International Evidence on Professional Interest Rate Forecasts: The Impact of Forecasting Ability

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International Evidence on Professional Interest Rate Forecasts: The Impact of Forecasting Ability*

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Abstract

This paper develops a model of honest rational professional forecasters with different abilities and submits it to empirical verification using data on 3- and 12-months ahead forecasts of short-term interest rates and of long-term bond yields for up to 33 countries collected by *Consensus Economics*. The main finding is that in many countries, less-precise forecasters weigh public information more heavily than more-precise forecasters who weigh their own private information relatively more heavily. One implication of this result is that less-precise forecasters herd after more-precise forecasters even in the absence of strategic considerations. We also document differences between the average forecasting errors of more- and less-able forecasters as well as substantial correlations between the forecast errors of different forecasters.

JEL: E47, G17
Keywords: Forecasting interest rates and bond yields, impact of forecasting ability on forecast formation.

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1 Introduction

The future course of interest rates is important for a number of reasons. When deciding how much to borrow and for how long, information about future rates is useful to credit demanders. For similar reasons, information about future rates is useful to credit suppliers. Accurate forecasting of future rates is obviously important for financial institutions, particularly banks that derive a large part of their income from spreads between borrowing and lending rates. Positive banking spreads are usually achieved by longer maturities on the asset side than on the liability side of a bank's balance sheet. Striking an optimal balance between high spreads and maintenance of adequate liquidity crucially depends on accurate forecasts of future rates.

Forecasting short-term interest rates that are intimately related to central bank policy is important for evaluating the stance of monetary policy, and beliefs about the future course of long-term yields constitute an important link in the transmission of monetary policy to economic activity and inflation.

This paper uses a large data set on professional interest rate forecasts collected by *Consensus Economics* to characterize the formation of such forecasts at the individual forecaster level. The data set includes professional forecasts of short-term interest rates for 33 countries and of long-term bond yields (10 years) for 23 countries between October 1989 and June 2017. The data comprise 3-months ahead and 12-months ahead forecasts for both short-term interest rates and long-term yields. This can be summarized by the following 2×2 matrix: 3- and 12-month interest rate forecasts and 3- and 12-month yield forecasts. The number of forecasters obviously varies across periods and countries. The average number of forecasters per country varies between a minimum of approximately 6 for emerging markets such as India, Thailand and Indonesia and a maximum of approximately 24 for developed economies such as the US and Germany.

We derive two hypotheses about the impact of differences in forecasting ability on the forecast formation processes of individual forecasters. The by now standard (non-strategic) notion of rational expectations posits that given the forecaster's understanding of the model that generates a given interest rate and the information at his disposal, each forecaster attempts to issue a point forecast that minimizes some measure of distance between the forecast and the subsequent realization of that rate. Due to the presence of noisy factors in both the forecasted variable and the signals used to forecast it, rational forecasts are not perfect. A widely used operationalization of rational forecasts in a stochastic world is the expected value of the forecasted variable conditional on the signals available to the forecaster.[1]

Since forecasters normally have access to both public and private information as well as to the current value of the interest rate, we posit that in addition to an observation of the latter, a typical forecaster possesses a private signal and has access to a publicly shared signal. The forecast is then taken to be identical to the expected value of the forecasted variable conditional on the current value of the interest rate (the prior), the private signal and the public signal.[2] For normally distributed stochastic variables, this framework yields a linear relationship between the forecast on the one hand and the three conditioning variables on the other.

The non-strategic Bayesian framework above yields one basic implication that is tested empirically. It states that forecasters with better forecasting ability assign higher weights to their private information than forecasters with lower forecasting ability. Consequently, abler (good, for brevity) forecasters rely less on public information than their less able counterparts (bad, for brevity). In the empirical part of the paper, good and bad forecasters are identified by their rolling past mean squared forecast errors. Bad forecasters exhibit a high mean squared error while for good forecasters the mean squared error is low.

Estimation of the forecasting formation processes at the level of individual forecasters in each country strongly supports the implications above for short-term interest rates in more than fifty percent of the countries. Although the numerical differences in weights between good and bad forecasters for long-term bond yields are in line with the implications above, the results are generally weaker, since there is a preponderance of cases in which the difference in weights between good and bad forecasters is not statistically significant.

This paper's structure is as follows. **Section 2** gives a short overview of the literature. **Section 3** presents a Bayesian model of honest forecasts and derives its implications for differences in the expectation formation processes of good and bad forecasters. **Section 4** presents the data, some of its characteristics and the algorithm used to classify forecasters into good and bad forecasting ability bins. Using this classification, the implications derived in **Section 3** are tested in

[1] For normal distributions, the best linear unbiased predictor minimizes the mean squared forecast error. An early influential example of this approach is Muth (1960), who shows that when a time series comprises a random walk and of a white noise that cannot be observed separately (not even ex post), the optimal predictor is given by adaptive expectations.

[2] The statistical literature refers to this type of forecast as a Bayesian forecast (DeGroot (1970), part 3). Broadly similar conceptual frameworks have been used to characterize forecasts of macroeconomic variables such as GDP growth, inflation rates, rates of change in bilateral exchange rates and earnings per share in the finance literature. Examples are Morris & Shin (2002) and Marinovic et al. (2013).

Section 5. This is followed by concluding remarks. Further information about the data and regression results appear in the appendix.

2 Literature review

An intriguing body of literature in both finance and economics (developed mainly during the last twenty-five years) argues, mostly on theoretical grounds, that professional forecasters possess strategic incentives to report forecasts that deviate systematically from "honest" Bayesian forecasts. Two types of deviations are identified, one that leads to herding in forecasts and the other to exaggeration in the opposite direction or "anti-herding" due to the existence of forecasting contests.

The rationale for the first type of deviation rests on the view that a forecaster wants to signal to the public that his private signal is endowed with good forecasting ability. Since forecasters share the same pool of a priori public information and the honest forecast is a weighted average of the private and public signals, the market can infer the private signal and its accuracy from the honest forecast. Consequently, the forecaster has an incentive to act in a way that leads the market to believe that his private signal is identical to his posterior honest forecast. This induces him to shade the reported forecast toward the prior mean forecast. When all forecasters do this, their forecasts are biased toward the prior mean and are more bunched than in the honest Bayesian case. Ottaviani & Sørensen (2006*a*,*b*) show that this leads to a reputational cheap talk equilibrium (à la Crawford & Sobel (1982)) in which the information transmitted to the market is less precise than under honest forecasting.[3]

Anti-herding behavior, or "bold" behavior, arises in forecasting contests in "winner takes all" situations. This is the case when the most accurate forecaster obtains a disproportionate fraction of public attention.[4] Admittedly, by exaggerating their private information, forecasters reduce the probability of winning, but they also increase their favorable public visibility conditional on winning. Being the single winner entails more glory and associated pecuniary benefits than sharing the prize with other fellows. Ottaviani & Sørensen (2006*b*) show that this induces forecasters to distance themselves from market consensus on the off chance of being right when few other forecasters are also right.

[3]See also Scharfstein & Stein (1990) and Trueman (1994).

[4]Forecasting contests are often run among meteorologists, such as the National Collegiate Weather Forecasting Contest, and among economists. An example is the Wall Street Journal's semi-annual forecasting survey.

Since reputational cheap talk and forecasting contests exert opposite effects on honest Bayesian forecasts, Bayesian forecasts may actually yield a reasonable approximation of reality after all.[5] This is in line with the general point of view taken in this paper. It is important to note that whether one agrees or disagrees with this point of view, individual forecasts are correlated across forecasters even in the absence of strategic effects, since all forecasters utilize the same pool of public information.

3 A Bayesian model of honest forecasts

This section presents the model used to anchor the empirical work. The model postulates that forecasts are equal to the expected values of the forecasted variables conditional on the information available to forecasters in each period (Bayesian expectations).[6] Forecasters observe two signals about the future state, θ_{t+h}, where t is the current time period and h is the forecast horizon. The state follows a random walk[7] and is given by

$$\theta_{t+h} = \theta_t + \delta_{t+h} \qquad \text{with } \delta_{t+h} \sim N\left(0, \sigma^2_{\delta}\right). \tag{1}$$

θ_t is known to all forecasters in period t, but the future cumulative innovations to the state, δ_{t+h}, are not known, and have to be forecasted. Each forecaster has access to one private and one common public signal. The private signal is observed solely by each individual forecaster and differs, therefore, across forecasters. By contrast, the public signal is the same for all forecasters in a given time period, t. As a proxy for the private signal available to forecaster i in period t, we take the previous period's forecast of the individual, $f_{i,t-1}$. As a proxy for the public signal, we take the mean forecast of the previous period, $f_{p,t-1}$. The two signals have the following form

$$\begin{aligned} f_{i,t-1} &= \theta_{t+h} + \varepsilon_{i,t+h} &\qquad \text{with } \varepsilon_{i,t+h} \sim N\left(0, \sigma^2_{\varepsilon i}\right) \\ f_{p,t-1} &= \theta_{t+h} + \eta_{t+h} &\qquad \text{with } \eta_{t+h} \sim N\left(0, \sigma^2_{\eta}\right). \end{aligned} \tag{2}$$

[5] Further discussion of this point and a comprehensive survey of the strategic forecasting literature appears in Marinovic et al. (2013).

[6] For a detailed introduction to Bayesian expectations, see, for example, Veldkamp (2011) p. 11 ff.

[7] Unit root tests support our assumption of a random walk for both short-term and long-term interest rates in the majority of countries. Using these time series, Augmented Dickey-Fuller tests mostly fail to reject the null hypothesis of a unit root against the stationary model alternative. Similar results are obtained for sub-samples before and after the outbreak of the global financial crisis (Aug-2007) .

$\varepsilon_{i,t+h}$ and η_{t+h} are noise terms in the signals and are statistically independent of each other and of the cumulative innovation, δ_{t+h}, to the state. Since direct data on private signals are not available, we use the lagged private forecast of individual i as a proxy for his current private information. Being a mixture of past private and public information, this proxy is a noisy index of the "pure" private signal. Since the current value of the state is known by all forecasters, the common prior of δ_{t+h} is zero, and correspondingly, that of θ_{t+h} is θ_t. The joint distribution of θ_{t+h}, $f_{i,t-1}$ and $f_{p,t-1}$ is given by

$$\begin{bmatrix} \theta_{t+h} \\ f_{i,t-1} \\ f_{p,t-1} \end{bmatrix} \sim N\left(\begin{bmatrix} \theta_t \\ \theta_t \\ \theta_t \end{bmatrix}, \begin{bmatrix} \sigma_\delta^2 & \sigma_\delta^2 & \sigma_\delta^2 \\ \sigma_\delta^2, & \sigma_\delta^2+\sigma_{\varepsilon i}^2 & \sigma_\delta^2 \\ \sigma_\delta^2 & \sigma_\delta^2 & \sigma_\delta^2+\sigma_\eta^2 \end{bmatrix}\right).$$

We use this joint distribution to derive the conditional forecast. For that purpose, we make use of the general formula for normally distributed conditional expectations (Bayesian expectations)[8]

$$\mathbb{E}\left[x_1|x_2\right] = \mu_1 + \Sigma_{12}\cdot\Sigma_{22}^{-1}\cdot(x_2-\mu_2)$$

with

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \text{ and } \Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}.$$

Here, x_2 is a vector of observed signals about x_1, μ is its prior, and Σ is the covariance matrix. In our case, the relevant conditional expectation is

$$f_{i,t} \equiv \mathbb{E}\left[\theta_{t+h}|\theta_t,\ f_{i,t-1},\ f_{p,t-1}\right]$$

and the general matrices above specialize to

$$x_2 = \begin{bmatrix} f_{i,t-1} & f_{p,t-1} \end{bmatrix}',\ \mu_1 = \begin{bmatrix} \theta_t \end{bmatrix},\ \mu_2 = \begin{bmatrix} \theta_t & \theta_t \end{bmatrix}'$$
$$\Sigma_{11} = \begin{bmatrix} \sigma_\delta^2 \end{bmatrix},\ \Sigma_{12} = \begin{bmatrix} \sigma_\delta^2 & \sigma_\delta^2 \end{bmatrix} \text{ and } \Sigma_{22} = \begin{bmatrix} \sigma_\delta^2+\sigma_{\varepsilon i}^2 & \sigma_\delta^2 \\ \sigma_\delta^2 & \sigma_\delta^2+\sigma_\eta^2 \end{bmatrix}$$

Applying the general formula to our framework yields[9]

$$f_{i,t} = w_i\cdot f_{i,t-1} + w_p\cdot f_{p,t-1} + w_\theta\cdot\theta_t \tag{3}$$

[8]See, for example, theorem B.7 in Greene (2012), p. 1081 ff.

[9]Note that $\Sigma_{22}^{-1} = \begin{bmatrix} \frac{\sigma_\eta^2+\sigma_\delta^2}{\sigma_{\varepsilon i}^2\sigma_\eta^2+\sigma_{\varepsilon i}^2\sigma_\delta^2+\sigma_\eta^2\sigma_\delta^2} & \frac{-\sigma_\delta^2}{\sigma_{\varepsilon i}^2\sigma_\eta^2+\sigma_{\varepsilon i}^2\sigma_\delta^2+\sigma_\eta^2\sigma_\delta^2} \\ \frac{-\sigma_\delta^2}{\sigma_{\varepsilon i}^2\sigma_\eta^2+\sigma_{\varepsilon i}^2\sigma_\delta^2+\sigma_\eta^2\sigma_\delta^2} & \frac{\sigma_{\varepsilon i}^2+\sigma_\delta^2}{\sigma_{\varepsilon i}^2\sigma_\eta^2+\sigma_{\varepsilon i}^2\sigma_\delta^2+\sigma_\eta^2\sigma_\delta^2} \end{bmatrix}$.

with weights

$$
\begin{aligned}
w_i &= \frac{\sigma_\eta^2\sigma_\delta^2}{\sigma_{\varepsilon i}^2\sigma_\eta^2 + \sigma_{\varepsilon i}^2\sigma_\delta^2 + \sigma_\eta^2\sigma_\delta^2} \\
w_p &= \frac{\sigma_{\varepsilon i}^2\sigma_\delta^2}{\sigma_{\varepsilon i}^2\sigma_\eta^2 + \sigma_{\varepsilon i}^2\sigma_\delta^2 + \sigma_\eta^2\sigma_\delta^2} \\
w_\theta &= \frac{\sigma_{\varepsilon i}^2\sigma_\eta^2}{\sigma_{\varepsilon i}^2\sigma_\eta^2 + \sigma_{\varepsilon i}^2\sigma_\delta^2 + \sigma_\eta^2\sigma_\delta^2}.
\end{aligned}
$$

The optimal predictor in **Equation (3)** makes sense only when the forecast horizons are overlapping. If forecast horizons are not overlapping, there is no reason why a forecaster should use his past forecast and the past mean forecast to form the current forecast. The forecast horizons in the empirical work are either 3- or 12-months. Hence, the forecast horizons are indeed overlapping in the empirical work.

Dividing the numerators and denominators on the right-hand sides of the expressions for the weights by $\sigma_{\varepsilon i}^2\sigma_\eta^2\sigma_\delta^2$, they can be expressed as

$$
\begin{aligned}
w_i &= \frac{\tau_{\varepsilon i}}{\tau_{\varepsilon i} + \tau_\eta + \tau_\delta} \\
w_p &= \frac{\tau_\eta}{\tau_{\varepsilon i} + \tau_\eta + \tau_\delta} \\
w_\theta &= \frac{\tau_\delta}{\tau_{\varepsilon i} + \tau_\eta + \tau_\delta}
\end{aligned} \tag{4}
$$

where $\sigma_\delta^2 = 1/\tau_\delta$, $\sigma_{\varepsilon_i}^2 = 1/\tau_{\varepsilon i}$, and $\sigma_\eta^2 = 1/\tau_\eta$ are the precisions of δ_{t+h}, ε_{t+h} and η_{t+h}. It is easy to see from **Equation (4)** that the sum $w_i + w_p + w_\theta = 1$. Note that when the precision of the public signal, τ_η, tends to zero, w_p also tends to zero, and the optimal predictor in **Equation (3)** reduces to the Muth (1960) optimal adaptive predictor.

In our more general case, forecasters observe a public signal in addition to the current observation on the state. They consequently have two pieces of public information. Summing up the weights given to public information in **Equation (4)** yields two weights, one for private information (w_i) and one for the combined public information ($w_{p+\theta}$)[10]

$$
\begin{aligned}
w_i &= \frac{\tau_{\varepsilon i}}{\tau_{\varepsilon i} + \tau_\eta + \tau_\delta} \\
w_{p+\theta} &= w_p + w_\theta = \frac{\tau_\eta + \tau_\delta}{\tau_{\varepsilon i} + \tau_\eta + \tau_\delta}.
\end{aligned} \tag{5}
$$

Our basic objective is to examine whether the model implies that the expectation formation processes of forecasters with different forecasting abilities differ systematically in order to subsequently test empirically for the potential existence of such differences. To do so, we start by considering, without loss of generality, two types of forecasters: One with higher forecasting ability, referred to as "Good (G)", and another with lower forecasting ability, referred to as " Bad (B)", where the only difference between the two types is that the private information of a G forecaster is more precise than that of a B forecaster. Formally,

$$\tau_{\varepsilon G} > \tau_{\varepsilon B}. \tag{6}$$

Equation (5) and **Equation (6)** imply the following hypothesis [11]

Claim 1 *Good forecasters weigh private information ($f_{i,t-1}$) more than bad forecasters*

$$w_i^G > w_i^B$$

Consequently, good forecasters weigh public information ($f_{p,t-1}$ and θ_t) less than bad forecasters

$$w_{p+\theta}^G < w_{p+\theta}^B$$

In summary, relatively more-precise forecasters rely more on their past private information and less on past public information in comparison to relatively

[10]Note that constant precisions over time are not required to support this statement. It suffices to assume that the relative precision of private and public information is constant over time. Therefore, our model allows for changes in uncertainty over time (changes in precisions τ_η, τ_{ε_i}, and τ_δ) as long as these changes affect all information pieces by the same scaling factor.

[11]This follows directly from the derivatives with respect to $\tau_{\varepsilon i}$ that are given by

$$
\begin{aligned}
\frac{\partial w_i}{\partial \tau_{\varepsilon i}} &= \frac{\tau_\eta + \tau_v}{\left(\tau_{\varepsilon i} + \tau_\eta + \tau_v\right)^2} > 0 \\
\frac{\partial w_{p+\theta}}{\partial \tau_{\varepsilon i}} &= -\frac{\tau_\eta + \tau_\delta}{\left(\tau_{\varepsilon i} + \tau_\eta + \tau_v\right)^2} < 0
\end{aligned}
$$

less-precise forecasters. Our claim above is closest to Trueman (1994), who shows within a strategic framework that analysts with greater forecasting ability are less influenced by past public forecasts. However, as just shown, this result arises here even in the absence of strategic incentives due to the attempt by each forecaster to obtain the best predictor he can obtain given his ability and information set.

4 Data description and classification of forecasters by the precision of their private information

This section provides a brief description of the data and presents the method used to classify forecasters into good (relatively more-precise) and bad (relatively less-precise) forecasters. It also presents some descriptive statistics on forecasters and forecasts and, when appropriate, interprets them in terms of the model of **Section 3**.

4.1 Data

The data comprises short-term interest rate forecasts and long-term yield forecasts collected and maintained by *Consensus Economics*. It comprises monthly forecasts of short-term interest rates for 33 countries (mostly with a maturity of 3-months) and forecasts of 10-year government bond yields for 23 countries. **Table 3** in the Appendix lists the countries and their country codes. Professional forecasters, such as financial institutions and other forecasting agencies, report their forecasts to *Consensus Economics*, starting at the earliest in October 1989 and ending in June 2017.[12] Two forecast horizons are provided – 3- and 12-months.

[12]To account for mergers, we adjusted the data set in identifying forecast agencies. There are three cases. First, we count forecast agencies' mergers as one agency if one of the merged agencies was not active in forecasting the particular country before the merger. For example, we regard *Credit Suisse*, *Credit Suisse First Boston* and *First Boston* as one forecast agency in ARG, since *Credit Suisse* merged with *First Boston* and entered the forecasting market for ARG through this merger. Second, if both forecast agencies were active before the merger, we count the newly merged agency as a new one if the new agency name does not clearly point to one of the two merged agencies. For example, *Bank of America* merged with *Merrill Lynch* in 2009. Both agencies made forecasts for the US before they merged. Therefore, it is not obvious who is now in charge of the forecasts reported under the name *Bank of America Merrill Lynch*. We treat the "new" agency as a new forecaster. Third, if a forecast agency was integrated into another but the agency's name did not change, we stick with this agency. For instance, *JP Morgan* acquired *Bear Stearns*; both agencies were actively forecasting interest rates in ARG before their merger. Since the name *Bear Stearns* vanished and the "new" agency is still called *JP Morgan*, we treat *JP Morgan* as the same agency as prior to the merger. Details of such mergers are available upon request.

Note that since the forecast horizons are longer than one month, three consecutive 3-month forecasts must be serially correlated. A similar statement applies to 12-month consecutive forecasts.

To calculate forecast errors, we employ realized end-of-month interest rates and government bond yields from *Thompson Reuters' Eikon*. Several amendments have been made by *Consensus Economics* over time in the forecasted variables. This was the case, for instance, when an interest rate lost economic relevance. These changes have been incorporated into the data set.

4.2 Procedure used to classify forecasters into "good" and "bad" bins

The procedure allows the data to determine changes in the forecasting ability of individual forecasters over time, in line with their recent forecasting performance. Forecasters are classified as relatively precise (good) or relatively imprecise (bad) forecasters by means of the following algorithm:

1. In month t, all "realized" forecast errors from $t-25$ to $t-1$ for each forecaster are calculated. For each country, time period, and forecaster, this yields the last 24 months of observed forecast errors.

2. Two selection criteria are applied to this matrix of forecast errors. First, forecasters with less than 12 observed forecast errors in this time window are dropped. Second, forecasters with a missing forecast at t or $t-1$ or both are eliminated. In addition, for each country, time periods in which there are less than 4 forecasters that match the two criteria are ignored.

3. The remaining forecasters are ranked by the size of their Mean Squared Error (MSE) using the observed forecast errors in the time window $t-25$ to $t-1$. For each country/period, this provides a distribution of forecasters by their MSE.

4. The bottom quarter of forecasters (lowest MSE within each country) are assigned to the basket of good forecasters in month t, and the upper quarter (highest MSE within each country) are assigned to the basket of bad forecasters in month t. Data on forecasters in the middle range of the distribution are dropped in order to sufficiently capture significant differences between the precisions of good and bad forecasters.

5. For each country and period t, we create a matrix with the overall lagged mean forecast, $\overline{f}_{t-1+h}$, the observed current state of the variable at t, θ_t, and the forecaster i's lagged individual forecast, $f_{i,t-1+h}$, where the index i runs only over the good and bad forecasters bins. This matrix provides the right-hand side variables for the estimation of **Equation (3)** for each of the forecasters who have been classified as either good or bad. The individual forecast made at t, $f_{i,t+h}$, provides the left-hand variable for the estimation of **Equation (3)**. Obviously, the number of forecasts per month in a given basket depends, inter alia, on the total number of forecasts available in period t for a given country.

6. The previous five steps are then repeated in period $t+1$ and so on.

The algorithm produces two sub-samples for each country, a sub-sample of good forecasters and a sub-sample of bad forecasters. Obviously the identities of forecasters in each sample change over time.

4.3 Some characteristics of good and bad forecasters

This subsection presents some descriptive statistics on the number of periods (months) forecaster i is included in the *Consensus Economics* survey (T_i), on the number of periods a forecaster classified as either good or bad remains in the sample (denoted respectively by T_G and T_B) and on average differences between the MSEs of good and bad forecasters. It also documents substantial positive correlations between the forecast errors of different forecasters and interprets those correlations in light of the model in **Section 3**.

The average term a forecaster stays in the survey (T_i) is approximately one-third to one-half of the overall sample length (T). On average, good and bad forecasters stay in the sample for a similar number of periods ($T_G = T_B$). However, the average number of periods during which a particular forecaster is classified as good or bad is much shorter than the average number of periods **any** forecaster remains in the sample (T_G and T_B are substantially smaller than T_i). This indicates that any particular individual achieves the status of a good forecaster for relatively short periods and that bad forecasters also move away from the poor forecasting category relatively quickly. In other words, there is a high degree of turnover between a forecaster being considered good or bad. **Table 4** in the Appendix provides detailed statistics on T_i, T_G and T_B for each country. It also shows the average number of forecasters used to classify as either good or bad in each country ($\overline{N}$).

Panel A of **Table 1** shows the ratios between the mean squared errors (MSEs) of good and bad forecasters for both short-term rates and long-term yields for the 3- and 12-month forecast horizons for each country.[13] The table reveals that a good forecaster's MSE is less than three-quarters that of a bad forecaster's MSE, on average. In addition, a good forecaster's performance is relatively better at the longer forecast horizons. In particular, the average ratio of MSEs between good and bad forecasters at the shorter horizon is 0.75 for rates (0.74 for yields), while at the longer horizons, this ratio is 0.70 (0.61 for yields). The overall message of these findings can be summarized as follows:

Fact 1: On average, the mean squared forecast error of a forecaster who is classified as good is approximately two-thirds the size of the mean squared forecast error of a forecaster who is classified as bad.

This finding is encouraging in that it implies that the algorithm described in **Subsection 4.2** captures non-negligible differences in the forecasting abilities of good and bad forecasters within a country. The existence of such differences in our data is a pre-condition for the identification of potential differences in the forecasting formation processes of good and bad forecasters (as implied by **Claim 1** of **Section 3**) when such differences do indeed exist.

Panel B of **Table 1** reveals that the forecast errors of individual forecasters display substantial positive correlations.[14] On average, the correlation is approximately three-quarters for both interest rates and yields at both forecast horizons (3-month and 12-month). This leads to the following

Fact 2: Individual forecast errors are highly correlated among each other.

This is consistent with the model of **Section 3**. In particular, it can be shown that the model implies that the covariances between the forecast errors of different forecasters are linear combinations of σ_δ^2 and σ_η^2. The dependence on the first variance means that when there is a surprise realization of some future innovation to the state, this surprise affects all forecasters in a similar direction. The dependence on the second variance is due to the fact that all forecasters are affected by similar noisy errors in public information.

[13] Note that this MSE is calculated on the basis of the current period's forecast, $f_{i,t+h}$, rather than on preceding periods forecasts that have been used to classify forecasters as either good or bad.

[14] Correlation is calculated as the average correlation of individual forecast errors among each other per country, variable and forecast horizon (the average of the lower triangle of the correlation matrix for the individual forecast errors excluding the diagonal).

Table 1: Stylized facts – Panel A

Fact 1: *On average, a good forecaster's mean squared forecast error is less than three-quarters the size of a bad forecaster's mean squared forecast error.*

	Interest rates		**Yields**			**Interest rates**		**Yields**	
	3-month	12-month	3-month	12-month		3-month	12-month	3-month	12-month
Data set Consensus Forecasts (advanced economies)					**Data set Asian Pacific Consensus Forecasts**				
USA	0.65	0.70	0.75	0.54	AUS	0.90	0.71	0.77	0.69
JPN	0.74	0.57	0.87	0.60	CHN	0.95	0.77		
DEU	0.81	0.68	0.75	0.64	HKG	0.87	0.66		
FRA	0.88	0.80	0.80	0.61	IND	0.77	0.80	0.85	0.61
GBR	0.79	0.52	0.72	0.55	IDN	0.59	0.71	0.66	0.86
ITA	0.87	0.95	0.71	0.84	MYS	0.75	0.61		
CAN	0.75	0.72	0.57	0.53	NZL	0.73	0.66	0.75	0.62
NLD	0.86	0.81	0.74	0.58	SGP	0.82	0.59		
NOR	0.64	0.91	0.72	0.71	KOR	1.13	0.91	0.46	0.26
ESP	0.68	0.74	0.55	0.52	TWN	0.75	0.65	0.48	0.46
SWE	0.87	0.65	0.77	0.61	THA	0.83	0.55	0.63	0.59
CHE	0.64	0.66	0.63	0.60					
Data set Eastern European Consensus Forecasts					**Data set Latin American Consensus Forecasts**				
CZE	0.53	0.55	0.80	0.53	ARG	0.59	0.52		
HUN	0.65	0.73	1.05	0.64	BRA	0.67	0.96		
POL	0.75	0.74	0.86	0.70	CHL	0.60	0.84		
TUR	0.91	0.89			MEX	0.75	0.70		
SVK	0.89	0.72	0.57	0.78	VEN	0.12	0.12		
Mean	**0.75**	**0.70**	**0.74**	**0.61**					

The table shows the average ratio between good and bad forecasters' MSEs per country, variable and forecast horizon. 3-month is the 3-month forecast horizon, while 12-month indicates the 12-month forecast horizon for interest rate and yield forecasts.

Table 1: Stylized facts – Panel B

Fact 2: *Individual forecast errors are highly correlated among each other.*

	Interest rates		Yields			Interest rates		Yields	
	3-month	12-month	3-month	12-month		3-month	12-month	3-month	12-month
Data set Consensus Forecasts (advanced economies)					**Data set Asian Pacific Consensus Forecasts**				
USA	0.73	0.81	0.85	0.80	AUS	0.83	0.79	0.83	0.80
JPN	0.70	0.72	0.78	0.74	CHN	0.70	0.78		
DEU	0.78	0.82	0.85	0.85	HKG	0.84	0.80		
FRA	0.70	0.74	0.80	0.78	IND	0.75	0.76	0.75	0.61
GBR	0.78	0.81	0.81	0.75	IDN	0.58	0.80	0.79	0.76
ITA	0.67	0.78	0.76	0.80	MYS	0.61	0.72		
CAN	0.83	0.82	0.80	0.82	NZL	0.76	0.80	0.80	0.79
NLD	0.71	0.78	0.80	0.73	SGP	0.76	0.75		
NOR	0.75	0.77	0.79	0.82	KOR	0.75	0.74	0.67	0.71
ESP	0.76	0.83	0.78	0.80	TWN	0.64	0.69	0.60	0.69
SWE	0.79	0.73	0.83	0.82	THA	0.76	0.79	0.79	0.76
CHE	0.81	0.79	0.79	0.83					
Data set Eastern European Consensus Forecasts					**Data set Latin American Consensus Forecasts**				
CZE	0.70	0.74	0.78	0.76	ARG	0.65	0.74		
HUN	0.75	0.73	0.65	0.72	BRA	0.71	0.88		
POL	0.83	0.89	0.72	0.64	CHL	0.76	0.87		
TUR	0.72	0.77			MEX	0.75	0.80		
SVK	0.76	0.77	0.71	0.53	VEN	0.43	0.45		
Mean	**0.73**	**0.77**	**0.77**	**0.75**					

The table shows the average correlation of individual forecast errors among each other per country, variable and forecast horizon (the average of the lower triangle of the correlation matrix for the individual forecast errors excluding the diagonal). 3-month is the 3-month forecast horizon, while 12-month indicates the 12-month forecast horizon for interest rate and yield forecasts.

5 Empirical test of the claim in Section 3

Claim 1 in **Section 3** implies that there should be systematic differences between the way good and bad forecasters utilize private versus public information in their forecast formation. Both claims are tested in this section by means of the following empirical counterpart of **Equation (3)**

$$\begin{aligned} f_{i,t+h} &= w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} \\ &\quad + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} \\ &\quad + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h} \end{aligned} \tag{7}$$

$f_{i,t+h}$ is the individual forecast for $t+h$ formed at time t. $\bar{f}_{t-1+h}$ is the observed mean forecast at time t comprising individual forecasts $f_{i,t-1+h}$ for $t-1+h$ formed at $t-1$. Thus, $\bar{f}_{t-1+h}$ is the empirical proxy for $f_{p,t-1}$. $i \in \{G, B\}$, D_B is a dummy for bad forecasters. The dummy is devised to capture potential differences in the expectation formation processes of good and bad forecasters. It implies that the relationships between the coefficients of good and bad forecasters are given by

$$w_i^B = w_i^G + w_i^D,\ w_p^B = w_p^G + w_p^D,\ w_\theta^B = w_\theta^G + w_\theta^D \tag{8}$$

and that to the extent that the weights of good and bad forecasters significantly differ from each other, the estimates of w_i^D, w_p^D and w_θ^D should differ significantly from zero. **Equation (7)** is estimated using heteroskedastic variance estimates.[15] **Table 5** in the Appendix reports the estimated regression coefficients and some regression summary statistics. It also shows the sum of weights for good and bad forecasters. In general, this sum is very close to one, as predicted by theory, although we did not impose this restriction on the estimation procedure.[16]

Table 2 reports the weight estimates for public and private information, their significance and the t-value for those weights using the estimates from **Table 5**. One-sided t-tests on the relevant dummies are performed to check whether **Claim 1** is supported by the data. To facilitate a quick impression of the main results in the table, cases in which the claim is supported but not significant are colored light green and those that are significant heavy green. Cases that are consistent with the opposites of the claim are marked in light red when insignificant

[15] We neither cluster around forecasters nor time.

[16] Imposing the restriction of "sum 1" leads to very similar regression results. They are available upon request.

and heavy red when significant.[17] A quick glance at **Table 2** highlights the preponderance of green entries, suggesting that more often than not, the claim is at least weakly supported by the data.

Claim 1 states that good forecasters weigh their private information more heavily than bad forecasters. Using the empirical proxies above, this statement is equivalent to $\widehat{w}_i^G > \widehat{w}_i^B$ or, equivalently, $\widehat{w}_i^D < 0$.[18] As can be seen from **Table 2** for short-term interest (Panels A and B), of the 33 countries, the weights given by good forecasters to their past individual forecasts are greater than the corresponding weights by bad forecasters for 27 (28) countries at the 3-month forecast horizon (12-month forecast horizon). This is significant for 17 countries at the shorter forecast horizon and for 18 countries at the longer forecast horizon at the 5%-level (t-stat < -1.64). The opposite of **Claim 1**, that $\widehat{w}_p^G < \widehat{w}_p^B$, is significant at the 5%-level (t-stat > 1.64) only for Thailand and Hungary for the 3-month forecast horizon. At the 12-month forecast horizon, there is only one country that supports the opposite of **Claim 1** (India).

For yields (**Table 2** Panel C and Panel D), 15 (14) countries support **Claim 1** at the 3-month forecast horizon (12-month forecast horizon). This is significant at the 3-month forecast horizon for two countries (Austria and Poland) and for Switzerland at the 12-month forecast horizon (t-stat < -1.64). The opposite of **Claim 1** is statistically significant at the 5%-level for the 3-month forecast horizon only for Germany. The opposite of **Claim 1** for the 12-month forecast horizon is significant for four countries (USA, Netherlands, Sweden, and Taiwan).

Claim 1 also predicts that the sum of weights on public information of good forecasters is smaller than that of bad forecasters. That is, good forecasters weight the sum of the weights on the state and the past mean forecast less than bad forecasters, $\widehat{w}_{p+\theta}^G < \widehat{w}_{p+\theta}^B$. For interest rates at the 3-month forecast horizon, this prediction is true for most of the countries (**Table 2** Panel A and Panel B). For 20 of 33 countries (many of which are advanced economies), it is even significant at the 5% level (t-stat > 1.64). For interest rates at the 12-month forecast horizon, **Claim 1** is supported in 30 countries, of which **Claim 1** obtains significant support in 20 countries. There is no country for which the opposite of **Claim 1** – bad forecasters weight public information less than good forecasters – is significant.

For yields (**Table 2** Panel C and Panel D), the results in 19 (14) countries support the second part of **Claim 1** at the 3-month forecast horizon (12-month forecast horizon). At the shorter forecast horizon, this is significant for 10 coun-

[17] We also perform one-sided tests to check whether the opposites of **Claim 1** is occasionally significant.

[18] The hats over the weights designate estimated coefficients

tries, and at the longer forecast horizon for 7 countries. For yields at the 12-month forecast horizon, the opposite of the second part of **Claim 1** is significant only for Sweden. For the 3-month forecast horizon, we find no statistically significant support for the opposite of the second part of **Claim 1** (t-stat < -1.64).

In summary, there is, overall, non-negligible empirical support for **Claim 1**, particularly so for short-term interest rate forecasts.

We do not experiment with robustness checks using alternative autoregressive proxies for public and private information because such proxies are inconsistent with the structural model in **Section 3**. For example, an autoregressive forecast as a proxy of public information violates our assumption that the state variable follows a random walk. As another proxy, we could use adaptive expectations for individual and mean forecasts.[19] However, such proxies are only loosely connected to our benchmark model and therefore do not lead to model consistent robustness checks either.

One may argue that the allocation of forecasters into the good and bad categories is due to luck. Actually, the fact (documented in **Table 4** in the Appendix) that forecasters move in and out of those two groups relatively quickly appears to be consistent with this view. However, this observation does not interfere with the main empirical finding of the paper for the following reason. As is the case with the general public a typical forecaster normally develops a feel about her own forecasting ability in each period on the basis of her relative performance during the recent past. Since the procedure we use to classify forecasters as good or bad in period t is based on her performance during periods $t-1$ to $t-25$ it captures the forecasting ability perceptions of each forecaster about herself as well as those of the public.

[19]This is $f_{i,t-1} = \lambda_i f_{i,t-2} + (1-\lambda_i)\theta_{t-1}$ and $\bar{f}_{t-1} = \lambda_p \bar{f}_{i,t-2} + (1-\lambda_p)\theta_{t-1}$.

Table 2: Weight estimates for interest rate and yield forecasts – Panel A

Short-term interest rates

		3-month forecast horizon						12-month forecast horizon					
		Private information			Public information			Private information			Public information		
		$\widehat{w}_i^G$	$\widehat{w}_i^B$	t-stat	$\widehat{w}_{p+\theta}^G$	$\widehat{w}_{p+\theta}^B$	t-stat	$\widehat{w}_i^G$	$\widehat{w}_i^B$	t-stat	$\widehat{w}_{p+\theta}^G$	$\widehat{w}_{p+\theta}^B$	t-stat
Data set Consensus Economics (advanced economies)													
USA	Oct-89	0.77*	0.45*	**-5.72***	0.25*	0.58*	**5.73***	0.82*	0.70*	**-3.14***	0.18*	0.31*	**3.27***
JPN	Oct-89	0.68*	0.53*	**-1.85***	0.30*	0.45*	**1.86***	0.71*	0.61*	-1.35	0.27*	0.38*	1.56
DEU	Oct-89	0.81*	0.32*	**-6.64***	0.17*	0.67*	**6.68***	0.91*	0.63*	**-7.00***	0.08*	0.36*	**7.08***
FRA	Oct-89	0.83*	0.40*	**-4.83***	0.14*	0.58*	**4.92***	0.80*	0.68*	**-2.30***	0.19*	0.32*	**2.37***
GBR	Oct-89	0.80*	0.48*	**-4.10***	0.19*	0.51*	**4.09***	0.96*	0.82*	**-4.80***	0.04	0.18*	**4.85***
ITA	Oct-89	0.74*	0.32*	**-3.14***	0.24*	0.65*	**3.18***	0.81*	0.63*	**-2.50***	0.18*	0.35*	**2.40***
CAN	Oct-89	0.51*	0.36*	-1.51	0.49*	0.65*	**1.67***	0.82*	0.69*	**-2.90***	0.19*	0.32*	**2.97***
NLD	Jan-95	0.99*	0.30*	**-5.35***	0.00	0.69*	**5.30***	0.90*	0.64*	**-3.25***	0.10*	0.35*	**3.21***
NOR	Jun-98	1.10*	0.41*	**-4.05***	-0.10	0.58*	**4.03***	0.85*	0.71*	-1.46	0.14	0.28*	1.43
ESP	Jan-95	0.88*	0.25*	**-4.25***	0.11	0.74*	**4.24***	0.91*	0.54*	**-5.44***	0.09*	0.45*	**5.34***
SWE	Jan-95	0.69*	0.27*	**-4.10***	0.31*	0.72*	**4.10***	0.76*	0.67*	-1.20	0.22*	0.33*	1.57
CHE	Jun-98	0.61*	0.46*	-0.92	0.39*	0.55*	1.00	0.95*	0.72*	**-3.31***	0.03	0.28*	**3.31***
Data set Eastern European Consensus Economics													
CZE	May-98	0.97*	0.32*	**-3.80***	0.02	0.71*	**4.05***	0.84*	0.57*	**-2.48***	0.14*	0.44*	**2.80***
HUN	May-98	0.28	0.64*	**2.00***	0.70*	0.35*	**-1.95***	0.78*	0.60*	-1.38	0.20*	0.39*	1.50
POL	May-98	0.91*	0.40*	**-3.86***	0.08	0.59*	**3.77***	0.80*	0.65*	-1.58	0.19*	0.35*	1.63
TUR	May-98	0.59*	0.42*	-0.96	0.38*	0.56*	1.03	0.76*	0.63*	-1.16	0.21*	0.35*	1.18
SVK	May-98	0.63*	0.82*	1.08	0.38*	0.17*	-1.16	0.96*	0.68*	**-2.21***	0.03	0.29*	**2.12***

The table shows the estimates for the regression

$f_{i,t+h} = w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h}$

where D_B is a dummy for bad forecasters. Note that the estimates w_i^D, w_p^D, and w_θ^D are thus interaction terms. We sum private information (approximated by $f_{i,t-1+h}$) and public information (approximated by $\bar{f}_{t-1}$ and θ_t). Therefore, $\widehat{w}_i^B = \widehat{w}_i^G + \widehat{w}_i^D$, $\widehat{w}_{p+\theta}^G = \widehat{w}_p^G + \widehat{w}_\theta^G$, and $\widehat{w}_{p+\theta}^B = \widehat{w}_p^G + \widehat{w}_p^D + \widehat{w}_\theta^G + \widehat{w}_\theta^D$. A * close to these values indicates a significant coefficient at the 5% level. (See, for example, Greene (2012), p. 201, to derive their variances for hypothesis testing.) t-stat is the t-value for either $\widehat{w}_i^D$ or $\widehat{w}_p^D + \widehat{w}_\theta^D$. Light green colors indicate that the estimates are in line with our claim, while dark green colors point to significant support of our claim at the 5% level. Symmetrically, light red indicates estimates in contradiction with our claim, while dark red points to significant contradiction. We use heteroskedasticity-consistent standard errors. The regressions are estimated for interest rate and yield forecasts with 3- and 12-month forecast horizons. The time period is Oct-1989 (earliest) to Jun-2017. The start of the time period is indicated.

Table 2: Weight estimates for interest rate and yield forecasts – Panel B

Short-term interest rates

		3-month forecast horizon						12-month forecast horizon					
		Private information			Public information			Private information			Public information		
		$\widehat{w}_i^G$	$\widehat{w}_i^B$	t-stat	$\widehat{w}_{p+\theta}^G$	$\widehat{w}_{p+\theta}^B$	t-stat	$\widehat{w}_i^G$	$\widehat{w}_i^B$	t-stat	$\widehat{w}_{p+\theta}^G$	$\widehat{w}_{p+\theta}^B$	t-stat
Data set Asia Pacific Consensus Economics													
AUS	Nov-90	0.68*	0.39*	**-3.85***	0.33*	0.61*	**3.84***	0.85*	0.73*	**-2.40***	0.16*	0.27*	**2.33***
CHN	Jul-03	0.78*	0.73*	-0.43	0.22*	0.27*	0.43	1.00*	0.55*	**-4.12***	0.00	0.44*	**4.10***
HKG	Dec-94	0.79*	0.40*	**-3.10***	0.21*	0.59*	**3.04***	0.71*	0.59*	-0.72	0.28*	0.41*	0.77
IND	Dec-94	0.56*	0.54*	-0.15	0.43*	0.47*	0.24	0.85*	1.07*	**2.07***	0.16*	-0.06	**-2.09***
IDN	Dec-94	0.25	0.70*	1.39	0.68*	0.28	-1.36	1.01*	0.37	**-2.40***	-0.04	0.59	**2.07***
MYS	Dec-94	0.65*	0.44*	-1.23	0.35*	0.55*	1.24	0.98*	0.80*	**-1.85***	0.02	0.19*	**1.67***
NZL	Dec-94	0.73*	0.56*	**-1.69***	0.26*	0.44*	**1.68***	0.84*	0.63*	**-2.75***	0.16*	0.37*	**2.76***
SGP	Dec-94	0.69*	0.54*	-1.11	0.31*	0.46*	1.12	0.86*	0.79*	-1.00	0.14*	0.21*	1.05
KOR	Dec-94	0.46	0.55*	0.32	0.53*	0.44*	-0.33	0.71*	0.63*	-0.66	0.28*	0.36*	0.60
TWN	Dec-94	0.77*	0.67*	-0.72	0.22*	0.32*	0.73	0.83*	0.62*	**-2.51***	0.15*	0.39*	**2.69***
THA	Dec-94	0.17	0.65*	**2.43***	0.78*	0.32*	**-2.34***	0.60*	0.66*	0.27	0.37*	0.32	-0.24
Data set Latin American Consensus Economics													
ARG	Apr-01	0.75*	0.66*	-0.63	0.29*	0.38*	0.62	0.78*	0.81*	0.40	0.25*	0.21*	-0.45
BRA	Apr-01	0.77*	0.37*	**-2.86***	0.23*	0.63*	**2.84***	0.67*	0.71*	0.47	0.33*	0.29*	-0.48
CHL	Apr-01	1.25*	-0.20	**-6.77***	-0.25	1.20*	**6.78***	0.94*	0.62*	**-3.55***	0.05	0.37*	**3.57***
MEX	Apr-01	0.77*	0.72*	-0.50	0.24*	0.29*	0.53	0.81*	0.74*	-1.08	0.18*	0.26*	1.22
VEN	Apr-01	0.75*	0.81*	0.51	0.26*	0.21*	-0.39	0.76*	0.97*	1.38	0.25*	0.05	-1.38

The table shows the estimates for the regression
$f_{i,t+h} = w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h}$
where D_B is a dummy for bad forecasters. Note that the estimates w_i^D, w_p^D, and w_θ^D are thus interaction terms. We sum private information (approximated by $f_{i,t-1+h}$) and public information (approximated by $\bar{f}_{t-1}$ and θ_t). Therefore, $\widehat{w}_i^B = \widehat{w}_i^G + \widehat{w}_i^D$, $\widehat{w}_{p+\theta}^G = \widehat{w}_p^G + \widehat{w}_\theta^G$, and $\widehat{w}_{p+\theta}^B = \widehat{w}_p^G + \widehat{w}_p^D + \widehat{w}_\theta^G + \widehat{w}_\theta^D$. A * close to these values indicates a significant coefficient at the 5% level. (See, for example, Greene (2012), p. 201, to derive their variances for hypothesis testing.) t-stat is the t-value for either $\widehat{w}_i^D$ or $\widehat{w}_p^D + \widehat{w}_\theta^D$. Light green colors indicate that the estimates are in line with our claim, while dark green colors point to significant support of our claim at the 5% level. Symmetrically, light red indicates estimates in contradiction with our claim, while dark red points to significant contradiction. We use heteroskedasticity-consistent standard errors. The regressions are estimated for interest rate and yield forecasts with 3- and 12-month forecast horizons. The time period is Oct-1989 (earliest) to Jun-2017. The start of the time period is indicated.

Table 2: Weight estimates for interest rate and yield forecasts – Panel C

		3-month forecast horizon						12-month forecast horizon					
		Private information			Public information			Private information			Public information		
		$\widehat{w}_i^G$	$\widehat{w}_i^B$	t-stat	$\widehat{w}_{p+\theta}^G$	$\widehat{w}_{p+\theta}^B$	t-stat	$\widehat{w}_i^G$	$\widehat{w}_i^B$	t-stat	$\widehat{w}_{p+\theta}^G$	$\widehat{w}_{p+\theta}^B$	t-stat
Long-term yields													
Data set Consensus Economics (advanced economies)													
USA	Oct-89	0.59*	0.54*	-1.11	0.42*	0.47*	1.16	0.75*	0.82*	**1.88***	0.26*	0.20*	**-1.70***
JPN	Oct-89	0.65*	0.59*	-0.94	0.35*	0.41*	0.97	0.56*	0.72*	1.55	0.46*	0.31*	-1.51
DEU	Oct-89	0.56*	0.65*	**2.32***	0.44*	0.36*	**-2.34***	0.77*	0.77*	-0.19	0.23*	0.24*	0.25
FRA	Oct-89	0.59*	0.51*	-1.53	0.41*	0.49*	1.57	0.79*	0.75*	-1.05	0.21*	0.26*	1.17
GBR	Oct-89	0.64*	0.62*	-0.58	0.36*	0.39*	0.64	0.85*	0.85*	0.21	0.16*	0.16*	0.01
ITA	Oct-89	0.46*	0.53*	0.89	0.52*	0.45*	-0.88	0.74*	0.69*	-0.80	0.25*	0.30*	0.82
CAN	Oct-89	0.60*	0.59*	-0.09	0.41*	0.42*	0.13	0.83*	0.75*	-1.58	0.18*	0.26*	1.51
NLD	Jan-95	0.66*	0.70*	0.50	0.35*	0.31*	-0.52	0.69*	0.86*	**2.57***	0.32*	0.15*	**-2.57***
NOR	Jun-98	0.60*	0.63*	0.19	0.41*	0.38*	-0.17	0.79*	0.83*	0.55	0.23*	0.18*	-0.54
ESP	Jan-95	0.58*	0.58*	0.01	0.42*	0.42*	-0.01	0.77*	0.71*	-1.04	0.23*	0.29*	1.03
SWE	Jan-95	0.64*	0.61*	-0.42	0.37*	0.39*	0.32	0.65*	0.87*	**3.67***	0.37*	0.14*	**-3.57***
CHE	Jun-98	0.72*	0.63*	-1.12	0.30*	0.38*	1.00	0.92*	0.81*	**-2.28***	0.10*	0.22*	**2.30***
Data set Eastern European Consensus Economics													
CZE	May-98	0.57*	0.60*	0.16	0.43*	0.41*	-0.18	0.67*	0.63*	-0.41	0.33*	0.40*	0.79
HUN	May-98	0.71*	0.52*	-1.36	0.27*	0.46*	1.38	0.65*	0.57*	-0.58	0.33*	0.42*	0.67
POL	May-98	0.75*	0.52*	**-2.11***	0.24*	0.47*	**2.06***	0.75*	0.68*	-0.73	0.25*	0.32*	0.71
SVK	May-98	0.47*	0.67*	1.21	0.51*	0.31*	-1.28	0.72*	0.62*	-0.57	0.29*	0.38*	0.49

The table shows the estimates for the regression
$f_{i,t+h} = w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h}$
where D_B is a dummy for bad forecasters. Note that the estimates w_i^D, w_p^D, and w_θ^D are thus interaction terms. We sum private information (approximated by $f_{i,t-1+h}$) and public information (approximated by $\bar{f}_{t-1}$ and θ_t). Therefore, $\widehat{w}_i^B = \widehat{w}_i^G + \widehat{w}_i^D$, $\widehat{w}_{p+\theta}^G = \widehat{w}_p^G + \widehat{w}_\theta^G$, and $\widehat{w}_{p+\theta}^B = \widehat{w}_p^G + \widehat{w}_p^D + \widehat{w}_\theta^G + \widehat{w}_\theta^D$. A * close to these values indicates a significant coefficient at the 5% level. (See, for example, Greene (2012), p. 201, to derive their variances for hypothesis testing.) t-stat is the t-value for either $\widehat{w}_i^D$ or $\widehat{w}_p^D + \widehat{w}_\theta^D$. Light green colors indicate that the estimates are in line with our claim, while dark green colors point to significant support of our claim at the 5% level. Symmetrically, light red indicates estimates in contradiction with our claim, while dark red points to significant contradiction. We use heteroskedasticity-consistent standard errors. The regressions are estimated for interest rate and yield forecasts with 3- and 12-month forecast horizons. The time period is Oct-1989 (earliest) to Jun-2017. The start of the time period is indicated.

Table 2: Weight estimates for interest rate and yield forecasts – Panel D

Long-term yields

		3-month forecast horizon						**12-month forecast horizon**					
		Private information			Public information			Private information			Public information		
		$\widehat{w}_i^G$	$\widehat{w}_i^B$	t-stat	$\widehat{w}_{p+\theta}^G$	$\widehat{w}_{p+\theta}^B$	t-stat	$\widehat{w}_i^G$	$\widehat{w}_i^B$	t-stat	$\widehat{w}_{p+\theta}^G$	$\widehat{w}_{p+\theta}^B$	t-stat
Data set Asia Pacific Consensus Economics													
AUS	Nov-90	0.65*	0.50*	**-2.49***	0.36*	0.51*	**2.47***	0.79*	0.76*	-0.54	0.23*	0.26*	0.68
IND	Dec-94	0.72*	0.51*	-0.88	0.27*	0.48*	0.89	0.68*	0.77*	0.47	0.31	0.22*	-0.45
IDN	Dec-94	0.60*	0.49*	-0.81	0.39*	0.51*	0.90	0.82*	0.78*	-0.30	0.18*	0.22*	0.34
NZL	Dec-94	0.57*	0.62*	0.83	0.44*	0.38*	-0.85	0.81*	0.78*	-0.54	0.20*	0.23*	0.57
KOR	Dec-94	0.64*	0.64*	-0.01	0.37*	0.38*	0.03	0.49*	0.59*	0.54	0.56*	0.52*	-0.20
TWN	Dec-94	0.47*	0.46*	-0.07	0.56*	0.56*	0.01	0.63*	0.85*	**1.64***	0.47*	0.19*	**-1.82***
THA	Dec-94	0.55*	0.35	-0.81	0.46*	0.65*	0.81	0.90*	0.82*	-0.80	0.15*	0.18*	0.28

The table shows the estimates for the regression

$f_{i,t+h} = w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h}$

where D_B is a dummy for bad forecasters. Note that the estimates w_i^D, w_p^D, and w_θ^D are thus interaction terms. We sum private information (approximated by $f_{i,t-1+h}$) and public information (approximated by $\bar{f}_{t-1}$ and θ_t). Therefore, $\widehat{w}_i^B = \widehat{w}_i^G + \widehat{w}_i^D$, $\widehat{w}_{p+\theta}^G = \widehat{w}_p^G + \widehat{w}_\theta^G$, and $\widehat{w}_{p+\theta}^B = \widehat{w}_p^G + \widehat{w}_p^D + \widehat{w}_\theta^G + \widehat{w}_\theta^D$. A * close to these values indicates a significant coefficient at the 5% level. (See, for example, Greene (2012), p. 201, to derive their variances for hypothesis testing.). t-stat is the t-value for either $\widehat{w}_i^D$ or $\widehat{w}_p^D + \widehat{w}_\theta^D$. Light green colors indicate that the estimates are in line with our claim, while dark green colors point to significant support of our claim at the 5% level. Symmetrically, light red indicates estimates in contradiction with our claim, while dark red points to significant contradiction. We use heteroskedasticity-consistent standard errors. The regressions are estimated for interest rate and yield forecasts with 3- and 12-month forecast horizons. The time period is Oct-1989 (earliest) to Jun-2017. The start of the time period is indicated.

6 Concluding remarks

Utilizing a data set on interest rate forecasts of up to 33 countries created by *Consensus Economics*, this paper reports two types of results. The first concerns the impact of forecasting ability on the formation of rate forecasts by professional forecasters. The second reports some salient stylized facts in the forecasting data.

The first and main finding of the paper is that abler (or more-precise) forecasters rely more on their private information than on public information in comparison to less-able forecasters who rely relatively more on public than on their own private information. This result is implied by a standard rational expectations Bayesian framework and is supported by professional forecasting data on short-term interest rates and long-term bond yields in many countries. One implication of this result is that less-able, or "bad", forecasters tend to partially herd after more-precise, or "good", forecasters. In particular, it implies that giving a higher weight to the prior mean forecast can arise even in the absence of various strategic motives (of the type surveyed by Marinovic et al. (2013)) as a byproduct of an honest attempt by each bad forecaster to produce forecasts that are as accurate as he is able to produce given his information and ability.

The second set of results concerns two stylized facts that stand out in the data set. First, forecast errors are strongly correlated across forecasters. This is consistent with the model in this paper. The model attributes this to a combination of the following two factors: (i) It occurs when an a priori unpredictable innovation causes all forecasters to err in the same direction. (ii) This is reinforced by the fact that they are all exposed to similar noises in public information. The second stylized fact is related to the classification method used to sort forecasters into good and bad forecasters. Application of this method reveals that, on average, the mean squared forecast error of a forecaster who is classified as good is approximately two-thirds the size of the mean squared forecast error of a forecaster who is classified as bad.

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Appendix Tables 3 to 5

Table 3: Consensus Economics data sets and country codes

Consensus Forecasts (advanced economies)		**Asia Pacific Consensus Forecasts**	
USA	United States of America	AUS	Australia
JPN	Japan	CHN	China
DEU	Germany	HKG	Hong Kong
FRA	France	IND	India
GBR	United Kingdom	IDN	Indonesia
ITA	Italy	MYS	Malaysia
CAN	Canada	NZL	New Zealand
NLD	Netherlands	SGP	Singapore
NOR	Norway	KOR	South Korea
ESP	Spain	TWN	Taiwan
SWE	Sweden	THA	Thailand
CHE	Switzerland		
Eastern European Consensus Forecasts		**Latin American Consensus Forecasts**	
CZE	Czech Republic	ARG	Argentina
HUN	Hungary	BRA	Brazil
POL	Poland	CHL	Chile
TUR	Turkey	MEX	Mexico
SVK	Slovakia	VEN	Venezuela

Table 4: Descriptive statistics – Panel A short-term interest rates

Short-term interest rates

	3-month forecast horizon					12-month forecast horizon				
	T	T_i	T_G	T_B	$\bar{N}$	T	T_i	T_G	T_B	$\bar{N}$
Data set Consensus Economics (advanced economies)										
USA	301	103.2	25.7	29.3	19.2	283	98.7	25.4	28.5	18.7
JPN	301	99.3	27.6	23.9	11.5	283	91.6	22.2	21.6	10.4
DEU	301	148.9	38.4	36.7	21.4	283	146.4	38.5	35.0	21.1
FRA	301	101.2	24.4	29.1	13.4	283	97.1	24.3	27.7	13.3
GBR	301	104.0	24.4	27.9	17.5	283	105.7	24.6	25.6	17.1
ITA	301	84.2	21.2	24.6	7.9	283	81.1	22.2	25.1	7.9
CAN	301	114.7	34.6	32.3	12.3	283	114.0	32.2	32.2	12.2
NLD	238	70.6	29.3	20.3	7.0	220	67.9	22.7	25.4	7.0
NOR	197	60.8	17.4	15.4	5.9	179	60.7	15.4	15.4	5.8
ESP	238	108.3	26.8	30.7	10.3	220	103.7	23.8	31.3	10.3
SWE	238	82.9	25.0	20.4	8.7	220	82.4	22.9	21.0	8.6
CHE	197	120.4	29.2	31.0	9.3	179	114.3	29.8	26.3	9.3
Data set Eastern European Consensus Economics										
CZE	116	54.6	15.0	23.8	9.3	107	51.6	17.2	18.4	9.2
HUN	116	48.6	17.8	19.3	7.5	107	46.2	16.1	16.1	7.4
POL	117	49.6	16.1	24.8	8.7	108	47.7	14.4	18.8	8.5
TUR	117	36.3	8.8	9.2	8.0	108	32.3	11.3	9.2	7.0
SVK	117	47.8	17.3	20.8	6.4	108	45.2	17.2	18.9	6.3
Data set Asia Pacific Consensus Economics										
AUS	288	105.4	34.0	32.8	12.7	270	100.2	32.0	33.2	12.3
CHN	136	50.3	13.2	12.0	7.0	118	47.2	14.5	10.9	6.6
HKG	239	62.4	21.0	19.4	8.2	221	58.5	22.1	19.4	8.0
IND	239	38.9	10.1	7.2	4.6	191	34.0	6.9	6.3	4.4
IDN	239	38.5	6.7	7.2	4.7	187	37.3	7.5	9.2	4.6
MYS	239	54.2	15.1	16.8	7.1	221	50.9	16.4	18.7	6.9
NZL	239	106.8	35.1	39.2	10.5	221	102.7	30.5	40.7	10.4
SGP	239	61.3	18.6	15.9	6.8	221	59.4	21.4	15.4	6.7
KOR	239	67.6	22.9	24.1	7.3	220	64.6	22.2	23.4	7.4
TWN	239	55.3	18.4	23.0	6.2	221	52.7	19.5	20.8	6.4
THA	239	43.6	13.2	14.6	5.2	221	41.8	17.9	11.4	5.1
Data set Latin American Consensus Economics										
ARG	162	54.3	18.1	16.3	11.5	144	51.8	15.9	15.9	10.2
BRA	163	65.4	20.5	17.7	11.9	145	62.0	15.8	17.8	11.3
CHL	161	75.4	19.4	16.2	11.5	145	69.8	15.9	15.9	11.3
MEX	163	67.6	18.4	19.6	13.3	145	63.7	20.5	19.7	12.9
VEN	161	61.4	22.0	15.5	6.6	139	61.5	14.6	12.8	6.4

T: Total number of months in *Consensus Forecasts* sample per country.
T_i: Average number of months a forecaster remains in the sample.
T_G: Average number of months a forecaster is classified as good.
T_B: Average number of months a forecaster is classified as bad.
$\bar{N}$: Average number of forecasters used in the classification scheme per country.

Table 4: Descriptive statistics – Panel B long-term yields

Long-term yields

	3-month forecast horizon					12-month forecast horizon				
	T	T_i	T_G	T_B	$\bar{N}$	T	T_i	T_G	T_B	$\bar{N}$
Data set Consensus Economics (advanced economies)										
USA	301	104.8	31.8	29.3	19.6	283	99.0	28.5	28.5	18.7
JPN	301	113.8	29.0	28.3	13.7	283	103.6	25.0	25.7	12.2
DEU	301	152.7	39.6	39.6	21.5	283	149.8	37.4	34.8	21.1
FRA	301	99.8	25.0	27.7	13.2	283	96.3	23.4	33.1	13.1
GBR	301	96.4	26.7	23.6	16.2	283	98.3	23.6	23.6	15.6
ITA	286	78.8	21.2	24.9	7.6	277	78.2	21.0	22.7	7.6
CAN	254	100.8	32.8	37.3	12.3	245	103.0	32.5	37.2	12.1
NLD	238	70.7	25.0	23.7	6.8	220	67.9	24.3	24.3	6.7
NOR	197	54.1	13.3	16.1	5.5	179	55.9	11.1	12.5	5.6
ESP	238	104.8	26.2	27.4	9.9	220	100.5	25.0	28.9	9.9
SWE	238	87.5	23.1	24.1	9.2	220	86.6	23.1	26.6	9.2
CHE	197	129.5	36.1	28.1	9.6	179	123.1	28.4	32.5	9.5
Data set Eastern European Consensus Economics										
CZE	106	49.3	16.3	20.0	9.2	88	48.6	15.6	19.8	9.3
HUN	106	42.8	15.8	18.7	7.0	88	40.2	13.8	16.6	6.7
POL	106	45.4	14.9	14.0	8.3	88	44.0	14.5	13.4	8.2
SVK	98	47.5	13.2	14.7	5.4	88	45.6	14.0	14.0	5.3
Data set Asia Pacific Consensus Economics										
AUS	241	104.4	29.3	35.7	12.9	232	101.5	30.0	35.7	12.3
IND	107	35.2	13.4	12.4	5.7	88	31.0	13.2	14.9	5.4
IDN	104	44.7	10.0	12.2	5.2	86	40.5	8.8	8.8	5.4
NZL	239	106.8	33.5	33.5	10.5	221	103.0	38.4	34.1	10.4
KOR	34	27.1	12.0	16.0	5.3	17	23.7	9.7	14.5	5.8
TWN	72	36.9	17.2	12.9	5.6	54	37.5	16.2	11.6	5.7
THA	102	39.7	9.8	12.0	5.1	86	36.2	10.5	10.5	4.9

T: Total number of months in *Consensus Forecasts* sample per country.
T_i: Average number of months a forecaster remains in the sample.
T_G: Average number of months a forecaster is classified as good.
T_B: Average number of months a forecaster is classified as bad.
$\bar{N}$: Average number of forecasters used in the classification scheme per country.

Table 5: Regression – Panel A short-term interest rates with 3-month horizon

	$\widehat{w}_i^G$	$\widehat{w}_i^D$	$\widehat{w}_p^G$	$\widehat{w}_p^D$	$\widehat{w}_\theta^G$	$\widehat{w}_\theta^D$	T	R^2	$\sum G$	$\sum B$
Data set Consensus Economics (advanced economies)										
USA	0.77*	-0.33*	-0.22*	0.43*	0.47*	-0.10	2984	0.99	1.02	1.02
	(0.04)	(0.06)	(0.05)	(0.07)	(0.04)	(0.05)				
JPN	0.68*	-0.15	-0.06	0.24*	0.36*	-0.09	1820	0.99	0.98	0.98
	(0.05)	(0.08)	(0.05)	(0.09)	(0.04)	(0.06)				
DEU	0.81*	-0.49*	-0.09	0.51*	0.26*	-0.02	3302	0.99	0.98	0.99
	(0.06)	(0.07)	(0.07)	(0.10)	(0.04)	(0.06)				
FRA	0.83*	-0.43*	-0.04	0.57*	0.18*	-0.13*	2096	0.99	0.98	0.98
	(0.07)	(0.09)	(0.09)	(0.11)	(0.05)	(0.06)				
GBR	0.80*	-0.32*	-0.37*	0.42*	0.56*	-0.10	2730	0.99	0.99	0.99
	(0.06)	(0.08)	(0.09)	(0.12)	(0.06)	(0.09)				
ITA	0.74*	-0.42*	-0.23*	0.45*	0.46*	-0.03	1232	0.99	0.97	0.97
	(0.09)	(0.13)	(0.09)	(0.15)	(0.06)	(0.08)				
CAN	0.51*	-0.15	0.02	0.27	0.46*	-0.10	1936	0.98	1.00	1.01
	(0.09)	(0.1)	(0.12)	(0.16)	(0.07)	(0.11)				
NLD	0.99*	-0.69*	-0.35*	0.75*	0.35*	-0.06	936	0.99	1.00	0.99
	(0.10)	(0.13)	(0.11)	(0.15)	(0.06)	(0.10)				
NOR	1.10*	-0.68*	-0.49*	0.73*	0.39*	-0.05	556	0.99	1.00	1.00
	(0.14)	(0.17)	(0.14)	(0.18)	(0.09)	(0.12)				
ESP	0.88*	-0.63*	-0.03	0.59*	0.14	0.04	1288	0.99	0.99	0.99
	(0.11)	(0.15)	(0.09)	(0.16)	(0.08)	(0.10)				
SWE	0.69*	-0.42*	0.03	0.51*	0.27*	-0.09	1100	0.98	1.00	1.00
	(0.07)	(0.10)	(0.08)	(0.14)	(0.07)	(0.11)				
CHE	0.61*	-0.15	-0.33*	0.42	0.72*	-0.26	992	0.98	1.00	1.01
	(0.15)	(0.16)	(0.16)	(0.22)	(0.14)	(0.20)				
Data set Eastern European Consensus Economics										
CZE	0.97*	-0.65*	0.01	0.53*	0.01	0.16*	570	0.99	0.99	1.02
	(0.15)	(0.17)	(0.14)	(0.17)	(0.06)	(0.07)				
HUN	0.28	0.37*	0.02	-0.19	0.68*	-0.16	462	0.99	0.98	0.99
	(0.15)	(0.18)	(0.11)	(0.18)	(0.09)	(0.12)				
POL	0.91*	-0.51*	-0.12	0.63*	0.20*	-0.12	546	0.98	1.00	0.99
	(0.11)	(0.13)	(0.14)	(0.16)	(0.06)	(0.07)				
TUR	0.59*	-0.17	-0.04	0.44	0.42*	-0.26	368	0.96	0.97	0.98
	(0.13)	(0.18)	(0.19)	(0.25)	(0.14)	(0.18)				
SVK	0.63*	0.20	-0.04	-0.37	0.41*	0.16	416	0.99	1.00	0.99
	(0.16)	(0.18)	(0.12)	(0.22)	(0.14)	(0.21)				

The table shows the estimates for the regression
$f_{i,t+h} = w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h}$
where D_B is a dummy for bad forecasters. A * close to these values indicates a significant coefficient at the 5% level. We use heteroskedasticity-consistent standard errors (in parentheses). T is the number of observations in the regression. $\sum G$ and $\sum B$ show the sum of the good (G) and bad (B) agents' total weights given to their corresponding information pieces. Theory predicts it equal to 1.

Table 5: Regression – Panel B short-term interest rates with 3-month horizon

	$\widehat{w}_i^G$	$\widehat{w}_i^D$	$\widehat{w}_p^G$	$\widehat{w}_p^D$	$\widehat{w}_\theta^G$	$\widehat{w}_\theta^D$	T	R^2	$\sum G$	$\sum B$
Data set Asia Pacific Consensus Economics										
AUS	0.68*	-0.29*	-0.25*	0.32*	0.58*	-0.03	1904	0.98	1.01	1.00
	(0.05)	(0.07)	(0.07)	(0.10)	(0.05)	(0.07)				
CHN	0.78*	-0.05	0.00	0.00	0.22	0.06	526	0.95	1.00	1.00
	(0.08)	(0.12)	(0.16)	(0.21)	(0.12)	(0.17)				
HKG	0.79*	-0.39*	-0.04	0.44*	0.25*	-0.05	1048	0.98	1.00	0.99
	(0.08)	(0.13)	(0.08)	(0.13)	(0.05)	(0.06)				
IND	0.56*	-0.02	0.14	0.16	0.29*	-0.13	302	0.92	0.99	1.01
	(0.12)	(0.16)	(0.09)	(0.16)	(0.09)	(0.11)				
IDN	0.25	0.44	0.30	-0.37	0.39*	-0.04	202	0.98	0.94	0.97
	(0.27)	(0.32)	(0.22)	(0.35)	(0.11)	(0.18)				
MYS	0.65*	-0.20	-0.27*	0.22	0.62*	-0.02	908	0.98	0.99	0.99
	(0.12)	(0.17)	(0.14)	(0.22)	(0.11)	(0.17)				
NZL	0.73*	-0.18	-0.21*	0.37*	0.47*	-0.19*	1332	0.98	1.00	1.00
	(0.08)	(0.10)	(0.09)	(0.13)	(0.04)	(0.08)				
SGP	0.69*	-0.16	-0.13	-0.03	0.44*	0.18	856	0.97	1.00	1.00
	(0.09)	(0.14)	(0.09)	(0.13)	(0.09)	(0.11)				
KOR	0.46	0.09	-0.09	-0.11	0.62*	0.02	914	0.98	0.99	0.99
	(0.24)	(0.29)	(0.19)	(0.22)	(0.18)	(0.22)				
TWN	0.77*	-0.10	-0.16	0.06	0.37*	0.04	736	0.99	0.99	0.99
	(0.09)	(0.14)	(0.08)	(0.14)	(0.07)	(0.09)				
THA	0.17	0.48*	0.38*	-0.23	0.40*	-0.23	556	0.96	0.95	0.97
	(0.17)	(0.20)	(0.12)	(0.16)	(0.15)	(0.16)				
Data set Latin American Consensus Economics										
ARG	0.75*	-0.09	0.03	0.13	0.26*	-0.04	980	0.94	1.04	1.03
	(0.12)	(0.14)	(0.13)	(0.16)	(0.06)	(0.08)				
BRA	0.77*	-0.40*	0.59*	0.36*	-0.37*	0.04	1024	0.97	1.00	1.00
	(0.10)	(0.14)	(0.12)	(0.16)	(0.05)	(0.07)				
CHL	1.25*	-1.44*	-0.57*	1.46*	0.32*	-0.02	972	0.96	1.00	1.00
	(0.16)	(0.21)	(0.25)	(0.28)	(0.14)	(0.18)				
MEX	0.77*	-0.05	-0.11	-0.05	0.35*	0.10	1138	0.98	1.00	1.01
	(0.08)	(0.10)	(0.10)	(0.13)	(0.09)	(0.11)				
VEN	0.75*	0.07	-0.10	-0.01	0.36*	-0.03	528	0.90	1.01	1.02
	(0.11)	(0.13)	(0.07)	(0.15)	(0.09)	(0.14)				

The table shows the estimates for the regression
$f_{i,t+h} = w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h}$
where D_B is a dummy for bad forecasters. A * close to these values indicates a significant coefficient at the 5% level. We use heteroskedasticity-consistent standard errors (in parentheses). T is the number of observations in the regression. $\sum G$ and $\sum B$ show the sum of the good (G) and bad (B) agents' total weights given to their corresponding information pieces. Theory predicts it equal to 1.

Table 5: Regression – Panel C short-term interest rates with 12-month horizon

	$\widehat{w}_i^G$	$\widehat{w}_i^D$	$\widehat{w}_p^G$	$\widehat{w}_p^D$	$\widehat{w}_\theta^G$	$\widehat{w}_\theta^D$	T	R^2	$\sum G$	$\sum B$
Data set Consensus Economics (advanced economies)										
USA	0.82*	-0.12*	0.12*	0.15*	0.06*	-0.01	2740	0.98	1.00	1.01
	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.03)				
JPN	0.71*	-0.10	0.10*	0.22*	0.17*	-0.11	1554	0.97	0.98	1.00
	(0.05)	(0.07)	(0.05)	(0.08)	(0.04)	(0.06)				
DEU	0.91*	-0.27*	0.12*	0.28*	-0.04*	0.00	3076	0.98	0.99	0.99
	(0.02)	(0.04)	(0.03)	(0.05)	(0.01)	(0.02)				
FRA	0.80*	-0.13*	0.20*	0.18*	-0.02	-0.05	1942	0.98	0.99	1.00
	(0.04)	(0.06)	(0.05)	(0.06)	(0.02)	(0.03)				
GBR	0.96*	-0.14*	0.08*	0.14*	-0.04*	0.00	2506	0.98	1.00	1.00
	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)	(0.03)				
ITA	0.81*	-0.18*	0.16*	0.17	0.02	0.01	1154	0.99	0.99	0.98
	(0.05)	(0.07)	(0.07)	(0.09)	(0.03)	(0.04)				
CAN	0.82*	-0.13*	0.05	0.18*	0.13*	-0.04	1804	0.96	1.01	1.01
	(0.03)	(0.05)	(0.04)	(0.05)	(0.03)	(0.04)				
NLD	0.90*	-0.26*	0.12*	0.26*	-0.02	-0.01	864	0.98	1.00	0.99
	(0.04)	(0.08)	(0.06)	(0.11)	(0.05)	(0.07)				
NOR	0.85*	-0.15	0.20*	0.11	-0.06	0.03	492	0.97	0.99	0.98
	(0.07)	(0.10)	(0.10)	(0.12)	(0.05)	(0.07)				
ESP	0.91*	-0.36*	0.11*	0.41*	-0.02	-0.04	1188	0.98	1.00	1.00
	(0.04)	(0.07)	(0.04)	(0.08)	(0.04)	(0.05)				
SWE	0.76*	-0.09	0.33*	0.08	-0.12*	0.04	1008	0.96	0.97	1.00
	(0.06)	(0.07)	(0.07)	(0.09)	(0.04)	(0.05)				
CHE	0.95*	-0.24*	0.01	0.23*	0.03	0.01	894	0.97	0.99	0.99
	(0.04)	(0.07)	(0.04)	(0.08)	(0.04)	(0.05)				
Data set Eastern European Consensus Economics										
CZE	0.84*	-0.26*	0.20*	0.25*	-0.06	0.05	516	0.97	0.98	1.02
	(0.07)	(0.11)	(0.07)	(0.12)	(0.04)	(0.06)				
HUN	0.78*	-0.17	0.02	0.32*	0.18*	-0.14*	418	0.96	0.98	0.99
	(0.07)	(0.13)	(0.06)	(0.15)	(0.05)	(0.07)				
POL	0.80*	-0.15	0.27*	0.08	-0.07	0.07	490	0.95	0.99	1.00
	(0.07)	(0.10)	(0.09)	(0.12)	(0.05)	(0.08)				
TUR	0.76*	-0.14	0.14	0.20	0.07	-0.06	294	0.92	0.98	0.98
	(0.09)	(0.12)	(0.10)	(0.15)	(0.05)	(0.07)				
SVK	0.96*	-0.28*	0.05	0.34*	-0.02	-0.07	378	0.97	0.98	0.97
	(0.10)	(0.13)	(0.08)	(0.12)	(0.06)	(0.08)				

The table shows the estimates for the regression
$$f_{i,t+h} = w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h}$$
where D_B is a dummy for bad forecasters. A * close to these values indicates a significant coefficient at the 5% level. We use heteroskedasticity-consistent standard errors (in parentheses). T is the number of observations in the regression. $\sum G$ and $\sum B$ show the sum of the good (G) and bad (B) agents' total weights given to their corresponding information pieces. Theory predicts it equal to 1.

Table 5: Regression – Panel D short-term interest rates with 12-month horizon

	$\widehat{w}_i^G$	$\widehat{w}_i^D$	$\widehat{w}_p^G$	$\widehat{w}_p^D$	$\widehat{w}_\theta^G$	$\widehat{w}_\theta^D$	T	R^2	$\sum G$	$\sum B$
Data set Asia Pacific Consensus Economics										
AUS	0.85*	-0.12*	0.07	0.22*	0.09*	-0.10*	1726	0.96	1.00	1.00
	(0.03)	(0.05)	(0.04)	(0.07)	(0.03)	(0.05)				
CHN	1.00*	-0.44*	0.02	0.34*	-0.02	0.10	436	0.93	1.00	1.00
	(0.06)	(0.11)	(0.11)	(0.13)	(0.06)	(0.08)				
HKG	0.71*	-0.12	0.21*	0.19	0.07*	-0.06	930	0.96	0.99	1.00
	(0.05)	(0.16)	(0.05)	(0.17)	(0.02)	(0.04)				
IND	0.85*	0.21*	0.04	-0.15	0.12	-0.07	152	0.95	1.01	1.00
	(0.08)	(0.10)	(0.07)	(0.11)	(0.06)	(0.07)				
IDN	1.01*	-0.63*	-0.14*	0.50	0.10	0.13	166	0.95	0.97	0.96
	(0.03)	(0.26)	(0.07)	(0.26)	(0.05)	(0.20)				
MYS	0.98*	-0.18	-0.12	0.15	0.14	0.02	822	0.92	1.00	0.99
	(0.06)	(0.10)	(0.11)	(0.19)	(0.08)	(0.12)				
NZL	0.84*	-0.21*	0.16*	0.21*	0.00	0.00	1220	0.95	1.00	1.00
	(0.05)	(0.08)	(0.05)	(0.08)	(0.02)	(0.03)				
SGP	0.86*	-0.06	0.01	0.04	0.13*	0.03	772	0.95	1.00	1.00
	(0.05)	(0.07)	(0.07)	(0.09)	(0.05)	(0.07)				
KOR	0.71*	-0.08	0.07	0.23	0.21*	-0.16	842	0.96	0.99	0.99
	(0.06)	(0.12)	(0.09)	(0.14)	(0.07)	(0.13)				
TWN	0.83*	-0.22*	0.11*	0.17	0.04	0.07	664	0.98	0.98	1.00
	(0.05)	(0.09)	(0.06)	(0.10)	(0.05)	(0.09)				
THA	0.60*	0.06	0.30*	-0.29	0.07*	0.23	500	0.94	0.98	0.98
	(0.10)	(0.21)	(0.09)	(0.26)	(0.02)	(0.17)				
Data set Latin American Consensus Economics										
ARG	0.78*	0.03	0.13*	0.01	0.11	-0.05	730	0.93	1.03	1.03
	(0.06)	(0.07)	(0.07)	(0.10)	(0.06)	(0.08)				
BRA	0.67*	0.04	0.38*	-0.01	-0.05*	-0.03	854	0.93	1.00	1.00
	(0.06)	(0.08)	(0.06)	(0.09)	(0.02)	(0.03)				
CHL	0.94*	-0.32*	0.13	0.35*	-0.08*	-0.04	856	0.91	1.00	1.00
	(0.07)	(0.09)	(0.08)	(0.10)	(0.03)	(0.04)				
MEX	0.81*	-0.07	0.15*	0.09	0.03	-0.01	984	0.96	0.99	1.00
	(0.05)	(0.06)	(0.05)	(0.07)	(0.03)	(0.05)				
VEN	0.76*	0.21	0.01	0.11	0.24*	-0.31	410	0.77	1.01	1.02
	(0.08)	(0.15)	(0.05)	(0.22)	(0.10)	(0.17)				

The table shows the estimates for the regression
$f_{i,t+h} = w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h}$
where D_B is a dummy for bad forecasters. A * close to these values indicates a significant coefficient at the 5% level. We use heteroskedasticity-consistent standard errors (in parentheses). T is the number of observations in the regression. $\sum G$ and $\sum B$ show the sum of the good (G) and bad (B) agents' total weights given to their corresponding information pieces. Theory predicts it equal to 1.

Table 5: Regression – Panel E long-term yields with 3-month horizon

	$\widehat{w}_i^G$	$\widehat{w}_i^D$	$\widehat{w}_p^G$	$\widehat{w}_p^D$	$\widehat{w}_\theta^G$	$\widehat{w}_\theta^D$	T	R^2	$\sum G$	$\sum B$
Data set Consensus Economics (advanced economies)										
USA	0.59*	-0.05	-0.09*	0.19*	0.51*	-0.14*	3052	0.98	1.01	1.01
	(0.03)	(0.05)	(0.03)	(0.05)	(0.02)	(0.03)				
JPN	0.65*	-0.06	-0.07	0.09	0.41*	-0.02	2148	0.98	0.99	0.99
	(0.04)	(0.06)	(0.05)	(0.07)	(0.03)	(0.05)				
DEU	0.56*	0.09*	-0.03	-0.02	0.47*	-0.07*	3324	0.99	1.00	1.00
	(0.03)	(0.04)	(0.02)	(0.04)	(0.02)	(0.03)				
FRA	0.59*	-0.08	-0.05	0.15*	0.45*	-0.07	2052	0.99	1.00	1.00
	(0.04)	(0.05)	(0.04)	(0.06)	(0.02)	(0.04)				
GBR	0.64*	-0.02	-0.13*	0.02	0.49*	0.00	2506	0.99	1.00	1.00
	(0.03)	(0.04)	(0.03)	(0.05)	(0.02)	(0.03)				
ITA	0.46*	0.07	0.00	0.08	0.52*	-0.15*	1146	0.99	0.99	0.99
	(0.05)	(0.08)	(0.05)	(0.09)	(0.05)	(0.06)				
CAN	0.60*	-0.01	-0.14*	0.25*	0.56*	-0.24*	1642	0.98	1.01	1.01
	(0.04)	(0.07)	(0.04)	(0.09)	(0.03)	(0.05)				
NLD	0.66*	0.04	-0.08	0.02	0.43*	-0.07	900	0.98	1.01	1.00
	(0.06)	(0.08)	(0.05)	(0.09)	(0.04)	(0.05)				
NOR	0.60*	0.03	-0.04	-0.06	0.45*	0.04	452	0.98	1.01	1.01
	(0.07)	(0.14)	(0.07)	(0.14)	(0.05)	(0.08)				
ESP	0.58*	0.00	0.06	0.09	0.36*	-0.09	1204	0.94	1.00	1.00
	(0.06)	(0.09)	(0.05)	(0.09)	(0.05)	(0.06)				
SWE	0.64*	-0.03	-0.07	0.13	0.44*	-0.11*	1156	0.98	1.01	1.01
	(0.05)	(0.07)	(0.05)	(0.08)	(0.03)	(0.05)				
CHE	0.72*	-0.09	-0.11*	0.28*	0.42*	-0.20*	1012	0.98	1.02	1.01
	(0.06)	(0.08)	(0.05)	(0.09)	(0.03)	(0.05)				
Data set Eastern European Consensus Economics										
CZE	0.57*	0.02	-0.02	0.00	0.45*	-0.03	520	0.98	1.01	1.00
	(0.13)	(0.15)	(0.10)	(0.13)	(0.05)	(0.07)				
HUN	0.71*	-0.19	-0.19*	0.25	0.46*	-0.06	412	0.97	0.98	0.99
	(0.09)	(0.14)	(0.09)	(0.17)	(0.08)	(0.12)				
POL	0.75*	-0.23*	-0.14*	0.36*	0.38*	-0.13	448	0.97	1.00	0.99
	(0.08)	(0.11)	(0.07)	(0.12)	(0.06)	(0.08)				
SVK	0.47*	0.20	0.11	-0.08	0.40*	-0.12	264	0.96	0.98	0.98
	(0.10)	(0.16)	(0.08)	(0.13)	(0.07)	(0.12)				

The table shows the estimates for the regression
$f_{i,t+h} = w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h}$
where D_B is a dummy for bad forecasters. A * close to these values indicates a significant coefficient at the 5% level. We use heteroskedasticity-consistent standard errors (in parentheses). T is the number of observations in the regression. $\sum G$ and $\sum B$ show the sum of the good (G) and bad (B) agents' total weights given to their corresponding information pieces. Theory predicts it equal to 1.

Table 5: Regression – Panel F long-term yields with 3-month horizon

	$\widehat{w}_i^G$	$\widehat{w}_i^D$	$\widehat{w}_p^G$	$\widehat{w}_p^D$	$\widehat{w}_\theta^G$	$\widehat{w}_\theta^D$	T	R^2	$\sum G$	$\sum B$
Data set Asia Pacific Consensus Economics										
AUS	0.65*	-0.15*	-0.07*	0.17*	0.44*	-0.03	1640	0.97	1.01	1.01
	(0.04)	(0.06)	(0.04)	(0.06)	(0.03)	(0.04)				
IND	0.72*	-0.21	-0.43*	0.31	0.71*	-0.10	322	0.85	0.99	0.99
	(0.10)	(0.23)	(0.14)	(0.19)	(0.09)	(0.18)				
IDN	0.60*	-0.11	-0.11	0.27	0.50*	-0.15	220	0.95	0.99	1.00
	(0.09)	(0.13)	(0.08)	(0.16)	(0.08)	(0.16)				
NZL	0.57*	0.05	-0.02	0.09	0.46*	-0.14*	1338	0.97	1.01	1.01
	(0.05)	(0.06)	(0.04)	(0.07)	(0.03)	(0.05)				
KOR	0.64*	0.00	-0.27*	0.50*	0.64*	-0.49*	96	0.91	1.01	1.02
	(0.12)	(0.2)	(0.12)	(0.19)	(0.09)	(0.18)				
TWN	0.47*	-0.01	-0.11	0.58*	0.66*	-0.58*	206	0.82	1.02	1.01
	(0.13)	(0.21)	(0.12)	(0.29)	(0.11)	(0.19)				
THA	0.55*	-0.19	-0.04	0.37	0.50*	-0.18	216	0.84	1.00	1.00
	(0.12)	(0.24)	(0.11)	(0.31)	(0.09)	(0.16)				

The table shows the estimates for the regression
$f_{i,t+h} = w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h}$
where D_B is a dummy for bad forecasters. A * close to these values indicates a significant coefficient at the 5% level. We use heteroskedasticity-consistent standard errors (in parentheses). T is the number of observations in the regression. $\sum G$ and $\sum B$ show the sum of the good (G) and bad (B) agents' total weights given to their corresponding information pieces. Theory predicts it equal to 1.

Table 5: Regression – Panel G long-term yields with 12-month horizon

	$\widehat{w}_i^G$	$\widehat{w}_i^D$	$\widehat{w}_p^G$	$\widehat{w}_p^D$	$\widehat{w}_\theta^G$	$\widehat{w}_\theta^D$	T	R^2	$\sum G$	$\sum B$
Data set Consensus Economics (advanced economies)										
USA	0.75*	0.07	0.05*	0.00	0.21*	-0.06*	2736	0.97	1.01	1.01
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.02)				
JPN	0.56*	0.16	0.07	-0.02	0.40*	-0.14*	1800	0.97	1.02	1.02
	(0.1)	(0.10)	(0.08)	(0.09)	(0.05)	(0.06)				
DEU	0.77*	-0.01	0.01	0.06	0.22*	-0.05*	3066	0.98	1.01	1.01
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.02)				
FRA	0.79*	-0.04	0.02	0.11*	0.19*	-0.06	1920	0.98	1.00	1.00
	(0.03)	(0.04)	(0.03)	(0.05)	(0.02)	(0.03)				
GBR	0.85*	0.01	-0.09*	-0.06	0.24*	0.06	2268	0.98	1.00	1.01
	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)				
ITA	0.74*	-0.06	0.01	0.12	0.24*	-0.06	1090	0.98	0.99	0.99
	(0.05)	(0.07)	(0.07)	(0.10)	(0.04)	(0.06)				
CAN	0.83*	-0.08	-0.05	0.19*	0.23*	-0.12*	1562	0.97	1.01	1.01
	(0.03)	(0.05)	(0.03)	(0.07)	(0.03)	(0.04)				
NLD	0.69*	0.18*	0.07	-0.07	0.26*	-0.11*	826	0.97	1.01	1.01
	(0.06)	(0.07)	(0.05)	(0.07)	(0.03)	(0.05)				
NOR	0.79*	0.04	0.02	-0.04	0.20*	-0.01	400	0.98	1.02	1.02
	(0.06)	(0.08)	(0.05)	(0.08)	(0.04)	(0.06)				
ESP	0.77*	-0.06	0.02	0.15*	0.21*	-0.09*	1100	0.93	1.01	1.00
	(0.03)	(0.06)	(0.03)	(0.07)	(0.02)	(0.04)				
SWE	0.65*	0.23*	0.15*	-0.17*	0.22*	-0.06	1064	0.96	1.01	1.02
	(0.05)	(0.06)	(0.05)	(0.07)	(0.03)	(0.04)				
CHE	0.92*	-0.11*	-0.04	0.10	0.14*	0.02	910	0.98	1.02	1.03
	(0.03)	(0.05)	(0.03)	(0.05)	(0.02)	(0.03)				
Data set Eastern European Consensus Economics										
CZE	0.67*	-0.04	0.07	0.10	0.26*	-0.02	436	0.96	1.00	1.03
	(0.06)	(0.09)	(0.06)	(0.10)	(0.04)	(0.06)				
HUN	0.65*	-0.08	0.09	0.29	0.24*	-0.19*	332	0.94	0.98	1.00
	(0.07)	(0.14)	(0.07)	(0.17)	(0.04)	(0.07)				
POL	0.75*	-0.07	0.08	0.04	0.17*	0.03	376	0.93	1.00	1.00
	(0.07)	(0.10)	(0.07)	(0.11)	(0.05)	(0.08)				
SVK	0.72*	-0.10	0.05	0.08	0.24*	0.01	224	0.93	1.01	1.00
	(0.09)	(0.18)	(0.07)	(0.15)	(0.07)	(0.11)				

The table shows the estimates for the regression
$f_{i,t+h} = w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h}$
where D_B is a dummy for bad forecasters. A * close to these values indicates a significant coefficient at the 5% level. We use heteroskedasticity-consistent standard errors (in parentheses). T is the number of observations in the regression. $\sum G$ and $\sum B$ show the sum of the good (G) and bad (B) agents' total weights given to their corresponding information pieces. Theory predicts it equal to 1.

Table 5: Regression – Panel H long-term yields with 12-month horizon

	$\widehat{w}_i^G$	$\widehat{w}_i^D$	$\widehat{w}_p^G$	$\widehat{w}_p^D$	$\widehat{w}_\theta^G$	$\widehat{w}_\theta^D$	T	R^2	$\sum G$	$\sum B$
Data set Asia Pacific Consensus Economics										
AUS	0.79*	-0.03	-0.04	0.01	0.26*	0.02	1498	0.95	1.01	1.02
	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.04)				
IND	0.68*	0.09	0.09	-0.04	0.23*	-0.05	238	0.80	0.99	1.00
	(0.19)	(0.20)	(0.21)	(0.24)	(0.07)	(0.11)				
IDN	0.82*	-0.04	-0.19*	0.32*	0.37*	-0.28*	176	0.91	1.00	1.00
	(0.08)	(0.12)	(0.06)	(0.15)	(0.08)	(0.12)				
NZL	0.81*	-0.03	-0.01	0.05	0.21*	-0.03	1228	0.95	1.01	1.01
	(0.03)	(0.05)	(0.03)	(0.06)	(0.02)	(0.04)				
KOR	0.49*	0.11	-0.19	0.08	0.75*	-0.12	58	0.77	1.04	1.11
	(0.17)	(0.20)	(0.25)	(0.39)	(0.20)	(0.42)				
TWN	0.63*	0.22	-0.08	0.05	0.55*	-0.32	162	0.75	1.09	1.04
	(0.12)	(0.14)	(0.10)	(0.15)	(0.12)	(0.20)				
THA	0.90*	-0.08	-0.30*	0.36*	0.45*	-0.33*	168	0.91	1.05	1.00
	(0.07)	(0.1)	(0.13)	(0.15)	(0.11)	(0.13)				

The table shows the estimates for the regression
$f_{i,t+h} = w_i^G \cdot f_{i,t-1+h} + w_i^D \cdot D_B \cdot f_{i,t-1+h} + w_p^G \cdot \bar{f}_{t-1+h} + w_p^D \cdot D_B \cdot \bar{f}_{t-1+h} + w_\theta^G \cdot \theta_t + w_\theta^D \cdot D_B \cdot \theta_t + e_{i,t+h}$
where D_B is a dummy for bad forecasters. A * close to these values indicates a significant coefficient at the 5% level. We use heteroskedasticity-consistent standard errors (in parentheses). T is the number of observations in the regression. $\sum G$ and $\sum B$ show the sum of the good (G) and bad (B) agents' total weights given to their corresponding information pieces. Theory predicts it equal to 1.

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