Combining Survey Forecasts and Time Series Models: The Case of the Euribor*

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Abstract

This paper reinterprets Maganelli's (2009) idea of "Forecasting with Judgment" to obtain a dynamic algorithm for combining survey data and time series models for macroeconomic forecasting. Unlike existing combination approaches which typically assign weights to alternative forecasts, the algorithm uses survey forecasts in estimating the parameter vector of a time series model. The methodology is applied to mid-term forecasts of the three-month Euribor.

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1 Introduction

During the last decade, the discipline of econometric forecasting has undergone dramatic changes. Major methodological advances have been made, among others, in the use of data at mixed sampling frequencies (Ghysels, Santa-Clara, and Valkanov (2006)), the evaluation of out-of-sample predictive ability by means of formal tests (e.g. Hansen (2005)) as well as the optimal use of large information sets. The latter strand of research includes methods from statistical learning (Hastie, Tibshirani, and Friedman (2009), Inoue and Kilian (2008)) as well as the exploitation of panel data sets with a large number of predictors (e.g. Forni, Giannone, Lippi, and Reichlin (2009)).

The idea of optimizing over available information is clearly reflected in forecast combination techniques which explicitly use forecasts from different sources. These sources can be different estimators as alternative means of processing information or forecasts based on different data sources. For example, Aiolfi and Timmermann (2006) analyze combinations of linear- and nonlinear time series models. Combinations of forecasts from time series- and survey data as two distinct sources of information have been considered by Elliott and Timmermann (2005), Aiolfi, Capistrán, and Timmermann (2010) and Wright (2010), among others. By combining several sources, one aims at averaging out idiosyncratic prediction errors and thus improve upon forecasts based on a single model. The empirical success of combinations has been demonstrated in a variety of studies during the last decades; see Timmermann (2006) for a recent review.

This paper explores a new dynamic method of combining survey- and time series forecasts. The potential advantages of survey forecasts over forecasts from time series methods are, at least theoretically, evident. Unlike time series models, experts participating in a survey are not confined to extrapolating historical patterns. If necessary, they may adopt a very short data filter and thus replace irrelevant historical information with relevant recent information. This is particularly advantageous in the presence of substantial structural breaks (e.g. Aiolfi, Capistrán, and Timmermann (2010)). The recent financial crisis is a drastic example, where due to large price changes of financial products, liquidity squeeze and subsequent government interventions, forecasting major macroeconomic aggregates using conventional time series techniques was nearly meaningless. Moreover, the information sets of experts

may contain private information and information difficult to quantify in terms of predictors. Still, the effectiveness of these potential virtues of survey data is by no means guaranteed in real-world applications. We therefore view the relative success of survey- and time series methods, as well of the potential of combinations, to be largely an empirical question.

The vast majority of forecast combination approaches considers a set of alternative predictions $\{y_{T+h|T}^j\}_{j=1,\dots,J}$, where y is the variable of interest; $T+h$ and T denote target- and origin date of the forecast, and j indexes the set of different models. In this setting, combination essentially boils down to specifying the weight ϑ_T^j of each individual model in the linear forecast combination $\sum_{j=1}^J \vartheta_T^j y_{T+h|T}^j$. The idea that different individual models should be given different weights at different points in time (i.e., that the ϑ_T^j 's should depend on T) is intuitive. In times of large structural breaks, for example, expert survey data may be preferable to time series forecasts which are likely to extrapolate outdated patterns observed from historical data. In contrast, predictions obtained from time series models may be advantageous during stable periods. Perhaps surprisingly, the implementation of this simple idea is by no means a trivial task. Many alternative dynamic specifications of the ϑ_T^j 's have been proposed in the literature; for example, Deutsch, Granger, and Teräsvirta (1994) consider weights based on past relative performance while Elliott and Timmermann (2005) analyze potential Markov Switching Regimes in the weights. Nevertheless, the finding that "simple combination schemes are hard to beat" (Timmermann (2006, p.181)) has reached the status of a stylized fact in the forecast combination literature (cf. also Jose and Winkler (2008)). The most striking example is provided by the empirical success of equally weighted averaging which sets $\vartheta_T^j = \frac{1}{J} \forall j, T$ (see Smith and Wallis (2009) and the references therein). Furthermore, a practical difficulty with modeling the combination weights ϑ_T^j is that beyond a first sample for estimating the individual models, a second sample containing out-of sample forecasts of these models is required for estimating the parameters which characterize the weights. Out-of-sample evaluation of the combined forecasts then requires a third sample of observations. Each of the three samples should contain a minimum number of observations in order to yield reliable results. This is very hard to ensure for many macroeconomic time series which are often available for short time spans and/or at low sampling frequencies. These concerns are particularly relevant for Euro area time series which are not available prior to 1999.

Motivated by the above-mentioned problems associated with modeling combination weights $\{v_T^j\}_j$ of alternative forecasts $\{y_{T+h|T}^j\}_j$, this paper explores an alternative way of combining forecasts from survey data and time series models. For this purpose, we reinterpret the idea of "forecasting with judgment" developed by Manganelli (2009) as a tool of employing "external information" in the estimation of an econometric model's parameters. More specifically, we interpret a consensus forecast obtained from survey data as external information of the kind considered by Manganelli (2009). If the consensus forecast is consistent with the parameter estimates based on time series data alone, we use it in its pure form. If it is not, we adjust it until the compromise between both sources is no longer rejected by the time series data. This approach can be interpreted as a form of shrinkage of the consensus forecast toward the forecast of a time series model. It has two attractive properties: First, it allows to produce time-varying combinations of survey data and time series models without requiring a separate sample for estimating the parameters of the combination. Second, the approach is parsimonious in that it is characterized by a single tuning parameter which governs the degree of shrinkage of the survey forecast toward the time series forecast.

We apply this approach to predict the three-month Euribor (short for "EUROpean InterBank Offered Rate"); we use expert forecasts from the "Financial Market Survey" administered by the Centre of European Economic Research (ZEW) to adjust the estimated parameters of three alternative time series models. The three-month Euribor is an indirect target of the monetary policy of the European Central Bank (ECB); as a consequence, forecasting the Euribor essentially corresponds to forecasting monetary policy. From an econometric perspective, the Euribor is an interesting object of study. Due to the impact of ECB interventions, it is subject to substantial structural instabilities which might to some degree be foreseen by financial experts participating in the ZEW survey. On the other hand, both levels and monthly changes of the Euribor display clear autocorrelation. In principle, this should be exploitable through the use of time series models.

This paper is organized as follows. In section 2, the methodology of Manganelli (2009) is adopted to combine survey data and time series models. Section 3 describes the data, and section 4 analyzes our empirical results. Section 5 concludes and gives an outlook on future research. Figures and tables are collected in an appendix.

2 Judgment Estimator

Manganelli (2009) develops an estimation approach which is based on two sources of information: Sample information $\mathbf{Y}$ used in frequentist econometric estimators,¹ and non-sample information available to the econometrician. Non-sample information - or what Manganelli (2009) terms "judgment" - is represented by the tuple $(\tilde{\theta}, 1 - \alpha)$, where $\tilde{\theta}$ is the econometrician's point guess of the econometric model's parameter vector θ , and $(1 - \alpha)$ represents the econometrician's confidence in her guess.

Denote by $\hat{\theta}$ the frequentist estimate of the model parameters that is obtained by minimizing an in-sample loss function $L(\theta, \mathbf{Y})$ (e.g. a mean squared error criterion or the negative of a likelihood function). The idea of the "judgment estimator" is to adjust the econometrician's guess $\tilde{\theta}$ towards the frequentist estimate $\hat{\theta}$ until the compromise estimate $\theta(w) = (1 - w)\tilde{\theta} + w\hat{\theta}$ incurs an in-sample loss $L(\theta(w), \mathbf{Y})$ that does not significantly exceed (at significance level α) the in-sample loss of the frequentist estimate $L(\hat{\theta}, \mathbf{Y})$. Formally the judgment estimate $\theta^* := \theta(w^*)$ of the model parameters is obtained from the following constrained optimization problem:

$$w^* = \min_w w \text{ s.t.} \tag{2.1}$$

- (1) $L(\theta(w), \mathbf{Y})$ is not significantly larger than $L(\hat{\theta}, \mathbf{Y})$,
- (2) $\theta(w) = (1 - w)\tilde{\theta} + w\hat{\theta}$,
- (3) $w \in [0; 1]$.

Put differently, the judgment estimate θ^* is the parameter vector on the segment between $\tilde{\theta}$ and $\hat{\theta}$, which (1) is at minimum distance from the parameter guess $\tilde{\theta}$ while (2) it incurs an in-sample loss that is not significantly larger than the loss at the frequentist estimate $\hat{\theta}$. The underlying idea is the following: Typically with moderately sized windows of serially dependent time series data overfitting is a serious issue.² If the parameter guess $\tilde{\theta}$ is informative then it will alleviate this issue by pulling the "overfitted frequentist estimate" towards the guess. If the parameter guess is

¹The estimation sample of frequentist estimators typically includes a history of past realizations of the variables involved in the model.

²In our view, overfitting occurs if extreme observations exert disproportionate influence on the parameter estimates. This typically occurs if large models are estimated on small windows of observations. Overfitted models typically have poor out-of-sample predictive accuracy. See Hastie, Tibshirani, and Friedman (2009, section 2.9) for an instructive discussion.

not informative then the data will pull it close to the frequentist estimate such that employing this information will do only minor harm. Under a set of regularity conditions, Manganelli shows that the judgment estimator has the same asymptotic properties as the frequentist estimator: As the frequentist estimator's variance collapses to zero, the "compromise" implies a weight of one for the frequentist estimate of the parameter vector θ .

The judgment estimator is similar to several existing approaches:

- (1) Penalized likelihood estimation (see González, Hubrich, and Teräsvirta (2009) for a recent application) maximizes the weighted sum of the log likelihood function and a term which penalizes distance to a parameter guess.
- (2) Bayesian econometrics requires prior distributions of model parameters instead of point guesses. Thus Bayesian econometrics is more demanding regarding the non-sample information available to the econometrician.
- (3) Pretest estimators are the binary counter part to the judgment estimator: If the in-sample-loss function is not significantly larger at the position of the parameter guess, then - like the judgment estimator - it opts for the parameter guess. Otherwise if the loss is statistically larger then it opts for the frequentist estimate. Thus - like for the frequentist estimator - overfitting is a severe issue.

Frequently the econometrician will not have in mind a point guess about the model's parameter vector but a (judgmental) point forecast of the relevant random variable some periods ahead. In order to apply the above methodology, Manganelli (2009) suggests to map this forecast into the parameter space of the econometric model. He proposes to obtain the image of the forecast in the parameter space by minimizing the in-sample loss function of the econometric model subject to the restriction that the parameters are such that they replicate the (non-sample) point forecast.

2.1 Application to Survey Data

We employ the judgment estimator as a novel approach of combining survey expectations data and time series models for the three-month Euribor. In particular we interpret consensus six-month ahead (point) expectations of the three-month Euri-

bor as non-sample information, which we use in the judgment estimators of three time series models.

Below we sketch the recursive procedure employed to obtain forecasts based on the judgment estimator. Classical frequentist estimates of the models are obtained by ordinary least squares. The origin dates of our forecasts are denoted $T = T_0, T_0 + 1, \dots, T_1$ where the time interval is one month (frequency of the survey). The corresponding forecasts refer to $T_0 + 6, T_0 + 7, \dots, T_1 + 6$, i.e. their forecast horizon is six months. For each origin date T and time series model:

(1.a) As suggested by Manganelli (2009), we obtain a synthetic parameter guess $\tilde{\theta}_T$ by mapping the consensus six-month ahead forecast of the three-month Euribor into the parameter space of the time series model. For this purpose we estimate the time series model by (constrained) least squares subject to the restriction that the model's six-month ahead forecast at date T (the end point of the recursive estimation window and the origin date of the corresponding consensus forecast) coincides with the consensus forecast at T . Thus we obtain the parameter vector which provides the best mean-squared-error in-sample fit under the constraint of giving the same forecast as the survey consensus at the end of the recursive estimation sample. This procedure is required because typically - if the number of model parameters exceeds one - a continuum of model parameters is compatible with a single point forecast.

(1.b) Based on the same data window we obtain an (unconstrained) estimate $\hat{\theta}_T$ of the model parameters by ordinary least squares.

(2) We test whether the parameter guess $\tilde{\theta}_T$ is compatible with the observed data. Therefore we test the null hypothesis $H_0 : \theta = \tilde{\theta}_T$ using a Wald test. The test statistic reads

$$[\hat{\theta}_T - \tilde{\theta}_T]' \hat{V} [\hat{\theta}_T]^{-1} [\hat{\theta}_T - \tilde{\theta}_T], \quad (2.2)$$

where $\hat{V} [\hat{\theta}_T]$ is an estimate of the variance-covariance matrix of the (unconstrained) estimate $\hat{\theta}_T$. Under the null hypothesis, the test statistic is asymptotically χ^2 -distributed with k degrees of freedom, where k is the dimension of θ . Above we closely follow Manganelli's interpretation of $\tilde{\theta}_T$ as the result of a mapping instead of interpreting it as an estimator. Alternatively, one may consider a test of the equal-

ity of the two estimators. In this case the difference between $\hat{\theta}_T$ and $\tilde{\theta}_T$ would be weighted by the inverse of the variance covariance matrix of the difference between the two estimators, similar to a Hausman test.³

(3.a) If the null hypothesis in (2) cannot be rejected (at significance level α) the judgment estimate is the (synthetic) parameter guess. Therefore our forecast of the three-month Euribor at $T + 6$ is the consensus forecast.⁴

(3.b) If the null hypothesis in (2) is rejected (at significance level α) we obtain the compromise parameter vector $\theta_T^* = (1 - w_T^*)\tilde{\theta}_T + w_T^*\hat{\theta}_T$ by determining the weights attached to the initial guess and the unconstrained estimate as:

$$\begin{aligned} w_T^* &= \min_{w_T} w_T \text{ s.t.} & (2.3) \\ (1) \quad & [\hat{\theta}_T - \theta(w_T)]' \hat{V} [\hat{\theta}_T]^{-1} [\hat{\theta}_T - \theta(w_T)] = \chi_{(k, 1-\alpha)}^2, \\ (2) \quad & \theta(w_T) = (1 - w_T)\tilde{\theta}_T + w_T\hat{\theta}_T, \\ (3) \quad & w_T \in [0; 1], \end{aligned}$$

where $\chi_{(k, 1-\alpha)}^2$ denotes the $(1 - \alpha) \times 100$ percent critical value of the χ^2 distribution with k degrees of freedom. Our forecast of the three-month Euribor at $T + 6$ is then computed based on the compromise parameter vector θ_T^* .

Note that for a given origin date T , the algorithm sketched above combines forecasts if and only if there is evidence of a difference between the synthetic parameter guess $\tilde{\theta}_T$ and the true parameter vector θ . If there is no evidence of a difference, $\tilde{\theta}_T$ (and thus the consensus forecast) is adopted in its pure form. The amount of evidence needed to trigger an adjustment of the consensus forecast is governed by the parameter α . A small value of α implies much confidence $(1 - \alpha)$ in the synthetic parameter guess $\tilde{\theta}_T$. Therefore ample evidence against equality of $\tilde{\theta}_T$ and θ is required to trigger an adjustment of $\tilde{\theta}_T$ (and thus of the consensus forecast). In contrast, a large value of α implies that even slight evidence against the equality of $\tilde{\theta}_T$ and θ suffices to trigger an adjustment of $\tilde{\theta}_T$. Summarizing, in practice a small value of α will typically lead to a forecast based on the judgment estimator that

³Alternatively, one may also consider a likelihood ratio version of this test which would not require the computation of the variance-covariance matrix of the difference of the two estimators. Alternatives to the test given in (2.2) will be left for future research.

⁴Recall that the synthetic parameter guess $\tilde{\theta}_T$ is estimated under the restriction that the forecast at origin T is the consensus forecast for $T + 6$.

is very similar (and often equal) to the consensus forecast; a large value of α will typically imply substantial shrinkage of the consensus forecast toward the forecast of the time series model.

This procedure is repeated for each period in the evaluation sample and for each time series model. Regarding our application, the judgment estimator can be seen as a novel approach of combining forecasts. Traditional approaches obtain the combined forecast as a weighted average of individual forecasts (cf. section 1). By contrast, the judgment estimator combines information on the parameter space of a time series model. Forecasts are then obtained with an estimated parameter vector that reflects information from the traditional frequentist sample and information from subjective expectations data. Thereby, through recursive (re-)estimation, weights display time variation. In the context of combinations at the level of individual forecasts, Timmermann (2006) observes that simple combination approaches - such as equally weighted averaging - often dominate more complex time-varying approaches. He conjectures that large uncertainty in the estimation of variance-covariance matrices of individual forecasts and realizations play a key role for the relatively poor performance of complex combination approaches (cf. also Smith and Wallis (2009)). In this regard the judgment estimator is parsimonious and thus promising: (1) It involves a single tuning parameter - α , which Manganelli interprets as the confidence of the econometrician in her point guess, and (2) the only parameters which have to be estimated are those of the time series model involved. Therefore - as opposed to traditional combination approaches - the judgment estimator does not require an extra training sample for combination weights.

In the following paragraphs we first outline the procedure by which we obtain a consensus survey forecast of the three-month Euribor, and we secondly present our time series models and show how we obtain synthetic parameter guesses (from the consensus forecasts) for each of the models.

2.2 Survey Forecasts

The individual survey forecasts used in this paper are stated as tendencies: Every month, each survey respondent reports whether she thinks that the three-month Eu-

riber is going to rise, stay the same or fall during the following six months.⁵ Thus - at each sample point in time - we need to transform a cross-section of tendency forecasts into a single consensus forecast. Many quantification methods which rely on different structural assumptions have been suggested in the literature; see Pesaran and Weale (2006) for a recent overview. In the following we employ the Carlson-Parkin approach (Carlson and Parkin (1975); henceforth CP) as a well-established quantification method. Contrary to the regression approach due to Pesaran (1984), it solely uses the cross-sectional information of the survey. In this sense, the quantified macro-forecast are "non-sample information" compared to econometric time series models.

Let $\Delta y_{t+6|t}^i$ be respondent i 's latent point forecast of the six-month change in the three-month Euribor between t and $t + 6$. The CP method assumes the following observation rule:

$$(R_{t+6|t}^i, S_{t+6|t}^i, F_{t+6|t}^i) = \begin{cases} (1, 0, 0) & \bar{\gamma}_{t+6|t} \leq \Delta y_{t+6|t}^i, \\ (0, 1, 0) & \underline{\gamma}_{t+6|t} < \Delta y_{t+6|t}^i < \bar{\gamma}_{t+6|t}, \\ (0, 0, 1) & \Delta y_{t+6|t}^i \leq \underline{\gamma}_{t+6|t}, \end{cases}$$

where $(R_{t+6|t}^i, S_{t+6|t}^i, F_{t+6|t}^i)$ ("Rise, Same, Fall") are binary variables coding respondent i 's six-month ahead directional forecast at time t . The notation reveals that we treat the thresholds $\bar{\gamma}_{t+6|t}$ and $\underline{\gamma}_{t+6|t}$ as potentially asymmetric, time-varying but cross-sectionally invariant parameters. The shares of "rise-sayers" $\bar{R}_{t+6|t}$ and "fall-sayers" $\bar{F}_{t+6|t}$ are computed as the cross-sectional means at time t of the variables $R_{t+6|t}^i$ and $F_{t+6|t}^i$ respectively.

Moreover, assume that the N_t individual forecasts $\{\Delta y_{t+6|t}^i\}_{i=1, \dots, N_t}$ at time t are independent draws from a normal distribution with mean $\mu_{t+6|t}$ and standard deviation $\sigma_{t+6|t}$. Then as $N_t \rightarrow \infty$, sampled shares approach population probabilities, i.e. the share of "Rise" responses $\bar{R}_{t+6|t}$ approaches $\Pr \left[\Delta y_{t+6|t}^i \geq \bar{\gamma}_{t+6|t} \right] = 1 - \Phi \left((\bar{\gamma}_{t+6|t} - \mu_{t+6|t}) / \sigma_{t+6|t} \right)$, while the share of "Fall" responses $\bar{F}_{t+6|t}$ approaches $\Pr \left[\Delta y_{t+6|t}^i \leq \underline{\gamma}_{t+6|t} \right] = \Phi \left((\underline{\gamma}_{t+6|t} - \mu_{t+6|t}) / \sigma_{t+6|t} \right)$, where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution.

⁵The respondents can also state that they have "no estimation". Since the share of respondents who answer in this way is never larger than four percent and equal to zero for most of the time we ignore this fraction.

Solving the resulting system of two linear equations, the CP estimator of the unknown parameter $\mu_{t+6|t}$ is given by

$$\hat{\mu}_{t+6|t}^{CP} = \frac{\bar{\gamma}_{t+6|t}\Phi^{-1}(\bar{F}_{t+6|t}) - \underline{\gamma}_{t+6|t}\Phi^{-1}(1 - \bar{R}_{t+6|t})}{\Phi^{-1}(\bar{F}_{t+6|t}) - \Phi^{-1}(1 - \bar{R}_{t+6|t})}. \quad (2.4)$$

Obviously the CP estimator above is not identified since it depends on the unknown thresholds $\bar{\gamma}_{t+6|t}$ and $\underline{\gamma}_{t+6|t}$. For our empirical application we use data from two special questionnaires collected by the data provider to estimate the thresholds.⁶

2.3 Time Series Models

This section introduces the time series models used in our empirical application and shows how to map the consensus forecast $\hat{\mu}_{T+6|T}^{CP}$ into the parameter spaces of these models. All models are estimated based on an expanding window of observations; we denote by T the time index of the last observation in the current estimation sample. In our empirical application below, T corresponds to T_0 = December 2001 in the first forecast recursion and to T_1 = January 2009 in the last recursion.⁷

Our first time series model is an AR(p) model for monthly changes in the three-month Euribor, denoted Δy_t .⁸ We recursively select the lag length p using the Schwarz information criterion. Consider the usual companion form matrices of an AR(p) process (e.g. Hamilton (1994, section 1.2)):

$$\mathbf{a} = \begin{bmatrix} a_1 & \dots & \dots & a_p \\ 1 & \bullet & \bullet & 0 \\ \vdots & \ddots & \bullet & \vdots \\ 0 & \bullet & 1 & 0 \end{bmatrix}, \quad \mathbf{a}_0 = \begin{bmatrix} a_0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad \Delta Y_T = \begin{bmatrix} \Delta y_T \\ \vdots \\ \Delta y_{T-p+1} \end{bmatrix}.$$

In order to match the survey forecast of the change of the Euribor rate during the next half year, we need $\hat{\mu}_{T+6|T}^{CP} \stackrel{!}{=} \sum_{j=1}^6 \widehat{\Delta y}_{T+j}$, where $\widehat{\Delta y}_{T+j}$ is the forecasted change of the three-month Euribor between $T+j-1$ and $T+j$, based on information up

⁶The data contains individually stated thresholds for several variables conditional on a specified level of the target variable at the time the forecast is to be stated. We estimate pooled regressions with the stated upper and lower thresholds as dependent variables and the base level of the target variable as the only linear predictor. For each time- t cross-section we then predict thresholds by the conditional mean estimates from the pooled regressions given the base level of the target variable.

⁷This implies that our estimation sample consists of 36 (121) observations in the first (last) forecast recursion.

⁸We discuss the issue of differencing the Euribor data in section 3 below.

to T .⁹ Defining $e_1 = \begin{bmatrix} 1 & \mathbf{0} & \dots & \mathbf{0} \end{bmatrix}$, we have $\widehat{\Delta y}_{T+j} = e_1 \left(\left[\mathbf{I}_p + \mathbf{a} + \dots + \mathbf{a}^{j-1} \right] \mathbf{a}_0 + \mathbf{a}^j \Delta Y_T \right)$. Consequently, the requirement that $\hat{\mu}_{T+\mathfrak{e}|T}^{CP} \stackrel{!}{=} \sum_{j=1}^{\mathfrak{e}} \widehat{\Delta y}_{T+j}$ can equivalently be stated as

$$e_1 \left(\left[\sum_{j=0}^5 (\mathfrak{e} - j) \mathbf{a}^j \right] \mathbf{a}_0 + \sum_{j=1}^{\mathfrak{e}} \mathbf{a}^j \Delta Y_T \right) \stackrel{!}{=} \hat{\mu}_{T+\mathfrak{e}|T}^{CP}. \quad (2.5)$$

Our second time series model is a trivariate VAR(1) for monthly changes of the Euribor at maturities one week, three months and one year. We denote the vector of monthly changes in the Euribor at these maturities by $\Delta \mathbf{y}_t$. In order to replicate the survey forecast, we require that the second element of the vector $\sum_{j=1}^{\mathfrak{e}} \widehat{\Delta y}_{T+j}$ be equal to the survey forecast $\hat{\mu}_{T+\mathfrak{e}|T}^{CP}$.¹⁰ Defining $e_2 = \begin{bmatrix} \mathbf{0} & 1 & \mathbf{0} \end{bmatrix}$, this implies the restriction

$$e_2 \left[\left(\sum_{j=0}^5 (\mathfrak{e} - j) A^j \right) \nu + \sum_{j=1}^{\mathfrak{e}} A^j \Delta \mathbf{y}_T \right] \stackrel{!}{=} \hat{\mu}_{T+\mathfrak{e}|T}^{CP}, \quad (2.6)$$

where ν and A denote the intercept vector and slope coefficient matrix of the VAR(1) model.

Instead of forecasting an interest rate at a single maturity or a specific set of maturities, Diebold and Li (2006) (henceforth DL) propose forecasting the (*level of the*) entire yield curve, i.e. the yield to a bond as a function of its maturity. For this purpose, they fit Nelson-Siegel polynomials to each time- t cross-section of yields at varying maturities. The polynomial has the following form:

$$y_t(\tau) = \beta_{1t} + \underbrace{\beta_{2t} \left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} \right)}_{L_1} + \underbrace{\beta_{3t} \left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau} \right)}_{L_2}, \quad (2.7)$$

where $y_t(\tau)$ denotes the Euribor with maturity τ months and β_{1t}, β_{2t} and β_{3t} are interpreted as factors determining level-, slope- and curvature of the yield curve, respectively.¹¹ Terms L_1, L_2 are maturity-specific factor loadings, and λ_t is a tuning parameter of the polynomial. DL suggest specifying this parameter such that the maturities at the middle of the maturities range load most heavily on the second

⁹For both the monthly AR forecasts $\widehat{\Delta y}_{T+j}$ and the monthly VAR forecasts $\widehat{\Delta \mathbf{y}}_{T+j}$ considered below, we suppress the origin date T to ensure readability.

¹⁰If we order the rates in $\Delta \mathbf{y}_t$ according to their maturities the second element is the three-month rate.

¹¹A slightly different alternative interpretation of $\beta_{1t}, \beta_{2t}, \beta_{3t}$ views the three quantities as long term-, short term- and medium term factors, respectively.

factor. We follow their recommendation and choose $\lambda_t \equiv \lambda$ such that it maximizes the loading on the second factor at maturity $\tau = 6$ months.¹² We then use a cross section of 13 Euribor rates at a given point in time (i.e. t fixed, τ ranging from one week to 12 months) to estimate the common factors $\beta_t = (\beta_{1t}, \beta_{2t}, \beta_{3t})'$ via least squares. This procedure is repeated for all points in time t in the estimation sample.

Equation (2.7) specifies a model for yields at a given point in time, as a function of their maturity. However, it refrains from making a statement about the relationship between yields $y_t(\tau_1)$ and $y_s(\tau_2)$ observed at different points in time $t \neq s$. For this purpose, DL suggest modeling the persistence in β_t by autoregressive models. Following their idea, we fit a VAR(1) to the sequence of cross-sectional factor estimates $\{\hat{\beta}_t\}_{t=1}^T$ corresponding to all observations of the estimation sample. We obtain a forecast of the three-month Euribor $y_t(3) \equiv y_t$ by imputing the VAR forecasts of the common factors, jointly with the fixed value for λ , into (2.7) and evaluating it at $\tau = 3$. Denoting $\hat{\beta}_t = [\hat{\beta}_{1,t} \ \hat{\beta}_{2,t} \ \hat{\beta}_{3,t}]'$, we thus have

$$\hat{\hat{\beta}}_{T+6} = \left(\sum_{j=0}^5 A_{\beta}^j \right) \nu_{\beta} + A_{\beta}^6 \hat{\beta}_T,$$

where ν_{β} and A_{β} denote the intercept vector and slope coefficient matrix of the VAR for the three factors and the "double hat" notation indicates that the forecasted vector of factors $\hat{\hat{\beta}}_{T+6}$ is estimated from generated regressors $\hat{\beta}_t, t = 1, \dots, T$.¹³ Defining

$$\delta = \left[1, \frac{1 - \exp(-3\lambda)}{3\lambda}, \frac{1 - \exp(-3\lambda)}{3\lambda} - \exp(-3\lambda) \right],$$

the requirement that the DL forecast of the six-month change in the Euribor rate be equal to the survey forecast corresponds to

$$\delta \hat{\hat{\beta}}_{T+6} - y_T \stackrel{!}{=} \hat{\mu}_{T+6|T}^{CP}. \quad (2.8)$$

3 Data

The consensus forecast is estimated from the qualitative responses to the "ZEW Financial Market Survey". This survey among financial experts is a monthly panel

¹²We obtain $\lambda \approx 0.2989$.

¹³As for the (V)AR forecasts above, we suppress the origin date T in the forecast $\hat{\hat{\beta}}_{T+6}$.

collected since December 1991. It focuses on major macroeconomic aggregates, such as economic activity and inflation, and on financial market variables, such as stock markets indices or interest rates. The primary focus of the survey is on six-month ahead predictions of the aforementioned quantities. Among the roughly 300 respondents who usually return their questionnaires in time, roughly 210 work for banks, another 40 respondents work for insurance companies, about 20 are employed as financial experts in industrial companies and the rest is employed in "other" enterprises.

To a limited extent the ZEW Financial Market Survey suffers from panel attrition and temporary non-response. In order to keep the number of cross-sectional units roughly constant new survey participants are added occasionally. The three-month Euribor is part of the survey since January 1999, when the ECB started controlling the Euro zone's monetary policy. The question with respect to the Euribor reads: [For the Eurozone] "...in the medium-term (six months) the short-term interest rates (three-month Interbank rate) will ... ☐ increase ☐ no change ☐ decrease ☐ no estimation". Figure 1 depicts the balance statistic of survey responses and actual six-month ahead changes. From eye-balling it seems that the balance statistics has a typical lead of two to four months before the actual change. Thus it often does not anticipate changes six months ahead but at shorter horizons.

The three-month Euribor is also available since the beginning of 1999. The series is highly persistent, with a first order autocorrelation of 96% and a fifth order autocorrelation of 67% in monthly rates. In line with this observation, an augmented Dickey Fuller Test (Dickey and Fuller (1979)) cannot reject the null hypothesis of a unit root with a p-value of roughly 40%. On the other hand, the KPSS test (Kwiatkowski, Phillips, Schmidt, and Shin (1992)) cannot reject the null hypothesis of stationarity with a p-value of roughly 15 %. Thus we cannot convincingly infer whether the series is stationary or not. We choose to model monthly changes in the Euribor rate in the two autoregressive specifications we consider; in contrast, the DL yield curve model by construction refers to levels of the series. Monthly changes in the Euribor still display a fair amount of persistence, with first order autocorrelation of 65% and fifth order autocorrelation of 13%. Due to this persistence we think that there is a reasonable amount of systematic variation in the series that we can exploit for time series modeling.

4 Empirical Results

Below we analyze the predictive performance of the survey predictor, the time series models as well as several bilateral combinations of the two: Dynamic combinations based on the judgment estimator, for a range of different values of the tuning parameter α , and simple equally weighted (EW) averages of survey- and time series forecasts. For brevity, we refer to combinations based on the judgment estimator as "dynamic combinations" in the following. The empirical success of equally weighted forecast averaging has been confirmed by many studies; see e.g. Timmermann (2006), Jose and Winkler (2008) and Smith and Wallis (2009). It is thus a natural benchmark for more complex combination schemes like the one considered here.¹⁴ We analyze the predictive performance of all forecasting methods in two subsamples: A pre-crisis sample which spans from June 2002 to August 2008 and the complete sample which also includes observations from September 2008 to July 2009. This split is motivated by the ECB's drastic interest rate cuts in response to the recent financial crisis (see ECB (2009)); these were hard to forecast by either method. A look at the pre-crisis sample - in addition to the complete sample - ensures that the results are not dominated by a small number of extreme observations.

Mean squared prediction errors (MSPEs) of all individual and combined forecasting methods are reported in the second column of tables 1 and 2 for the pre-crisis- and the complete sample, respectively. Furthermore, we use Diebold-Mariano (DM) tests for equal predictive ability (Diebold and Mariano (1995); West (2006)) to check whether differences in predictive performance are statistically significant. Let $(e_t^j)^2$ be the squared error made by method j in predicting the realization y_t ; we take this to be the loss incurred from method j in period t . The DM test's null hypothesis is given by $H_0 : E[d_t^{ij}] := E[(e_t^i)^2 - (e_t^j)^2] = 0$; it states that the expected loss incurred from method j equals the expected loss incurred from method i . The test statistic is obtained as the t-test statistic of an auxiliary regression of the loss differential d_t^{ij} on a constant.¹⁵ The third column of tables 1 and 2 displays DM test statistics for

¹⁴In an earlier version of this paper, the dynamic combination method was compared to the survey forecast as an individual model. This comparison is slightly misleading since it does not identify whether differences in forecast performance are due to combination *per se* or due to combination using the specific method analyzed in this paper. This question can be tackled by comparing the dynamic combination method to EW combination which is a simple combination scheme with a proven track record.

¹⁵Following West (2006), we use robust standard errors due to Newey and West (1987) and asymptotic normal critical values.

comparisons between dynamic- and EW combinations of the survey predictor and a time series model.

For both samples, the survey predictor yields a lower MSPE than the individual time series models; this is in line with the results of Nolte and Pohlmeier (2007). The ranking of the three time series models is the same for both samples: The VAR(1) outperforms AR which in turn outperforms the DL model.¹⁶

Our results regarding dynamic combinations of survey- and time series forecasts are mildly encouraging. The following main findings emerge from tables 1 and 2. First, dynamic combinations have the potential to improve upon EW combinations in terms of MSPE. For several values of α , dynamic combinations of the survey with DL significantly outperform EW combinations at the 10% and 5% levels for the pre-crisis sample. At the same time, when considering combinations of the survey with either AR or VAR, dynamic combinations are significantly outperformed by EW combinations for several choices of α . Second, and as expected, our results clearly point to the importance of the tuning parameter α . Combinations which favor the (ex post) more successful survey predictor (i.e. combinations with small values of α) have a clear tendency to perform better than combinations which favor the less successful time series models. Similarly, the relative performance of dynamic combinations vis-à-vis EW combination depends on α . While combinations using low values of α have a tendency to achieve lower MSPEs than EW combination, the converse is true for combinations using high values of α . At the same time, the latter combinations consistently achieve lower MSPEs than the time series models alone. Thus, in our application the performance of the ex post worse individual model imposes a fairly conservative lower bound on the performance of the combination using any value of α . We view this as an important positive aspect of our results since it indicates that even the ex post least favorable dynamic combination fares clearly better than the ex post worse model entering the combination.

The role of the parameter α deserves some further comment. From a mechanical

¹⁶In addition to the CP estimator of the survey consensus forecast (see section 2.2) reported in tables 1 and 2, we performed a simple regression of six-month changes in the Euribor ($y_t - y_{t-6}$) on a constant and the share of "rise-" and "fall" responses recorded at time t , $\bar{R}_{t+6|t}$ and $\bar{F}_{t+6|t}$. Compared to CP, this is a simple alternative way of quantifying the information in the survey data. The MSPEs of this regression during the pre-crisis- and complete samples are 0.167 and 0.708, respectively. Thus, the predictive performance of the regression is (1) inferior to the CP quantification method and (2) similar to that of the best time series model in both samples.

perspective, α simply sets the degree to which the survey forecast is adjusted in the direction of the time series forecast. In the absence of any economic or econometric reason why survey- or time series forecasts should be more precise *ex ante*, all values of α are on an equal footing. On the other hand, when adopting the interpretation of α as the significance level of a statistical test, choosing a value of α larger than, say, 10% is clearly at odds with common practice since "rejections" of a hypothesis at probability level exceeding 10% are typically not considered meaningful. If we focus on conventional values of $\alpha = 1\%, 5\%$ and 10% in tables 1 and 2, the performance of the new method considered here vis-à-vis EW is very satisfactory.

Summarizing, our results suggest that combining survey- and time series forecasts (be it by the EW- or the dynamic scheme) is a good strategy. First, there is a number of cases (e.g. EW combination between survey/VAR or dynamic combination of survey/DL with $\alpha \leq 0.1$ during the pre-crisis sample) in which combinations attain lower MSPEs than the survey predictor which is the *ex post* more precise individual forecasting method. Second, and perhaps more importantly, we find that both EW- and dynamic combination clearly tend to improve upon the *ex post* worse individual method. This suggests that combination is a good strategy for a risk-averse forecaster who, *ex ante*, does not know which method will perform well in the future.

In addition to analyzing its predictive performance, it may be insightful to consider the weights w_T generated by the dynamic combination approach. Figure 2 below plots w_T against the origin date T of the forecast, corresponding to a value of $\alpha = 0.05$ and all three time series models we consider. As figure 2 reveals, the weights w_T are clearly correlated both across time and across different models. The first-order autocorrelation coefficients of w_T are 0.45, 0.53 and 0.58 for the AR-, VAR- and DL models; the contemporaneous correlation between the w_T 's is 0.81 for AR/VAR, 0.35 for AR/DL and 0.33 for VAR/DL. These findings must be interpreted with caution: Since we employ an expanding window of observations, the standard errors of the time series models tend to be smaller for later periods T (*ceteris paribus*). This induces positive correlation between w_T and T since the initial (survey-implied) parameter guess tends to be rejected more frequently. Positive correlation between w_T and T , in turn, induces both autocorrelation in w_T and contemporaneous correlation in the w_T 's of different time series models. Nevertheless, the sudden increase in level and volatility of the weights depicted in figure 2 around the second half of the evaluation sample is interesting, as it suggests that survey- and

time series forecasts were harder to reconcile than at the beginning of the evaluation sample.

5 Conclusions

We reinterpret Manganelli's (2009) idea of forecasting with judgment to obtain a parsimonious dynamic algorithm for combining survey data and time series models to forecast the three-month Euribor series. Similar to existing studies (inter alia Timmermann (2006)) we find that combining forecasts is a good idea unless we have reliable ex ante information on the ex post performance of methods. First, forecast combinations typically outperform the worse predictor involved, and second, the accuracy of forecast combinations is typically more similar to the better predictor involved than to the worse.

Many studies on forecast combination (e.g. Smith and Wallis (2009)) find that simple forecast averaging is a competitive benchmark for more complex combination approaches. We show that across a wide range of values of its tuning parameter, the dynamic combination approach considered in this research shows similar forecasting accuracy as simple averaging of forecasts. As expected, values of the tuning parameter which give higher weight to the ex post better individual method tend to produce more accurate forecasts than those which give higher weight to the ex post worse method. We can imagine natural extensions to the methodology presented here:

First, the methodology (cf. equation 2.3) can be modified to account for the incremental randomness that arises since we have to estimate synthetic parameter guesses from point forecasts. The methodology applied here and in Manganelli (2009) treats the estimated parameter guess as if it arose from a deterministic mapping from forecasts to model parameters. In section 2.1 we make several suggestions how to circumvent this shortcoming.

Second, the methodology can be applied to forecasts instead of model parameters: Given a consistent estimate of the distribution of the time series model's forecast error, the test for equality of parameter vectors (cf. 2.3) can be replaced by a test for identical forecasts. Thus at first we would test whether the consensus forecast is compatible with the forecast obtained from a time series model. If we reject equal-

ity, we shrink the consensus forecast towards the time series model's forecast until equality can (just) not be rejected anymore.

Third, although contradicting the original notion of the parameter α as an (inverse) measure of confidence in non-sample information, an (in-sample) optimal parameter value could be estimated recursively. Beyond the training sample required for the estimation of a time series model, this would require an additional training sample for the tuning parameter.

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Appendix

Figure 1: Balance statistic and actual changes. The graph shows the scaled balance statistic of the tendency forecasts for the three month Euribor and the scaled six month change in the actual series. The balance statistic is obtained as the share of rise responses minus the share of fall responses. In the graph the series has been scaled by its standard deviation. The six month change in the actual series refers to the six month that follow the month which is depicted on the x-axis. Like the balance statistics it has been scaled by its standard deviation. Actual changes in the lower right corner of the lower panel are smaller than the minimum of the scale (y-axis) during eight months. For the sake of comparability we adopted the same scale as in the top panel.

Figure 2: Time series graph of weight w_T . w_T , the weight attached to the unconstrained model parameters θ_T plotted against T , the forecast origin. The graph shows w_T for $\alpha = 0.05$ and all three time series models we consider.

		MSPE	DM test stat vs. EW
survey		0.117	-
AR		0.165	-
VAR		0.146	-
DL		0.230	-
survey/AR	$\alpha = 0.01$	0.113	0.242
	$\alpha = 0.05$	0.115	0.019
	$\alpha = 0.1$	0.118	-0.277
	$\alpha = 0.25$	0.124	-0.959
	$\alpha = 0.5$	0.129	-1.458
	$\alpha = 0.75$	0.135	-1.777*
	$\alpha = 0.9$	0.144	-2.217**
	$\alpha = 0.95$	0.149	-2.406**
	$\alpha = 0.99$	0.157	-2.603***
	EW	0.115	-
survey/VAR	$\alpha = 0.01$	0.122	-1.542
	$\alpha = 0.05$	0.126	-1.833*
	$\alpha = 0.1$	0.128	-1.974**
	$\alpha = 0.25$	0.131	-2.180**
	$\alpha = 0.5$	0.134	-2.338**
	$\alpha = 0.75$	0.132	-2.550**
	$\alpha = 0.9$	0.132	-2.550**
	$\alpha = 0.95$	0.131	-2.518**
	$\alpha = 0.99$	0.130	-2.427**
	EW	0.100	-
survey/DL	$\alpha = 0.01$	0.112	1.464
	$\alpha = 0.05$	0.115	1.502
	$\alpha = 0.1$	0.116	1.529
	$\alpha = 0.25$	0.120	1.522
	$\alpha = 0.5$	0.126	1.357
	$\alpha = 0.75$	0.133	0.913
	$\alpha = 0.9$	0.141	0.224
	$\alpha = 0.95$	0.146	-0.297
	$\alpha = 0.99$	0.156	-1.111
	EW	0.143	-

Table 1: MSPEs for the pre-crisis sample. Pre-crisis sample with target dates June 2002 - August 2008 (75 observations). The table presents results for survey- and time series forecasts, as well as for bilateral dynamic combinations using the method presented in section 2 (with a range of different values for the tuning parameter α) and simple bilateral equally weighted (EW) averaging. Mean Squared Prediction Errors (MSPE) of all alternative methods and combinations are listed in the second column. Diebold-Mariano (DM) tests refer to the null hypothesis that dynamic combinations of the survey and a particular time series model have equal predictive ability as EW averaging of the same two methods; the relevant loss function is the squared prediction error. The third column reports the value of the DM test statistic; a positive (negative) value of the statistic indicates that dynamic combinations incur lower (higher) in-sample loss than EW averaging. One, two and three stars indicate significant rejections of equal predictive ability at the 10%, 5% and 1% levels.

		MSPE	DM test stat vs. EW
survey		0.611	-
AR		0.774	-
VAR		0.706	-
DL		1.010	-
survey/AR	$\alpha = 0.01$	0.651	0.645
	$\alpha = 0.05$	0.658	0.225
	$\alpha = 0.1$	0.666	-0.269
	$\alpha = 0.25$	0.682	-1.059
	$\alpha = 0.5$	0.704	-1.408
	$\alpha = 0.75$	0.723	-1.501
	$\alpha = 0.9$	0.741	-1.613
	$\alpha = 0.95$	0.751	-1.673*
	$\alpha = 0.99$	0.763	-1.744*
	EW	0.661	-
survey/VAR	$\alpha = 0.01$	0.607	0.390
	$\alpha = 0.05$	0.611	0.308
	$\alpha = 0.1$	0.616	0.156
	$\alpha = 0.25$	0.626	-0.221
	$\alpha = 0.5$	0.636	-0.843
	$\alpha = 0.75$	0.642	-1.532
	$\alpha = 0.9$	0.647	-1.951*
	$\alpha = 0.95$	0.649	-2.020**
	$\alpha = 0.99$	0.656	-2.067**
	EW	0.621	-
survey/DL	$\alpha = 0.01$	0.624	1.844*
	$\alpha = 0.05$	0.645	1.908*
	$\alpha = 0.1$	0.659	1.952*
	$\alpha = 0.25$	0.683	2.035**
	$\alpha = 0.5$	0.712	2.110**
	$\alpha = 0.75$	0.742	1.913*
	$\alpha = 0.9$	0.770	0.247
	$\alpha = 0.95$	0.787	-0.769
	$\alpha = 0.99$	0.820	-1.512
	EW	0.774	-

Table 2: MSPEs for the complete sample. Complete sample with target dates June 2002 - July 2009 (86 observations). All descriptions stated below table 1 apply.