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Forecasting Italian inflation with large datasets and many models

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Abstract

The aim of this paper is to propose a new method for forecasting Italian inflation. We expand on a standard factor model framework (see Stock and Watson (1998)) along several dimensions. To start with we pay special attention to the modeling of the autoregressive component of the inflation. Second, we apply forecast combination (Granger (2000) and Pesaran and Timmermann (2001)) and generate our forecast by averaging the predictions of a large number of models. Third, we allow for time variation in parameters by applying rolling regression techniques, with a window of three-years of monthly data. Backtesting shows that our strategy outrperforms both the benchmark model (i.e. a factor model which does not allow for model uncertainty) and additional univariate (ARMA) and multivariate (VAR) models. Our strategy proves to improve on alternative models also when applied to turning point prediction.

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1. Introduction

In this paper we focus on forecasting Italian inflation by combining factor models, following Stock and Watson (1998, 1999) and Marcellino, Stock and Watson (2000) with model selection procedures designed to deal with non-linearities and structural breaks by keeping track and combining the predictions of many models following Granger (2000) and Pesaran-Timmermann (2001).

Our aim is the evaluation of the potential improvement on the Stock and Watson (SW) methodology generated by allowing explicitly for model uncertainty and forecast combination.

Our forecast procedure is based on rolling estimation of a large number of models, a subset of which is selected in each period according to a best fit criterion. One additional feature of our approach is that we forecast inflation on a month-to-month basis. Year on year inflation forecast is then built by combining monthly forecasts. This approach has the advantage of producing a consistent set of inflation projections over the entire forecast horizon and uses information more efficiently (modeling year-on-year inflation directly forces the econometrician to use information lagged twelve months).

The performance of these models is then evaluated according to an out of sample, ex-post criterion. RMSE of the forecast errors are compared with our SW benchmark as well as with a number of alternative predictive methods: univariate autoregressive models, a VAR and a naïve, random-walk, forecast. Diebold-Mariano tests for the significance of the differences in MSEs of competing forecasting models are also carried out.

In section 2 we describe the general framework of our methodology.. In Section 3 we report our specific contribution to forecasting inflation, which consists of two main steps. First, we adopt a "thick modelling" approach by combining forecasts from all the possible models generated by an autoregressive specification for inflation augmented by factors extracted from over one hundred and fifty (see appendix) macroeconomic time-series. We specify the autoregressive component by considering a large class of models which includes, in addition to a single lag term of monthly inflation, selected combinations of AR and MA error terms. Our choice of the specification of the autoregressive component is time-varying and it is determined, in each period, by a best fit, within sample, criterion. Once the autoregressive component is determined, our forecast strategy is based on thick modeling: we average the inflation forecasts generated by a subset of a large number of models. The regressors of these models include all possible combinations of a fixed number of factors extracted from our dataset. In section 4 we supplement our work with sensitivity analysis along two dimensions. We expand the sample size over which models are estimated and show that a wider estimation window (five years) worsens the predictive power of our models. We show that our strategy achieves rewarding results in terms of predictive ability as we do clearly better than the SW type benchmark. Further insight is achieved by splitting our sample into two parts. We find that results in terms of autoregressive component selection and optimal time length over which models are estimated are robust. This analysis sheds also some light on the forecast combination issue. On an ex-post basis, we find that the optimal size of our subset of models to be considered for forecast combination on (i.e. the percentage number of the models that we chose to average) is reached at approximately 70%; further expansion in the number of models leads to virtually no improvement in forecast performance.

In section 5 we extend our benchmarking beyond the SW model and consider VAR, univariate (which, in our case is represented by the initially selected autoregressive component) and naïve forecasts. On a twelve month, year on year basis, our model outperforms all the alternative models, however we find interesting evidence when comparing month to month forecast results. Adding factors to the autoregressive part brings to diminishing returns in terms of predictive capability as we move forward along the forecast horizon. We conclude the section by undertaking additional comparison between our model and alternative methods. More precisely, we apply the Diebold-Mariano test to compare the performance of all different approaches. Results confirm the analysis based on RMSEs.

In section 6 we attempt an assessment of the cost of not having the dataset updated fully in line with the consumer price index, i.e. of having data released with delay with respect to the CPI index. Our measure of forecast uncertainty takes into account this factor. Model estimates along the historical interval rely on a data structure that emulates the same “ragged hedge” observed in the last time period of our interval; data are always extended to fill the missing information with a projection rule. We run an additional simulation in which we override that rule and assume no delay in information availability. The difference between the two RMSE measures show the potential improvement generated by better projection rules for the relevant variables. The difference is very small. In section 7 we adopt our strategy to forecast core inflation – as measured by the CPI index with the exclusion of food & energy prices – and we achieve a significant reduction of the RMSE. Finally in section 8 we extend the analysis to the capability to predict turning points of the inflation rate. We show that our best model fares better, in terms of RMSEs, than a VAR. Results are, initially, less clear-cut when we test for statistical difference. However, we also look at the issue of improving forecast performance by mean of waiting for consecutive turning point signals. We show that such a strategy is rewarding. To start with, the predictive capability of our method is markedly enhanced; furthermore, results become statistically different from those of the VAR.

2. The Benchmark Model

The framework developed by Stock and Watson (1998,1999) has become widely adopted for predicting time series. Recent applications for inflation forecasting can be found in Marcellino, Stock and Watson (2000), Angelini, Henry and Mestre (2001, 2002).

In this framework forecasts of inflation are based on a class of models of the following form:

$$\pi^{h}{}_{t+h} - \pi_t = \varphi + \alpha(L)\pi_t + \sum_{i=1}^{m} \beta(L)_j F_j + e_{t+h} \qquad (2.1)$$

where $\pi^{h}{}_{t+h} = (1200/h)\log(P_{t+h}/P_t)$ is the annual rate of h-period growth of the price level p_t, π_t is the annual rate of monthly inflation, F_J are factors – estimated by some variant of a principal component analysis from a large data set –, φ is a constant and e_{t+h} is the error term.

π_{t+h} represents the *h*-step ahead forecast of the inflation rate. Projections can be defined as “static”, as there is no need to iterate forward a model in order to achieve a *h* period ahead forecast. Factors model are applied to stationary variables; if the order of integration of inflation is deemed to be I(1), then the dependent variable becomes the mean acceleration of inflation over the period *t, t+h*.

Models are estimated using a rolling window of data for estimation. They are estimated on monthly or quarterly data and the forecast horizon does not usually exceed two years.

It is a consolidated practice to carry out performance evaluation relying on out of sample analysis based on historical data (backtesting). Root Mean Square Errors of the forecast from time *t+1* to time *t+h* are computed for several models and results are compared.

Although the ultimate scope of the addition of factors is to improve on the autoregressive component, this is not always achieved. Table 1 summarizes some evidence based on the available literature. Angelini, Henry and Mestre (2001) provide interesting insight. The authors forecast Euro area inflation over a rather large time interval (and in sub-samples) using the SW methodology. In addition to changing time intervals, they experiment also several specification using different combinations of factors. They find that factors can improve on the performance of autoregressive models, however their evidence points to a potential weakness. In presence of structural breaks, factors based models perform worse than purely autoregressive models. This happens, in their case, when the test period starts in 1992 rather than in 1995.

For the sake of our analysis we need to have a benchmark SW type model. In the remaining part of this section we describe the construction of such a model and its performance.

Our balanced dataset consists of monthly data spanning from 1989:1 to 2004:2 and it includes 153 variables. Data include real, monetary information and the coverage is generally national, however several key foreign variables are present. Details are provided in the appendix.

We proceed in two steps. First we estimate with OLS an autoregressive model as from equation 2.2

$$\pi^{h}{}_{t+h} - \pi_t = \varphi + \alpha(L)\pi_t \qquad (2.2)$$

where the autoregressive structure can include up to 11 dependent variables with number of lags chosen by BIC; *h* spans from 1 to twelve. The number of lags is subject to change as the models are estimated recursively. We call this model autoregressive model (ARM).

Then we add the estimated factors, as from equation 2.1, with different rules for F_J and $\beta(L)_J$. We tried several specifications, based either on a fixed number of factors (from 1 to 3) or on a time varying number of factors. These rules are called fixed because there is no ex-ante criterion to choose the number of F_J and $\beta(L)_J$ (Angelini, Henry and Mestre (2001)).

We based model selection on two criteria: a) lowest possible absolute value of the RMSE on a twelve month horizon; b) maximum improvement against the autoregressive component on its own.

We found out that best results are obtained by using only 1 factor (contemporaneous and with one period lag) and estimating S-W models along a a ten year sample. Such a long span of time is consistent with the approach usually taken in the literature. We tried both recursive and rolling regressions without significant differences in terms of performance. However, our preferred model has been estimated with a rolling regression. We label this model BSW.

The ten year estimation sample restricts the interval for which we can report the RMSE statistics to the period 1998:1 2004:2. Table 2 reports the RMSE respectively of the ARM and of the BSW model. The columns indicate the forecast horizon of the year on year inflation rate: from 1 month up to twelve months. Despite our effort we find no strong evidence that BSW dominates ARM. The BSW prevails over ARM only in certain time horizons: from 4 to 7 months ahead. This is consistent with the evidence reported in

Table 1[4]. Our estimation led us to detect a further potential drawback of such a methodology: independent year on year inflation forecasts along different time horizon often implies high and implausible jumps in the month-on month change of the price index.

3. Our strategy

Our aim, as outlined in the previous section, is to enhance the predictive capability of the SW class of models.
Our models can be represented by the following equations:

$$\Delta p_{t+h} = \varphi + \alpha \Delta p_{t+h-12} + \sum_{j=1}^{m} F_j \beta + \gamma ARMA \text{, with } h=1,\ldots,n \qquad (3.2)$$

where h is the forecast horizon, p is the log of the price index, Δ is the difference operator between time t and t-1 and ARMA are autoregressive and/or moving average error terms.
There are n such equations and the inflation forecast for time $t+n$ is achieved by exploiting the month to month forecasts in the following way:

$$\hat{p}_{t+h} = p_t \exp\left(\sum_{i=1}^{h} \Delta p_{t+i} \right) \qquad (3.3)$$

$$\hat{\pi}_{t+h} = 100 * \left(\frac{\hat{p}_{t+h}}{p_{t+h-12}} - 1 \right) \qquad (3.4)$$

Importantly, this approach allows us to produce an year on year inflation forecast with a monthly frequency and with a consistent profile. It should be once again mentioned that, on the contrary, in equation (2.2) the year on year forecasts for different time horizons are independent.
The model selection procedure requires two steps to be taken.
We initially chose the autoregressive component that will be used in the full model, i.e.:

$$\Delta p_{t+h} = \varphi + \alpha \Delta p_{t+h-12} + \gamma ARMA \qquad (3.5)$$

This is a time-varying specification (from now on called BESTARMA). In each period t and for each forecast horizon (for h ranging from 1 to n) we estimate a number of models that have the following structure:

$$\Delta p_{t+h} = \varphi + \alpha \Delta p_{t+h-12} + \gamma_1 AR(s) + \gamma_2 MA(q) \qquad (3.5a)$$

$$\Delta p_{t+h} = \varphi + \alpha \Delta p_{t+h-12} + \gamma_2 MA(q) \qquad (3.5b)$$

$$\Delta p_{t+h} = \varphi + \alpha \Delta p_t + \gamma_1 AR(s) + \gamma_2 MA(q) \qquad (3.5c)$$

$$\Delta p_{t+h} = \varphi + \alpha \Delta p_t + \gamma_2 MA(q) \qquad (3.5d)$$

[4] Furthermore, if we extend back to the year 1994 the out of sample test period, the performance of this models becomes very disappointing. They are always over performed by the autoregressive component. Indeed, this result is achieved for models estimated with a five year minimum span and we can not – yet – report results for model estimated along a 10 year time span.

where $10 \leq s \leq 14$, $s \geq h$ and $10 \leq q \leq 18$. The values of s and q where pre-selected after a relevant number of trial attempts on model specifications. Also, note that only up to one AR and one MA term are used at the same time. In facts, both parameters could be allowed to vary in the whole 1-18 range at some computational cost. With the mentioned values for s and q, the number of estimated models adds up to 90 equations for every t and every h. The within the sample selection criterion picks for every t and h the model that in the previous period featured the best corrected R-square value. All models are estimated with a rolling time window of three years. We end up with an autoregressive component that we call ARMAMOD.

The following step consists on adding factor regressors to the selected autoregressive component. We extract 7 principal components and for every period t we estimate all possible models that can arise including from 1 up to 7 factors, i.e. 128 models. The time interval remains the same, three years on a rolling basis. We call this class of models BESTARMA.

Note that also the coefficients of the selected autoregressive components are estimated; this implies that the α and γ parameters in equations 3.5 (a,b,c and d) will change with respect to the original values. There is no guarantee that the selected BESTARMA specification will be the best one on an ex-post basis and, indeed, the optimal strategy would have been to try jointly all the combinations of autoregressive specifications and principal components. However, we refrained from doing so due to computational costs.

Afterwards, we follow the thick modeling approach as initially envisaged by Granger (2000), Peasaran-Timmermann (2001) and, more recently, Aiolfi and Favero (2002). Rather than using the best ex-ante model – like in the consolidated SW framework – we look at the forecast made averaging the predictions of many models (Timmerman and Aiolfi , 2004). The results over the period 1998:1 2004:2 (the benchmark sample for BSW) are reported in table 3 in terms of RMSE of the forecast errors. Rows show the statistics generated by choosing on an ex-ante basis a given percentage of best-fitting models. It is evident that the averaging strategy works: results improve as we increase the percentage of forecasts that we average. The improvement increases with h, the forecast horizon, and the maximum improvement is achieved for the twelve months ahead horizon.

Finally, the RMSE of the BESTARMA model in the interval 1998-2002 is to a very significant extent below the BSW model. The improvement can tentatively be "decomposed" into a contribution coming from the "new" autoregressive component, one from the introduction of the principal components using only the best ex-ante model (BESTARMA) and one from thick modeling – i.e. the averaging of many models forecasts – (BESTARMA thick); see table 4.

4. Robustness

The evidence in favor of our strategy seems decisive as statistics show a remarkable improvement with respect to the SW benchmark. There are however a number of issues we want still to address. First we assess robustness of our conclusions, in terms of thick modeling, autoregressive component selection and optimal time length over which models are estimated.

We perform the analysis using of the complete data set (1994:1 2004:2) and also looking separately at two sub-samples. The first sub-sample, 1994:1 1997:12, is characterized by an initial upsurge of the inflation rate, followed by a marked slow-down; on the contrary,

the second sub-sample, 1998:1 2004:2 – for which results have been already partially displayed – features a more stable behavior.
Furthermore, we estimate additional fixed specifications ARMA models:

$$\Delta p_{t+h} = \varphi + \alpha\Delta p_{t+h-12} + \gamma_1 AR(12) + \gamma_2 MA(12)$$
$$\Delta p_{t+h} = \varphi + \alpha\Delta p_t + \gamma_1 AR(12) + \gamma_2 MA(18)$$
$$\Delta p_{t+h} = \varphi + \alpha\Delta p_{t+h-12} + \gamma_2 MA(12)$$
$$\Delta p_{t+h} = \varphi + \alpha\Delta p_t + \gamma_2 MA(18)$$

Table 5, and Table 6 report the results delivered by thick modeling for respectively the 1994-1997 and the 1994-2004 intervals. The results in favor of thick modeling strategy are clearly robust; in fact, the conclusion drawn in the previous section are confirmed. In the 1994-1997 period averaging the prediction of a large set of models improves the forecast statistics to a larger extent than in the full sample. Furthermore, the more we extend the forecast horizon, from one to twelve months, the larger is the improvement. The best statistics are achieved by averaging out the forecast at around 70 per cent.
The comparison of the forecast combination approach with the BESTARMA strategy are less clear-cut. Forecast combination dominates in the whole sample, but does not so in the two sub-samples. Results are displayed in tables 7,8 and 9. We conclude that risk adverse forecaster should lean towards averaging out a very large proportion of the models forecasts and use the BESTARMA model.
Figure 1 presents some graphical evidence on the performance of the BESTARMA twelve month ahead forecast, using the 10 and 90 percent of the best ex-ante models, against the BSW model. INFL represents the recorded rate of inflation. Additional insight is given by Figure 2, which shows the errors made by several models when the forecast of annual year on year inflation had been made in the month of December.
The remaining issue concerns the length of the estimation window – three years. The 3 year estimation interval of the BESTARMA strategy is much shorter than the standard adopted in the literature, which goes up to 10 years. Such a choice is based on a relevant number of experiments over different, gradually increasing, time interval estimation lenghts. The evidence we found suggests that: the BESTARMA model is less clearly preferable to fixed models but, the remaining part of the strategy (i.e. thick modeling and more careful selection of the autoregressive component) holds as it still outperforms the BSW model. More importantly, results are significantly worse than with a three year period. For the sake of comparison, we report (Table 10) the results of one additional run of the models in which the estimation interval is extended to five years. Conversely, we did not explore a further reduction of the time window. In facts, a three year horizon with monthly data leaves approximately 25 degrees of freedom to each estimated model.
Although, our choice was mostly dictated by a "practitioner approach" there seems to be also theoretical reasons to support it. By shortening the time interval we generate a faster update of both the loads of each factor and of regression coefficients. This strategy should dominate a choice based on a larger estimation window in presence of structural breaks.

5. Some additional benchmarking

In this section we move back to a benchmarking exercise. Here we consider simple models such as univariate autoregressive models and unrestricted VARs.
The autoregressive component of the BESTARMA model lends itself to provide an additional layer to our analysis. The transformations outlined in equations 3.3 and 3.4

allows us to measure the forecast performance of our BESTARMA model in terms of year-on-year inflation rate. With respect to that definition of inflation, we have shown that BESTARMA is the preferred specification at all forecast horizons. However, we loose track of the marginal contribution to the annual inflation stemming from the month-to-month forecasts method on which we rely. In Table 11 we can compare BESTARMA statistics with ARMAMOD, the autoregressive component on which BESTARMA is built. We find that the addition of the principal components loses gradually (i.e. moving ahead the forecast horizon) its comparative advantage up to the point that a better performance in forecasting monthly inflation twelve months ahead is achieved by using only the autoregressive component.

Consistently, if we opt for the introduction of principal components regressors for the first eleven monthly forecasts and, afterwards, we switch to the autoregressive only based forecast, then the combined results outperform our previously selected best forecast. This result seems to suggest that there might be a threshold beyond which it is not useful to use principal component indicators and it might become convenient to resort to a mixed strategy[5]. We also want to test our strategy against additional benchmarks. Inflation forecasts could be matched against structural models that include inflation pressure variables such as Philips curves and capacity utilization or even econometric models (like reported by Stock and Watson 1999 and Marcellino, Stock and Watson (2000). This kind of comparison could be object of future work. Here we use a VAR model estimated on a small set of variables normally used to predict inflation. We consider the following variables: Italian inflation (always), price index of combustible commodities in euro index in euros, Italian production price index (coke ovens and oil refining), nominal effective exchange rate, Italian output gap, US output gap (both estimated with quarterly data using the HP filter and then made monthly), German inflation and real interest rate. The final VAR is the best performing combination of models that include from 2 to 4 variables with two or three lags; where time lags could span from 1 to 12. The best VAR[6] is the one with the lowest RMSE of forecast on a twelve month forecast period; i.e., the same out of sample best performance criterion that we used for the factor models. It turned out to include just two variables – inflation itself and price index of combustible commodities – with three lags. With respect to initial efforts, not based on iterative programs, we further reduced the RMSE of approximately 35 percent. Contrary to the factor models we achieved the best results with an expanding window, i.e. with a recursive estimate.

In Table 12 we report also the VAR results. We find out that not only our BESTARMA model but also its autoregressive component (ARMAMOD) perform better. Table 12 contains, finally, the RMSE of a Naïve forecast rule (Atkeson, Ohanian, 2001 and Fisher, Te Liu, Zhou 2002), such that at time t+12 inflation is expected to take exactly the current value. The Naïve forecasts perform just slightly better than the VAR model and BSW model but the RMSE on the twelfth month ahead forecast is higher than BESTARMA model[7]

We have also used the Diebold-Mariano (1995) statistics to test its forecasting accuracy against the alternative – benchmark – VAR model. Suppose we want compare two series made of *n* forecasts and let $\{e_{it}\}_{t=1}^{n}$ and $\{e_{jt}\}_{t=1}^{n}$ be the forecast errors respectively of model *i* and of model *j*. We define $d_t=g(e_{it})-g(e_{jt})$, where g(.) is an arbitrary function.

[5] In appendix we reassess the comparative performance of the two approaches on a 13 to 24 month horizon and find that the principal component based methodology maintains some comparative advantage.

[6] The total amount of possible combinations we tried was over 24000.

[7] The comparison is on the period 1998:1 2004:2. If we extend the period from 1994:1 the performance of the naïve model worsens

The null hypothesis of the test will be that $E(d_t)=0$, i.e. that the difference in the forecasting performance of the two tests is statistically insignificant. There will be such a test for each of the *h* forecast periods.

Provided that $\{d_t\}_{t=1}^{n}$ is covariance stationary and it has short memory, it has been proved that the given its observed value $\bar{d}$ we have: $\sqrt{n}(\bar{d}-\mu)\xrightarrow{d}N(0,2\pi f_d(0))$. Where μ is the population mean, and $f_d(0)$ is the spectral density of d_t at frequency zero.

Accordingly, Diebold and Mariano suggest to use the following test:

$$DM=\frac{\bar{d}}{\sqrt{n^{-1}2\pi\cdot\hat{f}_d(0)}}$$

which, under the null hypothesis and provided that $2\pi\hat{f}_d(0)$ is a consistent estimate of $2\pi f_d(0)$, is asymptotically distributed as $N(0,1)$.

Such estimate is built starting from the observed autocorrelation of d_t. The goodness of the estimate rests, however, on the assumption that for each *h*-step ahead forecast horizon the autocorrelation of order equal or higher than *h* are equal to zero. This condition could be violated for several reasons, for instance seasonality. Therefore, in order to enforce the robustness of our test we compute the DM statistics for both year on year (INFL) and month over month price changes (INFLM).

We also provide the value of the modified DM test proposed by Harvey et al. (1997, 1998) that corrects for the size distortion (i.e. the low number of available observations). The test becomes:

$$DM^*=\left(\frac{n+1-2h+n^{-1}h(h-1)}{n}\right)^{1/2}DM$$

and it is distributed as a *t*-student.

We adopted two versions for the *g(.)* function; respectively, the mean absolute error (MAE) and the mean square error (MSE). They are used in the standard and in the modified DM test. Table 13 and 14 report the result achieved when comparing the forecast accuracy of the BESTARMA model with ARMAMOD, VAR, BESTARMA best equation and NAIVE forecasts for each time horizon included between 1 and 12.

The null hypothesis of equal forecasting accuracy is always – i.e. in case of year on year and month over month projections – rejected and for every *h* when comparing BESTARMA against the VAR and the NAÏVE forecasts. When the comparison is made against ARMAMOD on a month over month basis the null is accepted only with *h* equal to 11 and 12. Reminding that ARMAMOD is the autoregressive component of BESTARMA, we could reasonably argue that expanding the forecast horizon the information content of principal components becomes less relevant. This finding is, not surprisingly, consistent with the RMSE comparison reported in section 3. On a year on year basis the null hypothesis is always rejected, even for $h>10$. Since yearly inflation forecast are made by nesting monthly projections, a number of better monthly forecast are largely sufficient to make rejection the only outcome.

The null is accepted when comparing BESTARMA with BESTARMA best equation on a year on year basis. However, in the case of month over month the test is always rejected for $h>7$ (as well as for $h=4$); which would suggest that thick modelling becomes relevant when extending the time horizon of the forecast and when the information extracted from principal components becomes less relevant. Also in this case we find resemblance with conclusion drawn in section 3. Missing rejection of the null hypothesis in annual inflation

case could be explained with better monthly results not being “sufficiently better” for building up a statistically relevant difference.
Tables from 15 to 18 provide the DM and modified DM values when comparing forecast accuracy of each model against all the others. We stick to the 12 period ahead year over year forecast.

6. Real time forecasting and “real forecasting”

A primary goal for our work is to build a reliable instrument for predicting inflation in real-time environment. To this end, it is important to remark that such an instrument is expected to be based on the information set available at time *t*; with *t* being the period in which the most recent observation of CPI is released. Normally, many variables of the dataset will only be available with a lag with respect to the CPI index. Therefore, the *not available* information up to time *t* has to be “filled in”. We cope with this problem with simple projections rules, details of which are available in the appendix.
The out of sample statistics so far provided do take into account this devise as we wanted to account for reliability of our system in real forecasting exercises. This goal was achieved by replicating in each period of the historical interval the same conditions present in the last period of our dataset. For instance, in 2004:2 industrial production was available only up to time *t-l* (i.e. 2004:1). Consequently, in every period over which we backtested our model the actual industrial production data was used only up to a one period lag. The last observation, corresponding to period *t*, was overridden using our projection rule.
However, we wanted also to asses if the model performance is worsened by the unavailability of data up to time *t*. We ran the BESTARMA model along the historical interval switching off our real time forecast rule. Note that the difference between the two provides also an upward limit to the amount by which forecast can be improved with better projection rules for variables. Table 19 allows the comparison to be made. Interestingly, it would seem that the impact of data availability is negligible.

7. An application to core Inflation

According to a stream of literature, core inflation should be a relevant definition to be monitored by policy makers (see, for example, Wynne(1999)). So far SW models applications have devoted little attention to forecasting such a measure. The aim of this section is to fill this gap and provide an insight on to what extent a SW models performance is affected by changing the reference variable.
Clearly, being core inflation a less volatile measure than total inflation, we expect forecast statistics to improve.
We concentrate on core inflation measure released by EUROSTAT, i.e. CPI all items, excluding food and energy. The statistics provided in tables 20, 21 and 22 report the ratios between the RMSE achieved when predicting core inflation with respect to the RMSE portrayed in tables 7, 8 and 9 (the total inflation case). We restrict our analysis to the BESTARMA, ARMAMOD and the NAÏVE projections.

The evidence confirms our a-priori. RMSE are substantially reduced. On a twelve month horizon the RMSE reduction reaches, approximately, 25 per cent with the BESTARMA forecast strategy and 20 per cent in the NAÏVE forecast case. Improvement is more marked in the sub-sample (1994 – 1997) when total inflation was more volatile. Also the autoregressive model displays an improvement, which is actually larger than for the BESTARMA model: the RMSE ratio moves to 0.70 per cent. However, the absolute value of the BESTARMA RMSE remains lower than that of the autoregressive model ARMAMOD. This evidence is interesting because it shows that the principal components contribution is more relevant when predicting total CPI, which is more volatile than core inflation.

8. Turning point early detection

We have shown that BESTARMA makes a good job (comparatively to alternative models) in forecasting inflation behaviour over a one year time horizon. The main trust of this section is to use our inflation projections – hereafter extended to a 2 year interval – to forecast turning points. By doing so, we argue that the contribution that our modelling strategy brings to understanding future inflation outlook if further enhanced.
In our view, all projections up to one year ahead can be regarded as it "short term". As a matter of facts, gaining an insight on future inflation behaviour within this time frame is favoured by a number of factors. To start with, year on year inflation is constructed as a moving average of monthly price level changes with any *h*-periods ahead projection being conditional on the past (*12-h*) data. When *h* is relatively small, forecast errors are narrowed down. Furthermore, the scope for making large mistakes is also reduced by the presence of seasonal factors. However, beyond this threshold all carry-over and seasonal factor information disappears. Extending the time window poses a number of challenges. First of all, in paragraph 5 we found evidence that the contribution provided by principal components – which represents our information set – gradually looses predictive power. At the same time we observed that, as forecast horizon moves forward, month to month changes predicted by our model tend to stabilize to a constant rate. Overall, the likely result is that quantitative projections (i.e. punctual forecasts) on future behaviour of inflation become less "informative" and reliable.
Turning point early detection provides, in this respect, an useful mean to extend the time horizon over which to gain an insight on inflation outlook. If we can predict that – at given date – inflation behaviour is going to switch (from increasing to decreasing or vice versa), it becomes less relevant if further ahead our inflation forecast becomes less accurate. Importantly, the fact that our forecasting strategy produces an inflation forecasts and turning point prediction which are mutually consistent represents a factor of strength. In what follows we account for the suitability of the BESTARMA model to detect turning points.

8.1 methodological issues

As a first step, we extend the forecast horizon to twenty-four months[8]. In evaluating the turning point detection capability of our forecast method we shall resort again to an out

[8] Equations whose forecast horizon moves beyond 13 months are estimated with the same the procedure outlined in section 3. The main departure is that the autoregressive term characterized by a lag spanning from 8 to 14 months is dropped from the statistical component (ARMAMOD). Likewise, we continue

of sample testing strategy. Firstly, looking at the actual behaviour of the CPI index, we define the turning points. Second, we want to assess how well our rolling inflation forecast is able to achieve an early detection of them. The capability of our forecast strategy is then benchmarked against the VAR model previously described.
We adopt the turning point definition as suggested in the classical work of Bry and Boschan (1971) [9]. We skip the complete explanation concerning the procedure, detail of which is provided in the appendix, and concentrate on its main implications. Once the procedure is implemented the sequence of turning points presents the following characteristics:

a) A peak has to be followed by a trough and a trough by a peak.
b) Each phase (peak to trough or trough to peak) must be at least six months long.
c) A business cycle from peak to peak or from trough to trough must have a duration of at least 15 months – in order to distinguish business cycles from seasonal cycles –.
d) Turning points within six months of the beginning or end of the time series are not taken into account.
e) Peaks (or troughs) within 24 months of beginning (or end) of the series are ignored if any of the points before (or after) are higher (or lower) than the peak (trough).

We start by identifying inflation rate turning points along the historical dataset. Over the 1985-2002 time period six turning points of the inflation rate are found (1987:06 (troughs), 1989:06, 1994:07, 1995:11, 1999:02, 2001:01 and 2002:6). See figure 4.
The ensuing step would call for implementing the same exercise using inflation forecast produced by the BESTARMA and the VAR models and comparing their performance. However, the turning point sequence identified can not be used straight away. We need to go trough an additional preliminary step which consists in modifying the Bry-Boschan (BB form now on) procedure. In fact, the latter is designed to detect turning points using an historical dataset on an ex-post basis. In such a frameworks turning point detection in the two tales is not a relevant issue. “Special rules” (*d)* and *e)* above) deal with data truncation over the two ends of the interval. These rules make the BB procedure biased, if anything, toward discarding candidate turning points associated with recent data (i.e. data coinciding with the right end tale). Generally, turning point are finally accepted when more observations become available.
Conversely, the most relevant part of our data set is made out of forecasted numbers and our focus is placed exclusively on one extreme of the time interval – the right end tale –.

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deriving our inflation projections – i.e.100*log (P_{t+12} / P_t) – by nesting the outcome of month over month predicted price increases. Clearly, beyond the one-year threshold, inflation numbers entail now a forecasts for both P_{t+12} and P_t. Both values are projected averaging results of the same share of models; e.g. the best 10%, 20%, (…and so forth). The wider forecast interval lends itself to compare again our principal component based strategy (BESTARMA) against its statistical benchmark model ARMAMOD, the approach that provided the second best results. In facts, in section 3 we hinted that beyond a given horizon there might be no scope for using principal components. We reported that the “marginal” contribution to the predictive power of the statistical component was decreasing when progressively extending the forecast horizon. The set of tables (22-25) provides results on the 13 to 24 month ahead projections. Results are not clear cut; component based projections fare better only in portions of the time intervals considered. Although there might have been scope for nesting forecasts, but we did not further pursue this issue. Provided that there was no conclusive evidence in any direction we decided to stick to principal component based results also for second year projections.

[9] An alternative method is proposed by Gracià-Ferrer, Bujosa-Brun (2000) and implemented also by Bruno and Lupi (2002). Turning point is achieved, in this approach, working on a detrended (and seasonally adjusted) component of the selected variable. This approach, however, is most suitable for time series that are characterized by a business cycle pattern like, typically, the industrial production index..

The different perspective gives rise to two kinds of problems that have to be settled on a preliminary basis.
Keeping in mind that our forecast extends from time *t+1* to time *t+24*, the first problem we recon is that the BB complete procedure is highly demanding in terms of the length of the required forecast horizon. The combined effect of a preliminary smoothing of the time series, which uses up seven months of information, and the implementation of condition *d)* above restricts our capability to predict turning points up to 1 year ahead, approximately [10]. Concerning condition *e)*, this is to be disregarded. On its own, this condition would entail the loss of 24 month information and it would completely impede the capability to forecast turning points[11].
The elimination of condition *e)* brings about a potential source of mistakes in the determination of turning points. To start with, the modified procedure might signal the existence of turning point that – on an ex-post basis – end up being only “local” minima or maxima (i.e. when – as the forecast window moves forward – additional information is available the procedure will no longer recognize them as turning points).
It is important to clarify immediately that this problem arises also when the procedure is applied a data set that includes the observed price level up to 24 months ahead – i.e. to a perfect (error free) inflation rate forecast – when using a rolling time window. Figure 5 illustrates the concept. The variable TP_REALTIME represents the number of times in which the modified Bry-Boschan procedure (BBM from now on) identifies the presence of a turning point when using the historical data set. Comparison with figure 4 shows that the procedure assigns erroneously a turning point to period 1997:9. This mistake is made five times in a raw. Furthermore, assigning the turning point status to a local maximum/minimum can delay the identification of the true turning point. Turning point 1999:02 is not recognised as such until the procedures believes that 1997:9 is a turning point.
Concerning the timing of turning point detection, there is an additional drawback related to the usage of the BB procedure in a forecasting environment. Provided once again, a perfect twenty-four period ahead forecast, the earliest possible identification of a turning point can occur with a one, two or three periods anticipation/delay with respect to the expected one year (*t+12*) advance. As matter of facts, the requirement of having at lest twelve observations beyond each “candidate” turning point is binding only for the initial step of the procedure, which works with a smoothed inflation variable. Additional steps operate the search on the original series and this can cause the timeliness of turning point identification to drift ahead or backwards[12]. The 1995:11 pick is detected for the first time in 1994:8 (1995:11 represents time *t+14* when the forecasts starts from 1994:9).
In evaluating our forecast method we recon the existence of these drawbacks and “control” for them. We do so by assessing the turning point prediction capability of our strategy relative to the forecast made with the BBM procedure using actual inflation data. To make an example, again with reference to figure 5, if our model places for five consecutive periods a turning point in 1997:9 it is making the right prediction because that is the outcome of the REALTIME projection.

The BBM applied to our BESTARMA (we concentrate on the projections produced by the average of all models) and to the VAR model forecasts produces the results depicted,

[10] As clarified later on, it can actually occur that the identification happens with some anticipation or delay.
[11] The alternative solution was to extend the forecast horizon to 48 months leaving in place condition *e)*. This solution was discarded because it worsened the turning point detection performance when applied to the forecasted series. The inflation profile over the prolonged period becomes always smoothed and trend-like; with condition *e)* operating, this causes the existence of turning point to be excluded!
[12] See the appendix for a more detailed explanation.

respectively, in figure 6 and figure 7. The overall impression that we get is that scatters corresponding to the BESTARMA forecast appear closer to the turning points initially signalled in figure 5. One additional feature is worth remarking. The VAR model seems more prone to signal incorrectly the existence of false turning points; this happens, for instance, in 1998 and in 2000.
Moving to a quantitative assessment, we argue that a turning point forecast presents two desirable features. To start with the existence of a turning point has to be recognized as early as possible within the forecast horizon. Furthermore, the forecast should place the turning point as close as possible to the actual period of (or not too far away from) its occurrence. There is a potential trade off between these two – timeliness and precision – requirements, which can be explained with an example. Let's assume that there is a turning point in 1999:10. The assessment system should be able to account for errors made respectively by a forecast starting in 1999:1 – when the last available observation is 1998:12 – that locates a turning point in 1999:12 (early detection, wrong date) and by a forecast starting in 1999:5 but placing correctly the turning point in 1999:10 (late detection, right date). We also want to make sure that the two possible mistakes – i.e.: failure to forecast an existing turning point and signalling the presence of a turning point when no turning will actually occur in the forecast interval – are treated symmetrically.

A different layer of analysis concerns the relationship between reliability of turning point detection and "stability" of the signal. There are two issues involved. To start with, when a turning point is predicted for the first time, how confident we should be on this prediction? The first signal could be just erratic/noise and be reversed when an additional month of information is available and next projection is made. For this reason, we might want to wait for confirming evidence before we trust this prediction. Second, even if, several consecutive forecast rounds keeps signalling the existence of a turning point a further dilemma could arise. The occurrence of the turning points could be placed in different – and progressively later – periods. In that case, how far away can be the "new" predictions located from the first one for us to believe that a turning point is really going to happen? As a matter of facts, if a model keeps postponing the occurrence of a turning point we will start doubting that it will ever take place. Overall, an additional trade off seems to emerge between early detection of turning point and confidence one wants to put on it. Waiting for a consecutive number of (consistent) signals should provide a safer approach at the cost is loosing timeliness. Some guiding rule has to be worked out[13].

Finally, in designing the evaluation system, it necessary to take into account that we operate along rolling time windows and that there are repeated chances to detect the same turning point, with possibly different outcomes. In our exercise the number of chances is 24. The testing strategy which we adopt in the following section fulfils al the mentioned requirements.

8.2 procedure design and results

As previously mentioned, in what follows we consider all turning points signalled by the simplified Bry-Boschan as "real" turning points. We therefore assess the capability of our BESTARMA strategy and of the VAR benchmark relative to the REALTIME forecast.

[13] Clearly, we are interested on a binary (i.e. yes-no) answer to the question if a turning point is going to take place within the forecast interval. For an approach that focuses on a probabilistic nature of the answer see, for instance, Estrella and Mishkin (1995), who propose a probit-model to predict U.S. recessions.

We start by deriving binary variables from inflation forecasts. They take the values 1 and 0 if the inflation rate is included, respectively, between a peak and a trough or between a trough and a peak. In such a way, every change of phase corresponds a change of value of the binary variable. For each forecast horizon *h*, we shall call $d_{t,h}$ the binary variable identified by the BBM procedure applied to the actual inflation rate (i.e. the REALTIME) and $\hat{d}_{t,h}$ the series achieved using forecasting models.

The first building block of our assessment strategy is the Turning Point Error (TPE) statistics, which is defined as:

$$TPE_h = \frac{1}{T}\sum_{t=1}^{T}(d_{t,h} - \hat{d}_{t,h})^2$$

We build such a statistics for VAR and BESTARMA turning point projections matched against the REALTIME forecast. Table 27 reports, in the first two columns, the results for each time lead in our twenty-four period forecasting horizon. BESTARMA seems to fare much better. It is to be noted that values of TPE statistics stabilize in the final part of the time horizon, approximately after period *t+16*. This happens because the binary variable $\hat{d}_{t,h}$ is characterised by an increasing probability of assuming an incorrect sign only up to the time horizon when the procedure is capable to identify a turning point. By design – as previously outlined – the limit is located a few periods beyond time *t+12*. In the final part the forecast interval the value of the binary variable will not change in any case, therefore its probability of being incorrectly signed stabilizes.

An additional instrument suitable for comparing the two models performance is the sign test proposed by Pesaran e Timmermann (1992). We call the two forecasting models *x* and *y*.

Let $z_{t,h}$ be a binary variable which takes value 1 when $\hat{d}_{t,h}$ is equal to $d_{t,h}$ and 0 otherwise. Under the null hypothesis $\hat{d}_{t,h}$ and $d_{t,h}$ are independently distributed.

With

$\hat{P}_x = n^{-1}\sum_{t=1}^{n} d_{t,h} = \bar{d}_h$ the estimate of the probability that $d_{t,h}$ is equal to 1

$\hat{P}_y = n^{-1}\sum_{t=1}^{n} \hat{d}_{t,h} = \bar{\hat{d}}_h$ the estimate of the probability that $\hat{d}_{t,h}$ is equal to 1

$\hat{P} = n^{-1}\sum_{t=1}^{n} z_{t,h} = \bar{z}_h$ the estimated joint probability that $\hat{d}_{t,h}$ is equal to $d_{t,h}$

under the null hypothesis $\hat{d}_{t,h}$ and $d_{t,h}$ are independently distributed; $n\hat{P}$ has a binomial distribution with average being equal to nP_*; where

$$P_* = Pr(z_{t,h} = 1) = Pr(d_{t,h} = 1, \hat{d}_{t,h} = 1) + Pr(d_{t,h} = 0, \hat{d}_{t,h} = 0) = P_y P_x + (1 - P_y)(1 - P_x)$$

When substituting for the probabilities of the models *x* and *y* we have

$$\hat{P}_* = \hat{P}_y \hat{P}_x + (1 - \hat{P}_y)(1 - \hat{P}_x)$$

The test suggested by Pesaran e Timmermann(1995) is

$$S_n = \frac{\hat{P} - \hat{P}_*}{\left\{\hat{\text{var}}(\hat{P}) - \hat{\text{var}}(\hat{P}_*)\right\}^{1/2}} \qquad \sim \text{N}(0,1)$$

with $\hat{\text{var}}(\hat{P}) = n^{-1}\hat{P}_*(1 - P_*)$ and

$$\hat{var}(\hat{P}_*) = n^{-1}(2\hat{P}_y - 1)^2\hat{P}_x(1 - \hat{P}_x) + n^{-1}(2\hat{P}_x - 1)^2\hat{P}_y(1 - \hat{P}_y) + 4n^{-2}\hat{P}_y\hat{P}_x(1 - \hat{P}_y)(1 - \hat{P}_x)$$

Table 28 show results of the PT test applied to the VAR and BESTARMA models. The 95% critical rejection value is always (i.e. for any forecast horizon) exceed; therefore there is strong evidence of forecasting capability for both models.

A different perspective is provided by the previously presented Diebold and Mariano (DM) test, now to be applied to turning point prediction at the binary variables $d_{t,h}$ and $\hat{d}_{t,h}$. Results are displayed in the third and fourth column of table 27. Although the BESTARMA TPE is – for *h>5* – consistently lower, the predictive performance of the two tests is not statistically different across the whole forecast horizon.

This is not the final outcome of our comparative exercise as further insight will stem from the effort to strike the best compromise between early detection of turning points and the reliability of the signals. We want to find out whether it is convenient to wait for consecutive signals (and how many of them are required) before validating a turning point prediction. Assuming that several forecast rounds confirm the prediction of existence of a turning point, there is one additional dimension of the problem to be dealt with. We want to ascertain if the time period in which the turning point is placed can be allowed to be different from the first prediction (and by how many periods).
We experimented with several requirement rules entailing jointly a different number of consecutive signals – between 2 and 4 – and different allowed maximum distances between consecutive turning point predictions – between 0 and 12 –. We built the binary series corresponding to the forecasted turning point sequence accordingly; i.e. no change of value is allowed until the double requirement is fulfilled. A TPE statistics was then computed, for all double requirement combinations.
The impact of the new strategy on the TPE forecasting statistics is straightforward. Disregarding a signal leads to an improved performance in two cases: if future information (i.e. subsequent data releases) reveals that no turning point occurs within the time horizon of our forecast or if waiting for an additional signals makes it possible to better locate the exact timing of the turning point[14]. New TPE values and Timmerman tests for BESTARMA and VAR for the 24 period horizon can be found in tables 29-30 and 31-32, respectively. Table 33 reports for each *h*, the best strategy (i.e. the combination of consecutive signals and distance tolerated from the first signal) TPE associated to such strategy and the DM and modified DM tests between the BESTARMA and VAR best strategies. Results can be summarized as follows. A finding common to both models is that that waiting for more information, which is to say for one additional signal at least, is always rewarding. Concerning BESTARMA, the best combination within twelve months is generally provided by waiting for one additional signal and zero tolerated distance. Beyond that range we should wait for one an additional confirming

[14] It might be highly undesirable to locate too early or too late a turning point prediction. For instance this could lead to errors in timing of policy decisions.

signal; furthermore TPE values improve – become lower – as we increase the tolerated distance up until 4 periods. The overall message, conveyed also by figure 9, is that the optimal level of consecutive signals and of admitted tolerance increases as we extend the forecast horizon.

VAR statistics are less clear and more difficult to be explained. In particular, the combinations ordering is counter-intuitive as number of consecutive signals and tolerated distance tend to decrease when extending the forecast horizon.

An additional relevant finding is that using DM test to compare the best strategy for BESTARMA and VAR produces now different results. In most time horizons there is statistical evidence of different capability of turning point prediction. This is result represents a further improvement in the overall performance of our model and strengthens its capability to provide useful information regarding inflation also beyond the one year time-horizon.

9 Conclusions

This paper offers an empirical application of factor models and forecasts combination to forecasting Italian inflation. First, following Granger (2000) and Pesaran-Timmermann (2001), we combine the predictions of a large number of models, a subset of which is selected in each period according to a best fit criterion. We forecast inflation on a month to-month basis and year-on-year inflation forecast is then built by combining monthly forecasts. Model estimation is performed on a rolling basis along an historical dataset, so that our methodology can be benchmarked against alternative forecasts. Over an year horizon our forecasting strategy largely outperforms – via RMSE comparison – a standard SW model.

Forecasts combination and rolling regressions help a better modelling of non-linearities and structural breaks. Replacing year on year with monthly forecast provides gains inefficiency and introduces a further ("vertical") dimension of forecast combination as each separate monthly forecast is made out of a combination of different models.

We have also analysed robustness of our results along a number of dimensions. We expanded the sample size over which models are estimated and show that a wider estimation window (five years) worsens the predictive power of our models. Additionally, we split our forecast validation sample into two parts finding that results in terms of autoregressive component selection and optimal time length over which models are estimated are robust. Furthermore, RMSE and TPE statistics are computed also for a purely statistical model (the autoregressive component of our estimated equations) a VAR and a naïve forecast. Simple RMSE comparison as well as statistical test (Diebold and Mariano) show that our preferred forecast keeps prevailing. Finally, we attempted an assessment of the cost of having data less updated than the last CPI index monthly release. Forecasts produced by our model take into account this factor; we compared the results against the same forecast strategy applied to a data set in which there is no delay in information availability. The difference appeared to be very small. Our effort was also aimed at extending the forecast capability of our strategy beyond one year horizon. We used our projections to predict turning points. Considering that our inflation forecasts become gradually less accurate as the autoregressive component starts prevailing (i.e. factors add little predictive power beyond one year); turning point prediction conveys valuable information over inflation tendency further ahead. We have then extended the analysis to the capability to predict turning points of the inflation rate. We show that our best model fares better, in terms of RMSEs, than a VAR. Results are, initially, less clear cut when we test for statistical difference. However, we show that waiting for consecutive turning point signals represents a rewarding strategy. The predictive capability of our method is markedly enhanced and results become significantly different from those of the VAR.

Appendix

A-1 Procedure for programmed selection of turning points for monthly data

I. Determination of extremes and substitution of values
II. Determination of cycles in 12-month moving average (extremes replaced[15]).
A. Identification of points higher (or lower) than 5 months on either side
B. Enforcement of alternation of turns by selecting highest of multiple peaks (or lowest of multiple troughs).
III. Determination of corresponding turns in the Spencer[16] curve (extremes replaced)
A. Identification of highest (or lowest) value within ± 5 months of selected turns in 12-month moving average.
B. Enforcement of minimum cycle of duration of 15months by eliminating lower peaks and higher troughs of shorter cycles.
IV. Determination of corresponding turns in short-term moving average of 3 to 6 months, depending on MCD (months of cyclical dominance).
A. Identification of highest (or lowest) value within ± 5 months of selected turns in Spencer curve.
V. Determination of turning points in unsmoothed series.
A. Identification of highest (or lowest) value within ± 4 months, or MCD term, whichever is larger, of selected turn in short-term moving average
B. Elimination of turns within 6 months of beginning and end of series.
C. Elimination of peaks(or troughs) at both ends of series which are lower (or higher) than values closer to end.
D. Elimination of cycles whose duration is less than 15 months.
E. Elimination of phases whose durations is less than 5 months.
VI. Statement of final turning points.

Source: Bry and Boschan 1971, p. 21

A-2 24 Months Ahead Nested-Forecast

Two sets of RMSEs benchmark are provided for 13 to 24 months ahead forecast (tables 23-26). The first block of rows is built using the statistical approach results only. The last row reports the outcome when the use of the statistical benchmark method is restricted to the second year and, consequently, first year projections are drawn from the BESTARMA forecast. This strategy relies on a better first year forecast base and presents, obviously, lower year on year RMSEs. This can be verified in tables 23 and 24. There we find that the forecast performance of the principal components based strategy prevails slightly. Tables 25 and 26 provide the results for the underlying month over

[15] Extreme values are substituted for values of a Spencer curve in order to eliminate the influence of special events, i.e. like strikes etc.
[16] The Spencer curve is a 15-month moving average with negative weights at the extremes and positive and higher weights closer to the center. The weights on terms t - 7 to t + 7 are: -0.0094 -0.0188 -0.0156 0.0094 0.0656 0.1438 0.2094 0.2313 0.2094 0.1438 0.0656 0.0094 -0.0156 -0.0188 -0.0094

month forecasts. If we exclude the “thick” modelling, the autoregressive selection prevails over the best ex.-ante equation with principal component. Note also that tables 23 and 26 presents the small drawback of a different backtesting interval with respect to previous tables, this is due to the extended (from 1 year to two years) range of the forecast and to the length of our database.

A-3 Projection Rule of Not Available Data

. When we run the model we want to exploit all available information, even if - normally - many variables will only be available with a lag. Let *t* the time coinciding with the most recent CPI data release. The procedure of principal components extraction requires a dataset which has not missing observations. In order to cope with this problem we use the following devise: we do not include in the procedure for the extraction of factors all the series that have more than three not available data (*t*-3); we fill in missing observation of the remaining series using simple projection rules. The first rule keeps unchanged the level with respect to the last data available and it is used with the surveys and balance of payment series; the second rule, for the remaining time series, uses the average of monthly growth of the previous twelve months.

A-4 Steps of turning point detection in Bry-Boshan algorithm

In a preliminary stage the algorithm detects “candidate” turning points using a very smooth moving average of the inflation rate. Afterwards, stepwise, it reduces the smoothness of the moving average ending up with the actual series. This procedure and the many restriction which are imposed at each step do not assure a constant timing for the detection of a turning point even if an error free forecast is used. First of all, the local maximum (or minimum) on a thirteen months centred moving average (first step) or fifteen months weighted centred moving average (second step) does not necessarily coincide with the local maximum when using the unmodified data. Furthermore, the procedure needs 12 months data each side in the second step where the local peak (or trough) is identified on a interval of plus or minus 5 months on the Spencer curve (fifteen weighted centred moving average). Consequently, if the turning point selected does not coincide with *t+12*, but falls, say, at *t+12+i*, the correct range is not *t , t +24* but *t+i , t+i+24*. The following example will clarify the concept. Using BB we found that in 2001:1 there is a peak. Afterwards we used BBM operating on historical data with a rolling window. When the last observed inflation data was in 2000:1 (*t*), our set of projected data extended to 2002:1 (t+24). We might have expected to detect the turning point immediately (as 2001:1 is a time *t+12*). However, the BBM procedure was not able to detect a turning point until observed inflation reached 2000:3 (i.e. at *t+10*). This happened because of the following reason. In the first step, the thirteen months moving average founds a local maximum at 2001:2. In the second step (when the Spencer curve is used) the local peak moved to 2001:3. This located the candidate turning point at (*t+14*). However, in the second step available data ended at 2001:6 (*t+17*, i.e. *t+24* minus *7* month of data required to construct a moving average). Therefore the procedure excluded the peak until forecast arrive to *t+26* (*t+24+2*).

The Dataset

List of the variables used to extract the factors. The trasformation code (TR) are:

1) h difference, where h=forecast horizon
2) both level and h difference
3) Level

DATASET

	SA	CODICE EVIEWS	TR
OUTPUT			
IT INDUSTRIAL PRODUCTION	X	IP	2
IT INDUSTRIAL PRODUCTION - INVESTMENT GOODS	X	IPINV	2
IT INDUSTRIAL PRODUCTION – MANUFACTURING	X	IPMAN	2
IT INDUSTRIAL PRODUCTION - CONSUMER GOODS	X	IPCONS	2
IT INDUSTRIAL PRODUCTION: INTERMEDIATE MATERIALS		IPINT	2
IT INDUSTRIAL PRODUCTION – INTERMEDIATE GOODS	X	IPIND	2
IT INDUSTRIAL PRODUCTION - PASSENGER CARS		IPCAR	2
IT INDUSTRIAL PRODUCTION - COMMERCIAL VEHICLES		IPCOMV	2
IT COMPOSITE LEADING INDICATOR:REF.SERIES(IIP)LONG-TERM TREND		INDPR	2
DEMAND			
IT NEW ORDERS TO MANUFACTURING		ORDER	2
IT NEW ORDERS: MOTOR VEHICLES		ORDERCAR	2
IT RETAIL SALES		RETAIL	2
IT RETAIL SALES - FOOD, BEVERAGES AND TOBACCO	X	RETFOOD	2
IT RETAIL SALES - HOUSEHOLD EQUIPMENT	X	RETHH	2
IT MINING & MANUFACTURING - SALES		SALES	2
IT MINING & MANUFACTURING - SALES, INVESTMENT GOODS		SALINV	2
IT PASSENGER CARS REGISTERED		CARREG	2
IT MINING & MANUFACTURING - SALES, CONSUMER GOODS		SALCONS	2
IT MINING & MANUFACTURING - SALES, INTERMEDIATE GOODS		SALINT	2
ITALY-DS MARKET - PRICE INDEX		MKTPI	2
ITALY-DS MARKET - DIVIDEND YIELD		MKTDY	2
IT BOP: BALANCE ON GOODS		BOPNT	3
IT BOP: CURRENT ACCOUNT (NET)		BOPCA	3
IT BOP: BALANCE ON SERVICES		BOPNS	3
IT BOP: BALANCE ON INCOME		BOPNI	3
IT BOP: BALANCE ON CURRENT TRANSFERS		BOPNCT	3
IT EXPORTS FOB		EX	2
IT NET TRADE BALANCE		TRADEBAL	3
IT IMPORTS CIF		IMP	2
MONEY			
IT MONEY SUPPLY: M1 - ITALIAN CONTRIBUTION TO THE EURO AREA		M1	2
IT MONEY SUPPLY: M2 - ITALIAN CONTRIBUTION TO THE EURO AREA		M2	2
IT MONEY SUPPLY: M3 - ITALIAN CONTRIBUTION TO THE EURO AREA		M3	2
IT OFFICIAL RESERVES EXCLUDING GOLD		RESER	3
US EURO TO US $		RX_EU	2
IT NOMINAL EFFECTIVE EXCHANGE RATE		EFFRATE	2
IT TREASURY BILL RATE - 3 MONTH (EP)		R3M	2

IT TREASURY BILL-GROSS AUCTION ANNUAL RATE 6 MTH(WEIGHTED MEAN)		R6M	2
IT GOVERNMENT BONDS - 10-YEAR (GROSS)		R120Y	2

WAGES

IT WAGE PER EMPLOYEE		WPE	2
IT WAGE PER EMPLOYEE: BANKING & INSURANCE		WPEBANK	2
IT WAGE PER EMPLOYEE: COMMERCE		WPECOM	2
IT WAGE PER EMPLOYEE: CONSTRUCTION		WPECONS	2
IT WAGE PER EMPLOYEE: INDUSTRY		WPEINDSS	2
IT WAGE PER EMPLOYEE: TRANSPORTATION, COMM.		WPETRAN	2
IT WAGE PER EMPLOYEE: PRIVATE SERVICES		WPEPRSER	
IT WAGE PER EMPLOYEE: PRODUCTION AND DISTRIBUTION OF ELECTRICAL ENERGY		WPEELEC	2
IT WAGE PER EMPLOYEE: MARKET SERVICES		WPESER	2
IT HOURLY WAGES		HOURLYTOT	2
IT COMPENSATION PER EMPLOYEE - LARGE SIZED INDUSTRIES		COMEMP	2
IT LABOUR COST PER EMPLOYEE - LARGE SIZED INDUSTRIES		LABCOSPE	2
IT CONTRACTUAL HOURLY WAGE: MARKET SERVICES		HOURLYSER	2
IT CONTRACTUAL HOURLY WAGE: CONSTRUCTION		HOURLYCON	2
IT HOURLY WAGE RATE INDEX- ALL INDUSTRY - MANUAL WORKERS		HOURLYMAN	2
IT HOURLY RATES – INDUSTRY		WEARN	2
IT UNIT LABOUR COSTS, RELATIVE NORMALIZED	X	ULC	2
IT STANDARDIZED UNEMPLOYMENT RATE	X	UNRATE	2

SURVEYS

IT HOUSEHOLD CONFIDENCE INDEX		CONF	3
IT ECONOMIC SENTIMENT INDICATOR - ITALY	X	ESI	3
IT CONSUMER CONFIDENCE INDICATOR - ITALY	X	CCI	3
IT CONSTRUCTION COST INDEX - RESIDENTIAL		COSTCON	3
IT CONSUMER SURVEY: ECONOMIC SITUATION NEXT 12 MTH. - ITALY	X	PREVSSEITA1_FAM	3
IT CONSUMER SURVEY: FINANCIAL SITUATION NEXT 12 MTH.- ITALY	X	PREVSE1_FAM	3
IT CONSUMER SURVEY: PRICES LAST 12 MONTHS - ITALY	X	GIUPZ1_FAM	3
IT CONSUMER SURVEY: PRICES NEXT 12 MONTHS - ITALY	X	PREVPZ1_FAM	3
IT CONSUMER SURVEY: SAVINGS OVER NEXT 12 MONTHS - ITALY	X	PREVPRIS_FAM	3
IT CONSUMER SURVEY: UNEMPLOYMENT NEXT 12 MONTHS - ITALY	X	PREVD_FAM	3
IT INDUSTRIAL CONFIDENCE INDICATOR - ITALY	X	ICI	3
IT CONSTRUCTION CONFIDENCE INDICATOR - ITALY	X	CONSCI	3
IT CONSUMER SURVEY –CONVENIENCE OF PURCHASING DURABLE GOODS	X	CABD_FAM	3
IT BUSINESS TENDENCY SURVEYS: PRODUCTION (FUTURE TENDENCY)		TP_TOT	3
IT BUSINESS TENDENCY SURVEYS: PROSPECTS FOR TOTAL ECONOMY		TGE_TOT	3
IT BUSINESS SURVEY: CONSUMER GDS. - ECONOMY FORECAST		TGE_C	3
IT BUSINESS SURVEY: CONSUMER GDS. - SELLING PRICE FORECAST		TPZ_C	3
IT BUSINESS SURVEY: CONSUMER GDS.- EXPECTATIONS ON PRODUCTION		TP_C	3
IT BUSINESS SURVEY: INTERMEDIATE GDS. - ECONOMY FORECAST		TGE_INTER	3
IT BUSINESS SURVEY: INTERMEDIATE GDS. - EXPECTATIONS ON PRODUCTION		TP_INTER	3
IT BUSINESS SURVEY: INTERMEDIATE GDS-SELLING PRICE FORECAST		TPZ_INTER	3
IT BUSINESS SURVEY: INVESTMENT GDS. - ECONOMY FORECAST		TGE_INV	3
IT BUSINESS SURVEY: INVESTMENT GDS. – EXPECTATIONS ON PRODUCTION		TP_INV	3
IT BUSINESS SURVEY: INVESTMENT GDS.- SELLING PRICE FORECAST		TPZ_INV	3
IT BUSINESS SURVEY: LABOUR COST PER CAPITA(% CHG NEXT 12 MTH)		CLFUT12_TOT	3
IT BUSINESS SURVEY: SELLING PRICE FORECAST		TPZ_TOT	3
IT CONSTRUCTION SURVEY: PRICE EXPECTATIONS - ITALY	X	CPEXP	3
IT INDUSTRY SURVEY: SELLING PRC. EXPECT. MTH. AHEAD – ITALY	X	INDSELPR	3
IT RETAIL CONFIDENCE INDICATOR - ITALY	X	RCI	3

IT CONSUMER SURVEY – ECONOMIC SITUATION	TOTGIUSE_FAM	3
IT CONSUMER SURVEY –SAVING OPPORTUNITIES EXPECTATIONS	PREVCRISP_FAM	3
IT CONSUMER SURVEY –PURCHASE EXPECTATIONS – DURABLE GOODS	IABD_FAM	3
IT CONSUMER SURVEY –PURCHASE EXPECTATIONS – CAR	IAA_FAM	3
IT CONSUMER SURVEY –PURCHASE EXPECTATIONS – HOME	IAAB_FAM	3
IT CONSUMER SURVEY – HOME MAINTENANCE AND IMPROVEMENT (NEXT 12 MTH)	MMAB_FAM	
IT CONSUMER SURVEY – FINANCIAL SITUATIONS	GIUSFIN_FAM	3
IT CONSUMER SURVEY – HOUSEHOLDS' SITUATION	GIUSE_FAM	3
IT BUSINESS SURVEY: CONSUMER GDS –FINISHED GOODS INVENTORIES	GPF_C	3
IT BUSINESS SURVEY: INTERMEDIATE GDS –FINISHED GOODS INVENTORIES	GPF_INTER	3
IT BUSINESS SURVEY: INVESTMENT GDS –FINISHED GOODS INVENTORIES	GPF_INV	3
IT BUSINESS SURVEY: TOTAL –FINISHED GOODS INVENTORIES	GPF_TOT	3
IT BUSINESS SURVEY: CONSUMER GDS –ORDER-BOOK LEVEL	LOG_C	3
IT BUSINESS SURVEY: INTERMEDIATE GDS – ORDER-BOOK LEVEL	LOG_INTER	3
IT BUSINESS SURVEY: INVESTMENT GDS – ORDER-BOOK LEVEL	LOG_INV	3
IT BUSINESS SURVEY: TOTAL –ORDER-BOOK LEVEL	LOG_TOT	3
IT BUSINESS SURVEY: CONSUMER GDS –PRODUCTION LEVEL	LP_C	3
IT BUSINESS SURVEY: INTERMEDIATE GDS – PRODUCTION LEVEL	LP_INTER	3
IT BUSINESS SURVEY: INVESTMENT GDS –PRODUCTION LEVEL	LP_INV	3
IT BUSINESS SURVEY: TOTAL –PRODUCTION LEVEL	LP_TOT	3
IT BUSINESS SURVEY: CONSUMER GDS – LIQUIDITY SITUATION – LEVEL	SL_C	3
IT BUSINESS SURVEY: INTERMEDIATE GDS – LIQUIDITY SITUATION – LEVEL	SL_INTER	3
IT BUSINESS SURVEY: INVESTMENT GDS – LIQUIDITY SITUATION – LEVEL	SL_INV	3
IT BUSINESS SURVEY: TOTAL – LIQUIDITY SITUATION – LEVEL	SL_TOT	3
IT BUSINESS SURVEY: CONSUMER GDS – LIQUIDITY SITUATION – VARIATION	SLV_C	3
IT BUSINESS SURVEY: INTERMEDIATE GDS – LIQUIDITY SITUATION – VARIATION	SLV_INTER	3
IT BUSINESS SURVEY: INVESTMENT GDS – LIQUIDITY SITUATION – VARIATION	SLV_INV	3
IT BUSINESS SURVEY: TOTAL – LIQUIDITY SITUATION – VARIATION	SLV_TOT	3
IT BUSINESS SURVEY: CONSUMER GDS – MONEY COST EXPECTATIONS	TCD_C	3
IT BUSINESS SURVEY: INTERMEDIATE GDS – MONEY COST EXPECTATIONS	TCD_INTER	3
IT BUSINESS SURVEY: INVESTMENT GDS – MONEY COST EXPECTATIONS	TCD_INV	3
IT BUSINESS SURVEY: TOTAL – MONEY COST EXPECTATIONS	TCD_TOT	3
IT BUSINESS SURVEY: CONSUMER GDS – LIQUIDITY EXPECTATIONS	TL_C	3
IT BUSINESS SURVEY: INTERMEDIATE GDS – LIQUIDITY EXPECTATIONS	TL_INTER	3
IT BUSINESS SURVEY: INVESTMENT GDS – LIQUIDITY EXPECTATIONS	TL_INV	3
IT BUSINESS SURVEY: TOTAL – LIQUIDITY EXPECTATIONS	TL_TOT	3
IT BUSINESS SURVEY: CONSUMER GDS –PRICES VARIATION	PZV_C	3
IT BUSINESS SURVEY: INTERMEDIATE GDS – PRICES VARIATION	PZV_INTER	3
IT BUSINESS SURVEY: INVESTMENT GDS –PRICES VARIATION	PZV_INV	3
IT BUSINESS SURVEY: TOTAL –PRICES VARIATION	PZV_TOT	3
IT BUSINESS SURVEY: CONSUMER GDS –PRODUCTION VARIATION	PV_C	3
IT BUSINESS SURVEY: INTERMEDIATE GDS – PRODUCTION VARIATION	PV_INTER	3
IT BUSINESS SURVEY: INVESTMENT GDS –PRODUCTION VARIATION	PV_INV	3
IT BUSINESS SURVEY: TOTAL –PRODUCTION VARIATION	PV_TOT	3
		3

PRICES

IT CPI - FOOD	CPIFOOD	
IT PPI	PPI	2
IT PPI - CONSUMER GOODS	PPICONS	2
IT PPI - INVESTMENT GOODS	PPIINV	2
IT PPI - INTERMEDIATE GOODS	PPIINT	2
IT PPI - CLOTHING INDUSTRY	PPICLOTH	2
IT PPI - CHEMICAL PRODUCTS	PPICHE	2
IT PPI - COKE OVENS & OIL REFINING	PPIOIL	2

IT PPI - ELECTRIC ENERGY, GAS AND WATER	PPIENER	2
IT PPI - FOOD AND BEVERAGES	PPIFOOD	2
IT PPI - MANUFACTURING PRODUCTS	PPIMAN	2
IT PPI - MINERALS	PPIMIN	2
IT PPI - MOTOR VEHICLES,TRAILERS AND SIMILAR PRODUCT	PPIMOT	2
IT PPI - OTHER EXTRACTIVE INDUSTRIES	PPIOTHER	2
IT PPI - TEXTILE INDUSTRIES	PPITEX	2
IT TRADE-WIGHTED PRICE INDEX		2
INTERNATIONAL VARIABLES		
US CPI,ALL URBAN SAMPLE: ALL ITEMS-1975=100(DATASTREAM CALC)	USCPI	
BD CPI (1975=100)	CPI_BD	2
TRADE WEIGHTED PPI	PPI_ROW	2
OIL PRICE INDEX	PMCRUDE	2
RAW MATERIALS PRICE INDEX	PMTOT	2
US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP)	DOWJONES	2
US EURO-$ 3 MONTH (LDN:FT) - MIDDLE RATE	RMUS3	2
		2

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Table 1 MSE ratio with the AR model

Quarter ahead Month ahead	1Q 3M	2Q 6M	3Q	4Q 12M	8Q	Sample	Frequency	Nation	Notes
Forecasting inflation S&W				0.84		1984-1996	M	US	1 factor
Forecasting inflation S&W				0.86		1984-1996	M	US	m-factors
Marcellino, Stock, Watson	0.75	0.77				1993-1997	Q	IT	PC country
Marcellino, Stock, Watson	0.78	0.70				1993-1997	Q	EU	PC Euro
Marcellino, Stock, Watson*	2.19	1.67				1993-1997	Q	EU	PC Euro
Marcellino, Stock, Watson**	0.34	0.38				1993-1997	M	EU	PC Euro
Angelici, Henry, Mestre***	0.99	0.99	0.96	0.94	0.79	1992-1999	Q	EU	1 Factors 2 lag
Angelici, Henry, Mestre***	0.89	0.81	1.01	1.16	2.01	1992-1999	Q	EU	2 Factors 2 lag
Angelici, Henry, Mestre***	0.81	0.80	1.03	1.36	2.79	1992-1999	Q	EU	3 Factors 2 lag

** I(2) prices case*
*** Index price is the moving avarege on 3 month*
**** Overall Factors, Balanced Panel*

Table 2 *RMSE of out of sample forecast* ***Sample 1998:1 2004:2***

H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
ARM	0.14	0.22	0.29	0.36	0.44	0.50	0.51	0.58	0.62	0.67	0.73	0.78
BSW	0.14	0.23	0.32	0.34	0.41	0.45	0.50	0.62	0.66	0.79	0.86	0.83

Table 2 - RMSE of autoregressive model(ARM) and autoregressive model with factors (BSW)

Table 3 *RMSE of out of sample forecast* ***Sample 1998:1 2004:2***

H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
ALL	0.05	0.08	0.11	0.13	0.15	0.16	0.18	0.19	0.21	0.23	0.26	0.30
BEST 90%	0.05	0.08	0.11	0.13	0.15	0.16	0.17	0.19	0.21	0.23	0.26	0.29
BEST 80%	0.05	0.08	0.11	0.13	0.15	0.16	0.17	0.19	0.20	0.23	0.25	0.29
BEST 70%	0.05	0.08	0.11	0.13	0.15	0.16	0.17	0.19	0.20	0.22	0.25	0.29
BEST 60%	0.05	0.08	0.11	0.13	0.15	0.16	0.17	0.19	0.20	0.23	0.25	0.29
BEST 50%	0.05	0.08	0.11	0.13	0.15	0.16	0.17	0.19	0.20	0.23	0.25	0.29
BEST 40%	0.05	0.08	0.11	0.13	0.15	0.16	0.17	0.19	0.20	0.23	0.25	0.30
BEST 30%	0.05	0.08	0.11	0.13	0.15	0.15	0.17	0.19	0.21	0.23	0.25	0.30
BEST 20%	0.05	0.08	0.11	0.13	0.15	0.15	0.17	0.19	0.21	0.23	0.26	0.30
BEST 10%	0.05	0.08	0.11	0.13	0.15	0.15	0.17	0.19	0.22	0.25	0.27	0.32
BEST MODEL	0.05	0.07	0.10	0.14	0.16	0.16	0.18	0.21	0.25	0.26	0.28	0.33

Table 3 - RMSE of BESTARMA model – thick modelling approach

Table 4 *RMSE of out of sample forecast* ***Sample 1998:1 2004:2***

H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
BESTARMA Thick	0.05	0.08	0.11	0.13	0.15	0.16	0.18	0.19	0.21	0.23	0.26	0.30
BESTARMA	0.05	0.07	0.10	0.14	0.16	0.16	0.18	0.21	0.25	0.26	0.28	0.33
ARMAMOD	0.07	0.11	0.14	0.16	0.20	0.23	0.27	0.30	0.33	0.37	0.39	0.42
BSW	0.14	0.23	0.32	0.34	0.41	0.45	0.50	0.62	0.66	0.79	0.86	0.83

Figure 1: Inflation -12 month-ahead forecast

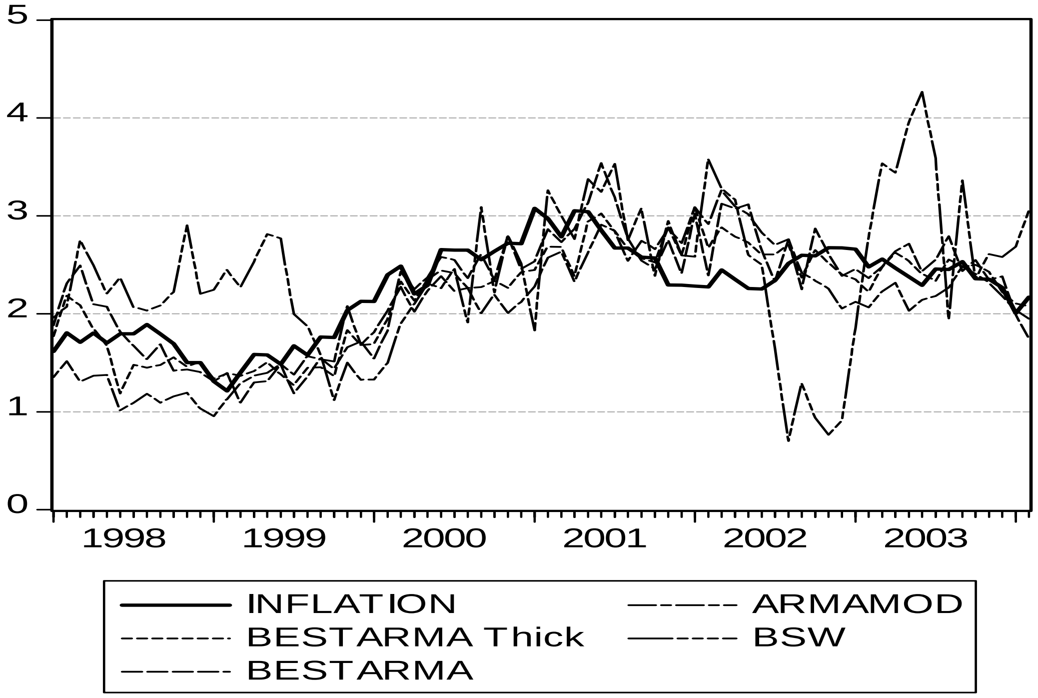
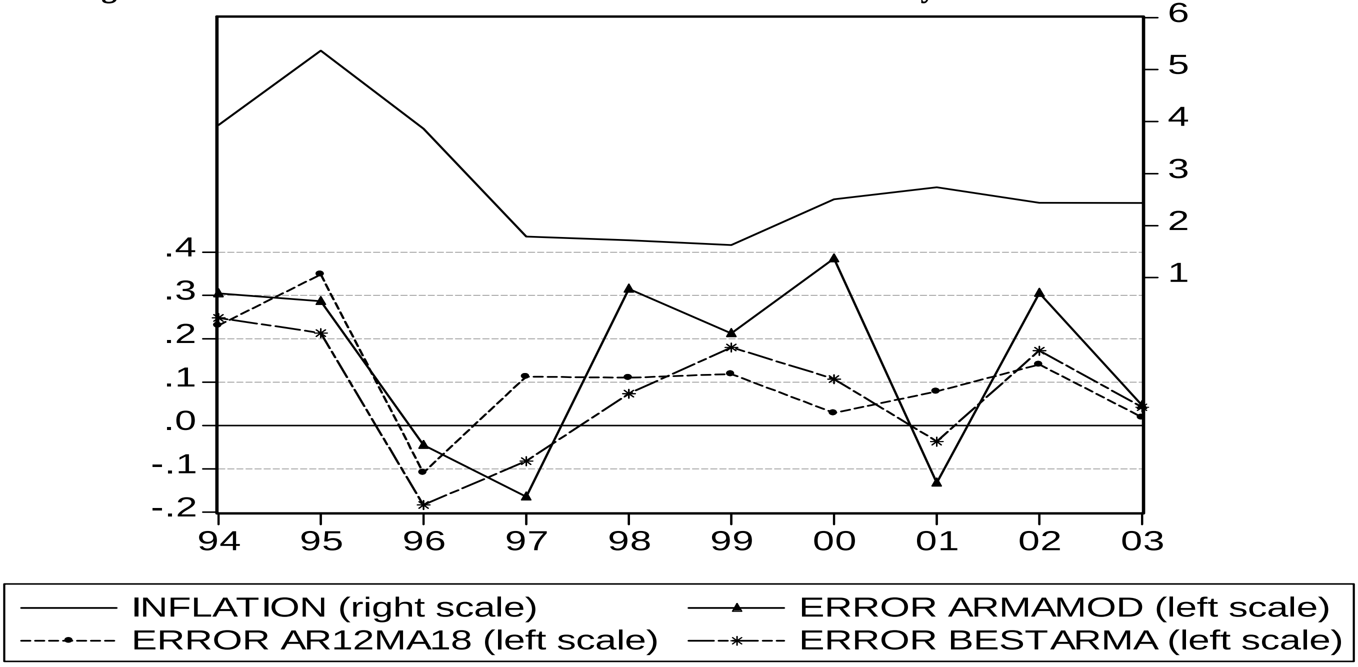


Figure 2: 12 month-ahead forecast made in December of each year



Annual inflation calculated as mean on the annual growth rate (right scale) and forecast calculated on December of the previous year for the next 12 months. ERR is error calculated like Y-Ỹ.

Table 5 *RMSE of out of sample forecast* ***Sample 1994:1 1997:12***

H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
ALL	0.08	0.14	0.18	0.22	0.27	0.32	0.38	0.43	0.49	0.54	0.61	0.72
BEST 90%	0.07	0.14	0.18	0.22	0.27	0.32	0.38	0.43	0.49	0.54	0.61	0.72
BEST 80%	0.07	0.14	0.17	0.22	0.27	0.31	0.38	0.42	0.49	0.53	0.60	0.72
BEST 70%	0.07	0.13	0.17	0.22	0.26	0.31	0.37	0.42	0.48	0.52	0.59	0.72
BEST 60%	0.07	0.13	0.17	0.21	0.26	0.30	0.37	0.41	0.47	0.52	0.59	0.72
BEST 50%	0.07	0.13	0.17	0.21	0.25	0.29	0.36	0.41	0.47	0.51	0.59	0.73
BEST 40%	0.07	0.13	0.17	0.21	0.25	0.29	0.36	0.41	0.47	0.51	0.59	0.73
BEST 30%	0.07	0.13	0.17	0.21	0.25	0.29	0.36	0.41	0.47	0.51	0.60	0.74
BEST 20%	0.07	0.13	0.17	0.21	0.25	0.29	0.36	0.41	0.47	0.51	0.60	0.74
BEST 10%	0.07	0.13	0.16	0.21	0.25	0.29	0.36	0.40	0.47	0.50	0.60	0.73
BEST MODEL	0.07	0.14	0.17	0.22	0.25	0.29	0.37	0.41	0.49	0.53	0.65	0.79

Table 5 - RMSE of BESTARMA model – thick modelling approach

Table 6	*RMSE of out of sample forecast*				***Sample 1994:1 2004:2***							
H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
ALL	0.06	0.11	0.14	0.17	0.21	0.24	0.28	0.31	0.35	0.39	0.44	0.51
BEST 90%	0.06	0.11	0.14	0.17	0.21	0.24	0.28	0.31	0.35	0.39	0.43	0.51
BEST 80%	0.06	0.10	0.14	0.17	0.20	0.23	0.27	0.30	0.35	0.38	0.43	0.51
BEST 70%	0.06	0.10	0.14	0.17	0.20	0.23	0.27	0.30	0.34	0.37	0.42	0.51
BEST 60%	0.06	0.10	0.14	0.17	0.20	0.23	0.27	0.30	0.34	0.37	0.42	0.51
BEST 50%	0.06	0.10	0.14	0.17	0.20	0.22	0.27	0.30	0.34	0.37	0.42	0.51
BEST 40%	0.06	0.10	0.13	0.17	0.20	0.22	0.27	0.30	0.33	0.37	0.42	0.51
BEST 30%	0.06	0.10	0.13	0.17	0.20	0.22	0.27	0.30	0.34	0.37	0.43	0.52
BEST 20%	0.06	0.10	0.13	0.17	0.20	0.22	0.26	0.30	0.34	0.37	0.43	0.52
BEST 10%	0.06	0.10	0.13	0.17	0.20	0.22	0.26	0.29	0.34	0.37	0.43	0.52
BEST MODEL	0.06	0.10	0.13	0.18	0.20	0.23	0.27	0.31	0.37	0.39	0.47	0.56

Table 6 - RMSE of BESTARMA model – thick modelling approach

Table 7	Ratio between Bestarma and other fixed model							***Sample 1994:1 2004:2***				
H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
MA(12)	0.67	0.65	0.64	0.65	0.63	0.64	0.62	0.62	0.63	0.63	0.63	0.67
AR(12)MA(12)	0.69	0.67	0.66	0.69	0.68	0.68	0.65	0.64	0.63	0.64	0.63	0.69
MA(18)	0.83	0.79	0.79	0.83	0.87	0.91	0.90	0.90	0.93	0.95	0.98	0.83
AR(12)MA(18)	0.95	0.90	0.89	0.96	0.98	0.95	0.94	0.92	0.94	0.95	0.98	0.95

Table 7 - Ratio between BESTARMA and other fixed model. Ratios are between mean of all equations forecast in each model. See the text for details.

Table 8	Ratio between Bestarma and other fixed model							***Sample 1994:1 1997:12***				
H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
MA(12)	0.65	0.68	0.65	0.63	0.64	0.62	0.63	0.60	0.60	0.61	0.62	0.63
AR(12)MA(12)	0.59	0.68	0.65	0.64	0.67	0.65	0.66	0.63	0.62	0.61	0.62	0.62
MA(18)	0.77	0.82	0.77	0.78	0.83	0.88	0.92	0.91	0.91	0.93	0.96	1.01
AR(12)MA(18)	0.95	0.97	0.87	0.87	0.95	0.96	0.93	0.92	0.92	0.91	0.93	0.97

Table 8 - Ratio between BESTARMA and other fixed model. Ratios are between mean of all equations forecast in each model. See the text for details.

Table 9	*Ratio between Bestarma and other fixed model*						***Sample 1998:1 2004:2***					
H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
MA(12)	0.59	0.66	0.66	0.65	0.68	0.68	0.70	0.71	0.71	0.73	0.69	0.63
AR(12)MA(12)	0.64	0.72	0.73	0.72	0.74	0.75	0.76	0.75	0.74	0.73	0.70	0.64
MA(18)	0.75	0.84	0.83	0.81	0.85	0.87	0.86	0.87	0.86	0.94	0.92	0.90
AR(12)MA(18)	0.85	0.92	0.97	0.94	0.97	1.03	1.02	0.99	0.96	1.04	1.03	1.03

Ratio between BESTARMA and other fixed model. Ratios are between mean of all equations forecast in each model. See the text for details.

Table 10	*BESTARMA RMSE 5 years window*							***Sample 1994:1 2004:2***				
H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
All	0.13	0.20	0.26	0.34	0.41	0.48	0.56	0.62	0.70	0.77	0.84	0.92
90%	0.13	0.20	0.26	0.34	0.41	0.48	0.55	0.62	0.69	0.77	0.84	0.92
80%	0.13	0.20	0.26	0.34	0.41	0.48	0.55	0.62	0.69	0.77	0.84	0.92
70%	0.13	0.19	0.26	0.34	0.41	0.48	0.55	0.62	0.69	0.77	0.84	0.92
60%	0.13	0.19	0.26	0.34	0.41	0.48	0.55	0.61	0.69	0.77	0.84	0.93
50%	0.13	0.19	0.26	0.34	0.41	0.48	0.55	0.61	0.69	0.77	0.85	0.94
40%	0.13	0.19	0.26	0.34	0.41	0.48	0.55	0.61	0.69	0.77	0.85	0.95
30%	0.13	0.19	0.26	0.34	0.41	0.48	0.55	0.61	0.69	0.77	0.85	0.96
20%	0.13	0.19	0.26	0.34	0.41	0.48	0.56	0.61	0.70	0.78	0.87	0.98
10%	0.13	0.19	0.26	0.34	0.41	0.48	0.56	0.62	0.71	0.79	0.88	1.01
Best	0.13	0.19	0.26	0.34	0.41	0.49	0.58	0.63	0.71	0.81	0.91	1.04

Table 10 - BESTARMA RMSE with a 5 years window in rolling regression

Table 11	*RMSE of out of sample forecast*						***Sample 1994:1 2004:2***					
H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
BESTARMA Thick	0.06	0.07	0.08	0.08	0.07	0.08	0.08	0.07	0.08	0.09	0.10	0.11
BESTARMA	0.06	0.08	0.07	0.10	0.07	0.08	0.09	0.11	0.12	0.11	0.14	0.19
ARMAMOD	0.08	0.09	0.10	0.09	0.10	0.09	0.09	0.10	0.10	0.10	0.10	0.10

Table 11 – RMSE of Δp_{t+h} forecast

Table 12	*RMSE of out of sample forecast*						***Sample 1994:1 2004:2***					
H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
BESTARMA Thick	0.06	0.11	0.14	0.17	0.21	0.24	0.28	0.31	0.35	0.39	0.44	0.51
ARMAMOD	0.09	0.15	0.20	0.24	0.29	0.33	0.39	0.44	0.50	0.57	0.62	0.68
VAR	0.19	0.30	0.40	0.49	0.59	0.68	0.78	0.87	0.97	1.05	1.11	1.18
NAÏVE	0.20	0.31	0.41	0.51	0.61	0.70	0.79	0.88	0.96	1.03	1.10	1.16

Table 12 – RMSE of inflation forecasts

Table 13 - Predictive accuracy test on the yearly growth rates forecast of CPI, comparing BESTARMA versus column-signed model

	H	1	2	3	4	5	6	7	8	9	10	11	12
VAR	DM MSE	-6.85 (0.00)	-3.98 (0.00)	-4.33 (0.00)	-4.43 (0.00)	-4.93 (0.00)	-5.01 (0.00)	-5.12 (0.00)	-5.09 (0.00)	-4.91 (0.00)	-4.92 (0.00)	-4.80 (0.00)	-4.94 (0.00)
	DM* MSE	-6.82 (0.00)	-3.93 (0.00)	-4.24 (0.00)	-4.30 (0.00)	-4.75 (0.00)	-4.78 (0.00)	-4.84 (0.00)	-4.77 (0.00)	-4.56 (0.00)	-4.53 (0.00)	-4.38 (0.00)	-4.47 (0.00)
	DM MAE	-10.72 (0.00)	-6.90 (0.00)	-6.07 (0.00)	-6.03 (0.00)	-7.24 (0.00)	-8.00 (0.00)	-7.58 (0.00)	-7.18 (0.00)	-7.25 (0.00)	-7.15 (0.00)	-6.71 (0.00)	-6.42 (0.00)
	DM* MAE	-10.68 (0.00)	-6.82 (0.00)	-5.94 (0.00)	-5.85 (0.00)	-6.97 (0.00)	-7.64 (0.00)	-7.17 (0.00)	-6.73 (0.00)	-6.74 (0.00)	-6.59 (0.00)	-6.13 (0.00)	-5.81 (0.00)
ARMAMOD	DM MSE	-4.52 (0.00)	-2.92 (0.01)	-3.13 (0.00)	-3.44 (0.00)	-3.41 (0.00)	-3.93 (0.00)	-4.76 (0.00)	-4.34 (0.00)	-4.51 (0.00)	-4.69 (0.00)	-4.19 (0.00)	-3.67 (0.00)
	DM* MSE	-4.50 (0.00)	-2.88 (0.01)	-3.06 (0.00)	-3.34 (0.00)	-3.29 (0.00)	-3.75 (0.00)	-4.51 (0.00)	-4.07 (0.00)	-4.19 (0.00)	-4.32 (0.00)	-3.83 (0.00)	-3.33 (0.00)
	DM MAE	-5.62 (0.00)	-3.09 (0.00)	-3.69 (0.00)	-4.12 (0.00)	-4.48 (0.00)	-5.92 (0.00)	-7.32 (0.00)	-7.39 (0.00)	-7.99 (0.00)	-7.56 (0.00)	-6.43 (0.00)	-5.16 (0.00)
	DM* MAE	-5.60 (0.00)	-3.05 (0.00)	-3.61 (0.00)	-4.00 (0.00)	-4.32 (0.00)	-5.65 (0.00)	-6.93 (0.00)	-6.93 (0.00)	-7.43 (0.00)	-6.97 (0.00)	-5.88 (0.00)	-4.67 (0.00)
BESTARMA Best Equation	DM MSE	0.79 (0.29)	0.60 (0.33)	1.23 (0.19)	-0.42 (0.36)	0.62 (0.33)	1.37 (0.16)	0.61 (0.33)	0.14 (0.40)	-0.53 (0.35)	-0.20 (0.39)	-0.76 (0.30)	-1.66 (0.10)
	DM* MSE	0.78 (0.29)	0.59 (0.33)	1.21 (0.19)	-0.41 (0.37)	0.59 (0.33)	1.31 (0.17)	0.58 (0.34)	0.13 (0.39)	-0.50 (0.35)	-0.18 (0.39)	-0.69 (0.31)	-1.51 (0.13)
	DM MAE	1.33 (0.17)	0.58 (0.34)	1.67 (0.10)	-0.54 (0.35)	-0.07 (0.40)	0.74 (0.30)	0.85 (0.28)	0.02 (0.40)	-0.29 (0.38)	0.14 (0.40)	0.05 (0.40)	-1.05 (0.23)
	DM* MAE	1.32 (0.17)	0.57 (0.34)	1.64 (0.10)	-0.52 (0.35)	-0.07 (0.40)	0.71 (0.31)	0.80 (0.29)	0.02 (0.40)	-0.27 (0.38)	0.13 (0.39)	0.05 (0.40)	-0.95 (0.25)
NAIVE	DM MSE	-6.18 (0.00)	-3.67 (0.00)	-4.02 (0.00)	-4.24 (0.00)	-4.74 (0.00)	-4.91 (0.00)	-5.09 (0.00)	-5.10 (0.00)	-4.93 (0.00)	-4.89 (0.00)	-4.78 (0.00)	-4.77 (0.00)
	DM* MSE	-6.15 (0.00)	-3.63 (0.00)	-3.93 (0.00)	-4.11 (0.00)	-4.56 (0.00)	-4.69 (0.00)	-4.81 (0.00)	-4.79 (0.00)	-4.58 (0.00)	-4.51 (0.00)	-4.36 (0.00)	-4.32 (0.00)
	DM MAE	-9.17 (0.00)	-6.34 (0.00)	-5.60 (0.00)	-5.92 (0.00)	-6.63 (0.00)	-7.16 (0.00)	-7.43 (0.00)	-7.30 (0.00)	-7.20 (0.00)	-6.92 (0.00)	-6.25 (0.00)	-5.81 (0.00)
	DM* MAE	-9.14 (0.00)	-6.26 (0.00)	-5.49 (0.00)	-5.75 (0.00)	-6.39 (0.00)	-6.83 (0.00)	-7.03 (0.00)	-6.84 (0.00)	-6.69 (0.00)	-6.38 (0.00)	-5.71 (0.00)	-5.26 (0.00)

Table 14 - Predictive accuracy test on the <u>monthly growth rates</u> forecast of CPI, comparing BESTARMA versus column-signed model

	H	1	2	3	4	5	6	7	8	9	10	11	12
VAR	DM MSE	-6.92 (0.00)	-5.24 (0.00)	-5.52 (0.00)	-5.00 (0.00)	-6.29 (0.00)	-6.22 (0.00)	-6.00 (0.00)	-6.11 (0.00)	-5.27 (0.00)	-5.75 (0.00)	-6.24 (0.00)	-4.74 (0.00)
	DM* MSE	-6.89 (0.00)	-5.17 (0.00)	-5.41 (0.00)	-4.85 (0.00)	-6.05 (0.00)	-5.94 (0.00)	-5.68 (0.00)	-5.73 (0.00)	-4.90 (0.00)	-5.30 (0.00)	-5.70 (0.00)	-4.29 (0.00)
	DM MAE	-10.78 (0.00)	-8.90 (0.00)	-7.66 (0.00)	-6.97 (0.00)	-9.50 (0.00)	-8.66 (0.00)	-9.46 (0.00)	-8.43 (0.00)	-7.64 (0.00)	-9.00 (0.00)	-8.83 (0.00)	-6.56 (0.00)
	DM* MAE	-10.74 (0.00)	-8.79 (0.00)	-7.50 (0.00)	-6.77 (0.00)	-9.15 (0.00)	-8.26 (0.00)	-8.95 (0.00)	-7.91 (0.00)	-7.11 (0.00)	-8.30 (0.00)	-8.07 (0.00)	-5.93 (0.00)
ARMAMOD	DM MSE	-4.54 (0.00)	-3.10 (0.00)	-2.37 (0.02)	-3.55 (0.00)	-3.05 (0.00)	-3.73 (0.00)	-2.87 (0.01)	-3.48 (0.00)	-2.50 (0.02)	-3.23 (0.00)	-0.80 (0.29)	1.10 (0.22)
	DM* MSE	-4.53 (0.00)	-3.06 (0.00)	-2.33 (0.03)	-3.45 (0.00)	-2.94 (0.01)	-3.56 (0.00)	-2.72 (0.01)	-3.27 (0.00)	-2.32 (0.03)	-2.98 (0.01)	-0.73 (0.31)	0.99 (0.24)
	DM MAE	-5.62 (0.00)	-3.10 (0.00)	-3.15 (0.00)	-2.63 (0.01)	-4.41 (0.00)	-4.91 (0.00)	-2.65 (0.01)	-3.94 (0.00)	-2.54 (0.02)	-3.35 (0.00)	-1.50 (0.13)	1.45 (0.14)
	DM* MAE	-5.60 (0.00)	-3.07 (0.00)	-3.09 (0.00)	-2.56 (0.02)	-4.24 (0.00)	-4.69 (0.00)	-2.51 (0.02)	-3.70 (0.00)	-2.36 (0.03)	-3.08 (0.00)	-1.37 (0.16)	1.31 (0.17)
BESTARMA Best Equation	DM MSE	0.76 (0.30)	-1.19 (0.20)	0.61 (0.33)	-4.86 (0.00)	-0.01 (0.40)	0.33 (0.38)	-1.85 (0.07)	-3.67 (0.00)	-3.73 (0.00)	-3.40 (0.00)	-4.06 (0.00)	-4.41 (0.00)
	DM* MSE	0.76 (0.30)	-1.17 (0.20)	0.60 (0.33)	-4.72 (0.00)	-0.01 (0.40)	0.31 (0.38)	-1.75 (0.09)	-3.44 (0.00)	-3.47 (0.00)	-3.13 (0.00)	-3.71 (0.00)	-3.99 (0.00)
	DM MAE	1.31 (0.17)	0.02 (0.40)	0.37 (0.37)	-4.64 (0.00)	-0.39 (0.37)	-0.68 (0.32)	-2.56 (0.02)	-4.10 (0.00)	-4.78 (0.00)	-3.06 (0.00)	-5.53 (0.00)	-5.94 (0.00)
	DM* MAE	1.30 (0.17)	0.02 (0.40)	0.37 (0.37)	-4.51 (0.00)	-0.37 (0.37)	-0.65 (0.32)	-2.42 (0.02)	-3.84 (0.00)	-4.45 (0.00)	-2.82 (0.01)	-5.05 (0.00)	-5.38 (0.00)

Table 15 - Diebold & Mariano test with 12-step ahead forecast of inflation (cpi annual growth rate) – MSE

	VAR		ARMAMOD		BESTARMA b.e.		NAIVE	
	DM	DM*	DM	DM*	DM	DM*	DM	DM*
BESTARMA	4.94 (0.00)	4.47 (0.00)	3.67 (0.00)	3.33 (0.00)	1.66 (0.10)	1.51 (0.13)	-4.77 (0.00)	-4.32 (0.00)
VAR	-	-	4.54 (0.00)	4.11 (0.00)	-4.89 (0.00)	-4.42 (0.00)	2.27 (0.03)	2.05 (0.05)
ARMAMOD	-	-	-	-	-2.20 (0.04)	-1.99 (0.06)	-4.18 (0.00)	-3.78 (0.00)
BESTARMA b.e.	-	-	-	-	-	-	-4.77 (0.00)	-4.32 (0.00)

Table 16 - Diebold & Mariano test with 12-step ahead forecast of inflation (cpi annual growth rate) - MAE

	VAR		ARMAMOD		BESTARMA b.e.		NAIVE	
	DM	DM*	DM	DM*	DM	DM*	DM	DM*
BESTARMA	6.42 (0.00)	5.81 (0.00)	5.16 (0.00)	4.67 (0.00)	1.05 (0.23)	0.95 (0.25)	-5.81 (0.00)	-5.26 (0.00)
VAR	-	-	5.02 (0.00)	4.54 (0.00)	-6.32 (0.00)	-5.72 (0.00)	1.93 (0.06)	1.74 (0.09)
ARMAMOD	-	-	-	-	-2.87 (0.01)	-2.59 (0.01)	-4.17 (0.00)	-3.78 (0.00)
BESTARMA b.e.	-	-	-	-	-	-	-5.78 (0.00)	-5.23 (0.00)

Table 17 - Diebold & Mariano test with 12-step ahead forecast of cpi monthly growth - MSE

	VAR		ARMAMOD		BESTARMA b.e.		NAIVE	
	DM	DM*	DM	DM*	DM	DM*	DM	DM*
BESTARMA	4.74 (0.00)	4.29 (0.00)	-1.10 (0.22)	-0.99 (0.24)	4.41 (0.00)	3.99 (0.00)	-4.55 (0.00)	-4.11 (0.00)
VAR	-	-	4.67 (0.00)	4.23 (0.00)	-0.14 (0.40)	-0.12 (0.40)	-0.27 (0.38)	-0.25 (0.39)
ARMAMOD	-	-	-	-	4.00 (0.00)	3.62 (0.00)	-4.55 (0.00)	-4.12 (0.00)
BESTARMA b.e.	-	-	-	-	-	-	-0.18 (0.39)	-0.16 (0.39)

Table 18 - Diebold & Mariano test with 12-step ahead forecast of cpi monthly growth - MAE

	VAR		ARMAMOD		BESTARMA b.e.		NAIVE	
	DM	DM*	DM	DM*	DM	DM*	DM	DM*
BESTARMA	6.56 (0.00)	5.93 (0.00)	-1.45 (0.14)	-1.31 (0.17)	5.94 (0.00)	5.38 (0.00)	-5.96 (0.00)	-5.40 (0.00)
VAR	-	-	7.25 (0.00)	6.56 (0.00)	-0.61 (0.33)	-0.55 (0.34)	0.90 (0.27)	0.81 (0.29)
ARMAMOD	-	-	-	-	5.63 (0.00)	5.10 (0.00)	-6.64 (0.00)	-6.01 (0.00)
BESTARMA b.e.	-	-	-	-	-	-	-0.33 (0.38)	-0.30 (0.38)

Table 19	*ALL - INFO /BESTARMA RMSE ratio*					***Sample 1994:1 2004:2***						
H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
All	1.02	0.98	0.98	0.99	0.98	0.98	0.99	0.99	1.00	1.00	1.00	1.00
90%	1.03	0.99	0.99	0.99	0.98	0.98	1.00	1.00	1.00	1.00	1.00	1.01
80%	1.04	0.99	0.99	1.00	0.99	0.98	1.00	1.00	1.00	1.00	1.00	1.01
70%	1.04	1.00	0.99	1.00	0.99	0.99	1.01	1.01	1.01	1.01	1.01	1.01
60%	1.05	1.01	1.00	1.01	1.00	0.99	1.01	1.01	1.01	1.01	1.01	1.01
50%	1.06	1.02	1.00	1.01	0.99	0.99	1.01	1.01	1.01	1.01	1.00	1.00
40%	1.07	1.02	1.00	1.02	0.99	0.99	1.01	1.00	1.00	1.00	1.00	1.00
30%	1.07	1.01	1.00	1.01	0.99	0.99	1.01	1.01	1.00	1.00	1.00	1.00
20%	1.08	1.01	1.00	1.01	0.99	0.98	1.01	1.01	1.00	1.00	1.00	0.99
10%	1.10	1.04	1.01	1.02	0.99	0.99	1.02	1.01	1.01	1.01	1.02	1.01
Best	1.12	1.02	1.01	1.01	0.99	1.00	1.03	1.01	1.01	1.01	1.00	0.99

Table 19 – Ratio of RMSE between BESTARMA with all information in dataset and BESTARMA with real information

Table 20 BESTARMA CORE / BESTARMA RMSE ratio						***Sample 1994:1 2004:2***						
H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
All	0.94	0.81	0.84	0.91	0.88	0.86	0.85	0.85	0.83	0.79	0.79	0.75
90%	0.96	0.83	0.84	0.91	0.88	0.87	0.85	0.85	0.83	0.80	0.79	0.75
80%	0.97	0.84	0.84	0.91	0.89	0.87	0.85	0.85	0.84	0.81	0.80	0.75
70%	0.98	0.84	0.84	0.91	0.90	0.88	0.86	0.86	0.85	0.82	0.81	0.75
60%	0.99	0.86	0.84	0.91	0.90	0.89	0.86	0.87	0.85	0.82	0.81	0.75
50%	1.01	0.87	0.83	0.91	0.91	0.90	0.87	0.88	0.86	0.83	0.82	0.74
40%	1.00	0.87	0.83	0.91	0.90	0.90	0.87	0.88	0.88	0.85	0.83	0.75
30%	0.99	0.86	0.83	0.90	0.90	0.89	0.87	0.88	0.89	0.86	0.83	0.75
20%	0.98	0.85	0.82	0.89	0.89	0.90	0.87	0.89	0.89	0.86	0.84	0.75
10%	0.96	0.86	0.83	0.89	0.89	0.91	0.88	0.91	0.90	0.89	0.86	0.78
Best	0.92	0.84	0.85	0.85	0.89	0.93	0.88	0.90	0.87	0.90	0.86	0.78
ARMAMOD	0.91	0.81	0.80	0.85	0.85	0.84	0.80	0.79	0.75	0.72	0.71	0.70

Table 20 - Ratio between RMSE Bestarma core inflation with RMSE Bestarma

Table 21 BESTARMA CORE / BESTARMA RMSE ratio ***Sample 1994:1 1997:12***

H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
All	0.94	0.74	0.77	0.86	0.82	0.80	0.79	0.79	0.77	0.74	0.76	0.72
90%	0.97	0.75	0.77	0.85	0.82	0.80	0.78	0.78	0.77	0.74	0.75	0.71
80%	0.97	0.76	0.77	0.85	0.82	0.80	0.79	0.78	0.77	0.75	0.76	0.71
70%	0.98	0.78	0.76	0.86	0.83	0.81	0.79	0.79	0.78	0.76	0.76	0.71
60%	1.01	0.80	0.76	0.86	0.84	0.82	0.80	0.80	0.78	0.76	0.76	0.70
50%	1.03	0.82	0.75	0.87	0.85	0.83	0.81	0.80	0.80	0.77	0.76	0.69
40%	1.02	0.82	0.75	0.87	0.84	0.83	0.81	0.81	0.81	0.79	0.78	0.69
30%	1.01	0.80	0.75	0.86	0.83	0.83	0.81	0.81	0.83	0.80	0.79	0.69
20%	1.00	0.79	0.73	0.84	0.82	0.84	0.81	0.82	0.84	0.81	0.80	0.70
10%	0.97	0.79	0.73	0.83	0.80	0.84	0.83	0.86	0.86	0.84	0.82	0.74
Best	0.92	0.76	0.72	0.81	0.82	0.86	0.82	0.85	0.83	0.84	0.81	0.72
ARMAMOD	0.86	0.80	0.78	0.83	0.84	0.84	0.80	0.80	0.75	0.73	0.71	0.69

Table 21 - Ratio between RMSE Bestarma core inflation with RMSE Bestarma

Table 22 BESTARMA CORE / BESTARMA RMSE ratio ***Sample 1998:1 2004:2***

H	*+1*	*+2*	*+3*	*+4*	*+5*	*+6*	*+7*	*+8*	*+9*	*+10*	*+11*	*+12*
All	0.94	0.94	0.95	1.00	1.00	1.01	1.01	1.03	1.01	0.95	0.91	0.88
90%	0.96	0.96	0.96	1.00	1.01	1.03	1.03	1.05	1.02	0.97	0.92	0.88
80%	0.96	0.96	0.96	1.01	1.01	1.03	1.04	1.06	1.04	0.98	0.93	0.89
70%	0.97	0.96	0.96	1.00	1.01	1.04	1.05	1.07	1.06	1.00	0.96	0.91
60%	0.98	0.96	0.95	0.99	1.01	1.03	1.03	1.07	1.06	1.01	0.97	0.92
50%	0.98	0.95	0.94	0.97	1.00	1.03	1.03	1.08	1.07	1.02	0.99	0.94
40%	0.98	0.95	0.94	0.98	1.01	1.03	1.03	1.07	1.07	1.02	0.99	0.94
30%	0.97	0.95	0.95	0.97	1.01	1.03	1.03	1.07	1.06	1.02	0.99	0.93
20%	0.95	0.95	0.95	0.97	1.02	1.03	1.03	1.06	1.04	1.01	0.99	0.94
10%	0.95	0.97	0.96	0.98	1.03	1.05	1.04	1.04	1.01	0.99	0.96	0.91
Best	0.91	1.00	1.05	0.91	0.98	1.07	1.05	1.03	0.98	1.05	1.00	0.97
ARMAMOD	0.99	0.83	0.84	0.89	0.87	0.82	0.81	0.78	0.73	0.71	0.71	0.70

Table 22 - Ratio between RMSE Bestarma core inflation with RMSE Bestarma

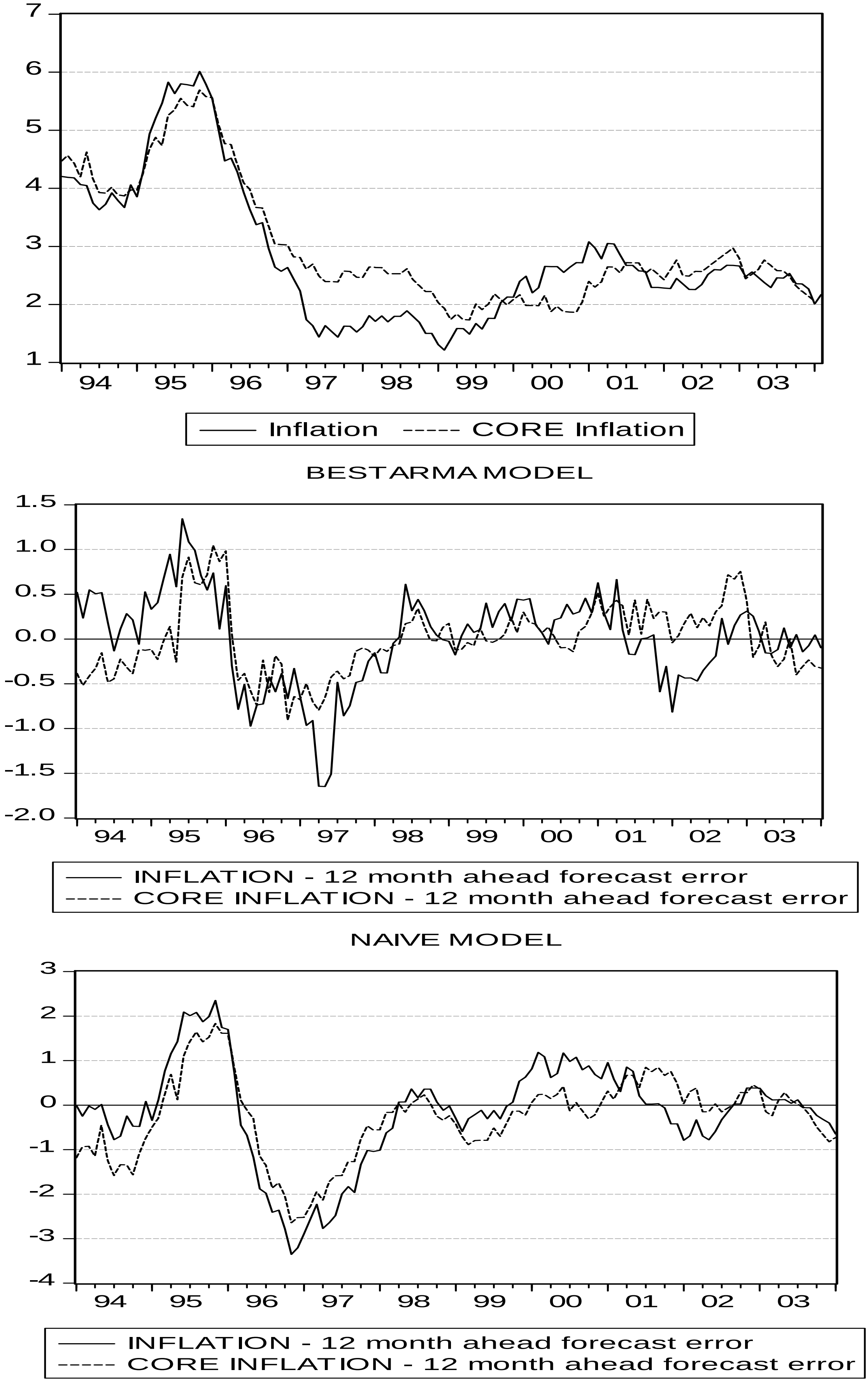


Figure 3 Error generated by Naïve model and BESTARMA model to forecasting"normal" and CORE Inflation

Table 23 RMSE of out of sample forecast ***Sample 1998:1 2004:2***

H	+13	+14	+15	+16	+17	+18	+19	+20	+21	+22	+23	+24
All	0.31	0.32	0.33	0.35	0.37	0.43	0.54	0.65	0.79	0.94	0.99	0.97
90%	0.31	0.32	0.34	0.35	0.37	0.44	0.55	0.65	0.79	0.95	1.00	0.97
80%	0.31	0.32	0.34	0.36	0.37	0.44	0.55	0.65	0.79	0.96	1.00	0.97
70%	0.31	0.32	0.34	0.36	0.38	0.45	0.56	0.66	0.80	0.97	1.01	0.97
60%	0.31	0.32	0.34	0.37	0.39	0.46	0.58	0.67	0.82	1.00	1.04	0.98
50%	0.31	0.32	0.35	0.39	0.40	0.48	0.60	0.70	0.85	1.02	1.06	0.99
40%	0.31	0.33	0.36	0.41	0.42	0.50	0.62	0.71	0.86	1.05	1.08	1.00
30%	0.32	0.34	0.37	0.43	0.44	0.52	0.63	0.72	0.88	1.07	1.10	1.02
20%	0.32	0.35	0.38	0.44	0.46	0.54	0.64	0.71	0.89	1.10	1.13	1.04
10%	0.34	0.37	0.41	0.46	0.48	0.56	0.67	0.73	0.90	1.13	1.16	1.08
Best	0.36	0.39	0.47	0.51	0.54	0.61	0.73	0.80	0.97	1.21	1.24	1.17
ARMAMOD	0.45	0.46	0.44	0.47	0.51	0.59	0.67	0.79	0.88	1.00	1.06	1.13
ARMAMOD with BESTARMA	0.32	0.35	0.36	0.38	0.41	0.48	0.57	0.70	0.84	0.99	1.08	1.13

Table23 – BESTARMA RMSE 13-24 month ahead forecast
Note: In the last line ARMAMOD with BESTARMA forecasts with BESTARMA until 12th month ahead and then innests ARMAMOD's forecast

Table 24 RMSE of out of sample forecast ***Sample 1995:1 2004:2***

H	*+13*	*+14*	*+15*	*+16*	*+17*	*+18*	*+19*	*+20*	*+21*	*+22*	*+23*	*+24*
All	0.55	0.57	0.59	0.62	0.65	0.70	0.78	0.84	0.91	1.03	1.09	1.14
90%	0.55	0.56	0.58	0.61	0.64	0.70	0.77	0.83	0.90	1.03	1.09	1.14
80%	0.55	0.56	0.58	0.61	0.64	0.69	0.77	0.82	0.89	1.02	1.08	1.12
70%	0.55	0.56	0.57	0.61	0.64	0.70	0.78	0.83	0.89	1.03	1.09	1.12
60%	0.55	0.56	0.57	0.61	0.64	0.70	0.79	0.83	0.90	1.04	1.10	1.13
50%	0.56	0.56	0.57	0.61	0.64	0.71	0.81	0.84	0.91	1.06	1.12	1.13
40%	0.56	0.56	0.57	0.61	0.64	0.72	0.82	0.85	0.91	1.07	1.13	1.14
30%	0.57	0.57	0.57	0.62	0.65	0.73	0.82	0.85	0.92	1.08	1.14	1.15
20%	0.57	0.56	0.57	0.62	0.66	0.74	0.82	0.84	0.91	1.09	1.15	1.16
10%	0.57	0.57	0.57	0.63	0.68	0.75	0.85	0.86	0.92	1.11	1.17	1.19
Best	0.60	0.61	0.63	0.68	0.74	0.83	0.93	0.93	0.99	1.20	1.26	1.30
ARMAMOD	0.77	0.79	0.83	0.85	0.88	0.92	0.98	1.05	1.10	1.13	1.20	1.26
ARMAMOD with BESTARMA	0.58	0.64	0.71	0.74	0.78	0.84	0.91	1.00	1.07	1.14	1.21	1.26

Table 24 – BESTARMA RMSE 13-24 month ahead forecast
Note: In the last line ARMAMOD with BESTARMA forecasts with BESTARMA until 12th month ahead and then innests ARMAMOD's forecast

Table 25 – RMSE of Δp_{t+h} out of sample forecast **Sample 1998:1 2004:2**

H	*+13*	*+14*	*+15*	*+16*	*+17*	*+18*	*+19*	*+20*	*+21*	*+22*	*+23*	*+24*
All	0.07	0.07	0.07	0.09	0.08	0.12	0.13	0.11	0.15	0.17	0.13	0.14
90%	0.07	0.07	0.07	0.09	0.08	0.13	0.14	0.11	0.16	0.18	0.13	0.13
80%	0.07	0.07	0.07	0.09	0.08	0.13	0.15	0.11	0.15	0.19	0.13	0.13
70%	0.07	0.07	0.08	0.09	0.08	0.14	0.16	0.11	0.15	0.20	0.13	0.13
60%	0.08	0.07	0.08	0.09	0.08	0.14	0.17	0.11	0.16	0.21	0.13	0.14
50%	0.08	0.07	0.08	0.10	0.09	0.15	0.18	0.11	0.16	0.22	0.13	0.14
40%	0.08	0.07	0.09	0.10	0.09	0.15	0.18	0.12	0.17	0.22	0.13	0.14
30%	0.09	0.08	0.09	0.11	0.09	0.15	0.18	0.12	0.18	0.23	0.14	0.15
20%	0.09	0.08	0.09	0.11	0.10	0.15	0.18	0.12	0.19	0.24	0.15	0.15
10%	0.10	0.09	0.10	0.11	0.12	0.16	0.19	0.12	0.20	0.26	0.15	0.16
Best	0.12	0.11	0.13	0.12	0.14	0.18	0.22	0.18	0.26	0.28	0.17	0.20
ARMAMOD	0.09	0.09	0.08	0.09	0.09	0.10	0.11	0.14	0.14	0.15	0.16	0.16

Table 25 – BESTARMA 13-24 month ahead forecast: RMSE of Δp_{t+h} out of sample forecast

Table 26 – RMSE of Δp_{t+h} out of sample forecast **Sample 1995:1 2004:2**

H	*+13*	*+14*	*+15*	*+16*	*+17*	*+18*	*+19*	*+20*	*+21*	*+22*	*+23*	*+24*
All	0.09	0.09	0.09	0.12	0.11	0.14	0.17	0.14	0.16	0.21	0.18	0.19
90%	0.09	0.08	0.09	0.12	0.11	0.14	0.17	0.14	0.16	0.21	0.18	0.19
80%	0.09	0.09	0.09	0.12	0.11	0.15	0.18	0.14	0.16	0.22	0.18	0.19
70%	0.09	0.09	0.09	0.13	0.11	0.15	0.19	0.13	0.16	0.23	0.19	0.20
60%	0.09	0.09	0.09	0.13	0.11	0.15	0.20	0.13	0.16	0.24	0.19	0.20
50%	0.10	0.09	0.09	0.14	0.11	0.16	0.21	0.13	0.16	0.24	0.20	0.20
40%	0.10	0.09	0.09	0.14	0.11	0.16	0.22	0.14	0.16	0.26	0.21	0.21
30%	0.10	0.10	0.09	0.15	0.12	0.17	0.22	0.15	0.17	0.27	0.22	0.21
20%	0.11	0.10	0.10	0.16	0.13	0.17	0.22	0.15	0.18	0.29	0.23	0.22
10%	0.12	0.10	0.11	0.17	0.14	0.19	0.24	0.16	0.19	0.31	0.25	0.24
Best	0.14	0.12	0.13	0.18	0.16	0.22	0.28	0.19	0.25	0.34	0.26	0.28
ARMAMOD	0.11	0.12	0.14	0.12	0.13	0.14	0.16	0.17	0.16	0.17	0.18	0.18

Table 26– BESTARMA 13-24 month ahead forecast: RMSE of Δp_{t+h} out of sample forecast

Table 27 – Turning Point Detection: TPE and Diebold and Mariano Tests

H	*TPE bestarma*	*TPE var*	*DM*	*DM_S**
1	0.10	0.30	-4.00 (0.00)	-3.99 (0.00)
2	0.10	0.29	-2.54 (0.02)	-2.51 (0.02)
3	0.13	0.32	-2.75 (0.01)	-2.70 (0.01)
4	0.14	0.32	-2.66 (0.01)	-2.59 (0.01)
5	0.14	0.34	-2.70 (0.01)	-2.61 (0.01)
6	0.18	0.32	-2.10 (0.04)	-2.02 (0.05)
7	0.20	0.31	-1.76 (0.09)	-1.67 (0.10)
8	0.22	0.28	-1.04 (0.23)	-0.98 (0.25)
9	0.22	0.32	-1.76 (0.08)	-1.65 (0.10)
10	0.22	0.32	-1.94 (0.06)	-1.80 (0.08)
11	0.24	0.33	-1.48 (0.13)	-1.36 (0.16)
12	0.22	0.32	-1.88 (0.07)	-1.72 (0.09)
13	0.28	0.34	-1.09 (0.22)	-0.98 (0.24)
14	0.29	0.35	-1.20 (0.19)	-1.08 (0.22)
15	0.30	0.37	-1.48 (0.13)	-1.32 (0.17)
16	0.31	0.38	-1.57 (0.12)	-1.39 (0.15)
17	0.31	0.39	-2.01 (0.05)	-1.76 (0.08)
18	0.32	0.39	-1.52 (0.13)	-1.32 (0.17)
19	0.32	0.39	-1.52 (0.12)	-1.31 (0.17)
20	0.32	0.39	-1.74 (0.09)	-1.49 (0.13)
21	0.32	0.39	-1.62 (0.11)	-1.37 (0.15)
22	0.32	0.39	-1.62 (0.11)	-1.36 (0.16)
23	0.32	0.39	-1.68 (0.10)	-1.39 (0.15)
24	0.32	0.39	-1.68 (0.10)	-1.38 (0.15)
Mean	0.24	0.35		

Table 28 –Turning Point detection: Timmermann and Pesaran Tests REALTIME versus BESTARMA and VAR models

H	BESTARMA	VAR
1	9.19 (0.00)	5.30 (0.00)
2	8.97 (0.00)	5.41 (0.00)
3	8.37 (0.00)	4.68 (0.00)
4	8.05 (0.00)	4.68 (0.00)
5	8.21 (0.00)	4.18 (0.00)
6	7.51 (0.00)	4.68 (0.00)
7	7.12 (0.00)	4.93 (0.00)
8	6.43 (0.00)	5.43 (0.00)
9	6.47 (0.00)	4.86 (0.00)
10	6.40 (0.00)	4.88 (0.00)
11	6.10 (0.00)	4.91 (0.00)
12	6.67 (0.00)	5.16 (0.00)
13	5.54 (0.00)	5.06 (0.00)
14	5.42 (0.00)	4.68 (0.00)
15	5.30 (0.00)	4.30 (0.00)
16	5.04 (0.00)	3.93 (0.00)
17	5.17 (0.00)	3.67 (0.00)
18	4.71 (0.00)	3.67 (0.00)
19	4.71 (0.00)	3.67 (0.00)
20	4.71 (0.00)	3.67 (0.00)
21	4.71 (0.00)	3.67 (0.00)
22	4.71 (0.00)	3.67 (0.00)
23	4.71 (0.00)	3.67 (0.00)
24	4.71 (0.00)	3.67 (0.00)

Table 29 – BESTARMA model 's TPE. with h=24.

	0	1	2	3	4	5	6	7	8	9	10	11	12
2	0.33	0.32	0.29	0.29	0.24	0.26	0.25	0.25	0.25	0.25	0.25	0.27	0.27
3	0.37	0.35	0.32	0.34	0.28	0.27	0.25	0.25	0.26	0.26	0.26	0.27	0.27
4	0.43	0.40	0.36	0.35	0.30	0.27	0.25	0.25	0.27	0.27	0.27	0.28	0.28

Table 29 – BESTARMA Model's TPE. Different strategies for h=24. Columns represents the maximum months tolerated from the first signal, rows the consecutive signals accepted

Table 30 – VAR model 's TPE. with h=24.

	0	1	2	3	4	5	6	7	8	9	10	11	12
2	0.53	0.48	0.44	0.45	0.44	0.45	0.42	0.41	0.41	0.41	0.41	0.41	0.41
3	0.54	0.53	0.49	0.50	0.50	0.51	0.47	0.45	0.45	0.44	0.43	0.43	0.43
4	0.54	0.55	0.52	0.53	0.51	0.54	0.51	0.49	0.48	0.47	0.46	0.46	0.46

Table 30 – BESTARMA Model's TPE. Different strategies for h=24. Columns represents the maximum months tolerated from the first signal, rows the consecutive signals accepted

Table 31 – BESTARMA model 's Timmermann test with h=24.

	0	1	2	3	4	5	6	7	8	9	10	11	12
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.14	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 31 – BESTARMA Model's TPE. Different strategies for h=24. Columns represents the maximum months tolerated from the first signal, rows the consecutive signals accepted

Table 32 – VAR model 'Timmermann test with h=24.

	0	1	2	3	4	5	6	7	8	9	10	11	12
2	0.37	0.22	0.04	0.06	0.04	0.06	0.01	0.01	0.00	0.00	0.00	0.00	0.00
3	0.30	0.37	0.31	0.34	0.32	0.35	0.14	0.06	0.05	0.04	0.02	0.02	0.02
4	0.24	0.22	0.39	0.37	0.40	0.35	0.36	0.24	0.18	0.15	0.07	0.07	0.07

Table 32 – BESTARMA Model's TPE. Different strategies for h=24. Columns represents the maximum months tolerated from the first signal, rows the consecutive signals accepted

Table 33 - BESTARMA and VAR' TPE best strategy for each h. C represents the number of consecutive detection (1 indicated only the first signal), E the error accepted for being a consecutive detection. In the last two column the DM test between the selected best strategy.

	BESTARMA			**VAR**			DM	DM_S*
H	*C*	*E*	*TPE*	*C*	*E*	*TPE*		
1	1	0	0.10	2	1	0.26	-3.65 (0.00)	-3.63 (0.00)
2	1	0	0.10	2	3	0.29	-2.57 (0.01)	-2.54 (0.02)
3	1	0	0.13	2	3	0.31	-2.89 (0.01)	-2.84 (0.01)
4	1	0	0.14	1	0	0.32	-2.66 (0.01)	-2.59 (0.01)
5	1	0	0.14	3	9	0.33	-2.68 (0.01)	-2.59 (0.01)
6	1	0	0.18	1	0	0.32	-2.10 (0.04)	-2.02 (0.05)
7	1	0	0.20	3	7	0.30	-1.54 (0.12)	-1.46 (0.14)
8	1	0	0.22	2	7	0.28	-0.92 (0.26)	-0.87 (0.27)
9	1	0	0.22	2	3	0.32	-1.70 (0.09)	-1.60 (0.11)
10	1	0	0.22	1	0	0.32	-1.94 (0.06)	-1.80 (0.08)
11	2	4	0.23	1	0	0.33	-1.53 (0.12)	-1.41 (0.15)
12	1	0	0.22	1	0	0.32	-1.88 (0.07)	-1.72 (0.09)
13	2	4	0.26	1	0	0.34	-1.50 (0.13)	-1.36 (0.16)
14	2	4	0.24	1	0	0.35	-1.92 (0.06)	-1.72 (0.09)
15	2	4	0.25	1	0	0.37	-2.37 (0.02)	-2.12 (0.04)
16	2	4	0.25	1	0	0.38	-2.72 (0.01)	-2.41 (0.02)
17	2	4	0.24	1	0	0.39	-3.02 (0.00)	-2.65 (0.01)
18	2	4	0.24	1	0	0.39	-2.78 (0.01)	-2.42 (0.02)
19	2	4	0.24	1	0	0.39	-2.90 (0.01)	-2.50 (0.02)
20	2	4	0.24	1	0	0.39	-2.96 (0.00)	-2.53 (0.02)
21	2	4	0.24	1	0	0.39	-3.25 (0.00)	-2.75 (0.01)
22	2	4	0.24	1	0	0.39	-3.55 (0.00)	-2.98 (0.01)
23	2	4	0.24	1	0	0.39	-3.25 (0.00)	-2.71 (0.01)
24	2	4	0.24	1	0	0.39	-3.10 (0.00)	-2.55 (0.02)

Table 34 – TPE's means for all h

BESTARMA

	0	1	2	3	4	5	6	7	8	9	10	11	12
2	0.29	0.28	0.26	0.26	0.22	0.23	0.23	0.23	0.23	0.23	0.23	0.24	0.24
3	0.34	0.32	0.30	0.31	0.25	0.24	0.23	0.24	0.24	0.24	0.24	0.24	0.24
4	0.39	0.36	0.33	0.33	0.27	0.25	0.24	0.24	0.25	0.25	0.25	0.26	0.26

VAR

	0	1	2	3	4	5	6	7	8	9	10	11	12
2	0.47	0.42	0.39	0.39	0.38	0.39	0.37	0.36	0.36	0.36	0.36	0.36	0.36
3	0.49	0.47	0.45	0.44	0.43	0.44	0.41	0.39	0.39	0.38	0.38	0.38	0.38
4	0.51	0.51	0.48	0.47	0.45	0.48	0.45	0.42	0.41	0.41	0.40	0.40	0.40

Table 34 – BESTARMA and VAR Models' TPE mean for all h between 1 and 24. Columns represents the maximum months tolerated from the first signal, rows the consecutive signals accepted

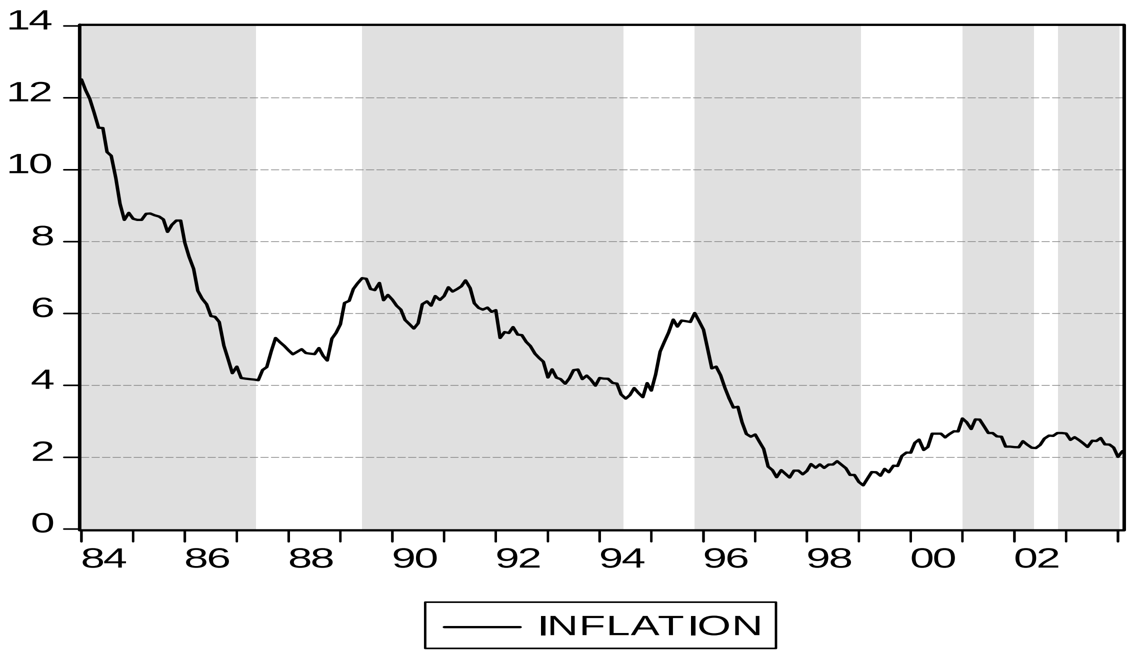


Figure 4 – Detected Turning point

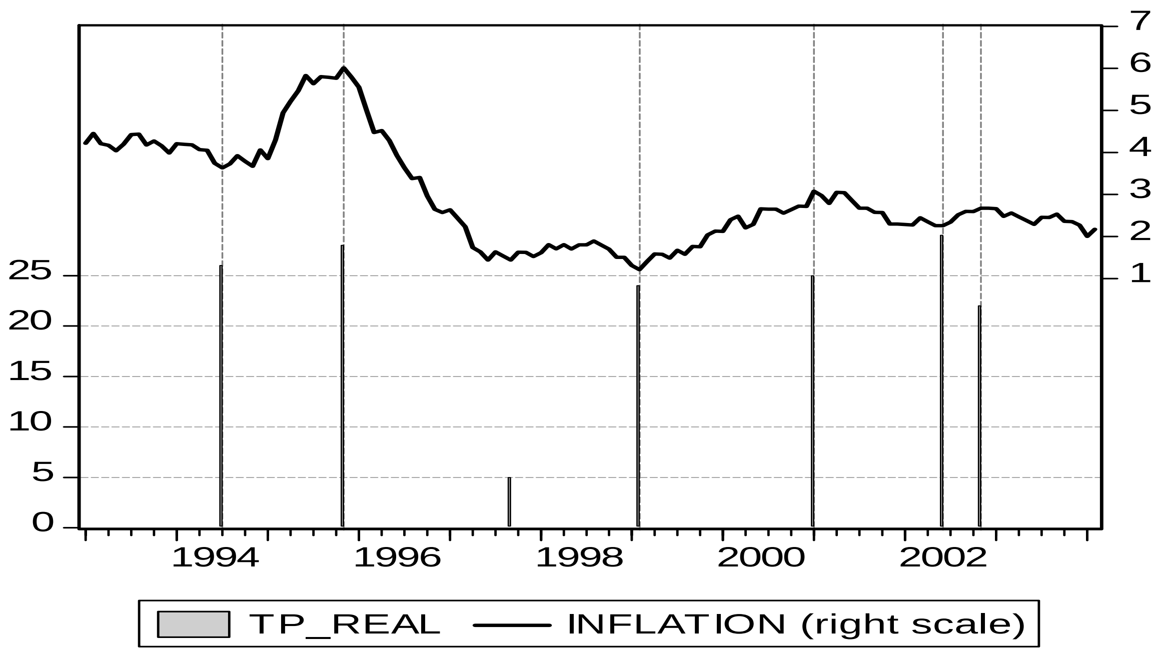


Figure 5 – Recursive procedure with REALTIME forecast. Vertical lines count the number of turning point sign from 1993:1 to t+12 where t is the timing of the effective turning point (dot vertical line)

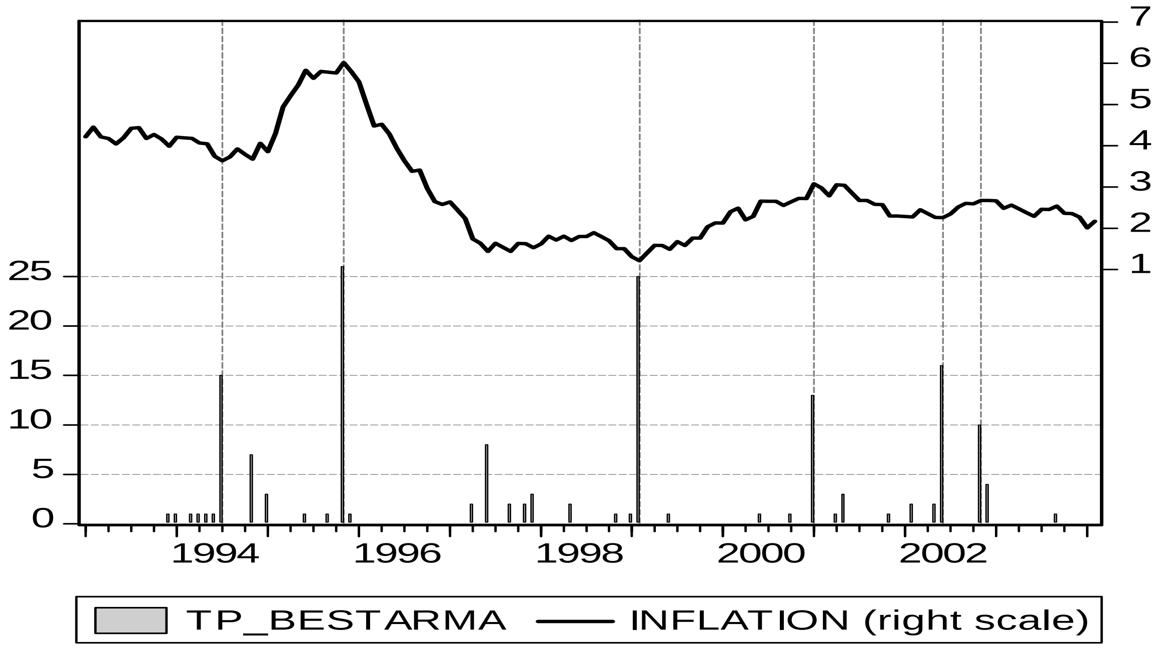


Figure 6 – Recursive procedure for BESTARMA forecast. Vertical lines count the number of turning point sign from 1993:1 to t+12 where t is the timing of the effective turning point (dot vertical line)

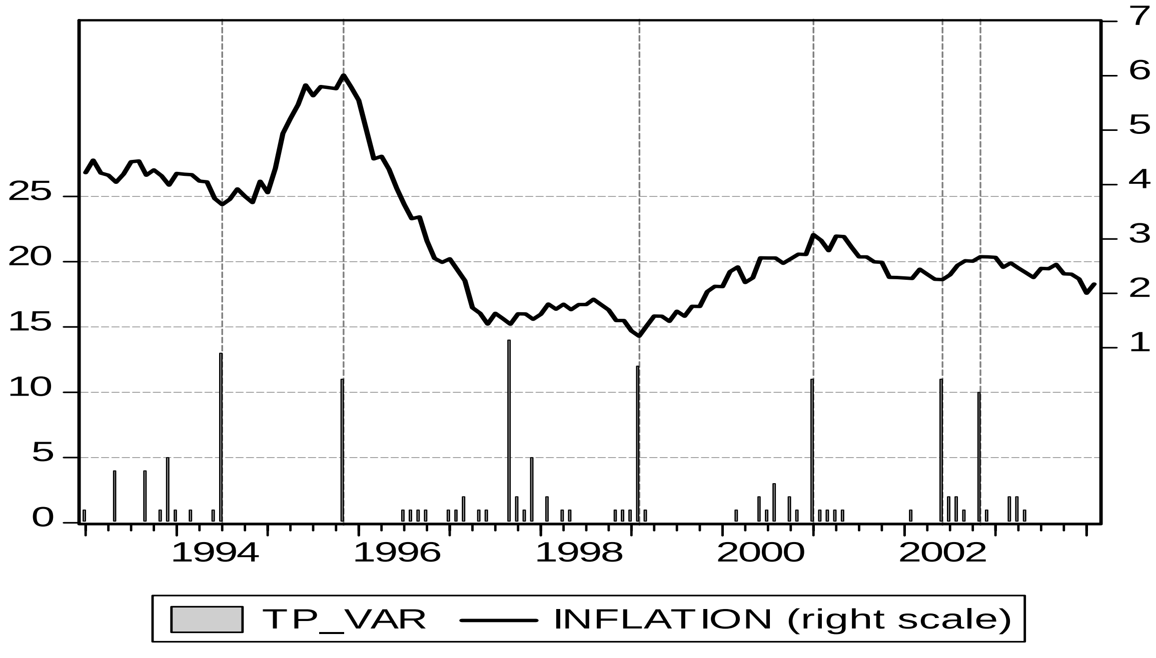


Figure 7 – Recursive procedure for VAR forecast. Vertical lines count the number of turning point sign from 1993:1 to t+12 where t is the timing of the effective turning point (dot vertical line).

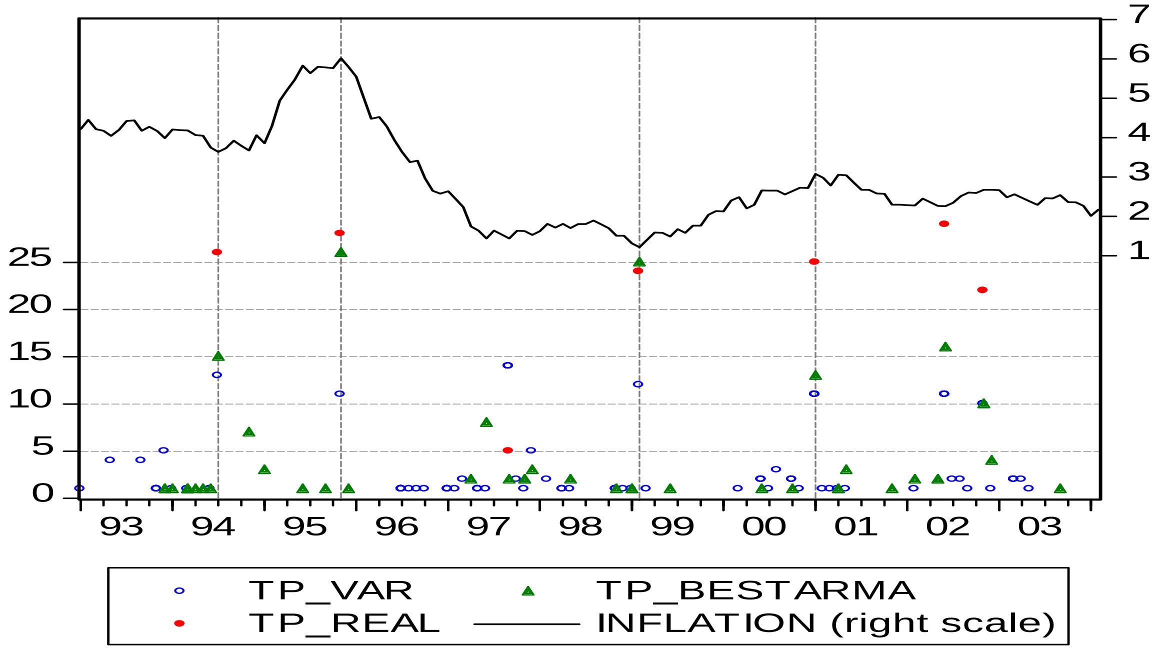


Figure 8 – Recursive procedure. TP_"name" is the number of signed turning point from 1993:1 to t+12 where t is the detected turning point.

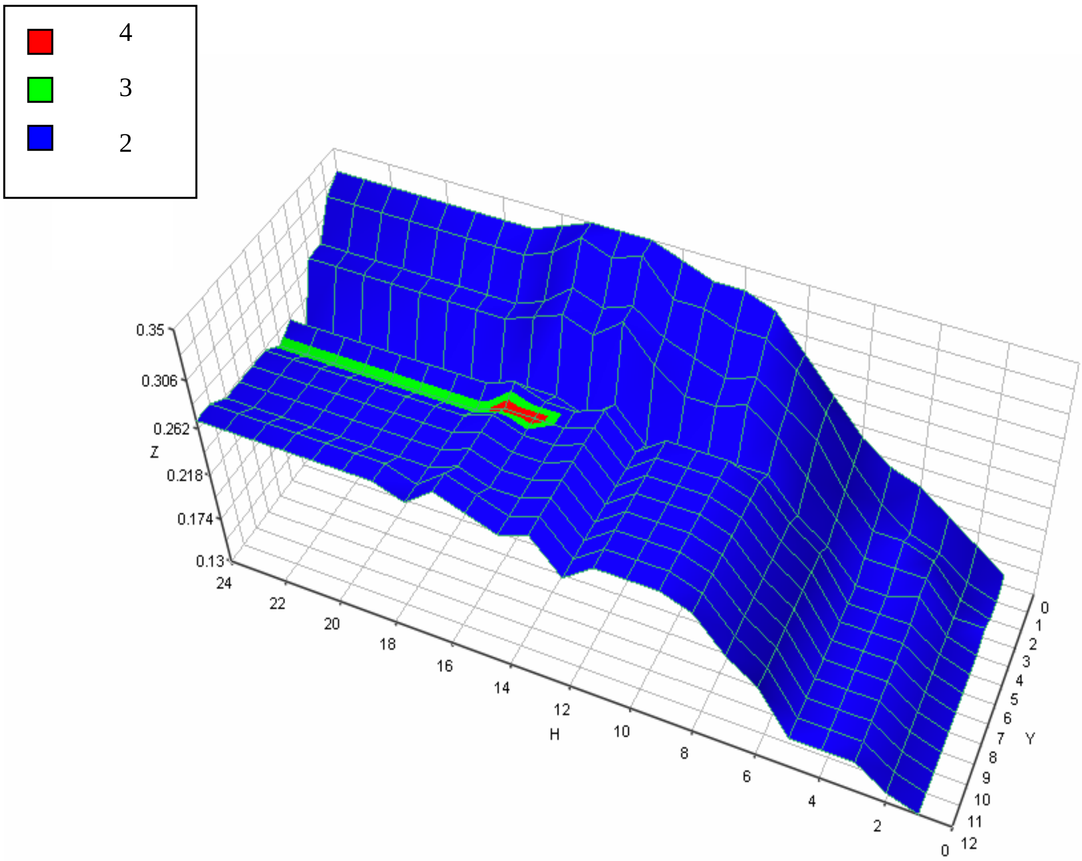


Figure 9 TPE (z scale) for every h and different error accepted to define consecutive tunring point signals (y scale. Different colors represent the number of consecutive signals that generates lower TPE.