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# 1 Introduction

During the last decades, major central banks have extended the communication of their prospective actions and tried to speak more clearly about their intentions. These efforts witness the view that the essence of central bank policy is the art of managing expectations (cf. Blinder, Ehrmann, Fratzscher, De Haan, and Jansen (2008)). In line with this literature, Nolte and Pohlmeier (2007) find that popular time-series models fail to outperform aggregate survey expectations from a panel of finance professionals in predicting six month ahead the three months Euribor. The three months Euribor – which is short for "EURopean InterBank Offered Rate" - 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.

We take Nolte and Pohlmeier's finding as a starting point to analyze whether time-series based models for interest rates are uninformative conditional on the information extracted from a survey panel administered by the Centre for European Economic Research (ZEW). We adopt the methodology proposed by Manganelli (2009) to combine survey expectations with econometric models. The idea is to interpret aggregate survey expectations as a prior belief, available before the estimation of the econometric model. We map the prior belief into the parameter space of the econometric model to obtain a parameter vector reflecting the prior beliefs. Then we estimate the econometric model and test whether the null hypothesis that the true parameter vector is equal to the one implied by prior beliefs. If we cannot reject, then we forecast with the prior beliefs parameter vector. Otherwise we adjust the parameter vector hypothesized under the null in the direction of the unrestricted parameter vector until we are no longer able to reject the null hypothesis. Then we use this parameter vector to forecast.

In line with the literature's finding of a steady increase in central bank transparency, we find that survey forecasts generally outperform time series forecasts of the Euribor. Moreover, we observe that Manganelli combined forecasts generally perform equally well as survey forecasts. In some instances, we even find that a combination can significantly outperform survey forecasts. Therefore, there seems to be the potential for us to help finance professionals to improve their forecasts.

Interestingly, the relationship between survey- and time series information appears to be of dynamic nature. While there are phases in which both sources are broadly consistent with each other (i.e., survey-implied parameter vectors are not rejected by the data), there are also clusters of time points for which all econometric models are inconsistent with the survey data. In particular, survey expectations during the recent financial crisis cannot be reconciled with the time series models we consider.

# 2 Individual Forecasting Methods

The individual forecasting methods we use include (1) a method to infer a consensus forecast of the three month Euribor from a cross-section of directional forecasts and (2) several time-series models.

## 2.1 Survey Quantification

The survey forecasts used in this research are stated as tendencies: Every month, each survey respondent reports whether she thinks that the short term interest rate is going to rise, stay the same or fall during the following six months. Since we want to compare survey forecasts to time series-based forecasts and realizations, we are not interested in a cross-section of individual tendency forecasts but in a single number that reflects the mean level forecast of the Euribor. Therefore we need to 'quantify' each time $t$ cross-section of tendency forecasts.

Let $\widehat{\Delta y}^{i}_{t,t+6}$ be respondent $i$'s unobserved forecast of the 6-month change in the three months Euribor $y_t$. The Carlson and Parkin (1975) quantification approach assumes the following observation rule:

$$(R^i_{t,t+6}, S^i_{t,t+6}, F^i_{t,t+6}) = \begin{cases} (1,0,0) & \overline{\gamma}_{t,t+6} \leq \widehat{\Delta y}^i_{t,t+6}, \\ (0,1,0) & \underline{\gamma}_{t,t+6} < \widehat{\Delta y}^i_{t,t+6} < \overline{\gamma}_{t,t+6}, \\ (0,0,1) & \widehat{\Delta y}^i_{t,t+6} \leq -\underline{\gamma}_{t+6|t}, \end{cases}$$

where $(R^i_{t,t+6}, S^i_{t,t+6}, F^i_{t,t+6})$ contains respondent $i$'s 6-month ahead directional forecast at time $t$. The notation reveals that we think of the thresholds $\overline{\gamma}_{t,t+6}$ and $\underline{\gamma}_{t,t+6}$ as potentially asymmetric, time-varying but cross-sectionally invariant parameters. The shares of 'rise-sayers' $R_{t,t+6}$ and 'fall-sayers' $F_{t,t+6}$ are computed as the the cross-sectional means at time $t$ of the variables $R^i_{t,t+6}$ and $F^i_{t,t+6}$ respectively.

Suppose we assume that the individual forecasts $\{\widehat{\Delta y}^i_{t,t+6}\}_{(i=1,\ldots,N_t)}$ are i.i.d. draws from a Normal distribution with mean $\mu_{t,t+6}$ and standard deviation $\sigma_{t,t+6}$. Then as $N_t \to \infty$, sampled shares approach population probabilities: The share of "Rise" responses $R_{t,t+6}$ approaches $P(\widehat{\Delta y}^i_{t,t+6} \geq \overline{\gamma}_{t,t+6}) = 1 - \Phi(\overline{\gamma}_{t,t+6} - \mu_{t,t+6}/\sigma_{t,t+6})$, while the share of "Fall" responses $F_{t,t+6}$ approaches $P(\widehat{\Delta y}^i_{t,t+6} \leq -\underline{\gamma}_{t,t+6}) \equiv \Phi(-\underline{\gamma}_{t,t+6} - \mu_{t,t+6}/\sigma_{t,t+6})$, where $\Phi(\cdot)$ denotes the cdf of the standard normal distribution.

Therefore, by solving the two asymptotic limits of the response shares for the unknown parameter $\mu_{t,t+6}$, we obtain

$$\mu_{t,t+6} = \frac{\overline{\gamma}_{t,t+6}\Phi^{-1}(F_{t,t+6}) + \underline{\gamma}_{t,t+6}\Phi^{-1}(1 - R_{t,t+6})}{\Phi^{-1}(F_{t,t+6}) - \Phi^{-1}(1 - R_{t,t+6})},$$

which is a valid approximation for $N_t$ sufficiently large. Hence only the thresholds $\overline{\gamma}_{t,t+6}$ and $\underline{\gamma}_{t,t+6}$ are unknown. We use data from two special questionnaires raised by the data provider (the ZEW, Mannheim) to infer thresholds. The threshold data contain 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 actual level of the target variable. We restrict our toolkit for survey quantification to this simple method since alternative methods - e.g. the method of Pesaran (1987) - would require us to impose restrictions on the rationality of the survey respondents forecasts.[1]

## 2.2 Time-series Based Models

We estimate three time-series based models: A univariate autoregression with $p$ lags of the dependent variable, a vector autoregression containing Euribor information at three maturities, and a model of the entire Euribor yield curve as proposed by Diebold and Li (2006). All models are estimated based on an expanding window of observations.

Both autoregressive models are based on monthly changes of the Euribor rate. For the univariate (AR) model, we recursively determine the lag length $p$ via the Schwarz information criterion. For the multivariate (VAR) model, we fix a lag length of one in order to avoid excessive uncertainty in estimating the parameters. Beneath changes of the 3-month Euribor rate (which is the quantity to be forecast), the VAR includes monthly changes of the 1-week and 1-year Euribor rates.

Instead of forecasting a single maturity or a discrete multitude of maturities of an interest rate, Diebold and Li (2006) propose to forecast the (*level of the*) entire yield curve. They fit a Nelson-Siegel poly-

[1] An assumption which usually needs to be imposed for identification in the Pesaran approach can be termed 'unbiasedness of the generated expectations over the sample period' (see Pesaran and Weale (2006)).

nomial to each time-$t$ cross-section of yields. The polynomial has the following form:

$$y_t(\tau) = \beta_{1t} + \beta_{2t} \underbrace{\left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau}\right)}_{A} + \beta_{3t} \underbrace{\left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau}\right)}_{B}, \tag{1}$$

where $\tau$ denotes the maturity, $\beta_{1t}, \beta_{2t}, \beta_{3t}$ are interpreted as common level, slope and curvature factors and terms $A, B$ are maturity-specific factor loadings. $\lambda_t$ is a tuning parameter of the polynomial.

Diebold and Li suggest to specify the parameter such that the maturities at the middle of the maturities range load most heavily on the second 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. We can now use the cross section of Euribor rates at a given point (i.e. $t$ fixed, $\tau$ varying) to estimate the common factors $\beta_t = (\beta_{1t}, \beta_{2t}, \beta_{3t})'$ via least squares. This procedure is repeated for all time points $t$ in the estimation sample.

Instead of modeling the dynamics in the interest rates at different maturities directly, Diebold and Li propose to model the dynamics in the (estimated) common factors. Following their idea, we fit a VAR(1) to the sequence of trivariate factor estimates $\hat{\beta}_t$ corresponding to all estimation sample observations. We obtain a Diebold-Li forecast by imputing the VAR forecasts of the common factors, jointly with the fixed value for $\lambda$ into (1) and evaluating it at $\tau = 3$.

# 3 Manganelli's Approach to "Forecasting with Judgement"

The (unknown) processes generating individual survey forecasts are likely to differ substantially from the processes postulated by statistical models. This heterogeneity renders combinations of expert- and time series information promising. However, owing partly to the "black box" character of survey expectations, there is no obvious way in which survey- and time series data might be combined.

Our goal is hence to avoid placing arbitrary parametric structure on the link between survey- and time series information. Therefore, we tackle the combination task at hand by reinterpreting the methodology proposed by Manganelli (2009). This methodology formalizes the use of prior information in the context of classical econometric inference. In our application, we interpret the (Carlson-Parkin based) survey forecast of the 6-month change in the Euribor rate as "prior information" which we seek to combine with time series information. If the prior information, in its pure form, is rejected by the time series data, a compromise between prior- (survey) and sample (time series) information is sought which can no longer be rejected on statistical grounds. In order to make our prior information testable, we map it into the parameter space of the time series model being used. For all of the three time series models, however, there are multiple parameter vectors which - together with the historical Euribor data - replicate the survey (point) forecast. Following Manganelli (2009), we therefore select as our prior the parameter vector $\tilde{\theta}_T$ which minimizes a standard least squares criterion[2], subject to the constraint that it must replicate the 6-month ahead survey forecast.

In the following, we briefly discuss the specific parameter restrictions for each of the three time series models. In each case, denote by $\widehat{\Delta y}^{CP}_{T,T+6}$ the Carlson-Parkin forecast (made at time $T$) of the change in the 3-month Euribor rate during the next six months.

[2]... Of course, the method could be applied to other criterion function - such as a likelihood.

### 3.1 Univariate Autoregression with p lags - AR(p)

Consider the usual companion form matrices of an AR($p$) process:

$$\mathbf{a} = \begin{bmatrix} a_1 & \dots & \dots & a_p \\ 1 & \mathbf{0} & 0 & 0 \\ \vdots & \ddots & \mathbf{0} & \vdots \\ 0 & \mathbf{0} & 1 & 0 \end{bmatrix} \qquad \mathbf{a_0} = \begin{bmatrix} a_0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

We estimate an AR($p$) model for monthly changes in the three months Euribor, denoted $\Delta y_t$. In order to match the survey forecast of the change of the Euribor rate during the next half year, we need $\widehat{\Delta y}^{CP}_{T,T+6} \overset{!}{=} \sum_{j=1}^{6} \widehat{\Delta y}_{T+j}$. Defining $\iota_1 = \begin{bmatrix} 1 & 0 & \dots & 0 \end{bmatrix}$, we have $\widehat{\Delta y}_{T+j} = \iota_1 \Big( \Big[ \mathbf{I}_p + \mathbf{a} + \ldots + \mathbf{a}^{j-1} \Big] \mathbf{a}_0 + \mathbf{a}^6 \Delta y_T \Big)$. Consequently, the requirement that $\widehat{\Delta y}^{CP}_{T,T+6} \overset{!}{=} \sum_{j=1}^{6} \widehat{\Delta y}_{T+j}$ can equivalently be stated as

$$\iota_1 \Big( \Big[ \sum_{j=0}^{5} (6-j) \mathbf{a}^j \Big] \mathbf{a}_0 + \sum_{j=1}^{6} \mathbf{a}^j \Delta y_T \Big) \overset{!}{=} \widehat{\Delta y}^{CP}_{T,T+6} \tag{2}$$

### 3.2 Vector Autoregression with a single Lag - VAR(1)

Here we model the vector $\Delta \mathbf{y}_t$ containing monthly differences of Euribor rates at maturities one week, three months and one year. In order to replicate the survey forecast, we require that the second element of the vector $\sum_{j=1}^{6} \widehat{\Delta \mathbf{y}}_{T+j}$ be equal to the survey forecast $\widehat{\Delta y}^{CP}_{T,T+6}$. Defining $\iota_2 = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix}$, this implies the restriction

$$\iota_2 \Big[ \big( \sum_{j=0}^{5} (6-j) A^j \big) \nu + \sum_{j=1}^{6} A^j \Delta \mathbf{y_T} \Big] \overset{!}{=} \widehat{\Delta y}^{CP}_{T,T+6} \tag{3}$$

### 3.3 Diebold-Li Yield Curve Model

Unlike the two other time series models, the Diebold-Li model considers monthly levels -rather than first differences- of the Euribor rate. Due to the Diebold-Li model,

$$y_t = \beta_{1,t} + \beta_{2,t} \Big( \frac{1 - \exp(3\lambda)}{3\lambda} \Big) + \beta_{3,t} \Big( \frac{1 - \exp(3\lambda)}{3\lambda} - \exp(-3\lambda) \Big)$$

As described above, we estimate the sequences of coefficients $\{\beta_{j,t}\}_{t=1}^{T}, j = 1,2,3$ from term structure data and fix $\lambda \approx 0.2989$. The Diebold-Li forecast of the 3-month Euribor rate follows from forecasts of the three time-varying factors $\beta_{j,t}, j = 1,2,3$. These forecasts, in turn, are generated by a VAR(1) model for the sequence of estimates $\{\hat{\beta}_{j,t}\}_{t=1}^{T}, j = 1,2,3$. Denoting $\hat{\beta}_t = \begin{bmatrix} \hat{\beta}_{1,t} & \hat{\beta}_{2,t} & \hat{\beta}_{3,t} \end{bmatrix}'$, we thus have

$$\hat{\beta}_{T+6|T} = \Big( \sum_{j=0}^{5} (6-j) A_\beta^j \Big) \nu_\beta + A_\beta^6 \hat{\beta}_T$$

where $\nu_\beta$ and $A_\beta$ denote the intercept vector and slope coefficient matrix of the VAR for the three factors. Defining $\iota_3 = \Big[ 1, \frac{1-\exp(3\lambda)}{3\lambda}, \frac{1-\exp(3\lambda)}{3\lambda} - \exp(-3\lambda) \Big]$, the requirement that the Diebold-Li forecasted six-month change in the Euribor rate be equal to the survey forecast corresponds to

$$\iota_3 \hat{\beta}_{T+6|T} - y_T \overset{!}{=} \widehat{\Delta y}^{CP}_{T,T+6} \tag{4}$$

### 3.4 Outline of the general strategy

Our procedure for combining survey- and time series information is completely analogous for all three time series models. The algorithm can be sketched as follows:

1. Compute the unconstrained Least Squares estimate $\hat{\theta}_T$, along with an estimate of its variance-covariance matrix, $\hat{V}(\hat{\theta}_T)$.
2. Compute the constrained LS estimate $\tilde{\theta}_T$, taking as given the survey forecast $\widehat{\Delta y}^{CP}_{T,T+6}$ as well as the Euribor data until time $T$
3. Test the null hypothesis $\theta = \tilde{\theta}_T$ using a Wald test.
   - If the H0 is not rejected at significance level $\alpha = 5\%$: Adopt the survey forecast $\widehat{\Delta y}^{CP}_{T,T+6}$ implied by the time series model with prior parameter vector $\tilde{\theta}_T$.
   - If the H0 is rejected, choose the parameters $\theta^*_T \equiv \omega_T\hat{\theta}_T + (1-\omega_T)\tilde{\theta}_T$ for which the hypothesis H0: $\theta = \theta^*_T$ achieves a p-value of 5%. Adopt the forecast which is implied by the time series model with parameter vector $\theta^*_T$.

Step 1 is standard: For all three time series models, the unconstrained LS estimates can be computed analytically. The usual asymptotic formulae can be used to estimate the variance-covariance matrix of the (V)AR parameter estimates (e.g. Lütkepohl (2007, section 3.6)). Since our focus is on forecasting, we do not implement more realistic and robust VCV estimates which might be obtained, e.g., from time series bootstrap procedures. Step 2 is slightly more involved. In all three cases, solving the constrained LS problem requires a numerical optimization procedure. We use the constrained optimization package of the Gauss programming language; neither of the three minimization problems causes any problems. The numerical solutions are computed within seconds and appear robust to the choice of starting values. Step 3 is initiated by computing the Wald statistic

$$[\hat{\theta}_T - \tilde{\theta}_T]' \left[\hat{V}(\hat{\theta}_T)\right]^{-1} [\hat{\theta}_T - \tilde{\theta}_T] \overset{H0}{\sim} \chi^2(k)$$

where $k$ is the dimension of $\theta$. If the prior parameter vector $\tilde{\theta}_T$ is rejected at level $\alpha = 5\%$, the adopted parameter vector $\theta^*_T$ satisfies

$$[\hat{\theta}_T - \theta^*_T]' \left[\hat{V}(\hat{\theta}_T)\right]^{-1} [\hat{\theta}_T - \theta^*_T] = \chi^2_{0.95}$$

i.e. the Wald test of the hypothesis $\theta = \theta^*_T$ achieves a p-value of 5%.[3]

The procedure outlined above has a number of attractive features. It allows a combination of survey- and term structure information without imposing arbitrary assumptions regarding the link of both sources. Rather than that, a well-defined algorithm is used for choosing a combination of both sources on statistical grounds. Compared to standard forecast combination strategies, the method is highly parsimonious: No in-sample data beyond the data needed for estimation of the individual models is required. In contrast, even very simple combination methods typically rely on a number of tuning parameters which must be estimated or validated (see Timmermann (2006)). This requires a second sample of data, beyond the one required for estimation of the individual models.

[3]The confidence level of $\alpha = 5\%$ represents a fairly high amount of trust in our prior forecast. The interpretation of $\alpha$ can most easily be understood by looking at two extreme cases. $\alpha = 0\%$ represents infinite trust in the prior (and zero trust in the data): No set of data could potentially lead to a modification of the prior, since the null that $\theta = \tilde{\theta}_T$ can never be rejected at a significance level of 0%. $\alpha = 100\%$ represents zero trust in the prior (and infinite trust in the data): For the hypothesis $\theta = \theta^*$ to achieve a p-value of 100%, we must have $\theta^* = \hat{\theta}$, i.e. the unconstrained parameter vector must be adopted.

### 3.5 A numerical example: Combining Survey data and AR time series forecasts

For illustrative purposes, we provide a numerical example of the combination algorithm at work. Suppose we're standing in December 2005 ($\leftrightarrow$ T = 85); the task is to forecast the Euribor rate of June 2006. The survey quantification predicts an increase of the Euribor rate by 0.6 percentage points between the two dates.

Using all data available up to December 2005, the Schwarz criterion recommends to use one lag for the AR model of monthly Euribor changes. The unrestricted AR(1) model entails parameter estimates (intercept and AR term) $\hat{\theta}_{85} \approx \begin{bmatrix} 0.00 & 0.53 \end{bmatrix}'$; it predicts a 0.05 percentage point increase of the Euribor rate between December and June.[4]

The "best" (in a least-squares sense) AR(1) model which replicates the survey forecast entails parameter estimates $\tilde{\theta}_{85} \approx \begin{bmatrix} 0.04 & 0.70 \end{bmatrix}'$. Using a Wald test, the null hypothesis that $\theta = \tilde{\theta}_{85}$ is clearly rejected at significance level $\alpha = 5\%$; the p-value associated with the null is zero up to two decimals. Hence, our prior information in its pure form is rejected by the time series data.

The compromise between $\tilde{\theta}_{85}$ and $\hat{\theta}_{85}$ which is at the verge of being rejected at level $\alpha = 5\%$ is given by $\theta^*_{85} = \omega_{85} \times \hat{\theta}_{85} + (1 - \omega_{85}) \times \tilde{\theta}_{85} = 0.095 \times \hat{\theta}_{85} + 0.905 \times \tilde{\theta}_{85} \approx \begin{bmatrix} 0.04 & 0.68 \end{bmatrix}'$. Hence, after a fairly moderate movement toward the unrestricted model, the compromise parameter vector $\theta^*_{86}$ can no longer be rejected.

The result of the combination in this case, an AR(1) model with parameters $\theta^*_{85}$, predicts an increase of the Euribor rate by 0.54 percentage points between December 2005 and June 2006. The realized change turns out to be 0.59 percentage points, so that the combined forecast is slightly less precise than the survey forecast, but much more precise than the time series forecast.

## 4 The Data

In order to construct the survey prior, we use a panel raised by the ZEW, Mannheim. The so-called "ZEW Financial Markets Survey" has been collected since December 1991 on a monthly basis. It focuses on macroeconomic quantities, such as economic activity and inflation, and on financial market quantities, such as stock markets or interest rates. The primary focus of the survey is on six-month ahead predictions of the aforementioned quantities. Among the roughly 300 respondent who usually return their questionnaires in time, roughly 210 work for banks, another 40 respondents work for insurance companies, about 20 are employed in industrial companies and the rest is employed in "other" enterprizes. The panel is unbalanced, since over time some respondents stop responding and new respondents are acquired. 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 (6 months) the short-term interest rates (3-month-Interbank rate) will ... ☐ increase ☐ no change ☐ decrease ☐ no estimation".

The target series of interest - the three month Euribor rate - is also available since the beginning of 1991. The series series is highly persistent, with a first order autocorrelation of 96% and a fifth order autocorrelation of 67%. In line with this observation, an augmented Dickey Fuller Test cannot reject the null hypothesis of a unit root with a p-value of roughly 40%. On the other hand, the KPSS test cannot reject the null hypothesis of stationarity with a p-value of roughly 15 %. Thus we cannot positively conclude on whether the series is stationarity or not. We choose to model monthly changes in the Euribor rate in the two autoregressive specifications we consider; in contrast, the Diebold-Li yield curve model by construction refers to levels of the series. Monthly changes in the Euribor still display

[4] By comparison with formula (2) above, note that the small absolute value of the predicted six-month change results from the combination of a very small intercept term and an AR coefficient far below unity.

a fair amount of persistence, with first order autocorrelation of 65% and fifth order autocorrelation of 13%.

# 5 Empirical Results

Below we evaluate 1) the predictive performance of the survey predictor and the time series models which have been presented above and 2) the predictive performance of the Manganelli combinations of the survey prior with the previously mentioned time series models. Moreover, we present the predictive performance of our models in two subsamples: a pre-crisis sample which spans from June 2002 to August 2008 and a crisis sample which contains 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 drastic cuts were hard to forecast by either method.

We compare predictive performances by root mean squared prediction errors (RMSPE). We test for equal predictive ability of time series models and the survey predictor using a test presented in West (2006) and originally invented by Diebold and Mariano (1995). Let $g()$ be a loss function[5], then we can state the test's null as: $H_0 : E[d_t^{ij}] := E[g(e_t^i) - g(e_t^j)] = 0$, where $e_t^j = y_t - y_{t|t-6}^j$ is the six-step ahead forecast error made by model $j$ at time $t$. Thus the null hypothesis states that the mean loss incurred from model $j$ equal the mean loss incurred from model $i$. The test statistic is obtained as the HAC t-test statistic of an auxiliary regression of the loss differential $d_{ij}^t$ on a constant. According to West (2006), we use asymptotic normal critical values.

## 5.1 Individual Models

For the individual models presented above, table 1 presents RMSPEs plus test statistics and p-values of a test for equal predictive ability against the survey predictor. Across all subsamples, as we expect from Nolte and Pohlmeier (2007), the survey predictor displays lower RMSPEs than all time-series based forecasts. While for the non-crisis sample we can reject equal predictive ability for the AR and Diebold-Li predictions vs. the survey predictor, across the entire sample period only the Diebold and Li model is significantly outperformed by the survey predictor. Thus it seems as if the relative performance of the models under consideration is not time-invariant.

| *Method* | *Start* | *End* | *RMSPE* | *DM-Test vs survey* | *p-value (DM)* |
|---|---|---|---|---|---|
| *Survey* | *2002M06* | *2009M07* | 0.781 | . | . |
| *AR* | *2002M06* | *2009M07* | 0.880 | −1.393 | 0.164 |
| *VAR* | *2002M06* | *2009M07* | 0.840 | −1.261 | 0.207 |
| *DL* | *2002M06* | *2009M07* | 1.005 | −1.849 | 0.064 |
| *Survey* | *2002M06* | *2008M08* | 0.341 | . | . |
| *AR* | *2002M06* | *2008M08* | 0.406 | −1.904 | 0.057 |
| *VAR* | *2002M06* | *2008M08* | 0.383 | −0.875 | 0.382 |
| *DL* | *2002M06* | *2008M08* | 0.480 | −2.075 | 0.038 |

Table 1: RMSPEs, Diebold-Mariano test statistics and p-values for tests of equal predictive ability of the survey predictor and forecasts of an AR(p), a VAR(1) and the Diebold-Li model.

## 5.2 Combined Forecasts with Survey Prior

For Manganelli-type combinations of time-series models with a survey prior, table 2 presents RMSPEs plus test statistics and p-values of a test for equal predictive ability against the survey predictor. As compared to the individual forecasts, all Manganelli combinations display lower root mean squared

[5] We use a squared loss function.

prediction errors. This result is non-trivial since the novel shrinkage method we use is with respect to model parameters, not point forecasts.[6]
We find that for the non-crisis sample, two of the three combinations improve on the survey predictor alone in terms of RMSPEs. Interestingly, the combination with the simple autoregression, which represents a very parsimonious approach to model the persistence in the true process, can significantly outperform the survey predictor on a 10% test level.

| *Mglli, Survey&* | *Start* | *End* | *RMSPE* | *DM-Test vs survey* | *p-value (DM)* |
|---|---|---|---|---|---|
| *Survey only* | *2002M06* | *2009M07* | 0.781 | . | . |
| *AR* | *2002M06* | *2009M07* | 0.806 | −0.826 | 0.409 |
| *VAR* | *2002M06* | *2009M07* | 0.782 | −0.030 | 0.976 |
| *DL* | *2002M06* | *2009M07* | 0.803 | −1.083 | 0.279 |
| *Survey only* | *2002M06* | *2008M08* | 0.341 | . | . |
| *AR* | *2002M06* | *2008M08* | 0.335 | 1.737 | 0.082 |
| *VAR* | *2002M06* | *2008M08* | 0.354 | −1.574 | 0.116 |
| *DL* | *2002M06* | *2008M08* | 0.339 | 0.199 | 0.843 |

Table 2: RMSPEs, Diebold-Mariano test statistics and p-values for tests of equal predictive ability of the survey predictor and Manganelli combinations of the time-series based predictors with the survey prediction prior.

### 5.3 Dynamics in the combination Weights

Figure 1 below plots the combination parameter $\omega_T$ against time, for all three time series models we consider. Interestingly, the plot reveals clear correlation patterns along two dimensions: First, for each individual model, the sequence of parameters $\omega_T$ displays autocorrelation. The first-order autocorrelation is 0.58 for the VAR model, 0.26 for the AR model and 0.52 for the Diebold-Li model. Second, the parameters $\omega_T$ corresponding to any two different models are contemporaneously correlated. The contemporaneous correlation of the $\omega_T$'s is 0.63 for VAR/AR, 0.33 for VAR/DL and 0.27 for AR/DL.

Hence, there seem to be periods in which survey expectations are broadly consistent with "the data" as represented by the three time series models, and periods in which there are systematic deviations between survey expectations and mechanical time series forecasts. The former periods are associated with low (often zero) values of $\omega_T$, i.e. the survey-implied parameter vector needs little or no adjustment in order not to be rejected by the data. The latter periods are characterized by the opposite pattern, i.e. high values of $\omega_T$ implying substantial corrections of the survey-implied parameter vectors.

We view these findings as an interesting by-product of our forecast combination exercise. As Pesaran and Weale (2006) note, little is known about the process which generates the expectations data recorded by surveys such as the ZEW Finanzmarkttest. Panelists might use econometric methods themselves, they might use heuristic judgement, they might talk to/copy from each other - we don't know. Our findings hint that the relationship between "soft" survey expectations and "hard facts" represented by time series models might be time-varying. Clearly, however, these findings should be checked for a broader set of macroeconomic variables for which longer time series of survey expectations are available.

[6] If we were to consider some linear combination of the (relatively) precise survey forecast and the noisy time series forecast, then the finding that this combination performs better than the time series forecast would be very unsurprising. In contrast, our combination method is linear only with respect to different parameter vectors. Since the individual forecasts are nonlinear functions of the parameter vectors, our combined forecast is a complicated nonlinear function of the individual forecasts. It is not intuitively clear why this combination should outperform the worse of the individual forecasts.

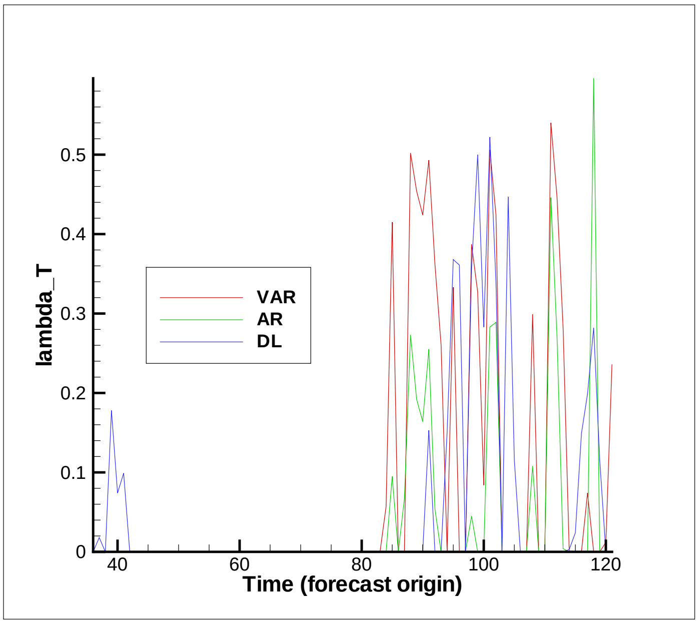


Figure 1: Plot of $\omega_T$, the weight attached to the unconstrained model parameters, against $T$, the forecast origin. $T = 40$ corresponds to April 2002.

# 6 Conclusion

Our first finding that survey forecasts of the Euribor rate clearly outperform time series models reflects increased transparency (and hence, predictability) of central bank policy.

The forecasts obtained from our forecast combination algorithm clearly improve upon the time series forecasts. Furthermore, we find evidence that the survey forecasts can successfully be combined with time-series models.

Clearly, there is other time series information which might sensibly be combined with survey forecasts. Examples include macroeconomic variables which potentially affect the ECB's policy decisions (see Taylor (1993)) or indicators of central bank communication which are based on linguistic analysis of ECB press conferences.[7] Whether these quantities are informative conditional on survey information is an issue for future research.

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[7] See http://www.kof.ethz.ch/news/?t=mp for an indicator constructed by the ETH Zurich's Konjunkturforschungsstelle.

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