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In 2004 all publications will carry a motif taken from the €100 banknote.

1 The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the European Central Bank. We thank an anonymous referee and Adrian Page for comments, remaining errors are our own.
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Abstract

Standard measures of prices are often contaminated by transitory shocks. This has prompted economists to suggest the use of measures of underlying inflation to formulate monetary policy and assist in forecasting observed inflation. Recent work has concentrated on modelling large datasets using factor models. In this paper we estimate factors from datasets of disaggregated price indices for European countries. We then assess the forecasting ability of these factor estimates against other measures of underlying inflation built from more traditional methods. The power to forecast headline inflation over horizons of 12 to 18 months is adopted as a valid criterion to assess forecasting. Empirical results for the five largest euro area countries as well as for the euro area are presented.

Keywords: Core Inflation, Dynamic Factor Models, Forecasting.
JEL-classification: E31, C13, C32.

Non-technical summary

The aim of monetary policy in most modern economies is maintaining price stability over the medium term. A common problem faced by those responsible for monetary policy decisions is that standard measures of prices are often contaminated by three main types of transitory shocks: i) measurement errors, ii) regular seasonal fluctuations, and iii) other non-monetary factors, such as for example a good or bad harvest. This has prompted economists to suggest the use of 'filtered' versions of published price indexes as measures of underlying inflation.

Two major approaches for filtering a price index have been traditionally adopted. The first approach exploits the cross section dimension, and relies on modifying the weights attached to the different subcomponents of consumer price indexes. The weights are modified so that the more volatile subcomponents of consumer price indexes are either set to zero or assigned smaller values. The second approach exploits the time series dimension of the aggregate price index series, and builds a measure of underlying inflation at a point in time as the weighted sum of observations from the past and the future. The aim of this approach is to isolate the persistent component of aggregate inflation, i.e. that component that does not vanish in future periods but leaves a permanent mark.

In recent work, Kapetanios (2002) proposed a new method of estimating dynamic factor models that exploits both the cross section dimension and the time series dimension. This method is easy to implement and can also accommodate cases where the number of variables exceeds the number of observations. This method forms part of a large set of algorithms used in the engineering literature for estimating state space models called subspace algorithms.

This paper presents an assessment of the reliability of measures of underlying inflation built from subspace algorithms against other measures built from more traditional methods. The power to forecast headline inflation over horizons of 12 to 18 months is adopted as a valid criterion to assess reliability. Empirical results for the five largest euro area countries as well as for the euro area are presented. Results show that measures of core inflation built by means of dynamic factor methods perform well in comparison to traditional measures. This paper also warns that measures of underlying inflation based on methods that ignore the time series dimension of price indexes may fail to cointegrate with headline inflation.

1 Introduction

Monetary policy in most modern economies aims at maintaining price stability over the medium term. A common problem faced by those responsible for monetary policy decisions is that standard measures of prices are often contaminated by three main types of transitory shocks: i) measurement errors, ii) regular seasonal fluctuations, and iii) other non-monetary factors, such as for example a good or bad harvest. This has prompted economists to suggest the use of 'filtered' versions of published price indexes as measures of underlying inflation, see for example Bryan and Cecchetti (1994) and Vega and Wynne (2001).

Two major approaches for filtering a price index have been adopted. The first approach exploits the cross section dimension, and in effect acts upon the original series by modifying the weights attached to its different subcomponents. An example in this vein is a study conducted for the euro area HICP by Vega and Wynne (2001) which suggested that a trimmed mean measure of underlying inflation outperforms a measure computed by excluding unprocessed food and energy prices. The second approach exploits the time series dimension of the price index series, and builds a measure of underlying inflation at a point in time as the weighted sum of observations from the past and the future. The justification for this approach follows the suggestion by Blinder (1997) to identify the persistent component of aggregate inflation as an underlying measure of inflation, i.e. that component that does not vanish in future periods but leaves a permanent mark. Bryan and Cecchetti (1993) were the first to propose a method that exploit both the cross section as well as the time series dimension. They proposed to model a vector of subcomponents of the US Consumer Price Index (CPI) by means of a dynamic factor index model. This model has a state space representation, and maximum likelihood methods in combination with the Kalman filter can be implemented to estimate the unknown parameters, along the lines explained in Harvey (1993).[1]

[1]Wynne (1999) provide a review on conceptual and practical problems that arise in the measurement of core inflation.

However, maximum likelihood estimation of a state space model is not practical when the dimension of the model becomes too large due to the computational cost. The modelling strategy proposed by Bryan and Cecchetti (1993) is therefore difficult to implement for levels of disaggregation of the subcomponents of the price index finer than the two-digit level. Additionally, their method can not be implemented when the number of observations is smaller than the number of price subcomponents employed. In recent work, Kapetanios (2004) has proposed a new method of estimating factor models based on subspace algorithms that also exploits both the cross section dimension and the time series dimension and, importantly, the method does not require iterative estimation techniques. This makes possible a high degree of disaggregation of the price index series. This method can also accommodate cases where the number of variables exceeds the number of observations as shown also in Kapetanios (2004). The method forms part of a large set of algorithms used in the engineering literature for estimating state space models called subspace algorithms.

This paper presents an assessment on the reliability of measures of underlying inflation built from subspace algorithms against other measures built from more traditional methods. The power to forecast headline inflation over horizons of 12 to 18 months is adopted as a valid criterion to assess reliability.[2] Empirical results for the five largest euro area countries as well as for the euro area are presented.

The method proposed by Kapetanios (2004) is described in section 2. Section 3 describes a variety of methods used in the literature to compute measures of underlying inflation. The methods reviewed in this section will be referred to as 'traditional' methods in this paper. Section 4 provides details

[2] Vega and Wynne (2001) suggested also the ability to track trend inflation as a criterion to assess reliability of core inflation measures.

on the nature of the forecasting exercise conducted to assess the reliability of different measures of underlying inflation and presents the empirical results. Finally, section 5 concludes.

2 Dynamic Factor Method

We consider the following state space model.

$$\begin{aligned} x_t &= Cf_t + Du_t, \quad t = 1, \dots, T \\ f_t &= Af_{t-1} + Bu_{t-1} \end{aligned} \tag{1}$$

x_t is an n-dimensional vector of strictly stationary zero-mean variables observed at time t. f_t is an m-dimensional vector of unobserved states (factors) at time t and u_t is a multivariate standard white noise sequence of dimension n. The aim of the analysis is to obtain estimates of the states f_t, for $t = 1, \dots, T$. This state space model may not appear familiar as the presence of the same error term in both the transition and measurement equations is non-standard. However, as Hannan and Deistler (1988, Ch. 1) show, (1), referred to as the prediction error representation of the state space model, is equivalent to the following more common representation

$$\begin{aligned} x_t &= Cf_t + D^* u_t, \quad t = 1, \dots, T \qquad (2) \\ f_t &= Af_{t-1} + B^* v_{t-1} \end{aligned}$$

where u_t and v_t are multivariate standard orthogonal white noise sequences. We concentrate on (1) as it forms the basis for deriving the dynamic factor estimation algorithm.

Subspace algorithms avoid expensive iterative techniques and rely instead on matrix algebraic methods to provide estimates for the factors as well as the parameters of the state space representation. A review of existing subspace algorithms is given by Bauer (1998) in an econometric context. Another review with an engineering perspective may be found in Overschee and Moor (1996).

The starting point of most subspace algorithms is the following representation of the system which follows from the state space representation (2) and the assumed nonsingularity of D.

$$X_t^f = \mathcal{O}\mathcal{K}X_t^p + \mathcal{E}E_t^f \tag{3}$$

where $X_t^f = (x_t', x_{t+1}', x_{t+2}', \ldots)'$, $X_t^p = (x_{t-1}', x_{t-2}', \ldots)'$, $E_t^f = (u_t', u_{t+1}', \ldots)'$,

$$\begin{aligned} \mathcal{O} &= [C', A'C', (A^2)'C', \ldots]' \\ \mathcal{K} &= [\bar{B}, (A - \bar{B}C)\bar{B}, (A - \bar{B}C)^2\bar{B}, \ldots] \end{aligned}$$

where $\bar{B} = BD^{-1}$ and

$$\mathcal{E} = \begin{pmatrix} D & 0 & \ldots & 0 \\ CB & D & \ddots & \vdots \\ CAB & \ddots & \ddots & 0 \\ \vdots & & CB & D \end{pmatrix}$$

The derivation of this representation is easy to see once we note that (i) $X_t^f = \mathcal{O}f_t + \mathcal{E}E_t^f$ and (ii) $f_t = \mathcal{K}X_t^p$. The best linear predictor of the future of the series at time t is given by $\mathcal{O}\mathcal{K}X_t^p$. The state is given in this context by $\mathcal{K}X_t^p$ at time t. The task is therefore to provide an estimate for $\mathcal{K}$. Obviously, the above representation involves infinite dimensional vectors.

In practice, truncation is used to end up with finite sample approximations given by $X_{s,t}^f = (x_t', x_{t+1}', x_{t+2}', \ldots, x_{t+s-1}')'$ and $X_{q,t}^p = (x_{t-1}', x_{t-2}', \ldots, x_{t-q}')'$. Then an estimate of $\mathcal{F} = \mathcal{O}\mathcal{K}$ may be obtained by regressing $X_{s,t}^f$ on $X_{q,t}^p$. Following that, the most popular subspace algorithms use a singular value decomposition of an appropriately weighted version of the least squares estimate of $\mathcal{F}$, denoted by $\hat{\mathcal{F}}$. In particular the algorithm we will use, due to Larimore (1983), applies a singular value decomposition to $\hat{\Gamma}^{f^{-1/2}}\hat{\mathcal{F}}\hat{\Gamma}^{p^{1/2}}$, where $\hat{\Gamma}^f$, and $\hat{\Gamma}^p$ are the sample covariances of $X_{s,t}^f$ and $X_{q,t}^p$ respectively. These weights are used to determine the importance of certain directions in $\hat{\mathcal{F}}$. Then, the estimate of $\mathcal{K}$ is given by

$$\hat{\mathcal{K}} = \hat{S}_m^{1/2}\hat{V}_m'\hat{\Gamma}^{p^{-1/2}}$$

where $\hat{U}\hat{S}\hat{V}'$ represents the singular value decomposition of $\hat{\Gamma}^{f^{-1/2}}\hat{\mathcal{F}}\hat{\Gamma}^{p^{1/2}}$, $\hat{V}_m$ denotes the matrix containing the first m columns of $\hat{V}$ and $\hat{S}_m$ denotes the heading $m \times m$ submatrix of $\hat{S}$. $\hat{S}$ contains the singular values of $\hat{\Gamma}^{f^{-1/2}}\hat{\mathcal{F}}\hat{\Gamma}^{p^{1/2}}$ in decreasing order. Then, the factor estimates are given by $\hat{\mathcal{K}}X_t^p$. More details on the method, including its asymptotic properties, may be found in Kapetanios and Marcellino (2003). Once an estimate of the factor is obtained then the parameters of the state space model may be estimated using standard regression techniques and the factor estimates in the measurement and transition equations. Thus, it is possible to produce forecasts for the factors.

2.1 Dealing with large datasets

Up to now we have outlined an existing method for estimating factors which requires that the number of observations be larger than the number of elements in X_t^p. Given the work of Stock and Watson (2002), on modelling very large datasets with factor models, this is rather restrictive. We therefore follow Kapetanios and Marcellino (2003) who suggested a modification of the existing methodology to allow the number of series in X_t^p be larger than the number of observations. The problem arises in this method because the least squares estimate of $\mathcal{F}$ does not exists due to rank deficiency of $X^{p'}X^p$ where $X^p = (X_1^p, \ldots, X_T^p)'$. As we mentioned in the previous section we do not necessarily want an estimate of $\mathcal{F}$ but an estimate of the states $X^p\mathcal{K}'$. That could be obtained if we had an estimate of $X^p\mathcal{F}'$ and used a singular value decomposition of that. But it is well known (see e.g. Magnus and Neudecker (1988)) that although $\hat{\mathcal{F}}$ may not be estimable $X^p\mathcal{F}'$ always is using least squares methods. In particular, the least squares estimate of $X^p\mathcal{F}'$ is given by

$$\widehat{X^p\mathcal{F}'} = X^p(X^{p'}X^p)^+X^{p'}X^f$$

where $X^f = (X_1^f, \ldots, X_T^f)'$ and A^+ denotes the unique Moore-Penrose inverse of matrix A. Once this step is modified then the estimate of the factors may be straightforwardly obtained by applying a singular value decomposition to $\widehat{X^p\mathcal{F}'}$. Kapetanios (2004) chooses to set both weighting matrices to the identity matrix in this case. In our results below we will pursue two alternative subspace methods. Method 1, denoted in the tables below as SS1, relies on the singular value decomposition of $X^p(X^{p\prime}X^p)^+X^{p\prime}X^f = \hat{U}\hat{S}\hat{V}'$. Then, the factor estimates are given by $\hat{U}_m\hat{S}_m^{1/2}$. Method 2, denoted SS2, relies on the singular value decomposition of $(X^{p\prime}X^p)^+X^{p\prime}X^f = \hat{U}\hat{S}\hat{V}'$. Here the factor estimates are given by $X^p\hat{U}_m\hat{S}_m^{1/2}$. Note that $X^p(X^{p\prime}X^p)^+X^{p\prime} = I$ when the number of columns of X^p exceeds its number of rows. We therefore see that SS1 essentially decomposes X^f, and resembles the approximate dynamic factor methodology of Stock and Watson (2002) based on principal components. The SS2 method, on the other hand is genuinely dynamic in that it exploits the dynamic relationship between X^f and X^p to estimate the factor.

3 Measures of Underlying Inflation

Headline inflation will be defined as $\pi_t = 100\ln(P_t/P_{t-12})$, where P_t is a price index measure. For our purposes, we defined n as the number of subcomponents of the price measure, and w_i for $i = 1$ to n as the weights associated with the i-th subcomponent, it follows that $P_t = \sum_{i=1}^{n} w_i P_{i,t}$ where $P_{i,t}$ is the price index for subcomponent i at time t.

Dynamic factor measures. Dynamic factor measures of underlying inflation are built from a state space system such as that in (1), where x_t is defined as a $n \times 1$ vector with elements $x_{i,t} = 100\ln(P_{i,t}/P_{i,t-12})$ for $i = 1$ to n. The measure of underlying inflation is the first factor estimate of $\hat{\mathcal{F}}X_t^p$. As stated above, when the estimate of this first factor relies on a singular value decomposition of $X^p(X^{p\prime}X^p)^+X^{p\prime}X^f$, this will be denoted by SS1 in our empirical results below, and when the first factor relies on a singular value decomposition of $(X^{p\prime}X^p)^+X^{p\prime}X^f$, this will be denoted by SS2.

Excluding measures. These measures simply exclude certain subcomponents of the price index to compute a core inflation measure. This translates into zeroing out some of the weights w_i, and scaling the non-zero weights so that they add to one, these newly defined weights, say $\tilde{w}_i$ are then used to compute a new aggregate price index, $\tilde{P}_t = \sum_{i=1}^{p} \tilde{w}_i P_{i,t}$ for $p < n$. Four measures, corresponding to four alternative weightings will be tested in this paper. These are defined as follows: i) EX1, excludes the energy components; ii) EX2, excludes energy and food components; iii) EX3, excludes energy and unprocessed food components; and iv) EX4, excludes energy and seasonal food components. Additionally, and following ECB (2004, pp. 27-28) we build a measure that aims at excluding components whose prices are subject to a certatin degree of government control; i.e. this measure excludes administered prices. We will denote this measure as ADM.[3]

Trimmed Mean measures. Define the headline 'ordered' rate of inflation as: $\pi_t^o = \sum_{j=1}^{n} w_j^o \pi_{j,t}^o$ for $j = 1$ to n, where the inflation rate for the subcomponents, $\pi_{j,t}^o$, are 'ordered' from smallest to largest, and w_j^o define their corresponding weights. A trimmed measure of inflation is then defined as follows:

$$\pi_t^{2\alpha} = \frac{1}{1-2\alpha} \sum_{j=m+1}^{n-p} w_j^o \pi_{j,t}^o$$

where m and p are chosen such that $\sum_{j=1}^{m} w_j^o = \sum_{j=n-p+1}^{n} w_j^o = \alpha$. We have defined a total of 6 trimmed measures of underlying inflation, with the size of the trimming (2α) ranging between values of 1% to 50%. These measures are denoted as: TR1, TR5, TR10, TR20, TR30 and TR50. Note that the median in effect can be seen as a trimmed measure, that trims 50% on the left and 50% on the right. We denote the underlying measure of inflation built from the median as MED.

[3]The ADM measure excludes: tobacco, energy, sewerage collection, refuse collection, medical and paramedical services, dental services, hospital services, passenger transport by railway, postal services, education and social protection.

Edgeworth Index. This measure is defined as $EDGE = \sum_{j=1}^{n} w_j^e \pi_{j,t}$ for $j = 1$ to n, where the weights w_j^e are inversely related to the volatility of $\pi_{j,t}$, and defined as follows:

$$w_j^e = \frac{\sigma_{i,t}^{-2}}{\sum_{j=1}^{n} \sigma_{j,t}^{-2}}$$

where $E(\pi_{j,t} - E\pi_{j,t})^2 = \sigma_{j,t}^2$.

Unobserved Component model measure. We adopt the unobserved component (UC) model proposed by Harvey and Jaeger (1993) to extract a measure of underlying inflation. This measure exploits only the time series dimension.

$$\pi_t = \mu_t + \gamma_t + \varepsilon_t$$

where μ_t is a trend component, γ_t is a cyclical component and ε_t an irregular noise component with standard deviation σ_ε. The trend component μ_t is for our purposes a measure of underlying inflation, and will be referred to as the UC measure of underlying inflation in this paper. Details on the structure of the trend component μ_t and the stochastic cycle γ_t can be found in Harvey and Jaeger (1993). The model can be written in State Space form and the Kalman filter implemented to extract the state component. Given that there are parameters to be estimated, maximum likelihood estimation in combination with the Kalman filter must be used.

Quah and Vahey (1995) measure. Quah and Vahey (1995) provided a method to construct a measure of underlying inflation by placing dynamic restrictions on a vector autorregression (VAR) system with Δy and $\Delta \pi$ as endogenous variables, where y denotes the logarithm of industrial production. They adopt an identification strategy similar to that in Blanchard and Quah (1989), by which they assume that the first kind of disturbance has no impact on output in the long run. Underlying inflation is defined as the movements in inflation associated with this first disturbance. This measure will be denoted as QV in the paper.

4 Data and Empirical Results

4.1 Data

Our empirical results will be conducted for the euro area (EA), and the largest five countries of the euro area in terms of GDP; namely Germany (DE), France (FR), Italy (IT), The Netherlands (NL) and Spain (SP). The Harmonised Index of Consumer Prices (HICP) is therefore the obvious choice of price measure to use. One of the principle objectives of the European Union is to promote economic and social progress, and in order to conduct its policies, there is a need for monitoring the economic performance across countries. This can only be achieved if the available statistical information is comparable.

Work on the harmonisation of consumer price indices across EU countries started in 1993, and by March 1997 the first figures of a harmonised index of consumer prices (HICP) for each member state were being published. The HICP has been designed to ensure the comparability of consumer price indices across EU countries. Eugenio Domingo Solans (member of the Executive Board of the ECB) has pointed out that the HICP was the only serious contender for the measurement of inflation in 1998, see Solans (2001). He further stated that from the perspective of the ECB, the HICP possesses some very attractive qualities. First, it covers a large proportion of household expenditure. Second, it is available monthly and in a timely manner. Third, it is aggregable in the sense that the country pieces fit together without gaps or overlaps. Four, it is subject to only minor revisions. Finally, it is based on actual monetary transactions. These features and the fact that it is comparable across countries, and can therefore be aggregated, makes the HICP the optimal choice for monitoring price developments in euro area countries.

4.2 Empirical Results

Figures 1 and 2 display the year on year changes in % the HICP for the euro area and largest five countries of the euro area, which we define in this paper as the measure of headline inflation. Table 1 shows the Augmented Dickey-Fuller statistic to test for the presence of a unit root in the series of headline inflation and in the measures of underlying inflation. The unit root hypothesis cannot be rejected in most cases for the sample under study (January 1996 to May 2004); only for certain underlying measures of inflation for Italy the unit root hypothesis is rejected[4]. Table 2 shows the results of testing for cointegration between headline inflation and the alternative measures of underlying inflation. This table suggests that measures of underlying inflation built from methods that exploit the cross section dimension but ignore the time series dimension fail to provide a series of underlying inflation that cointegrates with headline inflation. The only exception to these results is the Netherlands. This might potentially point to the fact that price developments in the markets for the different subcomponents of the price index in the Netherlands may be more highly correlated than in some other countries. Whenever price developments in alternative product markets follow different patterns, excluding measures of underlying inflation will not share a trend with headline inflation. We understand that the number of observations available to test for cointegration is not very large, and hence these results should be treated with caution. Table 2 also provides the probability values of an exogeneity test of the underlying measure with respect to headline inflation. Once more, these results reported in the table warn against methods that ignore the time series dimension.

There is no doubt that a measure of underlying inflation represents an appealing concept for monitoring price developments because it removes those

[4]Note that the theoretical analysis of Kapetanios and Marcellino (2003) on dynamic factor models is carried out for stationary models. Nevertheless as they discuss in the conclusion, their results on consistency of factor estimates readily extend to unit root nonstationary processes.

fluctuations associated with short run developments and this provides relevant information for the implementation of monetary policy. It is also clear that, in principle and depending on the definition, it should help forecasting observed inflation by concentrating on the signal provided by the underlying measure of inflation. The problem in practice is how to discriminate between measures of underlying inflation such as those built on the basis of the statistical methods described in this paper. Different measures often provide a very different picture on price developments. We follow the convention in the literature that adopts the power of the alternative measures of core inflation to forecast headline inflation over the medium to long horizon as a valid selection criterion.

This section reports predictive accuracy results for all measures of underlying inflation. A total of 15 bivariate Vector Autorregressive (VAR) models have been estimated, all VAR models contain headline inflation as one of its variables, and a measure of underlying inflation as the second variable. We need to fit a VAR model as we do not have forecasts for most underlying measures of inflation. For the SS1 and SS2 methods we do not need to fit a bivariate regression to observed inflation and the SS measure of underlying inflation. The reason is that we have a forecast of the underlying inflation measure through the estimation of the state space model following estimation of the factor. So, in this case we use a univariate AR model of inflation augmented by the current value of the relevant SS measure of underlying inflation. The use of current information in the SS forecasting models demonstrates the potential of the methodology as it provides an independent means of forecasting underlying inflation and thereby essentially exogenises underlying inflation with respect to observed inflation for forecasting. The assumption of exogeneity of underlying inflation with respect to observed inflation follows straightforwardly from the setup of the state space model assumed to underlie the evolution of the measure of underlying inflation.

Further, we consider the forecasting results obtained by means of a simple autorregressive (AR) model of headline inflation. The AR model is usually taken as a benchmark model in similar forecasting analyses. The Akaike information criterion is used to select the number of lags in the VAR and AR models. The sample under study is January 1996 to May 2004. The sample used for the computation of the underlying measures of inflation is January 1996 to November 2000. The sample period for the forecasting exercise is November 2000 to May 2004. Both the alternative measures of underlying inflation and the VAR models are recursively estimated over the forecasting sample.

Tables 3 reports the forecasting performance of the dynamic factor methods against the traditional methods. Table 3 shows the Relative Root Mean Square Forecasting Error (RMSE) of the traditional method against the SS1 and SS2 methods. Diebold and Mariano (1995) tests of forecasting accuracy are provided in table 4. Finally, table 5 ranks all methods from best to worst according to their accuracy at forecasting inflation over a 12 and 18 month horizon.

With the exception of Germany, the dynamic factor methods provide always either the best or close to best performance. Those methods that perform best for Germany display a rather bad performance in France, Italy, the Netherlands, Spain and the euro area. This is not the case for the subspace method SS1, which does not have a very low ranking for Germany either. The performance of the SS1 method is always very good with the exception of Germany.

5 Conclusion

This paper has explored the forecasting ability of core inflation measures built using dynamic factor methods against those built using more traditional techniques. Dynamic factor methods allow both the cross section dimension and the times series dimension of the data to be exploited in building a core inflation measure. These methods are applicable to large datasets. The measures of core inflation built by means of dynamic factor methods are found to perform well in comparison to traditional measures in terms of their forecasting performance. This paper has also warned that measures of underlying inflation based on methods that ignore the time series dimension may fail to cointegrate with headline inflation.

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Table 1: Unit root test.[a]

		DE	FR	IT	NL	SP	EA
HICP	τ	-0.33	0.52	-2.68	-0.86	-0.64	-0.51
	τ_μ	-2.64	-0.75	-4.71	-2.18	-2.60	-1.46
EX1	τ	-0.66	0.25	-1.04	-0.97	-0.65	-0.69
	τ_μ	-2.43	-0.80	-3.08	-1.85	-2.06	-1.55
EX2	τ	-0.67	-0.13	-1.30	-0.52	-0.80	-0.51
	τ_μ	-2.53	-1.37	-3.11	-1.75	-2.72	-2.41
EX3	τ	-0.49	1.07	-1.15	-0.73	-0.74	-0.29
	τ_μ	-2.25	0.09	-3.12	-1.64	-2.71	-2.14
EX4	τ	-0.45	0.76	-1.10	-0.84	-0.81	-0.27
	τ_μ	-2.55	-0.38	-3.16	-1.78	-2.12	-2.06
ADM	τ	-0.37	0.14	-0.95	-0.36	-0.83	-0.37
	τ_μ	-1.79	-1.28	-2.74	-2.12	-2.85	-2.36
TR1	τ	-0.66	0.35	-0.86	-0.74	-0.68	-0.59
	τ_μ	-2.47	-0.93	-2.56	-1.91	-2.52	-1.46
TR5	τ	-0.65	0.27	-0.87	-0.75	-0.64	-0.29
	τ_μ	-1.98	-0.97	-2.65	-1.85	-2.55	-1.32
TR10	τ	-0.75	0.10	-0.83	-0.76	-0.54	-0.40
	τ_μ	-1.97	-1.38	-2.64	-1.44	-2.38	-1.63
TR20	τ	-0.92	0.01	-0.76	-0.84	-0.56	-0.51
	τ_μ	-2.05	-1.14	-2.63	-1.56	-1.83	-1.93
TR30	τ	-0.97	0.09	-0.72	-0.82	-0.59	-0.48
	τ_μ	-2.10	-1.09	-2.64	-1.56	-1.81	-1.94
TR50	τ	-0.86	0.15	-0.70	-0.59	-0.50	-0.72
	τ_μ	-2.11	-0.98	-2.83	-1.62	-1.63	-1.76
MED	τ	-1.17	0.68	-1.23	-0.47	-0.47	-0.99
	τ_μ	-1.97	-1.56	-3.75	-1.79	-1.26	-1.94
EDGE	τ	-1.60	-0.05	-1.04	-0.76	-0.94	-1.46
	τ_μ	-2.09	-0.75	-2.83	-1.00	-2.32	-1.83
UC	τ	-0.31	0.20	-2.26	-0.86	-0.77	-0.47
	τ_μ	-2.44	-1.44	-4.39	-2.33	-2.26	-1.65
QV	τ	-1.23	0.41	-3.68	-1.47	-0.26	-0.73
	τ_μ	-1.93	-0.70	-4.24	-2.74	-2.22	-1.60
SS1	τ	-2.90	-1.63	-2.56	-1.62	-1.23	-2.34
	τ_μ	-2.87	-1.63	-2.88	-1.60	-1.19	-2.32
SS2	τ	-1.14	-0.45	-0.92	-1.57	-0.31	0.00
	τ_μ	-1.25	-2.09	-5.34	-3.60	-2.39	-1.58

[a]This tables presents the Augmented Dickey-Fuller statistics computed without and intercept τ and with and intercept τ_μ. The 5% critical values are -1.95 and -2.86 respectively. The criterium followed to determine the number of lags is that suggested by Perron (1989); namely choose a lag length such that the t-statistics associated with that lag k is significant, but the t-statistic of lag $k+1$ is not significant. Following Perron, we treat that parameter as significant when the t-statistic is larger than 1.6.

Table 2: Cointegration and Exogenity Tests.[a]

		DE	FR	IT	NL	SP	EA
EX1	Coint.	-	-	-	-	-	-
	Exogen.	0.046**	0.854	0.445	0.050**	0.110	0.880
EX2	Coint.	-	-	-	√	-	-
	Exogen.	0.002**	0.159	0.014**	0.077*	0.046**	0.320
EX3	Coint.	-	-	-	√	-	-
	Exogen.	0.013**	0.165	0.671	0.077*	0.088*	0.574
EX4	Coint.	-	-	-	√	-	-
	Exogen.	0.036**	0.281	0.368	0.067*	0.048**	0.719
ADM	Coint.	-	-	-	-	-	-
	Exogen.	0.006**	0.626	0.241	0.007**	0.069*	0.697
TR1	Coint.	-	-	-	-	√	-
	Exogen.	0.186	0.552	0.999	0.569	0.465	0.127
TR5	Coint.	-	-	-	-	-	-
	Exogen.	0.919	0.459	0.834	0.023**	0.758	0.195
TR10	Coint.	-	-	-	-	-	-
	Exogen.	0.938	0.336	0.853	0.107	0.268	0.161
TR20	Coint.	-	-	-	-	-	-
	Exogen.	0.869	0.275	0.931	0.557	0.022**	0.299
TR30	Coint.	-	-	-	-	-	-
	Exogen.	0.694	0.193	0.660	0.637	0.011**	0.130
TR50	Coint.	-	-	√	-	-	-
	Exogen.	0.611	0.093*	0.153	0.806	0.013**	0.109
MED	Coint.	-	-	√	-	-	-
	Exogen.	0.526	0.098*	0.212	0.859	0.082*	0.185
EDGE	Coint.	-	-	-	-	-	-
	Exogen.	0.901	0.115	0.379	0.557	0.234	0.914
UC	Coint.	√	√	√	√	√	√
	Exogen.	0.162	0.007**	0.040**	0.107	0.990	0.008**
QV	Coint.	-	-	√	-	-	-
	Exogen.	0.344	0.193	0.000**	0.079*	0.006**	0.018**
SS1	Coint.	-	-	-	-	-	-
	Exogen.	0.140	0.396	0.000**	0.025**	0.619	0.702
SS2	Coint.	-	-	-	-	√	-
	Exogen.	0.000**	0.874	0.111	0.101	0.001**	0.018**

[a]The cointegration test conducted is that of Johansen (1988). The exogeneity test is conducted along the lines explained in Lütkepohl (1991, ch. 11), values reported are probability values.

Table 3: Forecasting performance of Subspace Methods. Relative RMSE values.[a]

	Model	SS1 Horizon 1	SS1 6	SS1 12	SS1 18	SS2 Horizon 1	SS2 6	SS2 12	SS2 18
DE	AR	0.985	1.163	1.528	2.778	0.997	1.107	1.346	2.022
	EX1	1.086	0.856	0.793	0.790	1.099	0.815	0.699	0.575
	EX2	1.104	0.843	1.110	1.095	1.116	0.803	0.978	0.797
	EX3	1.045	0.853	0.830	0.816	1.057	0.812	0.731	0.594
	EX4	1.057	0.739	0.746	1.135	1.069	0.704	0.657	0.826
	ADM	0.991	0.650	0.337	0.156	1.002	0.619	0.297	0.114
	TR1	1.082	1.032	1.825	6.848	1.095	0.983	1.608	4.985
	TR5	1.096	0.776	0.831	1.143	1.109	0.739	0.732	0.832
	TR10	0.988	1.192	2.194	10.870	0.999	1.135	1.933	7.911
	TR20	0.992	1.151	1.401	1.443	1.003	1.096	1.234	1.050
	TR30	0.997	1.209	2.126	2.536	1.009	1.151	1.872	1.845
	TR50	0.988	1.231	2.223	10.786	0.999	1.172	1.958	7.851
	MED	1.035	0.976	1.433	2.465	1.047	0.930	1.263	1.794
	EDGE	1.050	0.814	0.635	0.348	1.062	0.775	0.559	0.253
	UC	1.034	0.165	0.004	0.000	1.046	0.157	0.004	0.000
	QV	1.033	0.332	0.019	0.001	1.045	0.316	0.016	0.001
FR	AR	1.048	1.188	1.123	0.534	1.054	1.113	1.118	1.107
	EX1	1.106	0.740	0.628	0.258	1.113	0.693	0.625	0.534
	EX2	1.162	0.613	0.123	0.007	1.169	0.574	0.122	0.014
	EX3	1.149	0.633	0.129	0.007	1.155	0.593	0.128	0.015
	EX4	1.135	0.603	0.139	0.008	1.142	0.565	0.139	0.017
	ADM	1.084	0.702	0.577	0.167	1.091	0.658	0.575	0.345
	TR1	1.018	1.204	0.920	0.161	1.024	1.128	0.916	0.334
	TR5	1.013	1.064	0.624	0.082	1.018	0.997	0.622	0.169
	TR10	1.012	0.841	0.256	0.010	1.017	0.788	0.254	0.021
	TR20	1.016	0.861	0.664	0.291	1.022	0.806	0.661	0.603
	TR30	0.978	0.807	0.532	0.233	0.984	0.756	0.530	0.482
	TR50	0.975	0.878	0.597	0.310	0.981	0.823	0.595	0.642
	MED	0.959	1.195	0.304	0.024	0.965	1.120	0.303	0.050
	EDGE	1.108	0.798	0.378	0.045	1.115	0.747	0.376	0.094
	UC	0.985	0.000	0.000	0.000	0.991	0.000	0.000	0.000
	QV	1.053	0.826	0.559	0.159	1.059	0.774	0.557	0.329
IT	AR	1.028	0.920	0.935	0.887	0.987	1.481	2.632	4.586
	EX1	1.148	0.452	0.103	0.013	1.102	0.729	0.289	0.070
	EX2	1.107	0.599	0.120	0.011	1.063	0.965	0.338	0.059
	EX3	1.155	0.378	0.047	0.003	1.108	0.609	0.134	0.018
	EX4	1.207	0.390	0.087	0.011	1.158	0.629	0.245	0.059
	ADM	1.119	0.748	0.581	0.457	1.074	1.204	1.636	2.363
	TR1	0.986	0.728	0.195	0.030	0.947	1.172	0.548	0.155
	TR5	1.007	0.678	0.145	0.019	0.967	1.091	0.408	0.096
	TR10	1.199	0.471	0.095	0.009	1.151	0.759	0.269	0.044
	TR20	1.109	0.444	0.035	0.002	1.065	0.715	0.097	0.010
	TR30	1.041	0.675	0.088	0.007	0.999	1.087	0.247	0.037
	TR50	1.032	0.806	0.243	0.034	0.991	1.299	0.684	0.176
	MED	0.995	1.026	0.787	0.279	0.955	1.652	2.215	1.446
	EDGE	0.982	0.794	0.336	0.064	0.942	1.278	0.946	0.333
	UC	1.081	0.426	0.047	0.003	1.038	0.686	0.132	0.014
	QV	1.155	0.381	0.027	0.001	1.108	0.613	0.076	0.006

[a] Values reported in this table are the Relative Root Mean Square Error, i.e. the ratio between the root mean square error of the subspace method and the traditional methods. A value smaller than 1 indicates the subspace method is best.

Table 3 (cont): Forecasting performance of Subspace Methods. Relative RMSE values.[a]

		SS1				SS2			
		Horizon				Horizon			
	Model	1	6	12	18	1	6	12	18
NL	AR	0.980	1.009	0.851	0.629	0.969	1.021	0.967	1.016
	EX1	1.011	0.931	0.935	0.978	1.000	0.942	1.063	1.580
	EX2	1.013	0.784	0.660	0.409	1.001	0.793	0.750	0.660
	EX3	1.038	0.771	0.777	1.015	1.026	0.780	0.883	1.639
	EX4	1.053	0.848	0.687	0.543	1.041	0.858	0.781	0.876
	ADM	1.091	0.909	0.829	0.489	1.079	0.920	0.943	0.790
	TR1	0.847	1.040	0.966	0.932	0.837	1.052	1.098	1.505
	TR5	0.888	1.128	1.017	0.951	0.878	1.141	1.156	1.536
	TR10	0.902	1.114	1.016	0.941	0.892	1.126	1.154	1.520
	TR20	0.875	1.007	0.639	0.130	0.866	1.019	0.726	0.210
	TR30	0.899	0.928	0.478	0.078	0.889	0.939	0.543	0.125
	TR50	0.887	0.940	0.463	0.071	0.877	0.951	0.526	0.115
	MED	0.844	1.051	0.964	0.912	0.834	1.063	1.095	1.473
	EDGE	0.965	0.782	0.633	0.335	0.954	0.791	0.720	0.540
	UC	0.917	0.000	0.000	0.000	0.906	0.000	0.000	0.000
	QV	0.955	0.975	0.940	0.764	0.945	0.986	1.069	1.234
SP	AR	0.928	0.871	0.482	0.268	0.914	0.971	0.367	0.056
	EX1	1.093	0.671	0.570	0.492	1.077	0.747	0.434	0.103
	EX2	1.002	0.596	0.387	0.234	0.987	0.664	0.294	0.049
	EX3	1.039	0.616	0.489	0.319	1.023	0.686	0.373	0.067
	EX4	1.046	0.590	0.376	0.220	1.029	0.658	0.287	0.046
	ADM	0.986	0.713	0.387	0.246	0.970	0.794	0.294	0.052
	TR1	0.907	0.809	0.386	0.220	0.893	0.901	0.294	0.046
	TR5	1.050	0.760	0.426	0.313	1.034	0.847	0.325	0.066
	TR10	1.068	0.743	0.487	0.456	1.051	0.827	0.371	0.096
	TR20	1.057	0.724	0.523	0.360	1.040	0.806	0.399	0.075
	TR30	1.008	0.719	0.409	0.234	0.993	0.801	0.311	0.049
	TR50	0.981	0.797	0.423	0.265	0.966	0.888	0.322	0.055
	MED	0.949	0.829	0.482	0.298	0.934	0.923	0.367	0.062
	EDGE	0.966	0.779	0.523	0.282	0.951	0.868	0.398	0.059
	UC	0.928	0.004	0.000	0.000	0.914	0.004	0.000	0.000
	QV	1.034	0.948	0.270	0.039	1.018	1.056	0.206	0.008
EA	AR	0.996	0.984	1.129	1.395	1.001	1.027	1.088	1.298
	EX1	1.029	0.701	0.760	0.835	1.033	0.731	0.732	0.777
	EX2	0.988	0.714	0.803	1.064	0.993	0.744	0.774	0.990
	EX3	1.003	0.644	0.696	0.734	1.007	0.672	0.670	0.683
	EX4	1.060	0.561	0.719	1.109	1.064	0.585	0.693	1.032
	ADM	0.999	0.613	0.545	0.262	1.003	0.639	0.525	0.244
	TR1	0.871	0.569	0.249	0.077	0.875	0.594	0.239	0.072
	TR5	0.894	0.621	0.318	0.120	0.898	0.647	0.306	0.112
	TR10	0.863	0.675	0.442	0.218	0.867	0.705	0.426	0.203
	TR20	0.885	0.709	0.689	0.688	0.889	0.739	0.664	0.641
	TR30	0.923	0.658	0.610	0.364	0.927	0.686	0.588	0.339
	TR50	1.030	0.589	0.345	0.121	1.035	0.614	0.332	0.113
	MED	0.949	0.571	0.318	0.117	0.954	0.595	0.306	0.109
	EDGE	1.073	0.659	0.360	0.116	1.077	0.688	0.347	0.108
	UC	0.975	0.000	0.000	0.000	0.979	0.000	0.000	0.000
	QV	1.121	0.991	1.595	1.537	1.126	1.034	1.536	1.430

[a]Values reported in this table are the Relative Root Mean Square Error, i.e. the ratio between root mean square error of the subspace method and the traditional methods. A value smaller indicates the subspace method is best.

Table 4: Forecasting performance of Subspace Methods. Diebold-Mariano tests.[a]

		SS1				SS2			
		Horizon				Horizon			
	Model	1	6	12	18	1	6	12	18
DE	AR								
	EX1	–				–			
	EX2		+				+		
	EX3						+		
	EX4							+	
	ADM							+	
	TR1								
	TR5		+				+		
	TR10								
	TR20			–				–	
	TR30								
	TR50								
	MED								
	EDGE		+				+		
	UC		+	+	+		+	+	+
	QV		+	+			+	+	
FR	AR				+	–	–		–
	EX1				+	–		+	+
	EX2		+	+			+	+	
	EX3	–	+	+		–	+	+	
	EX4	–				–			
	ADM			+	+	–		+	+
	TR1		–						
	TR5				+				+
	TR10			+	+		+	+	+
	TR20				+			+	
	TR30		+	+	+		+	+	+
	TR50			+	+				
	MED			+	+		–		+
	EDGE	–	+	+	+	–	+	+	+
	UC								
	QV		+	+					
IT	AR				+				
	EX1								
	EX2		+						
	EX3								
	EX4					–			
	ADM			+	+				
	TR1								
	TR5								
	TR10	–				–			
	TR20								
	TR30								
	TR50								
	MED			+					
	EDGE		+						
	UC			+	+		+	+	+
	QV								

[a]The sign '+' indicates the performance of the Subspace method is significantly better; the sign '–' indicates a performance significantly worse, in both cases at a 5% level of significance.

Table 4 (cont): Forecasting performance of Subspace Methods. Diebold-Mariano tests.[a]

		SS1				SS2			
		Horizon				Horizon			
	Model	1	6	12	18	1	6	12	18
NL	AR								
	EX1								
	EX2		+				+		
	EX3								
	EX4		+		+		+		
	ADM				+				
	TR1								
	TR5							–	
	TR10								
	TR20	+		+				+	
	TR30		+	+			+	+	
	TR50	+							
	MED								
	EDGE		+				+		
	UC								
	QV								
SP	AR	+							
	EX1		+	+	+			+	+
	EX2		+		+		+		+
	EX3								+
	EX4								
	ADM		+		+		+		+
	TR1			+	+			+	+
	TR5		+						
	TR10		+	+				+	+
	TR20		+	+				+	+
	TR30		+		+				+
	TR50			+	+			+	+
	MED								
	EDGE			+				+	
	UC			+				+	
	QV								
EA	AR				–			–	
	EX1		+				+		
	EX2		+						
	EX3		+				+		
	EX4			+				+	
	ADM		+				+		
	TR1	+	+			+	+		
	TR5		+				+		
	TR10	+	+	+		+	+	+	
	TR20						+		
	TR30			+					
	TR50			+	+			+	+
	MED		+				+		
	EDGE			+	+	–		+	+
	UC		+				+		
	QV	–		–		–		–	

[a]The sign '+' indicates the performance of the Subspace method is significantly better according to the Diebold and Mariano (1995) test; the sign '–' indicates a performance significantly worse, in both cases at a 5% level of significance.

Table 5: Ranking of Models. [a]

	DE	FR	IT	NL	SP	EA
			Forecasting Horizon = 12			
1	TR50	AR	**SS1**	TR5	**SS2**	AR
2	TR10	**SS2**	AR	TR10	**SS1**	QV
3	TR30	**SS1**	MED	**SS1**	EX1	**SS2**
4	TR1	TR1	ADM	TR1	EDGE	**SS1**
5	AR	TR20	**SS2**	MED	TR20	EX2
6	TR20	EX1	EDGE	QV	EX3	EX1
7	MED	TR5	TR50	EX1	TR10	EX4
8	**SS2**	TR50	TR1	**SS2**	MED	EX3
9	EX2	ADM	TR5	AR	AR	TR20
10	**SS1**	QV	EX2	ADM	TR5	TR30
11	TR5	TR30	EX1	EX3	TR50	ADM
12	EX3	EDGE	TR10	EX4	TR30	TR10
13	EX1	MED	TR30	EX2	EX2	EDGE
14	EX4	TR10	EX4	TR20	ADM	TR50
15	EDGE	EX4	UC	EDGE	TR1	MED
16	ADM	EX3	EX3	TR30	EX4	TR5
17	QV	EX2	TR20	TR50	QV	TR1
18	UC	UC	QV	UC	UC	UC
			Forecasting Horizon = 18			
1	TR10	**SS1**	**SS1**	EX3	**SS2**	QV
2	TR50	AR	AR	**SS1**	**SS1**	AR
3	TR1	**SS2**	ADM	EX1	EX1	EX4
4	AR	TR50	MED	TR5	TR10	**SS2**
5	TR30	TR20	**SS2**	TR10	TR20	EX2
6	MED	EX1	EDGE	TR1	EX3	**SS1**
7	TR20	TR30	TR50	MED	TR5	EX1
8	**SS2**	ADM	TR1	QV	MED	EX3
9	TR5	TR1	TR5	AR	EDGE	TR20
10	EX4	QV	EX1	**SS2**	AR	TR30
11	EX2	TR5	EX2	EX4	TR50	ADM
12	**SS1**	EDGE	EX4	ADM	ADM	TR10
13	EX3	MED	TR10	EX2	EX2	TR50
14	EX1	TR10	TR30	EDGE	TR30	TR5
15	EDGE	EX4	EX3	TR20	EX4	MED
16	ADM	EX3	UC	TR30	TR1	EDGE
17	QV	EX2	TR20	TR50	QV	TR1
18	UC	UC	QV	UC	UC	UC

[a] The models are ranked from best to worst according to their performance at forecasting headline inflation over a 12 and 18 month horizon. **SS1** denotes the subspace method 1, and **SS2** the subspace method 2.

Figure 1: Harmonised index of Consumer Prices. Year on Year changes (%).

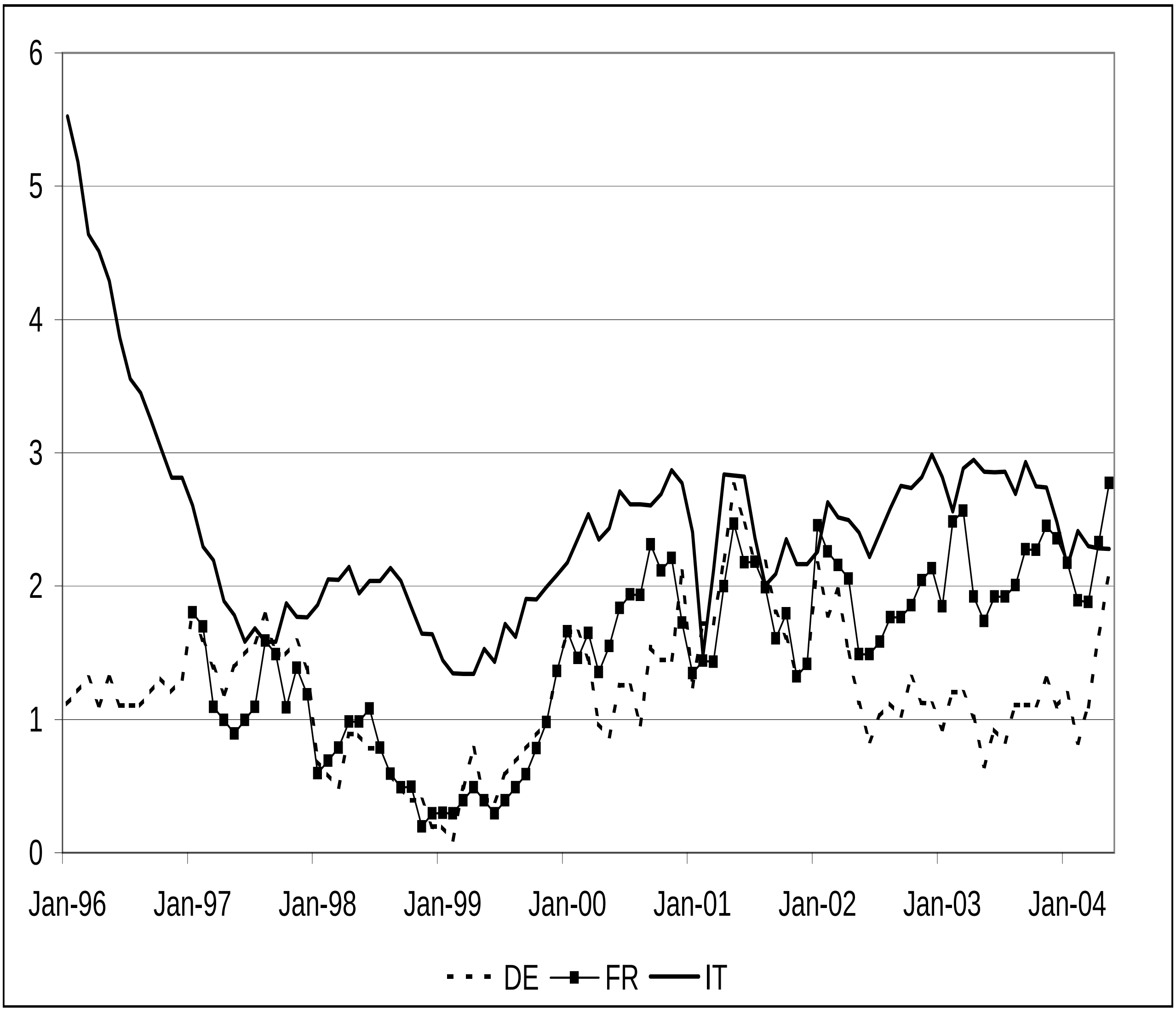
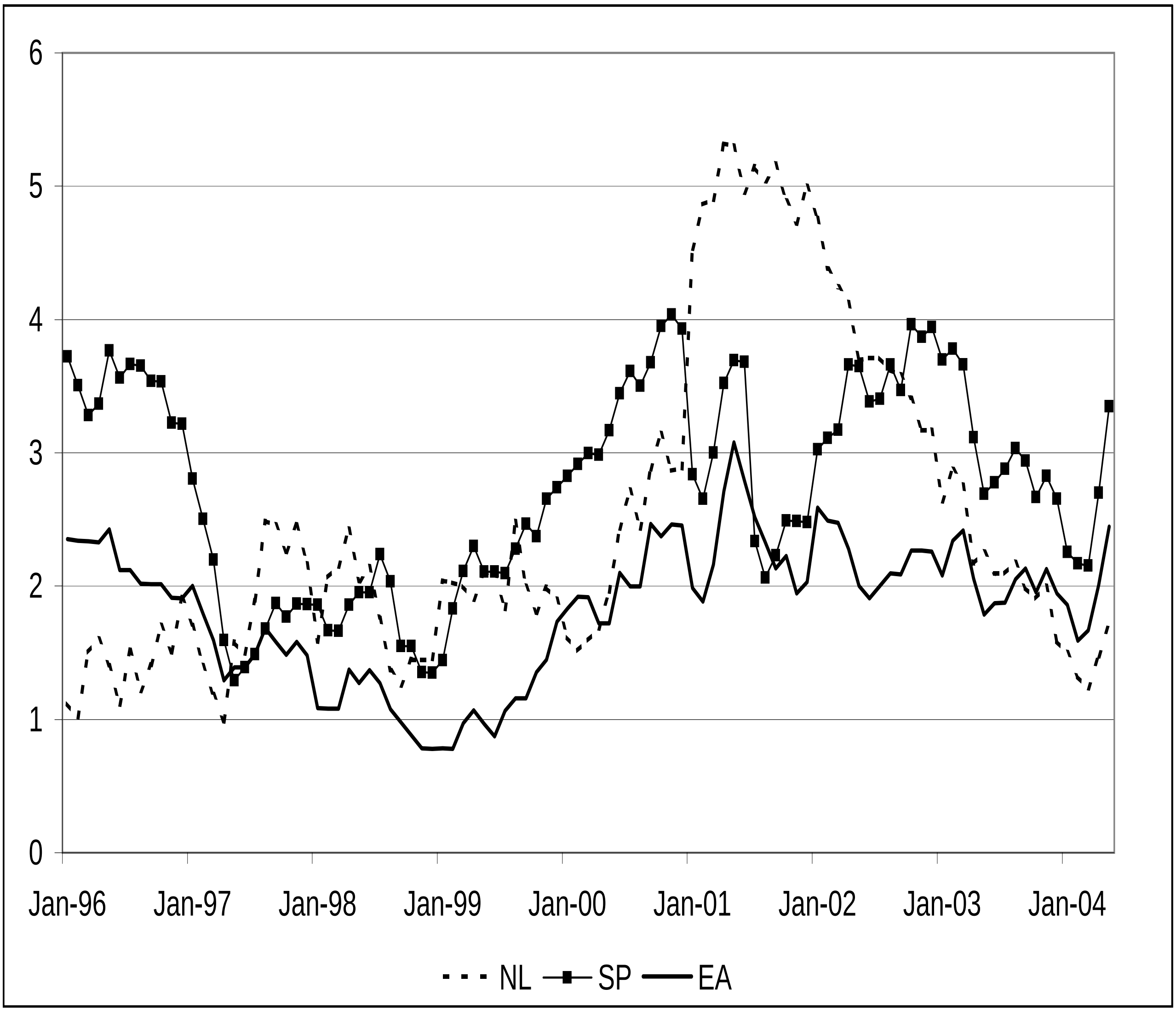


Figure 2: Harmonised index of Consumer Prices. Year on Year changes (%).



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