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INTERNATIONAL EVIDENCE ON PROFESSIONAL INTEREST RATES 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 three and twelve months ahead forecasts of short term interest rates and of long term bond yields for up to 33 countries using data 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. The second part of the paper discusses and examines the cross-country relationships between measures of forecast uncertainty, dispersion of forecasts across individual forecasters and the variabilities of short term interest rates and of long term bonds. The main findings are: (i) Forecast uncertainty and dispersion are positively and significantly related across countries for both short rates and yields. (ii) A similar positive, albeit somewhat weaker, association is found between uncertainty and variability. (iii) Dispersion of short term interest rate forecasts and the variability of those rates are also positively associated. The paper also documents 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 Classification: E47, G17

Keywords: Forecasting interest rates and bond yields, impact of forecasting ability on forecast formation, cross-country relation between forecast dispersion and uncertainty.

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International evidence on professional interest rates forecasts: The impact of forecasting ability*

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November 29, 2017

Abstract

This paper develops a model of honest rational professional forecasters with different abilities and submits it to empirical verification using data on three and twelve months ahead forecasts of short term interest rates and of long term bond yields for up to 33 countries using data 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.

The second part of the paper discusses and examines the cross-country relationships between measure of forecast uncertainty, dispersion of forecasts across individual forecasters and the variabilities of short term interest rates and of long term bonds. The main findings are: (i) Forecast uncertainty and dispersion are positively and significantly related across countries for both short rates and yields. (ii) A similar positive, albeit somewhat weaker, association is found between uncertainty and variability. (iii) Dispersion of short

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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. Acccurate forecasts of future rates is obviously important for financial institutions and in particular for 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 maintainance 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 rates 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 as well as to document systematic cross country differences in forecast dispersion and forecast uncertainty. The data set includes professional forecasts of short term interest rates for 33 countries and of long term ten years bond yields for 23 countries between October 1989 and June 2017. The data consists of three months ahead and 12 months ahead forecasts for both short term interest rates and long term yields. This can be summarized by the following 2x2 matrix: three and twelve months interest rate forecasts and three and twelve months yield forecasts. The number of forecasters obviously varies across periods and countries. The average number of forecasters per country varies between a minimum of about 6 for emerging markets like India, Thailand and Indonesia and a maximum of around 24 for developed economies such as the US and Germany.

The first and main part of the paper derives a couple of hypotheses about the impact of differences in forecasting ability on the forecast formation processes of individual forecasters. The second part documents cross country differences in the variability of interest rates and bond yields, in the magnitudes of their forecast errors and in their cross sectional distributions. It also documents some systematic relations between those variables and interprets them in light of existing literature.

We start by a brief description of the first part. The, by now standard (non strategic), notion of rational expectations posits that given his 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 on 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 relation between the forecast on one hand and the three conditionning variables on the other.

The non strategic Bayesian framework above yields two basic implications that are tested empirically. The first is that forecasters with better forecasting ability assign higher weights to their private information than forecasters with lower forecasting ability. The second is that the abler or good (for short) 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.

[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 is composed of a random walk and of a white noise that cannot be observed separarately (not even expost) 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 as well as earnings per share in the finance literature. Examples are Morris & Shin (2002) and Marinovic et al. (2013).

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 for long term bond yields, the numerical differences in weights between good and bad forecasters 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.

An intriguing literature in both finance and economics (that 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 the "honest" Bayesian forecasts. Two types of deviations are identified; one that leads to herding in forecasts and the other to exageration in the opposite direction or "anti-herding" that is 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 apriori public information and the honest forecast is a weighted average of the private and of the public signal the market can infer the private signal and its accuracy from the honest forecast. As a consequence 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 that their forecasts are biased toward the prior mean and more bunched than in the honest Bayesian case. Ottaviani & Sørensen (2006*a*,*b*) show that this leads to a reputational cheap talk equilibrum (a 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

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

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

this induces forecasters to distance themselves from market consensus on the off chance of being right when few other forecasters are also right.

Since reputational cheap talk and forecasting contests exert opposite effects on honest Bayesian forecasts these forecast may actually yield 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 disgrees 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.

The second part of the paper documents the existence of positive and significant cross country relations between different measures of variability for short term interest rates and long term yields. These measures include forecast dispersion, forecasts uncertainty and variabilities of the forecasted variables. In particular, the average cross sectional distribution of short term interest rates and of long term yields' forecasts and the root mean square forecast errors are positively and significantly related across countries. For short term rates those two variables are also positively related to the standard deviation of such rates.[6] Similar, but not always significant, regularities are found for long term bond yields and forecasts.

The paper's structure follows. Section 2 presents a Bayesian model of honest forecasts and derives its implications for differences in the expectation formation processes of good and bad forecasters. Section 3 presents the data, some of its characterictics and the alogarithm used to classify forecasters into good and bad forecasting abilities' bins. Using this classification the implications derived in Section 2 are tested in Section 4. Section 5 presents evidence on cross country relations between various measures of rates and of yields variabilities. This is followed by concluding remarks. Further information about the data appears in the appendix.

2 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

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

[6]Cukierman (1984) documents similar regularities for inflationary expectations.

expectations).[7] 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 and is given by

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

θ_t is known to all forecasters in period t but the future cummulative innovations to the state, δ_{t+h}, is not and has 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

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

$\varepsilon_{i,t+h}$ and η_{t+h} are noise terms in the signals and are statistically independent of each other as well as of the cummulative innovation, δ_{t+h} to the state.[8] Since the current value of the state is known by all forcasters 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)[9]

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

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

[8] Since direct data on private signals is not avaialble 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 informtion this proxy is a noisy index of the "pure" private signal.

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

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 are the 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

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

Applying the general formula to our framework yields[10]

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

with weights

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

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

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 three months or one year. 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 $\sigma^2_{\varepsilon i}\sigma^2_{\eta}\sigma^2_{\delta}$ 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 $\sigma^2_{\delta} = 1/\tau_{\delta}$, $\sigma^2_{\varepsilon_i} = 1/\tau_{\varepsilon i}$, and $\sigma^2_{\eta} = 1/\tau_{\eta}$ 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 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 ($w_{p+\theta}$)

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

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 that 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 refered 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:

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

Equations Equation 5 and Equation 6 imply the following two hypotheses[11]

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

$$w_i^G > w_i^B$$

Claim 2 *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 less precise forcasters. The two hypotheses above are 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 get given his ability and information set.

3 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 sction 2.

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

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

3.1 Data

The data consists of short-term interest rate forecasts and long-term yield forecasts collected and maintained by *Consensus Economics*. It consists *of* monthly forecasts of short-term interest rates for 33 countries (mostly with maturity of three months) and forecasts of 10 year government bond yields for 23 countries. Table 3 in the Appendix lists the countries and their countrycodes. 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 months and 12 months. Note that, since the forecast horizons are longer than one month, three consecutive 3 months forecasts must be serially correlated. A similar statement applies to 12 months 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. Those changes have been incorporated in the data set.

3.2 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 into relatively precise (good) and relatively imprecise (bad) forecasters by means of the following alogarithm:

[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 *Merill 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 Merill Lynch*. We treat the "new" agency as a new forecaster. Third, if a forecast agency was integrated in another but the agency's name did not change, we stick with this agency. For instance, *JP Morgan* acquired *Bear Stearns*; both agencies where active 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.

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) are assigned to the basket of good forecasters in month t and the upper quarter (highest MSE) are assigned to the basket of bad forecasters in month t. Data on forecasters in the middle range of the distribution is dropped in order to capture sufficiently 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 forecaster's i lagged individual forecast, $f_{i,t-1+h}$, where the index i runs only over the good and the bad forecasters bins. This matrix provides the right-hand side variables for the estimation of Equation 3 for each of the forecasters that 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, interalia, 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.

3.3 Some characteristics of good and bad forecasters

This subsection presents some descriptive satistics 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 MSE of good and bad forecasters. It also documents substantial positive correlations between the forecast errors of different forcasters and interprets those correlations in light of the model in Section 2.

The average term a forecaster stays in the survey (T_i) is about a third to a 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 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 as 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 (MSE) of good and bad forecasters for both short term rates and long term yields for the three and twelve months forecast horizons.[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, good forecasters performance is relatively better at the longer forecast horizons. In particular, the average ratios of MSEs between good and bad forecasters at the shorter horizon are 0.75 for rates (0.74 for yields) while at the longer horizons these ratios are 0.70 (0.61 for yields). The overall message of those findings can be summarized as follows:

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

This finding is encouraging in that it implies that the the algorithm described in subsection 3.2 captures non negligible differences in the forecasting abilities

[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.

of good and bad forcasters. 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 the claims of Section 2) when such differences do indeed exist.

Panel B of Table 1 reveals that the forecast errors of individual forecasters display substantial positive correlations. On average the correlation is about 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 2. 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 of 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.

Table 1: Stylized facts – Panel A

Fact 1: *On average a good forecaster's mean squared forecast error is less than three-quarters of 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 Europe 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' MSE's 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	0.731	0.808	0.848	0.798	AUS	0.834	0.787	0.826	0.804
JPN	0.704	0.715	0.784	0.739	CHN	0.696	0.778		
DEU	0.780	0.824	0.848	0.847	HKG	0.835	0.802		
FRA	0.698	0.735	0.804	0.777	IND	0.749	0.756	0.753	0.605
GBR	0.783	0.811	0.807	0.753	IDN	0.578	0.799	0.791	0.764
ITA	0.667	0.782	0.757	0.798	MYS	0.610	0.719		
CAN	0.828	0.819	0.801	0.818	NZL	0.761	0.803	0.802	0.789
NLD	0.707	0.780	0.797	0.730	SGP	0.761	0.752		
NOR	0.747	0.772	0.790	0.823	KOR	0.750	0.740	0.674	0.712
ESP	0.763	0.831	0.778	0.804	TWN	0.637	0.692	0.601	0.690
SWE	0.791	0.727	0.827	0.817	THA	0.758	0.785	0.794	0.757
CHE	0.808	0.792	0.792	0.831					
Data set Eastern Europe Consensus Forecasts					**Data set Latin American Consensus Forecasts**				
CZE	0.695	0.735	0.782	0.756	ARG	0.654	0.741		
HUN	0.751	0.727	0.645	0.715	BRA	0.712	0.875		
POL	0.828	0.888	0.722	0.644	CHL	0.757	0.872		
TUR	0.722	0.765			MEX	0.751	0.801		
SVK	0.755	0.774	0.706	0.529	VEN	0.425	0.452		
Mean	**0.728**	**0.771**	**0.771**	**0.752**					

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.

4 Empirical test of the claims in Section 2

Claim 1 and **Claim 2** in Section 2 imply that there should be systematic differences between the way good and bad forecasters utilize private versus public information in their forecasts' formation. Both of those claims are tested in this section by means of the following empirical counterpart of Equation 3.

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

Here $i \in \{G, B\}$, D_B is a dummy for bad forecasters and $\bar{f}_{t-1+h}$ is the empirical proxy for $f_{p,t-1}$. The dummy is devised to capture potential differences in the expectation formation processes of good and bad forecasters. It implies that the relations 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. Table 2 reports the estimates, their significance and the t-value for the coefficients of the dummies.

Equation 7 is estimated using heteroskedastic variance estimates. One-sided t-tests on the relevant dummies are performed to check whether **Claim 1** and **Claim 2** are supported by the data. To facilitate a quick impression of the main results in the table cases in which a claim is supported but not significant are coloured in light green and those that are significant in heavy green. Cases that are consistent with the opposites to the claims are marked in light red when insignificant and in heavy red when significant.[14] A quick glance at Table 2 highlights the preponderance of green entries suggesting that, more often than not, the two claims are, 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 , eqivalently, $\widehat{w}_i^D < 0$.[15] As can be seen from Table 2 for short-term interest (Panel A and B), out of 33 countries, the weights given

[14] We also perform one sided tests to check whether the opposites to claims 1 and 2 are occasionally significant.

[15] The hats over the weights designate estimated coefficients

by good forecasters to their past individual forecasts are bigger 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 to 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 to **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-months forecast horizon for two countries (Austria and Poland) and for Switzerland at the 12-month forecast horizon (t-stat < -1.64). The opposite to **Claim 1** is statistically significant at the 5%-level for the 3-month forecast horizon only for Germany. The opposite to **Claim 1** for the 12-month forecast horizon is significant for four countries (USA, Netherlands, Sweden, and Taiwan).

Table 2: Regression weights 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 Europe 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, thus, are interaction terms. We sum up 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 those values indicates 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 hypotheses while dark green colors point to a significant support of our hypotheses on the 5%-level. Symmetrically, light red indicates estimates in contradiction of our hypotheses while dark red points to significant contradiction. We use heteroscedasticity-consistent standard errors. The regressions are estimated for interest rate and yield forecasts with 3 and 12-month forecast horizons. The time period is from Oct-1989 (earliest) to Jun-2017. The start of time period is indicated.

Table 2: Regression weights 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 Latina 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, thus, are interaction terms. We sum up 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 those values indicates 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 hypotheses while dark green colors point to a significant support of our hypotheses on the 5%-level. Symmetrically, light red indicates estimates in contradiction of our hypotheses while dark red points to significant contradiction. We use heteroscedasticity-consistent standard errors. The regressions are estimated for interest rate and yield forecasts with 3 and 12-month forecast horizons. The time period is from Oct-1989 (earliest) to Jun-2017. The start of time period is indicated.

Table 2: Regression weights for interest rate and yield forecasts – Panel C

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 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 Europe 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, thus, are interaction terms. We sum up 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 those values indicates 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 hypotheses while dark green colors point to a significant support of our hypotheses on the 5%-level. Symmetrically, light red indicates estimates in contradiction of our hypotheses while dark red points to significant contradiction. We use heteroscedasticity-consistent standard errors. The regressions are estimated for interest rate and yield forecasts with 3 and 12-month forecast horizons. The time period is from Oct-1989 (earliest) to Jun-2017. The start of time period is indicated.

Table 2: Regression weights 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, thus, are interaction terms. We sum up 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 those values indicates 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 hypotheses while dark green colors point to a significant support of our hypotheses on the 5%-level. Symmetrically, light red indicates estimates in contradiction of our hypotheses while dark red points to significant contradiction. We use heteroscedasticity-consistent standard errors. The regressions are estimated for interest rate and yield forecasts with 3 and 12-month forecast horizons. The time period is from Oct-1989 (earliest) to Jun-2017. The start of time period is indicated.

Claim 2 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, $\widehat{w}^G_{p+\theta} < \widehat{w}^B_{p+\theta}$. For interest rates at the 3-months forecast horizon, this prediction is true for most of the countries (Table 2 Panel A and Panel B). For 20 out 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 twelve months forecast horizon, **Claim 2** is supported in 30 countries out of which **Claim 2** obtains significant support in 20 countries. There is no country for which the opposite to **Claim 2** is significant.

For yields (Table 2 Panel C and Panel D), results in 19 (14) countries support **Claim 2** at the 3-month forecast horizon (12-month forecast horizon). At the shorter forecast horizon this is significant for 10 countries and at the longer forecast horizon for 7 countries. For yields at the 12-month forecast horizon, the opposite to **Claim 2** is significant only for Sweden. For the 3-month forecast horizon we find no statistically significant support for the opposite to **Claim 2** (t-stat < -1.64).

In summary there is, overall, non negligible empirical support for **both claims** particularly for interest rate forecasts.

5 Evidence on cross country relations between forecast dispersion, forecast uncertainty and the variability of interest rates

This section presents cross-country evidence on the relation between forecast dispersion and forecast uncertainty as well as on the cross-country relation between each of those two variables and the variablity of short term interest rates and yields.

Using data on GNP growth and inflation forecasts for the US Zarnowitz & Lambros (1987) find that forecast dispersion and forecast uncertainty are positively related. Ottaviani & Sørensen (2006*b*) report a similar regularity for GDP growth in the US. Cukierman & Wachtel (1979) report positive and significant correlations between the cross sectional variance of inflationary expectations and the variance of nominal income change in the US. A positive correlation between inflation uncertainty and the variance of nominal income change in the US is documented in Cukierman & Wachtel (1982). To our knowledge the relations

between those different types of variabilities have not been investigated across countries, nor for additional macro variables such as interest rates. This section attempts to partially fill this gap.

5.1 Interest rates' forecast dispersion versus uncertainty

Operational proxies are required to examine the relation between forecast dispersion and forecast uncertainty. The operational proxy used for the dispersion of interest rate forecasts in a given country is the average, over time, standard deviation of the cross-sectional distribution of individual forecasts. The operational proxy for forecast uncertainty is the average, over time, root mean squared forecast error. Figure 1 plots least squares regression lines between those two variables along with the individual countries' observations. The four panels of the figure correspond respectively to short term interest rate forecasts at the three and twelve months forecast horizons and to three and twelve months forecasts of long term yields on bonds. The coefficient ρ shown in each panel denotes the corresponding coefficient of correlation and the number in parenthesis next to it reports the statistical significance of ρ. In this and the subsequent two figures outlier countries have been excluded. In the presence of outliers results are generally stronger than reported here.

All four panels in Figure 1 strongly support the conclusion that there is a positive and significant cross-country association between forecast uncertainty and the dispersion of interest rate forecasts across individual forecasters. This evidence is consistent with the view that, as uncertainty about interest rates increases, consensus about the future course of interest rates diminishes. In other words in countries characterized by more uncertain short term rates and yields there will be less consensus about the future course of those variables.

5.2 Interest rates' uncertainty versus variability

Although uncertainty and variability are not synonymous it is likely that they have common elements. The reason is that part, but not all, of the variability is forecastable (Cukierman & Wachtel (1982)). The four panels of Figure 2 show the relation between our measure of interest rate forecast uncertainty and interest rates' variability for the three and twelve months forecast horizons for both short term rates and long term yields using a format identical to that of Figure 1. Variability of a rate or yield in a given country is proxied by the standard deviation of that variable over time.

Figure 1: Interest rates' forecast dispersion versus uncertainty

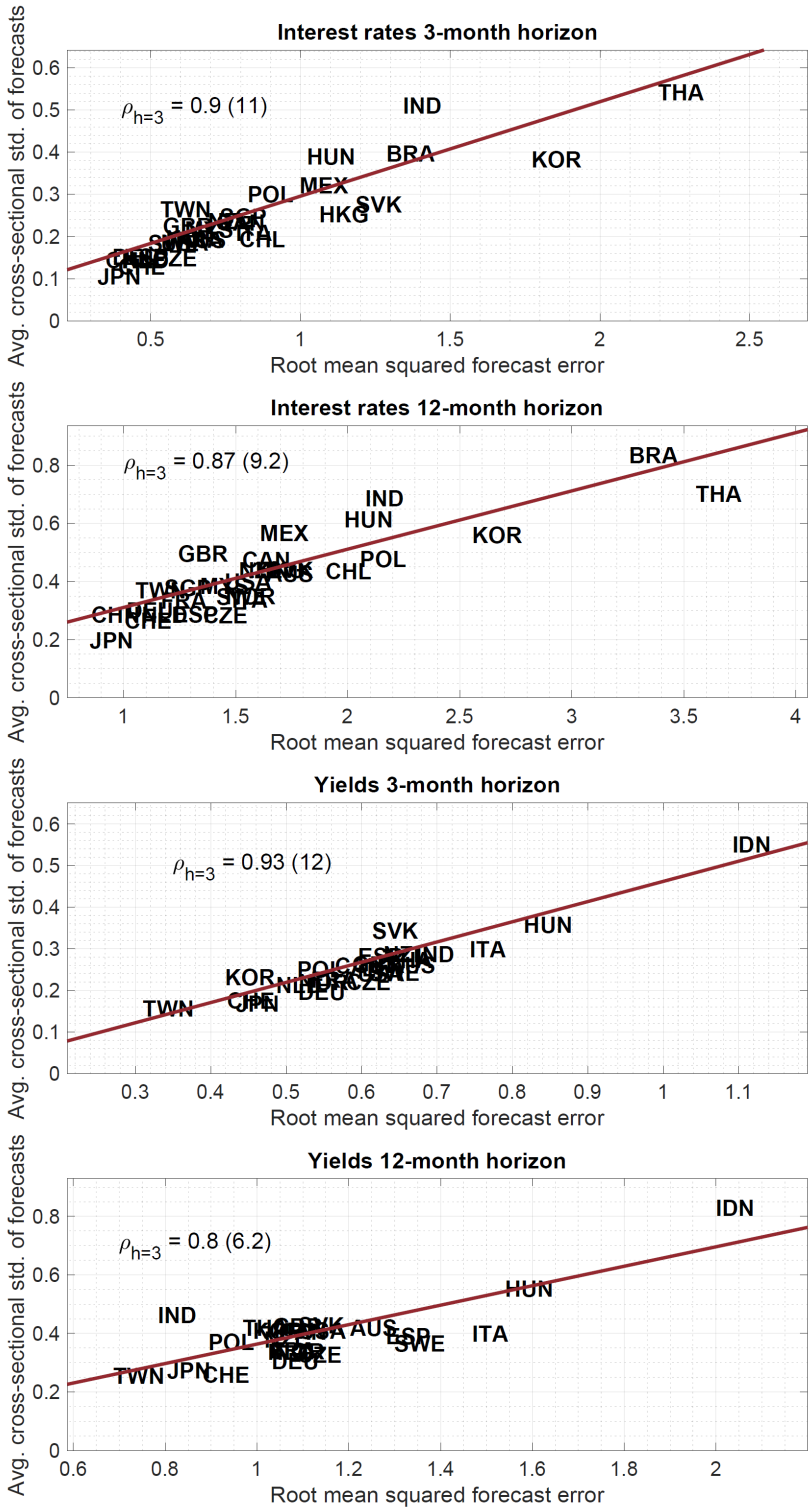
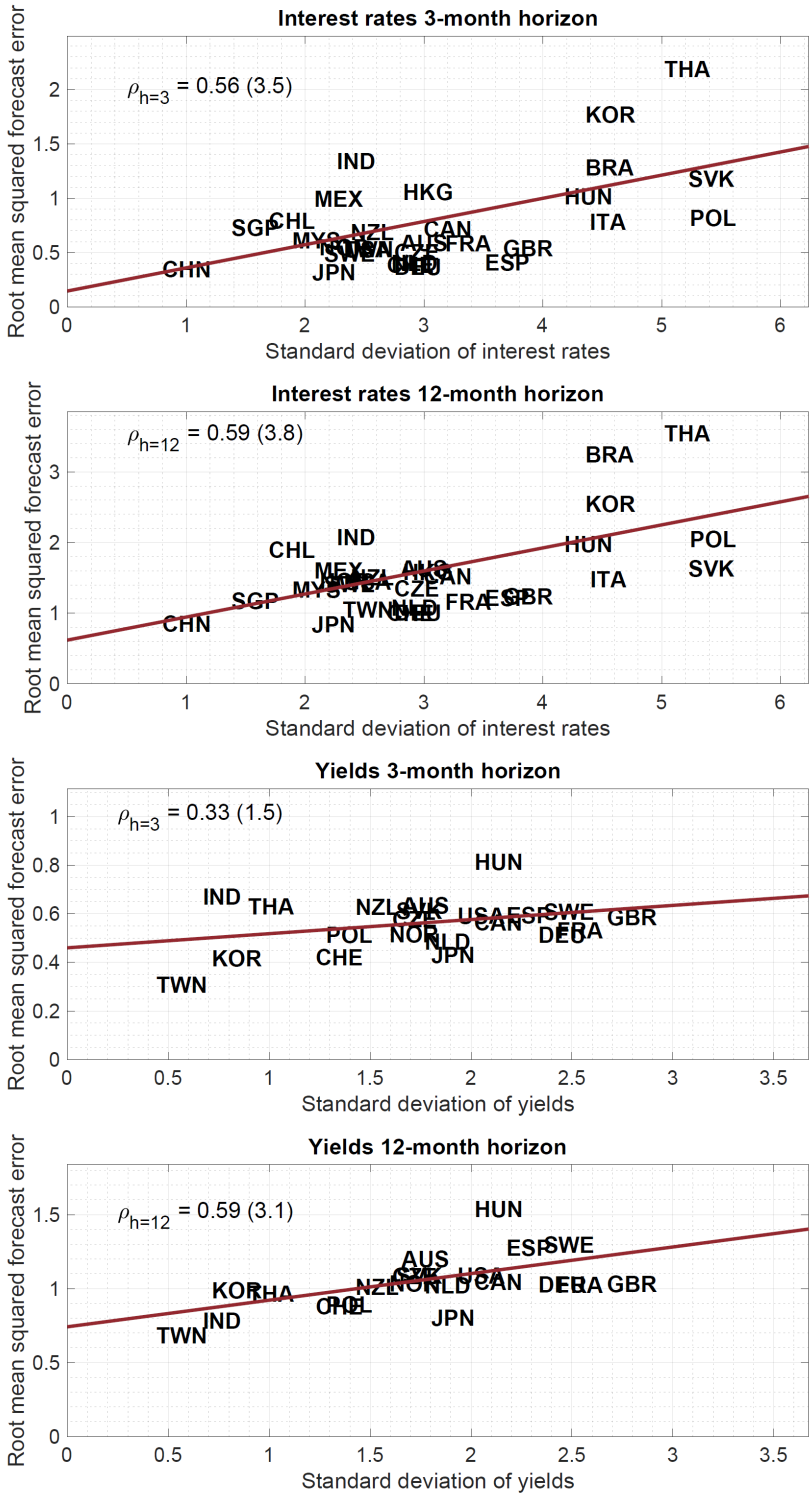


Figure 2: Interest rates' uncertainty versus variability



In all four cases the relation is positive. Excluding the case of yield forecasts at the three months horizon this relation is also significant. But the significance is not as strong as in the case of the relation between dispersion and uncertainty shown in Figure 1. This supports the view that part of the variability in rates and yields is forecastable but that the other part of variabiliy is not forecastable apriori.

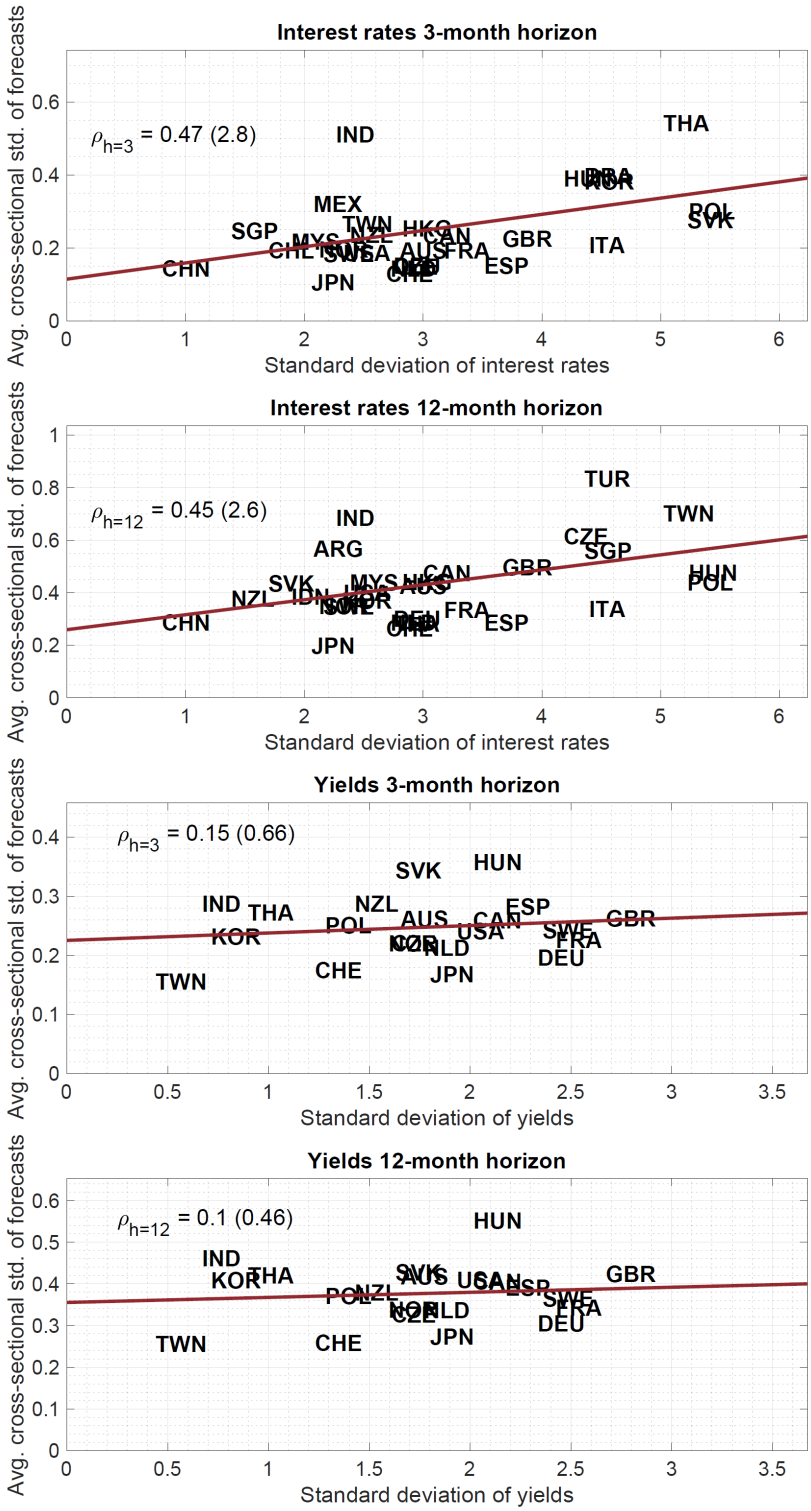
5.3 Interest rates' forecast dispersion versus variability

Figure 1 documented a relatively strong positive association between dispersion and forecast uncertainty. Figure 2 documented a, somewhat weaker, positive association between forecast uncertainty and variability. A natural third step is to also examine directly the relation between dispersion and variability. We use the same empirical proxies for those two concepts as in the previous two figures. This is done in the four panels of Figure 3 using the same formats as in the previous two figures.

Figure 3 shows that there is a small and significant positive relation between forecast dispersion for short term interest rates at both forecast horizons but no meaningful relation between those variables for long term yields. Of all the three relations investigated in this section this is the weakest.

In summary, the results reported in this section are consistent with the view that the most meaningful cross-country relation is the positive association between forecast dispersion and forecast uncertainty.

Figure 3: Interest rates' forecast dispersion versus variability



6 Concluding remarks

Utilizing a data set on interest rates forecasts of up to 33 countries created by *Consensus Economics* this paper reports three types of results. The first concerns the impact of forecasting ability on the formation of rates' forecasts by professional forecasters. The second documents cross-coutry relations between forecast uncertainty, forecast dispersion and interest rates variability. The third 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 takes it roots from literature on measures of variability, uncertainty and dispersion. Variability is often taken as a measure of uncertainty in finance and economics. But, when some of the variability is forecastable variance and uncertainty generally differ. Recognizing this difference existing literature has used two, more direct, measures of uncertainty. One is the root mean square forecast error and the other is a measure of dispersion of individual forecasts from the mean forecast. The first measure appears as the most direct measure of forecast uncertainty. The second is actually a direct measure of disagreement among forecasters rather than a direct measure of uncertainty. Nonetheless, the literature has occasionally used it as a measure of forecast uncertainty due to the existence of some evidence that it is positively related to the first measure (Zarnowitz & Lambros (1987)). Further details about the relations among these three measures of variability in the context of US inflationary expectations appears in chapter 4 of Cukierman (1984).

Availability of forecasting data for a sample of up to 33 countries makes it possible to examine the relation between these three measures of variability across countries. The data generally supports the conclusion that all the three measures above are positively related across countries for both short term interest rates and

long term bond yields at the three and twelve months forecast horizons.[16] The strongest associations is found between forecast dispersion and the root mean square forecast error providing some further support for using the former as a proxy for uncertainty. The weakest positive association found is between dispersion and variability.

The third set of results concerns two stylized facts that stand out in the data set. First, forecast errors are strongly correlated across forcasters. This is consistent with the model in this paper. The model attributes this to a combination of the following two factors: (i) When an apriori unforecastable innovation realizes all forecasters 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 that is classified as good is about two-thirds of the size of the mean squared forecast error of a forecaster that is classifieed as bad.

References

Crawford, V. P. & Sobel, J. (1982), 'Strategic Information Transmission', *Econometrica* **50**(6), 1431–1451.

Cukierman, A. (1984), *Inflation, Stagflation, Relative Prices and Imperfect Information*, Cambridge University Press Cambridge, London and New-York.

Cukierman, A. & Wachtel, P. (1979), 'Differential Inflationary Expectations and the Variability of the Rate of Inflation: Theory and Evidence', *The American Economic Review* **69**(4), 595–609.

Cukierman, A. & Wachtel, P. (1982), 'Inflationary Expectations: Reply and Further Thoughts on Inflation Uncertainty', *The American Economic Review* **72**(3), 508–512.

DeGroot, M. H. (1970), *Optimal Statistical Decisions*, McGraw-Hill, New-York, San Fransisco and London.

Greene, W. H. (2012), *Econometric Analysis*, 7th edn, Pearson Education Limited.

[16]One exception to this statement concerns the correlation between forecasts dispersion and the variability of long term yields which is not significantly different from zero.

Marinovic, I., Ottaviani, M. & Sørensen, P. (2013), 'Forecasters' Obejctives and Strategies', *Handbook of Economic Forecasting* **2**, 690 – 720.

Morris, S. & Shin, H. S. (2002), 'Social Value of Public Information', *The American Economic Review* **92**(5), 1521–1534.

Muth, J. F. (1960), 'Optimal Properties of Exponentially Weighted Forecasts', *Journal of the American Statistical Association* **55**(290), 299–306.

Ottaviani, M. & Sørensen, P. N. (2006*a*), 'Reputational cheap talk', *RAND Journal of Economics* **37**(1), 155–175.

Ottaviani, M. & Sørensen, P. N. (2006*b*), 'The strategy of professional forecasting', *Journal of Financial Economics* **81**(2), 441–466.

Scharfstein, D. S. & Stein, J. C. (1990), 'Herd behavior and investment', *The American Economic Review* **80**(3), 465–479.

Trueman, B. (1994), 'Analyst forecasts and herding behavior', *The Review of Financial Studies* **7**(1), 97–124.

Veldkamp, L. L. (2011), *Information Choice in Macroeconomics and Finance*, Princeton University Press.

Zarnowitz, V. & Lambros, L. A. (1987), 'Consensus and Uncertainty in Economic Prediction', *Journal of Political Economy* **95**(3), 591–621.

Appendix Tables 3 & 4

Table 3: Consensus Economics data sets and countrycodes

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 Europe 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 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 Eastern Europe 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 Latina 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 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
Data set Eastern Europe 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

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.