EUROPEAN CENTRAL BANK

EUROSYSTEM

WORKING PAPER SERIES

NO 900 / MAY 2008

FORECASTING INFLATION AND TRACKING MONETARY POLICY IN THE EURO AREA

DOES NATIONAL INFORMATION HELP?

by Riccardo Cristadoro, Fabrizio Venditti and Giuseppe Saporito

EUROPEAN CENTRAL BANK

EUROSYSTEM

WORKING PAPER SERIES

NO 900 / MAY 2008

FORECASTING INFLATION AND TRACKING MONETARY POLICY IN THE EURO AREA

DOES NATIONAL INFORMATION HELP? [1]

by Riccardo Cristadoro [2], Fabrizio Venditti and Giuseppe Saporito

In 2008 all ECB publications feature a motif taken from the €10 banknote.

1 The views expressed in this paper are solely the responsibility of the author and should not be interpreted as reflecting the views of the ECB or Banca d'Italia.

2 All authors: Banca d'Italia, Research Department, via Nazionale 91, I – 00184 Rome, Italy; email: riccardo.cristadoro@bancaditalia.it, fabrizio.venditti@bancaditalia.it; giuseppe.saporito@bancaditalia.it (Cagliari Branch at Banca d'Italia).

Address
Kaiserstrasse 29
60311 Frankfurt am Main, Germany

Postal address
Postfach 16 03 19
60066 Frankfurt am Main, Germany

Telephone
+49 69 1344 0

Website
http://www.ecb.europa.eu

Fax
+49 69 1344 6000

ISSN 1561-0810 (print)
ISSN 1725-2806 (online)

CONTENTS

Abstract

The ECB objective is set in terms of year on year growth rate of the Euro area HICP. Nonetheless, a good deal of attention is given to national data by market analysts when they try to anticipate monetary policy moves. In this paper we use the Generalized Dynamic Factor model to develop a set of core inflation indicators that, combining national data with area wide information, allow us to answer two related questions. The first is whether country specific data actually bear any relevance for the future path of area wide price growth, over and above that already contained in area wide data. The second is whether in order to track ECB monetary policy decisions it is useful to take into account national information and not only area wide statistics. In both cases our findings point to the conclusion that, once area wide information is properly taken into account, there is little to be gained from considering national idiosyncratic developments.

Keywords: forecasting, dynamic factor model, inflation, Taylor rule, monetary policy

JEL Classification: C25, E37, E52

Non-technical summary

The ECB monetary policy objective of maintaining price stability in the euro area is defined in terms of the year on year rate of growth of the area wide Harmonized Index of Consumer Prices (HICP) over the medium run. Given the forward-looking nature of its objective, predicting inflation emerges as a crucial task both for the Central Bank, whose interest rates decisions respond to changes in expected price growth, and for analysts that want to track the ECB moves.

An important issue that naturally arises in forecasting euro area inflation is how to deal with the availability of both aggregate and national information in an economic area where a centralized monetary policy coexists with a decentralized fiscal policy and segmented labour markets. In such a context looking at national data could in principle provide some additional information on future inflation, over and above that contained in area wide data.

The aim of this paper is to assess the value added of national information to forecast euro area inflation and to track euro area interest rates. To gauge the predictive content of national variables we propose a set of core inflation indicators, computed using the Generalized Dynamic Factor Model, that combine both national and area wide data to predict inflation at different horizons. As a corollary to this approach, we also explore the issue recently raised in the related literature of whether "more data" in factor models is always "better". To do so we report a careful analysis of different data-reduction methods and assess the gains in forecast accuracy arising from them.

To assess whether national information is relevant for tracking monetary policy we proceed in two steps.

First, we compare the forecasting performance of our core indicators with that of univariate models built with alternative predictors. In this context we also consider the potential gains of using national information as summarized by national core indexes or an area wide core measure estimated on a data set that does not include only area wide statistics.

Second, we check whether one can "track" ECB monetary policy decision using the euro core index and the output gap, in a simple Taylor rule framework, and test whether national information helps in rationalizing interest rates developments.

The main results of our analysis can be summarized as follows.

- Core inflation indexes based on common factors estimated on large datasets have good forecasting properties both for national and area wide inflation rates. Consistently with the ECB monetary policy objective we define our inflation forecast target as the twelve month rate of change of the Harmonized Index of Consumer Prices. When compared with simple univariate models or with simple regression models that use variables routinely scrutinized by the ECB Governing Council in their Monetary and Economic assessment, our core inflation indexes almost always provide the best signals for future inflation at the horizons relevant for monetary policy. The prediction of euro area inflation does not improve when including national data in the information set. Furthermore the use of different selection criteria does not generally lead to more precise forecast than those obtained estimating the common factors on the full information set.

- The good forecasting performance of our core indicators allows us to consider them as natural candidates for analyzing interest rate behaviour in the euro area. We find that the core inflation index estimated on area wide data, together with a survey based output gap measure, contributes significantly to tracking short term interest rates movements. The use of national information, proxied by our national core inflation indexes, on the other hand, does not add any significant explanatory power to the baseline Taylor rule regression.
- We conclude that the area wide core inflation index appropriately summarizes all the relevant information, both for forecasting medium term inflation developments and for tracking the ECB monetary policy. Conditioning on area wide data, the use of national information turns out to be irrelevant for both aims.

1 Introduction

The ECB primary objective is maintaining price stability in the euro area. This objective has been given a more precise quantitative definition by the Governing Council of the ECB as a year on year rate of growth of the area wide Harmonized Index of Consumer Prices (HICP) *close but below 2 percent over the medium run.* A key aspect of this definition is that the ECB, recognizing that monetary policy affects the economy with long and variable lags, pursues price stability over the medium term, and thus it "needs to act in a forward looking manner".[1] Therefore, much in the spirit of the forecast inflation targeting strategy advocated by Svensson (2005), predicting inflation is a crucial task both for the Central Bank and for analysts that want to track the ECB moves.

Forecasting inflation in the euro area, where a centralized monetary policy coexists with decentralized fiscal policies and segmented labour markets, leaves room for national data that could in principle provide some additional information on future inflation, over and above that contained in area wide statistics. A recent strand of literature has discussed the merits, from an optimal monetary policy point of view, of looking at disaggregated information even when, as in the case of the ECB, the loss function only depends on aggregate quantities (De Grauwe (2000), Altissimo *et al.* (2005), Angelini *et al.* (2006), Aoki (2001)).[2]

The ECB has repeatedly stressed that national information is instrumental in gaining a better assessment of euro area developments that remain the only determinants of policy decisions as shown by this quote from former chief economist Otmar Issing:[3]

"The ECB/Eurosystem has a mandate to maintain price stability for the euro area as a whole. All our internal work, our analysis and assessment of economic information, our policy discussions and our policy decisions are directed unambiguously at this aim. Does this mean that we ignore sectoral, regional or country-specific information? Not at all [...] but, I should stress that this effort is made on the understanding that such disaggregated evidence helps us in better assessing the picture at the aggregate level."

The aim of this paper is to assess *first* the value added of national information in forecasting euro area inflation[4] and *second* its usefulness in tracking euro area interest rates. We focus on the three largest countries of the euro area (Germany, France and Italy), covering around 70 percent of the euro area GDP.

To gauge the predictive content of national variables we propose a set of core inflation indicators, computed using the Generalized Dynamic Factor Model (henceforth GDFM, see Forni, Hallin, Lippi and Reichlin (henceforth FHLR, 2000)), that combine both national and area wide

[1] See ECB (2004), p.54.

[2] The main message conveyed by these papers is that interest rates should react more aggressively to imbalances in the countries or sectors that respond to policy with more delay.

[3] See http://www.ecb.int/events/conferences/html/mpimphet.en.html

[4] The ECB projection exercises typically follow a bottom up approach, aggregating national forecasts into euro area projections.

data to predict inflation at different horizons. We set our discussion in the GDFM framework because, as shown by Cristadoro *et al.* (2005), core indexes computed with this method have proved very good predictors of inflation over the medium term horizon, which is the one the ECB focusses on when setting interest rates. From a methodological point of view we also extend the work by Cristadoro *et al.* (2005) by investigating two issues that have recently received attention in the diffusion index literature. First we check whether the empirical performance of the factor model benefits from a pre-screening of the series included in the dataset. Second, we investigate whether extracting factors that account for the bulk of the medium-long run common variance, rather than for the common variance across all frequencies, improves the forecasting ability of the model.

To assess whether national information is relevant in tracking monetary policy decisions we proceed in two steps. First, we estimate a Taylor-type reaction function in which the short term interest rate responds to its own lag, to a survey measure of the output gap, and to the area wide core inflation index. We then add national core inflation indexes to the conditioning set and test whether, controlling for the euro core index and the output gap, they contribute significantly to interest rates movements.

Our results suggest that augmenting area wide data with national information or using only national data does not lead to any improvement in the forecasting power of the model at any horizon and that, conditional on area wide data, the inclusion of national idiosyncratic developments in the information set does not lead to any improvement in tracking short term euro area interest rates.

The paper is structured as follows. Section 2 describes the dataset and the econometric methodology. Section 3 analyzes the dynamic correlation structure of the panel and collects some stylized facts on the degree of commonality found in the data. Section 4 discusses the forecasting exercise. In section 5 the importance of national variables in the reaction function of the ECB is assessed. Section 6 concludes.

2 Data and methodology

2.1 Data

Our dataset is a collection of almost 600 monthly time series covering all the main economic domains for which statistics are available: prices, industrial productions, financial markets, labour markets, surveys and other indicators (see table 1 where we report the distribution of variables across domains and countries).

Looking at the dataset by country, Germany and the euro area account for about half of the data collection. Given their economic relevance for the euro area we have also included in our information set variables that do not belong to euro area countries (more than 30 series from USA, Japan and the UK). Looking at the dataset by block of variables, the broader collection is that of prices (more than 150 variables, covering both consumer and producer prices). Surveys, that are very timely statistics and contain also information on price expectations constitute slightly less than a fifth of the dataset (128 variables). Real activity indicators (so called "hard data") are industrial production (92 series) and labour market variables (40 series). Financial variables comprise 36 interest rates on government bills and bonds as well as some market rates. Finally we have included the national and area wide components of money aggregates (M1, M2, and M3).

2.1.1 Data transformation

Prior to the factor analysis data are inspected to remove seasonality and outliers. We have cleaned series from deterministic seasonality by regressing each variable on a set of monthly dummies and their interaction with a linear trend. Unit roots, detected via KPSS and ADF tests, are removed by applying the appropriate filters (see last column of table 1).

2.1.2 Data Realignment

The time series in the panel are updated with different rapidity hence at the end of the sample data are "unbalanced": some series are available till the very last month, others have missing values at the end of the sample. We take into account this "end-of-sample unbalancing" problem by shifting the monthly series as follows: let T be the last month in the sample and $y^*_{i,T}$, $i = 1, \ldots, n$, be our monthly variables, after all transformations described above, but before re-alignment. Let's assume that the $i - th$ variable is released with k_i months of delay and therefore the last available observation at time T is $y^*_{i,T-k_i}$ (that is, the values between $T - k_i$ and T are missing). Then we set:

$$y_{i,t} = y^*_{i,t-k_i}, \qquad for\ t = k_i + 1, ..., T \tag{1}$$

so that the last available observation of y_i is always T for all.[5] This realignment allows us to compute the core index up to the most recent date exploiting all the series in the dataset. The time shift of variables with less timely updates is automatically taken care of when computing the covariance matrices from which factors are extracted.

2.2 The econometric methodology

Following FHLR (2000) we postulate a dynamic factor model structure for our panel: each series $y_{i,t}$, is the sum of two mutually orthogonal unobservable components, the *common component* $\chi_{i,t}$ which is “strongly correlated” across variables and the *idiosyncratic component* $\xi_{i,t}$ which is “poorly correlated”. The common component is driven by a small number, say q, of common

[5]Note that this procedure implies setting to missing value the first k_i observations of the i^{th} series. The estimation sample therefore goes from $max(k_i) + 1$ to T.

shocks $u_{h,t}$, $h = 1, \ldots, q$, which are the same for all cross-sectional units, but are (possibly) loaded with different coefficients and lag structures. By contrast, the *idiosyncratic components* are driven by variable-specific shocks. Hence, we have

$$y_{i,t} = \chi_{i,t} + \xi_{i,t} = b_i(L)u_t + \xi_{i,t} = \sum_{h=1}^{q} b_{ih}(L)\ u_{ht} + \xi_{i,t} \tag{2}$$

for $i = 1, \ldots, n$ where u_t is a $(q \times 1)$ vector of dynamic shocks and $b_i\,(L)$ is a vector of polynomials in the lag operator describing the loadings of these shocks into the i^{th} variable (see in FHLR (2000) and Forni and Lippi (2001)).

The impulse-response function $b_{i,h}(L)$, $h = 1, \ldots, q$, is a s-order polynomial in the lag operator, i.e. $b_{i,h}(L)u_{ht} = b_{i,h0}u_{ht} + b_{i,h1}u_{ht-1} + \cdots + b_{i,hs}u_{ht-s}$. so that any given variable can react with a different impulse-response profile to each of the q shocks. In particular, with reference to the delay with which the shocks are loaded, some of the $y_{i,t}$ will be 'leading' with respect to inflation some 'coincident' and some 'lagging'. This model can be reparameterized under mild conditions in a "static factor setup" (with $r = q(s+1)$ factors f_j obtained from the shocks appearing in equation (2) considering $u_{h,t}$ and $u_{h,t-1}$ as 2 different shocks):

$$y_{i,t} = \chi_{i,t} + \xi_{i,t} = \lambda_i F_t + \xi_{i,t} = \sum_{k=1}^{r} \lambda_{i,k} f_{t,k} + \xi_{i,t} \tag{3}$$

The common component $\chi_{i,t}$, which retains panel-wide common shocks but it is clean from measurement errors and sector specific sources of volatility, is estimated via *cross sectional smoothing* in the following way: *first* one estimates the covariance structure of the common and the idiosyncratic components ($\widehat{\Gamma}_\chi$ and $\widehat{\Gamma}_\xi$) as the inverse Fourier transform of the corresponding spectral density matrices ($\widehat{\Sigma}_\chi$ and $\widehat{\Sigma}_\xi$) obtained through dynamic principal component on $\widehat{\Sigma}_y$ (the spectral density of the observables) and *then* one projects the observed variables on the eigenvectors $\mathbf{v}_t$ (the generalized principal components of the y's), that span the same information space as u_t[6]:

$$\hat{\chi}_{i,t} = proj\,(y_{i,t}/\mathbf{v}_t) = proj\,\left(\chi_{i,t}/\mathbf{v}_t\right)$$

where the generalized eigenvectors v_j, $j = 1, \ldots, s$, satisfy[7]

$$v_j\hat{\Gamma}_\chi(0) = \mu_j v_j \hat{\Gamma}_\xi(0) \tag{4}$$

Loosely speaking, first appropriate averages of the variables are constructed and then all series are projected on them. The estimated common components $\chi_{i,t}$ are the basis of our core inflation indexes.

[6] The static factors are given by $f_{j,t} = v'_{j,t}y_t$

[7] See FHLR (2005).

2.2.1 Direct and indirect core inflation measures

In this paper we experiment with four alternative ways to construct a core inflation measure. Since we want to estimate the medium-long run component of the inflation process, a viable core inflation is the projection of month on month price growth on the generalized principal components.[8]

More precisely, assuming that HICP is the first variable of the panel a *direct* measure of core inflation is:

$$\widehat{\pi}_{d,t} = \left(\chi_{1,\ t}\sigma_1 + \mu_1\right) * 12 \tag{5}$$

where μ_1 is the mean and σ_1 is the standard deviation of the original variable $y_{1,t}$.[9]

A reasonable alternative to the direct projection of the HICP onto the space spanned by the factors is measuring the medium-long run component of inflation at time t via a centered bilateral filter between $t-6$ and $t+6$, as in band-pass filtering. The end of sample problem can be overcome by noticing that the inverse Fourier transform that precedes the eigenvalue decomposition provides us with all the covariances necessary to estimate the common components k steps ahead: $\chi_{1,\ t+k}$ (see Cristadoro *et al.* 2005). Using these forecasts we can build an *indirect* measure of core inflation:

$$\widehat{\pi}_{i,t} = \sum_{k=-6}^{6} \left(\chi_{1,\ t+k}\sigma_1 + \mu_1\right) \tag{6}$$

The appeal of this alternative is that it potentially provides extra smoothing and a more timely signal, provided the forecasts turn out to be sufficiently accurate.

2.2.2 Smooth factors and core inflation measures

Two more versions of the core inflation indexes, alternative to the ones proposed in (5) and (6), can be obtained by modifying the eigenvalue problem (4) that delivers the static factors used for the estimation of the common components.

A crucial ingredient of Cristadoro *et al.* (2005) core inflation index is the intertemporal smoothing obtained by projecting the HICP only on the medium-long run component of the common factors. A preliminary smoothing of the factors can however be performed by extracting the generalized eigenvectors v_j, $j = 1, \ldots, s$ that satisfy the modified condition:

$$v_j \hat{\Gamma}_{\chi^L} = \mu_j v_j \left(\hat{\Gamma}_{\chi^S} + \hat{\Gamma}_{\xi}\right) \tag{7}$$

where $\hat{\Gamma}_{\chi^S}$ and $\hat{\Gamma}_{\chi^L}$ are - respectively - the covariance matrices of the short run and long run common component ($\chi_t = \chi_t^L + \chi_t^S$). The generalized principal components that satisfy condition

[8] This core index is computed using the generalized eigenvectors that are the solution of equation (4) and the covariance matrix of the common components obtained via inverse fourier transform of the spectral density on the frequency band of interest (corresponding to a period of one year or more, see Cristadoro *et al.* 2005).

[9] We multiply $\left(\chi_{1,\ t}\sigma_1 + \mu_1\right)$ by 12 in equation (5) to obtain an annualized core inflation rate, since $\chi_{1,\ t}$ is obtained as the projection of the month on month inflation rate onto the common factors.

(7) differ from those satisfying condition (4) as they maximize the ratio of the medium-long run common variance to the residual variance rather than the ratio of common to idiosyncratic variance see Altissimo *et al.* (2007). They are therefore smoother than the ones obtained by solving (4). By projecting inflation on these alternative generalized principal components we can therefore obtain the smooth common component of inflation $\chi^L_{1,\,t}$ and construct two more alternative core inflation indexes: a *direct smooth* measure of core inflation:

$$\widehat{\pi}_{d(s),t} = \left(\chi^L_{1,\,t}\sigma_1 + \mu_1\right) * 12 \tag{8}$$

and an *indirect smooth* measure of core inflation

$$\widehat{\pi}_{i(s),t} = \sum_{k=-6}^{6} \left(\chi^L_{1,\,t+k}\sigma_1 + \mu_1\right) \tag{9}$$

2.2.3 Core inflation and forecasting

The literature on forecasting in a large data set context has developed various ways to use diffusion indexes to predict economic variables (see Boivin and Ng (2006) for a survey of the different methods and an evaluation of their performance). Here we follow Cristadoro *et al.* (2005) and use the current value of our core inflation measures as a forecast of future inflation. To clarify this point let us define our target variable $\pi_{t+h} = (1 - L^{12})P_{t+h}$, that is the twelve months $HICP$ inflation rate h steps ahead, where h=6, 12, 18, 24, and consider four different forecasts of the target variable:

$$\widehat{\pi}^f_{t+h} = \widehat{\pi}_{d,t} \tag{10}$$
$$\widehat{\pi}^f_{t+h} = \widehat{\pi}_{i,t} \tag{11}$$
$$\widehat{\pi}^f_{t+h} = \widehat{\pi}_{d(s),t} \tag{12}$$
$$\widehat{\pi}^f_{t+h} = \widehat{\pi}_{i(s),t} \tag{13}$$

Note that the target variable is a year on year percentage change, while the core inflation indexes are the medium-long run component of the month on month price changes. Implicit in the use of the common component of a month on month change is that the factor model is able to extract the medium-long run information contained in the month on month change, providing the same smoothing of high frequency noise (but without inducing any phase shift) of the twelve month moving average filter implied in $(1 - L^{12})$.

3 Dynamic Correlations and stylized facts

The basic stylized fact that motivates the use of factor models is that macroeconomic variables comove, especially at business cycle frequencies.[10] This allows a parsimonious representation of

[10] Business cycle frequencies are usually defined as those frequencies that corresponds to oscillation (periods) between 2 and 8 years. While we experimented with different frequency bands, in the remainder we report results

the correlation structure of a large panel of time series based on a limited number of common shocks. While various statistical tests have been proposed in the literature to determine the exact number of common shocks, we rely on a less formal method to infer the dynamic rank of the panel: we look at the variance explained by the largest dynamic factors as we increase their number until they are sufficient to capture the bulk of the variation in the panel. Since the variance explained by each dynamic principal component is simply measured by its corresponding eigenvalue, all we need to do is to inspect the behaviour of the largest dynamic eigenvalues.

Figure 1 shows the eight largest dynamic eigenvalues computed first on the whole dataset and then on the national subsets. In the three countries the fraction of variance explained by the first eigenvalue has a peak at very low frequency and declines thereafter. In Germany and Italy however, it also explains a large portion of the seasonal variance, while high frequency movements in French data are homogeneously captured by the first few dynamic shocks. The second point that emerges from Figure 1 is that the fourth largest eigenvalue captures around ten percent of the total variance at all frequencies, suggesting that a structure with four or less than four dynamic shocks should be able to retain the bulk of total variation in the data.

To support this intuition in Table 2 we report the relative variance explained by the first five dynamic factors in the whole dataset. The first four factors explain around sixty percent of the total variation in the panel. When we focus on frequencies corresponding to periodicities lower than one or two years this figure rises to 75 and 80 percent, respectively. Adding one more factor gives a negligible gain in terms of explained variance. In Table 3 we repeat this exercise for a selected number of series of interest in the euro area and in the three countries. At least three interesting points emerge from Table 3. First, looking at the last two columns, it is evident that for unemployment, inflation and industrial production a model with three to four dynamic factors is able to summarize between 60 and 90 percent of total variance at periodicities lower than two years. Second, for all the industrial productions series, going from three to four factors entails a sizeable gain in terms of explained variance. Third, moving from the first to the last column, it is comforting to see that for most of the variables the variance explained by the factor model increases with the periodicity considered. This is not true however for the retail sales in Italy and Germany suggesting that their volatility is concentrated at very low periodicities, probably accounting for the high frequency peak of the first dynamic eigenvalue observed in Figure 1.

Finally we checked both by domain and country, that the panel contains a sufficient number of variables that lead euro area inflation. We have first computed the dynamic correlations between the common component of each variable and the year on year HICP euro area growth. We have then classified each variable as leading, lagging and coincident, depending on whether its maximum dynamic correlation with the target occurs at negative, positive or zero lags. Finally we have calculated the percentage of leading, lagging and coincident variables within

for overall variation, and periods longer than 1 or 2 years.

each block and country, the average lag (or lead) at which the maximum correlation is found (this is obviously zero for the coincident variables) and the average of their correlation with the inflation rate. Results are reported in Table 4. Four interesting facts emerge. First, most of labour and survey data are either leading or coincident, while half or more than half of the variables in the other blocks are lagging with respect to the inflation rate. Also, labour market variables, on average, lead inflation by more than eight months. Second, survey data show the highest average correlation (0.46) among the leading variables. Third, the country by country analysis confirms that the distribution of leading, lagging and coincident variables is extremely well balanced among them. Finally, looking at the last line, where results for the whole dataset are reported, both the percentage of leading variables (around 35 percent) and the average lead (six months) suggest that the information in the dataset can be useful to forecast inflation.

4 Forecasting euro area inflation: does national information help?

The analysis carried out in the previous section suggests that a model relying on four dynamic shocks should also guarantee good inflation forecasts. In this section we first compare the forecasting performance (at horizons from 6 to 24 months ahead) of the core inflation indexes (10) to (13) with that of simple alternatives described in the following equations:

$$\pi_{t+h} = \alpha(L)\pi_t + \varepsilon_t \tag{14}$$

$$\pi_{t+h} = \beta(L)x_t + \varepsilon_t \tag{15}$$

$$\pi_{t+h} = \gamma(L)\pi_t + \delta(L)x_t + \varepsilon_t \tag{16}$$

where the left hand side variable is our target $\pi_{t+h} = (1 - L^{12})P_{t+h}$, *i.e.* the twelve months $HICP$ inflation rate h steps ahead, where h=6, 12, 18, 24. The first equation is an AR model, the second is a univariate regression equation on a chosen exogenous variable (x_t) and the third is a mix of the first two. The length of the lag polynomials in $\alpha(L)$, $\beta(L)$, $\gamma(L)$, $\delta(L)$ is selected on the basis of the Akaike Information Criterion. In addition we consider two naive forecasting models: a random walk and a running mean of the twelve months changes in P_{t-h}. The exogenous variables used in (14) to (16) competing models are chosen among those the ECB routinely looks at in its economic analysis: unit labour costs, monetary aggregates (M1, M2, M3) and industrial production in the manufacturing sector. All variables are expressed as three months percentage rates of growth. When we focus on a given country, π_t is obviously the inflation rate of that country. For the euro area we also consider a prediction based on a weighted average of the country forecasts.

4.1 Alternative GDFM forecasting exercises: targeted predictors.

To verify whether the forecasting performance of the baseline GDFM models benefits from a pre-selection of the variables to be inlcuded in the dataset we have analyzed two different criteria of choice: (i) the percentage of variance explained by the common factors at medium-long run frequencies (*commonality* criterion) and (ii) the correlation of each variable in the panel with future inflation (*threshold* criterion).

4.1.1 Commonality criterion

Our *commonality* criterion consists of retaining only the series in which the fraction of the variance (within a given frequency band) accounted for by the common factors increases as the spectral frequency decreases. This choice is motivated by the observation that most of the variance of our forecasting target, the year on year inflation rate in the euro area, is concentrated at very low frequencies. Since our forecasting method is based on a projection of the inflation rate on the space spanned by the common factors, excluding the variables whose variance is mainly determined by seasonal and other high frequency waves might improve the fit and give better forecasting results.

Our *commonality* selection algorithm works as follows:

1. Compute the spectral density matrix of the common components $\Sigma_{\chi}(\omega)$ and of the variables $\Sigma_y(\omega)$.

2. Evaluate for each variable j the share of total variance explained by the common component on all frequencies and on frequencies lower than $\omega = \pi/6$. These can be easily obtained as the ratios of the sum of diagonal elements of $\Sigma_{\chi}(\omega)$ over $[0, \pi]$ and over $\left[0, \frac{\pi}{6}\right]$, respectively, over those computed for $\Sigma_y(\omega)$, (call these two ratios λ_j and $\lambda_j^{\pi/6}$).

3. Keep the j^{th} variable in the panel only if $\lambda_j^{\pi/6} > \lambda_j$.

4. Then we recompute the different core inflation measures on this set of selected predictors Y_s and then form the forecasts as in equations (10) to (13).

4.1.2 Threshold criterion

This criterion uses a statistical test to check if, in a regression of the variable to be predicted on the h^{th} lag of the candidate variable, the coefficient of the regression is significantly different from zero. Our implementation is drawn from Bai and Ng (2007) where this test is performed controlling for the lags of the variables to be forecast. The selection algorithm is based on the following steps:

1. For each variable $y_{j,t}$, $j = 1, 2, ..., n$, in the panel, perform the regression

$$\pi_t = \lambda y_{j,t-h} + \beta(L)\pi_{t-h} + \varepsilon_t \tag{17}$$

   where $\beta(L) = (\beta_1 + \beta_2 L + \beta_3 L^2 + \beta_4 L^3)$

2. Compute $t_\lambda^j(h)$, the absolute value of a t-test on the λ coefficient associated with the candidate variable y_j.

3. Rank the variables according to their predictive power by sorting $t_\lambda^1(h)$, $t_\lambda^2(h)$, ..., $t_\lambda^N(h)$.

4. Keep only the variables whose predictive power exceeds a threshold significance level α^*.

5. As above, we then recompute the different core inflation measures on this set of selected predictors Y_s and form the forecasts as in equations (10) to (13).

Our implementation differs from that of Bai and Ng (2007) in one important aspect as they let the set of predictors vary with the forecasting horizon h in (17), therefore allowing their factors to depend on a different information set at each forecasting horizon. Since we focus on the forecasting properties of a core inflation index in the medium-long run, we find discomforting the idea of a different core inflation index for each time horizons, therefore we keep the dataset fixed. This strategy implies a further choice: assigning a weight to the different forecasting horizons in deciding whether to include or not a variable in our information set.[11] Our subjective choice has fallen on keeping in the information set the variables whose *average* t-stat at 6 and 12 months horizon is higher than 1.28.

4.2 Results

Summing up, we conduct five different exercises:

1. A forecast based on the competing models 14 to 16
2. A GDFM forecast based on the whole dataset
3. A GDFM forecast based on the dataset selected with the commonality criterion
4. A GDFM forecast based on the dataset selected with the threshold criterion
5. A GDFM forecast based on the national dataset (area wide data for the euro area).

The results for Germany, France, Italy and the euro area are reported in Tables 5 to 8. These tables are organized in five panels, corresponding to the five forecast exercises described above, and havefour columns corresponding to the four different forecast horizons (6, 12, 18, 24). All Root Mean Squared Forecast Error (RMSFE) are expressed as a fraction of that of $\widehat{\pi}_d$, whose RMSFE is reported at the bottom of the table.

[11] What to do with a series that has a strongly significant correlation with inflation 6 months ahead, so that its $t_\lambda^j(6)$ exceeds the threshold value α^*, but whose forecasting power at other horizons is very poor?

4.2.1 Germany

The first block of rows of Table 5 shows that, in the case of Germany, the core inflation index outperforms most of the alternative models across all horizons, but it is dominated by the regression models on monetary aggregates (especially M2).

Pre-screening the variables, through the commonality or the thresholding criteria and using the indirect smooth method to construct the core inflation index, lowers the RMSFE by 20 percent at short horizons and by around 10 percent at medium/long term horizons. No significant improvements are obtained by limiting the information to the national data.

4.2.2 France

In the case of France, the upper panel of Table 6 shows that the factor model improves substantially upon other methods. Restricting the information set through the commonality criterion slightly improves the forecasts, especially when we use indirect measures of the core inflation index ($\widehat{\pi}_{i,t}$ and $\widehat{\pi}_{i(s),t}$). Finally, considering only national data gives good results, suggesting that there is an important national component that gets washed out when extracting the factors from a larger dataset.

4.2.3 Italy

Most of the the single equation forecasting models for Italy perform very poorly. This is likely to be due to the fact that the month on month growth of HICP shows a structural break in 2001, when Eurostat started compiling HICP indexes inclusive of temporary price reductions (see Figure 2) causing a dramatic increase of the volatility of the index that cannot be readily captured by the coefficient of the single equation models. On the other hand simpler alternatives, like the random walk and the twelve months running mean, give forecasts that are very hard to beat. As regards factor model forecasts, the gap between the GDFM and the random walk, especially when using the indirect measures of core inflation computed on national data alone, closes up at horizons longer than six months.

4.2.4 Euro area

The first block of results in Table 8 confirms that some monetary aggregates (especially M2) contain important information over long term inflation dynamics. As for factor model forecasts, applying the thresholding selection and using the indirect smooth method to compute the core inflation index improves with respect to the benchmark model by around 20 percent at horizons longer than 6 months, outperforming the forecasts based on monetary indicators at all but the 12 months horizons.

4.2.5 Does national information help in forecasting euro area inflation?

As a first way to test whether national information is relevant for forecasting euro area inflation, we compute a core inflation index based solely on area wide data, i.e. we check if the accuracy of inflation forecasts would diminish if one were to conceal national data to the policy maker. It turns out that using only area wide data produces results remarkably similar to those based on the whole dataset as can be seen by comparing the second and fifth panel of table 8.

Our second test consists of combining national core indexes (computed on national data only) to derive a euro area forecast. This aggregate forecast is a weighted average of the core indexes of Germany, France and Italy in which the weights are the coefficients of an OLS projection of the euro area core index on the three national ones (estimated between 1992 and 1998 and kept constant over the forecasting period). This forecast is significantly outperformed by all the other specifications over all horizons.

4.3 Comments

It is useful to draw some general conclusions on the forecasting exercise.

First, for Italy and France inflation rates seem to have an important national component that is better captured by restricting the information set to national data. Using the national forecasts to predict euro area inflation, however, does not improve on using only area wide variables or principal components extracted from the whole dataset (where national factors are averaged out). This answers our first question: within our methodology, national variables do not seem to have predictive content for future area inflation, over and above that provided by area wide data. *Second*, our results suggest that pre-screening the variables rather than using blindly all the available information can improve the factor forecasts, but only marginally.[12] *Third*, forecasts based on the indirect method or on smooth factors perform generally better, in line with the fact that we are predicting a smooth variable (the *year on year* inflation rate) projecting an extremely volatile variable (the *month on month* inflation rate) on few factors.

5 The ECB reaction function: does national information matter?

This section investigates whether using national information improves the tracking of common monetary policy in the euro area. Given its target, the ECB monetary policy should respond to the common component and give zero weights to the idiosyncratic ones. We show that in fact a simple Taylor rule that includes the euro area core inflation as a proxy for inflation forecast, gives a good ex post explanation of short term interest rates behaviour. Then, to formally test the hypothesis that country information does not enter this simplified ECB reaction function,

[12] Selecting variables according to a given criterion is appealing, but it has a shortcoming when measuring core inflation in real life situation, since potentially it implies a core measure based on a different dataset at each point in time.

we augment the information set of the Taylor rule by including also *purely* national information, obtained from the country core indexes as the residual of their projection on the area wide core indicator.

5.1 The empirical strategy

A number of studies have analyzed the interest rate setting behavior of the ECB by estimating empirical reaction functions, among which a prominent role is played by Taylor rules type regressions (see Carstensen (2006)). The Taylor rule describes the policy rate as a function of the deviation of inflation from its target and of output from its potential. A few changes on this basic setup are usually introduced by different authors to solve three problems. *First*, to take into account the forward looking nature of monetary policy, researchers have replaced current inflation with inflation expectations (see Peersman and Smets (1999)[13]). *Second*, to accommodate the real time nature of monetary policy decisions, which usually rely on available soft data to infer real economic activity developments, some studies have used survey based measures of the output gap as a proxy for deviations of output from its potential (see Sauer and Sturm (2003)). *Third*, as Central Bankers show a preference for smooth adjustments towards the optimal policy target (see Clarida (1998)), Taylor regressions typically include the lagged policy rate among the conditioning variables.

Our empirical implementation of the Taylor rule incorporates these variants. We assume that the Central Bank stabilizes inflation at time $t+h$ around a constant target and that the monetary policy rule consists of a gradual adjustment of the policy rate i_{t+1} towards the target rate i^*_{t+1}. Therefore the nominal interest rate follows a partial adjustment process:

$$i_{t+1} = \boldsymbol{\rho} i_t + (1-\boldsymbol{\rho}) i^*_{t+1} \tag{18}$$

toward the policy target i^*_{t+1}:

$$i^*_{t+1} = r^* + E_t\pi_{t+h} + \boldsymbol{\beta}(y_t - y^*_t) + (\boldsymbol{\delta} - 1)(E_t\pi_{t+h} - \pi^*) + \varepsilon_{t+1} \tag{19}$$

where r^* is the natural real rate of interest, $E_t\pi_{t+h}$ is the expected rate of inflation at time $t+h$ given the information available at time t, π^* is the inflation target, $y_t - y^*_t$ is the deviation of output from its potential and ε_{t+1} is a monetary policy shock.[14] Rearranging terms, equation (19) can be rewritten as:

$$i^*_{t+1} = \boldsymbol{\gamma} + \boldsymbol{\beta}(y_t - y^*_t) + \boldsymbol{\delta} E_t\pi_{t+h} + \varepsilon_{t+1} \tag{20}$$

[13] These authors find that a forward looking measure for inflation inserted in a Taylor rule for european interest rates estimated on a 1975-1997 sample fits fairly well.

[14] The timing convention adopted is motivated by the following consideration. We compute our measures (core and output gap) with data available at the end of period (month) t. Then we see if this information is helpful in explaining the policy rate set at the beginning of the next period (*i.e.* after the Governing Council meeting in period $t+1$). We do not introduce any correction to take into account the changes intervened in the operational framework of the ECB in the period considered (see ECB 2004, chp. 4).

where $\gamma = r^* - (\boldsymbol{\delta} - 1)\pi^*$.

Multiplying both terms of (20) by $(1 - \boldsymbol{\rho})$ and substituting from (18) we arrive at the final empirical specification:

$$i_{t+1} = \boldsymbol{\rho} i_t + (1 - \boldsymbol{\rho})\boldsymbol{\gamma} + (1 - \boldsymbol{\rho})\boldsymbol{\beta}(y_t - y_t^*) + (1 - \boldsymbol{\rho})\boldsymbol{\delta} E_t \pi_{t+h} + \varepsilon_{t+1} \tag{21}$$

Following Carstensen and Colavecchio (2006) our baseline model is given by the *reduced form parameterization*:

$$i_{t+1} = \rho i_t + \gamma + \beta(y_t - y_t^*) + \delta E_t \pi_{t+h} + \varepsilon_{t+1} \tag{22}$$

where $\rho = \boldsymbol{\rho}$, $\gamma = (1 - \boldsymbol{\rho})\boldsymbol{\gamma}$, $\beta = (1 - \boldsymbol{\rho})\boldsymbol{\beta}$ and $\delta = (1 - \boldsymbol{\rho})\boldsymbol{\delta}$. We estimate equation (22) and then back out the structural (bold faced) parameters inverting these relationships. The correct standard errors for the structural parameters are derived with the delta method.

5.2 Data issues

Estimation of equation (22) requires the preliminary qualification of three points. *First*, we need to choose the interest rate to be used as dependent variable: i_{t+1}. Using the MRO rate[15] as the dependent variable requires appropriate techniques to handle the discrete jumps in this variable. Like other authors we use the 3-month Euribor as a convenient simplification, since it is the market rate that the policy maker has to influence to affect economic choices and therefore stabilize inflation. In the upper panel of Figure 3 we plot the 3-month Euribor and the MRO rate: the two rates move closely together, displaying a correlation of 0.98. *Second*, we need a monthly and timely measure of the output gap, $y_t - y_t^*$. Carstensen and Colavecchio (2006) suggest the use of survey based measures of the output gap since these are both timely and forward looking, hence good proxies of the information that Central Banks might consider in their decision making process. We follow this suggestion and use the percentage deviation of the EU Economic Sentiment Indicator from its historic average as our measure of economic slack. Comparison of the upper and the lower panel of Figure 3 reveals that this measure of the output gap is strongly correlated with short term interest rates and leads them by few months. This intuition is confirmed by the dynamic correlations between current output gap and future values of the 3-month Euribor, which increase gradually from a value of 0.48 at contemporaneous lead to a maximum of 0.73 at 8 months lead (see the upper panel of Figure 4). The lower panel of Figure 4 shows that this output gap measure also leads year on year inflation 6 to 12 months ahead. *Third*, we need to specify the time horizon $t + h$ at which the monetary policy maker would like to close the gap between inflation and its target and also specify a measure of inflation expectations $E_t \pi_{t+h}$. Since the forecasting exercise has shown that the factor model based core inflation index is a good predictor of inflation over a broad spectrum of forecast horizons, we

[15] This is the interest rate on main refinancing operations, the key rate set by the Eurosystem (it is the central rate in the interest rate corridor), and it is closely related to the interbank overnight rates (EONIA). For a more complete description of the monetary policy instruments and strategy see ECB (2004).

leave h unspecified and replace $E_t\pi_{t+h}$ with the euro core inflation index based on the indirect smooth method and estimated only on area wide data: $\widehat{\pi}^{aw}_{i(s),t}$.

Therefore our baseline specification is:

$$i_{t+1} = \rho i_t + \gamma + \beta(y_t - y_t^*) + \delta E_t \widehat{\pi}^{aw}_{i(s),t} + \varepsilon_{t+1} \tag{23}$$

On this basis we test for the relevance of national information, separating the information contained in the country core indexes that is correlated with area wide core inflation from purely national one by regressing the country core indexes on the area wide core. Then we augment equation (23) with the residuals of these regressions ($\widehat{u}_t^{ger}$, $\widehat{u}_t^{fra}$, $\widehat{u}_t^{ita}$) obtaining the following model :

$$i_{t+1} = \rho_m i_t + \gamma_m + \beta_m(y_t - y_t^*) + \delta_m \widehat{\pi}^{aw}_{i(s),t} + \delta^m_{ger}\widehat{u}_t^{ger} + \delta^m_{fra}\widehat{u}_t^{fra} + \delta^m_{ita}\widehat{u}_t^{ita} + \varepsilon_{t+1} \tag{24}$$

and perform an F-test that the parameters $(\widehat{\delta}^m_{ger}, \widehat{\delta}^m_{fra}, \widehat{\delta}^m_{ita})$ are jointly zero.

In the first two columns of Table 9 we report the results obtained when taking equation (23) to the data. The coefficients of the lagged policy rate ρ (0.94) and on the output gap β (0.07) are statistically significant, indicating a strong degree of interest rate smoothing and a prompt adjustment of interest rates to cyclical output movements. More importantly, the parameter δ (0.13) is significantly different from zero, indicating that interest rates react very strongly to the information content summarized by our core inflation index.[16] Conditional on the previous level of the interest rate and on the output gap a one percent growth of the core index over the previous month triggers an interest rate increase of 13 basis points.

The last two columns of Table 9 show the results obtained when estimating equation (24). The coefficients on the lagged interest rate, on the output gap and on the euro area core index are qualitatively unchanged and still significant. On the other hand $\widehat{\delta}^m_{ger}$,$\widehat{\delta}^m_{fra}$ and $\widehat{\delta}^m_{ita}$ are not significantly different from zero. The null hypothesis that $(\widehat{\delta}^m_{ger}, \widehat{\delta}^m_{fra}, \widehat{\delta}^m_{ita})$ are jointly zero gives an F-probability of 0.59 (Wald test) and therefore cannot be rejected at a 95 percent confidence level, supporting the hypothesis that short term interest rates movements in the euro area do not reflect national shocks.

Finally we back out from the estimated equation (23) the structural parameters measuring the response of the interest rates to expected inflation and to the output gap. The so called *Taylor principle* requires the policy rate to respond more than one to one to deviation of inflation from its target, so that the *real* rate of interest is affected. In Table (10) we report the estimation results. The long term response of the interest rate to the output gap is 1.25. The structural coefficient governing the policy response to deviations of inflation from its target is 2.3, *in line with existing evidence*, confirming both the forward looking and the stabilizing nature of the ECB reaction function.

[16] Other inflation measures introduced in (24) as an alternative to our core index (like the year on year change of overall HICP, or of HICP net of food and energy) turn out to be not significant.

6 Conclusions

In this paper we address two questions: (i) whether national variables contain relevant information on the future path of euro area inflation, over and above that provided by area wide data, and (ii) whether, controlling for euro area objectives, national inflation gaps improve the ex-post explanation of short term interest rates in the euro area.

To answer the first question we propose national and area wide core inflation measures based on the GDFM methodology. These indicators are shown to outperform most naive inflation forecasts at horizons relevant for the monetary policy. Compared with an aggregation of national core indexes or with an index estimated on a dataset that includes national information, the euro area core index estimated only on euro area variables performs better or equally well in predicting area wide inflation.

To answer the second question we first verify that the euro area core index contributes significantly to tracking monetary policy when inserted in a Taylor rule equation. Then we check if the components of the national core indexes that are orthogonal to the euro area core measure enter significantly in the Taylor rule. They turn out to be insignificant, thus supporting the conclusion that the area wide measure is sufficient to explain policy choices.[17]

An interesting development of our research is to recast our monetary policy tracking exercise in a different fashion, using the MRO rate and therefore a discrete choice model. This would allow a more careful analysis of the timing of the moves and the information content of the indicators proposed.

A further issue would be taking full advantage of real time data to check the robstness of the results. Finally one could exploit the existing testing procedures to verify the significance of the differences in forecast accuracy we document in this paper (see the tests proposed by Giacomini and White (2006), Diebold and Mariano (1995) and West (1996)).

[17] This finding does not rule out that other kinds of country information could turn out relevant in explaining policy moves. For instance, the theoretical literature on currency areas has underlined that it might be optimal for the monetary policy to respond to inflation dispersion among countries; we have not tested this possibility. We thank an anonymous referee for pointing this out.

References

[1] Altissimo, F., Benigno P. and Rodriguez Palenzuela, D. (2005). Long-Run Determinants of Inflation Differentials in a Monetary Union, NBER Working Papers 11473, National Bureau of Economic Research.

[2] Altissimo, F., Cristadoro, R., Forni, M., Lippi, M. and Veronese, G. (2007), New Eurocoin: tracking economic growth in real time, Banca d'Italia, Tema di discussione 631.

[3] Angelini, P., Del Giovane, P., Siviero, S. and Terlizzese, D. (2006), Monetary Policy in the euro area, what role for national information?, Banca d'Italia, mimeo.

[4] Aoki, K. (2001), Optimal Monetary Policy Response to Relative Price Changes, Journal of Monetary Economics, 48, 55-80.

[5] Bai, J. and Ng, S. (2007), Forecasting Economic Time Series with Targeted Variables, Journal of Econometrics, forthcoming.

[6] Boivin, J. and Ng, S. (2005), Understanding and Comparing Factor-Based Forecasts, International Journal of Central Banking, 1(3), 117-151.

[7] Carstensen, K. (2006), Estimating the ECB Policy Reaction Function, German Economic Review, 7, 1–34.

[8] Carstensen, K. and Colavecchio, R. (2006), The ECB monetary policy and its Taylor-type reaction function, Rivista Italiana degli Economisti, 1, 51-86.

[9] Clarida, R. Gali, J. and Gertler, M. (1998), Monetary Policy Rules in Practice: Some International Evidence, , European Economics Review, June, 42, 1033-1067.

[10] Cristadoro, R., Forni, M., Reichlin, L. and Veronese, G. (2005), A core inflation index for the euro area, Journal of Money Credit and Banking, 37, 539-60.

[11] De Grauwe, P. (2000), Monetary Policies in the presence of asymmetries, CEPR discussion paper 2393.

[12] Diebold, F. X. and Mariano, R. S. (1995), Comparing Predictive Accuracy, Journal of Business & Economic Statistics, 13(3), 253-63.

[13] ECB (2004) The monetary policy of the ECB, European Central Bank.

[14] Forni, M., Hallin, M., Lippi, M. and Reichlin, L. (2000), The generalized factor model: identification and estimation, The Review of Economics and Statistics, 82, 540-554.

[15] Forni, M., M. Hallin, M. Lippi, and Reichlin, L. (2005), The generalized factor model: one-sided estimation and forecasting, Journal of the American Statistical Association, 100, 830-40.

[16] Forni, M. and Lippi, M. (2001), The generalized dynamic factor model: representation theory, Econometric Theory, 17, 1113-41.

[17] Gali, J. (2003), Monetary Policy in the Early Years of EMU, in 'EMU and Economic Policy in Europe: the Challenges of the Early Years', edited by M. Buti and A. Sapir, Edward Elgar.

[18] Giacomini, R. and White, H. (2006), Tests of Conditional Predictive Ability, Econometrica, 74(6), 1545-1578.

[19] Peersman, G.and Smets, F. (1999), The Taylor rule, a useful Monetary Policy Benchmark for the euro area. International Finance, 2(1), 85-116.

[20] Sauer S. and Sturm, J.E. (2003), Using Taylor Rules to understand ECB monetary policy, CESifo Working Paper 1110.

[21] Svensson, L. (2005), Monetary Policy with Judgment: Forecast Targeting, International Journal of Central Banking, 1(1), 1-54.

[22] West, K. D. (1996), Asymptotic Inference about Predictive Ability, Econometrica, 64, 1067-1084.

	Italy	Germany	France	Spain	Belgium/Netherlands	Euro+others	Total	Trans.	Filter
Consumer Price	6	10	6	6	7	7	42	Log	1-L
Producer Price	25	22	15	17	15	19	113	Log	1-L
Exchange rates	1	1	1	1	2	7	13	Log	1-L
Industrial Production	10	23	15	13	6	25	92	Log	1-L
Employment statistics	5	7	4	4	1	4	25	Log	1-L
Wages	3	4	2	2	3	-	14	Log	1-L
Interest rates	6	9	6	4	4	7	36	-	1-L
Money aggregates	3	5	3	-	3	3	17	Log	1-L
Share indexes	1	1	1	1	-	8	12	Log	1-L
Survey	24	27	31	5	10	31	128	-	-
Other Indicators	20	39	10	3	6	1	79	-	-
All Dataset	104	148	94	56	57	112	570	-	-

Table 1: Summary of the variables included in the dataset by country, domain and transformations

Note to Table 1: in the column "Trans." we report whether the variables are subject to a log transformation. The (-) symbol stands for no transformation. In the column "Filter" we report whether the variables have been differenced (1-L) prior to the analysis. The (-) symbol stands for no differencing. .

q	Tot	< 1 year	< 2 years
1	0,27	0,41	0,43
2	0,41	0,59	0,62
3	0,50	0,68	0,71
4	0,58	0,75	0,79
5	0,64	0,80	0,84

Table 2: Share of the variance of the panel explained by the first q dynamic factors (q=1,2,...,5) over the whole spectrum (Tot) and at frequencies corresponding to periodicities below one (<1 year) and two years (<2 years)

Selected Variables	Tot		<1 year		<2 years	
	q=3	q=4	q=3	q=4	q=3	q=4
Euro area HICP	0,61	0,68	0,72	0,76	0,79	0,82
Euro area Industrial Production - Manufacturing	0,65	0,75	0,73	0,85	0,72	0,89
Euro area Unemployment rate	0,64	0,69	0,87	0,91	0,91	0,94
Germany HICP	0,49	0,56	0,52	0,62	0,66	0,69
Germany Industrial Production - Manufacturing	0,65	0,73	0,64	0,78	0,66	0,85
Germany Unemployment Rate	0,34	0,38	0,71	0,76	0,78	0,83
Germany Unit Labour Costs	0,52	0,62	0,51	0,67	0,48	0,69
Germany Retail Sales	0,80	0,83	0,22	0,25	0,31	0,36
Italy HICP	0,46	0,53	0,71	0,74	0,78	0,79
Italy Industrial Production - Manufacturing	0,39	0,47	0,46	0,50	0,55	0,59
Italy Unemployment Rate	0,48	0,53	0,61	0,64	0,68	0,71
Italy Unit Labour Costs	0,36	0,48	0,47	0,55	0,46	0,52
Italy Retail Sales	0,36	0,45	0,10	0,12	0,10	0,13
France HICP	0,49	0,57	0,52	0,54	0,59	0,61
France Industrial Production - Manufacturing	0,47	0,54	0,67	0,78	0,68	0,83
France Unemployment Rate	0,76	0,81	0,86	0,90	0,90	0,95
France Unit Labour Costs	0,42	0,55	0,29	0,52	0,22	0,47
France Retail Sales	0,53	0,62	0,68	0,76	0,72	0,81

Table 3: Share of the variance of selected variables explained by the first three (q=3) and four (q=4) dynamic factors over the whole spectrum (Tot) and at frequencies corresponding to periodicities below one (<1 year) and two years (<2 years)

Domain/Country	Number of variables	Lagging			Leading			Coincident	
		%	Aver. corr	Aver. lag	%	Aver. corr.	Aver. lag	%	Aver. corr.
Prices	168	59	0.34	7.96	24	0.30	-7.05	17	0.47
Industrial Productions	92	57	0.12	3.58	36	0.10	-7.03	8	0.15
Labour market	39	15	0.31	5.33	51	0.37	-8.15	33	0.59
Financial	64	44	0.24	9.07	47	0.27	-5.83	9	0.23
Surveys	128	16	0.43	7.71	39	0.51	-6.38	45	0.47
Various	79	51	0.11	5.25	35	0.13	-6.29	14	0.16
Germany	148	44	0.20	5.88	36	0.27	-6.51	20	0.34
Italy	104	49	0.30	6.92	25	0.31	-6.81	26	0.38
France	94	35	0.26	6.33	45	0.30	-6.52	20	0.45
Spain	56	63	0.29	6.34	14	0.31	-6.00	23	0.56
Belgium	32	31	0.19	7.90	44	0.20	-6.21	25	0.44
Netherlands	24	29	0.20	8.43	50	0.28	-7.58	21	0.48
Euro+others	112	40	0.27	7.29	41	0.34	-7.07	19	0.47
All dataset	570	43	0.25	6.63	35	0.30	-6.70	22	0.43

Table 4: Classification of the variables (grouped by block of variables and by country) in leading, lagging and coincident with respect to euro area year on year inflation.

Note to Table 4: the variables in the panel are classified in lagging, leading or coincident, depending on whether their maximum correlation with euro area inflation is found at positive, negative or zero lag. For each block of variables and country we report the percentage of variables falling into each of the three categories (lagging, leading or coincident), the average of their maxima correlations with euro area inflation and and the average lag at which the maximum correlation is found (for the category "Coincident" this column is missing since the average lag is 0). For example, the first row tells us that 59% of the price variables lag euro area inflation by around 8 months, with an average correlation of 0.34, 24% of the price variables lead euro area inflation by around 7 months, with an average correlation of 0.30, and the remaining 17% of the price variables are coincident with euro area inflation with an average correlation of 0.47. .

h	6	12	18	24
Alternative forecasting models				
AR	0.89	1.01	1.26	1.31
ULC	1.21	1.07	1.17	1.07
M1	1.12	0.94	0.79	0.78
M2	0.97	0.74	0.83	0.75
M3	1.96	1.60	1.38	1.40
IP (Manufacturing)	1.57	1.21	1.16	0.92
ULC +AR	1.12	1.32	1.61	1.75
M1+AR	1.11	1.22	1.76	1.89
M2+AR	1.03	1.28	1.66	1.80
M3+AR	1.03	1.27	1.71	1.97
IP (Manufacturing)+AR	1.10	1.24	1.74	1.78
RW	1.00	1.02	1.29	1.28
running mean	0.96	1.03	1.18	1.34
Core index (all dataset)				
$\hat{\pi}_d$	1.00	1.00	1.00	1.00
$\hat{\pi}_i$	0.95	0.95	0.98	1.00
$\hat{\pi}_{d(s)}$	0.91	0.89	0.87	0.94
$\hat{\pi}_{i(s)}$	0.87	0.85	0.88	0.94
Core index (Commonality)				
$\hat{\pi}_d$	1.00	0.98	0.97	0.98
$\hat{\pi}_i$	0.93	0.93	0.95	0.97
$\hat{\pi}_{d(s)}$	0.91	0.88	0.87	0.94
$\hat{\pi}_{i(s)}$	0.87	0.84	0.87	0.92
Core index (Thresholding)				
$\hat{\pi}_d$	0.90	0.90	0.87	0.91
$\hat{\pi}_i$	0.85	0.85	0.88	0.92
$\hat{\pi}_{d(s)}$	0.83	0.85	0.84	0.91
$\hat{\pi}_{i(s)}$	0.80	0.80	0.84	0.90
Core index (National Dataset)				
$\hat{\pi}_d$	1.09	1.09	1.11	1.12
$\hat{\pi}_i$	1.03	1.03	1.07	1.08
$\hat{\pi}_{d(s)}$	1.01	1.02	1.02	1.08
$\hat{\pi}_{i(s)}$	0.95	0.96	0.99	1.03
RMSFE($\hat{\pi}_d$)	[0.58]	[0.71]	[0.67]	[0.72]

Table 5: Forecast accuracy: Germany

Note to Tables 5 to 8: the estimation period for the forecasting equations starts in January 1992. Each equation is estimated using information up to T-h, then the h steps ahead forecast is computed, where T runs from January 2001 to August 2006 and h=6, 12, 18, 24. The RMSFE is therefore computed on 68 data points spanning the January 2001-August 2006 period.

h	6	12	18	24
Alternative forecasting models				
AR	0.94	1.00	1.24	1.17
ULC	1.23	1.32	1.47	1.07
M1	1.61	1.38	1.36	1.04
M2	1.33	1.16	1.29	1.10
M3	1.20	1.01	1.20	1.05
IP (Manufacturing)	1.29	1.08	1.19	0.99
ULC +AR	0.95	1.58	1.49	1.44
M1+AR	0.97	0.99	1.32	1.34
M2+AR	1.01	1.04	1.23	1.32
M3+AR	0.99	0.99	1.26	1.33
IP (Manufacturing)+AR	0.96	1.18	1.31	1.35
RW	0.82	0.91	1.20	1.09
running mean	1.08	1.03	1.06	1.12
Core index (all dataset)				
$\hat{\pi}_d$	1.00	1.00	1.00	1.00
$\hat{\pi}_i$	0.96	0.94	0.98	0.96
$\hat{\pi}_{d(s)}$	1.02	1.02	1.01	0.90
$\hat{\pi}_{i(s)}$	1.01	0.97	1.01	0.92
Core index (Commonality)				
$\hat{\pi}_d$	0.93	0.94	0.92	0.94
$\hat{\pi}_i$	0.89	0.88	0.91	0.89
$\hat{\pi}_{d(s)}$	0.98	0.96	0.96	0.87
$\hat{\pi}_{i(s)}$	0.96	0.92	0.96	0.88
Core index (Thresholding)				
$\hat{\pi}_d$	1.10	1.03	1.05	1.04
$\hat{\pi}_i$	1.02	0.96	1.03	0.99
$\hat{\pi}_{d(s)}$	1.09	1.02	1.06	0.94
$\hat{\pi}_{i(s)}$	1.06	0.98	1.05	0.96
Core index (National Dataset)				
$\hat{\pi}_d$	0.95	1.04	0.94	0.90
$\hat{\pi}_i$	0.91	0.89	0.91	0.87
$\hat{\pi}_{d(s)}$	0.97	1.02	0.93	0.89
$\hat{\pi}_{i(s)}$	0.94	0.90	0.93	0.87
RMSFE($\hat{\pi}_d$)	[0.43]	[0.52]	[0.52]	[0.67]

Table 6: Forecast accuracy: France

h	6	12	18	24
Alternative forecasting models				
AR	0.98	0.81	0.65	0.71
ULC	0.81	0.82	0.74	0.70
M1	1.74	1.26	1.18	1.32
M2	1.48	1.77	2.35	2.57
M3	1.90	1.53	2.31	3.06
IP (Manufacturing)	1.36	1.17	1.22	1.29
ULC +AR	0.87	1.08	1.49	2.53
M1+AR	1.06	1.37	1.38	1.70
M2+AR	1.22	1.57	2.03	2.27
M3+AR	1.40	2.19	2.33	2.99
IP (Manufacturing)+AR	0.91	1.08	1.08	1.67
RW	0.61	0.67	0.76	0.82
running mean	0.60	0.74	0.79	0.90
Core index (all dataset)				
$\hat{\pi}_d$	1.00	1.00	1.00	1.00
$\hat{\pi}_i$	0.91	0.92	0.92	0.91
$\hat{\pi}_{d(s)}$	0.97	1.00	1.01	0.98
$\hat{\pi}_{i(s)}$	0.95	0.97	0.97	0.94
Core index (Commonality)				
$\hat{\pi}_d$	1.02	1.02	1.01	1.00
$\hat{\pi}_i$	0.94	0.95	0.96	0.95
$\hat{\pi}_{d(s)}$	1.01	1.04	1.05	1.00
$\hat{\pi}_{i(s)}$	0.98	0.98	0.99	0.95
Core index (Thresholding)				
$\hat{\pi}_d$	0.99	1.02	1.01	0.95
$\hat{\pi}_i$	0.96	0.99	0.98	0.92
$\hat{\pi}_{d(s)}$	1.00	1.06	1.09	1.02
$\hat{\pi}_{i(s)}$	1.00	1.01	1.01	0.94
Core index (National Dataset)				
$\hat{\pi}_d$	1.01	1.07	1.01	1.02
$\hat{\pi}_i$	0.91	0.95	0.89	0.84
$\hat{\pi}_{d(s)}$	0.96	1.04	1.02	1.04
$\hat{\pi}_{i(s)}$	0.90	0.95	0.92	0.87
RMSFE($\hat{\pi}_d$)	[0.55]	[0.61]	[0.61]	[0.60]

Table 7: Forecast accuracy: Italy

h	6	12	18	24
Alternative forecasting models				
AR	0.99	1.09	1.62	2.36
ULC	1.56	1.40	1.91	1.81
M1	1.99	1.08	1.03	0.92
M2	0.91	0.67	0.98	0.82
M3	1.18	0.98	1.29	1.00
IP (Manufacturing)	1.51	1.17	1.24	0.88
ULC +AR	1.01	1.23	1.72	1.91
M1+AR	1.06	1.16	1.58	1.99
M2+AR	1.05	1.14	1.66	1.81
M3+AR	1.10	1.16	1.87	1.79
IP (Manufacturing)+AR	1.16	1.29	1.68	1.61
RW	0.97	0.98	1.46	1.34
running mean	1.12	0.98	1.18	1.27
Core index (all dataset)				
$\hat{\pi}_d$	1.00	1.00	1.00	1.00
$\hat{\pi}_i$	0.93	0.90	0.94	0.94
$\hat{\pi}_{d(s)}$	0.97	0.93	0.89	0.86
$\hat{\pi}_{i(s)}$	0.91	0.84	0.87	0.86
Core index (Commonality)				
$\hat{\pi}_d$	1.00	1.00	1.00	0.99
$\hat{\pi}_i$	0.92	0.89	0.92	0.92
$\hat{\pi}_{d(s)}$	0.97	0.91	0.89	0.86
$\hat{\pi}_{i(s)}$	0.91	0.83	0.86	0.85
Core index (Thresholding)				
$\hat{\pi}_d$	0.95	0.97	0.92	0.90
$\hat{\pi}_i$	0.88	0.85	0.85	0.85
$\hat{\pi}_{d(s)}$	0.95	0.91	0.83	0.80
$\hat{\pi}_{i(s)}$	0.87	0.81	0.80	0.79
Core index (Area wide Dataset)				
$\hat{\pi}_d$	0.98	0.99	1.00	0.99
$\hat{\pi}_i$	0.91	0.89	0.93	0.94
$\hat{\pi}_{d(s)}$	0.95	0.92	0.88	0.86
$\hat{\pi}_{i(s)}$	0.90	0.83	0.86	0.86
Core index (Aggregate from National Core Indexes)				
$\hat{\pi}_d$	1.36	1.18	1.18	1.21
$\hat{\pi}_i$	1.43	1.24	1.29	1.29
$\hat{\pi}_{d(s)}$	1.29	1.08	1.18	1.16
$\hat{\pi}_{i(s)}$	1.37	1.14	1.27	1.24
RMSFE($\hat{\pi}_d$)	[0.31]	[0.44]	[0.41]	[0.53]

Table 8: Forecast accuracy: euro area

	Coef	T-prob	Coef	T-prob
Lagged rate	0.94	0.00	0.92	0.00
Constant	-0.00	0.37	-0.00	0.43
Output gap	0.07	0.00	0.06	0.00
Core Euro area	0.13	0.03	0.15	0.04
$\hat{u}_t^{ger}$			0.01	0.87
$\hat{u}_t^{fra}$			-0.10	0.08
$\hat{u}_t^{ita}$			0.08	0.07
$Adj.R^2$	0.98		0.98	
N. obs.	90		90	

Table 9: Parameter estimates of the Taylor rule using euro area and national core indexes (see equations 23 and 24)

Note to table 9: the estimation period starts in February 1999 and ends in July 2006.

	Coef	T-prob
$\boldsymbol{\rho}$ - Lagged rate	0.94	0.00
$\boldsymbol{\gamma}$ - Constant	-0.02	0.00
$\boldsymbol{\beta}$ - Output gap	1.25	0.00
$\boldsymbol{\delta}$ - Expected Inflation	2.30	0.00

Table 10: Structural parameter estimates of the Taylor rule using euro area core inflation

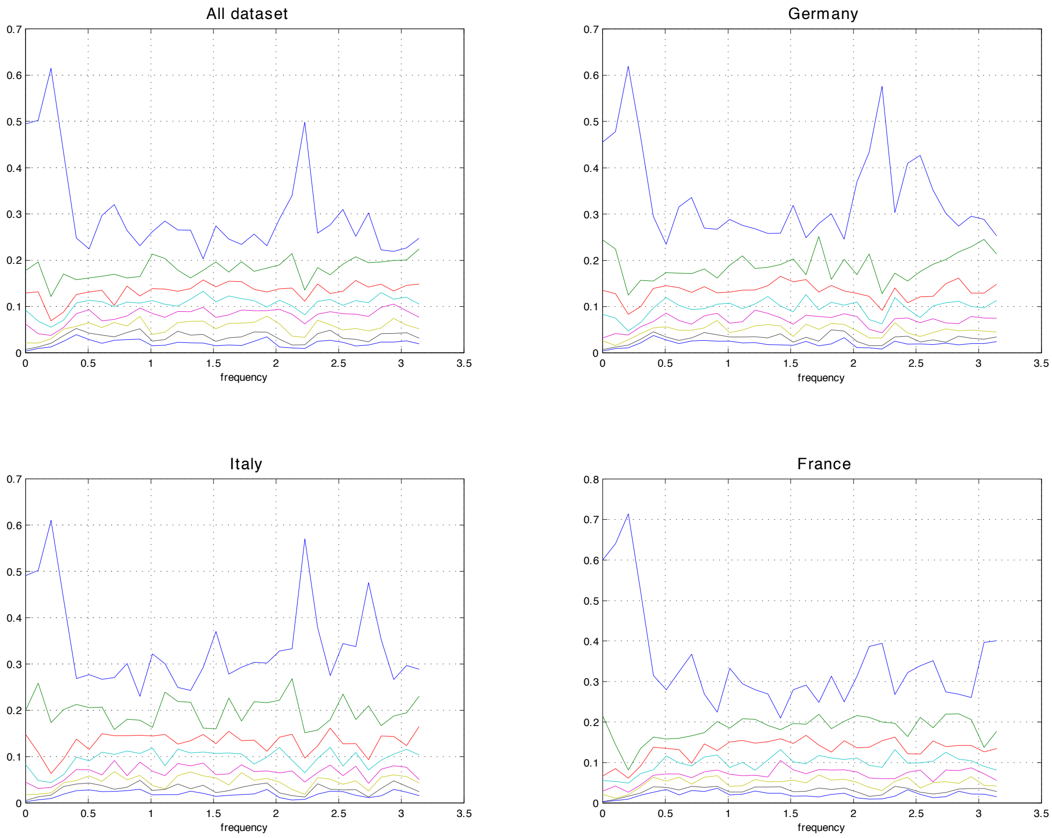
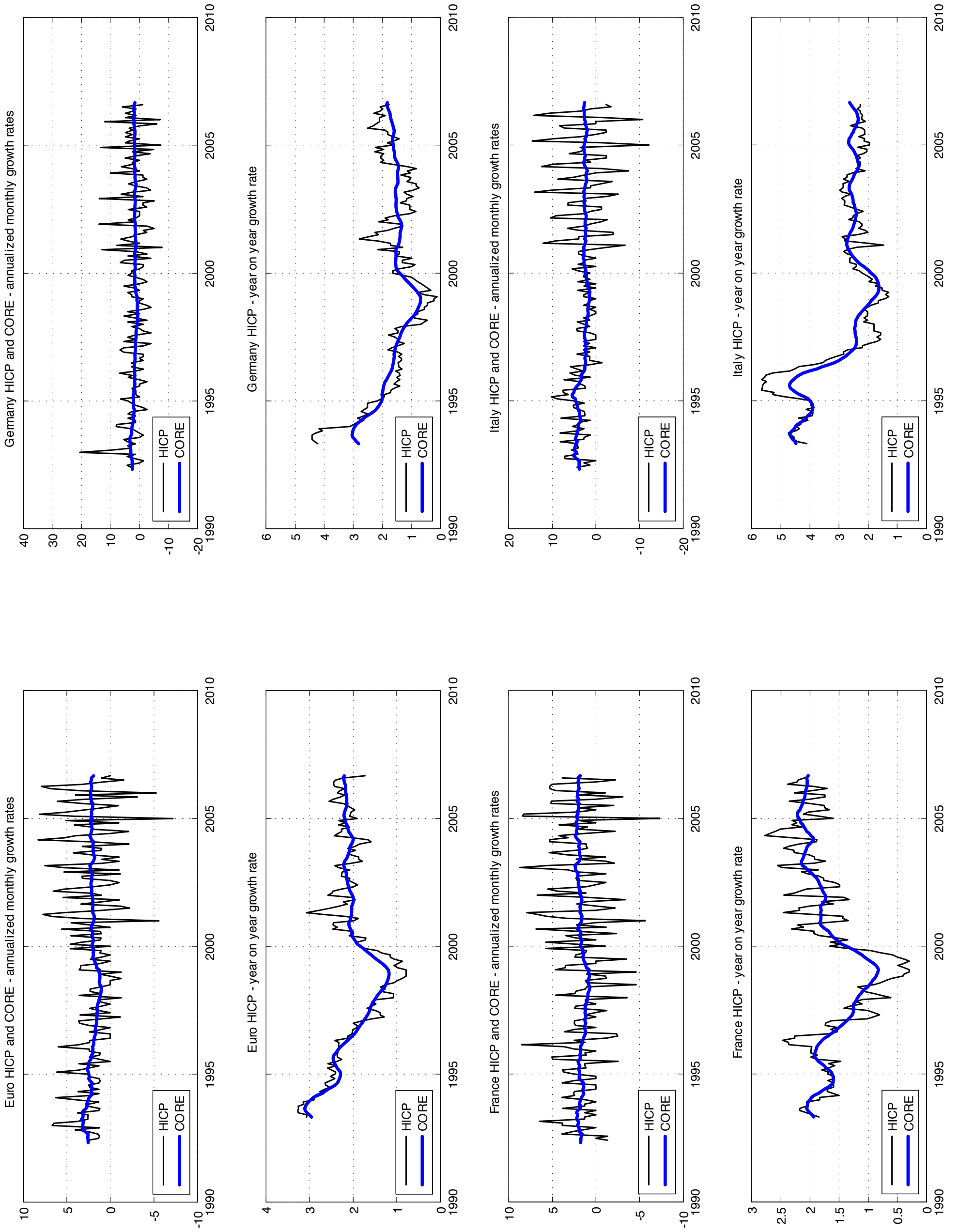


Figure 1: Spectral shape of the first eight dynamic eigenvalues



Euro HICP and CORE - annualized monthly growth rates
Euro HICP - year on year growth rate
France HICP and CORE - annualized monthly growth rates
France HICP - year on year growth rate
Germany HICP and CORE - annualized monthly growth rates
Germany HICP - year on year growth rate
Italy HICP and CORE - annualized monthly growth rates
Italy HICP - year on year growth rate
HICP
CORE
1990
1995
2000
2005
2010

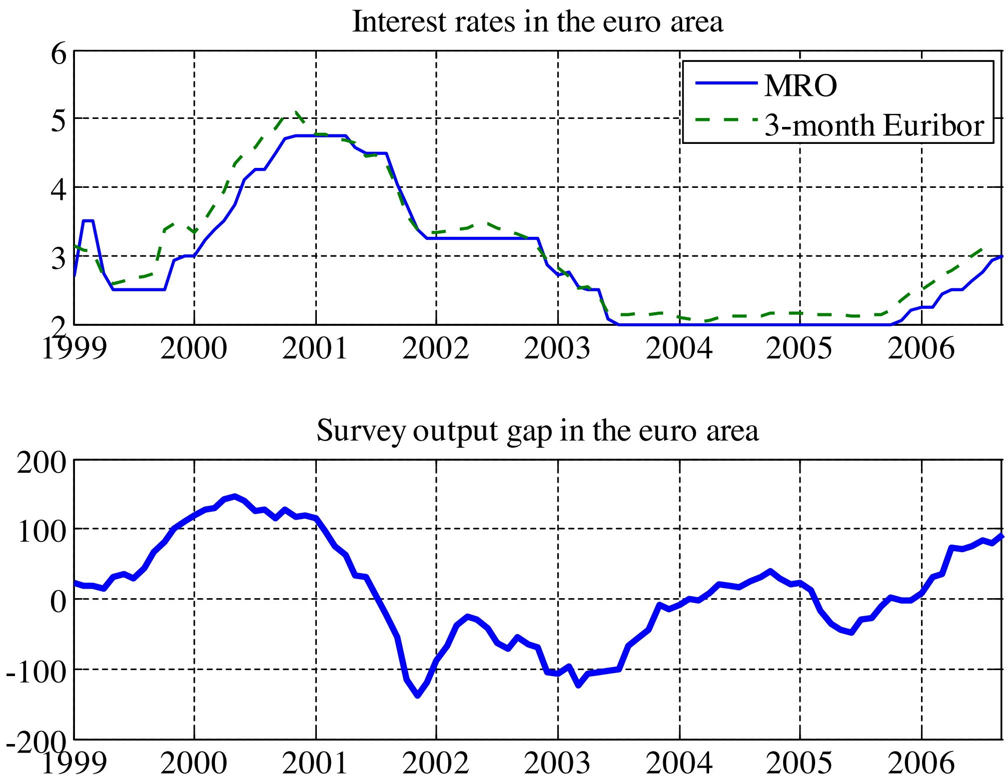


Figure 3: 3-Month Euribor, Main Refinincing Operation rate (MRO) and EU Economic Sentiment Indicator

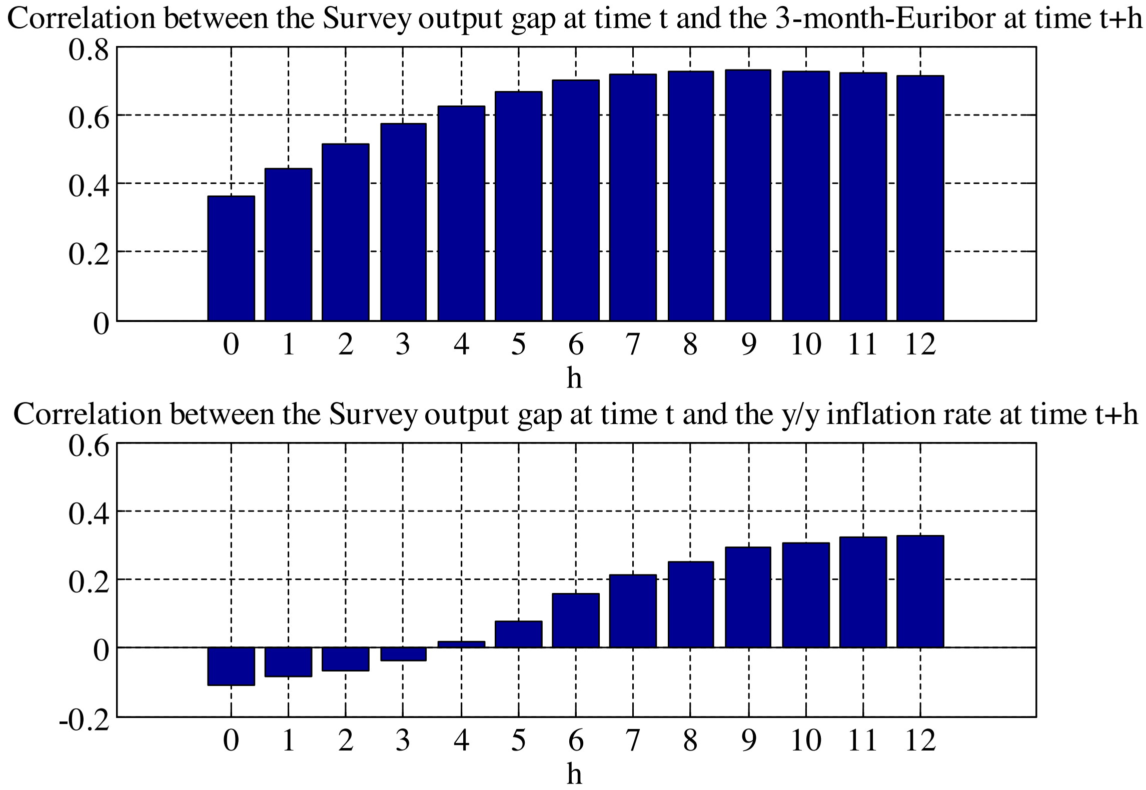


Figure 4: Dynamic cross-correlations between the EU Economic Sentiment Indicator and, respectively, the 3-Month Euribor and the year on year euro area inflation rate

European Central Bank Working Paper Series

For a complete list of Working Papers published by the ECB, please visit the ECB's website (http://www.ecb.europa.eu).

862 "Stock market volatility and learning" by K. Adam, A. Marcet and J. P. Nicolini, February 2008.

863 "Population ageing and public pension reforms in a small open economy" by C. Nickel, P. Rother and A. Theophilopoulou, February 2008.

864 "Macroeconomic rates of return of public and private investment: crowding-in and crowding-out effects" by A. Afonso and M. St. Aubyn, February 2008.

865 "Explaining the Great Moderation: it is not the shocks" by D. Giannone, M. Lenza and L. Reichlin, February 2008.

866 "VAR analysis and the Great Moderation" by L. Benati and P. Surico, February 2008.

867 "Do monetary indicators lead euro area inflation?" by B. Hofmann, February 2008.

868 "Purdah: on the rationale for central bank silence around policy meetings" by M. Ehrmann and M. Fratzscher, February 2008.

869 "The reserve fulfilment path of euro area commercial banks: empirical testing using panel data" by N. Cassola, February 2008.

870 "Risk management in action: robust monetary policy rules under structured uncertainty" by P. Levine, P. McAdam, J. Pearlman and R. Pierse, February 2008.

871 "The impact of capital flows on domestic investment in transition economies" by E. Mileva, February 2008.

872 "Why do Europeans work part-time? A cross-country panel analysis" by H. Buddelmeyer, G. Mourre and M. Ward, February 2008.

873 "The Feldstein-Horioka fact" by D. Giannone and M. Lenza, February 2008.

874 "How arbitrage-free is the Nelson-Siegel model?" by L. Coroneo, K. Nyholm and R. Vidova-Koleva, February 2008.

875 "Global macro-financial shocks and expected default frequencies in the euro area" by O. Castrén, S. Dées and F. Zaher, February 2008.

876 "Are sectoral stock prices useful for predicting euro area GDP?" by M. Andersson and A. D'Agostino, February 2008.

877 "What are the effects of fiscal policy shocks? A VAR-based comparative analysis" by D. Caldara and C. Kamps, March 2008.

878 "Nominal and real interest rates during an optimal disinflation in New Keynesian models" by M. Hagedorn, March 2008.

879 "Government risk premiums in the bond market: EMU and Canada" by L. Schuknecht, J. von Hagen and G. Wolswijk, March 2008.

880 "On policy interactions among nations: when do cooperation and commitment matter?" by H. Kempf and L. von Thadden, March 2008.

881 "Imperfect predictability and mutual fund dynamics: how managers use predictors in changing systematic risk" by G. Amisano and R. Savona, March 2008.

882 "Forecasting world trade: direct versus "bottom-up" approaches" by M. Burgert and S. Dées, March 2008.

883 "Assessing the benefits of international portfolio diversification in bonds and stocks" by R. A. De Santis and L. Sarno, March 2008.

884 "A quantitative perspective on optimal monetary policy cooperation between the US and the euro area" by S. Adjemian, M. Darracq Pariès and F. Smets, March 2008.

885 "Impact of bank competition on the interest rate pass-through in the euro area" by M. van Leuvensteijn, C. Kok Sørensen, J. A. Bikker and A. A. R. J. M. van Rixtel, March 2008.

886 "International evidence on sticky consumption growth" by C. D. Carroll, J. Slacalek and M. Sommer, March 2008.

887 "Labor supply after transition: evidence from the Czech Republic" by A. Bičáková, J. Slacalek and M. Slavík, March 2008.

888 "House prices, money, credit and the macroeconomy" by C. Goodhart and B. Hofmann, April 2008.

889 "Credit and the natural rate of interest" by F. De Fiore and O. Tristani, April 2008.

890 "Globalisation, domestic inflation and global output gaps: evidence from the euro area" by A. Calza, April 2008.

891 "House prices and the stance of monetary policy" by M. Jarociński and F. Smets, April 2008.

892 "Identification of New Keynesian Phillips Curves from a global perspective" by S. Dées, M. H. Pesaran, L. V. Smith and R. P. Smith, April 2008.

893 "Sticky wages: evidence from quarterly microeconomic data" by T. Heckel, H. Le Bihan and M. Montornès, May 2008.

894 "The role of country-specific trade and survey data in forecasting euro area manufacturing production: perspective from large panel factor models" by M. Darracq Pariès and L. Maurin, May 2008.

895 "On the empirical evidence of the intertemporal current account model for the euro area countries" by M. Ca'Zorzi and M. Rubaszek, May 2008.

896 "The Maastricht convergence criteria and optimal monetary policy for the EMU accession countries" by A. Lipińska, April 2008.

897 "DSGE-modelling when agents are imperfectly informed" by P. De Grauwe, April 2008.

898 "Central bank communication and monetary policy: a survey of theory and evidence" by A. S. Blinder, M. Ehrmann, M. Fratzscher, J. De Haan and D.-J. Jansen, April 2008.

899 "Robust monetary rules under unstructured and structured model uncertainty" by P. Levine and J. Pearlman, April 2008.

900 "Forecasting inflation and tracking monetary policy in the euro area: does national information help?" by R. Cristadoro, F. Venditti and G. Saporito, May 2008.

ISSN 1561-0810