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ABSTRACT

A Core Inflation Index for the Euro Area*

This Paper proposes an index of core inflation for the euro area that exploits information from a large panel of time series on disaggregated prices, industrial production, labour market indicators, and financial and monetary variables. The index is the result of a smoothing operation at both the cross-sectional and time series level. By extracting the common component of national inflation and disregarding the idiosyncratic one, we clean inflation from measurement error, discrepancies in data recording and dynamics originated by national or sectoral idiosyncratic shocks (cross-sectional smoothing). By extracting the component with periodicity longer than one year we clean from high frequency variation and seasonal components which are not relevant for monetary policy (time series smoothing). The indicator is shown to have a number of desirable characteristics and to perform very well as a forecaster of the euro area harmonized consumer price index at one and two years horizon, which is the relevant horizon for the ECB monetary policy.

JEL Classification:
Keywords: core inflation, dynamic factor model, inflation forecast and monetary policy

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NON-TECHNICAL SUMMARY

1 Introduction

The growing importance given to the goal of price stability and the introduction of explicit inflation targets by many central banks has stimulated research on the construction of reliable inflation measures and, in particular, on core inflation indexes (see for example Cecchetti, 1994). Given the institutional arrangements within the European Monetary Union these problems have a great relevance for the monetary policy in the Euro Area. The mandate of the European Central Bank is to maintain price stability: this goal was given a precise quantitative content in terms of the monetary union Harmonized Index of Consumer Prices (HICP), whose year on year growth rate should not exceed 2% in the medium term. The two pillars strategy followed by the ECB implies that the Central Bank should monitor a large number of monetary and real indicators with the aim of obtaining a reliable picture of the current and future inflation outlook. Some authors (see Galí, 2001) have recently argued that it would be useful to have a core inflation indicator for the euro area, able to summarise the wide range of statistics analysed under the two pillars and free of the distortions and short term volatility of the HICP. Economists at the ECB have recently published several papers on this topic[1] and one article on the evaluation of existing core inflation measures was published in the ECB Monthly Bulletin[2].

This paper proposes a new index of core inflation for the euro area and documents its predictive power in forecasting inflation at six, twelve, eighteen and twenty-four months horizons. Different methods of estimating a core index have been discussed in the literature. One of them involves the removal from the CPI basket of those items that are believed to have little correlation with long term movements of inflation. This is obtained via limited influence estimators or considering an index net of food and energy prices (e.g. Bryan and Cecchetti, 1994). In the same spirit, Bryan and Cecchetti (1993) by estimating the common component on a small panel of disaggregated prices, obtain an estimate of the bias in the U.S. CPI. Alternatively, as in Quah and Vahey (1995), one can exploit the dynamic links existing among prices and real activity to extract a *core* or "long run" component of the inflation process[3]. While in the former case information coming from sources other than the price cross-section is typically disregarded, in the latter no use is made of the disaggregated price data.

Our method retains the basic intuitions of both approaches by offering a unified framework for the identification of the underlying sources of price fluctuations. The methodology builds on Forni, Hallin, Lippi and Reichlin (2000, 2001a) and it is applied to a large panel of data comprising prices, as well as real and nominal variables. We exploit the empirical fact that the

[1] Angelini et al. (2000a), Angelini et al. (2000b), Morana (2000), and Vega and Wynne (2000).

[2] The ECB is rather skeptical about the usefulness of a core index claiming that "in no way can a single measure be trusted to capture, by itself, the deep sources of inflationary or deflationary pressures prevailing in the economy, and so replace a broadly based assessment of price developments" (ECB Monthly Bulletin, July 2001).

[3] See among others Blix (1995), Bagliano and Morana (2000) and Golinelli et al. (2001).

series of interest exhibit strong comovements to postulate a dynamic factor model. The latter decomposes each series of the panel into two unobserved orthogonal components, one which is "strongly correlated" with all other variables (*common component)* and one which is "poorly correlated" (*idiosyncratic component).*

We define the core inflation index as the medium- and long- run common component of the Euro area CPI. Our goal is then to clean the CPI from the idiosyncratic component and from the high frequency movements of the common component. The procedure is in three steps. First, we estimate the covariance of the common components of the panel at all relevant leads and lags thereby exploiting the information on the dynamic structure of the panel. Second, we estimate the factors that generate the common component by minimizing the variance of the idiosyncratic component with respect to the total variance[4] This achieves the goal of cross-sectional smoothing. Third, we extract the long run common component of our series by projecting onto the leads and lags of the factors estimated in step two. This final step produces an estimate of the long run component which exploits the multivariate information of our data set. A specific procedure is designed to handle the end of sample unbalance.

Our methodology improves on existing methods. We use information contained in a large cross-section to eliminate the idiosyncratic noise, getting rid in this way of *local* shocks, i.e. shocks specific to a region or sector that do not propagate across the euro area. Within the same framework, the cross-section is also used to achieve intertemporal smoothing, i.e. the cleaning from seasonal and high frequency dynamics. Our core index is thus obtained via a procedure that wipes out the high frequency noise, improving on standard univariate intertemporal smoothing methods used for business cycle analysis (e.g., Hodrick and Prescott, Baxter and King or Christiano and Fitzgerald). Furthermore, unlike structural VAR procedures[5], while still taking into full account the dynamic structure of the data, we use all available information by extracting the relevant signal from hundreds of time series. Finally, by suitably exploiting both the cross-sectional and the time-series dimensions, we obtain an indicator which, unlike the existing ones, is at the same time smooth and non lagging and is not subject to important revisions.

Our claim is that the core index presented here provides a better estimation of the euro area inflation in comparison with the 12-month growth of CPI or other commonly used measures. It can usefully complement the ECB monetary strategy by providing a methodologically well grounded synthesis of the large set of data examined under the first and the second pillar.

A crucial test of the usefulness of the indicator is its predictive power for inflation. As is well known, forecasting inflation proved always to be a difficult task[6], it is therefore an impor-

[4]For a detailed explanation of the method see Forni, Hallin, Lippi and Reichlin, 2001b

[5]See Quah and Vahey (1995), Folkertsman and Hubrich (2001), Bagliano et al (2001).

[6]See Stock and Watson (2001).

tant result that our indicator clearly outperforms other core measures and common univariate forecasting methods. In particular its current level proves to be a good forecast of inflation over horizons relevant for monetary policy.

As a byproduct of our exercise we obtain relevant information on the dynamic covariance structure of European inflation that can be exploited to construct empirically founded structural models. We leave this to future research.

The paper is organized as follows. In section two, we illustrate our methodology euristically. In section three, we briefly describe the data and report information on the structure of the EURO inflation in terms of a dynamic factor model which is the result of our estimates. In section four, we report the time series of our core inflation index, analyze its turning points and compare it graphically with alternative measures of inflation and its core. In section five we address questions related to the degree of synchronization of sectoral and national prices, their leading and lagging structure and their correlations with indicators of the real side of the economy and relevant financial variables. In section six, we perform a forecasting exercise by running a horse race on out-of-sample performance of predictive models using our index as a regressor and alternative models such as standard autoregressive models and equations containing alternative predictors. Section seven concludes.

2 Theory

The basic theory and technical solutions in this paper are essentially the same as those proposed in Altissimo et al. (2001) for the indicator of the economic activity. Most of the technical material can be found in Appendix B. Here we provide only the basic equation of the model and give the main intuitions behind the method employed.

2.1 The model and the theoretical indicator

As anticipated above, we rely on the Generalized Dynamic Factor Model proposed in Forni, Hallin, Lippi and Reichlin (2000) and Forni and Lippi (2001). As in the traditional dynamic factor model, introduced by Sargent and Sims (1977) and Geweke (1977), each variable, say x_{jt}, is represented as the sum of two mutually orthogonal unobservable components: the 'common component', call it χ_{jt}, and the 'idiosyncratic component', ξ_{jt}. The common component is driven by a small number, say q, of common 'factors' or common shocks u_{ht}, $h = 1, \ldots, q$, which are the same for all of the cross-sectional units, but possibly are loaded with different coefficients and lag structures. By contrast, the 'idiosyncratic component' is driven by specific shocks. In the traditional factor model, such component is orthogonal to all of the other idiosyncratic components in the cross-section, while in the GDFM a limited amount of correlation is allowed (see below). In this sense, the model can be regarded as a generalization of the traditional dynamic model. Since the GDFM is designed to handle a large cross-section of time series, it is convenient to assume an infinite cross-sectional dimension, i.e. $j = 1, \ldots, \infty$. Hence, we have

$$x_{jt} = \chi_{jt} + \xi_{jt} = \mathbf{b}_j(L)\mathbf{u}_t + \xi_{jt} = \sum_{h=1}^{q} b_{jh}(L)\ u_{ht} + \xi_{jt} \tag{1}$$

for $j = 1, \ldots, \infty$.

The impulse-response function $b_{jh}(L)$, $h = 1, \ldots, q$, is a s-order polynomial in the lag operator, i.e. $b_{jh}(L)u_{ht} = b_{jh0}u_{ht} + b_{jh1}u_{ht-1} + \cdots + b_{jhs}u_{ht-s}$. We do not put restrictions on the coefficients $b_{jh1}, \ldots, b_{jhs}$. Hence the model is quite flexible, in that the reaction of each variable to a given common shock may be small or large, negative or positive, immediate or delayed. Moreover, a variable can react with a given impulse-response profile, say, to shock 1 and with a completely different profile to shock 2. This can accomodate a very wide range of different behaviors of the common components χ_{jt}, $j = 1, \ldots, \infty$. In particular, with reference to the delay with which the shocks are loaded, some of them will be 'leading' with respect to the European CPI, some will be 'coincident' and some will be 'lagging'. Estimating the model enables us to see whether there are prices (or countries) which anticipate the changes of the general price index and to unveil the lead-lag relations of prices with the other variables in the system.

To conclude the presentation of the model, let us say that we need the additional assumptions listed in Forni, Hallin, Lippi and Reichlin (2000), both for estimation purposes and in order to distinguish the idiosyncratic from the common components in a context where the traditional orthogonality assumption is relaxed. We refer to the paper above for their precise formulation. Loosely speaking, the assumptions concern what could be called the 'total amount of cross-correlation' in the system, and ensure that such amount is small for the idiosyncratic components and large for the common ones.

Now let us discuss the properties of the model with reference to the main features of our proposed indicator. As anticipated in the introduction, we focus on the European CPI, but we clean it both from the idiosyncratic component and the high frequency noise. Since both operations entail a variance reduction we can call them respectively the 'cross-sectional smoothing' and the 'temporal smoothing'. We shall discuss these two operations in turn.

The idiosyncratic component is intended to capture shocks that are specific to a country or to a sector, such as, say, technology shocks affecting the price of a particular industry. According to our estimates, local or sectoral shocks do not explain a large fraction of the European inflation, because negative and positive shocks approximately cancel out in the aggregate; however, they are non-negligible.

We think that monetary policy should not react with common, Europe-wide measures to shocks having essentially a local or sectoral nature, even if they are so important to affect the European CPI to a certain extent. Local or sectoral measures are better suited in such cases. If this idea is correct, cross-sectional smoothing will provide a better index, as far as the role of such index is to provide a signal for policy intervention by the European Central Bank.

In addition to local and sectoral shocks, the idiosyncratic component reasonably includes measurement errors, insofar as these errors are independent of the other shocks affecting the variable and are poorly correlated with most of the other variables in the panel. Eliminating measurement errors is an additional reason for cross-sectional smoothing.

Cleaning from the idiosyncratic noise is then a first important advantage of using the factor model to construct a core inflation indicator. However, the idiosyncratic noise is not the only one affecting the variables, and in particular the CPI. As is well known, the common components χ_{jt}, just like any other stationary variable, can be decomposed into the sum of waves of different periodicity (the so-called 'spectral decomposition')[7] More specifically, we can disentangle a medium- and long-run component, say χ_{jt}^L and a short-run component, say χ_{jt}^S, by aggregating respectively waves of periodicity larger than, or smaller than, a given critical period τ. This can be done by applying to the series the theoretical band-pass filter discussed in Sargent (1987) and Baxter and King (1999), i.e.

$$\chi_{jt} = \chi_{jt}^L + \chi_{jt}^S = d^L(L)\chi_{jt} + d^S(L)\chi_{jt}, \tag{2}$$

where $d^S(L) = 1 - d^L(L)$ and $d^L(L)$ is a two-sided, symmetric, infinite-order, square-summable filter whose k-th coefficient is

$$d_k^L = \frac{1}{\pi k} \sin\left(k \cdot \frac{2\pi}{\tau}\right)$$

In other words, the European prices are affected both by long-lasting shocks and shorter-run movements, including both seasonal and very short-run, high-frequency changes. With monthly data, such short-run movements are typically responsible of a large fraction of total volatility. We think that, in constructing the price index, such short-run and seasonal noise should be washed out, in order to unveil the underlying medium- and long-run tendencies. Once again, the reason is that the index should be a signal for policy, and, taking into account the delay with which monetary policy measures affect the economy, there is simply no point in reacting to transitory shocks. Hence, our proposed price indicator is the medium and long-run common component of the European CPI. Assuming without loss of generality that the European CPI is the first variable in our panel, our core indicator is then χ_{1t}^L. While the idea of the temporal smoothing is not new in the core literature, the way in which we do it, by exploiting the cross-sectional information, is novel. This point will be clear in a moment.

[7] See e.g. Brockwell and Davis (1987). For a discussion on the interpretation see Lippi (2001).

2.2 The estimation procedure

It should be stressed that our price indicator χ_{1t}^L is a theoretical entity which is not observed, and therefore has to be estimated. In what follow we shall describe shortly our estimation procedure.

Estimation is in three steps. In the first one we estimate the covariance structure of the common and the idiosyncratic components. More precisely, we estimate the spectral density matrix of the common and the idiosyncratic components by means of a dynamic principal component procedure explained in detail in Appendix B. The theoretical basis of such procedure is in Forni, Hallin, Lippi and Reichlin (2000) and consistency of the entries of this matrix as both n and T go to infinity can easily be shown on the basis of the results in that paper.

From the estimated spectral-density matrices we can obtain the auto-covariances and cross-covariances at all leads and lags by applying the inverse Fourier transform. Notice that we can easily get also covariances for the long-run and the short-run components χ_{jt}^L and χ_{jt}^S simply by applying such transformation to the relevant band of the estimated spectra and cross-spectra.

In the second step, we compute an estimate of the static factors, following Forni, Hallin, Lippi and Reichlin (2001). With the term "static factors" we mean the $q(s+1)$ shocks appearing in equation 1, including the lagged u_t's, so that, say, u_{1t} and u_{1t-1} are different static factors. The static factors are not identified in the model unless we introduce additional assumptions, so that we shall in fact estimate a vector of linear combinations of such factors, say $\mathbf{v}_t$, spanning the same information space.

Such estimates, say $\hat{v}_t$, are obtained as the generalized principal components of the x's, a construction which involves the (contemporaneous) variance-covariance matrices of the common and the idiosyncratic components estimated in the first step (see Appendix B). The generalized principal components have an important "efficiency" property: they are the contemporaneous linear combinations of the x's with the smaller idiosyncratic-common variance ratio. As shown in the paper quoted above, they can consistently approximate any point in the common-factor space, including the common components χ_{jt}'s, as $n, T \to \infty$ in a proper way. Similarly, we can produce forecasts of the common components (and the factors themselves) simply by projecting χ_{jt+k} (or the k-th lead of the factors) on $\hat{v}_t$. This forecast approximates consistently the theoretical projection.

In the third and final step we use the static factors to get our estimate of χ_{1t}^L. Let us observe that, having an estimate of the leads and the lags of χ_{1t}, obvious estimates of our indicator χ_{1t}^L could be obtained by applying the truncation of the filter $d_j^L(L)$ proposed by Baxter and King (1999) or the data-dependent approximation suggested by Christiano and Fitzgerald (2001). Such univariate filtering, however, would not exploit the superior information embedded in the cross-sectional dimension of the model and would generally require long leads of the series thus creating an end of sample problem.

By contrast, here we project χ^L_{1t} on the leads and lags of the estimated static factors $\mathbf{v}_{t-m}, \dots \mathbf{v}_{t+m}$. We do not perform OLS, but use the projection coefficients derived by the covariance matrices of the cyclical components estimated in the first step. Clearly, at the end of the sample, we are forced to project only on the contemporaneous and lagged factors. The lag-window size m should increase with the sample size T, but at a slower rate. Consistency of such estimator is ensured, for appropriate relative rates of m, T and n, by the fact that (a) χ^L_{1t} is a linear combination of the present, past and future of the static factors; (b) both the factors and the covariance matrices involved are estimated consistently.

This approach resembles, in a multivariate framework, the procedure by Christiano and Fitzgerald (2001) to approximate the band-pass filter. However, exploiting the superior information embedded in the cross-sectional dimension, enables us to obtain a good smoothing by using a very small window (for the cyclical indicator of the economic activity in Altissimo at al. we use $m = 1$, while here we use $m = 0$, i.e. we project statically). This is very important in that we get readily a reliable end-of-sample estimation and are not forced to revise our estimates for a long time (say 12 months or more) after the first release, as with the univariate procedure.

Price data are typically affected by large short-run volatility. An important reason why people look at the 12-th difference rather than the 1-st difference is that the former is a kind of temporal smoothing of the latter. Precisely, it is the sum of the past twelve first differences. Howerver this smoothing entails a backward time phase shift. In other words, what we obtain in this way is a reasonably smooth thing, which unfortunately describes what was going on about six months ago. By contrast, our smoothing does not entail any phase shift, so that our indicator is cleaned from high frequency noise without being backward looking.

Intuition suggests that our core inflation indicator should then be a good predictor for future inflation. As explained in what follows, this is in fact the case: our index is the best predictor that we can find for the yearly European CPI at 6, 12, 18 and 24 months.

To conclude this Section, we mention that we have a procedure that handles the end-of-sample unbalance. Typically data referring to period T become available some periods later and different variables have in general a different delay. Hence if we want to estimate the model as it stands we are forced to wait until the latest observation arrives. Clearly we can reduce the problem by eliminating from the data set series whose delay is larger than a given value. But even so we are necessarily left with a few months, at the end of the sample, for which some observations are available and some others are not. In the Appendix, we explain our procedure to handle this problem.

3 The Dataset and its covariance structure

3.1 The Dataset

The recent empirical research on forecasting inflation, both in the US and in Europe, reflects the lack of theoretical consensus on the original sources of price fluctuations[8]. To date there seems to be little agreement on what variables constitute an optimal set of forecasters of inflation, and some researchers have argued that indicator variables used *in isolation* have very limited predictive power (Cecchetti et al. 2000).

One strand of analysis, relying on the modern Phillips-curve based models, focuses on the search for proper measures of real economic activity to forecast inflation (Stock and Watson, 1999). In contrast monetary theories of inflation provide support for different candidate indicators to forecast inflation that are based on various money aggregates. For the euro area, Nicoletti (2001) provides evidence that monetary aggregates contain useful and additional information on medium-long term inflation prospects relative to the other non-monetary indicators. Finally the forward looking nature of asset prices and other financial variables have inspired the exploration of their ability to forecast inflation (Stock an Watson, 2001). However as concluded by these authors "...the variables with the clearest theoretical justification for use as predictors often have scant empirical predictive content".

Also in the design of the ECB monetary policy strategy different potential sources of inflationary pressures are considered. On the one hand, it is recognized that inflation is ultimately a monetary phenomenon and thereby a prominent role is assigned to monetary aggregates, the so called first pillar. On the other hand, the second pillar consists in "a broadly-based assessment of the outlook for price developments and the risks to price stability", entailing the use of a wide range of indicators, believed to have leading properties for price developments.

To construct the core inflation indicator we collected a wide range of statistics including both monetary and real variables. Hence we have tailored the choice of variables in the dataset to cover all the above mentioned macroeconomic phenomena for the six largest countries of the euro area.

Our dataset includes more than 400 monthly time series[9]. Price variables, being the focus of our analysis, constitute almost one third of the dataset (130 series) and comprise consumer, producer and commodity prices. Relevant information for future price dynamics can potentially be derived by price expectations. For european countries these are available through the EC surveys that are conducted each month and concern manufacturing, retail and construction sectors as well as consumers.

[8] Despite the everlasting sequence of claims of success of the Phillips curve tradition (Mankiw 2000), and claims of breakdown of the same tradition (Atkeson, Ohanian 2001).

[9] A more detailed description of the dataset is in Appendix A and refer to Table A1 for a synthesis.

As a measure of real activity we included the general industrial production indices of the six largest european countries, together with their breakdown by final destination (consumption, investment and intermediate goods). Sales and turnover indices have also been considered for the same countries. Furthermore, the confidence indicators derived from the EC Surveys are widely used in short term analisys and have been selected among real activity measures.

In view of the importance of the Phillips Curve in the analysis of inflation dynamics a natural choice of variable would also include labor market statistics: in particular wages, unemployment and, wherever available, vacancies.

The selection of an appropriate set of statistics for monetary and financial markets is a more complex task given the multiplicity of alternative definitions of money and the rapidly evolving range of instruments created by financial operators. Given their central role in the ECB monetary policy strategy we included the national components of M1, M2 and M3, as well as the corresponding european aggregates. We also constructed real measures of money, by deflating the nominal quantities with the national CPIs[10].

To capture the complex financial enviroment of modern economies a relatively large collection of interest rates has been considered. Our panel contains almost 80 nominal interest rates (on Government bills and bonds as well as on private loans); we also constructed interest rate spreads and real interest rates based on Government long and short term maturities. Other financial variables that might contain useful information for future price developments, like stock market prices and exchange rates were also considered.

3.2 The estimation of the covariance structure of the data

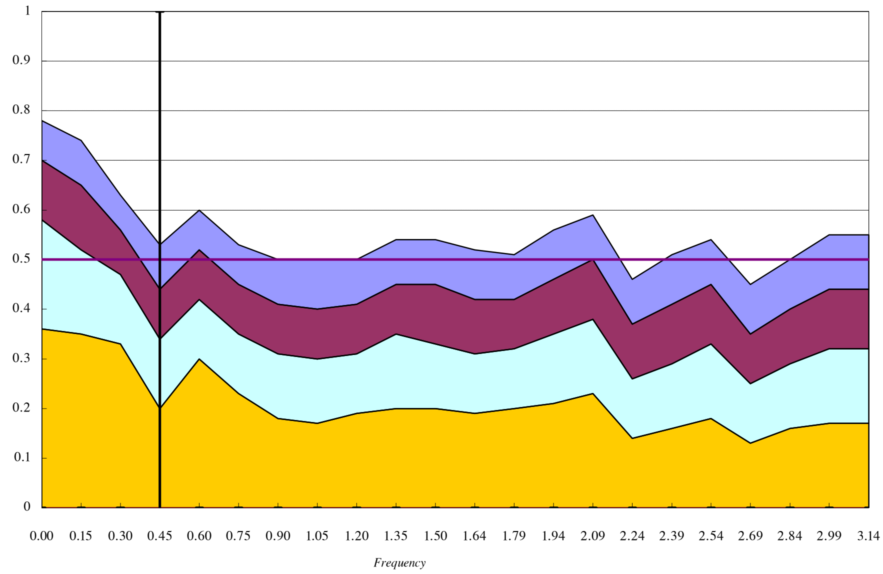
We now turn to the first step of our method i.e. the estimation of the covariance structure of the data and the determination of the number of common factors driving the panel. The estimation of the spectral densities requires variables to be covariance stationary and free of any deterministic component. The data treatment involved three steps: the first consisted in the outlier removal, then deterministic seasonality, when present, was removed, finally, if necessary to achieve stationarity, the data were log-differenced[11].

The analysis of the spectral density matrix of the data reveals that 4 common dynamic factors are sufficient to explain more than 50% of the observed varaibility of the series on the $[0, \pi]$ interval and more than 60% on the $[0, \frac{\pi}{7}]$ interval (see table A2 and figure 1).

[10] Despite the recent empirical evidence on the importance of other monetary indicators such as the nominal/real money gap, or the money *overhang* (Trecroci and Vega 2000), we do not proceed in their construction, given the arbitrary nature of their definition and estimation.

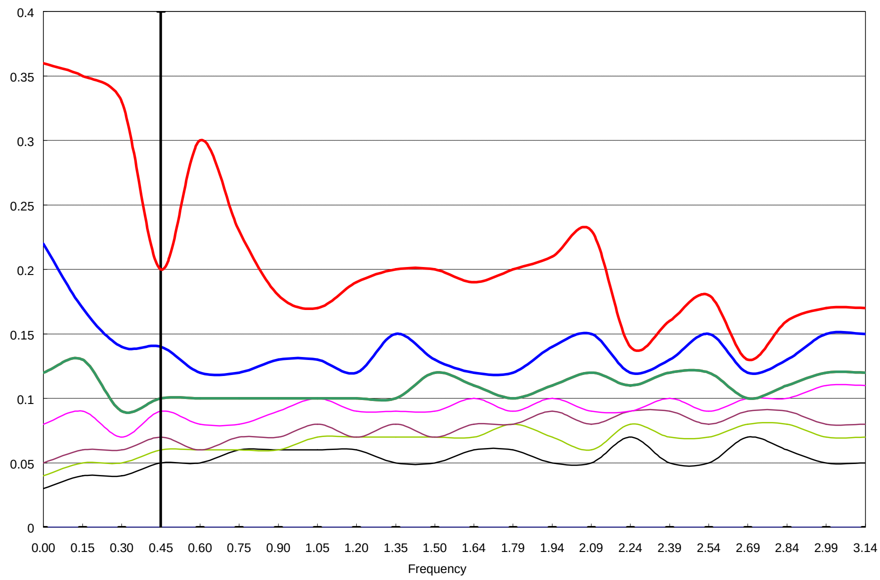
[11] Deterministic seasonality was removed by regressing each variable on a set of monthly dummies and their interaction with a linear trend. The log differencing was applied only to variables displaying I(1) behaviour. See appendix A for details.

Figure 1: Cumulated variance explained by first 4 dynamic common factors



As is more clearly revealed in figure 2, most of the explanatory power of the common dynamic factor is at businness cycle frequences (the vertical line in the graph corresponds to fluctuation of periodicity longer than 14 months). The peak at frequency 0.60 corresponds to periodicity of one year and reveals some common seasonality left in the data after the dummy regression that can be interpreted either as an imperfect removal of seasonals or as a filter induced peak.

Figure 2: First seven eigenvalues of the spectral density matrix of the data



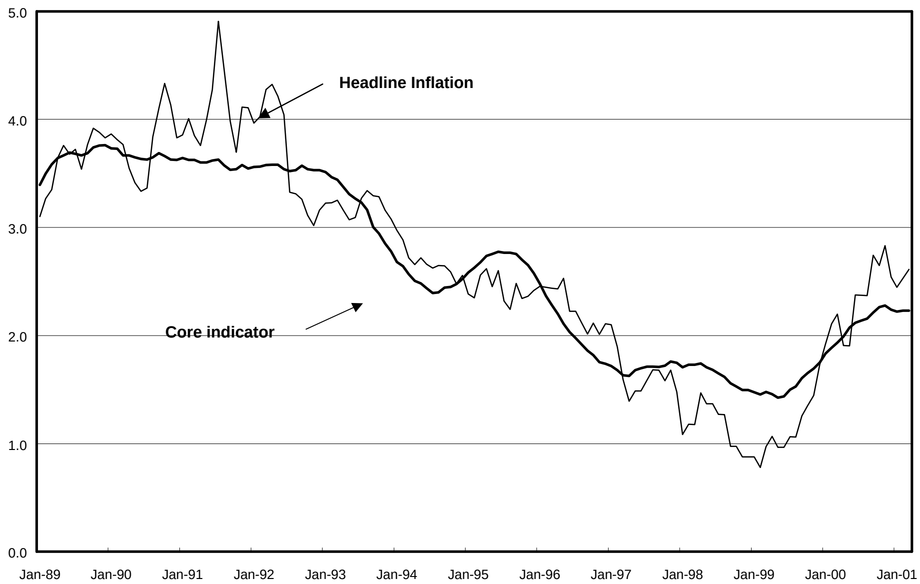
4 The inflation indicator for the euro area

In Section 2, we have described our index of core inflation, $core_t$, as the long run common component of the Euro Area HICP. To be more precise, we define $core_t$ as:

$$core_t = \sum_{k=1}^{12} w_k \cdot \left(\chi_{k,\ t}^{L} \sigma_k + \mu_k\right) \tag{3}$$

where the weights w_k are those used by Eurostat in the aggregation of HICP and are based on the final national consumption of each country, $\chi_{k,t}^{L}$ is the long run common component of the HICP in country k, standardized and expressed in deviation from the mean, and σ_k and μ_k are the standard deviation and the mean of the original log differenced HICP series. This *core* indicator has to be interpreted as a measure of the area wide common price fluctuations at medium to long term perioditicity; factors that are specific to a particular country will not be reflected in the core index and should not, in principle, be considered for the monetary policy of the euro area. On the contrary if the shock is shared by the majority of the European economies and it has an impact on the inflation rate beyond the short term, this is reflected in the core index. The estimate of our core inflation index is shown in Figure 3, where to allow a comparison with the ECB target, the core inflation is expressed as a 12-month difference.

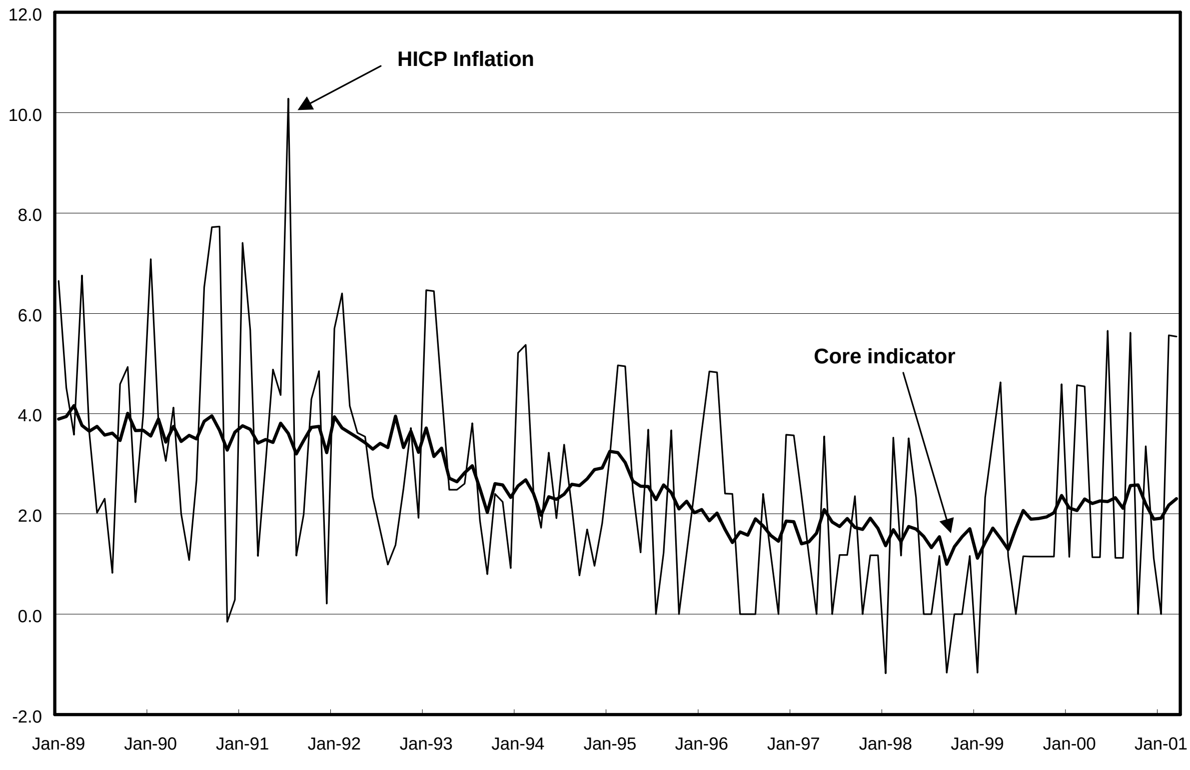
Figure 3: Core vs actual HICP inflation
(year on year percentage changes)



Visual inspection of figure 3 reveals that in the ninties the euro area inflation process has experienced three phases. The first episode lasted from the beginning of the ninties to the end of summer 1993, and it is characterised by a stable core inflation at around 3.5% (while headline inflation was fluctuating from 3% to 5%). The second phase, only briefly interruped in 1995, is dominated by the deceleration in price dynamics that preceded the monetary union: core inflation monotonically declined, stabilising below 2% by the end of 1997, as a result of tight monetary policies and wage moderation in Europe. The current phase, that began in the summer of 1999, is characterised by an increase in the core inflation that rose to above 2% at the beginning of last year, stabilising afterwards. Also in this last episode the pattern followed by the core index has been remarkably smooth, avoiding, in particular, the rather large downswing of the headline inflation at the beginning of 1999 that rised worries about a deflation in Europe.

Figure 4 clearly illustrates the effects of our cross-sectional and intertemporal smoothing. The annualized month on month changes of the core indicator are immune to the high-frequency volatility of the HICP measure.

Figure 4: Core inflation vs HICP inflation
(month on month changes at an annual rate)



Summary statistics can give a more precise characterization of the main features of our indicator. Compared with the headline inflation, as should be expected, the core indicator is smoother with a standard deviation 20% lower and much narrower fluctuations over the sample period (the range is 2 percentage points, while for headline inflation it is more than 4, see Table 1).

The mean core inflation (by construction) is close to the headline average over the sample and the two indicators show a correlation coefficient of 0.94. If we restrict the analysis to the period for which the commonly used HICP net of unprocessed food and energy prices (p^{NFE}) is available for the euro area (January 1996 onward, considering year on year changes) the comparison of the statistics reveals that our core indicator has a standard deviation of 0.28, the p^{NFE} has a deviation of 0.41, while correlation of these two measures with headline inflation has been 0.92 and 0.48 respectively. All these are indications of a better tracking performance of the core measure proposed vis a vis other commonly used indexes; this issues will be further investigated in Section 6, where the forecasting properties of alternative indicators of future inflation will be explored.

Table 1: Summary Statistics

	Jan. 1989 - Mar. 2001		Jan. 1996 - Mar. 2001			
	Euro area headline inflation	Core inflation indicator	Euro area headline inflation	Core inflation indicator	Index excluding unprocessed food and energy	Index excluding food and energy
Standard deviation	1.00	0.82	0.58	0.28	0.41	0.42
Mean	2.66	2.65	1.74	1.82	1.53	1.55
Median	2.61	2.58	1.68	1.73	1.49	1.51
Correlation with headline inflation		0.94		0.92	0.48	0.46
Maximum	4.91	3.76	2.83	2.48	2.75	2.79
Minimum	0.78	1.42	0.78	1.42	0.92	0.92

5 The relationship of the Core Inflation index with real and nominal variables

The analysis performed at this stage reveals some interesting features of the dynamic structure of the panel.

The series included in the dataset show an high degree of comovement at lower frequencies, the variance of the common components being more than 60% of total variance of the series on average. The feature is shared by all sectors even though this ratio is greater for interest rates, prices and wages (above 65%) and lower for surveys, share indexes and industrial productions (below 50%). Monetary aggregates in this respect are in the middle of the distribution.

Activity indicators, like industrial productions are, generally speaking, inversely related to inflation[12]: a decrease in core inflation tends to be followed by an increase in real activity. Among the survey indicators, answers to questions concerning the general economic situation are negatively related to inflation, while those related to past or expected price trends are positively related to the core measure. However, as mentioned above, the association among these variables is rather weak.

The relation between core inflation and interest rates, on the other hand, is very strong. Nominal interest rates are generally leading (10 months on average) and positively associated with price variables while ex post real interest rates are lagging. Rather surprisingly the spreads between long and short term interest rates are negatively related to the core index and lagging. A possible explanation for this result is that our indicator captures only longer run movements of inflation and interest spreads might have little informative content for the trend component of the inflationary process, being more related to shorter term dynamics. In this sense the signal they provide might not be very useful for monetary policy purposes.

No clear pattern emerges from the analysis of the behaviour of monetary aggregates. In any case, M3 for the Euro Area displays a strong positive correlation with our core index and a long lead (more than one year); while the real measure of M3, still retaining leading properties, has a weaker relation.

Turning to labour markets, wage rates in manufacturing and minimum wages are also strongly related with inflation and, on average, slightly leading. Vacancies are generally inversely related with inflation and lagging. In the case of unemployment no clear lead/lag relation emerges.

As far as prices are concerned, food prices generally share little commonality both in term of variance explained by the common factors and of correlation with the core index. This result provides some justification for the heuristic approach of looking at the consumer price index net of these items. On the other hand, energy prices, show a slightly higher commonality and are generally leading, hence, once their common component has been estimated they do provide some useful information about future overall inflation. Excluding them altogether from the index is therefore not always appropriate.

6 Forecasting inflation in the euro area

In this section we evaluate the forecasting ability of our core inflation indicator and compare it with some alternative indicators that have been proposed in the literature. Our target variable

[12] Of 46 industrial production indicators included in the panel, 39 are countercyclical with respect to our inflation measure.

will be the year on year rate of growth of the european HICP, computed as $\pi_t = 100 * (\log(P_t) - \log(P_{t-12}))$[13] which is the ECB reference measure for inflation.

We compute out-of-sample forecasts from different single equation models involving the candidate indicators in isolation and in conjunction with the lags of the target variable. Finally, we also examine a naive forecast of future inflation based on current values of our core index. In the first two cases the core index generally performs better than the other variables, but, as recently noted by Atkenson and Ohanian (2001), a simple random walk model of inflation often does better than state of the art models. The random walk forecast is indeed hard to beat with our monthly data, but the naive forecast based on the current value of the core index outperforms it at all horizons considered.

We use monthly data from Jan. 1996 to Mar. 2001. The starting point of our forecasting exercise coincides with the first date for which official HICP data on the euro area inflation are available[14]. We consider 14 alternative monthly indicators, that the ECB routinely monitors to produce the broad assessment of price pressuress in the euro area. In particular we have the three main euro area monetary aggregates, M1, M2, and M3; a group of indicators of *current* real activity like industrial production and the confidence indicators extracted from the European surveys in the manufacturing, construction and retail sectors. We also use the overall unemployment rate as an indicator of labor market tightness. Finally we analyze the predictive content of data on current and expected price trends as surveyed among consumers and industrial sector firms.

6.1 The methodology

The forecasts of inflation in the euro area are produced using the following bivariate linear model:

$$\pi_{t+h} = \alpha + \beta(L)\pi_t + \gamma(L)x_t^i + \varepsilon_{t+h} \tag{4}$$

where π_t is the percentage change in the HICP series at time t, and x_t^i is the candidate indicator i under exam. For each model, 13^2 different lags combinations of the dependent variable and the indicator (from lag 0 to lag 12) are estimated and used to forecast inflation.

Furthermore, three alternative transformations of each indicator are considered. The first one is the annual rate of growth: for example when considering M1 we adopt the transformation $(1 - L^{12})\log(M1_t) * 100$. The second transformation is the monthly rate of growth at an annual

[13] Where P_t is the level of the overall harmonized price index fro the euro area.

[14] The HICP data starts only in January 1995. Earlier data comes only in the form of national CPIs that, unlike the HICP, are not constructed according to a common set of rules.

rate of the indicator in its seasonally adjusted version[15]: for M1 this would be $(1-L)\log(M1_t^{SA}) * 1200$. The third transformation is the quarterly rate of growth, at an annual rate, of the indicator in its seasonally adjusted version. The $(1-L^{12})$ transformation while taking care of any seasonal component in the indicator variable has the disadvantage of making the transformed variable considerably lagging with respect to $(1-L)$ transformation.

At each step we produce the forecast of the year on year HICP growth rate 6, 12, 18 and 24 months ahead, using data prior to the forecasting period. For example the 6 months ahead forecast of inflation rate in Jan.1996 is obtained by using models estimated only up to Jul.1995, while the 12 months ahead forecast of the same month uses models estimated only up to Jan. 1995. Each model-lag combination produces a time series of 63 forecast errors

We assess the accuracy of alternative inflation forecasts by comparing the root mean squared error ($RMSE$) for each set of forecasts. The $RMSE$ of model i, in forecasting inflation h steps ahead, is given by, $RMSE_i^h = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\pi_{t+h} - \widehat{\pi}_{t+h|t}^i)^2}$,where $\widehat{\pi}_{t+h|t}^i$is the time t forecast, from model i, of the inflation prevailing at time $t+h$.

At the outset we looked at two simple models, traditionally used as benchmarks to assess the forecast ability of an indicator: the random walk model (or naive forecast) and the autogressive scheme. In any given period t, the random walk forecast of inflation h steps ahead is the inflation rate in period t; hence the forecast error of the random walk is given by $(\pi_{t+h} - \pi_t)$, i.e. the acceleration of the inflation in the forecasting range. As expected from the strong persistence in the inflation process, the $RMSE$ for the random walk model is very small at the 6 months horizon, 0.184; it more than doubles at the 12 months horizon becoming 0.485, rises to 0.754 at the 18 months horizon, and to 0.913 for the forecast of two years ahead inflation (Table 2).

We considered 13 different specifications of the autoregressive model, using lags from 0 to 12: averaging across these specifications the $RMSE$ for the AR model is well above the one of the random walk model. In particular the shorter is the forecast horizon considered the poorer is the relative performance of the AR model[16]. In particular this pattern is not due to large errors produced by models with a particular lag combination, since by looking at the distribution of the $RMSE$ for AR models with different lag orders we learn that the median $RMSE$ is close to the average at all forecast horizons.

[15] By construction our core inflation measure does not have any seasonal pattern, therefore we do not seasonally adjust it.

[16] In other terms the Theils's U coefficient (the ratio between the AR model and the random walk $RMSE$) falls with the length of the forecast horizons.

		RMSE at forecast horizon of 6 months	12 months	18 months	24 months
Random Walk of Inflation		0.429	0.696	0.868	0.956
	All lags: 0 - 12				
AR inflation model	**minimum**	0.445	0.859	1.134	1.475
	mean	0.485	0.887	1.189	1.565
	maximum	0.515	0.906	1.256	1.655
	median	0.478	0.895	1.183	1.565
	Data dependent lag selection				
	BIC	0.507	0.906	1.256	1.524
	Akaike	0.484	0.906	1.181	1.510

Table 2: Random-walk & Autoregressive Model RMSE (1996 - 2001)

The same picture emerges when the lag order of the AR model is selected in a data dependent way: at each step we produce a forecast only from the AR model with the best in sample performance according to the Bayesian Information Criteria (BIC), and calculate the $RMSE$ statistics by averaging the resulting squared forecast errors[17]. Following this method does not lead to any improvement, the $RMSE$ of the AR model being always above the random walk model. This is not surprising however because the in-sample performance of any model (as measured by this type of Information Criteria) tells us nothing about its out-of-sample forecasting ability. Next we analyze how the alternative indicators perform in predicting the inflation rate when they are used as the only regressors in the rhs of our model, i.e. by assuming $\beta(L) = 0$ in equation 4.

As done for the AR model we compare forecasting performance on the basis of $RMSE$ statistics for each model. Table C2 in Appendix C reports results for all the indicators and for all the transformations considered[18]. Some interesting results are thus obtained. First, our core inflation indicator outperforms systematically the autoregressive model: in particular when using the monthly rates of growth (center panel of Table C2). Second, few other variables are

[17] This practice introduced by Stock and Watson (1999), appears currently to be standard practice.

[18] In Table C2 and C3 the cells are shaded whenever the variable indicated under the row heading outperforms the AR model (whose RMSE are reported in the upper part of the table). For example in the first panel of Table C2 the median RMSE, across lags from 0 to 12 of the rhs variable, for our core inflation index at horizons of 6 and 12 months is lower than the median one obtained from all lag combinations of the AR model. Correspondingly those cells are shaded in grey.

able, on their own, to provide forecasts that outperform the autoregressive model: these are the two broadest euro area monetary aggregates (M2 and M3) and, to a lesser extent, the consumer survey indicators of price trends (past and expected). However their superiority with respect to the autoregressive scheme is limited to the farthest horizons of 18 and 24 months. Finally all the measures of real activity and of labor market conditions perform poorly.

However none of the indicators performs better than the random walk model of inflation, for all forecast horizons. This fact is in line with the evidence recently presented for the U.S. inflation by Atkeson and Ohanian (2001) and it is also robust with respect to the kind of transformation used for the indicator (one-, three- or twelve-month differences).

The results of Table C2 just provide a first idea of the predictive content of the alternative indicators; a more complete picture emerges when one considers the forecasting performance of alternative indicators used in conjunction with lagged inflation (Table C3).

Again our core inflation index produces systematically better forecasts than those of the AR model and of the other candidate indicators. More importantly, at horizons beyond 12 months they outperform the forecasts produced by the random walk model. Euro area M2 and M3 also outperform the AR model, however they generally do not produce better forecasts than the random walk model.

The picture improves dramatically when we use a forecasting model that we label "naive core model". In this specification our core inflation index is used *as such* to forecast inflation: this means that our forecast at time t for the inflation rate at time $t+h$ ($\widehat{\pi}_{t+h}$), is just π_t^{Core}. Since we have constructed our core inflation measure to reflect only fluctuations of frequency lower than $\frac{\pi}{7}$, we anticipate that it should have a good predictive content in itself. Indeed Table 3 below shows that the "naive core model" ouperforms the random walk model of inflation at all forecast horizons, including the shortest ones of 6 and 12 months.

		RMSE at forecast horizon of 6 months	12 months	18 months	24 months
Random Walk of Inflation		0.429	0.696	0.868	0.956
	Transformation of the core inflation index				
Naive Core Inflation model	**(1- L)**	0.387	0.498	0.687	0.792
	$(1-L^3)$	0.370	0.510	0.684	0.794
	$(1-L^6)$	0.375	0.548	0.704	0.795
	$(1-L^{12})$	0.445	0.609	0.735	0.803

Table 3: Forecast performance of the Random-walk vs Core Inflation naive model (1996-2001)

An objection that can be moved against the results obtained so far is that we have not really used only information up to time t when forecasting inflation at horizone $t+h$, since our core index is based on a variance covariance structure that is estimated over the full sample. This is a serious objection even though one can expect that covariances will not change dramatically as new data are added. In any case we explored the predictive perfomance of the core indicator in a "full real time" exercise. At each step we re-estimated not only the forecasting regression but also the dynamic factor model on which the core indicator is based. As expected results are affected only when we consider a forecasting horizon that spans the period 1996 to 2001. In this case the initial estimates of our core index are rather poor since they are based on a rather short time series[19]. The RMSE of the forecast obtained in this way are still rather good compared with alternatives, but no longer dominate all other forecasts. On the other hand, if we focus on the shorter horizon 1999-2001, that coincides with the monetary union period, the forecasting performance of the core index (and of the naive forecast in particular) is once again superior with respect to all alternatives (see table 4).

Table 4: Forecast performance of the Random-walk vs Core Inflation naive model in REAL TIME

		RMSE at forecast horizon of			
		6 months	12 months	18 months	24 months
Random Walk of Inflation		0.517	0.873	1.091	1.089
AR model of inflation		0.418	0.770	0.961	1.160
	Transformation of the core inflation index				
Naive Core Inflation model	**(1- L)**	0.432	0.676	0.912	0.980
	$(1-L^3)$	0.417	0.682	0.904	0.963
	$(1-L^6)$	0.437	0.719	0.912	0.936
	$(1-L^{12})$	0.522	0.785	0.906	0.909

Table 4 - Random-walk & Core Inflation naive model in REAL TIME (1999 - 2001)

These results are extremly promising and emphasize the quality of the procedure that we have proposed. Not only we outperform the random walk model of inflation, but also the

[19]When predicting the inflation rate in January 1999, in the 2 years ahead forecasting exercise, the core index and the regression model are estimated with data only up to January 1994. Hence the covariances of the data are estimated on a relatively short time range (1987-1994).

forecasts from all the other proposed indicators. In particular these results suggest that our indicator extracts optimally the underlying sources of inflationary pressures capturing most of the information relevant for the analysis of current and future price dynamics. In this sense the core index we propose is a methodologically well founded and convenient way of synthesizing the large set of statistics analysed under the first and the second pillar by the ECB.

7 Conclusions

Monetary policy makers have available an ever-expanding set of indicators that may contain useful information on price pressures in the economy. However no clear methodology exists to conveniently summarize all this information in a unified framework. This paper develops a new core inflation indicator for the Euro area that exploits the information from a large monthly database containing more than 400 series, regarding prices as well as other real and nominal variables.

Our core inflation indicator results from the combination of a smoothing procedure along the cross-sectional and temporal dimension: this operation is achieved by extracting the medium- and long-run common component of the Euro area CPI, using a dynamic factor model approach.

The core index we propose has major advantages over the more traditional inflation measures. It provides a more timely and more precise signal of the inflationary process. During some episodes the core inflation indicator departed from the actual headline inflation, giving a more reliable picture of the future price developments (as in the spring of 1999, when it clearly shows that fears of a deflation were misplaced). Moreover our core index turns out to have substantial predictive ability for the euro area inflation over horizons of 6,12,18 and 24 months. The forecasts produced by a naive core model (simply obtained by setting future inflation equal to the current core index level) outperform all the alternative univariate models considered, confirming its ability to successfully summarize all the information regarding the inflationary pressures. These features make our core inflation index a relevant tool for the ECB monetary policy strategy.

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8 Appendix A: the data set

This appendix provides a brief description of the data series used in this paper.The full cross-section comprises 450 series taken from a variety of sources: Eurostat, BIS, OECD, ECB data archives, Bank of Italy, National Statistical Offices, and Datastream. The data cover with great detail the six largest countries of the euro area, while, due to data limitations, only aggregate data for the other countries have been collected.

There are 140 aggregate and sectoral level price variables: consumer price series were reconstructed by linking HICP data, to national CPI data for each country; producer prices are obtained mainly from Eurostat, and in general we sought to maintain the same sectoral coverage of the industrial production series.

We included industrial production and other indicators of economic activity (like sales and turnover indexes), for a total of about 60 series. Labor market variables (essentially unemployment, vacancies and wages) are around 20.

Financial variables are by far the most represented group, with 90 interest rates, 40 monetary aggregates and 20 stock prices and exchange rates.

Finally some survey statistics have also been included (see table A1 for details).

Our method entails the estimation of the spectral matrix of the data and therefore requires a proper pre-treatment of the data so that anomalous values that can bias the estimation and non stationarity is taken care of. Hence prior to the analysis we removed outliers and other deterministic effects using the routines embodied in Tramo-Seats. We also removed deterministic seasonality by regressing the series on a set of dummy[20]. Interest rates, exchange rates and share prices were not seasonally adjusted and for the first two groups no outlier detection was performed.

Preliminary inspection revealed that our data are not affected by the same kind of non-stationarity. Given the large number of variables in the panel, careful individual treatment of non-stationarity was not feasible. Rather, we followed an automatic procedure treating in the same way all the series of a given economic class (e.g. industrial production, consumer prices and so on). Then we checked whether this resulted in an improper treatment of the data, such as over-differencing, incomplete removal of outliers or inadequate seasonal adjustment. The kind of stationarity inducing transformation applied to each class was also confronted with the results obtained with commonly used unit root tests, that appear to broadly confirm our choice (see table A1).

[20]The regressors also included the same dummies interacted with an yearly trend to capture evolving deterministic seasonality that might be present in the data.

SECTOR	Number of variables	Data Transformation	ADF with constant		ADF with constant & trend	
			5%	10%	5%	10%
Consumer prices	45	*(1-L)log*	9	6	3	0
Producer prices	94	*(1-L)log*	3	2	9	5
Industrial production	46	*(1-L)log*	0	0	0	0
E.C. survey & price expectations	62	*(1-L)*	2	0	2	2
Monetary aggregates - nominal	21	*(1-L)log*	0	0	0	0
Monetary aggregates - real	21	*(1-L)log*	0	0	0	0
Interest rates - spreads	6	*none*	4	4	4	4
Real interest rates (ex post)	12	*none*	9	8	6	6
Nominal interest rates	78	*(1-L)log*	0	0	9	3
Exchange rates	11	*(1-L)log*	0	0	0	0
Share prices and indexes	11	*(1-L)log*	0	0	0	0
Employment statistics	10	*(1-L)*	2	2	2	2
Wages	9	*(1-L)log*	0	0	0	0
Other indicators	8	*(1-L)log*	0	0	0	0

Table A1 - Stationarity Tests for Transformed Data[1]

[1] Each column under ADF reports the number of cases in which the test detected a unit root in the transformed variables.

VARIANCE EXPLAINED BY FIRST TEN COMMON FACTORS										
Freq.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
0.00	0.36	0.22	0.12	0.08	0.05	0.04	0.03	0.03	0.02	0.01
0.15	0.35	0.17	0.13	0.09	0.06	0.05	0.04	0.02	0.02	0.01
0.30	0.33	0.14	0.09	0.07	0.06	0.05	0.04	0.03	0.03	0.03
0.45	0.2	0.14	0.1	0.09	0.07	0.06	0.05	0.04	0.04	0.03
0.60	0.3	0.12	0.1	0.08	0.06	0.06	0.05	0.04	0.03	0.03
0.75	0.23	0.12	0.1	0.08	0.07	0.06	0.06	0.05	0.04	0.03
0.90	0.18	0.13	0.1	0.09	0.07	0.06	0.06	0.05	0.04	0.03
1.05	0.17	0.13	0.1	0.1	0.08	0.07	0.06	0.05	0.04	0.03
1.20	0.19	0.12	0.1	0.09	0.07	0.07	0.06	0.05	0.05	0.03
1.35	0.2	0.15	0.1	0.09	0.08	0.07	0.05	0.04	0.03	0.03
1.50	0.2	0.13	0.12	0.09	0.07	0.07	0.05	0.04	0.04	0.03
1.64	0.19	0.12	0.11	0.1	0.08	0.07	0.06	0.05	0.04	0.03
1.79	0.2	0.12	0.1	0.09	0.08	0.08	0.06	0.05	0.04	0.03
1.94	0.21	0.14	0.11	0.1	0.09	0.07	0.05	0.04	0.03	0.03
2.09	0.23	0.15	0.12	0.09	0.08	0.06	0.05	0.04	0.03	0.03
2.24	0.14	0.12	0.11	0.09	0.09	0.08	0.07	0.06	0.05	0.04
2.39	0.16	0.13	0.12	0.1	0.09	0.07	0.05	0.05	0.04	0.03
2.54	0.18	0.15	0.12	0.09	0.08	0.07	0.05	0.04	0.04	0.03
2.69	0.13	0.12	0.1	0.1	0.09	0.08	0.07	0.06	0.05	0.04
2.84	0.16	0.13	0.11	0.1	0.09	0.08	0.06	0.05	0.04	0.03
2.99	0.17	0.15	0.12	0.11	0.08	0.07	0.05	0.04	0.03	0.03
3.14	0.17	0.15	0.12	0.11	0.08	0.07	0.05	0.04	0.03	0.03
mean over [0, PI]	**0.21**	**0.14**	**0.11**	**0.09**	**0.08**	**0.07**	**0.05**	**0.04**	**0.04**	**0.03**
CUMULATED over [0, PI]	***0.21***	***0.35***	***0.46***	***0.55***	***0.63***	***0.69***	***0.75***	***0.79***	***0.83***	***0.86***
mean over [0, 0.45]	**0.31**	**0.17**	**0.11**	**0.08**	**0.06**	**0.05**	**0.04**	**0.03**	**0.03**	**0.02**
CUMULATED over [0, 0.45]	***0.31***	***0.48***	***0.59***	***0.67***	***0.73***	***0.78***	***0.82***	***0.85***	***0.88***	***0.90***

Table 2A

Appendix B: Technical details

B.1 Estimating the covariances of the common components

In the first step of our procedure, we estimate the spectral-density matrix and the covariances of the common components. We start by estimating the spectral-density matrix of $\mathbf{x}_t = \begin{pmatrix} x_{1t} & \cdots & x_{nt} \end{pmatrix}'$. Let us denote the theoretical matrix by $\Sigma(\theta)$ and its estimate by $\hat{\Sigma}(\theta)$. The estimation is accomplished by using a Bartlett lag-window of size $M = 18$, i.e. by computing the sample auto-covariance matrices $\hat{\Gamma}(k)$, multiplying them by the weights $w_k = 1 - \frac{|k|}{M+1}$ and applying the discrete Fourier transform:

$$\hat{\Sigma}_x(\theta) = \frac{1}{2\pi} \sum_{k=-M}^{M} w_k \cdot \hat{\Gamma}(k) \cdot e^{-i\theta k}.$$

The spectra were evaluated at 101 equally spaced frequencies in the interval $[-\pi, \pi]$, i.e. at the frequencies $\theta_h = \frac{2\pi h}{100}$, $h = -50, \ldots, 50$.
Then we performed the dynamic principal component decomposition (see Brillinger, 1981). For each frequency of the grid, we computed the eigenvalues and eigenvectors of $\hat{\Sigma}(\theta)$. By ordering the eigenvalues in descending order for each frequency and collecting values cosrresponding to different frequencies, the eigenvalue and eigenvector functions $\lambda_j(\theta)$ and $U_j(\theta)$, $j = 1, \ldots, n$, are obtained. The function $\lambda_j(\theta)$ can be interpreted as the (sample) spectral density of the j-th principal component series and, in analogy with the standard static principal component analysis, the ratio

$$p_j = \int_{-\pi}^{\pi} \lambda_j(\theta) d\theta / \sum_{j=1}^{n} \int_{-\pi}^{\pi} \lambda_j(\theta) d\theta$$

represents the contribution of the j-th principal component series to the total variance in the system. Letting $\Lambda_q(\theta)$ be the diagonal matrix having on the diagonal $\lambda_1(\theta), \ldots, \lambda_q(\theta)$ and $U_q(\theta)$ be the $(n \times q)$ matrix $\begin{pmatrix} U_1(\theta) & \cdots & U_q(\theta) \end{pmatrix}$ our estimate of the spectral density matrix of the vector of the common components $\chi_t = \begin{pmatrix} \chi_{1t} & \cdots & \chi_{nt} \end{pmatrix}'$ is given by

$$\hat{\Sigma}_\chi(\theta) = U(\theta)\Lambda(\theta)\tilde{\mathbf{U}}(\theta) \tag{5}$$

where the tilde denotes conjugation. Given the correct choice of q, consistency results for the entries of this matrix as both n and T go to infinity can easily be obtained from Forni, Hallin, Lippi and Reichlin (2000). Results on consistency rates can be found in Forni, Hallin, Lippi and Reichlin (2001a).

Following Forni, Hallin, Lippi and Reichlin (2000), we identified the number of common factors q by requiring a minimum amount of explained variance: we selected $q = 4$.

An estimate of the spectral density matrix of the vector of the idiosyncratic components $\xi_t = \begin{pmatrix} \xi_{1t} & \cdots & \xi_{nt} \end{pmatrix}'$ can be obtained as the difference $\hat{\Sigma}_\xi(\theta) = \hat{\Sigma}(\theta) - \hat{\Sigma}_\chi(\theta)$.

Starting from the estimated spectral-density matrix we obtain estimates of the covariance matrices of χ_t at different leads and lags by using the inverse discrete Fourier transform, i.e.

$$\hat{\Gamma}_\chi(k) = \frac{2\pi}{101} \sum_{h=-50}^{50} \hat{\Sigma}_\chi(\theta_h) e^{i\theta_h k}.$$

Moreover, we compute estimates of the covariance matrices of the medium- and long-run component $\chi_t^L = (\chi_{1t}^L, ..., \chi_{nt}^L)'$ by applying the inverse tranform to the frequency band of interest, i.e. $[-2\pi/\tau, 2\pi/\tau]$. Precisely, letting $\Gamma_{\chi^L}(k) = \mathrm{E}\left(\chi_t^L \chi_{t-k}^{L\prime}\right)$, the corresponding estimate will be

$$\hat{\Gamma}_{\chi^L}(k) = \frac{2\pi}{2H+1} \sum_{h=-H}^{H} \hat{\Sigma}_\chi(\theta_h) e^{i\theta_h k},$$

where H is defined by the conditions $H/101 > \tau$ and $(H+1)/101 < \tau$.

B.2 Estimating the static factors

Starting from the covariances estimated in the first step, we estimate the static factors as linear combinations of (the present of) the observable variables x_{jt}, $j = 1, \ldots, n$. Indeed, as observed in the main text, the static factors appearing in representation (1), i.e. u_{ht-k}, $h = 1, \ldots, q$, $k = 1, \ldots, s$, are not identified without imposing additional assumptions and therefore cannot be estimated. This however is not a problem, since we need only a set of $r = q(s+1)$ variables forming a basis for the linear space spanned by the u_{ht}'s and their lags. We can then obtain $\hat{\chi}_{jt}$ by projecting χ_{jt} on such factors and $\hat{\chi}_{jt}^L$ by projecting χ_{jt}^L on the leads and the lags of such factors.

Our strategy is to take the first r generalized principal components of $\hat{\Gamma}_\chi(0)$ with respect to the diagonal matrix having on the diagonal the variances of the idiosyncratic components ξ_{jt}, $j - 1, \ldots, n$, denoted by $\hat{\Gamma}_\xi(0)$. Precisely, we compute the generalized eigenvalues μ_j, i.e. the n complex numbers solving $\det(\Gamma_\chi^T(0) - z\hat{\Gamma}_\xi(0)) = 0$, along with the corresponding generalized eigenvectors V_j, $j = 1, \ldots, n$, i.e. the vectors satisfying

$$V_j \hat{\Gamma}_\chi(0) = \mu_j V_j \hat{\Gamma}_\xi(0),$$

and the normalizing condition

$$V_j \hat{\Gamma}_\xi(0) V_i' = \begin{cases} 0 & \text{for} \quad j \neq i, \\ 1 & \text{for} \quad j = i. \end{cases}$$

Then we order the eigenvalues in descending order and take the eigenvectors corresponding to the largest r eigenvalues. Our estimated static factors are the generalized principal components

$$v_{jt} = V_j' \mathbf{x}_t, \quad j = 1, \ldots, r.$$

The motivation for this strategy is that, if $\hat{\Gamma}_\xi(0)$ is the variance-covariance matrix of the idiosyncratic components (i.e. the ξ_{jt}'s are mutually orthogonal), the generalized principal components are the linear combinations of the x_{jt}'s having the smallest idiosyncratic-common variance ratio (for a proof see Forni, Hallin, Lippi and Reichlin, 2001b). We diagonalize the idiosyncratic variance-covariance matrix since, as shown in the paper cited above, this gives better results under simulation when n is large with respect to T as is the case here.

By using the generalized principal components and the covariances estimated in the first step we can estimate and forecast χ_t. Precisely, setting $\mathbf{V} = (V_1 \ \cdots \ V_r)$ and $\mathbf{v}_t = (v_{1t} \cdots v_{rt})' = \mathbf{V}'\mathbf{x}_t$, our estimate of χ_{t+h}, $h = 0, \ldots, s$, given the information available at time t, is

$$\begin{aligned} \hat{\chi}_{t+h} &= \hat{\Gamma}_\chi(h)\mathbf{V}\left(\mathbf{V}'\hat{\Gamma}(0)\mathbf{V}\right)^{-1}\mathbf{v}_t \\ &= \hat{\Gamma}_\chi(h)\mathbf{V}\left(\mathbf{V}'\hat{\Gamma}(0)\mathbf{V}\right)^{-1}\mathbf{V}'\mathbf{x}_t. \end{aligned} \tag{6}$$

In Forni, Hallin, Lippi and Reichlin (2001b) it is shown that, as both n and T go to ∞ in a proper way, $\hat{\chi}_t$ converges in probability, entry by entry, to χ_t, and $\hat{\chi}_{t+h}$ converges to the theoretical projection of χ_{t+h} on the present and the past of $u_{1t}, \ldots, u_{qt}$.

B.3 Estimating the cyclical part of the common components

Finally we estimate the medium- and long-run common components χ_{jt}^L by using the covariances estimated in the first step in order to project χ_{jt}^L on the present and m leads and lags of the estimated static factors.

Set $\mathbf{V}_t = (\mathbf{v}_{t+m}' \cdots \mathbf{v}_t' \cdots \mathbf{v}_{t-m}')'$ and

$$\mathbf{W} = \left(\underbrace{\begin{array}{cccc} \mathbf{V} & 0_{n\times r} & \cdots & 0_{n\times r} \\ 0_{n\times r} & \mathbf{V} & \cdots & 0_{n\times r} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{n\times r} & 0_{n\times r} & \cdots & \mathbf{V} \end{array}}_{2m+1 \text{ blocks}} \right).$$

Moreover, set $\mathbf{X}_t = (\mathbf{x}_{t+m}' \cdots \mathbf{x}_t' \cdots \mathbf{x}_{t-m}')'$, so that $\mathbf{V}_t = \mathbf{W}'\mathbf{X}_t$. The sample variance-covariance matrix of $\mathbf{X}_t$ is

$$\mathbf{M} = \begin{pmatrix} \hat{\Gamma}(0) & \hat{\Gamma}(1) & \cdots & \hat{\Gamma}(2m) \\ \hat{\Gamma}'(1) & \hat{\Gamma}_0 & \cdots & \hat{\Gamma}(2m-1) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\Gamma}'(2m) & \hat{\Gamma}'(2m-1) & \cdots & \hat{\Gamma}(0) \end{pmatrix},$$

while $\mathrm{E}\left(\chi_t^L X_t'\right)$ can be estimated by

$$\mathbf{R} = \left(\begin{array}{ccccc} \hat{\Gamma}'_{\chi^L}(m) & \cdots & \hat{\Gamma}'_{\chi^L}(0) & \cdots & \hat{\Gamma}_{\chi^L}(m) \end{array} \right).$$

Our estimate of the common cyclical components is then

$$\hat{\chi}_t^L = \mathbf{RW}\left(\mathbf{W}'\mathbf{MW}\right)^{-1}\mathbf{W}'\mathbf{X}_t. \tag{7}$$

At the end of the sample, i.e. from $T-m$ onward, we have the problem that $\mathbf{x}_{T+h}$, $h > 0$, is not available. Our estimate is then obtained by substituting our forecast of the common components $\hat{\chi}_{T+h}$, in place of $\mathbf{x}_{T+h}$ and applying the formula 7.

B.4 Treatment of the end-of-sample unbalance

Let us assume that T is the last date for which we have observations for all of the variables in the data set and that there are some variables for which we have observations until dates $T+1, \ldots, T+w$. Without loss of generality we can then reorder the variables in such a way that

$$\mathbf{x}_t = \left(\begin{array}{cccc} \mathbf{x}_t^{1\prime} & \mathbf{x}_t^{2\prime} & \cdots & \mathbf{x}_t^{w\prime} \end{array} \right),$$

where $\mathbf{x}_{jt}$, $j = 1, ..., w$, is such that the last available observation reefers to $T + j - 1$. Correspondingly, the sample covariance matrices $\hat{\Gamma}(k)$ are partitioned as follows

$$\hat{\Gamma}(k) = \begin{pmatrix} \hat{\Gamma}^{11}(k) & \hat{\Gamma}^{12}(k) & \cdots & \hat{\Gamma}^{1w}(k) \\ \hat{\Gamma}^{21}(k) & \hat{\Gamma}^{22}(k) & \cdots & \hat{\Gamma}^{2w}(k) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\Gamma}^{w1}(k) & \hat{\Gamma}^{w2}(k) & \cdots & \hat{\Gamma}^{ww}(k) \end{pmatrix}.$$

A similar partition holds for $\hat{\Gamma}_\chi(k)$.

Our idea is simply to shift the variables in such a way to retain, for each one of them, only the most updated observation, and compute the generalized principal components for the re-aligned vector. In such a way we are able to get information on the factors u_{hT+j}, $h = 1, \ldots, q$, $j = 1, \ldots, w$, and to exploit it in prediction.

Precisely, we set

$$\mathbf{x}_t^* = \left(\begin{array}{cccc} \mathbf{x}_t^{1\prime} & \mathbf{x}_{t+1}^{2\prime} & \cdots & \mathbf{x}_{t+w-1}^{w\prime} \end{array} \right).$$

Notice that the sample covariance matrices of $\mathbf{x}_t^*$ are then

$$\hat{\Gamma}^*(k) = \left(\begin{array}{cccc} \hat{\Gamma}^{11}(k) & \hat{\Gamma}^{12}(k-1) & \cdots & \hat{\Gamma}^{1w}(k-w+1) \\ \hat{\Gamma}^{21}(k+1) & \hat{\Gamma}^{22}(k) & \cdots & \hat{\Gamma}^{2w}(k-w+2) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\Gamma}^{w1}(k+w-1) & \hat{\Gamma}^{w2}(k+w-2) & \cdots & \hat{\Gamma}^{ww}(k) \end{array} \right)$$

and the matrices $\hat{\Gamma}_\chi^*(k)$ are defined in the same way. Then we compute the matrix $\mathbf{V}^*$ of the generalized eigenvectors of $\hat{\Gamma}_\chi^*(k)$ with respect to $\hat{\Gamma}_\xi(k)$ (the latter matrix is diagonal and thefore is the same for $\mathbf{x}_t$ and $\mathbf{x}_t^*$) and obtain forecasts of χ_{T+h}^* as in equation (7):

$$\hat{\chi}_{T+h}^* = \hat{\Gamma}_\chi^*(h)\mathbf{V}^* \left(\mathbf{V}^{*\prime}\hat{\Gamma}_0^*\mathbf{V}^*\right)^{-1} \mathbf{V}^{*\prime}\mathbf{x}_T^*.$$

Finally we use the forecasts in $\hat{\chi}_{T+h}^*$, $h = 1, \ldots$ to replace missing data and to get the forecasts of χ_{T+h}, $h > w$, which are needed to apply (7).

9 Appendix C: Tables and Figures

SECTOR	Number of variables	Explained variance	Leading		Coincident		Lagging	
All data set	447	0.63	219	49.0%	37	8.3%	191	42.7%
Consumer prices	45	0.67	15	33.3%	15	33.3%	15	33.3%
Producer prices	94	0.71	50	53.2%	8	8.5%	36	38.3%
Industrial production	46	0.46	6	13.0%	3	6.5%	37	80.4%
E.C. survey & price expectations	62	0.52	23	37.1%	1	1.6%	38	61.3%
Monetary aggregates - nominal	21	0.59	10	47.6%	1	4.8%	10	47.6%
Monetary aggregates - real	21	0.56	7	33.3%	2	9.5%	12	57.1%
Interest rates - spreads	6	0.72	1	16.7%	0	0.0%	5	83.3%
Real interest rates (ex post)	12	0.79	2	16.7%	2	16.7%	8	66.7%
Nominal interest rates	78	0.77	78	100.0%	0	0.0%	0	0.0%
Exchange rates	11	0.60	3	27.3%	0	0.0%	8	72.7%
Share prices and indexes	11	0.47	7	63.6%	0	0.0%	4	36.4%
Employment statistics	10	0.63	3	30.0%	0	0.0%	7	70.0%
Wages	9	0.65	3	33.3%	5	55.6%	1	11.1%
Other indicators	8	0.48	4	50.0%	0	0.0%	4	50.0%

Table C1- Properties of the dataset

TABLE C2: Univariate Results RHS= lags of candidate indicate indicator

TRANSFORMATION FOR RHS VARIABLES: $(1 - L^{12}) * \log(X_t)$

Indicator	Statistic	Forecast Horizon: 6 months	12 months	18 months	24 months
Benchmarks: Random Walk	RMSE	0.429	0.696	0.868	0.956
Benchmarks: AR models (lags: 0-12)	Minimum	0.445	0.859	1.134	1.475
	Mean	0.485	0.887	1.189	1.565
	Maximum	0.515	0.906	1.256	1.655
	Median	0.478	0.895	1.183	1.565
	BIC	0.507	0.906	1.256	1.524
	Akaike	0.484	0.906	1.181	1.51
Core Inflation	Minimum	0.452	0.673	1.707	1.421
	Mean	0.48	0.692	1.796	1.713
	Maximum	0.527	0.717	1.939	1.973
	Median	0.474	0.692	1.783	1.701
	BIC	0.465	0.695	1.825	1.709
	Akaike	0.498	0.7	1.715	1.535
Unemployment	Minimum	1.456	1.559	1.582	1.442
	Mean	1.476	1.606	1.627	1.567
	Maximum	1.5	1.651	1.699	1.903
	Median	1.477	1.61	1.625	1.493
	BIC	1.502	1.68	1.604	1.444
	Akaike	1.499	1.653	1.658	1.638
Industrial Production	Minimum	1.373	1.512	1.702	1.751
	Mean	1.471	1.676	1.76	1.779
	Maximum	1.554	1.79	1.805	1.821
	Median	1.479	1.688	1.763	1.767
	BIC	1.434	1.72	1.85	1.806
	Akaike	1.466	1.759	1.857	1.901
M1	Minimum	1.432	1.595	1.638	1.569
	Mean	1.455	1.678	1.668	1.652
	Maximum	1.507	1.811	1.725	1.864
	Median	1.444	1.647	1.649	1.597
	BIC	1.427	1.658	1.777	1.675
	Akaike	1.437	1.736	1.744	1.791
M2	Minimum	0.976	0.871	0.76	1.068
	Mean	1.141	1.038	0.969	1.117
	Maximum	1.277	1.167	1.107	1.195
	Median	1.139	1.048	1.009	1.105
	BIC	1.05	1.033	1.04	1.195
	Akaike	0.976	0.885	0.994	1.28
M3	Minimum	0.819	0.888	0.772	0.973
	Mean	0.899	0.913	0.838	1.049
	Maximum	0.989	0.944	0.87	1.265
	Median	0.891	0.908	0.854	1.006
	BIC	0.919	0.949	0.863	1.083
	Akaike	0.838	0.873	0.823	1.166
Business activity survey	Minimum	1.33	1.499	1.681	1.637
	Mean	1.433	1.666	1.742	1.68
	Maximum	1.592	1.8	1.797	1.699
	Median	1.414	1.681	1.742	1.682
	BIC	1.543	1.823	1.793	1.649
	Akaike	1.564	1.815	1.83	1.649
Construction survey	Minimum	1.276	1.447	1.759	1.858
	Mean	1.371	1.729	1.936	1.886
	Maximum	1.465	1.956	2.056	1.944
	Median	1.376	1.737	1.965	1.87
	BIC	1.301	1.862	1.965	1.977
	Akaike	1.42	1.927	2.066	1.963
Industry survey	Minimum	1.474	1.518	1.842	1.855
	Mean	1.576	1.846	2.032	1.898
	Maximum	1.65	2.045	2.125	2.007
	Median	1.57	1.863	2.058	1.885
	BIC	1.481	1.747	2.237	2.028
	Akaike	1.525	1.945	2.135	1.958
Retail survey	Minimum	1.351	1.451	1.654	1.706
	Mean	1.382	1.563	1.693	1.73
	Maximum	1.428	1.663	1.734	1.769
	Median	1.377	1.57	1.693	1.73
	BIC	1.38	1.573	1.743	1.738
	Akaike	1.403	1.608	1.752	1.767
Price expectations building	Minimum	1.369	1.485	1.618	1.586
	Mean	1.445	1.614	1.661	1.608
	Maximum	1.56	1.728	1.686	1.633
	Median	1.431	1.628	1.669	1.603
	BIC	1.413	1.668	1.788	1.645
	Akaike	1.507	1.724	1.73	1.652
Price Trends over last 12 months (consumer survey)	Minimum	0.958	0.855	0.806	0.85
	Mean	1.195	1.058	0.935	0.911
	Maximum	1.319	1.235	1.067	1.067
	Median	1.242	1.039	0.939	0.881
	BIC	0.958	0.859	0.804	0.921
	Akaike	0.958	0.855	0.806	0.926
Price Trends over next 12 months (consumer survey)	Minimum	1.281	1.274	1.1	1.231
	Mean	1.354	1.353	1.28	1.29
	Maximum	1.377	1.394	1.376	1.392
	Median	1.369	1.359	1.327	1.275
	BIC	1.335	1.436	1.262	1.276
	Akaike	1.281	1.298	1.103	1.275
Selling price intentions for the months ahead (industry survey)	Minimum	1.543	1.639	1.698	1.503
	Mean	1.699	1.921	1.84	1.655
	Maximum	1.839	2.169	1.979	1.82
	Median	1.702	1.934	1.832	1.664
	BIC	1.543	1.639	1.698	1.921
	Akaike	1.592	1.704	2.053	1.864

TRANSFORMATION FOR RHS VARIABLES: $(1 - L) * \log(X_t)$

Indicator	Horizons	6	12	18	24
Benchmarks: Random Walk	RMSE	0.429	0.696	0.868	0.956
Benchmarks: AR model	Minimum	0.445	0.859	1.134	1.475
	Mean	0.485	0.887	1.189	1.565
	Maximum	0.515	0.906	1.256	1.655
	Median	0.478	0.895	1.183	1.565
	BIC	0.507	0.906	1.256	1.524
	Akaike	0.484	0.906	1.181	1.51
Core Inflation	Minimum	0.385	0.578	0.801	1.061
	Mean	0.409	0.613	0.846	1.149
	Maximum	0.436	0.662	0.887	1.31
	Median	0.406	0.61	0.86	1.117
	BIC	0.399	0.594	0.833	1.124
	Akaike	0.424	0.674	0.825	1.125
Unemployment	Minimum	1.411	1.613	1.653	1.539
	Mean	1.437	1.643	1.666	1.575
	Maximum	1.469	1.677	1.68	1.632
	Median	1.437	1.639	1.666	1.567
	BIC	1.475	1.682	1.688	1.604
	Akaike	1.456	1.674	1.686	1.549
Industrial Production	Minimum	1.397	1.5	1.555	1.616
	Mean	1.43	1.601	1.686	1.744
	Maximum	1.484	1.76	1.788	1.801
	Median	1.418	1.573	1.69	1.756
	BIC	1.402	1.635	1.766	1.776
	Akaike	1.435	1.642	1.748	1.733
M1	Minimum	1.344	1.511	1.562	1.614
	Mean	1.354	1.601	1.665	1.742
	Maximum	1.377	1.701	1.814	1.851
	Median	1.353	1.594	1.653	1.754
	BIC	1.356	1.511	1.583	1.632
	Akaike	1.356	1.565	1.779	1.832
M2	Minimum	1.339	1.344	1.155	1.185
	Mean	1.379	1.447	1.341	1.33
	Maximum	1.4	1.502	1.512	1.538
	Median	1.382	1.469	1.349	1.299
	BIC	1.4	1.495	1.362	1.285
	Akaike	1.405	1.41	1.186	1.185
M3	Minimum	0.99	1.033	0.964	0.865
	Mean	1.112	1.126	1.057	0.998
	Maximum	1.287	1.308	1.297	1.365
	Median	1.089	1.1	1.02	0.924
	BIC	1.126	1.111	0.984	0.951
	Akaike	1.023	1.04	1.019	0.978
Business activity survey	Minimum	1.323	1.486	1.559	1.603
	Mean	1.34	1.531	1.652	1.693
	Maximum	1.382	1.613	1.734	1.729
	Median	1.335	1.523	1.656	1.716
	BIC	1.382	1.489	1.702	1.722
	Akaike	1.361	1.588	1.694	1.695
Construction survey	Minimum	1.309	1.485	1.552	1.607
	Mean	1.322	1.52	1.686	1.741
	Maximum	1.37	1.641	1.876	1.857
	Median	1.314	1.499	1.67	1.731
	BIC	1.37	1.488	1.719	1.809
	Akaike	1.358	1.556	1.866	1.876
Industry survey	Minimum	1.456	1.574	1.599	1.626
	Mean	1.528	1.674	1.721	1.731
	Maximum	1.57	1.8	1.871	1.803
	Median	1.541	1.67	1.709	1.747
	BIC	1.456	1.574	1.599	1.691
	Akaike	1.5	1.634	1.851	1.77
Retail survey	Minimum	1.354	1.474	1.552	1.606
	Mean	1.374	1.5	1.63	1.71
	Maximum	1.392	1.54	1.691	1.804
	Median	1.375	1.493	1.637	1.709
	BIC	1.392	1.492	1.648	1.666
	Akaike	1.392	1.534	1.667	1.738
Price expectations building	Minimum	1.366	1.494	1.553	1.602
	Mean	1.377	1.534	1.629	1.647
	Maximum	1.397	1.611	1.69	1.666
	Median	1.375	1.519	1.638	1.661
	BIC	1.385	1.503	1.688	1.655
	Akaike	1.386	1.577	1.665	1.63
Price Trends over last 12 months (consumer survey)	Minimum	1.351	1.301	1.139	1.106
	Mean	1.372	1.418	1.337	1.333
	Maximum	1.394	1.486	1.511	1.569
	Median	1.37	1.436	1.352	1.31
	BIC	1.422	1.539	1.266	1.286
	Akaike	1.392	1.31	1.139	1.111
Price Trends over next 12 months (consumer survey)	Minimum	1.385	1.469	1.441	1.41
	Mean	1.389	1.485	1.509	1.507
	Maximum	1.393	1.491	1.543	1.586
	Median	1.388	1.49	1.519	1.508
	BIC	1.392	1.491	1.502	1.434
	Akaike	1.392	1.505	1.456	1.421
Selling price intentions for the months ahead (industry survey)	Minimum	1.423	1.52	1.552	1.499
	Mean	1.52	1.65	1.624	1.521
	Maximum	1.615	1.782	1.715	1.573
	Median	1.514	1.646	1.617	1.514
	BIC	1.433	1.52	1.552	1.573
	Akaike	1.514	1.534	1.576	1.565

TRANSFORMATION FOR RHS VARIABLES: $(1 - L^3) * \log(X_t)$

		0.655	0.835	0.932	0.978
Indicator	Horizons	6	12	18	24
Benchmarks: Random Walk	RMSE	0.429	0.696	0.868	0.956
Benchmarks: AR model	Minimum	0.445	0.859	1.134	1.475
	Mean	0.485	0.887	1.189	1.565
	Maximum	0.515	0.906	1.256	1.655
	Median	0.478	0.895	1.183	1.565
	BIC	0.507	0.906	1.256	1.524
	Akaike	0.484	0.906	1.181	1.51
Core Inflation	Minimum	0.387	0.582	0.766	0.939
	Mean	0.417	0.622	0.81	1.035
	Maximum	0.449	0.659	0.856	1.198
	Median	0.416	0.616	0.81	1.024
	BIC	0.401	0.582	0.766	0.94
	Akaike	0.452	0.652	0.766	0.94
Unemployment	Minimum	1.435	1.618	1.645	1.522
	Mean	1.461	1.649	1.658	1.552
	Maximum	1.493	1.693	1.673	1.601
	Median	1.457	1.645	1.656	1.552
	BIC	1.496	1.706	1.661	1.564
	Akaike	1.488	1.685	1.67	1.522
Industrial Production	Minimum	1.415	1.514	1.6	1.682
	Mean	1.46	1.641	1.716	1.754
	Maximum	1.535	1.811	1.799	1.781
	Median	1.446	1.613	1.72	1.772
	BIC	1.415	1.694	1.819	1.785
	Akaike	1.421	1.69	1.791	1.76
M1	Minimum	1.355	1.537	1.601	1.636
	Mean	1.37	1.626	1.704	1.761
	Maximum	1.383	1.747	1.897	1.863
	Median	1.371	1.616	1.669	1.778
	BIC	1.361	1.536	1.757	1.718
	Akaike	1.356	1.642	1.87	1.872
M2	Minimum	1.307	1.298	1.102	1.103
	Mean	1.378	1.415	1.279	1.263
	Maximum	1.413	1.496	1.434	1.446
	Median	1.385	1.412	1.294	1.242
	BIC	1.413	1.495	1.281	1.234
	Akaike	1.353	1.404	1.102	1.103
M3	Minimum	0.958	1.004	0.971	0.885
	Mean	1.079	1.088	1.035	0.998
	Maximum	1.221	1.197	1.109	1.114
	Median	1.07	1.072	1.034	0.978
	BIC	1.106	1.072	0.965	0.913
	Akaike	1	1.008	1.104	1.157
Business activity survey	Minimum	1.336	1.485	1.581	1.634
	Mean	1.354	1.554	1.672	1.698
	Maximum	1.387	1.652	1.748	1.721
	Median	1.35	1.541	1.676	1.707
	BIC	1.362	1.629	1.736	1.72
	Akaike	1.356	1.626	1.723	1.699
Construction survey	Minimum	1.328	1.481	1.553	1.64
	Mean	1.335	1.551	1.728	1.766
	Maximum	1.345	1.719	1.929	1.865
	Median	1.333	1.508	1.733	1.783
	BIC	1.343	1.481	1.877	1.757
	Akaike	1.357	1.688	1.915	1.88
Industry survey	Minimum	1.484	1.58	1.619	1.676
	Mean	1.554	1.709	1.761	1.757
	Maximum	1.592	1.853	1.899	1.838
	Median	1.565	1.706	1.762	1.765
	BIC	1.484	1.58	1.77	1.765
	Akaike	1.504	1.739	1.873	1.887
Retail survey	Minimum	1.372	1.468	1.571	1.648
	Mean	1.389	1.506	1.639	1.728
	Maximum	1.401	1.562	1.69	1.817
	Median	1.392	1.501	1.649	1.712
	BIC	1.4	1.501	1.666	1.737
	Akaike	1.402	1.54	1.674	1.766
Price expectations building	Minimum	1.376	1.494	1.571	1.609
	Mean	1.394	1.551	1.64	1.642
	Maximum	1.438	1.634	1.695	1.655
	Median	1.387	1.541	1.645	1.649
	BIC	1.38	1.534	1.723	1.662
	Akaike	1.38	1.605	1.676	1.646
Price Trends over last 12 months (consumer survey)	Minimum	1.345	1.236	1.075	1.029
	Mean	1.383	1.383	1.267	1.245
	Maximum	1.4	1.47	1.439	1.504
	Median	1.386	1.392	1.268	1.21
	BIC	1.54	1.463	1.226	1.157
	Akaike	1.345	1.236	1.075	1.03
Price Trends over next 12 months (consumer survey)	Minimum	1.399	1.469	1.408	1.341
	Mean	1.405	1.484	1.484	1.467
	Maximum	1.41	1.49	1.524	1.559
	Median	1.405	1.487	1.502	1.468
	BIC	1.404	1.529	1.467	1.383
	Akaike	1.439	1.505	1.422	1.343
Selling price intentions for the months ahead (industry survey)	Minimum	1.497	1.569	1.569	1.49
	Mean	1.576	1.699	1.64	1.509
	Maximum	1.67	1.854	1.738	1.541
	Median	1.575	1.692	1.628	1.504
	BIC	1.497	1.569	1.569	1.524
	Akaike	1.534	1.569	1.563	1.457

TABLE C3: RHS = Lags of dep.variable + lags of the candidate indicator

TRANSFORMATION FOR RHS VARIABLES: $(1 - L^{12}) * \log(X_t)$

		Horizons	6	12	18	24
Benchmarks	Random Walk	RMSE	0.429	0.696	0.868	0.956
	AR model	Minimum	0.445	0.859	1.134	1.475
		Mean	0.485	0.887	1.189	1.565
		Maximum	0.515	0.906	1.256	1.655
		Median	0.478	0.895	1.183	1.565
		BIC	0.507	0.906	1.256	1.524
		Akaike	0.484	0.906	1.181	1.51
	Core Inflation	Minimum	0.369	0.685	1.708	0.944
		Mean	0.417	0.74	1.85	1.39
		Maximum	0.489	1.073	2.082	1.804
		Median	0.42	0.718	1.841	1.394
		BIC	0.427	0.691	1.766	1.568
		Akaike	0.456	1.042	1.89	1.066
	Unemployment	Minimum	0.426	0.965	1.273	1.598
		Mean	0.579	1.227	1.517	1.896
		Maximum	0.698	1.464	1.871	2.584
		Median	0.588	1.245	1.509	1.831
		BIC	0.521	1.191	1.33	1.766
		Akaike	0.57	1.436	1.634	2.134
	Industrial Production	Minimum	0.439	0.923	1.447	1.747
		Mean	0.53	1.166	1.59	1.915
		Maximum	0.624	1.374	1.791	2.127
		Median	0.537	1.161	1.587	1.903
		BIC	0.514	1.157	1.56	2.022
		Akaike	0.541	1.355	1.713	2.065
	M1	Minimum	0.426	0.809	0.993	1.339
		Mean	0.471	0.856	1.051	1.584
		Maximum	0.512	0.954	1.214	1.968
		Median	0.476	0.843	1.026	1.558
		BIC	0.503	0.809	1.015	1.466
		Akaike	0.449	0.836	1.108	1.704
	M2	Minimum	0.426	0.722	0.816	1.323
		Mean	0.46	0.775	0.888	1.448
		Maximum	0.501	0.819	0.945	1.608
		Median	0.456	0.773	0.902	1.449
		BIC	0.495	0.757	0.902	1.441
		Akaike	0.479	0.777	0.923	1.712
	M3	Minimum	0.448	0.843	0.935	1.278
		Mean	0.534	0.915	0.983	1.369
		Maximum	0.6	1.035	1.087	1.461
		Median	0.536	0.904	0.983	1.371
		BIC	0.55	0.854	0.935	1.431
		Akaike	0.559	0.88	1.03	1.365
	Business activity survey	Minimum	0.401	0.776	1.129	1.392
		Mean	0.493	1.05	1.249	1.526
		Maximum	0.689	1.337	1.359	1.67
		Median	0.469	1.06	1.251	1.525
		BIC	0.604	1.16	1.23	1.453
		Akaike	0.633	1.333	1.331	1.486
	Construction survey	Minimum	0.443	0.869	1.318	1.508
		Mean	0.516	1.129	1.451	1.662
		Maximum	0.596	1.345	1.589	1.779
		Median	0.505	1.137	1.46	1.687
		BIC	0.588	1.289	1.492	1.641
		Akaike	0.579	1.324	1.616	1.703
	Industry survey	Minimum	0.487	0.915	1.52	1.693
		Mean	0.573	1.236	1.677	1.926
		Maximum	0.665	1.444	1.901	2.079
		Median	0.569	1.25	1.662	1.93
		BIC	0.568	1.104	1.828	2.002
		Akaike	0.553	1.415	1.91	1.857
	Retail survey	Minimum	0.419	0.89	1.327	1.563
		Mean	0.487	1.043	1.444	1.779
		Maximum	0.557	1.24	1.633	2.035
		Median	0.482	1.035	1.428	1.735
		BIC	0.518	1.092	1.433	1.872
		Akaike	0.475	1.18	1.465	1.953
	Price expectations building	Minimum	0.407	0.776	1.112	1.382
		Mean	0.473	0.95	1.204	1.508
		Maximum	0.56	1.108	1.284	1.704
		Median	0.467	0.969	1.205	1.508
		BIC	0.471	0.986	1.182	1.544
		Akaike	0.519	1.039	1.282	1.551
	Price Trends over last 12 months (consumer survey)	Minimum	0.408	0.78	1.028	1.262
		Mean	0.493	0.87	1.109	1.395
		Maximum	0.579	0.96	1.163	1.567
		Median	0.491	0.861	1.106	1.371
		BIC	0.517	0.875	1.141	1.411
		Akaike	0.511	0.949	1.049	1.415
	Price Trends over next 12 months (consumer survey)	Minimum	0.425	0.877	1.126	1.499
		Mean	0.525	0.985	1.233	1.711
		Maximum	0.647	1.151	1.503	2.102
		Median	0.526	0.973	1.192	1.661
		BIC	0.517	0.895	1.126	1.66
		Akaike	0.623	1.087	1.485	1.902
	Selling price intentions for the months ahead (industry survey)	Minimum	0.459	0.898	1.207	1.384
		Mean	0.519	1.049	1.378	1.658
		Maximum	0.559	1.192	1.543	1.97
		Median	0.517	1.049	1.361	1.654
		BIC	0.539	0.898	1.268	1.754
		Akaike	0.504	0.964	1.524	1.708
	CORE INFLATION REAL TIME	Minimum	0.356	0.744	1.168	1.099
		Mean	0.421	0.931	1.603	2.051
		Maximum	0.424	0.936	1.589	2.237
		Median	0.499	1.121	1.904	6.874
		BIC	0.455	0.988	1.471	6.274
		Akaike	0.387	0.939	1.247	6.411
	NAIVE CORE REAL TIME	delta1	0.612	0.820	0.986	1.090
		delta3	0.583	0.804	0.962	1.071
		delta6	0.561	0.791	0.941	1.039
		delta12	0.587	0.798	0.933	1.020

TRANSFORMATION FOR RHS VARIABLES: $(1 - L) * \log(X_t)$

		Horizons	6	12	18	24
Benchmarks	Random Walk	RMSE	0.429	0.696	0.868	0.956
	AR model	Minimun	0.445	0.859	1.134	1.475
		Mean	0.485	0.887	1.189	1.565
		Maximun	0.515	0.906	1.256	1.655
		Median	0.478	0.895	1.183	1.565
		BIC	0.507	0.906	1.256	1.524
		Akaike	0.484	0.906	1.181	1.51
	Core Inflation	Minimun	0.303	0.608	0.732	0.865
		Mean	0.349	0.625	0.805	0.977
		Maximun	0.399	0.653	0.887	1.161
		Median	0.344	0.625	0.814	0.971
		BIC	0.356	0.612	0.848	1.091
		Akaike	0.333	0.651	0.808	0.994
	Unemployment	Minimun	0.469	0.993	1.25	1.416
		Mean	0.531	1.115	1.319	1.504
		Maximun	0.602	1.251	1.444	1.593
		Median	0.525	1.123	1.303	1.498
		BIC	0.503	1.166	1.276	1.48
		Akaike	0.58	1.212	1.364	1.526
	Industrial Production	Minimun	0.461	0.983	1.264	1.483
		Mean	0.518	1.138	1.473	1.686
		Maximun	0.572	1.356	1.653	1.786
		Median	0.519	1.12	1.479	1.702
		BIC	0.506	1.184	1.541	1.738
		Akaike	0.474	1.252	1.713	1.743
	M1	Minimun	0.462	0.983	1.215	1.388
		Mean	0.518	1.051	1.279	1.508
		Maximun	0.56	1.109	1.357	1.618
		Median	0.518	1.059	1.281	1.509
		BIC	0.515	1.024	1.379	1.472
		Akaike	0.505	1.095	1.387	1.464
	M2	Minimun	0.458	0.825	0.91	1.097
		Mean	0.496	0.968	1.08	1.318
		Maximun	0.534	1.109	1.257	1.573
		Median	0.496	0.992	1.08	1.292
		BIC	0.52	0.996	1.213	1.294
		Akaike	0.478	0.983	1.052	1.249
	M3	Minimun	0.458	0.896	0.917	0.834
		Mean	0.493	0.917	1.009	1.079
		Maximun	0.516	0.963	1.17	1.507
		Median	0.495	0.915	0.994	0.981
		BIC	0.499	0.943	1.036	1.103
		Akaike	0.507	0.927	0.955	0.854
	Business activity survey	Minimun	0.471	0.981	1.255	1.459
		Mean	0.502	1.025	1.3	1.524
		Maximun	0.528	1.101	1.373	1.599
		Median	0.499	1.022	1.295	1.524
		BIC	0.517	1.022	1.454	1.613
		Akaike	0.481	1.102	1.416	1.598
	Construction survey	Minimun	0.477	1.005	1.288	1.477
		Mean	0.527	1.099	1.432	1.608
		Maximun	0.566	1.234	1.613	1.763
		Median	0.526	1.091	1.415	1.599
		BIC	0.521	1.025	1.547	1.739
		Akaike	0.49	1.215	1.603	1.65
	Industry survey	Minimun	0.52	1.137	1.41	1.567
		Mean	0.598	1.281	1.578	1.774
		Maximun	0.661	1.435	1.828	1.982
		Median	0.605	1.28	1.56	1.762
		BIC	0.548	1.142	1.669	1.736
		Akaike	0.543	1.284	1.749	1.665
	Retail survey	Minimun	0.461	0.968	1.252	1.466
		Mean	0.508	1.036	1.369	1.6
		Maximun	0.563	1.135	1.47	1.763
		Median	0.507	1.025	1.375	1.61
		BIC	0.517	1.007	1.419	1.663
		Akaike	0.479	1.078	1.404	1.57
	Price expectations building	Minimun	0.47	0.984	1.248	1.457
		Mean	0.509	1.039	1.298	1.52
		Maximun	0.528	1.135	1.376	1.592
		Median	0.512	1.031	1.291	1.521
		BIC	0.515	1.017	1.439	1.597
		Akaike	0.479	1.129	1.423	1.529
	Price Trends over last 12 months (consumer survey)	Minimun	0.436	0.923	1.092	1.268
		Mean	0.471	0.968	1.184	1.417
		Maximun	0.528	1.007	1.285	1.602
		Median	0.466	0.968	1.176	1.389
		BIC	0.506	1.044	1.21	1.445
		Akaike	0.519	0.956	1.097	1.291
	Price Trends over next 12 months (consumer survey)	Minimun	0.448	0.971	1.199	1.356
		Mean	0.48	1.015	1.255	1.458
		Maximun	0.518	1.069	1.309	1.604
		Median	0.477	1.013	1.247	1.446
		BIC	0.512	1.031	1.217	1.395
		Akaike	0.488	1.039	1.21	1.394
	Selling price intentions for the months ahead (industry survey)	Minimun	0.476	0.992	1.251	1.391
		Mean	0.558	1.156	1.387	1.537
		Maximun	0.627	1.358	1.504	1.631
		Median	0.555	1.15	1.396	1.53
		BIC	0.53	1.024	1.313	1.516
		Akaike	0.487	1.039	1.281	1.407
	CORE INFLATION REAL TIME	Minimun	0.406	0.751	0.838	1.028
		Mean	0.426	0.791	0.957	1.090
		Maximun	0.431	0.792	0.940	1.103
		Median	0.463	0.829	1.035	1.273
		BIC	0.473	0.814	0.958	1.137
		Akaike	0.419	0.855	0.828	1.090
	NAIVE CORE REAL TIME	delta1	0.612	0.820	0.986	1.090
		delta3	0.583	0.804	0.962	1.071
		delta6	0.561	0.791	0.941	1.039
		delta12	0.587	0.798	0.933	1.020

TRANSFORMATION FOR RHS VARIABLES: $(1 - L^{3}) * \log(X_t)$

		Horizons	6	12	18	24
Benchmarks	Random Walk	RMSE	0.429	0.696	0.868	0.956
	AR model	Minimun	0.445	0.859	1.134	1.475
		Mean	0.485	0.887	1.189	1.565
		Maximun	0.515	0.906	1.256	1.655
		Median	0.478	0.895	1.183	1.565
		BIC	0.507	0.906	1.256	1.524
		Akaike	0.484	0.906	1.181	1.51
	Core Inflation	Minimun	0.307	0.583	0.739	0.871
		Mean	0.359	0.628	0.804	0.973
		Maximun	0.414	0.655	0.937	1.138
		Median	0.352	0.629	0.801	0.955
		BIC	0.359	0.615	0.804	1.076
		Akaike	0.352	0.65	0.918	1.052
	Unemployment	Minimun	0.472	0.987	1.235	1.426
		Mean	0.561	1.149	1.335	1.519
		Maximun	0.632	1.313	1.502	1.641
		Median	0.562	1.148	1.315	1.509
		BIC	0.533	1.206	1.286	1.452
		Akaike	0.595	1.247	1.389	1.587
	Industrial Production	Minimun	0.484	1.004	1.316	1.587
		Mean	0.537	1.174	1.504	1.712
		Maximun	0.596	1.399	1.663	1.771
		Median	0.533	1.149	1.508	1.724
		BIC	0.511	1.253	1.643	1.763
		Akaike	0.507	1.316	1.707	1.793
	M1	Minimun	0.467	0.993	1.197	1.356
		Mean	0.53	1.046	1.269	1.461
		Maximun	0.577	1.12	1.377	1.579
		Median	0.528	1.044	1.259	1.454
		BIC	0.501	1.022	1.472	1.461
		Akaike	0.509	1.136	1.372	1.426
	M2	Minimun	0.46	0.793	0.842	1.007
		Mean	0.498	0.948	1.008	1.234
		Maximun	0.536	1.2	1.239	1.58
		Median	0.499	0.956	1	1.192
		BIC	0.523	0.984	1.018	1.236
		Akaike	0.499	0.979	0.878	1.119
	M3	Minimun	0.47	0.885	0.928	0.8
		Mean	0.509	0.91	0.996	1.016
		Maximun	0.526	0.929	1.139	1.432
		Median	0.51	0.91	0.988	0.981
		BIC	0.511	0.911	1.013	1.059
		Akaike	0.545	0.916	1.037	0.818
	Business activity survey	Minimun	0.485	0.974	1.241	1.474
		Mean	0.508	1.03	1.286	1.508
		Maximun	0.532	1.149	1.383	1.53
		Median	0.507	1.025	1.277	1.509
		BIC	0.518	1.158	1.447	1.597
		Akaike	0.526	1.105	1.407	1.595
	Construction survey	Minimun	0.503	1.024	1.318	1.485
		Mean	0.548	1.135	1.459	1.612
		Maximun	0.586	1.371	1.661	1.75
		Median	0.549	1.112	1.441	1.604
		BIC	0.53	1.025	1.696	1.783
		Akaike	0.528	1.326	1.769	1.756
	Industry survey	Minimun	0.563	1.142	1.433	1.659
		Mean	0.631	1.318	1.616	1.81
		Maximun	0.686	1.505	1.934	1.976
		Median	0.637	1.318	1.603	1.806
		BIC	0.584	1.142	1.726	1.848
		Akaike	0.589	1.395	1.857	1.968
	Retail survey	Minimun	0.472	0.961	1.26	1.493
		Mean	0.519	1.048	1.376	1.604
		Maximun	0.578	1.156	1.473	1.749
		Median	0.52	1.045	1.393	1.595
		BIC	0.524	1.021	1.411	1.735
		Akaike	0.516	1.075	1.512	1.729
	Price expectations building	Minimun	0.491	0.965	1.235	1.467
		Mean	0.523	1.045	1.284	1.5
		Maximun	0.568	1.178	1.387	1.548
		Median	0.521	1.035	1.273	1.495
		BIC	0.518	1.022	1.418	1.579
		Akaike	0.513	1.155	1.401	1.637
	Price Trends over last 12 months (consumer survey)	Minimun	0.445	0.91	1.045	1.232
		Mean	0.481	0.95	1.137	1.376
		Maximun	0.537	0.991	1.219	1.565
		Median	0.479	0.948	1.132	1.345
		BIC	0.482	1.02	1.167	1.327
		Akaike	0.514	0.94	1.052	1.246
	Price Trends over next 12 months (consumer survey)	Minimun	0.456	0.97	1.168	1.291
		Mean	0.493	1.022	1.229	1.426
		Maximun	0.535	1.087	1.277	1.567
		Median	0.49	1.02	1.233	1.417
		BIC	0.473	1.031	1.205	1.361
		Akaike	0.547	1.081	1.168	1.342
	Selling price intentions for the months ahead (industry survey)	Minimun	0.531	1.029	1.273	1.405
		Mean	0.6	1.192	1.38	1.539
		Maximun	0.665	1.411	1.477	1.641
		Median	0.599	1.176	1.383	1.551
		BIC	0.565	1.038	1.305	1.531
		Akaike	0.54	1.05	1.303	1.503
	CORE INFLATION REAL TIME	Minimun	0.398	0.706	0.828	0.935
		Mean	0.434	0.739	0.875	0.995
		Maximun	0.436	0.74	0.875	1.008
		Median	0.47	0.764	0.918	1.255
		BIC	0.456	0.742	0.892	1.031
		Akaike	0.439	0.777	0.841	1.099
	NAIVE CORE REAL TIME	delta1	0.612	0.820	0.986	1.090
		delta3	0.583	0.804	0.962	1.071
		delta6	0.561	0.791	0.941	1.039
		delta12	0.587	0.798	0.933	1.020