the coefficients in the A^k innovation term matrices of the ACM model. It is, however, less clear cut and we generally do not observe a uniform sign pattern across coefficients. An interesting finding is that for both scenarios we observe for the DAX30 that the A^3 matrices have significant positive coefficients, implying that forecasters do not learn from short term past mis-prediction when these financial series are in a downward move. Moreover, they neither seem to learn when this series is in an upward move in a perfect forecast scenario. These results show on the contrary that their degree of mis-prediction is accelerated. To some extent this can be related to the concept of "trend following" proposed by Barberis et al. (2015). They provide evidence that many stock market investors exhibit a kind of "trend following behaviour" in the sense that they form their predictions of future stock market returns based on past returns, meaning that they expect the stock market to perform well in the near future if it has recently performed well and vice versa. The professional forecasters we consider in our dataset may also follow past trends to form their beliefs/expectations about the future, and therefore they are unable to revise their predictions so rapidly to follow up and down movements. Additionally these results can be either related to bubbles observed for these series or be attributed to an optimism bias.[3] If we take a closer look at the graphics in the third row in Figure 1 for the DAX30, which represents the shares of up/same/down answered by the survey participants (sample probabilities), we see that approximately 60% of the participants always predict that the price of the DAX30 in the next 6 months will go up. This suggests that the participants are most of the time optimistic concerning the assessment of the 6 month ahead forecast of the DAX30, and might confirm the exhibition of an optimistic bias.

For the USD/EUR series and the short term interest rate respectively, we observe a similar but less pronounced effect for the upward state matrices A^1, for the downward state matrices A^3respectively. On the contrary, we see that for the inflation series the A^1 matrix has significant negative coefficients, implying that forecasters do learn from short term past mis-prediction if this macro series is in an upward move.[4] All results shed more light on the time horizon in learning and contradict to a certain

[3]Optimism bias is the tendency for people to over-estimate the likelihood of positive events and under-estimate the likelihood of negative events. See Weinstein (1980), among others.

[4]This is in line with Ang et al. (2007), who provide evidence that survey data can predict future inflation.

extent previous findings in the literature. Many observations from psychology, political science, and organizational behavior indicate that people exhibit a taste for consistency. Meyvis, Ratner & Levav (2010) show that people are unable to recognize their forecasting error, due to the fact that they exhibit a tendency to recall their affective forecast to be in conformity with their actual experience. In this respect, they do not revise their beliefs and continue to rely on the same incorrect beliefs for their subsequent forecasts, so that they are unable to learn from past mis-predictions. This is in line with the findings of Wilson, Meyers & Gilbert (2001) and Fischhoff (1975) that people erroneously remember their past predictions.

Long-term Learning

Our observation that individuals tend to learn from their past long term mistakes (through the $Performance_{it}$ variable) but not from the short ones (specification of the error terms) is in contrast more consistent with the information processing mechanism put forward in relatively new macroeconomic models. Calvo (1983), Mankiw & Reis (2002), Lorenzoni (2010) and Mankiw & Reis (2010) among others developed so called delayed information processing models in which only a share of individuals receives up-to-date information to provide more realistic mechanisms for information processing, whereas Woodford (2002) and Sims (2010) introduced models with partial information processing in which individuals only observe a noisy information signal. Our result, that professional forecasters are able to correct/revise their mis-predictions in the long run but not in the short run is also related to the theory of "*inattentiveness*" proposed by Reis (2006a,b), highlighting that individual forecasters need time to process new information, and that new information is only progressively incorporated in their predictions, due to their limitations in acquiring and processing information (Coibion & Gorodnichenko (2012)). This result is also supported by Andrade & LeBihan (2013) who show that participants of the ECB Survey of Professional Forecasters fail to update systematically their forecasts as a result of new information disclosure, and that they differ in their frequency of updating.

Heterogeneity among Forecasters

Our second set of results show that heterogeneity among forecasters matters. Interestingly, we find that in cases where the reliability variable is significantly different from zero, it is always positive implying that those forecasters who are more painstaking in returning the questionnaire in time do not necessarily provide better forecasts. For the DAX30 in both scenarios this result can be again related to the fact that 60% of the participants always predict that the price will go up. This result can in addition also find support in the delayed information processing models literature (Calvo (1983), Mankiw & Reis (2002), Lorenzoni (2010) and Mankiw & Reis (2010)). Those professional forecasters who delay the returning of the questionnaire have practically more time to process the available information, such that delaying the return of the questionnaire then plays in their favor. They take more time, and consequently make less mistakes and more accurate predictions.[5]

We find that experts from insurance and industry firms seem to generate a higher degree of misclassification (if significant the respective dummy variable coefficients are positive except for one case) which might be explained by less resources and information and by the fact that they might face a further distance in their day-to-day business to the variables of interest and thus have less experience with these variables than their colleagues from banks. A similar finding can be made with respect to the coefficient of the manager dummy variable which is if significant always positive (except for one case the USD/EUR series) which might also reflect a less time and effort effect. Recent literature on "*rational inattention*" (Sims 2010, 2003) suggests that heterogeneity of expectations/believes is related to dispersion of information.[6] Our results shed, indeed, light on the heterogeneity of the forecasts between two groups: the bankers and the others, and their "rational inattention". Bankers can be considered as being more "attentive" than the other group and therefore generate less misclassification/mis-predictions than managers, and experts from insurance and industry firms. This shows that the latter may have only partial information or so called "rational inattention", given that their day-to-day business is less related to the macro and financial variables of interest in this study. Alternative explanations given in the literature suggest that domain knowledge and experience improves forecast accuracy (Harvey, Bolger & McClelland (1994)). Stickel (1992) analyzes the performance of

[5]Nevertheless, this result contradicts to a certain extent the literature investigating the relationship between conscientiousness and job success. Several psychological studies, indeed, have shown that conscientiousness is highly positively correlated with job success (e.g. Barrick & Mount (1991) and Robertson & Kinder (1993)), in the sense that employees having a higher interest in their job, and therefore have a higher degree of conscientiousness, are more successful.

[6]Nevertheless, Patton & Timmermann (2010) come to a kind of opposite result in their study. Patton & Timmermann (2010) indeed, show in their empirical analysis of cross-sectional dispersion in forecasters' predictions of macroeconomic variables that heterogeneity in forecasters' information sets does not play a major role in explaining the cross-sectional dispersion in predictions of macroeconomic variables. Their result suggests that differences in predictions/believes cannot be explained by differences in information sets.

security analysts on the Institutional Investor All-American Research Team relative to the performance of other analysts. He shows that the members of this team are more accurate in forecasting earnings, and forecast more frequently than other analysts, suggesting that experience has a positive impact on forecasting ability. In an experiment, where information is cumulatively distributed among traders, meaning that some investors know more than others by having the same plus some extra information, Huber, Kirchler & Sutter (2008) address the question whether having more information than others about the intrinsic value of an asset always leads to higher returns when trading in financial markets. They show that only the best informed traders outperform the less informed ones. In the same manner, Ackert, Church & Zhang (2002) show that well informed traders are able to exploit their informational advantage to outperform less informed ones. Those papers support our result that bankers may possess extra information that enable them to make a better assessment about the future development of the financial variables than experts from insurance and industry firms.

Finally our last results show that the predictions are not consistent with average rational expectations. Table 2 contains the mean misclassification matrices $\tilde{\Pi}$, and we observe that all matrices differ from the identity matrix[7], which clearly shows that forecasters reveal a prediction behavior which is not consistent with average rational expectations.

5 Robustness Check

In this section we present some robustness checks to assess the credibility of our results. We previously found no general qualitative differences in the effects of the explanatory variables on the degree of misclassification between the perfect forecast and the 6 months ahead forecasting scenarios, and that is why we solely focus on the 6 months ahead forecasting scenario in this section.

We split our sample period into crisis/turmoil periods and non crisis periods, in order to detect a difference in the forecasting behaviour of our professional forecasters. Here we are considering 5 periods of turmoil, namely the European Currency Crisis[8] from April 1992 to June 1993, which peaked on the 16th September 1992, also called "Black

[7]We defined previously in Section 3 that the forecaster's' expectations are rational in the sense of Muth (1961), if the misclassification matrix is the identity matrix, $\Pi_{i,t+h} = \mathrm{I}_K$.

[8]It reflects the withdraw of the UK and Italy from the European Monetary System.

6 months ahead forecasting scenario

Variable	Inflation		Short Term Interest Rate		Long Term Interest Rate		DAX		USD/EUR	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Insurance_i	-0.0130	-0.1929	-0.0382	-0.5512	-0.0017	-0.0162	0.2473	3.4395	0.3018	4.0894
Industry_i	0.0518	0.6174	-0.1987	-1.5807	0.5528	4.4048	0.9237	10.1283	-0.0374	-0.4207
Manager_i	-0.0769	-1.1210	0.1261	1.5626	0.0619	0.7651	0.1549	1.9657	-0.1706	-2.7296
Reliability_i	0.0225	0.1623	0.4594	2.7248	-0.2700	-1.3595	1.1797	6.9640	-0.2141	-1.4012
Performance_{it}	-1.5250	-61.9919	-0.5405	-32.1726	-1.5109	-25.4360	-3.4863	-50.8207	-1.9912	-46.8518

perfect forecast scenario

Variable	Inflation		Short Term Interest Rate		Long Term Interest Rate		DAX		USD/EUR	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Insurance_i	0.0529	1.3634	0.0211	0.6394	-0.1311	-2.9795	0.1655	4.2219	0.0858	2.5385
Industry_i	0.3895	8.9540	0.0454	0.9458	0.3768	5.5493	0.4560	9.2683	0.0706	1.4379
Manager_i	0.0938	2.4947	0.1272	3.4102	-0.0804	-1.8483	0.0408	0.9358	0.0035	0.0895
Reliability_i	0.3019	4.1470	0.0005	0.0076	0.3562	3.2799	0.7057	7.2528	0.1576	1.9267
Performance_{it}	-0.2689	-19.6277	-0.0870	-10.6098	1.2670	64.6429	-1.4607	-93.0382	-0.3850	-27.1127

Table 1: Estimation results for the covariates in the misclassification probability for inflation rate, short term interest rate, long term interest rate, DAX and USD/EUR FX-rate

6 months ahead forecasting scenario

Inflation	Short Term Interest Rate	Long Term Interest Rate	DAX	USD/EUR
$\begin{pmatrix} 0.2961 & 0.4449 & 0.2589 \\ 0.1419 & 0.5264 & 0.3316 \\ 0.3754 & 0.4189 & 0.2055 \end{pmatrix}$	$\begin{pmatrix} 0.3334 & 0.2056 & 0.4608 \\ 0.6175 & 0.0468 & 0.3355 \\ 0.0874 & 0.7599 & 0.1525 \end{pmatrix}$	$\begin{pmatrix} 0.4411 & 0.3829 & 0.1758 \\ 0.6287 & 0.0391 & 0.3320 \\ 0.2707 & 0.6500 & 0.0792 \end{pmatrix}$	$\begin{pmatrix} 0.6024 & 0.2586 & 0.1389 \\ 0.2605 & 0.5267 & 0.2126 \\ 0.8607 & 0.0441 & 0.0951 \end{pmatrix}$	$\begin{pmatrix} 0.2493 & 0.2691 & 0.4815 \\ 0.8334 & 0.1085 & 0.0579 \\ 0.2363 & 0.4284 & 0.3351 \end{pmatrix}$

perfect foresight scenario

Inflation	Short Term Interest Rate	Long Term Interest Rate	DAX	USD/EUR
$\begin{pmatrix} 0.4665 & 0.4570 & 0.0764 \\ 0.3023 & 0.5942 & 0.1033 \\ 0.1582 & 0.3420 & 0.4996 \end{pmatrix}$	$\begin{pmatrix} 0.5287 & 0.4286 & 0.0425 \\ 0.2313 & 0.6740 & 0.0945 \\ 0.1225 & 0.3328 & 0.5445 \end{pmatrix}$	$\begin{pmatrix} 0.3393 & 0.4804 & 0.1801 \\ 0.6274 & 0.1618 & 0.2107 \\ 0.3828 & 0.4542 & 0.1629 \end{pmatrix}$	$\begin{pmatrix} 0.6054 & 0.2562 & 0.1382 \\ 0.5960 & 0.1781 & 0.2258 \\ 0.6548 & 0.2493 & 0.0958 \end{pmatrix}$	$\begin{pmatrix} 0.4702 & 0.2729 & 0.2567 \\ 0.4204 & 0.0017 & 0.5777 \\ 0.2298 & 0.3734 & 0.3967 \end{pmatrix}$

Table 2: Mean misclassification matrices $\tilde{\Pi}$ for the 6 months ahead forecasting and the perfect foresight scenario inflation rate, short and long term interest rate, DAX and USD/EUR FX-rate. ACM parameter estimates of the coefficient matrix G given by Equation (15).

Wednesday", the Mexican Economic Crisis[9] in 1994, the Russian financial crisis[10] in 1998, the burst of the Dot-Com Bubble from March 2000 to October 2002, and the recent financial crisis from August 2007 to February 2009. This set-up will help us to analyse the forecasting behaviour more specifically during these particular periods.

We construct a measure of the degree of misclassification computed as being the sum of the elements of the squared differences between the estimated misclassification matrix and the identity matrix at every point in time. The closer the value of this measure is to 0, the more the professional forecasters form their expectations rationally on average. We then compute the correlation between the price changes/returns and the inverse of the misclassification measure for each series under consideration.

Table 4 shows the mean misclassification matrices for the 6 months ahead forecasting scenario of all variables during crisis and non crisis periods, while Table 3 presents the correlation coefficients between price changes/returns and the inverse of the misclassification measure during the two sub periods. Altogether we consider 90 months of crisis and 152 of calm periods. We observe that the correlations are, when significant, always negative during non-crisis periods, suggesting that during those quieter periods more misclassification is generated, so that forecasters seem to deviate more from the rational expectations hypothesis on average. However, the result is less clear cut during crisis periods. We observe for both financial series a significant negative correlation. This implies that forecasters misclassify more during crisis periods, and that is why they deviate more from the rational expectation hypothesis; a phenomena also observed by examining the average estimated misclassification matrices in Table 4. On the opposite, we observe a significant positive correlation for short term interest rates, suggesting that our forecasters deviate less from the rational expectation hypothesis during crisis periods for that macro variable. This result sheds light on the fact that our forecasters form their expectations differently depending on the nature of the variable they are asked to predict and the overall economic climate.

Overall, we observe more misclassification during non-crisis periods regardless of the variable under consideration (the correlations are always negative). Whereas this result holds for the financial variables during crisis periods, it reverses for the short term interest rate. One could argue, that there is more homogeneous information available

[9]The Mexican Economic Crisis saw the devaluation of the Mexican Peso, with a bailout mostly funded by the US

[10]It resulted in the Russian government and the Russian Central Bank devaluing the ruble and defaulting on its debt.

for macro variables, so that during crisis periods forecasters are more focused, and interpret this homogeneous information in the same way, and therefore generate less mis-predictions. On the opposite, given the easy access to information about financial markets, and given the fact that this information is highly dispersed and heterogeneous, forecasters have more difficulties to come up with a consensus during crisis periods, and therefore this situation leads to more misclassification, i.e. they deviate more from the rational expectation hypothesis.

crisis periods				
Inflation	Short Term Interest Rate	Long Term Interest Rate	DAX	USD/EUR
-0.1784	0.5106***	-0.2717	-0.3961**	-0.0808*
non crisis periods				
-0.5225***	-0.4203***	-0.0202***	-0.0394**	0.0574

Table 3: Correlation coefficients between the returns and the misclassification measure for the two sub-samples. To test the significance of the correlation coefficients, we performed a rank correlation test. ***, **, and * denote that the coefficient is statistically significantly different from zero at the 1%, 5% and 10% significance level respectively

6 Concluding Remarks

In this paper, we present a new empirical approach to analyse individual expectation formation processes based on tendency survey data. Using a dynamic quantal response model with misclassification we define qualitative mispredictions in terms of deviations from the qualitative rational expectation forecast and relate them to individual and macro factors driving these individual mispredictions. Our approach is consistent with the rather general definition of expectations as subjectively held beliefs by individuals. Since individual expectations are taken from individuals' qualitative responses to survey questions, no assumption on the individual expectation formation process is necessary. In this sense our approach is double robust. First, it is robust against the critique of classical tests of the rational expectation hypothesis based on aggregate time series data which require distributional and/or functional form assumptions. Second, the approach does not require an aggregation rule by considering individual forecasts at any time period with the equivalent outcome at the macro level.

Our results show that surveys are useful to predict macro-variables, as already mentioned in Ang et al. (2007), and represent a timely source of information (Lui et al.

Inflation	Short Term Interest Rate	Long Term Interest Rate	DAX	USD/EUR
crisis				
$\begin{pmatrix} 0.3306 & 0.4352 & 0.234 \\ 0.1492 & 0.4224 & 0.428 \\ 0.2933 & 0.4296 & 0.277 \end{pmatrix}$	$\begin{pmatrix} 0.3072 & 0.2202 & 0.4725 \\ 0.6009 & 0.0491 & 0.3498 \\ 0.0823 & 0.7131 & 0.2044 \end{pmatrix}$	$\begin{pmatrix} 0.3784 & 0.3688 & 0.2527 \\ 0.6004 & 0.0363 & 0.3631 \\ 0.2262 & 0.6889 & 0.0847 \end{pmatrix}$	$\begin{pmatrix} 0.6939 & 0.2233 & 0.0827 \\ 0.1476 & 0.5574 & 0.2948 \\ 0.7790 & 0.0753 & 0.1456 \end{pmatrix}$	$\begin{pmatrix} 0.2429 & 0.2856 & 0.4713 \\ 0.8445 & 0.1025 & 0.0529 \\ 0.2715 & 0.4170 & 0.3114 \end{pmatrix}$
non crisis				
$\begin{pmatrix} 0.2756 & 0.4507 & 0.2736 \\ 0.1376 & 0.5880 & 0.2743 \\ 0.4241 & 0.4125 & 0.1632 \end{pmatrix}$	$\begin{pmatrix} 0.3489 & 0.1971 & 0.4539 \\ 0.6274 & 0.0454 & 0.3271 \\ 0.0905 & 0.7876 & 0.1217 \end{pmatrix}$	$\begin{pmatrix} 0.4782 & 0.3913 & 0.1303 \\ 0.6455 & 0.0408 & 0.3136 \\ 0.2971 & 0.6269 & 0.0759 \end{pmatrix}$	$\begin{pmatrix} 0.5482 & 0.2795 & 0.1722 \\ 0.3274 & 0.5085 & 0.1639 \\ 0.9091 & 0.0256 & 0.0651 \end{pmatrix}$	$\begin{pmatrix} 0.2530 & 0.2593 & 0.4875 \\ 0.8269 & 0.1121 & 0.0608 \\ 0.2155 & 0.4352 & 0.3491 \end{pmatrix}$

Table 4: Mean misclassification matrices $\tilde{\Pi}$ for the 6 months ahead forecasting scenario for the inflation rate, short and long term interest rate, DAX and USD/EUR FX-rate during crisis and non crisis periods.

(2010)). For all series (inflation rate, short and long term interest rate, DAX30, and the USD/EUR exchange rate with respect to Germany) considered, we find a specific learning pattern. We observe a general long term learning effect, reflected by the fact that forecasters who gave a better assessment in the past continue to do so in the future, whereas we do not observe a general short term learning effect. Furthermore, we observe for the DAX30 series that the forecasters do not learn from short term past misprediction if these financial series are in a downward move but rather accelerate their degree of misprediction. For the USD/EUR series and the short term interest rate respectively, we observe a similar but less pronounced effect for upward state, and for the downward state respectively. Forecasters who are more reliable in returning the questionnaire in time do not provide better forecasts. Managers, experts from insurance and industry firms seem to generate a higher degree of misclassification than bankers, indicating that better informed participants outperform the less informed ones.

The estimation of the misclassification matrix allows us not only to systematically analyse forecasting behavior at the individual level, but also in terms of average forecasts for specific groups of forecasters or the overall group of survey respondents. Our results suggest that our forecasters form their expectations differently depending on the variables they are predicting. Because the underlying time series are reasonably long, estimates of certain subperiods were used for a systematic analysis of individual forecasting behavior in different scenarios (crisis times vs calm times). More misclassification was observed during non-crisis periods regardless of the variable under consideration as well as for the financial variables during crisis periods. We found less misclassification for the short term interest rate during crisis periods. These findings suggest that forecasters might have asymmetric or different loss functions

In future research our approach can be used to test specific expectation hypotheses or learning algorithms. Moreover, the degree of homogeneity of the individual misclassification matrices could also be used as a simple measure of the degree of consensus among forecasters. Although the goal of our study is to develop an econometric method to detect the sources of directional forecasting errors rather than developing another forecasting method, our approach can be used to improve forecasts based on individual forecasts. For instance our estimates can be used to construct subsamples of superior forecasters to improve the overall forecasting performance of the survey data. Moreover, by computing a reverse misclassification matrix in the spirit of time-reversible Markov chains it would be possible to exploit the information on misclassifications systematically to obtain misclassification corrected tendency forecasts.

References

Ackert, L., B. K. Church, & P. Zhang (2002): "Market Behavior in the Presence of Divergent and Imperfect Private Information: Experimental Evidence from Canada, China, and the United States," *Journal of Economic Behavior and Organization*, 47, 435–450.

Anderson, O. (1951): "Konjunkturtest und Statistik, Möglichkeiten und Grenzen einer Quantifizierung von Testergebnissen," *Allgemeines Statistisches Archiv*, 35, 209–220.

Andrade, P. & H. LeBihan (2013): "Inattentive Professional Forecasters," *Journal of Monetary Economics*, 60, 967–982.

Ang, A., G. Bekaert, & M. Wei (2007): "Do macro variables, asset markets, or surveys forecast inflation better?" *Journal of Monetary Economics*, 54, 1163–1212.

Barberis, N., R. Greenwood, L. Jin, & A. Shleifer (2015): "X-CAPM: An Extrapolative Capital Asset Pricing Model," *Journal of Financial Economics*, 115, 1–24.

Barrick, M. & M. Mount (1991): "The Big Five Personality Dimensions and Job Performance: a Meta-Analysis," *Personnel Psychology*, 44, 1–26.

Calvo, G. A. (1983): "Staggered Prices in a Utility-Maximizing Framework," *Journal of Monetary Economics*, 12 (3), 383–398.

Carlson, J. A. & M. Parkin (1975): "Inflation Expectations," *Economica*, 42, 123–138.

Coibion, O. & Y. Gorodnichenko (2012): "What Can Survey Forecasts Tell Us about Information Rigidities?" *Journal of Political Economy*, 120, 116–159.

Dustmann, C. & A. van Soest (2004): "An Analysis of Speaking Fluency of Immigrants Using Ordered Response Models with Classification Errors," *Journal of Business and Economic Statistics*, 22, 312–321.

Fischhoff, B. (1975): "Hindsight $\neq$ Foresight: the Effect of Outcome Knowledge on Judgment under Uncertainty," *Journal of Experimental Psychology: Human Perception and Performance*, 1, 288–299.

Gourieroux, C. & J. Pradel (1986): "Direct Test of the Rational Expectation Hypothesis," *European Economic Review*, 30, 265–284.

HARVEY, N., F. BOLGER, & A. MCCLELLAND (1994): "On the Nature of Expectations," *British Journal of Psychology*, 85, 203–229.

HAUSMAN, J. (2001): "Mismeasured Variables in Econometric Analysis: Problems from the Right and Problems from the Left," *The Journal of Economic Perspectives*, 15, 57–67.

HAUSMAN, J., J. ABREYAVA, & F. M. SCOTT-MORTON (1998): "Misclassification of the Depedent Variable in a Disctrete Response Setting," *Journal of Econometrics*, 87, 239–269.

HUBER, J., M. KIRCHLER, & M. SUTTER (2008): "Is More Information Always Better? Experimental Financial Markets with Cumulative Information," *Journal of Economic Behavior and Organization*, 65, 86–104.

LORENZONI, G. (2010): "Optimal Monetary Policy with Uncertain Fundamentals and Dispersed Information," *Review of Economic Studies*, 77 (1), 305–338.

LUI, S., J. MITCHELL, & M. R. WEALE (2010): "Qualitative business surveys: signal or noise?" *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 174, 327–348.

MANKIW, N. G. & R. REIS (2002): "Sticky Information Versus Sticky Prices: A Proposal To Replace The New Keynesian Phillips Curve," *The Quarterly Journal of Economics*, 117 (4), 1295–1328.

—— (2010): "Chapter 5 - Imperfect Information and Aggregate Supply," *in:* FRIEDMAN, B. M. & M. WOODFORD, eds., "Handbook of Monetary Economics," vol. 3, Elsevier, pp. 183–229.

MARCELLINO, M., J. H. STOCK, & M. W. WATSON (2006): "A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series," *Journal of Econometrics*, 135, 499 – 526.

MEYVIS, T., R. RATNER, & J. LEVAV (2010): "Why We Don't Learn to Accurately Forecast Our Feelings: How Misremembering Our Predictions Blinds Us to Our Past Forecasting Errors," *Journal of Experimental Psychology: General*, 139, 579–589.

MUTH, J. F. (1961): "Rational Expectations and the Theory of Price Movements," *Econometrica*, 29 (3), 315–335.

Patton, A. J. & A. Timmermann (2010): "Why do forecasters disagree? Lessons from the term structure of cross-sectional dispersion," *Journal of Monetary Economics*, 57, 803–820.

Pesaran, M. & M. Weale (2006): "Survey Expectations," *in:* Elliott, G., C. Granger, & A. Timmermann, eds., "Handbook of Economic Forecasting," vol. 1, chap. 14, Elsevier, pp. 715–776.

Pesaran, M. H. (1984): "Expectations Formations and Macro-Econometric Modelling," *in:* Malgrange, P. & P.-A. Muet, eds., "Contemporary Macroeconomic Modelling," Basil Blackwell, Oxford, pp. 27–55.

—— (1985): "Formation of Inflation Expectations in British Manufacturing Industries," *The Economic Journal*, 95, 948–975.

—— (1987): *The Limits to Rational Expectations*, Basil Blackwell, Oxford.

Reis, R. (2006a): "Inattentive Consumers," *Journal of Monetary Economics*, 53 (8), 1761–1800.

—— (2006b): "Inattentive Producers," *Review of Economic Studies*, 73 (3), 793–821.

Robertson, I. & A. Kinder (1993): "Personality and Job Competencies: the Criterion-Related Validity of Some Personality Variables," *in:* Cooper, C. & D. Bosseau, eds., "Trends in Organisational Behaviour," vol. 1, Wiley, pp. 75–89.

Russell, J. R. & R. F. Engle (2005): "A Discrete-State Continuous-Time Model of Financial Transactions Prices and Times," *Journal of Business & Economic Statistics*, 23 (2), 166–180.

Sims, C. A. (2003): "Implications of Rational Inattention," *Journal of Monetary Economics*, 50, 665–690.

—— (2010): "Chapter 4 - Rational Inattention and Monetary Economics," *in:* Friedman, B. M. & M. Woodford, eds., "Handbook of Monetary Economics," vol. 3, Elsevier, pp. 155–181.

Stickel, S. E. (1992): "Reputation and Performance Among Security Analysts," *The Journal of Finance*, 47, 1811–1836.

Weinstein, N. (1980): "Unrealistic optimism about future life events," *Journal of Personality and Social Psychology*, 39, 806–820.

Wilson, T. D., J. Meyers, & D. T. Gilbert (2001): "Lessons From the Past: Do People Learn From Experience That Emotional Reactions Are Short-Lived?" *Personality and Social Psychology Bulletin*, 27, 1648–1661.

Woodford, M. (2002): "Imperfect Common Knowledge and the Effects of Monetary Policy," *in:* Aghion, P., R. Frydman, J. Stiglitz, & M. Woodford, eds., "Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps," Princeton University Press, pp. 25–58.

A Appendix

A.1 Data

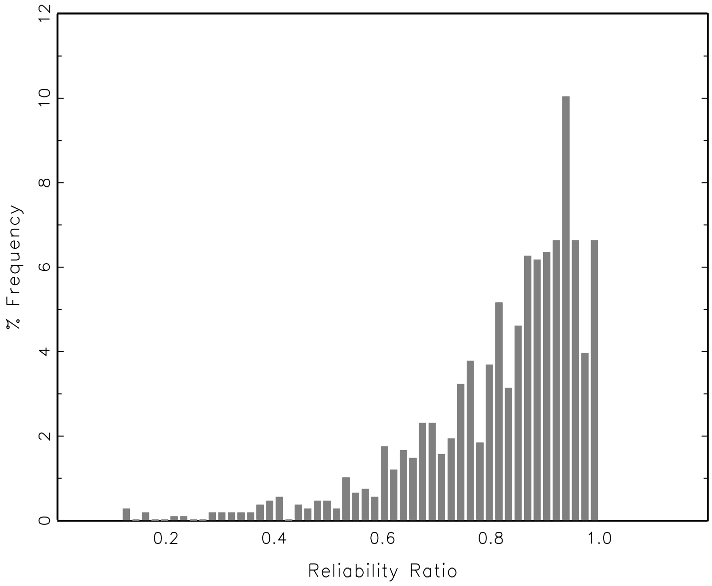

Figure 2: Distribution of the response rate across experts. The response rate for each expert is computed as the number of questionnaire returns in time over the number of overall returns of the questionnaire.

A.2 Outputs

Par.	inflation Est.	inflation t-stat	short term interest rate Est.	short term interest rate t-stat	long term interest rate Est.	long term interest rate t-stat	DAX Est.	DAX t-stat	USD/EUR Est.	USD/EUR t-stat
	GLARMA Model									
c_2^1	0.1916	10.8864	-1.5506	-119.2769	0.0691	2.4504	-0.8988	-11.1652	-2.2111	-101.4266
c_3^1	-1.1169	-33.7432	-4.8696	-125.1825	-2.1717	-72.1495	-1.3781	-19.3553	-3.3579	-170.4518
c_1^2	4.4144	35.8312	-1.9272	-87.6000	-4.3394	-30.2819	2.8853	9.1918	5.1416	0.4347
c_3^2	2.0086	36.2563	0.2907	20.0483	4.1956	24.0436	-1.3275	-4.3269	-0.0728	-0.0032
c_1^3	-2.7614	-103.8120	-1.6294	-95.2865	0.3389	21.0497	1.2349	29.1250	-3.2590	-152.2897
c_2^3	-1.4682	-74.9082	-0.5235	-48.0275	0.6595	25.1718	0.4150	6.1209	0.0650	2.7778
a_{21}^1	-1.5333	-58.5229	0.6013	43.2590	0.6043	13.4888	1.2266	6.4626	3.0495	65.4399
a_{31}^1	-2.4668	-39.0935	-0.4384	-3.0110	3.2440	94.5773	0.8304	5.1228	5.4364	188.1107
a_{22}^1	-2.6326	-77.4294	5.5720	170.3976	-0.5167	-9.1290	1.0057	9.3380	2.1208	60.4217
a_{32}^1	-6.6444	-57.6271	9.3487	134.1277	0.7952	12.7029	0.7804	7.5183	3.9075	174.4420
a_{23}^1	-0.9652	-45.1028	8.2725	188.8699	0.2267	6.2110	0.5060	5.4176	2.8647	93.3127
a_{33}^1	-1.1866	-22.4310	7.3165	45.6425	1.5819	38.8673	0.3734	4.2097	3.7412	157.1933
a_{11}^2	-7.0258	-38.6245	1.1316	38.2297	21.6073	9.9573	-6.2898	-6.7163	12.4827	0.1151
a_{31}^2	-19.5392	-3.6328	-6.8375	-137.2992	-12.7806	-3.7167	5.8418	7.7932	-11.8902	-0.0159
a_{12}^2	-20.5203	-53.6619	1.8007	53.4332	6.9608	29.6709	0.7750	0.6654	-8.3229	-0.3199
a_{32}^2	-30.3038	-5.7227	-10.4772	-74.8906	-8.9927	-27.2671	4.6943	4.3166	8.3811	0.2190
a_{13}^2	-44.1393	-18.2183	3.0537	57.9450	5.9565	35.4132	-0.4187	-1.0002	-14.5468	-0.1952
a_{33}^2	-6.4510	-51.2798	-3.9391	-46.5615	-4.9208	-20.4692	-0.7220	-0.4670	20.7472	0.2480
a_{11}^3	2.1871	58.0133	1.7246	94.2404	-0.1916	-12.6053	4.1867	27.1687	2.0869	59.9684
a_{21}^3	1.0521	41.0977	1.1294	110.7255	-0.2828	-8.5438	3.9334	16.3009	-0.3077	-9.2402
a_{12}^3	0.0650	1.7016	-0.3412	-12.3177	1.2224	55.3122	3.7208	10.8605	4.3030	135.3145
a_{22}^3	-0.4380	-15.8123	-0.1078	-7.8116	0.2704	6.2884	3.6899	9.4954	-0.0810	-1.2796
a_{13}^3	1.9052	62.2614	-0.5497	-8.6160	0.5439	22.9494	0.8153	15.1825	5.0720	173.1058
a_{23}^3	1.2343	62.3384	0.5249	30.6959	0.6947	17.9974	0.4917	5.6323	-0.4631	-13.9488
	Covariates									
Insurance_i	0.0529	1.3634	0.0211	0.6394	-0.1311	-2.9795	0.1655	4.2219	0.0858	2.5385
Industry_i	0.3895	8.9540	0.0454	0.9458	0.3768	5.5493	0.4560	9.2683	0.0706	1.4379
Manager_i	0.0938	2.4947	0.1272	3.4102	-0.0804	-1.8483	0.0408	0.9358	0.0035	0.0895
Reliability_i	0.3019	4.1470	0.0005	0.0076	0.3562	3.2799	0.7057	7.2528	0.1576	1.9267
Performance_{it}	-0.2689	-19.6277	-0.0870	-10.6098	1.2670	64.6429	-1.4607	-93.0382	-0.3850	-27.1127
Mean $\ln \mathcal{L}$	-283.259		-247.965		-290.743		-257.910		-300.036	

Table 5: Estimation results for the perfect forecast scenario: inflation rate (column 1), short term interest rate (column 2), short term interest rate (column 3), DAX (column 4), USD/EUR TX-rate(column 5).

	inflation		short term interest rate		long term interest rate		DAX		USD/EUR	
Par.	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
	GLARMA Model									
c_2^1	2.8633	78.0191	2.9608	34.1499	2.6968	20.3840	0.0164	0.1116	-8.4136	-75.0544
c_3^1	-2.2461	-50.1362	-4.7365	-162.2089	-5.4109	-55.7825	-1.6734	-12.6294	-4.8502	-84.4983
c_1^2	-5.2781	-18.9519	2.2650	16.6667	-4.4995	-9.5897	3.4532	10.3266	4.8241	2.0869
c_3^2	4.1260	60.5874	3.9490	23.5480	4.1796	9.1337	2.7987	8.5326	3.3623	1.4090
c_1^3	-0.1956	-6.9362	-4.6996	-106.5669	-1.4709	-15.2425	1.5402	7.8823	-5.2013	-74.3043
c_2^3	-2.1907	-48.8996	-3.4183	-91.3984	-1.1911	-12.1417	-1.2074	-1.4186	2.1779	48.2905
a_{21}^1	-4.0768	-63.6006	-30.9707	-56.4850	-15.1632	-8.5215	1.8376	5.7859	-13.1783	-0.0061
a_{31}^1	3.9774	97.2469	5.5559	209.6566	9.3596	65.5893	5.5448	19.6903	9.1772	93.9324
a_{22}^1	9.3178	1.2477	-4.1347	-12.6560	7.6473	1.0135	2.0809	9.0395	-0.6472	-0.0001
a_{32}^1	21.2628	2.8512	15.7637	93.6643	2.4513	0.0025	3.3947	16.4074	11.2790	113.1294
a_{23}^1	-3.4514	-64.7542	-9.7899	-11.4878	-4.9675	-26.0898	-1.1440	-6.4306	45.4784	6.4151
a_{33}^1	-2.1322	-3.7526	36.6687	73.9736	-3.6931	-0.0566	-1.9122	-4.3838	40.3182	5.6841
a_{11}^2	-0.8027	-0.0471	31.0830	1.3828	22.0604	14.5729	-7.8284	-8.8727	25.6128	0.1631
a_{31}^2	-7.2316	-55.1609	-31.6840	-1.3185	-10.1338	-6.5731	-8.3559	-7.8644	-8.6322	-0.0402
a_{12}^2	12.6179	20.4869	-0.8653	-4.8072	10.2979	13.1435	0.2465	0.4235	-17.8566	-0.1926
a_{32}^2	-27.2339	-11.2124	-18.2751	-8.2865	-3.3662	-4.3057	-1.4596	-2.5589	-6.9552	-2.6100
a_{13}^2	-3.5376	-0.0187	-25.2171	-0.9636	7.9175	14.4744	-9.5520	-1.9901	4.8755	0.2754
a_{33}^2	-5.6926	-45.2872	15.1311	0.6766	-2.4354	-4.4136	-2.9733	-7.1166	0.9516	0.0519
a_{11}^3	6.7001	83.9612	29.5527	120.4267	8.5309	20.1533	10.9493	16.3033	0.2206	0.0556
a_{21}^3	8.9718	102.6522	31.3908	134.0914	11.0552	24.7708	0.8613	0.0616	-0.9720	-18.1682
a_{12}^3	16.3218	11.4869	0.1667	0.0030	14.2125	8.8568	10.0431	1.1838	10.7679	91.2534
a_{22}^3	21.2459	14.9157	24.9244	34.2886	11.3041	7.1283	1.3968	0.0079	-0.1777	-1.5629
a_{13}^3	-1.5127	-20.6936	26.4336	109.1846	-3.2266	-3.2533	0.9551	4.2734	9.0057	102.9223
a_{23}^3	3.8339	58.0894	26.4144	112.6414	4.2386	24.2900	2.0427	2.1347	-2.8484	-33.4712
	Covariates									
Insurance_i	-0.0130	-0.1929	-0.0382	-0.5512	-0.0017	-0.0162	0.2473	3.4395	0.3018	4.0894
Industry_i	0.0518	0.6174	-0.1987	-1.5807	0.5528	4.4048	0.9237	10.1283	-0.0374	-0.4207
Manager_i	-0.0769	-1.1210	0.1261	1.5626	0.0619	0.7651	0.1549	1.9657	-0.1706	-2.7296
Reliability_i	0.0225	0.1623	0.4594	2.7248	-0.2700	-1.3595	1.1797	6.9640	-0.2141	-1.4012
Performance_{it}	-1.5250	-61.9919	-0.5405	-32.1726	-1.5109	-25.4360	-3.4863	-50.8207	-1.9912	-46.8518
Mean $\ln \mathcal{L}$	-292.948		-254.543		-283.246		-283.274		-284.488	

Table 6: Estimation results for the 6 months ahead forecasting scenario: inflation rate (column 1), short term interest rate (column 2), short term interest rate (column 3), DAX (column 4), USD/EUR FX-rate (column 5).