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Keywords: Evaluating forecasts, Macroeconomic Forecasting, Rationality, Survey Data, Fixed-Event Forecasts
JEL classification: C25, E32, E37

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JONAS DOVERN AND JOHANNES WEISSER

September 17, 2008

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1. Introduction

In this paper, we use survey data to analyze the rationality of professional macroeconomic forecasts in the G7-countries. In the first part of the paper, we analyze both individual forecasts and average forecasts, so-called consensus forecasts; our analysis encompasses tests of unbiasedness as well as tests of weak efficiency of forecasts. In the second part of the paper, we present how our results for average forecasts relate to those for individual forecasts and whether we can identify any structural patterns in the entirety of our results.

Our results are related to two strands of the literature involving forecasts or expectations of economic variables. First, they provide evidence on whether the assumption of rationality of forecasts and expectations that is usually made in standard economic models is backed up by the characteristics of observed forecasts. Since the work by Pigou

Jonas Dovern, The Kiel Institute for the World Economy (IfW), jonas.dovern@ifw-kiel.de. Johannes Weisser, Max Planck Institute of Economics, weisser@econ.mpg.de. The views presented in this paper reflect the authors' opinion, and do not necessarily coincide with those of the IfW or the Max Planck Institute of Economics. We are grateful to Helmut Herwartz and Christian Merkl as well as to all participants of the Brown-Bag Seminar at Kiel University for valuable comments and suggestions.

(1927) or Keynes (1936), it is widely accepted that expectations and forecasts play a crucial role in all kinds of economic dynamics. Muth (1961) introduced the notion of rational expectation, which has since played a central role in economic thinking. In the context considered in this paper, expectations are measured by forecasts from survey data and a forecast is usually said to be rational if it is unbiased and makes use of all available information in an efficient way. Since most of the currently used work horse models in macroeconomics – as, for instance, the New-Keynesian models (Woodford, 2003) – heavily rely on the concept of rational expectations, it is important that econometricians analyze forecasts to check whether they are indeed rational. A rejection of the rationality hypothesis for observed forecasts would clearly call the use of rational expectations in economic modeling into question. In addition, a clearer understanding of the nature of forecasts made so far would clearly help to improve the properties of future forecasts (see e.g. Stekler, 2007).

Second, our results are based on an approach, in which some of the assumptions usually made in the literature dealing with the analysis of macroeconomic forecasts are modified. This literature dates back to early contributions by Ball (1962), Mincer and Zarnowitz (1969), Figlewski and Wachtel (1981), or Nordhaus (1987), who introduced the basic model framework for analyzing fixed event forecasts. A couple of more recent contributions have made proposals to improve the econometric approach for testing rationality of fixed event forecasts. These include Keane and Runkle (1990) and Batchelor and Dua (1991), who introduce the analysis in a panel framework using the Generalized Methods of Moments (GMM) method, or Davies and Lahiri (1995), who develop the analytic framework for analyzing three dimensional panels of survey data.[1]

One weak point of the empirical literature on survey data is that outside the US there is only a limited number of data sets, which provide information on forecasts, so that existing evidence is predominantly focused on the US economy. Notable exceptions are Harvey et al. (2001), who analyze a set of selected individual forecasts for the UK from the *Consensus* data set, Gallo et al. (2002), who analyze the evolution of macroeconomic forecasts for the US, the UK, and Japan, Bowles et al. (2007), who analyze the performance of forecasts summarized in the Survey of Professional Forecasters conducted by the European Central Bank, Isiklar et al. (2006) or Ager et al. (2007), who use data from the *Consensus* data set on forecasts for a set of industrialized countries, Timmermann (2007), who analyzes the performance of IMF forecasts from the World Economic Outlook for

[1]Pesaran and Weale (2006) and Stekler (2002) present nice summaries of the commonly used approaches. The latter contribution also provides an overview about the most prominent survey data sets that are used in empirical research on forecast efficiency.

various countries, and Batchelor (2001), who compares the forecasts made by the IMF and the OECD to private sector forecasts. However, the entire existing international studies, with the exception of Harvey et al. (2001), make exclusive use of average forecasts, so called consensus forecasts, rather than analyzing individual forecasts.

It should be noted at this point that there are arguments against the assumption that published forecasts reflect true expectations and should, thus, be rational if made by rational agents. Some of the cases made in the literature are the following. First, forecasters might seek to maximize public attention. If this is the case, an unbiased forecast is not optimal anymore, since the utility of the forecaster depends on more than one argument (Laster et al., 1999). Second, forecasters might produce so-called "intentional" forecast in some situations (Stege, 1989). A forecaster could, for example, predict a specific event to provoke a policy action that actually prevents the realization of the event. Third, Forecasters might have asymmetric loss functions (Capistran and Timmermann, 2006). They could, for example, have different weights concerning a possible over- or underestimation of an outcome. We believe, however, that these arguments are not particularly strong a priori. We, therefore, abstract from them and start in this paper with the null hypothesis of rational forecasts, which are unaffected by these issues.

This paper adds to the literature in three ways. First, it provides evidence on the rationality of consistently collected *individual* forecasts for all the G7-counties and for four different macroeconomic variables; such broad evidence is missing in the literature although it is especially important to analyze individual forecasts, since unbiasedness tests using consensus forecasts can be proven to be inconsistent under assumptions that are fairly realistic (see, e.g., Bonham and Cohen, 2001, and the references therein). Second, it introduces a modification of the approach used to model the forecast errors of fixed event forecasts as it is, for instance, put forward by Davies and Lahiri (1995) or Clemens et al. (2007). Finally, the paper goes one step further than most studies dealing with rationality tests of forecasts by analyzing the correlation between the results from different tests; we check, for example, whether once a forecaster is known to produce inefficient forecasts he is also more likely to be biased.

Our findings confirm the result of previous studies that any analysis based on average forecasts should be treated with caution since even if all individual forecasts are rational the hypothesis of rationality is often rejected by the aggregate data. Furthermore, we find that there are not only large differences in the performance of forecasters across countries but also across different macroeconomic variables; in general, the forecasts for inflation are most often consistent with the hypothesis of rational forecasts while forecasts tend to

be biased in situations where forecasters have to learn about large structural shocks or gradual changes in the trend of a variable. In addition, we find some weak evidence that inefficient forecasts are more likely to be significantly biased than efficient forecasts.

The remainder of this paper is structured as follows. Section 2 discusses the model we use to analyze the unbiasedness and efficiency of forecasts. Section 3 presents a brief overview on the data that we use. Section 4 elaborates on the results for the individual forecasts (4.2) and the consensus forecasts (4.1). Section 5 discusses the results and their implications. Section 6 concludes the paper.

2. Model

The panel data set that we use in this paper contains so-called fixed event forecasts. Since these panels exhibit a special correlation structure, it is important to give a clear picture of the nature of the data before moving to the description of the tests that we are going to use.

The panel possesses a three dimensional structure of the kind introduced in Davies and Lahiri (1995). For each country and variable we have a NTH-vector of forecasts for T years made by N forecasters with forecast horizons ranging from one month to H months

$$F = [f_{1,1,H}, f_{1,1,H-1}, \ldots, f_{1,1,1}, f_{1,2,H}, \ldots, f_{1,T,1}, f_{2,1,H}, \ldots, f_{N,T,1}]' \ . \tag{1}$$

In other words, for each year we collect a sequence of H forecasts from each forecaster, starting H months before the year ends and ending in the last month of the respective year. Figure 1 shows a schematic diagram of the data structure. This structure will be of importance later on when we derive the correlation between different forecast errors.

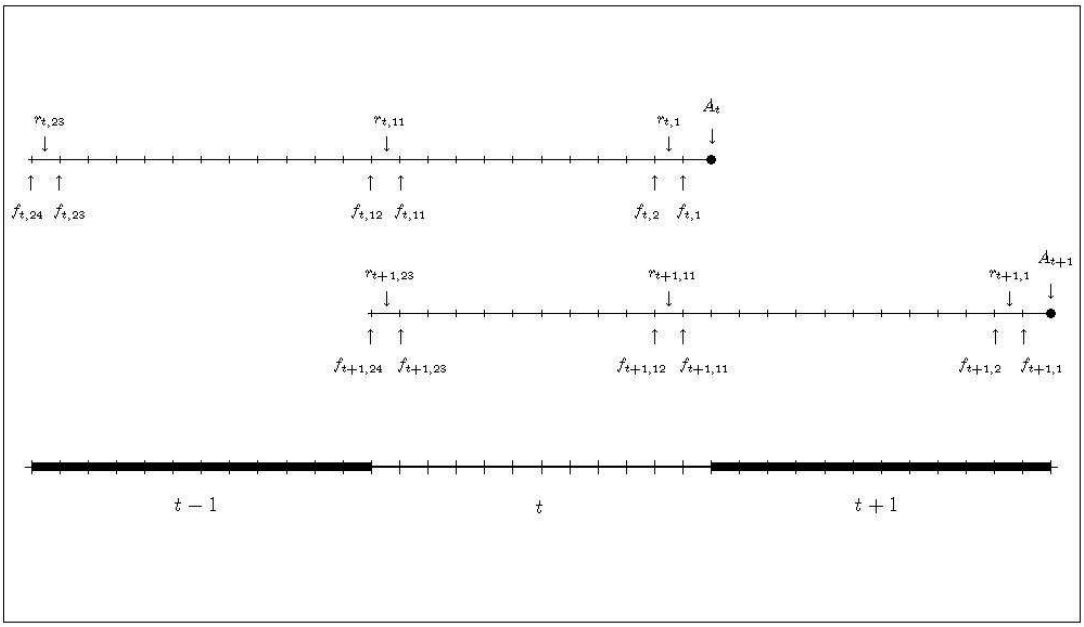
We assume that the forecast error for each forecast can be decomposed into different parts

$$e_{i,t,h} = A_t - f_{i,t,h} = \phi_i + \lambda_{t,h} + \epsilon_{i,t,h} \ , \tag{2}$$

where A_t denotes the realization of a variable for year t and ϕ_i is the individual bias of the forecasts of forecaster, i. The first error term, $\lambda_{t,h}$, is common to all forecasters and reflects the occurrence of macroeconomic shocks that hit an economy between the date at which the forecast is made and the end of year t. Following the literature, we assume that these shocks are cumulated over h months in an arithmetic way, so that the error term can be written $\lambda_{t,h} = \sum_{k=1}^{h} u_{t,k}$.[2] We assume that $u_{t,h}$ is distributed with a zero mean

[2]Since a shock occurring in a specific month will most surely have different effects on a variable for two different years ($u_{t,k} \neq u_{t+1,k+12}$), it would in fact be more accurate to speak of the accumulation of *effects*

FIGURE 1. Forecast Data Structure



and a variance of σ_u^2. Since $u_{t,h}$ and $u_{t+1,h+12}$ occur at the same point in time, we deviate from the iid-assumption and allow for a non-zero covariance, say ω_u, between the latter two shocks. In contrast to Davies and Lahiri (1995), for example, we do not restrict ω_u such that it is equal to σ_u^2.

The second error term $\epsilon_{i,t,h}$ can be treated in two different ways. On the one hand, it can be seen as an independently and identically distributed idiosyncratic shock. This is the view taken in Davies and Lahiri (1995) or Clemens et al. (2007). On the other hand, it can be assumed that over time each forecaster receives a flow of private information on the outcome for the variable that is forecasted. This will be the view taken in this paper. As for $\lambda_{t,h}$, the variance of $\epsilon_{i,t,h}$ is monotonically decreasing in h in this setup. Since the specific way this decline occurs has not been determined by the assumptions made so far, we opt also here for an arithmetic accumulation of iid-shocks to keep the model as simple as possible, i.e. $\epsilon_{i,t,h} = \sum_{k=1}^{h} \eta_{i,t,k}$, where the $\eta_{i,t,k}$ are distributed with mean 0 and variance γ_i. Since they are caused by the same shocks or changes in private information, $\eta_{i,t,k}$ and $\eta_{i,t+1,k+12}$ are allowed to have a non-zero correlation. The same applies to $\eta_{i,t,k}$ and $\eta_{j,t,k}$ or $\eta_{j,t+1,k+12}$ for $i \neq j$, since the private information sets are not necessarily mutually exclusive, i.e., there might be some overlap of the information sets that causes non-zero correlations.

of shocks rather than the shocks themselves. To enhance readability of the paper, however, we decided to continue using the wording *accumulation of shocks*.

Note that if $N = 1$, as is the case when we analyze the consensus forecasts, we face an identification problem because the two processes $\lambda_{t,h}$ and $\epsilon_{i,t,h}$ are no longer distinguishable. In this case we can write (omitting subscript i)

$$A_t - f_{t,h} = \phi + \sum_{k=1}^{h} (u_{t,k} + \eta_{t,k}) = \phi + \sum_{k=1}^{h} u^*_{t,k} \ . \tag{3}$$

Again, the $u^*_{t,k}$ are distributed with mean 0 and Variance $\sigma^2_{u^*}$ and show a potentially non-zero correlation between $u^*_{t,k}$ and $u^*_{t+1,k+12}$.

2.1. **Test of Unbiasedness.** In this section, we present the test that we use to analyze whether forecasters produce unbiased forecasts. The approach tests whether the ϕ_i in equation 2 are equal to zero; that is we test if each forecaster does not systematically over- or underestimate the outcome for a specific variable.

2.1.1. *Test Design.* We can examine this hypothesis by testing the zero restriction on the elements of $\Phi = [\phi_1, \ldots, \phi_N]'$ in the system of equations

$$e = A - F = \Phi \otimes i_{TH} + \underbrace{\lambda + \epsilon}_{=\nu} \ , \tag{4}$$

where e is the vector of stacked forecast errors, A is given by $i_N \otimes (A^+ \otimes i_H)$ with $A^+ = (A_1, A_2, \ldots, A_T)'$ and i_{TH}, i_N and i_H are vector of ones of dimension TH, N and H respectively. λ and ϵ are vectors of length NTH in which we stack the appropriate $\lambda_{t,h}$ and $\epsilon_{i,t,h}$ respectively.[3]

A consistent estimate for Φ can be obtained by estimating the following regression by ordinary least squares (OLS):

$$e = (I_N \otimes i_{TH})\, \Phi + \nu \ , \tag{5}$$

where I_N denotes the identity matrix of dimension N. Now, the crucial point is to note that while a simple OLS regression gives consistent point estimates, we cannot base our test on the standard errors of this regression, since the elements of ν are clearly not *iid* due to the special correlation structure caused by the structure of the panel data set. On the contrary, the assumptions made regarding the structure of forecast errors allows us to obtain a covariance matrix, $E[\nu\nu'] = \Sigma$, that has a very special shape and is neither diagonal nor homoscedastic. Formally, we have the following elements of Σ for two forecasters, say i and j, given that $H = 24$ in our data set and accounting for the

[3]The operator $\otimes$ denotes the Kronecker Product.

fact that a year has 12 months:

$$(6) \qquad Cov\left(\nu_{i,t_1,h_1}, \nu_{j,t_2,h_2}\right) = Cov\left(\sum_{k=1}^{h_1} u_{t_1,k} + \sum_{k=1}^{h_1} \eta_{i,t_1,k}, \sum_{k=1}^{h_2} u_{t_2,k} + \sum_{k=1}^{h_2} \eta_{j,t_2,k}\right)$$

$$= \begin{cases} min\{h_1, h_2\} \cdot \left[\sigma_u^2 + \gamma_i^2\right] & \text{for } i = j,\ t_1 = t_2 \\ min\{h_1, h_2 - 12\} \cdot \left[\omega_u + \psi_i\right] & \text{for } i = j,\ t_2 = t_1 + 1,\ h_2 \geq h_1 + 12 \\ min\{h_1, h_2\} \cdot \left[\sigma_u^2 + \zeta_{ij}\right] & \text{for } i \neq j,\ t_1 = t_2 \\ min\{h_1, h_2 - 12\} \cdot \left[\omega_u + \tau_{ij}\right] & \text{for } i \neq j,\ t_2 = t_1 + 1,\ h_2 \geq h_1 + 12 \\ 0 & \text{else.} \end{cases}$$

Clearly, the different non-zero cases deserve some more explanation. All of these correlations are potentially non-zero due to the fact that the forecast errors are correlated across several dimensions. First, they are correlated within the maximum forecast horizon H since $\lambda_{t,h}$ and $\epsilon_{i,t,h}$ are the accumulation of period-specific shocks; this refers to the first case shown in equation 6. Second, the forecast errors are correlated between subsequent years since the forecast horizons are of overlapping nature; this refers to the second case shown in equation 6, with $\omega_u = Cov\left(u_{t,h}, u_{t+1,h+12}\right)$ capturing the covariance between the impacts of a shock on the outcome in the two subsequent years and $\psi_i = Cov\left(\eta_{i,t,h}, \eta_{i,t+1,h+12}\right)$ denoting the covariance between the impacts of private informational changes on the forecasts for these two years. Finally, the forecast errors are correlated across different forecasters since forecast errors are produced at the same time and are all subject to the same subsequent macroeconomic shocks summarized by $\lambda_{t,h}$. In addition, we assume, as stated above, that the private information sets might overlap, which induces additional correlation that is reflected by the terms $\zeta_{ij} = Cov\left(\eta_{i,t,h}, \eta_{j,t,h}\right)$ and $\tau_{ij} = Cov\left(\eta_{i,t,h}, \eta_{j,t+1,h+12}\right)$.

In matrix notation, Σ can be written as the following expression of Kronecker Products:

$$(7) \qquad \Sigma = \underbrace{\left[\Upsilon \otimes (I_T \otimes A)\right]}_{\sigma_u^2,\ \gamma_i^2,\ and\ \zeta_{ij}} + \underbrace{\left[\Pi \otimes (diag(i_{T-1}, 1) \otimes B + diag(i_{T-1}, -1) \otimes B')\right]}_{\omega_u,\ \psi_i,\ and\ \tau_{ij}},$$

where $diag(i_{T-1}, 1)$ and $diag(i_{T-1}, -1)$ are $T \times T$ matrices with 1 on the first diagonal respectively above or below the main diagonal and all other elements equal to 0. The $N \times N$ matrices Υ and Π and the $H \times H$ matrices A and B are given by

$$\Upsilon = \begin{bmatrix} \sigma_u^2+\gamma_1^2 & \sigma_u^2+\zeta_{12} & \cdots & \sigma_u^2+\zeta_{1N} \\ \sigma_u^2+\zeta_{21} & \sigma_u^2+\gamma_2^2 & \cdots & \sigma_u^2+\zeta_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_u^2+\zeta_{N1} & \sigma_u^2+\zeta_{N2} & \cdots & \sigma_u^2+\gamma_N^2 \end{bmatrix} \quad \Pi = \begin{bmatrix} \omega_u+\psi_1 & \omega_u+\tau_{12} & \cdots & \omega_u+\tau_{1N} \\ \omega_u+\tau_{21} & \omega_u+\psi_2 & \cdots & \omega_u+\tau_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \omega_u+\tau_{N1} & \omega_u+\tau_{N2} & \cdots & \omega_u+\psi_3 \end{bmatrix}$$

$$A = \begin{bmatrix} 24 & 23 & 22 & \cdots & & 3 & 2 & 1 \\ 23 & 23 & 22 & \cdots & & 3 & 2 & 1 \\ 22 & 22 & 22 & \cdots & & 3 & 2 & 1 \\ 21 & 21 & 21 & \cdots & & 3 & 2 & 1 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 3 & 3 & 3 & \cdots & & 3 & 2 & 1 \\ 2 & 2 & 2 & \cdots & & 2 & 2 & 1 \\ 1 & 1 & 1 & \cdots & & 3 & 1 & 1 \end{bmatrix} \quad B = \begin{bmatrix} 12 & 11 & 10 & \cdots & 2 & 1 & 0 & \cdots & 0 \\ 12 & 11 & 10 & \cdots & 2 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 12 & 11 & 10 & \cdots & 2 & 1 & 0 & \cdots & 0 \\ 11 & 11 & 10 & \cdots & 2 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 2 & 2 & 2 & \cdots & 2 & 1 & 0 & \cdots & 0 \\ 1 & 1 & 1 & \cdots & 1 & 1 & 0 & \cdots & 0 \end{bmatrix}$$

Given Σ, the covariance matrix of the Generalized Methods of Moments (GMM) estimator can be written as

$$Var(\hat{\Phi}) = \left[(I_N \otimes i_{TH})'(I_N \otimes i_{TH})\right]^{-1} \left[(I_N \otimes i_{TH})'\Sigma(I_N \otimes i_{TH})\right] \left[(I_N \otimes i_{TH})'(I_N \otimes i_{TH})\right]^{-1} . \tag{8}$$

The standard errors corresponding to the elements of $\hat{\Phi}$ are obtained by taking the square roots of the elements of the main diagonal of $Var(\hat{\Phi})$. Under the nullhypothesis that a specific element of Φ, say ϕ_i, is equal to zero, the test statistic has the following asymptotical standard distribution

$$t_{\phi_i} = \frac{\hat{\phi}_i}{\sqrt{Var(\hat{\Phi})_{(i,i)}}} \overset{asy.}{\rightarrow} N(0,1) , \tag{9}$$

where the subscript (i, j) refers to the element of the matrix that is defined by the i-th row and the j-th column of the matrix. Naturally, Σ is not observed and has to be replaced by a consistent estimate, say $\hat{\Sigma}$, before computation of the test statistics is possible. In the next section we show, how such a consistent estimate can be constructed.

2.1.2. *Estimation of Variance.* We construct an estimator for Σ by consistently estimating the different terms that show up in the covariance matrix, i.e. we first estimate σ_u^2, ω_u, γ_i^2, ψ_i, ζ_{ij}, and τ_{ij} for all combinations of i and j. To this end, we follow the approach

proposed by Davies and Lahiri (1995). In a first step, we estimate

$$\hat{\lambda}_{t,h} = \frac{1}{N}\sum_{i=1}^{N}\left(A_t - f_{i,t,h} - \hat{\phi}_i\right) \tag{10}$$

for all combinations of $t = 1, \ldots, T$ and $h = 1, \ldots, H$. In a second step, we can use these estimates to construct an estimator for $\epsilon_{i,t,h}$ as

$$\hat{\varepsilon}_{i,t,h} = A_t - f_{i,t,h} - \hat{\phi}_i - \hat{\lambda}_{t,h}\ . \tag{11}$$

These first two steps are meant to separate those parts of the variances and covariances of the forecast errors that can be attributed to the existence of common macroeconomic shocks on the one hand and idiosyncratic information changes on the other hand. Stacking the estimates, we can use the vectors $\hat{\lambda}$ and $\hat{\epsilon}$ to estimate all unknown elements of Σ. Thus, in a third step we obtain estimates for the six parameters by applying the OLS estimator to the following regression equations:

$$\begin{aligned}
&(\hat{\lambda} \odot \hat{\lambda}) && = \kappa_{24}\,\sigma_u^2 + \tilde{\omega}_{\sigma_u^2} && \\
&(\hat{\lambda}_{12-1} \odot \hat{\lambda}_{24-13}) && = \kappa_{12}\,\omega_u + \tilde{\omega}_{\omega_u} && \\
&(\hat{\epsilon} \odot \hat{\epsilon}) && = (I_N \otimes \kappa_{24})\,\gamma^2 + \tilde{\omega}_{\gamma^2} && \\
&(\hat{\epsilon}_{12-1} \odot \hat{\epsilon}_{24-13}) && = (I_N \otimes \kappa_{12})\,\psi + \tilde{\omega}_{\psi} && \\
&(\hat{\epsilon}_i \odot \hat{\epsilon}_j) && = \kappa_{24}\,\zeta_{ij} + \tilde{\omega}_{\zeta_{ij}} && \text{for } i = 1, \ldots, N-1 \text{ and } j = i, \ldots, N \\
&\begin{bmatrix}\hat{\epsilon}_{i,12-1}\\ \hat{\epsilon}_{j,12-1}\end{bmatrix} \odot \begin{bmatrix}\hat{\epsilon}_{j,24-13}\\ \hat{\epsilon}_{i,24-13}\end{bmatrix} && = \begin{bmatrix}\kappa_{12}\\ \kappa_{12}\end{bmatrix}\tau_{ij} + \tilde{\omega}_{\tau_{ij}} && \text{for } i = 1, \ldots, N-1 \text{ and } j = i, \ldots, N
\end{aligned}\ ,$$

where $\kappa_h = i_T \otimes [h, h-1, \ldots, 1]'$, $\gamma^2 = [\gamma_1^2, \ldots, \gamma_N^2]'$, and $\psi = [\psi_1, \ldots, \psi_N]'$. Furthermore, we use the notations $\hat{\lambda}_{h_2-h_1}$ and $\hat{\epsilon}_{h_2-h_1}$ to refer to those elements of $\hat{\lambda}$ or $\hat{\epsilon}$ respectively which correspond to forecast horizons between h_1 and h_2 months.

Note again that if $N = 1$ – as it is for instance the case when we analyze the consensus forecasts – equation 2 reduces to equation 3. In this special case the structure of Σ simplifies significantly as we can drop all terms that refer to differences in private information. Formally, the covariance matrix reduces to

$$\Sigma = \underbrace{\left[\sigma_{u^*}^2\ (I_T \otimes A)\right]}_{\sigma_{u^*}^2} + \underbrace{\left[\omega_{u^*}\ (diag(i_{T-1}, 1) \otimes B + diag(i_{T-1}, -1) \otimes B')\right]}_{\omega_{u^*}}\ . \tag{12}$$

The non-zero elements are now given by

$$(13) \qquad Cov(\nu_{t_1,h_1}, \nu_{t_2,h_2}) = Cov\left(\sum_{k=1}^{h_1} u^*_{t_1,k}, \sum_{k=1}^{h_2} u^*_{t_2,k}\right)$$

$$= \begin{cases} min\{h_1, h_2\} \cdot \sigma^2_{u^*} & \text{for } t_1 = t_2 \\ min\{h_1, h_2 - 12\} \cdot \omega_{u^*} & \text{for } t_2 = t_1 + 1 \text{ und } h_2 \geq h_1 + 12 \\ 0 & \text{else .} \end{cases}$$

The unknown parameters $\sigma^2_{u^*}$ and ω_{u^*} can be estimated following Clemens et al. (2007). The proposed method uses the fact that the variances (covariances) of the forecast errors are multiples of $\sigma^2_{u^*}$ (ω_{u^*}) which are proportional to the respective forecast horizon (size of overlap of the forecast horizons). Estimates are obtained by estimating the following regressions by OLS

$$(14) \qquad \hat{\nu} \odot \hat{\nu} = \kappa_{24}\, \sigma^2_{u^*} + \bar{\omega}$$

$$(15) \qquad \hat{\nu}_{12-1} \odot \hat{\nu}_{24-13} = \kappa_{12}\, \omega_{u^*} + \bar{\omega}_{12} \ ,$$

where the notation is chosen as above such that $\hat{\nu}_{h_2-h_1}$ includes only those elements of $\hat{\nu}$ that corresponds to forecast horizons between h_1 and h_2 months.

2.2. **Test of (Weak) Efficiency.** With respect to the efficiency of the forecasts, we use the concept of weak-form efficiency that has been originally proposed by Nordhaus (1987). The concept starts from the notion of strong efficiency of forecasts which requires that all information that is revealed at the time a forecast is made is taken into account during the forecasting process. In other words: If a series of forecasts is strongly efficient, it would have not been possible to reduce the average forecast error by using any information available also to the forecaster. Since the amount of potentially relevant information is immense and any selection for an empirical analysis would be ad-hoc, Nordhaus (1987) proposes to restrict the relevant information set to lagged values of the forecast itself. He shows that under weak form efficiency the revisions of forecasts should be uncorrelated. It should be intuitively clear that for efficient forecasts the current forecast shouldn't reveal any information on future revisions – or as Nordhaus states (p. 673):

> If I could look at your most recent forecasts and accurately say, "Your next forecast will be 2% lower than today's", then you can surely improve your forecasts.

2.2.1. *Test design.* Weak form efficiency of a sequence of forecasts can be tested using the an equation of the form

$$r_{i,t,h} = \beta_i \, r_{i,t,h+k} + \xi_{i,t,h} \ , \tag{16}$$

where $r_{i,t,h}$ is defined as $f_{i,t,h} - f_{i,t,h+1}$ and $\xi_{i,t,h}$ is an *iid* innovation term. The hypothesis of weak-form efficiency implies $\beta_i = 0$.

Stacking the data on all individual forecasts and using the notation $r = [r_{1,1,H-(k+1)}, \ldots, r_{1,1,1}, r_{1,2,H-(k+1)}, \ldots, r_{N,T,1}]'$, $r_{+k} = \left[r_{1,1,H-1}, \ldots, r_{1,1,(k+1)}, r_{1,2,H-1}, \ldots, r_{N,T,(k+1)}\right]'$,[4] $\beta = [\beta_1, \ldots, \beta_N]'$, and $\xi = \left[\xi_{1,1,H-(k+1)}, \ldots, \xi_{N,T,1}\right]'$ we obtain a system of equation

$$r = (i_{T(H-(k+1))} \otimes \beta) r_{+k} + \xi \ . \tag{17}$$

Since also the covariance matrix of ξ, say $\Xi = E[\xi\xi']$, exhibits a special structure that is non-diagonal and heteroscedastic, we make use of the GMM estimator to obtain consistent estimates of the standard errors for β.

To derive the exact form of Ξ, we first note that (using equation 2) we can rewrite the forecast revisions as

$$\begin{aligned} r_{i,t,h} &= f_{i,t,h} - f_{i,t,h+1} = e_{i,t,h+1} - e_{i,t,h} \\ &= \lambda_{t,h+1} - \lambda_{t,h} + \epsilon_{i,t,h+1} - \epsilon_{i,t,h} \\ &= u_{t,h+1} + \eta_{i,t,h+1} \ . \end{aligned} \tag{18}$$

It is evident that under the Null hypothesis $\beta = 0$[5] we obtain the following expressions for the elements of Ξ:

$$\begin{aligned} Cov\left(\tau_{i,t_1,h_1}, \tau_{j,t_2,h_2}\right) &= Cov\left(u_{t_1,h_1+1} + \eta_{i,t_1,h_1+1}, u_{t_2,h_2+1} + \eta_{j,t_2,h_2+1}\right) \\ &= \begin{cases} \sigma_u^2 + \gamma_i^2 & \text{for } i = j,\ t_2 = t_1,\ h_2 = h_1 \\ \omega_u + \psi_i & \text{for } i = j,\ t_2 = t_1 + 1,\ h_2 = h_1 + 12 \\ \sigma_u^2 + \zeta_{ij} & \text{for } i \neq j,\ t_2 = t_1,\ h_2 = h_1 \\ \omega_u + \tau_{ij} & \text{for } i \neq j,\ t_2 = t_1 + 1,\ h_2 = h_1 + 12 \\ 0 & \text{else.} \end{cases} \end{aligned} \tag{19}$$

[4]Note that both vectors are of length $NT(H-(k+1))$ since we loose one observation per target year due to the fact that there is no revision of the forecast available for $h = H$ and we loose another k observation for each target year due to the fact that we include the lagged revisions as regressor in the equation.

[5]Note at this point that the assumption of private information for $\epsilon_{i,t,h}$ is crucial for the result that under weak-rationality $\beta_i = Cov(r_{i,t,h}, r_{i,t,h+1}) = Cov(u_{t,h+1} + \eta_{i,t,h+1}, u_{t,h+2} + \eta_{i,t,h+2}) = 0$. Under the assumption that the $\epsilon_{i,t,h}$ represent ordinary iid shocks we would get $\beta_i = Cov(u_{t,h+1} - \epsilon_{i,t,h} + \epsilon_{i,t,h+1}, u_{t,h+2} - \epsilon_{i,t,h+1} + \epsilon_{i,t,h+2}) = -Var(\varepsilon_{i,t,h+1}) = -\sigma^2_{\epsilon_i} \neq 0$.

In matrix notation, Ξ can be written as the following expression of Kronecker Products:

$$\Xi = \underbrace{\left[\Upsilon \otimes I_{T(H-(k+1))}\right]}_{\sigma_u^2,\, \gamma_i^2,\, and\ \zeta_{ij}} + \underbrace{\left[\Pi \otimes (diag(i_{T-1}, 1) \otimes C)\right] + \left[\Pi \otimes (diag(i_{T-1}, -1) \otimes C')\right]}_{\omega_u,\, \psi_i,\, and\ \tau_{ij}} , \tag{20}$$

where $C = diag(i_{H-(k+1)-(12-k)}, -(12-k))$ is a $(H-(k+1)) \otimes (H-(k+1))$ matrix with ones on the $(12-k)$-th diagonal below the main diagonal and zero entries otherwise. Υ as well as Π are defined in Section 2.1. Given Ξ, the covariance matrix for the GMM estimator of β can be written as

$$Var(\hat{\beta}) = \left(r'_{+k} r_{+k}\right)^{-1} r'_{+k}\, \Xi\, r_{+k} \left(r'_{+k} r_{+k}\right)^{-1} . \tag{21}$$

The standard errors corresponding to the elements of $\hat{\beta}$ are obtained by taking the square roots of the elements of the main diagonal of $Var(\hat{\beta})$. Under the Null that a specific element of β, say β_i, is equal to zero, the test statistic has the following asymptotic standard distribution

$$t_{\beta_i} = \frac{\hat{\beta}_i}{\sqrt{Var(\hat{\beta})_{(i,i)}}} \overset{asy.}{\rightarrow} N(0,1) , \tag{22}$$

where the subscript (i, j) refers to the element of the matrix that is defined by the i-th row and the j-th column of the matrix. Naturally, Ξ is not observed and has to be replaced by a consistent estimate, say $\hat{\Xi}$, before computation of the test statistics is possible. In the next section we show how such a consistent estimate can be constructed.

2.2.2. *Estimation of Variance.* The approach for estimating Ξ is the same that has been proposed in Section 2.1.2. First, we derive estimators for the single elements of Ξ and replace these elements in a second step by their estimates to consistently estimate Ξ.

Due to the simpler structure of Ξ (as opposed to Σ), we can simply estimate the six parameters used in equation 19 as averages of appropriate selections of cross-products of the $u_{t,h}$ and $\eta_{i,t,h}$. Formally, the estimators are given by

$$\hat{\sigma}_u^2 = \frac{1}{T(H-(k+1))} \sum_{t=1}^{T} \sum_{h=1}^{H-(k+1)} (\hat{u}_{t,h+1}^2)$$

$$\hat{\omega}_u = \frac{1}{(T-1)(H/2-(k+1))} \sum_{t=1}^{T-1} \sum_{h=1}^{(H/2-(k+1))} (\hat{u}_{t,h+1} \cdot \hat{u}_{t+1,h+13})$$

$$\hat{\gamma}_i^2 = \frac{1}{T(H-(k+1))} \sum_{t=1}^{T} \sum_{h=1}^{H-(k+1)} \left(\hat{\eta}_{i,t,h+1}^2\right) \qquad \text{for } i = 1, \ldots, N$$

$$\hat{\psi}_i = \frac{1}{(T-1)(H/2-(k+1))} \sum_{t=1}^{T-1} \sum_{h=1}^{(H/2-(k+1))} (\hat{\eta}_{i,t,h+1} \cdot \hat{\eta}_{i,t+1,h+13}) \qquad \text{for } i = 1, \ldots, N$$

$$\hat{\zeta}_{ij} = \frac{1}{T(H-(k+1))} \sum_{t=1}^{T} \sum_{h=1}^{H-(k+1)} (\hat{\eta}_{i,t,h+1} \cdot \hat{\eta}_{j,t,h+1}) \qquad \text{for } i = 1, \ldots, N-1 \text{ and } j = i, \ldots, N$$

$$\hat{\tau}_{ij} = \frac{1}{(T-1)(H/2-(k+1))} \sum_{t=1}^{T-1} \sum_{h=1}^{(H/2-(k+1))} (\hat{\eta}_{i,t,h+1} \cdot \hat{\eta}_{j,t+1,h+13})$$

$$+ \frac{1}{(T-1)(H/2-(k+1))} \sum_{t=1}^{T-1} \sum_{h=1}^{(H/2-(k+1))} (\hat{\eta}_{j,t,h+1} \cdot \hat{\eta}_{i,t+1,h+13}) \qquad \text{for } i = 1, \ldots, N-1 \text{ and } j = i, \ldots, N \quad ,$$

where $\hat{u}_{t,h}$ and $\hat{\eta}_{i,t,h}$ are consistently estimated by

$$\hat{u}_{t,h} = \frac{1}{N} \sum_{i=1}^{N} r_{i,t,h-1} \qquad \text{for } t = 1, \ldots, T \text{ and } h = k+1, \ldots, H-1$$

$$\hat{\eta}_{i,t,h} = r_{i,t,h-1} - \hat{u}_{t,h} \ .$$

Note that if $N = 1$ we re-write equation 18 as $r_{t,h} = u^*_{t,h+1}$. In this case the expression for Ξ reduces to

$$\Psi = \underbrace{\left[\sigma^2_{u^*} \, I_{T(H-(k+1))}\right]}_{\sigma^2_{u^*}} + \underbrace{\left[\omega_{u^*} \, (diag(i_{T-1}, 1) \otimes C + diag(i_{T-1}, -1) \otimes C')\right]}_{\omega_{u^*}} \quad ,$$

where $Cov(u^*_{t_1,h_1}, u^*_{t_2,h_2})$ is given by $\sigma^2_{u^*}$ if $t_1 = t_2$ and $h_1 = h_2$ or ω_{u^*} if $t_2 = t_1 + 1$ and $h_1 = h_2 + 12$ respectively. The two unknown parameters can be estimated by OLS from

$$\hat{\tau} \odot \hat{\tau} = i_{T(H-(k+2))} \sigma^2_{u^*} + \bar{\omega} \tag{23}$$

$$\hat{\tau}_{(12-(k+2))-1} \odot \hat{\tau}_{(24-(k+2))-13} = i_{(T-1)(\frac{H}{2}-(k+2))} \omega_{u^*} + \bar{\omega} \tag{24}$$

in this case. The vectors $\hat{\tau}_{(12-(k+2))-1}$ and $\hat{\tau}_{(24-(k+2))-13}$ are of dimension $(T-1)(\frac{H}{2}-(k+2))$ and contain those entries of $\hat{\tau}$ which correspond to the forecast horizons $12-(k+2)$ to 1 and $24-(k+2))$ to 13 respectively.

3. Data

In this study, we rely on data from the surveys conducted by *Consensus Economics*, a London-based firm.[6] Each month, starting in October 1989, *Consensus Economics* polls institutions like investment banks or research institutes for economics about their forecasts for the most common macroeconomic variables. Since most of the panelists are located in the country they are forecasting upon, country-specific expertise is guaranteed. The largest samples are available for the G7-countries, on which we concentrate in this paper.[7]

[6]The company's web page is available under `http://www.consensuseconomics.com`.

[7]Information from the Consensus data set have been used in a sequence of papers during recent years to analyze the properties of macroeconomic forecasts. Most contributions, however, consider only data on the average forecasts and do not analyze individual forecasts. Notable exceptions are Lahiri and

A big advantage of the data set is that estimates are comparable across countries as well as across panelists. This is assured through the procedure the surveys are conducted; *Consensus Economics* publishes its survey for all countries in the second week of each month based on a foregoing survey period of two weeks.

We concentrate on forecasts for four different variables: the annual growth rate of gross domestic product (GDP), the annual inflation rate, the annual growth rate of industrial production, and the annual growth rate of private consumption expenditure. It is important to note that there occurred some changes in the definition of the target variables in some of the countries. More specifically, while the inflation is based on the consumer price index in general, the relevant figure which had to be forecasted in the United Kingdom (UK) was based on the Retail Price Index at the beginning of our sample. Forecasts for CPI inflation have been introduced in 2004.[8] Furthermore, forecaster were asked to target the annual growth rate of the gross national product (GNP) rather than that of GDP in Germany and Japan until 1992 and 1993 respectively. For German forecast, there is another break in the data due to the switch from West-German data to data for the reunified Germany. In our data set forecasts for GDP growth and inflation refer to West-Germany until 1996; for forecasts on growth of industrial production and private consumption expenditures the change was made in 1995.

A final issue regarding data concerns the realizations that we use to evaluate the forecast errors. A priori it is not clear whether forecasters aim to predict the first data release or the final outcome after a series of revisions. Since incentive issues and anecdotal evidence suggest, however, that the initial releases by the statistical authorities are most important for forecasters, it has become standard in the literature to use these data rather than revised ex-post figures for the evaluation of macroeconomic forecasts (see e.g. Croushore, 2006). We follow this approach and compute forecast errors based on the historical data as they are listed in the publications of *Consensus Economics* in May of the subsequent year since those figures should reflect the initial releases in all cases. To give an example: We use the annual figures for 1996 as they are reported together with the forecasts made in May 1997 to evaluate all forecasts that have been made for 1996 during the years 1995 and 1996.

Sheng (forthcoming), who propose a model for disagreement among forecasters and estimate it based on individual forecasts on GDP growth from the Consensus data set, Batchelor (2007), who uses a similar disaggregated data set to analyze the bias in forecasts for GDP growth, and to some extend Harvey et al. (2001), who analyze the properties of forecasts of a selected group of panelists form the Consensus data for the UK.

[8]An additional break occurred in May 1997 when the underlying Retail Price Index changed to a version that excludes interest payments on mortgages.

The structure of the survey data set fits exactly the framework discussed in section 2. In each month, the participating institutions are asked to state their forecasts for the current and the subsequent calender year. That leaves us with a sequence of $H = 24$ forecasts from each panelist for each annual figure starting with the first forecast made in January of the preceding year and ending with the last forecast made in December of the year for which the forecast is made. Since the maximum forecast horizon exceeds one year, we have to deal with the overlapping nature of forecasts as described in Section 2. We include in our sample forecasts for the years 1991–2005, i.e. $T = 15$ in our analysis. The number of panelists covered by the data set varies considerably across countries but also over time. The average numbers of panelists range from 15 for Canada to 30 for United Kingdom.

4. Results

4.1. **Individual Forecasts.** In this section we present all results concerning the properties of the individual forecasts. For both – the tests of unbiasedness (Section 4.1.1) as well as the tests of weak efficiency (Section 4.1.2) – we include those panelists in the sample who made a forecast at more than 50% of the possible dates. Thereby, we avoid the influence of small sample problems which could arise from those panelists that reported only a few forecasts.[9]

An additional feature of the data that we have to deal with is given by the fact that the record of most of the forecasters includes a bunch of missing values, i.e. the panel is heavily unbalanced. There are two reasons for that. First, the set of panelists who take part in the *Consensus* survey changes continuously. Hence, there are some forecasters that enter the panel at a later stage, while other forecasters leave the panel after the first part of the time period covered by our data set. Second, some forecasters do not submit there forecast on a regular basis, i.e. some of them do not provide their current forecasts for some of the months. To minimize the reduction of our data base due to the second issue, we interpolate a missing value in all those cases, in which a forecast is missing only for one month in a row *and* the two adjacent forecasts are equal to each other. Formally, if $f_{i,t,h}$ is missing *and* $f_{i,t,h+1} = f_{i,t,h-1}$, we set the missing forecast equal to $f_{i,t,h+1}$.

For the estimation, we follow Davies and Lahiri (1995) and deal with missing values by simply deleting the appropriate elements in the vectors of forecast errors or revisions and the corresponding rows and columns in the covariance matrices respectively. Those

[9]The threshold of 50% is of course arbitrary. Results for the included panelists are, however, robust to the inclusion of more forecasters in the used sample.

compressed matrices can be directly used in the GMM estimation procedure (Blundell et al., 1992).

4.1.1. *Unbiasedness.* The analysis of the biases present in the individual forecasts reveal some interesting differences across countries as well as variables. The results are listed in Appendix A as Tables A-1 to A-7. The overall performance of the individual panelists in terms of unbiasedness of their forecasts is best for the inflation forecasts. Except for the UK, there are either no forecasters at all or just one or two who fail to produce unbiased inflation forecasts. This is especially surprising for Italy that underwent a significant transition from a high inflation regime towards a low inflation regime during the early sample period. One could imagine that forecasters adjusted only slowly to this new environment causing forecasts to be biased upwards. This is actually what can be observed for the inflation forecasts in the UK, where inflation was very high at the beginning of our sample period and declined considerably to low levels in the mid of the 1990s. All but three panelist, which entered the sample rather late, have overestimated inflation on average. After all, 6 out of 30 did so significantly on a 95% confidence level.

The same argument applies to the bias that is found for most of the forecasts for GDP growth in the continental European countries. Here, the wide majority of forecasters overestimate growth on average. This phenomenon is most pronounced in Germany and Italy but applies to a lesser extend also to France. The same applies (although less pronounced) to the forecast for growth of industrial production and private consumption in those three countries. Batchelor (2007) shows that this kind of bias can be inevitable in an environment of declining trend growth rates since rational forecasters have to gradually learn about the new trend.

A very special picture is given by the combination of forecasts for GDP growth and for growth of industrial production in the UK. While forecasts for the former are generally unbiased, the results show strong evidence for rejecting the hypothesis of unbiased forecasts for the latter forecasts; most panelist on average overestimate growth of industrial production by about 1 to 1.5 percentage points. This might reflect the fact that although the trend growth of overall output remained relatively constant over the sample, there has been a shift of the structural composition of the economy in the UK from production oriented sectors towards services – especially towards the financial sector – which had to be learned by the forecasters. A similar phenomenon can be observed when comparing forecasts on GDP growth for the US, which are generally unbiased, to forecasts for growth of private consumption in the US, which tend to underestimate consumption growth. Again it seems that it has been hard for almost all panelists to anticipate the gradual decline in

the saving rate of private households as well as to proper estimate additional consumption effects of huge increases in household wealth that was caused by the stock market boom of the late 1990s and the real estate booms during the time from 2002 until the end of our sample.

In general, we can conclude that biased forecasts seem to be produced in times of structural changes or gradual developments that have to be learned by the forecasters; this source for bias in macroeconomic forecasts is also supported by the results in Andolfatto et al. (2008) who analyze the properties of artificial forecast generated within a standard dynamic stochastic general equilibrium model. On the contrary, forecasts seem to be unbiased in general for stable economies without large structural shocks. One example is Canada where the structure of the economy and the medium term growth trend have not fundamentally changed since the introduction of inflation targeting in 1991. As a consequence, there are only three cases among all forecasts for the Canadian economy in which the panelist produced biased forecasts.

4.1.2. *Weak Efficiency.* For testing weak efficiency of individual forecasts we followed the literature (Clemens, 1995, Harvey et al., 2001, Isiklar et al., 2006) by setting k in equation 16 equal to 1. This makes indeed sense, since by the time a new revision is made each forecaster knows about his most recent previous forecast revision. The results are displayed in Tables B-1 to B-7 in Appendix B.

The analysis of the individual forecasts' properties in terms of weak efficiency reveal an interesting contrast between the forecasts made for GDP growth and those for the other variables under investigation in this paper. For the majority of forecasts for growth of industrial production and private consumption as well as for the inflation rate we cannot reject the hypothesis of weakly efficient forecasts; only few series of forecast show a significant correlation between proceeding forecast revisions. In those cases, the estimated coefficient is mostly negative which means that those forecasters tend to overreact to incoming news, i.e. they initially revise their forecasts by an amount that is too large and undo parts of this revision during the next forecasting round.

In contrast, we find much more deviations from weak efficiency for forecasts of GDP growth in all counties but Italy and Japan.[10] Those forecasts for GDP growth that deviate from weak efficiency show a strong tendency towards forecast smoothing in general. This means that forecasters tend to process new information only slowly which results in

[10]The fact that we find weakly efficient forecasts for GDP growth for Japan is in contrast to the results of Ashiya (2003) who analyzes the reaction to news of forecasters for GDP growth in a slightly different modeling framework and based on a different set of private sector forecasts; he concludes that the individual forecasters tend to significantly overreact to new information.

positively autocorrelated revisions.[11] Also Gallo et al. (2002) find that forecasters tend to stick to their past forecast even when the authors control in their study for the most recently observed average forecast and the dispersion of forecasts. Batchelor and Dua (1992) rationalize such a forecasting behavior by noting that in reality forecasters might not have a single objective which is minimizing the expected squared errors. They are likely to take into account as well that their clients might "mistrust forecasters who make frequent [erratic] revisions to forecasts" (p. 179). The fact that the forecast for GDP growth is the part of a comprehensive macroeconomic forecast published by any forecaster, which is most widely anticipated and discussed by clients or the media, might bring about that it is exactly this forecast for which incentive and reputation considerations make forecasters deviate from their true expectations. This would explain why we find the strong tendency for forecast smoothing only for forecasts on GDP growth.

4.2. **Consensus Forecast.** In this section, we present the results concerning the properties of the average forecast, the so-called *consensus forecast.*[12] Average forecasts have been frequently used in empirical research although results based on them should be treated with caution because of inconsistency problems due to the aggregation bias (Bonham and Cohen, 2001) caused for instance by not-accounting for private information (Figlewski and Wachtel, 1981) or the fact that the aggregation might cancel out deviations from unbiasedness of individual forecasters (Keane and Runkle, 1990). We, therefore, present the results based on average forecasts to discuss (Section 5) their relation the results for individual forecasts.

4.2.1. *Unbiasedness.* We can simply use the framework presented in section 2.1 with $N = 1$ to analyze the consensus forecasts. The results are given in Tables C-1 to C-7 in Appendix C. Initially, let's focus on the first line of each table. The estimation outcomes show that for all countries we cannot reject the hypothesis that the consensus forecasts for inflation are unbiased. For all other variables the picture is mixed. First, the average forecasts for growth of private consumption are biased upwards in Germany while they are significantly too pessimistic in the US. For the other five countries the corresponding forecasts are unbiased. Second, consensus forecasts for GDP growth are unbiased in all countries but Germany and Italy where they tend to be too optimistic on average. And finally, the average forecasts for growth of industrial production are biased upwards in

[11]This phenomenon is also known as *conservatism* in psychology (Phillips and Edwards, 1966, Edwards, 1968).

[12]Note that all panelists are included in the computation of the average forecast. Hence, unlike in the analysis of individual forecasts we do not exclude those panelists who reported less than 50% of all possible forecasts over the entire sample.

Canada, France, Italy, and the UK while being unbiased for the remaining three countries. We will elaborate more on how those results relate to the findings of Section 4.1.1 in Section 5.

So far we have assumed that bias does not vary with respect to the forecast horizon. Since it is a reasonable hypothesis that this might be wrong, we relax the restriction of a constant bias for the average forecasts.[13] To do this robustness analysis, we write the aggregated forecast errors as

$$e_{t,h} = A_t - f_{t,h} = \phi_h + \sum_{k=1}^{h} u^*_{t,k} \ ,$$

where now ϕ_h is a horizon-specific bias. A consistent estimator for ϕ_h is given by $\phi_h = 1/T \sum_{t=1}^{T} e_{t,h}$. It can be implemented by regressing the vector of errors on dummy variables for each forecast horizon

$$e = (i_T \otimes I_H)\Phi + \tilde{\nu} \ , \tag{25}$$

where now $\Phi = [\phi_H, \ldots, \phi_1]'$. Note that under the joint hypothesis that the forecasts are unbiased for all forecast horizons ($H_0 : \phi_H = \cdots = \phi_1 = 0$), the structure for the covariance matrix of $\tilde{\nu}$ is equal to the one derived for ν above.

The corresponding results are given from the second rows downwards in Tables C-1 to C-7. The evidence shows that in those cases, where the bias is estimated significantly different from zero under the assumption that the bias is constant across different forecast horizons, this is due to the forecasts with a horizon of more than 4 or 5 quarters. While in almost all of those cases all horizon specific biases are estimated significantly different from zero for longer forecast horizons, forecasts with a smaller horizon are usually found to be unbiased. Notable deviations from that pattern are the forecasts for GDP growth in Italy and for growth of industrial production in Italy and the UK, which are biased even for forecast horizons as small as 8 months. In those cases where the restricted model does not indicate any bias, the horizon specific biases are either not distinguishable from zero for all forecast horizons (e.g. for growth of private consumption in Canada) or just for the very long horizons (e.g. for inflation in the UK).

4.2.2. *Weak Efficiency.* The results from the tests of weak efficiency for the consensus forecasts demonstrate very well that caution is required when working with average forecast data. In contrast to the setup for the analysis of individual forecasts we set $k = 2$ for

[13]Note that we cannot do the same in the analysis of individual forecasts since for the wide majority of panelists the data sets includes so many missing values that the estimate for each horizon-specific bias would be based on 10 or even less observations.

the analysis of the consensus forecasts (Isiklar, 2005). The reason is that it is not clear whether each forecaster knows already about the most recent consensus forecast when a new forecast is produced since in the extreme case the forecasts have to be reported two weeks before a new consensus forecast is published and additionally the production process for each forecast might last more than a week depending on the institutional framework of a specific forecaster. In any case, each forecaster should know about the average forecast published two month ago.

Table D-1 in Appendix D shows the results for implementations of the test based on equation 16. It is obvious that the results taken at face value would lead to completely different conclusions than those seen in Section 4.1.2. Clearly, all average forecasts except three cases[14] show evidence for forecast smoothing, i.e. incoming information gets reflected in the average forecast in a very sluggish way. The effect is indeed most strongly visible for forecasts for GDP growth also here, but even for variables for which the individual forecasters tend to overreact to news we find the opposite deviation from weak efficiency in the consensus forecast (e.g. growth of private consumption in Germany).

Like mentioned already in the previous section it is possible to estimate horizon specific biases for the consensus forecasts. If we relax the assumption of one single bias for all forecast horizons, this has implications for the construction of the test on weak efficiency. Namely, the unconditional expectation for a revision is no longer equal to zero under the nullhypothesis in that case. We, therefore, expand equation 16 by including constant terms for each forecast horizon. Thus, the new equation on which we base the robustness check for our results is

$$r_{i,t,h} = \alpha_h + \beta_i r_{i,t,h+k} + \tau_{i,t,h} \ . \tag{26}$$

The results that are given in Table D-2 confirm the evidence presented in the previous paragraph.[15] The point estimates for the correlations between two subsequent revisions do not change qualitatively. The maximum difference between two corresponding point estimates is 0.12.

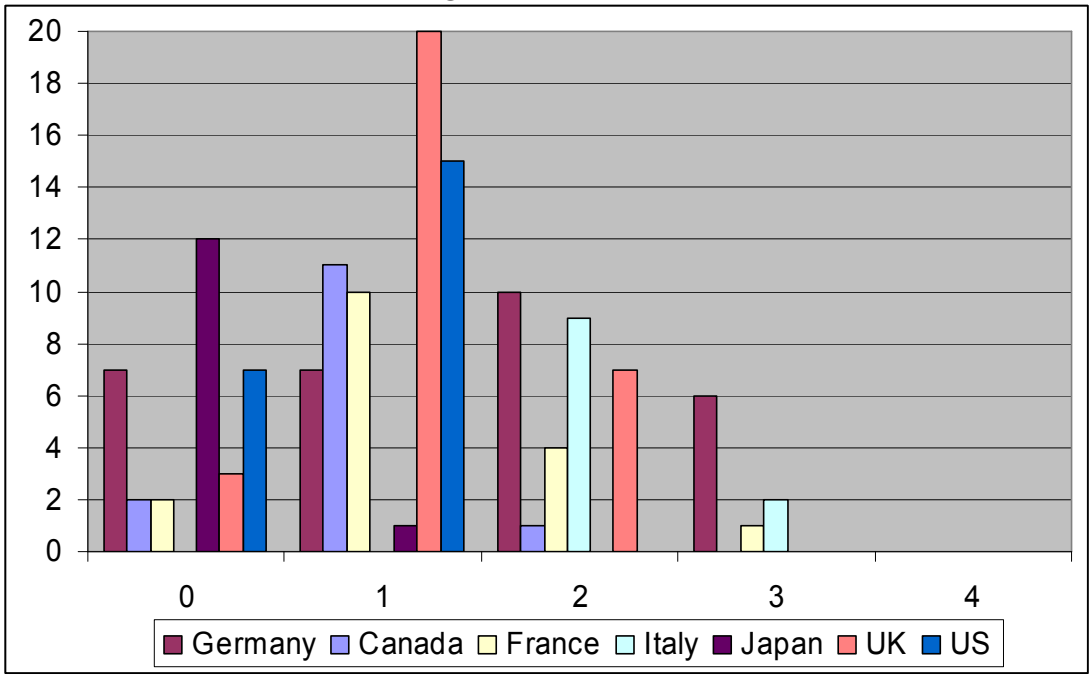
5. Discussion of Results

In general, our findings confirm, based on a broad data base, previous results about rationality properties of macroeconomic forecasts. In addition, we were able to point

[14]Those are the inflation forecasts in Italy and the United Kingdom and the forecasts for growth of industrial production in Canada.

[15]To save space the estimates of the horizon-effects are not presented in this paper. They are, however, available from the authors upon request.

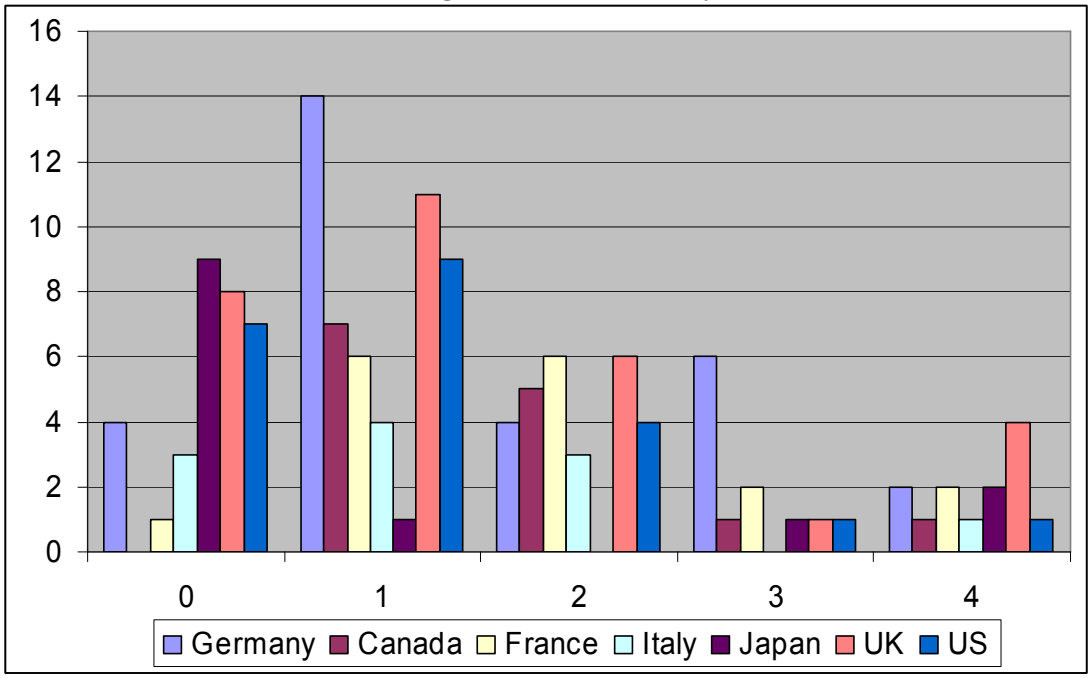
FIGURE 2. Histogram for Biasedness of Forecasts



to some interesting particularities across countries and variables in Section 4. In what follows, we discuss the results of the previous section in more detail.

A natural question that arises when looking at forecast properties across variables is whether the non-rational forecasts for all variables are mostly produced by a group of "bad" forecasters who produce "bad" forecasts for all variables. The other option would be that in most cases a forecaster who produces non-rational forecasts for one variable is not likely to produce non-rational forecasts also for other variables. Figures 2 and 3 show, for each country, histograms for the frequency of biased and inefficient forecasts respectively. Since we include 4 variables in our sample a frequency of 4 reflects the number of panelists who produce biased or inefficient forecasts for all of the analyzed variables. The numbers suggest that while there are no panelists at all that produce exclusively biased forecasts and only a few that are biased in three out of four cases, the histogram for inefficiency of forecasts is more uniformly distributed for most of the countries. We find certain forecasters, all of whose forecasts are inefficient, for each of the countries. And also the frequency of 3 inefficient forecasts is larger than for the analysis of forecast bias. The results suggest that reputation issues might indeed play an important role for certain forecasters. While the public or clients probably do not keep track whether a forecaster produces biased results over a couple of years, they probably note immediately if forecasters revise their forecasts in an erratic way that would be implied by weak-efficiency. For this reason, there seem to be some forecasters that produce inefficient forecasts "on purpose" for all variables.

FIGURE 3. Histogram for Inefficiency of Forecasts



The comparison of results for biasedness and efficiency leads us to the next question. Are "bad" forecasters that produce inefficient forecasts more likely to produce also biased forecasts? While this issue could certainly be treated in an individual paper in a more careful and comprehensive manner, we present some basic results based on the results of the previous section. First, we look at the correlation between the degree of inefficiency – as measured by the absolute values of the size of β_i in equation 16 – and the size of the bias in absolute values. Since the average bias differs significantly across variables and countries, we include country and variable specific dummies in a regression of the bias on the degree of inefficiency. The results suggest that an increase of the absolute value of the autocorrelation of revisions by 0.1 goes in line with a bias that is 0.04 higher in absolute values. This effect is significant at a 95% confidence level. Second, we use a probit model to cross-check this result. We regress an indicator, which takes the value 1 if a particular series of forecasts is biased and 0 otherwise, on a constant and an indicator that takes the value 1 if the same series of forecasts is efficient and 0 otherwise. The estimated effect is not distinguishable from zero on a conventional confidence level. In summary, the first result suggests that producing weakly inefficient forecasts increase the expected bias of those forecasts significantly. The second result shows, however, that the effect is not large enough to be reflected also in the analysis of binary indicators.

The relation between results for the consensus forecasts and those based on individual forecasts has already been addressed briefly in Section 4.2. The most pronounced result it that almost all consensus forecasts exhibits characteristics of forecast smoothing and

are, thus, not weakly efficient. Table 1 summarizes these results and confronts them with the corresponding frequencies of efficient individual forecasts. It is evident that even if the wide majority of forecasters is weakly efficient the consensus forecast is not so in most of the cases. This phenomenon can be explained by the fact that new information is processed by some forecasters slower than by others. It results in positiv autocorrelation of the revisions of the consensus forecasts. Table 2 shows similar results for the analysis of biases. It can be seen that naturally the consensus is unbiased if there are only a few individual panelists who produce biased forecasts. As soon as there is a significant fraction of forecasters who report biased forecasts, it depends on the correlation of their biases whether the consensus will be biased or not. If forecasters deviate into both directions from unbiasedness, the biases might cancel out in the aggregate. This, however, is not the case in our sample. As already mentioned in Section 4.1.1, forecasters tend to be biased into the same direction for a specific target variable. Therefore, the consensus is biased if there is a sizable fraction of biased individual forecasts.

It is also interesting to check whether a forecaster's performance in terms of rationality is systematically influenced by her characteristics. In what follows we concentrate on two important features of the panelists; namely whether a forecaster is a private or a publicly financed institution and whether the origin of an institution is in the country for which a forecast is made or in a foreign country. While the first issue might influence the performance due to different incentive structures, the second point might reveal the importance for the construction of forecasts of collection of private or at least detailed information on an economy. Again, we use the degree of inefficiency (size of bias) – as defined above – as the dependent variable. We regress these on two dummy variables capturing the two characteristics; to control for country and variable differences we include dummies for all countries and variables as well as their interaction terms. While we cannot find significant differences in terms of the size of the bias between home and foreign or private and public forecasters, the groups differ with respect to their forecasts efficiency properties on a marginal significance level. The autocorrelation between consecutive forecast revisions is 0.02 ($pval$: 0.06) smaller for panelists originating in the same country than on average. This indicates that they are able to better judge the relevance of incoming news than forecasters located outside the country. Private forecasters produce forecast revisions that show an autocorrelation which is 0.03 ($pval$: 0.09) higher than on average. Anecdotal evidence suggests that this result is caused by different incentives from the relation to clients and the payment scheme in the private sector as opposed to the public sector. A second explanation might be the fact that public institutions tend to be more

research focused and use probably more model based methods to produce their forecasts, which reduces the risk of inefficiency induced by subjective judgmental factors.

6. Conclusion

In this paper, we analyzed the rationality of macroeconomic forecasts in G7-countries based on survey data from the *Consensus* data set. We analyzed both individual forecasts and average forecasts. The evidence on the properties of forecasts for all G7-counties and four different macroeconomic variables lead us to several conclusions. First, our results confirm that data on average forecasts should be used with caution since even in a situation where all individual forecasts are rational the hypothesis of rationality is often rejected based on the aggregate data. Second, we find large difference in the performance of forecasters across countries and different macroeconomic variables. Third, among the four kinds of forecasts that we analyze, inflation forecasts perform best in terms of unbiasedness. Fourth, forecasts tend to be biased in situations where forecasters have to learn about large structural shocks or gradual changes in the trend of a variable. Finally, the correlation between the efficiency properties of a panelist's forecasts and their properties concerning bias is weak. Parts of the results suggest, however, that a forecast which is inefficient is also more likely to show a significant bias.

There are several dimensions along which the study could be expanded in the future. For simplicity, we have assumed that the variance of the macroeconomic shocks ($\lambda_{t,h}$) as well as the variance of the idiosyncratic forecast error ($\epsilon_{i,t,h}$) decay linear if h goes to 1. One could also imagine that other (more general) functional forms are more appropriate to match the data. As soon as enough longer time series become available for individual forecasters one could implement the assumption of a horizon specific bias also in the analysis of individual forecasts. Taking into account correlations across countries – like Isiklar et al. (2006) do in their analysis of consensus forecasts – would clearly be desirable. Currently however, this would require too much computational power for the estimation of the covariance matrices. Finally, it would be promising to investigate whether the results concerning the inefficiency of the consensus forecasts could be used to construct forecasts that are superior in terms of forecast accuracy.

TABLE 1. Comparison of Individual and Consensus Forecasts (Efficiency)

	GDP			Inflation			Ind. Prod.			Priv. Cons.		
	# Indiv.	# Eff.	Cons. Eff.?	# Indiv.	# Eff.	Cons. Eff.?	# Indiv.	# Eff.	Cons. Eff.?	# Indiv.	# Eff.	Cons. Eff.?
Germany	24	15	No	26	21	No	23	18	No	27	18	No
Canada	12	7	No	13	12	No	2	2	Yes	12	11	No
France	15	6	No	15	13	No	7	5	No	15	12	No
Italy	10	8	No	10	9	Yes	7	4	No	10	9	No
Japan	10	10	No	11	10	No	10	10	No	10	10	No
United Kingdom	26	19	No	25	18	Yes	24	20	No	24	21	No
United States	21	13	No	20	17	No	20	16	No	20	18	No

TABLE 2. Comparison of Individual and Consensus Forecasts (Bias)

	GDP			Inflation			Ind. Prod.			Priv. Cons.		
	# Indiv.	# Unb.	Cons. Unb.?	# Indiv.	# Unb.	Cons. Unb.?	# Indiv.	# Unb.	Cons. Unb.?	# Indiv.	# Unb.	Cons. Unb.?
Germany	29	15	No	30	0	Yes	28	7	Yes	29	19	No
Canada	14	0	Yes	14	0	Yes	4	2	No	14	1	Yes
France	17	5	Yes	17	2	Yes	8	4	No	17	1	Yes
Italy	11	11	No	11	0	Yes	8	8	No	11	2	Yes
Japan	13	0	Yes	13	1	Yes	13	0	Yes	13	0	Yes
United Kingdom	30	1	Yes	30	6	Yes	28	24	No	29	0	Yes
United States	22	0	Yes	22	2	Yes	21	0	Yes	22	12	No

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A. Tests on Unbiasedness for Individual Forecasts

Table A-1. Germany

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
1	-0.54	-2.16	1	-0.06	-0.41	1	-1.27	-2.02	1	-0.47	-1.63
2	-0.50	-2.08	2	0.01	0.09	2	-1.03	-1.70	2	-0.45	-1.87
3	-0.69	-2.56	3	-0.17	-1.11	3	-1.42	-2.27	3	-0.58	-2.11
4	-0.50	-2.09	4	-0.03	-0.22	4	-1.15	-1.91	4	-0.47	-2.00
5	-0.57	-2.38	5	-0.08	-0.52	5	-1.20	-2.11	5	-0.61	-2.44
6	-0.38	-1.16	6	-0.18	-0.90	6	-1.60	-2.08	6	-0.17	-0.52
7	-0.39	-1.67	7	-0.01	-0.09	7	-0.84	-1.49	7	-0.44	-1.75
8	-0.58	-2.34	8	-0.09	-0.67	8	-0.86	-1.47	8	-0.58	-2.25
9	-0.52	-2.13	9	-0.05	-0.33	9	-1.23	-2.19	9	-0.67	-2.64
10	-0.70	-2.90	10	0.01	0.07	10	-0.96	-1.70	10	-0.61	-2.36
11	-0.64	-2.54	11	-0.19	-1.25	11	-0.93	-1.61	11	-0.67	-2.51
14	-0.61	-2.60	14	-0.09	-0.65	14	-1.08	-1.95	14	-0.63	-2.54
15	-0.60	-2.50	15	-0.03	-0.23	15	-1.21	-2.15	15	-0.58	-2.34
16	-0.40	-1.59	16	0.03	0.18	16	-0.89	-1.55	16	-0.53	-2.05
17	-0.36	-1.52	17	-0.17	-1.15	17	-0.55	-0.97	17	-0.45	-1.80
19	0.01	0.02	19	-0.30	-1.45	19	-0.95	-1.19	19	0.05	0.14
20	-0.45	-1.75	20	0.13	0.86	20	-0.77	-1.35	20	-0.51	-2.03
21	-0.54	-2.28	21	0.02	0.16	21	-1.19	-2.11	21	-0.62	-2.46
22	-0.44	-1.43	22	-0.17	-0.93	22	-1.30	-1.87	22	-0.27	-0.92
23	-0.42	-1.25	23	-0.22	-0.97	23	-1.46	-1.83	23	-0.05	-0.14
24	-0.39	-1.63	24	-0.07	-0.50	24	-0.95	-1.54	24	-0.44	-1.78
25	-0.37	-1.54	25	0.13	0.91				25	-0.50	-2.08
26	-0.57	-2.30	26	-0.07	-0.49	26	-1.07	-1.81	26	-0.66	-2.56
27	-0.42	-1.61	27	-0.12	-0.77	27	-0.66	-1.05	27	-0.51	-1.85
28	-0.51	-1.90	28	-0.09	-0.54	28	-0.60	-0.92	28	-0.67	-2.32
29	-0.39	-1.45	29	0.09	0.50	29	-0.48	-0.71	29	-0.63	-2.17
30	-0.50	-1.82	30	-0.11	-0.71	30	-0.76	-1.17	30	-0.70	-2.33
31	-0.70	-2.42	31	0.10	0.62	31	-0.82	-1.15	31	-0.89	-3.00
32	-0.69	-2.64	32	-0.13	-0.81	32	-0.85	-1.37	32	-0.69	-2.49
			34	0.02	0.12						

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors. *Id* refers to the number given to a forecaster in our data set.

Table A-2. Canada

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
2	-0.28	-1.06	2	0.05	0.15	2	-1.18	-2.06	2	-0.04	-0.18
3	-0.25	-0.95	3	0.13	0.41				3	0.07	0.32
4	-0.23	-0.89	4	0.02	0.06				4	-0.06	-0.26
9	-0.24	-0.80	9	0.09	0.26	9	-1.02	-1.65	9	-0.01	-0.05
11	-0.33	-0.95	11	0.19	0.47				11	-0.32	-0.97
12	-0.30	-0.77	12	0.18	0.43				12	-0.15	-0.47
13	-0.35	-1.30	13	0.55	1.80				13	0.02	0.07
15	-0.37	-1.38	15	0.30	0.96				15	-0.08	-0.32
16	-0.26	-1.01	16	0.13	0.42	16	-0.42	-0.85	16	0.01	0.06
17	-0.55	-1.58	17	0.42	1.08				17	-0.14	-0.47
18	-0.36	-1.38	18	0.26	0.85				18	-0.05	-0.22
21	0.06	0.21	21	0.44	1.34	21	-1.11	-2.08	21	0.52	2.02
23	-0.17	-0.59	23	0.45	1.28				23	0.32	1.14
25	-0.11	-0.31	25	0.32	0.87				25	0.38	1.22

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors. *Id* refers to the number given to a forecaster in our data set.

Table A-3. France

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
1	-0.34	-1.45	1	-0.17	-1.27	1	-0.90	-1.81	1	-0.10	-0.71
3	-0.45	-1.91	3	-0.12	-0.90	3	-0.96	-1.97	3	-0.19	-1.34
4	-0.35	-1.42	4	-0.17	-1.26	4	-0.63	-1.22	4	-0.19	-1.25
5	-0.61	-2.53	5	-0.15	-1.05	5	-1.39	-2.83	5	-0.30	-2.05
6	-0.70	-2.16	6	-0.01	-0.03	6	-1.33	-1.98	6	-0.32	-1.56
7	-0.34	-1.39	7	-0.11	-0.78				7	-0.07	-0.45
8	-0.38	-1.65	8	-0.10	-0.75				8	-0.17	-1.19
9	-0.54	-2.25	9	-0.18	-1.37	9	-1.22	-2.44	9	-0.25	-1.71
13	-0.31	-1.27	13	-0.10	-0.70				13	-0.10	-0.63
14	-0.52	-2.34	14	-0.07	-0.54				14	-0.27	-1.94
16	-0.49	-2.06	16	-0.05	-0.36				16	-0.31	-1.93
17	-0.28	-1.17	17	-0.13	-0.98				17	-0.06	-0.41
18	-0.29	-0.94	18	-0.52	-2.90	18	-0.65	-1.03	18	-0.21	-1.09
19	-0.29	-1.10	19	-0.06	-0.41				19	-0.16	-0.96
21	-0.27	-0.90	21	-0.44	-2.53	21	-0.73	-1.18	21	-0.19	-1.06
25	-0.33	-1.13	25	-0.14	-0.87				25	-0.12	-0.66
26	-0.30	-1.02	26	0.10	0.57				26	-0.04	-0.24

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors. *Id* refers to the number given to a forecaster in our data set.

Table A-4. Italy

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
1	-0.66	-3.41	1	0.18	0.71	2	-1.59	-2.05	1	-0.48	-1.98
2	-0.59	-2.30	2	0.36	1.09	3	-1.53	-2.55	2	-0.26	-0.80
3	-0.59	-2.95	3	0.19	0.76	5	-1.48	-2.46	3	-0.31	-1.27
5	-0.56	-2.77	5	0.19	0.76				5	-0.44	-1.85
8	-0.54	-2.80	8	0.16	0.65	8	-1.74	-2.99	8	-0.33	-1.40
9	-0.63	-3.14	9	0.32	1.20				9	-0.45	-1.83
10	-0.65	-3.47	10	0.25	1.07				10	-0.42	-1.84
11	-0.62	-3.19	11	0.10	0.38	11	-1.37	-2.31	11	-0.46	-1.91
12	-0.61	-3.11	12	0.01	0.02	12	-1.31	-2.23	12	-0.48	-2.01
14	-0.59	-2.86	14	0.29	1.06	14	-1.30	-2.03	14	-0.39	-1.50
16	-0.67	-2.89	16	0.13	0.46	16	-1.93	-2.65	16	-0.38	-1.32

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors. *Id* refers to the number given to a forecaster in our data set.

Table A-5. Japan

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
1	-0.30	-0.75	1	-0.15	-1.09	1	-1.29	-1.26	1	-0.58	-1.75
2	-0.24	-0.52	2	-0.29	-1.77	2	-1.63	-1.44	2	-0.29	-0.74
5	-0.46	-1.19	5	-0.17	-1.23	5	-1.42	-1.50	5	-0.42	-1.22
7	-0.25	-0.67	7	-0.06	-0.44	7	-1.43	-1.60	7	-0.59	-1.87
8	0.19	0.53	8	-0.09	-0.67	8	-0.87	-0.91	8	-0.15	-0.47
11	-0.33	-0.89	11	-0.22	-1.66	11	-1.39	-1.50	11	-0.59	-1.83
12	-0.24	-0.57	12	-0.02	-0.16	12	-1.29	-1.25	12	-0.47	-1.31
13	0.23	0.59	13	0.03	0.28	13	-0.50	-0.53	13	-0.32	-0.99
15	-0.26	-0.64	15	-0.11	-0.77	15	-1.47	-1.49	15	-0.29	-0.83
16	-0.28	-0.70	16	-0.27	-1.96	16	-1.41	-1.45	16	-0.53	-1.59
18	-0.32	-0.77	18	-0.01	-0.06	18	-1.15	-1.16	18	-0.44	-1.26
22	-0.22	-0.55	22	-0.23	-1.76	22	-1.41	-1.35	22	-0.44	-1.29
23	-0.42	-0.94	23	-0.08	-0.51	23	-1.11	-1.02	23	-0.33	-0.83

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors. *Id* refers to the number given to a forecaster in our data set.

Table A-6. United Kingdom

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
1	-0.33	-0.94	1	-0.21	-1.11	1	-1.13	-1.91	1	-0.10	-0.27
2	-0.22	-0.81	2	-0.13	-0.97	2	-1.22	-2.51	2	0.09	0.31
3	-0.30	-1.08	3	-0.27	-2.08	3	-1.20	-2.43	3	0.03	0.10
6	-0.29	-1.05	6	-0.08	-0.66	6	-1.38	-2.90	6	0.09	0.33
8	-0.59	-1.97	8	-0.25	-1.58	8	-1.87	-3.60	8	-0.01	-0.03
9	-0.21	-0.61	9	-0.34	-2.13	9	-1.53	-2.54	9	0.20	0.59
11	-0.25	-0.88	11	-0.07	-0.50	11	-1.52	-3.01	11	0.07	0.25
13	-0.30	-1.03	13	-0.52	-2.13	13	-1.57	-3.25	13	0.17	0.60
14	-0.51	-1.73	14	-0.18	-1.12	14	-1.49	-2.95	14	0.07	0.24
18	-0.13	-0.32	18	-0.04	-0.17	18	-1.20	-1.73	18	0.09	0.21
19	-0.42	-1.52	19	-0.21	-1.61	19	-1.82	-3.84	19	0.10	0.36
20	-0.21	-0.76	20	-0.09	-0.68	20	-1.46	-3.01	20	0.30	1.07
21	-0.12	-0.33	21	-0.42	-2.57	21	-0.92	-1.53	21	0.29	0.81
22	-0.43	-1.35	22	-0.27	-1.54	22	-1.65	-3.00	22	0.03	0.09
23	-0.05	-0.18	23	-0.10	-0.61	23	-1.37	-2.85	23	0.41	1.40
24	-0.33	-1.04	24	-0.22	-1.18	24	-0.93	-1.66	24	0.01	0.01
25	-0.34	-1.08	25	-0.36	-1.81	25	-1.64	-3.05	25	-0.03	-0.09
27	-0.52	-1.31	27	-0.37	-1.97	27	-1.62	-2.50	27	-0.15	-0.38
29	-0.26	-0.92	29	-0.39	-2.20	29	-1.59	-2.85	29	-0.11	-0.33
30	-0.26	-0.78	30	-0.24	-1.69	30	-1.37	-2.51	30	0.20	0.63
31	-0.42	-1.24	31	-0.34	-1.89	31	-1.53	-2.63	31	0.04	0.13
33	-0.30	-0.90	33	-0.26	-1.53	33	-1.20	-2.01	33	0.21	0.61
35	-0.17	-0.63	35	-0.19	-1.45	35	-1.37	-2.89	35	0.08	0.27
37	-0.13	-0.47	37	-0.21	-1.49	37	-1.16	-2.20	37	0.20	0.71
40	-0.24	-0.76	40	-0.11	-0.46				40	0.39	1.24
41	-0.01	-0.02	41	0.20	1.04						
42	0.12	0.40	42	-0.18	-1.23	42	-1.16	-2.15	42	0.52	1.68
43	-0.22	-0.67	43	-0.20	-1.25	43	-1.49	-2.65	43	0.16	0.46
44	0.00	0.01	44	0.15	0.87	44	-1.35	-2.38	44	0.56	1.68
45	-0.15	-0.47	45	0.02	0.14	45	-1.56	-2.84	45	0.38	1.17

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors. *Id* refers to the number given to a forecaster in our data set.

Table A-7. United States

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
1	0.10	0.37	1	-0.32	-1.90	1	-0.99	-1.70	1	0.41	1.67
9	0.18	0.68	9	-0.01	-0.05	9	-0.54	-0.99	9	0.35	1.45
13	0.23	0.87	13	-0.06	-0.40	13	-0.41	-0.77	13	0.57	2.37
14	0.14	0.48	14	-0.15	-0.88	14	-0.80	-1.36	14	0.44	1.68
16	0.27	1.03	16	-0.16	-1.05	16	-0.12	-0.22	16	0.56	2.29
17	0.26	0.94	17	-0.18	-1.14	17	-0.59	-1.05	17	0.63	2.49
18	0.11	0.43	18	0.14	0.90	18	-0.51	-1.00	18	0.40	1.66
19	-0.07	-0.26	19	-0.27	-1.71	19	-0.41	-0.72	19	0.19	0.74
27	0.24	0.80	27	-0.64	-3.52	27	-0.24	-0.39	27	0.48	1.67
28	0.25	0.94	28	-0.04	-0.24	28	-0.18	-0.33	28	0.46	1.82
31	0.28	1.05	31	-0.06	-0.38	31	-0.35	-0.66	31	0.50	2.03
33	0.08	0.28	33	-0.17	-1.05	33	-0.69	-1.30	33	0.65	2.60
34	0.44	1.58	34	-0.10	-0.59	34	-0.28	-0.51	34	0.72	2.87
35	0.37	1.32	35	-0.27	-1.64	35	-0.07	-0.13	35	0.62	2.33
36	0.33	1.12	36	-0.02	-0.10	36	-0.10	-0.17	36	0.58	2.20
37	-0.15	-0.49	37	-0.36	-2.02	37	-1.05	-1.80	37	0.20	0.72
39	0.39	1.42	39	-0.12	-0.76	39	-0.22	-0.42	39	0.52	2.17
41	0.27	0.94	41	-0.03	-0.16	41	-0.50	-0.85	41	0.57	2.15
43	0.37	1.29	43	-0.05	-0.29	43	-0.43	-0.74	43	0.66	2.42
44	0.36	1.24	44	-0.04	-0.21				44	0.51	1.86
45	0.15	0.45	45	-0.22	-0.97	45	-0.78	-1.15	45	0.49	1.53
46	0.38	1.32	46	0.02	0.09	46	-0.49	-0.84	46	0.62	2.32

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors. *Id* refers to the number given to a forecaster in our data set.

B. Tests on Weak Efficiency for Individual Forecasts

Table B-1. Germany

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
1	0.08	1.29	1	-0.12	-1.97	1	-0.33	-4.82	1	0.01	0.13
2	-0.02	-0.25	2	0.01	0.22	2	-0.12	-1.65	2	-0.04	-0.63
3	0.29	3.92	3	-0.10	-1.17	3	0.13	1.61	3	0.13	1.63
5	0.16	2.86	4	-0.10	-0.78	5	0.07	1.16	5	0.00	-0.07
7	0.19	3.01	5	-0.17	-2.96	7	0.16	2.36	6	-0.11	-1.70
8	0.05	0.88	7	-0.19	-3.22	8	0.07	1.06	7	-0.04	-0.75
9	0.10	1.74	8	0.04	0.76	9	0.03	0.45	8	-0.13	-2.63
10	0.15	2.26	9	0.04	0.61	10	-0.02	-0.24	9	-0.03	-0.54
11	0.09	1.52	10	0.05	0.80	11	-0.17	-2.46	10	-0.08	-1.53
14	0.09	1.48	11	-0.17	-2.75	14	-0.11	-1.57	11	-0.28	-5.16
15	0.23	3.86	14	-0.04	-0.58	15	-0.11	-1.63	14	-0.13	-2.19
16	-0.05	-0.82	15	0.06	1.03	16	-0.10	-1.43	15	0.04	0.62
17	0.19	3.15	16	-0.12	-1.76	17	0.02	0.26	16	-0.24	-4.06
19	0.02	0.22	17	0.08	1.30	19	-0.10	-1.13	17	-0.25	-4.40
20	0.07	1.04	19	-0.03	-0.34	20	-0.03	-0.38	19	-0.22	-3.00
21	0.13	2.08	20	0.04	0.63	21	0.14	1.72	20	-0.05	-0.94
22	0.09	1.26	21	0.00	-0.07	22	0.19	2.23	21	-0.09	-1.55
			22	-0.18	-2.00				22	-0.12	-1.49
									23	-0.13	-1.63
24	0.04	0.65	24	-0.05	-0.71	24	0.07	0.88	24	-0.17	-2.82
25	0.06	0.89	25	-0.04	-0.46				25	-0.06	-0.75
26	0.22	3.56	26	0.13	1.83	26	0.10	1.28	26	-0.10	-1.87
27	-0.04	-0.51	27	0.12	1.61	27	-0.17	-1.83	27	-0.16	-2.11
28	0.18	2.64	28	-0.05	-0.84	28	-0.12	-1.66	28	-0.08	-1.27
29	0.10	1.23	29	-0.04	-0.45	29	-0.13	-1.55	29	-0.10	-1.12
30	0.07	0.87	30	0.05	0.61	30	-0.24	-3.64	30	-0.03	-0.42
			31	0.08	0.92				31	-0.22	-2.76

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the revisions under the Nullhypothesis. *Id* refers to the number given to a forecaster in our data set.

Table B-2. Canada

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
2	0.25	3.85	2	0.09	1.13				2	0.09	1.16
3	-0.01	-0.15	3	0.00	-0.05				3	-0.02	-0.25
4	0.15	2.32	4	-0.07	-1.39				4	0.00	-0.07
9	0.23	2.59	9	-0.07	-0.90				9	0.06	0.77
			11	0.00	-0.01						
13	0.31	4.84	13	-0.08	-1.34				13	0.01	0.19
15	0.07	1.24	15	-0.07	-1.10				15	-0.06	-1.00
16	0.24	4.52	16	0.03	0.60	16	-0.06	-0.97	16	-0.07	-1.21
17	0.05	0.77	17	0.01	0.12				17	-0.05	-0.56
18	-0.01	-0.16	18	-0.07	-0.98				18	-0.20	-3.51
21	0.09	1.37	21	-0.21	-3.17	21	0.11	1.68	21	-0.08	-1.33
23	0.14	1.74	23	-0.11	-1.28				23	-0.02	-0.26
25	0.07	0.96	25	0.15	1.86				25	0.05	0.65

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the revisions under the Nullhypothesis. *Id* refers to the number given to a forecaster in our data set.

Table B-3. France

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
1	0.22	3.13	1	0.10	1.63	1	-0.08	-1.45	1	0.07	1.04
3	0.17	2.25	3	-0.13	-2.18	3	0.05	0.76	3	0.04	0.68
4	0.22	3.12	4	-0.11	-1.83	4	-0.17	-2.80	4	0.17	2.53
5	0.34	4.33	5	0.03	0.40	5	-0.01	-0.20	5	0.09	1.28
7	0.20	2.17	7	0.05	0.60				7	-0.07	-0.81
8	0.15	2.35	8	-0.07	-1.15				8	0.01	0.23
9	0.28	4.00	9	0.12	2.14	9	0.04	0.70	9	0.00	0.08
13	0.06	0.85	13	-0.06	-1.09				13	-0.11	-1.97
14	0.01	0.11	14	-0.11	-1.62				14	-0.04	-0.67
16	0.00	0.01	16	-0.01	-0.16				16	-0.01	-0.14
17	0.22	2.81	17	0.04	0.54				17	0.04	0.53
18	0.07	0.72	18	-0.03	-0.34				18	-0.04	-0.57
19	0.00	0.06	19	0.04	0.58	18	0.04	0.41	19	0.05	0.72
21	0.30	3.64	21	0.12	1.19	21	0.21	2.10	21	0.20	2.03
25	-0.02	-0.15	25	-0.11	-1.17				25	-0.05	-0.57

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the revisions under the Nullhypothesis. *Id* refers to the number given to a forecaster in our data set.

Table B-4. Italy

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
1	0.08	1.26	1	-0.02	-0.35				1	-0.06	-0.86
3	-0.03	-0.47	3	-0.14	-2.64	3	-0.11	-1.75	3	-0.18	-3.45
5	0.14	2.34	5	0.06	0.72	5	0.16	2.56	5	0.01	0.15
8	0.12	1.83	8	0.11	1.83	8	0.13	1.94	8	-0.03	-0.58
9	-0.01	-0.13	9	-0.04	-0.52				9	-0.07	-0.81
10	0.02	0.27	10	0.00	0.00				10	-0.01	-0.15
11	-0.08	-1.40	11	-0.04	-0.73	11	-0.08	-1.33	11	-0.02	-0.29
12	-0.07	-1.23	12	-0.01	-0.11	12	-0.13	-2.12	12	-0.03	-0.42
14	0.11	1.44	14	-0.02	-0.26	14	0.14	1.84	14	0.00	0.06
16	0.23	2.82	16	0.02	0.26	16	-0.16	-1.99	16	0.12	1.46

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the revisions under the Nullhypothesis. *Id* refers to the number given to a forecaster in our data set.

Table B-5. Japan

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
1	0.03	0.52	1	0.01	0.10	1	0.00	-0.05	1	-0.02	-0.26
5	0.00	-0.04	5	-0.11	-1.81	5	-0.02	-0.40	5	0.01	0.10
7	-0.03	-0.37	7	-0.14	-1.99	7	0.05	0.78	7	-0.08	-1.03
11	0.00	0.00	11	0.01	0.11	11	0.00	0.05	11	-0.06	-0.92
			12	-0.05	-0.62						
13	0.04	0.49	13	-0.02	-0.19	13	-0.05	-0.48	13	-0.05	-0.69
15	0.08	1.01	15	-0.12	-1.86	15	0.10	1.37	15	-0.03	-0.46
16	0.10	1.44	16	-0.01	-0.08	16	0.07	1.10	16	-0.03	-0.39
18	-0.02	-0.26	18	-0.07	-1.14	18	-0.06	-0.88	18	0.02	0.35
22	-0.04	-0.51	22	-0.14	-1.77	22	-0.04	-0.47	22	0.01	0.17
23	0.08	1.01	23	-0.12	-1.54	23	0.10	1.25	23	-0.10	-1.22

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the revisions under the Nullhypothesis. *Id* refers to the number given to a forecaster in our data set.

Table B-6. United Kingdom

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
						1	-0.23	-2.89			
2	0.03	0.34	2	-0.01	-0.19	2	-0.03	-0.39	2	-0.01	-0.15
3	0.12	1.92	3	-0.28	-4.35	3	-0.05	-0.65	3	-0.01	-0.17
6	0.04	0.74	6	-0.16	-2.43	6	0.02	0.31	6	-0.33	-6.28
8	0.08	1.10	8	-0.49	-7.41	8	-0.13	-1.83	8	-0.12	-1.53
9	0.16	2.73	9	0.07	1.11	9	0.12	1.70	9	0.17	2.27
11	-0.14	-2.42	11	-0.03	-0.44	11	0.04	0.53	11	0.06	0.93
13	0.03	0.47	13	0.04	0.64	13	0.00	0.03	13	0.00	-0.02
18	0.07	1.03	18	0.01	0.08	18	0.10	1.41	18	0.09	1.10
19	0.09	1.73	19	-0.16	-2.93	19	0.02	0.42	19	0.02	0.40
20	-0.01	-0.16	20	-0.02	-0.27	20	-0.20	-3.62	20	0.00	0.03
21	0.22	3.14	21	0.08	0.94	21	0.03	0.33	21	0.08	1.03
22	0.13	1.53							23	-0.06	-0.91
23	0.12	2.06	23	0.01	0.22	23	0.08	1.46	25	0.10	1.17
25	0.05	0.75	25	0.04	0.72	25	0.03	0.47	29	-0.14	-2.32
29	-0.10	-1.61	29	0.01	0.15	29	-0.07	-1.18	30	0.09	1.21
30	0.22	3.68	30	0.08	1.21	30	0.17	2.51	31	0.03	0.43
31	0.26	3.78	31	-0.08	-1.05	31	-0.04	-0.60	33	0.05	0.51
33	-0.08	-1.19	33	-0.01	-0.08	33	0.12	1.43	35	-0.07	-0.60
35	0.15	1.74	35	0.05	0.58	35	0.13	1.50	37	-0.10	-1.38
37	-0.01	-0.18	37	-0.06	-0.81	37	0.11	1.55	40	-0.07	-0.88
40	0.08	0.89	40	-0.43	-5.63						
41	-0.01	-0.08	41	-0.25	-2.96				42	-0.01	-0.11
42	-0.05	-0.41	42	-0.08	-0.86	42	0.01	0.06	43	0.03	0.34
43	0.29	3.40	43	-0.04	-0.42	43	0.10	1.29	44	0.00	0.01
44	-0.03	-0.31	44	-0.19	-2.23	44	-0.04	-0.52			
45	0.12	1.54	45	-0.03	-0.32	45	0.17	2.44	45	0.07	0.83

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the revisions under the Nullhypothesis. *Id* refers to the number given to a forecaster in our data set.

Table B-7. United States

GDP			Inflation			Ind. Prod.			Priv. Cons.		
id	beta	t-stat	id	beta	t-stat	id	beta	t-stat	id	beta	t-stat
1	0.08	1.06	1	-0.09	-1.14	1	-0.17	-2.25	1	0.05	0.64
9	0.18	3.04	9	0.01	0.16	9	0.05	0.66	9	0.08	1.38
13	0.05	0.84	13	-0.13	-1.85	13	0.06	0.96	13	0.02	0.32
14	0.10	1.41	14	-0.02	-0.17	14	0.03	0.37	14	-0.01	-0.10
16	0.09	1.40	16	-0.05	-0.87	16	0.04	0.65	16	0.08	1.35
17	0.15	2.06	17	-0.03	-0.37	17	0.07	0.88	17	0.00	0.04
18	0.22	3.61	18	0.04	0.63	18	0.12	1.68	18	0.06	0.92
19	0.01	0.20	19	-0.09	-1.03	19	0.08	1.05	19	0.07	0.84
27	-0.12	-1.11				27	-0.08	-0.71			
28	0.02	0.33	28	-0.13	-1.56	28	-0.18	-2.41	28	-0.08	-1.09
31	0.11	1.24	31	-0.32	-4.07	31	0.19	2.18	31	-0.02	-0.22
33	-0.06	-0.81	33	-0.10	-1.34	33	-0.11	-1.68	33	0.09	1.14
34	0.13	2.18	34	0.11	1.78	34	0.03	0.44	34	0.03	0.44
35	0.20	2.64	35	-0.17	-2.46	35	0.00	0.04	35	-0.18	-2.38
37	-0.02	-0.24	37	-0.08	-0.96	37	-0.14	-1.78	37	-0.04	-0.50
39	0.23	2.77	39	0.09	1.15	39	0.09	1.27	39	0.20	2.46
41	0.03	0.36	41	-0.10	-1.16	41	-0.12	-1.21	41	-0.06	-0.75
43	0.21	2.59	43	0.10	1.14	43	-0.02	-0.18	43	0.07	0.98
44	0.06	0.88	44	-0.10	-1.31				44	-0.03	-0.43
45	0.22	1.86	45	-0.17	-1.93	45	-0.23	-2.47	45	0.10	0.99
46	0.13	2.05	46	0.17	2.09	46	-0.03	-0.27	46	0.01	0.19

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the revisions under the Nullhypothesis. *Id* refers to the number given to a forecaster in our data set.

C. Tests on Unbiasedness for Consensus Forecasts

Table C-1. Germany

	GDP		Inflation		Ind. Prod.		Priv. Cons.	
Horizon	beta	t-stat	beta	t-stat	beta	t-stat	beta	t-stat
restr.	-0.52	-2.24	-0.03	-0.20	-1.00	-1.78	-0.56	-2.27
24	-1.12	-2.77	-0.09	-0.37	-1.91	-1.92	-1.16	-2.53
23	-1.04	-2.64	-0.09	-0.38	-1.84	-1.91	-1.08	-2.43
22	-1.01	-2.64	-0.09	-0.39	-1.80	-1.93	-1.05	-2.45
21	-0.98	-2.63	-0.09	-0.40	-1.83	-2.02	-1.01	-2.44
20	-0.99	-2.73	-0.08	-0.36	-1.79	-2.04	-0.97	-2.45
19	-0.97	-2.76	-0.06	-0.28	-1.73	-2.05	-0.95	-2.51
18	-0.91	-2.69	-0.05	-0.23	-1.69	-2.08	-0.92	-2.56
17	-0.90	-2.75	-0.04	-0.20	-1.63	-2.10	-0.87	-2.57
16	-0.84	-2.67	-0.07	-0.36	-1.63	-2.20	-0.83	-2.62
15	-0.73	-2.41	-0.07	-0.42	-1.53	-2.18	-0.75	-2.52
14	-0.63	-2.17	-0.06	-0.37	-1.15	-1.73	-0.67	-2.45
13	-0.49	-1.80	-0.01	-0.09	-0.97	-1.55	-0.54	-2.19
12	-0.41	-1.59	0.03	0.19	-0.83	-1.44	-0.50	-2.31
11	-0.35	-1.42	0.06	0.46	-0.76	-1.37	-0.42	-2.02
10	-0.24	-1.01	0.07	0.53	-0.68	-1.29	-0.33	-1.65
9	-0.15	-0.65	0.03	0.22	-0.57	-1.14	-0.27	-1.46
8	-0.13	-0.63	0.01	0.12	-0.43	-0.90	-0.25	-1.43
7	-0.10	-0.50	0.02	0.19	-0.35	-0.80	-0.16	-0.97
6	-0.09	-0.51	0.01	0.07	-0.26	-0.63	-0.15	-1.00
5	-0.08	-0.48	0.01	0.08	-0.20	-0.53	-0.12	-0.86
4	-0.10	-0.67	-0.01	-0.17	-0.19	-0.56	-0.13	-1.01
3	-0.08	-0.62	-0.01	-0.19	-0.14	-0.48	-0.11	-1.04
2	-0.11	-1.07	-0.03	-0.48	-0.06	-0.25	-0.12	-1.36
1	-0.09	-1.16	-0.02	-0.50	0.05	0.32	-0.01	-0.11

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors.

Table C-2. Canada

	GDP		Inflation		Ind. Prod.		Priv. Cons.	
Horizon	beta	t-stat	beta	t-stat	beta	t-stat	beta	t-stat
restr.	-0.28	-1.09	0.23	0.76	-0.91	-2.01	0.04	0.16
24	-0.52	-1.17	0.11	0.22	-1.29	-1.74	-0.14	-0.35
23	-0.55	-1.28	0.05	0.10	-1.35	-1.86	-0.09	-0.22
22	-0.57	-1.36	0.10	0.21	-1.47	-2.06	-0.10	-0.27
21	-0.57	-1.40	0.10	0.22	-1.46	-2.09	-0.09	-0.26
20	-0.59	-1.47	0.11	0.23	-1.48	-2.16	-0.08	-0.24
19	-0.56	-1.44	0.10	0.23	-1.47	-2.20	-0.07	-0.22
18	-0.56	-1.49	0.09	0.20	-1.48	-2.27	-0.08	-0.24
17	-0.52	-1.45	0.14	0.31	-1.50	-2.35	-0.09	-0.27
16	-0.47	-1.36	0.13	0.31	-1.33	-2.13	-0.06	-0.20
15	-0.37	-1.10	0.12	0.30	-1.27	-2.10	0.02	0.07
14	-0.30	-0.95	0.16	0.38	-1.20	-2.03	0.07	0.25
13	-0.24	-0.78	0.23	0.58	-1.09	-1.90	0.07	0.29
12	-0.15	-0.53	0.31	0.79	-0.91	-1.64	0.13	0.55
11	-0.13	-0.46	0.34	0.90	-0.78	-1.48	0.17	0.75
10	-0.10	-0.39	0.40	1.09	-0.95	-1.89	0.17	0.77
9	-0.13	-0.54	0.38	1.12	-0.74	-1.55	0.18	0.84
8	-0.13	-0.56	0.35	1.08	-0.65	-1.44	0.15	0.76
7	-0.09	-0.42	0.32	1.05	-0.52	-1.24	0.08	0.46
6	-0.08	-0.40	0.32	1.15	-0.34	-0.88	0.13	0.75
5	-0.09	-0.46	0.32	1.27	-0.25	-0.71	0.13	0.81
4	-0.06	-0.34	0.33	1.42	-0.14	-0.43	0.13	0.97
3	-0.01	-0.06	0.33	1.66	-0.07	-0.24	0.11	0.88
2	0.00	-0.03	0.33	2.03	-0.02	-0.07	0.10	0.99
1	0.01	0.13	0.37	3.19	-0.16	-1.02	0.04	0.55

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors.

Table C-3. France

	GDP		Inflation		Ind. Prod.		Priv. Cons.	
Horizon	beta	t-stat	beta	t-stat	beta	t-stat	beta	t-stat
restr.	-0.44	-1.87	-0.15	-1.08	-1.06	-2.17	-0.19	-1.33
24	-0.89	-2.11	-0.26	-1.03	-1.77	-2.03	-0.49	-2.07
23	-0.88	-2.16	-0.25	-1.03	-1.74	-2.05	-0.47	-2.04
22	-0.86	-2.18	-0.23	-0.99	-1.76	-2.14	-0.45	-1.97
21	-0.89	-2.34	-0.21	-0.94	-1.80	-2.26	-0.48	-2.17
20	-0.85	-2.31	-0.19	-0.88	-1.73	-2.25	-0.43	-2.02
19	-0.83	-2.34	-0.23	-1.11	-1.71	-2.32	-0.39	-1.85
18	-0.78	-2.29	-0.21	-1.04	-1.61	-2.26	-0.35	-1.74
17	-0.75	-2.29	-0.21	-1.13	-1.53	-2.26	-0.33	-1.67
16	-0.68	-2.19	-0.23	-1.31	-1.51	-2.33	-0.27	-1.41
15	-0.53	-1.79	-0.21	-1.24	-1.29	-2.11	-0.17	-0.95
14	-0.47	-1.68	-0.21	-1.38	-1.20	-2.09	-0.14	-0.80
13	-0.39	-1.52	-0.16	-1.14	-1.05	-1.96	-0.09	-0.52
12	-0.32	-1.34	-0.08	-0.64	-0.87	-1.77	-0.05	-0.29
11	-0.29	-1.28	-0.06	-0.50	-0.84	-1.78	-0.03	-0.22
10	-0.27	-1.25	-0.05	-0.41	-0.77	-1.71	-0.03	-0.23
9	-0.25	-1.19	-0.03	-0.31	-0.67	-1.58	-0.05	-0.39
8	-0.21	-1.09	-0.05	-0.46	-0.71	-1.76	-0.05	-0.36
7	-0.15	-0.84	-0.10	-1.04	-0.63	-1.67	-0.09	-0.77
6	-0.11	-0.67	-0.11	-1.20	-0.47	-1.34	-0.07	-0.59
5	-0.09	-0.61	-0.10	-1.24	-0.45	-1.43	-0.05	-0.52
4	-0.08	-0.58	-0.11	-1.47	-0.39	-1.38	-0.03	-0.29
3	0.00	0.00	-0.08	-1.28	-0.31	-1.25	0.01	0.08
2	0.01	0.07	-0.07	-1.43	-0.33	-1.63	-0.01	-0.10
1	-0.03	-0.39	-0.07	-1.84	-0.25	-1.78	0.00	0.00

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors.

Table C-4. Italy

	GDP		Inflation		Ind. Prod.		Priv. Cons.	
Horizon	beta	t-stat	beta	t-stat	beta	t-stat	beta	t-stat
restr.	-0.63	-3.34	0.18	0.74	-1.56	-2.66	-0.44	-1.90
24	-1.23	-3.79	0.22	0.53	-2.37	-2.34	-0.97	-2.40
23	-1.21	-3.83	0.25	0.61	-2.43	-2.47	-0.96	-2.44
22	-1.19	-3.85	0.21	0.52	-2.46	-2.57	-0.93	-2.43
21	-1.15	-3.85	0.18	0.47	-2.48	-2.66	-0.94	-2.52
20	-1.13	-3.90	0.19	0.50	-2.46	-2.72	-0.90	-2.48
19	-1.11	-3.93	0.19	0.53	-2.42	-2.77	-0.88	-2.51
18	-1.05	-3.85	0.20	0.57	-2.39	-2.84	-0.85	-2.49
17	-1.03	-3.92	0.29	0.84	-2.35	-2.89	-0.83	-2.52
16	-0.97	-3.88	0.26	0.79	-2.20	-2.82	-0.75	-2.38
15	-0.77	-3.22	0.15	0.47	-1.95	-2.62	-0.53	-1.76
14	-0.70	-3.06	0.17	0.57	-1.85	-2.60	-0.46	-1.59
13	-0.63	-2.89	0.19	0.67	-1.73	-2.57	-0.39	-1.40
12	-0.57	-2.81	0.21	0.78	-1.59	-2.51	-0.33	-1.27
11	-0.50	-2.56	0.19	0.74	-1.53	-2.54	-0.33	-1.30
10	-0.46	-2.47	0.17	0.69	-1.44	-2.50	-0.23	-0.98
9	-0.39	-2.23	0.17	0.70	-1.21	-2.22	-0.16	-0.71
8	-0.36	-2.16	0.15	0.69	-1.09	-2.11	-0.13	-0.59
7	-0.25	-1.58	0.13	0.64	-0.91	-1.88	-0.09	-0.47
6	-0.18	-1.25	0.12	0.62	-0.81	-1.82	-0.07	-0.36
5	-0.12	-0.91	0.14	0.79	-0.70	-1.72	-0.01	-0.08
4	-0.13	-1.13	0.13	0.80	-0.57	-1.57	-0.01	-0.09
3	-0.04	-0.39	0.09	0.68	-0.25	-0.80	0.05	0.36
2	-0.01	-0.16	0.13	1.13	-0.21	-0.80	0.05	0.50
1	-0.01	-0.11	0.14	1.77	-0.10	-0.55	0.06	0.79

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors.

Table C-5. Japan

	GDP		Inflation		Ind. Prod.		Priv. Cons.	
Horizon	beta	t-stat	beta	t-stat	beta	t-stat	beta	t-stat
restr.	-0.28	-0.75	-0.13	-1.14	-1.35	-1.43	-0.36	-1.41
24	-0.86	-1.28	-0.32	-1.55	-2.69	-1.61	-0.82	-1.79
23	-0.86	-1.31	-0.31	-1.56	-2.81	-1.73	-0.79	-1.77
22	-0.83	-1.31	-0.31	-1.61	-2.70	-1.71	-0.78	-1.81
21	-0.78	-1.27	-0.29	-1.52	-2.51	-1.64	-0.73	-1.74
20	-0.80	-1.35	-0.33	-1.83	-2.65	-1.80	-0.74	-1.84
19	-0.66	-1.15	-0.29	-1.63	-2.43	-1.71	-0.70	-1.81
18	-0.49	-0.90	-0.23	-1.38	-2.08	-1.52	-0.58	-1.57
17	-0.47	-0.90	-0.18	-1.11	-2.04	-1.56	-0.55	-1.56
16	-0.50	-1.00	-0.22	-1.42	-2.09	-1.67	-0.57	-1.69
15	-0.29	-0.62	-0.15	-1.05	-1.57	-1.33	-0.38	-1.20
14	-0.21	-0.46	-0.13	-0.92	-1.37	-1.23	-0.35	-1.19
13	-0.12	-0.29	-0.09	-0.72	-1.23	-1.18	-0.25	-0.89
12	0.11	0.29	-0.06	-0.50	-1.01	-1.05	-0.03	-0.11
11	0.15	0.40	-0.03	-0.29	-0.91	-0.98	0.04	0.16
10	0.12	0.34	-0.07	-0.67	-0.81	-0.92	0.05	0.23
9	0.12	0.36	-0.04	-0.38	-0.78	-0.93	0.07	0.33
8	0.15	0.48	-0.05	-0.48	-0.72	-0.91	0.06	0.29
7	0.01	0.05	-0.03	-0.29	-0.67	-0.91	-0.13	-0.65
6	-0.07	-0.27	-0.01	-0.16	-0.33	-0.49	-0.24	-1.34
5	-0.10	-0.40	-0.01	-0.17	-0.24	-0.39	-0.25	-1.55
4	-0.19	-0.83	-0.01	-0.10	-0.32	-0.57	-0.31	-2.09
3	-0.07	-0.38	0.03	0.44	-0.19	-0.40	-0.23	-1.84
2	-0.06	-0.38	0.01	0.14	-0.07	-0.17	-0.21	-2.06
1	-0.07	-0.66	0.01	0.38	-0.07	-0.26	-0.21	-2.82

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors.

Table C-6. United Kingdom

	GDP		Inflation		Ind. Prod.		Priv. Cons.	
Horizon	beta	t-stat	beta	t-stat	beta	t-stat	beta	t-stat
restr.	-0.24	-0.91	-0.20	-1.52	-1.43	-3.21	0.18	0.69
24	-0.45	-0.96	-0.61	-2.64	-2.43	-3.07	0.33	0.71
23	-0.54	-1.17	-0.47	-2.09	-2.54	-3.32	0.22	0.48
22	-0.57	-1.27	-0.46	-2.12	-2.51	-3.38	0.20	0.45
21	-0.54	-1.25	-0.43	-2.07	-2.47	-3.45	0.18	0.42
20	-0.55	-1.31	-0.43	-2.11	-2.47	-3.57	0.19	0.45
19	-0.55	-1.38	-0.43	-2.22	-2.41	-3.63	0.14	0.35
18	-0.52	-1.35	-0.41	-2.21	-2.33	-3.66	0.17	0.45
17	-0.47	-1.28	-0.34	-1.90	-2.25	-3.70	0.16	0.43
16	-0.43	-1.23	-0.32	-1.88	-2.16	-3.75	0.17	0.47
15	-0.39	-1.16	-0.31	-1.90	-2.03	-3.73	0.19	0.57
14	-0.32	-1.02	-0.24	-1.58	-1.81	-3.57	0.22	0.68
13	-0.25	-0.84	-0.19	-1.32	-1.67	-3.55	0.20	0.66
12	-0.16	-0.59	-0.13	-1.02	-1.46	-3.39	0.22	0.78
11	-0.12	-0.46	-0.09	-0.69	-1.25	-3.04	0.22	0.81
10	-0.12	-0.49	-0.01	-0.06	-1.08	-2.75	0.19	0.75
9	-0.07	-0.31	0.00	0.00	-0.92	-2.47	0.21	0.87
8	-0.06	-0.27	-0.01	-0.06	-0.76	-2.16	0.17	0.75
7	-0.02	-0.10	-0.01	-0.07	-0.55	-1.66	0.18	0.83
6	0.07	0.38	0.01	0.14	-0.43	-1.40	0.20	1.00
5	0.07	0.42	0.03	0.32	-0.29	-1.03	0.19	1.02
4	0.09	0.56	0.03	0.35	-0.23	-0.91	0.13	0.81
3	0.04	0.30	0.03	0.51	-0.15	-0.71	0.13	0.89
2	0.02	0.18	0.03	0.62	-0.11	-0.64	0.11	0.92
1	0.01	0.09	0.05	1.24	-0.11	-0.86	0.05	0.57

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors.

Table C-7. United States

	GDP		Inflation		Ind. Prod.		Priv. Cons.	
Horizon	beta	t-stat	beta	t-stat	beta	t-stat	beta	t-stat
restr.	0.18	0.71	-0.13	-0.92	-0.48	-0.95	0.48	2.07
24	0.19	0.43	-0.29	-1.10	-0.84	-0.95	0.71	1.72
23	0.15	0.35	-0.29	-1.11	-0.97	-1.14	0.71	1.77
22	0.15	0.36	-0.23	-0.94	-0.97	-1.16	0.69	1.78
21	0.17	0.42	-0.24	-1.00	-1.01	-1.25	0.66	1.75
20	0.15	0.37	-0.29	-1.24	-1.10	-1.41	0.63	1.72
19	0.14	0.36	-0.29	-1.29	-1.02	-1.35	0.63	1.79
18	0.15	0.39	-0.24	-1.13	-1.00	-1.37	0.63	1.86
17	0.18	0.50	-0.21	-1.05	-0.89	-1.28	0.64	1.99
16	0.23	0.66	-0.24	-1.25	-0.83	-1.24	0.68	2.22
15	0.37	1.14	-0.17	-0.96	-0.68	-1.06	0.79	2.71
14	0.45	1.44	-0.12	-0.71	-0.39	-0.65	0.79	2.88
13	0.41	1.41	-0.07	-0.47	-0.33	-0.57	0.73	2.85
12	0.43	1.56	-0.01	-0.05	-0.25	-0.47	0.71	3.00
11	0.35	1.32	0.07	0.54	-0.25	-0.48	0.63	2.81
10	0.24	0.96	0.06	0.47	-0.23	-0.48	0.55	2.57
9	0.14	0.59	-0.01	-0.11	-0.29	-0.63	0.38	1.86
8	0.07	0.30	-0.06	-0.52	-0.23	-0.52	0.19	1.01
7	0.05	0.26	-0.10	-0.93	-0.13	-0.31	0.15	0.85
6	0.05	0.28	-0.11	-1.14	-0.08	-0.21	0.14	0.84
5	0.10	0.57	-0.09	-1.03	-0.04	-0.12	0.15	1.01
4	0.08	0.51	-0.09	-1.15	-0.02	-0.06	0.15	1.08
3	0.08	0.58	-0.07	-0.95	0.01	0.02	0.12	1.02
2	0.04	0.36	-0.06	-1.05	0.03	0.12	0.05	0.49
1	-0.01	-0.08	-0.07	-1.64	0.02	0.13	0.01	0.10

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the forecast errors.

D. Tests on Weak Efficiency for Consensus Forecasts

Table D-1. Without Horizon-Effects

	GDP		Inflation		Ind. Prod.		Priv. Cons.	
	beta	t-stat	beta	t-stat	beta	t-stat	beta	t-stat
Germany	0.49	8.36	0.19	3.23	0.46	7.41	0.32	5.32
Canada	0.27	4.63	0.17	3.31	0.00	0.06	0.17	2.92
France	0.34	5.25	0.14	2.42	0.33	5.48	0.24	4.04
Italy	0.34	5.65	0.06	1.09	0.38	5.86	0.19	3.34
Japan	0.25	4.23	0.20	3.51	0.33	5.23	0.18	3.02
United Kingdom	0.37	6.88	0.09	1.77	0.49	8.62	0.29	5.26
United States	0.23	3.96	0.23	3.93	0.28	4.97	0.16	2.70

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the revisions under the Nullhypothesis.

Table D-2. With Horizon-Effects

	GDP		Inflation		Ind. Prod.		Priv. Cons.	
	beta	t-stat	beta	t-stat	beta	t-stat	beta	t-stat
Germany	0.43	7.40	0.20	3.32	0.44	7.18	0.23	3.99
Canada	0.26	4.41	0.16	3.19	-0.02	-0.40	0.17	2.92
France	0.29	4.54	0.14	2.45	0.30	4.86	0.21	3.59
Italy	0.24	4.09	0.10	1.81	0.28	4.40	0.12	2.10
Japan	0.26	4.32	0.19	3.45	0.35	5.64	0.16	2.75
United Kingdom	0.36	6.69	0.06	1.20	0.37	6.61	0.30	5.32
United States	0.22	3.82	0.27	4.59	0.27	4.73	0.12	2.09

Notes: T-statistics are based on the GMM estimation which accounts for the special correlation patterns of the revisions under the Nullhypothesis. Estimates of the horizon-effects are not presented. They are, however, available from the authors upon request.