Real time forecasts of inflation: the role of financial variables*

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Abstract

We present a mixed frequency model for daily forecasts of euro area inflation. The model combines a monthly index of core inflation with daily data from financial markets; estimates are carried out with the MIDAS regression approach. The forecasting ability of the model in real time is compared with that of standard VARs and of daily quotes of economic derivatives on euro area inflation. We find that the inclusion of daily variables helps to reduce forecast errors with respect to models that consider only monthly variables. The mixed frequency model also displays superior predictive performance with respect to forecasts solely based on economic derivatives.

KEYWORDS: forecasting inflation, real time forecasts, dynamic factor models, MIDAS regression, economic derivatives.

JEL: C13, C51, C53, E37, G19.

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1 Introduction

This paper deals with daily forecasts of inflation. The need to forecast inflation as frequently as possible has become increasingly important for both institutional and market operators. On the one hand, a timely update of the macroeconomic projections is essential for conducting a "modern" monetary policy based on the market expectations (see Woodford (2003)); on the other hand, financial market operators tend to continuously update their expectations as new information becomes available, and to exploit this information to modify their investment strategies.[1] A common approach to forecast inflation is to construct models based on monthly variables that are highly correlated with (future) inflation. Forecasts from these models can be quite accurate but not very timely since, by construction, they do not account for any important information that might become available within the month. A solution to this problem is to look at financial indicators, such as movements in the yields curve or interest rates spreads, that are available on a daily basis and that can give us some timely information about changes in the inflation expectations. An alternative solution, which we present in this paper, is to combine the two approaches just mentioned to construct an indicator of monthly inflation using both monthly and daily data. More precisely, we propose a mixed frequency model where we combine a monthly core inflation index, constructed using a generalized dynamic factor model, with daily prices of commodities and financial assets. This approach has the advantage that incorporates in the same model long run inflation dynamics (as a mean of core inflation index) with recent news on current and future inflation expectations.

The idea behind our approach is the straightforward. Factor models have recently become a popular tool to forecast macro variables. They allow us to construct economic indicators by handling in a parsimonious way the information contained in a large number of variables (see for instance Stock and Watson (2006)). In particular, the Generalized Dynamic Factor models, proposed by Forni et al. (2002), henceforth FHRL, by extracting a few common long run components from observable variables, can explain most of the variability of the data at low and medium frequency. Because of their large-scale structure, factor models might not be very convenient to forecast

[1]See Bernanke and Kuttner (2005) for an analysis of the reaction of asset prices to monetary policy shocks using daily data.

inflation in real time. On the one hand, they would require to frequently update a large database; on the other, since factor models are characterized by an unbalanced end of sample (ragged-edge), as the data become available at different times, they can produce inaccurate short term predictions. The latter is a well-known problem in the literature that might affect the forecasting properties of the models, especially for short horizons forecasts (see Marcellino and Schumacher (2008)). The approach we propose to overwhelm this problem is to use mixed frequency data models where, together with a factor model indicator, relevant explanatory variables sampled at a higher frequency, are included; specifically, for the Euro area inflation we chose daily financial variables. We consider a recent class of mixed frequency models, the Mixed Data Sampling Regression Models (MIDAS), proposed by Ghysels et al. (2002, 2006).[2] There is a small but fast growing literature on MIDAS models. Most of the early applications were on financial data[3] but more recently there has recently been a small number of applications to macroeconomic variables. Clements and Galvao (2007) use a MIDAS model to forecast monthly US quarterly macro variables, Ghysels and Wright (2008), to track daily survey expectations on US macro variables and Marcellino and Schumacher (2008) to produce monthly estimate of the German GDP. The use of asset prices to forecast macro variables is not new in the literature. In an extensive review Stock and Watson (2003) showed that financial variables have a marginal predictive content but it is often hard to detect. In this respect, our results can be seen as an alternative way to exploit this predictive content without altering the temporal structure of the data.

We run a few forecasting exercises to asses the forecast accuracy of our indicator compared to standard monthly models and market expectations. Our conclusions are the following. First, predictions from our mixed frequency model outperforms those of standard benchmark models based only on monthly variables. From this result we can infer that the inclusion of the daily variables helps to reduce the forecasting errors. We then show that the daily forecasts of our model are also more accurate than those implied in financial market expectations extracted from the euro area HICP futures contracts. These contracts can be regarded as the most direct daily assessment

[2] Another class of mixed frequency models, proposed by Mittnik and Zadrozny (2005) and more recently by Aruoba et al. (2007), is based on a state-space representation where they use the Kalman filter to construct high frequency unobserved indicators for the low frequency variable.

[3] See the works mentioned above.

of market expectations on the euro area consumer inflation.

The paper is organized as follows. Section 2 review the link between financial variables and inflation and describes the economic derivatives we used in our analysis. Section 3 describes our mixed frequency models in details. In Section 4 we assess the forecasting ability of our models compared to VARs and market daily expectations. Section 5 concludes.

2 Role of financial variables

As already mentioned above, if keeping track of persistent movements in inflation is important to pursue the task of price stability, it is also important for central banks to monitor the evolution of current inflation in real time. This is usually done by looking at the information embodied in high frequency variables, such as the yield curve, bond yields, and quotes on HICP economic derivatives. On the one hand, economic theory suggests the existence of a link between financial variables and inflation; on the other, since these variables are forward looking and observed in real time (without revisions), they have potentially useful information about inflation expectations. There is a large literature suggesting that financial variables can help predict inflation.[4] However, the empirical evidence is still mixed and model dependent as pointed out by Stock and Watson (2003) and Ang et al. (2007). One of the reasons for this puzzle might lie on the different frequencies at which inflation and financial variables are sampled. Specifically, even if daily financial data contain useful information about current and future movements of inflation, the fact that inflation is sampled at a lower frequency makes it hard to exploit such predictive power. Solutions to this problem are to either sample daily data at a lower frequency by choosing, for instance, the last observation of the month or to prefilter daily data to convert it to a monthly frequency. Both these approaches may discard useful information and corrupt the potential relation between the variables. As we show below, we overwhelm this problem using a mixed frequency data model. This approach allows us to combine in the same model monthly determinants of inflation, with the daily information coming from financial markets. In this way, we aim to capture the medium-low frequencies of inflation using monthly regressors without discarding any useful information coming from financial data to

[4] Using a factor models Forni et al. (2003) showed some evidence for to the euro area while Giannone et al. (2008) for the US.

predict short term movements in inflation.

2.1 Economic derivatives

Economic derivatives are securities whose payoff are dependent upon macroeconomic data releases. They were introduced in 2002 and have recently become popular for their ability to mitigate some of the market and basis risks found in standard investment vehicles. Since their yields are tied to future data releases of a certain macroeconomic variable, they can be also considered as a good measure of the market beliefs about future realizations of the economy. The use of economic derivatives to extract market expectations for US variables has been recently put forward by Wolfers and Gurkaynak (2006) who concluded that their predictive ability is more accurate than that of the survey data. Furthermore, according to Beber and Brandt (2007) they can also be used to measure the distribution of the market uncertainty about macroeconomic variables, and their effect on stock and bond market.

In this paper we consider future contracts on the euro area inflation, defined as the yearly percentage change of the Household Index of Consumer Price (HICP) excluding tobacco, released monthly by Eurostat.[5] These futures were introduced in 2005 and are traded daily on the Chicago Mercantile Exchange (CME) and quoted up to 12 months of releases.[6] Eurostat releases the HICP excluding tobacco for the current month around 15 days after the end of the month. Therefore the economic derivatives cover the current month data and the 11 months ahead.

An alternative way to extract market expectations of inflation is to look at the so called "break-even" inflation rate. This is defined as the difference between yields of inflation-linked bonds and those of fixed rate bonds. We preferred to use the future contracts since differently from the break even inflation rate they are less affected by liquidity and risk premium, which are usually difficult to disentangle from the expectation itself. Furthermore, inflation indexed bonds are also influenced by microstructure and tax factors that are hard to quantify.

[5] The impact of tobacco on the overall index is negligible and estimated to be at most 2.5%. The correlation between the two indexes is 0.94.

[6] For a detailed description of the contract see Grannan and Srinivasan (2007). Nowadays there are more than 1.5 million contracts for the Euro Area HICP traded every day. The bid-ask spread for these contracts is reasonably tight implying a low liquidity premium in the market.

3 Our two-step approach

As already mentioned, a key aspect of our approach is to model the low and high frequency variability of inflation separately. In this section we describe the two components that, in our view, should be used for this purpose: a core inflation index to model the medium-to-low frequencies of inflation and daily financial variables to model the high frequencies.

3.1 Modelling long-medium term component of inflation

In the last few years large-dimensional factor models have become increasingly important in the construction of reliable coincident and leading indicators to assess present and future economic conditions.[7] Factor models allow us to represent parsimoniously the information embodied in large data set by assuming that there exist few common factors that drive the dynamics of data. In particular, in the generalized dynamic factor model (GDFM) these factors are chosen in order to explain most of the variability of the data at medium and low frequency. In this way, they disentangle the medium-long run cyclical component from the short term dynamics in order to minimize the effects of idiosyncractic and transient shocks.

More specifically, if $x_{i,t}$ $i = 1, ...N$ is a panel of interest variables, the dynamic factor model assumes that they admit the following representation

$$x_{i,t} = \chi_{i,t} + \xi_{i,t} = \sum_{j=1}^{p} b_{i,j}(L) f_{j,t} + \xi_{i,t}$$

where $\chi_{i,t}$and $\xi_{i,t}$ are respectively the common component and the idiosyncratic component of $x_{i,t}$. They are, by construction, unobserved, stationary and mutually orthogonal. The common component $\chi_{i,t}$ is driven by a few common factors $f_{j,t}$ which are possibly loaded with different coefficients and lags. An important feature of the GDFM is that under the assumption that the variables $x_{i,t}$ are stationary, the common component can be represented as the integral of waves of different frequency, the so called "spectral representation". In particular, by aggregating waves of different frequency we can

[7]Factor models have been used to predict macroeconomic variables in the US (e.g. Stock and Watson (2002)) and in the euro area (e.g. Altissimo et al. (2006)) and to produce measures of core inflation for the euro area (Cristadoro et al. (2005)).

decompose $\chi_{i,t}$ into the sum of a cyclical medium-long run component $\chi^L_{i,t}$ and a non-cyclical, short run component, $\chi^S_{i,t}$, i.e.

$$\chi_{i,t} = \chi^L_{i,t} + \chi^S_{i,t}$$

The core inflation is an estimate of $\chi^L_{i,t}$, the unobserved component of inflation which drives persistent movements in the inflation index.[8] In this way we can eliminate not only seasonality from the data but also the effects of transient and idiosyncratic shocks. A detailed description on the estimation of $\chi^L_{i,t}$ can be found in FHLR (2002). The index is constructed using a large number of both national and sectorial prices together with monetary aggregates and other macroeconomic variables.[9]

A drawback of the model is that all the variable have been transformed to the same frequency, i.e. monthly. Furthermore, as already mentioned above, they are also characterized by an unbalanced end of sample, as the data become available with different lags. This can potentially affect the forecasting properties of the model especially in the very short run. Few approaches have been proposed to reduce the effects of such ragged edge data and they have been surveyed in Marcellino and Schumacher (2008). The approach we propose is to use the core inflation index to extract the medium- and long run component of inflation and model the short run component using high frequency financial data that are available more timely.

3.2 A mixed frequency model for real time forecast of inflation

In this section we present the mixed frequency model we construct to forecast inflation in real time. We follow the mixed data sampling regression (MIDAS) approach proposed by Ghysels et al. (2002, 2006). The main feature of the MIDAS model is to allow us to construct a regression model that combines both monthly and daily variables. The MIDAS approach assumes that the response to the high frequency explanatory variables follow a distributed lag polynomials, in order to prevent over parameterization. Specifically, if $x^d_{i,t}$ is

[8] In particular, for persistent movements of inflation we refer to periodicity of at least one year.

[9] A complete list of the variable used in the construction of the EA inflation index can be found in Cristadoro et. al (2008)

a set of daily variables and $B\left(L^{\frac{1}{d}};\boldsymbol{\theta}_i\right)$ the daily lag polynomial, the mixed frequency data model we specify for inflation π_t is given by

$$\begin{aligned}
\pi_t &= \alpha_0 + \rho\pi_{t-1} + \sum_{i=1}^{N}\beta_i B\left(L^{\frac{1}{d}};\boldsymbol{\theta}_i\right)x_{i,t}^d + \alpha_t^{'}\chi_{i,t}^L + \varepsilon_t \\
&= \alpha_0 + \rho\pi_{t-1} + \sum_{i=1}^{N}\beta_i \sum_{k=1}^{K} b\left(k;\boldsymbol{\theta}_i\right)L^{\frac{k}{d}}x_{i,t}^d + \alpha_t^{'}\chi_{i,t}^L + \varepsilon_t
\end{aligned}$$

where the lag coefficient $b\left(k;\boldsymbol{\theta}_i\right)$ are function of a small set of parameters θ, N is the number of daily variables and $\chi_{i,t}^L$ is the core inflation index described in the previous section. $L^{\frac{k}{d}}$ is the daily lag operator which range from the last day on month t up to K days before. This means that $L^{\frac{1}{d}}x_t^d = x_{t-\frac{1}{d}}^d$ is the last observation of the current month t, and more generally, $x_{t-\frac{k}{d}}^d$ is the $(d-k)th$ observation of the month. In order to avoid spurious seasonality in the model, the loading β_i is restricted to be

$$\beta_i = (1-\rho L)\,\delta_i$$

The lag coefficient $b\left(k;\boldsymbol{\theta}_i\right)$ is assumed to follow a distributed lag function that depends on a small set of parameters $\boldsymbol{\theta}_i$, i.e.

$$b\left(k;\boldsymbol{\theta}_i\right) = \frac{f\left(k;\boldsymbol{\theta}_i\right)}{\sum_{k=1}^{K} f\left(k;\boldsymbol{\theta}_i\right)}$$

This allow us to reduce the number of parameter to estimate in the model. In general there are many ways of parameterizing $f\left(k;\boldsymbol{\theta}_i\right)$. Two common approaches are the exponential Almon polynomial, introduced by Almon (1965), and the Beta polynomials recently proposed by Ghysels et al. (2002, 2006). The first assumes that $f\left(k;b_i\right)$ has the following functional form,

$$f\left(k;\boldsymbol{\theta}_i\right) = e^{\theta_{i,1}k+\theta_{i,2}k^2}$$

The exponential Almon polynomials can generate different shapes including increasing, decreasing, single and multiple humped patterns. The second method of parameterization is based on the Beta density function defined as

$$f\left(x;b_1,b_2\right) = B\left(b_1,b_2\right)^{-1}x^{b_1-1}\left(1-x\right)^{b_2-1}$$

where $B(b_1, b_2) \equiv \Gamma(b_1)\Gamma(b_2)/\Gamma(b_1 + b_2)$ and $\Gamma(\cdot)$ is the gamma function. The Beta density is a very flexible distribution that allows many shaped weighting functions including uniform, humped and sharply decreasing (increasing) patterns. The models we specify for the EA inflations are described in details below. We estimate them using non linear quasi maximum likelihood. Furthermore, in order to improve accuracy, we assume that the loadings of the daily variables and the parameters in the vector $\boldsymbol{\theta}$ are uncorrelated and use a recursive two stage estimation approach.[10]

4 Two forecasting applications in real time

In this section we specify three mixed frequency models for the EA HICP and assess their forecasting performance in two different exercises. In the first, we evaluate the monthly forecast accuracy of the three model with respect to other standard models. Then, we compare daily predictions of the models with the forecasts implied in the quotes of EA HICP future contracts.

4.1 Three mixed frequency models

We specify three different models for the EA inflation. Each model is supposed to captures different sources of shocks that according to economic theory should cause movements in inflation. All the models are characterized by the same monthly variables but different daily variables. The monthly variables are: lagged inflation, lagged yearly change of oil price and the core inflation index lagged five.[11] In particular, we chose the recent core inflation proposed by Cristadoro et al. (2008) which extend the earlier work of Cristadoro et al. (2005). The daily variables includes short and long term interest rates, interest rate spreads, stock indexes, commodity prices and exchange rates. More specifically, in the first model (M1) we include the short term rate and changes in the interest rate spread and in the oil future prices. The second model (M2) is designed to capture recent shocks coming from outside the euro area that are not yet embodied in the lagged core inflation. For this reason we considered changes in the wheat price, in the oil futures

[10] The codes for this paper were written in Matlab and they are available upon request from the authors.

[11] This is consistent with the evidence in Cristadoro et al. (2005) that the core inflation index has its strongest predictive power at horizons of at least six months.

quotes and in the exchange rate. Finally, the third model (M3) focuses only on the information coming from the interest rates and it includes long term rates, changes in the interest rate spread and in the short term rate. We use monthly and daily data ranging from May 1992 to September 2007.[12]

4.2 Real time forecasts of monthly inflation

In the first exercise we compute the Root Mean Squared Forecast Error (RMSFE) of our mixed frequency models and compare them with those from univariate and multivariate models. In particular, among the univariate models we consider a random walk, an AR model and an ARMA model whose order is chosen with the Schwarz criterion. Among the multivariate models we choose two VARs: the first has the same monthly variables as our models (inflation, core inflation and oil price) while the second also includes the interest rate as economic theory would suggest. We use ten years of data as burning period and then we run recursive forecasts for the monthly inflation starting from May 2002 until September 2007.

Table 1 reports the RMSFE for all models: our mixed frequency models outperform all the univariate models as well as the VAR models. The average reduction in the forecast errors is more than 20% for current and one month ahead inflation. This result is quite important since it implies that the daily variables improve the forecast properties of the model. It has also to be noticed that the ratio between the RMSFE of the compound models and those of the VARs is similar for the two horizons. Among the compound models, M2 performs better meaning that foreign variables are quite influential to predict future movements in domestic EA inflation.

4.3 Model forecasts vs market expectations

In the second application, we fully exploit the high frequency structure of our models and run a daily forecasting exercise. For this purpose we compare daily predictions of our model with the inflation expectations extracted from the economic derivatives. In particular, we use the inflation rate implied in the daily quotes of euro area inflation futures. Since these contracts were introduced in September 2005, we have over two years of daily data. For each

[12] Daily data for the financial variables are taken from DATASTREAM; Euro Area HICP CME future quotes are extracted from Bloomberg whereas monthly data for HICP and interest rates from the ECB Statistical Data Warehouse (SDW).

day of the sample we estimate the model and generate current and one step ahead forecasts of inflation. As already mentioned, future contracts can be considered a good candidate for this exercise since they incorporate the latest news on possible movements on inflation that becomes available in financial markets (as Figure 1 shows they track euro area inflation quite accurately).

In Figure 2 we show the boxplot for the daily forecast errors of the future contracts and for those of the three mixed frequency models. The left panel refers to the distribution of the forecast errors for the current month while the right panel for one-month ahead. All the mixed frequency models produce not only more accurate but are also less volatile forecasts, especially for current inflation. This can be also seen in Table 2, where we report the RMSFE for the models and the predictions of the future contracts. The improvement is on average around 30% for current inflation and somewhat smaller for one month ahead inflation. The evolution of the daily forecasts can be seen in figure 1 where we plot the daily forecast of model one (M1), the inflation rate extracted from the quotes of the future contracts and actual inflation. Apart from a couple of episodes when our model could not capture a sudden drop in inflation, it seems that they track inflation closer than the market expectations. Finally, differently to what we shown in the previous exercise, M1 seems to perform slightly better than the other models.

We computed the Diebold-Mariano (DM) test to assess whether this improvement in the forecasts is statistically significant. The DM statistics in Table 3 show that model predictions for current inflation are significantly more accurate than that of derivative; however, there is no strong evidence for one month ahead. In order to asses the goodness of this result, we also computed the Chong and Hendry (1986) forecast encompassing regression to check whether our models encompass the information of the derivatives over future releases of inflation.[13] Specifically, we regress the daily series of inflation π_t^d over a constant, the future contracts expectations D_t^d and our model projections $\widehat{M}_t^d$:

$$\pi_t^d = \beta_0 + \beta_1 D_t^d + \beta_2 \widehat{M}_t^d \tag{1}$$

The results in Table 4 show a very different picture for the two forecasting horizons. For current inflation, the coefficient β_2 is much bigger β_1 confirming that the model forecasts are more accurate than those extracted

[13] In fact, as recently shown by Busetti et. al (2008), the Diebold Mariano test can be characterized by low size compared to forecast emcompassing tests.

from the future contracts. However, both coefficients are significant suggesting that future contracts have a small but significant predictive content that is not captured by our model. This suggests that we could further reduce the forecast error by combining the prediction from our models with those from the financial derivatives. For this reason in Table 5 we show the RMSFE for the combined predictions obtained with estimated weights and equal weights. Not surprisingly we find that by combining the two forecasts with the estimated weights we can brings a non negligible reduction in the RMSFE especially for the one-month-ahead predictions.

5 Concluding remarks

In this paper we present a simple model to forecast euro area inflation in real time. It is based on a mixed frequency model which allows us to combine two components useful for short term predictions: a monthly core inflation index derived from a dynamic factor model that captures persistent changes in inflation, and daily financial market variables which are particularly useful for providing timely information on the most recent shocks. Given the lack of daily models for inflation, we assess the forecasting ability of our models with respect to standard VAR models and economic derivatives on euro area inflation. We find that the inclusion of the daily variables helps to reduce the forecasting errors with respect to models with only monthly variables. Furthermore, it also outperforms forecasts from daily economic derivatives. The predictive ability of asset and commodity daily prices on current inflation rate is consistent with a forward looking behavior in price setting mechanism of firms that could be interesting to study with a structural economic model.

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Table 1

Monthly forecasting accuracy

(RMSFE of recursive forecasts from 2002:5 to 2007:9)

	steps ahead	
	0	1
Compound models		
M1	0.158	0.226
M2	**0.148**	**0.208**
M3	0.163	0.216
Univariate models		
RW	0.185	0.261
AR(1)	0.181	0.250
ARMA(2,1)	0.184	0.248
Multivariate models		
VAR_MIDAS	**0.169**	**0.234**
VAR_ECON	0.173	0.244

Legenda:

RW = random walk of inflation

VAR_MIDAS= VAR(2) with inflation, core inflation and oil prices

VAR_ECON= VAR(3) with inflation, core inflation, oil prices and interest rates.

Note: in each entry Root Mean Square Forecast Error (RMSFE) is reported. The first estimation period starts in may 1992 and ends in may 2002. Subsequent estimates follow the recursive scheme (keeping fixed the starting date). Daily forecasts for M1, M2 and M3 are aggregated to produce monthly predictions.

Table 2

RMSFE of daily predictions

	Econ deriv	M1	M2	M3
current month	0.166	0.123	0.132	0.140
one month ahead	0.233	0.219	0.224	0.211

Note: Each entry reports the RMSFE of the different predictors. The model's prediction errors refer to the recursive unconditional out of sample forecast form October 2005 to September 2007.

Table 3

Comparing predictive accuracy:

Diebold Mariano forecasting test

	current month			one month ahead		
	M1	M2	M3	M1	M2	M3
MSE	0.012 (2.883)	0.010 (2.277)	0.008 (1.618)	0.006 (0.763)	0.004 (0.434)	0.010 (0.943)
MAE	0.044 (3.754)	0.037 (3.061)	0.035 (2.786)	0.015 (0.889)	0.028 (1.748)	0.032 (1.909)

Note: the test is on the difference between derivative and model prediction errors. The null hypothesis is that the expected error of the competing forecast is equal to that of the futures market.

MSE: test on the squared residuals

MAE: test on the absolute residuals

Table 4

Forecast encompassing test : combination weights

	current month			one month ahead		
	M1	M2	M3	M1	M2	M3
Coefficients:						
constant	-0.136	-0.188	-0.228	0.044	0.176	0.036
	(-1.366)	(-2.113)	(-2.262)	(0.296)	(1.277)	(0.241)
derivatives	0.297	0.351	0.414	0.389	0.388	0.384
	(3.083)	(3.670)	(4.017)	(4.835)	(4.650)	(4.590)
model	0.769	0.634	0.691	0.609	0.517	0.588
	(9.749)	(8.893)	(7.821)	(6.356)	(6.442)	(5.997)
Test a diagnostics:						
Wald F statistic	38.23	30.78	23.76	22.27	21.97	21.15
P value, %	0	0	0	0	0	0
Test b diagnostics:						
Wald F statistic	3.37	5.74	6.23	15.86	12.33	7.65
P value, %	1.8	0.0	0.2	0	0	0

Note: (1) test a: the null hypotesis is that future forecasts encompass model forecasts
(2) test b: the null hypotesis is that model forecasts encompass future forecasts
(3) in brackets: heteroskedasticity and autocorrelation consistent (Newey West) t-stat of the coefficients.

Table 5

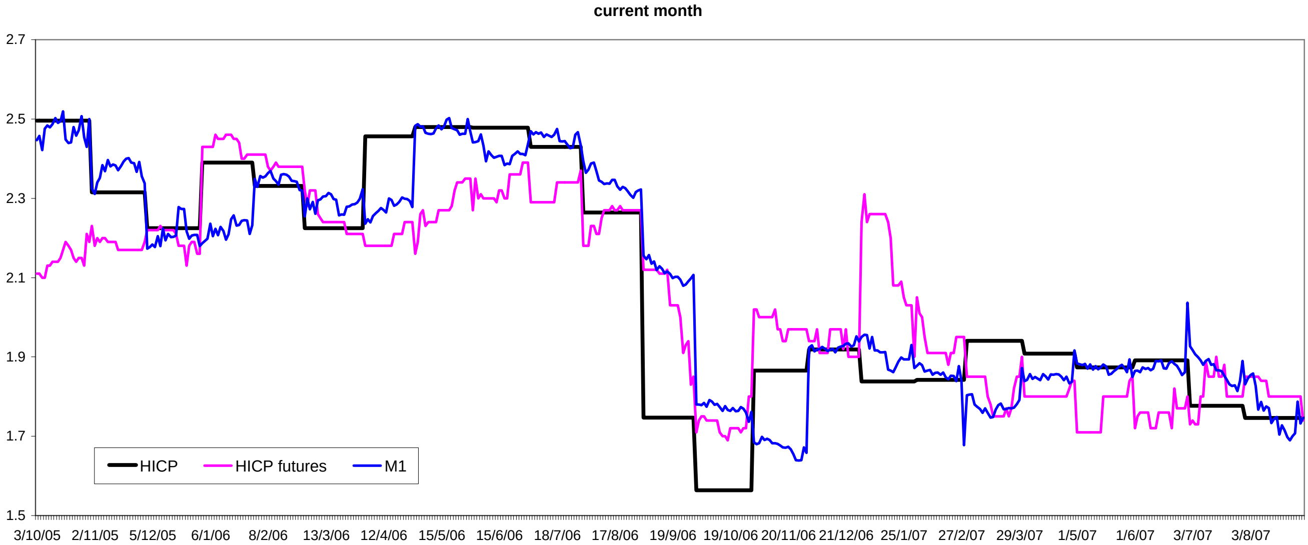
RMSFE of combined daily predictions

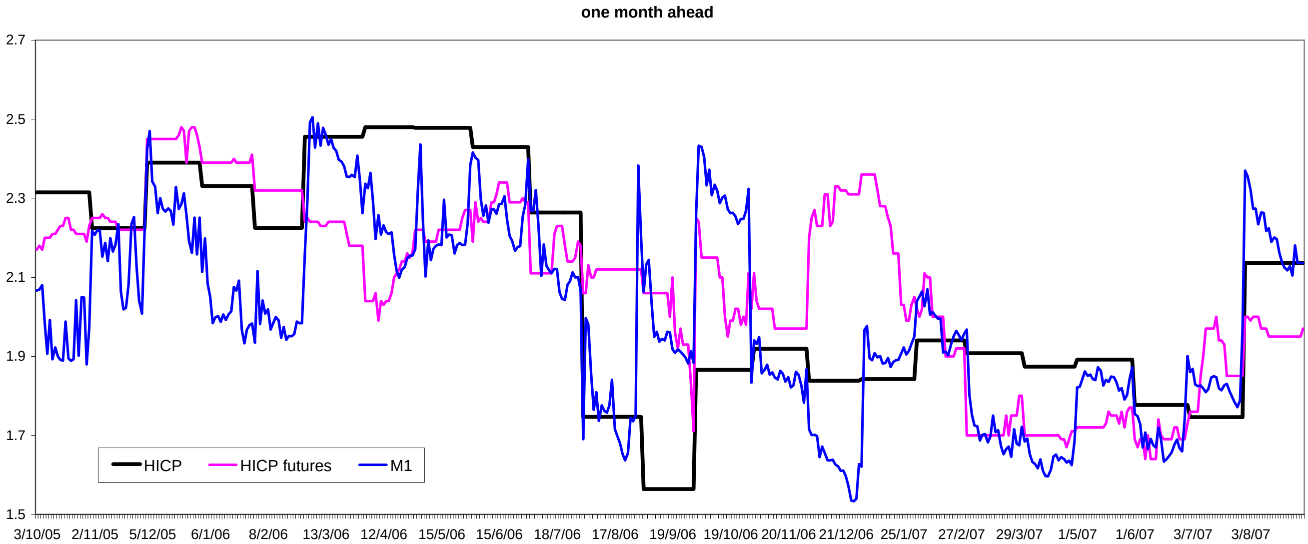
	Econ deriv	Combined predictions		
		M1	M2	M3
Equal weights				
current month	0.166	0.124	0.127	0.130
one month ahead	0.233	0.192	0.195	0.190
Estimated weights				
current month	0.166	**0.117**	0.123	0.128
one month ahead	0.233	0.191	0.195	**0.189**

Note: Estimated weights are those of forecast encompassing regressions (Table 4).

Figure 1

Daily forecasts





Legenda:
HICP futures= Inflation rate implied in the HICP future contracts (source: Bloomberg)
HICP = HICP inflation rate projected on daily data (source: our elaboration based on Eurostat)
m1 = inflation predictions of model 1

Figure 2

Box-Plots of daily forecast errors