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Forecasting Austrian HICP and its Components using VAR and ARIMA Models

Friedrich Fritzer, Gabriel Moser, Johann Scharler

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Editorial

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Friedrich Fritzer [1,2] Gabriel Moser [3] Johann Scharler [4]

July 2002

Abstract

The purpose of this paper is to evaluate the performance of VAR and ARIMA models to forecast Austrian HICP inflation. Additionally, we investigate whether disaggregate modelling of five subcomponents of inflation is superior to specifications of headline HICP inflation. Our modelling procedure is to find adequate VAR and ARIMA specifications that minimise the 12 months out-of-sample forecasting error. The main findings are twofold. First, VAR models outperform the ARIMA models in terms of forecasting accuracy over the longer projection horizon (8 to 12 months ahead). Second, a disaggregated approach improves forecasting accuracy substantially for ARIMA models. In case of the VAR approach the superiority of modelling the five subcomponents instead of just considering headline HICP inflation is demonstrated only over the longer period (10 to 12 months ahead).

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[2]Corresponding author. Oesterreichische Nationalbank, Economic Analysis Division, Otto-Wagner-Platz 3, POB 61, A-1011 Vienna, E-Mail: friedrich.fritzer@oenb.co.at

[3]Oesterreichische Nationalbank, Otto-Wagner-Platz 3, POB 61, A-1011 Vienna, E-Mail: gabriel.moser@oenb.co.at

[4]Simon Fraser University, Department of Economics, 8888 University Drive, Burnaby, B.C., Canada V5A 1S6, E-Mail: scharler@sfu.ca

1 Introduction

One of the most important goals for many central banks is to maintain a low and stable growth of the price level. Because the instruments of monetary policy show their impact on this goal variable only with a lag it is necessary to produce accurate and reliable forecasts of the inflation rate in order to enable the monetary authorities to counteract in a timely manner inflationary/deflationary pressures that may arise in the future.

The generally accepted measure of the price level is the harmonised consumer price index (HICP), which is composed of a weighted average of five subindexes that reflect the development of prices of goods produced in certain sectors of the economy, namely unprocessed food (HICPA), processed food (HICPB), non-energy industrial goods (HICPC), energy (HICPD) and services (HICPE).

For a detailed picture of future inflationary or deflationary pressure it is necessary to generate forecasts of all these subindexes. One question that will be addressed in this paper lies at the heart of every forecasting exercise: which forecasting method should be used? We compare two classes of methods to forecast Austrian HICP inflation in terms of their out-of-sample forecasting accuracy. Univariate (ARIMA) models and multivariate (VAR) models. The reasons why we limit our consideration to time series methods are twofold. First, we are mainly interested in the monthly pattern of HICP inflation with a horizon of up to 12 months. Time series models might have an advantage over structural econometric models in this respect. Second, as reviewed in Fildes and Stekler [8] time series models provide a viable alternative to large structural models. In some cases time series forecasts outperform forecasts produced by structural models unless the latter are not augmented with nonreplicable "add-factors" derived from forecaster judgement. The structure of large models is derived from economic theory and takes the form of various restrictions on the parameters of the equations to be estimated. The most widely used restriction is the so-called exclusion restriction, which implies that a certain variable does not explain the behaviour of the variable to be forecasted. These models have lost much of their appeal due to the famous critique of Sims [21]. Especially the "incredible" exclusion restrictions have led to a different approach in econometric modelling that avoids such restrictions. This approach uses so-called vector autoregressive (VAR) models where all variables in the system are treated endogenously in the sense that no variable is excluded from explaining other variables.

An alternative to the multiequation VAR approach is to model the future development of a variable exclusively by its own past behaviour. These so-called ARIMA models are based on the theory of stochastic difference equations. In the ARIMA modelling process (based on Box and Jenkins [2]) the order of the difference equation is chosen to adequately fit the data.

Since it is difficult to decide a priori which of these two approaches is more suitable for the particular task of forecasting the Austrian HICP and its components, we will estimate and forecast all these indices using both methods and compare them by their respective forecasting performance.

Our model selection strategy is definitely one of "data-mining". We do not pay primary attention to estimate the true data generation process and focus instead on forecasting accuracy. As Hendry and Mizon [13] state "Much previous work on economic forecasting has considered the properties of forecasts when: 1. the data generation process (DGP) is known; 2. the DGP is constant; and 3. the econometric model coincides with the DGP. These assumptions are strong, and unlikely to be fulfilled in practice". Hence models are always simplified representations which are incorrect in many ways.

A second question posed in this paper is to compare the forecast accuracy of the aggregated subindices with that of forecasting HICP inflation directly. Hubrich [15] addresses the same question at the euro area level. A disaggregated approach in forecasting HICP inflation has the advantage of possibly yielding more information. On the basis future price development can be judged more accurately. In addition, disaggregate information allows the central bank to communicate more effectively with the public. The disadvantage of the disaggregated approach is that some components might be difficult to forecast due to, for example, strong and changing seasonal patterns.

The structure of the paper is as follows. Section 2 provides the empirical evidence on optimal ARIMA and VAR specifications for the purpose of forecasting HICP inflation and its subcomponents. In section 3 the forecast performance of the ARIMA versus VAR approach is evaluated. Section 4 draws conclusions. In appendix A we discuss basic principles of ARIMA and VAR modelling and our approach in choosing variables for the VAR specifications. In addition comments on forecasting accuracy measures are included. Appendix B lists the variables tested for inclusion in the VAR models and appendix C provides the results of the leading indicator analysis. Appendix D contains figures of VAR and ARIMA forecasts for the HICP and its subcomponents.

2 Model specification

In this section we present our main decisions regarding the specification of the two classes of models (VAR and ARIMA) we used to forecast the Austrian HICP and its components. Section 2.1 comprises the choice of ARIMA specifications and presents the estimation results. Section 2.2 contains information on the variables which were selected for the VAR models. The VAR specifications are presented in section 2.3.

2.1 ARIMA Models

The work of Box and Jenkins [2] proved to be among the most influential publications in applied forecasting. As a result there was a massive spread of statistical models and, in particular, of the so-called ARIMA model. The Box-Jenkins method proposed a systematic way in ARIMA modelling which consists of an iterative procedure of (1) formulating a plausible model (identification), (2) fitting the model to the data (estimation), (3) diagnostic checking, and if necessary, adjusting the model. In the identification stage a (seasonal) ARIMA$(p, d, q) \times (P, D, Q)$[1] model is chosen, i.e. the parameters p, d, q, P, D, Q are selected. Box-Jenkins proposed to examine the autocorrelation and partial autocorrelation functions in order to select a model applicable to a particular situation. Hence this stage is subject to heuristic methods that may vary with each time series expert. On account of this we try to automate this stage as much as possible so as to enhance reproducibility and objectivity of the model selection procedure. The conditions of stationarity and invertibility presumed by the Box-Jenkins method were met. To achieve stationarity we performed unit and seasonal differencing at lag 12 to achieve stationarity.

An automatic modelling method for univariate time series: Contrary to the inspection of sample autocorrelation and partial autocorrelation functions in the identification stage we circumvent this process by estimating a whole range of models and ranking them according to information criteria in a first step. In a second step a couple of top-ranked models are evaluated according to their out-of-sample forecasting performance in the following way: The top-five-ranked models were estimated for the period 1990:01 1996:02. Out-of-sample forecasts are generated up to 1997:02. Comparison with the true value of the respective price index gives one realization of the forecast errors up to 12 months ahead for each model. The next step is to estimate the models for 1990:01 1996:03[2] and to generate forecasts up to

[1] For a definition of the notation see appendix A.

[2] For the non-energy industrial goods index we used a shorter sample starting at January 1995 as there is a break in the data at the end of 1994. Consequently estimation was conducted over the period 1995:01 to 2001:05 and only in-sample forecasts were performed.

1997:03. This procedure is repeated up to an estimation period that includes 2000:05 and generates a 12-months ahead forecast for 2001:05. This rolling method of forecasting yields a sample of 53 12-months ahead forecast errors for each specification and subindex except the non-energy industrial goods index. From these 12-months ahead forecasts the forecasting accuracy statistics, as defined in appendix A.3, are computed[3] (The choice of the forecasting statistic does not have an influence on the ranking of the models).

In tables 1 to 3 the top-five specifications were ranked according to the Bayes criterion of Schwarz (SCI) although the Hannan-Quinn and Akaike Information criteria were also considered in evaluating the specifications. Additionally the best performers were evaluated as to whether they pass diagnostic tests, i.e. (1) no autocorrelation of residuals, (2) parameter stability over the sample from January 1990 to May 2001 and the subsample from January 1990 to January 1996 (the start of the out-of-sample forecasting period), (3) significance of parameter estimates.

Table 1: Top-five models according to SIC: HICP and Services

Rank	HICP		Services	
	Model	SIC	Model	SIC
1	**(0,1,0)x(0,1,1)**	-12.076	(1,1,2)x(1,1,0)	-12.055
2	(1,1,0)x(0,1,1)	-12.057	**(1,1,0)x(1,1,0)**	-12.037
3	(0,1,1)x(0,1,1)	-12.056	**(0,1,1)x(1,1,0)**	-12.031
4	(0,1,0)x(1,1,1)	-12.051	**(1,1,0)x(0,1,1)**	-12.021
5	(1,1,0)x(1,1,1)	-12.029	(1,1,2)x(1,1,1)	-12.019

Note: A seasonal ARIMA model of order (p,d,q) and seasonal ARIMA terms (P,D,Q) is abbreviated (p,d,q)x(P,D,Q) (see equation 3 in appendix A for the general specification). For example, with monthly data (1,1,0)x(0,1,1) denotes the seasonal ARIMA model $y_t = \delta + \phi_1 y_{t-1} + \Theta_1 \epsilon_{t-12}$, where $y_t = (1-L)(1-L^{12})x_t = x_t - x_{t-1} - x_{t-12} + x_{t-13}$. Bold face numbers indicate models which pass diagnostic tests.

For the HICP both the Schwarz and Hannan-Quinn information criteria suggest model (0,1,0)x(0,1,1). The Akaike information criterion instead ranks model (1,1,4)x(1,1,1) as the best specification. Although this specification is far worse than the top-five models in terms of forecasting accuracy.[4]

[3]The RATS code for the optimisation procedure described was kindly provided by A. Meyler of the Central Bank of Ireland.

[4](1,1,4)x(1,1,1)is not even ranked among the top twenty specifications.

The Akaike criterion tends to overfit the data because it does not penalise the introduction of more parameters to the same extent as the Bayesian and Hannan-Quinn criteria.[5] With a view to forecasting, introducing of too many parameters is undesirable if this leads to an overfitting of random features that will not be relevant for future data. The latter is clearly what specification (1,1,4)x(1,1,1) does. Model (0,1,0)x(0,1,1) is the preferable ARIMA specification because it outperforms in terms of forecasting accuracy and is the only one of the top-5-ranked models which pass the diagnostic stage. The remaining specifications exhibit either unstable or insignificant parameter estimates.

In case of the subcomponent services the three considered information criteria suggest model (1,1,2)x(1,1,0) although this specification does not pass diagnostic tests due to unstable parameter estimates. The same holds true for model (1,1,2)x(1,1,1). Models (1,1,0)x(1,1,0), (0,1,1)x(1,1,0), (1,0,0)x(0,0,1) remain to be evaluated according to their forecasting performance. Independent of the accuracy measure (1,1,0)x(1,1,0) outperforms the other specifications although the difference is very small.

Table 2: Top-five models according to SIC: Non-Energy Industrial Goods and Energy

Rank	Non Energy Industrial Goods		Energy	
	Model	SIC	Model	SIC
1	**(0,1,0)x(1,1,0)**	-11.943	**(0,1,0)x(1,1,1)**	-8.525
2	**(0,1,0)x(1,1,1)**	-11.936	(0,1,1)x(1,1,1)	-8.523
3	**(0,1,0)x(0,1,1)**	-11.934	(1,1,0)x(1,1,1)	-8.519
4	(0,1,1)x(1,1,0)	-11.915	**(0,1,0)x(0,1,1)**	-8.506
5	(1,1,0)x(1,1,0)	-11.915	(0,1,1)x(0,1,1)	-8.500

Note: For definitions see Table 1.

For the non-energy industrial goods component the top-three models pass the diagnostic stage. The information criteria suggest different models as the most appropriate specification. The Hannan-Quinn and the Schwarz criterion suggest models (0,1,0)x(1,1,1) and (0,1,0)x(1,1,0) respectively. The Akaike Information criterion suggests a more complicated specification, namely (1,1,3)x(1,1,1). The latter is not among the top five according to the Schwarz criterion. Parameter estimates are unstable as well as those for specifications ranked fourth and fifth. The top-ranked model according to the Schwarz cri-

[5] See also the discussion of the information criteria in appendix A.3.

terion clearly outperforms the other specifications in terms of forecasting accuracy.

For the energy component of the HICP we decided to carry over models (0,1,0)x(1,1,1) and (0,1,0)x(0,1,1) to the forecasting evaluation stage. According to the Hannan-Quinn and Akaike criteria model, (0,1,1)x(1,1,1) is top-ranked but does not have stable parameter estimates as well as those for the third and fifth specification. Specification (0,1,0)x(0,1,1) does have the best forecasting accuracy.

Table 3: Top-five models according to SIC: Processed food and Unprocessed food

Rank	Processed Food		Unprocessed Food	
	Model	SIC	Model	SIC
1	**(0,1,0)x(0,1,1)**	-11.091	(0,1,0)x(0,1,1)	-8.345
2	**(2,1,1)x(0,1,1)**	-11.075	**(0,1,1)x(0,1,1)**	-8.332
3	(1,1,0)x(0,1,1)	-11.059	**(1,1,0)x(0,1,1)**	-8.329
4	(0,1,1)x(0,1,1)	-11.058	(1,1,1)x(0,1,1)	-8.317
5	(0,1,0)x(1,1,1)	-11.056	(0,1,0)x(1,1,1)	-8.315

Note: For definitions see Table 1.

In case of the processed food component (0,1,0)x(0,1,1), (2,1,1)x(0,1,1) pass the diagnostic statistics whereas the remaining classified specifications exhibit unstable and/or insignificant parameter estimates. The Akaike and Hannan-Quinn information criteria suggest (2,1,1)x(0,1,1). (0,1,0)x(0,1,1) is proposed by the Schwarz information criterion. In terms of forecasting accuracy the less complicated specification (0,1,0)x(0,1,1) dominates.

For the unprocessed food component models ranked first and fifth are not specified properly due to autocorrelated residuals. The model ranked fourth does not have stable parameter estimates. (0,1,1)x(0,1,1) and (1,1,0)x(0,1,1) pass the diagnostic stage. The Akaike criterion suggests (0,1,6)x(0,1,1) and the Hannan-Quinn criterion (0,1,1)x(0,1,1). Both specifications lack appropriateness due to parameter instability. (0,1,1)x(0,1,1)[6] has a better forecasting performance compared to (1,1,0)x(0,1,1) but the difference is quite small.

The preferred ARMA models, in terms of out-of-sample forecast accuracy are presented in table 4.

[6]It is noteworthy in this case that accuracy improves with the length of the forecast horizon.

Table 4: "Optimal" ARMA models

Specification	Services	Non-Energy Industrial Goods	Energy
AR(1)	-0.25 (-2.96)		
SAR(12)	-0.36 (-3.81)	-0.54 (-6.23)	
SMA(12)			-0.74 (-10.97)
Diagnostic checks	Statistic		
Adjusted R^2	0.16	0.22	0.33
Ljung-Box Q statistic	Q(32)=37.02 (0.25)	Q(33)=37.18 (0.28)	Q(33)=30.32 (0.60)

Specification	Processed Food	Unprocessed Food	HICP
MA(1)		-0.17 (-2.01)	
SMA(12)	-0.73 (-11.16)	-0.43 (-5.40)	-0.57 (-7.35)
Diagnostic checks	Statistic		
Adjusted R^2	0.24	0.13	0.23
Ljung-Box Q statistic	Q(33)=42.73 (0.12)	Q(32)=41.54 (0.12)	Q(31)=32.40 (0.50)

Note: The estimation period is January 1990 to May 2001. One regular and seasonal difference ($\Delta_1\Delta_{12}$) is taken from the logarithmic variables. AR(1) and MA(1) are the first autoregressive and moving average components. SAR(12) and SMA(12) the 12^{th} multiplicative autoregressive and moving average seasonal components. T-values are in brackets of parameter estimates. P-values are in brackets of diagnostic statistics.

2.2 Variable selection for the VAR models

In our analysis we tried a wide variety of possible indicators (see appendix B) which can roughly be divided into two categories. First the "macro" variables which were supposed to influence all indicators, for instance M1, industrial production and interest rates. Second, we tried to find sector-specific variables which are likely to influence the price movements in the subindexes. For instance car sales as a possible driving force for the non-energy industrial goods index or the wholesale price index for meat as an indicator of inflation in the processed food component.

Running the prefitting regressions (see equation 8 in appendix A) yielded the following results (F-statistics and associated p-values are given in appendix C):

The subindex for processed food seems to be mainly driven by credit to nonbanks, wholesale prices for unprocessed food and the long-term interest rate, which are significant at 1, 3, 6 and 12 leads. The German consumer price index has leading indicator properties for up to 6 leads. Also the monetary aggregate M1 is somewhat significant over 6 and 12 leads.

The subindex for unprocessed food is influenced by three variables: the most influential indicator seems to be the spread between long- and short-term interest rates (with leading indicator properties at 3, 6 and 12 leads). Wholesale prices for unprocessed food and the German consumer price index appear to influence the index in the medium run (6 leads).

Prefitting the energy price index revealed that world energy prices and wholesale energy prices forecast the index well over the full horizon while orders and credit to nonbanks do so over 3 and 12 leads respectively.

For the services subindex, only M1 turned out to be significant over all forecast horizons. The variable credit to nonbanks has leading indicator properties for up to 6 leads. Industrial production and the world price of energy and the nominal wage index are significant at 12 leads.

Our VAR model for headline HICP includes M3 and the interest rate spread, which seem to have leading indicator properties up to 12 leads. Sales price expectations proved to be significant over the medium term (1 to 6 leads) while credit to nonbanks was significant at 12 leads.

The prefitting regressions were not conducted for the index of non-energy industrial goods prices since this series has a serious break at 1994:12 leaving too few observations for estimating a VAR model.

2.3 VAR models

The prefitting regressions described above have pinned down a set of explanatory variables which are most relevant for every subindex of the HICP (except the non-energy industrial goods price index for which only an ARIMA model could be estimated). The next step in our analysis consists of setting up VAR models for the subindexes which can then be used for forecasting purposes. The forecast of the HICP itself is generated as a weighted sum of the forecasts of the subindexes. Alternatively a VAR for the HICP itself is estimated.

As mentioned in the section on the theory of VAR modelling we faced two decisions, namely how many lags to include in the VARs and how to deal with the apparent nonstationarity present in all subindexes and explanatory variables. Our model building strategy is as follows:

With respect to the problem of nonstationarity we decided to run the risk of overparameterisation and to estimate all systems in levels rather than in first differences. Ideally, imposing cointegration should improve the accuracy of forecasts, particularly for longer forecasting horizons. However, when working with real data imposing cointegration has not yet proved to be unambiguously superior. For example, Allen and Fildes [1] found no clear evidence in favour of imposing cointegration in published forecasting studies.[7]

The advantages of a VAR in levels are the incorporation of information which would be lost if the series are differenced. In addition ordinary least squares will give consistent estimates. Also, we decided to include time trends in every VAR in order to control for the deterministic part of the trending behaviour in the variables.

The selection of the lag structure in the VARs proceeds as follows: The first step of this procedure is to estimate most models with a minimum lag length of 4 and a maximum lag length of 14 for the period 1987:01 1996:02. Simulated out-of-sample forecasts are generated up to 1997:02. The next step is to estimate the models for 1987:01 1996:03 and to generate forecasts up to 1997:03. This procedure is repeated up to an estimation period that includes 1999:12[8] and generates a 12-months-ahead forecast for 2000:12. This

[7] One reason for that finding is that some authors do not impose the correct order of cointegration vectors. Clements and Hendry [5] state "In terms of empirical practice, it appears that imposing too few cointegration vectors may impose greater costs in forecast accuracy than allowing the presence of 'spurious' level terms. ... estimating and forecasting with an additional 'spurious' levels term is likely to be no more costly in terms of forecast accuracy than underestimating the cointegrating rank by one".

[8] December 2000 was the latest month for which observations of all variables used in the VARs were available. The estimation period was constrained to December 1999 so as to retain 12 months for out-of-sample forecasts.

rolling method of forecasting yields a sample of 47 12-months-ahead forecast errors for each specification and subindex except the non-energy industrial goods index. From these simulated 12-months-ahead forecasts the root mean squared error, as defined in appendix A.3, is computed and the specification that minimises this criterion is chosen. The automated model selection procedure described above results in specifications shown in table 5.

Table 5: "Optimal" VAR models

Index	Endogenous Variables	Exogenous Variables	Lags
Unprocessed Food	HICPA, GHPUPF, TL, VPIDE	RLONG-RSHORT, deterministic trend	1 to 4
Processed Food	HICPB, GHPUPF, TL, VPIDE, CREDIT	RLONG-RSHORT, deterministic trend	1 to 2 and 10 to 14
Services	HICPE, TL, CREDIT, IP, M1,	RSHORT, deterministic trend	1 to 2 and 9 to 10
Energy	HICPD, ORDERS, GHP-E, VPIDE	PWORLD_EF, EX$, RLONG-RSHORT, deterministic trend	1 to 6 and 10
Headline HICP	HICP, M3, CREDIT, P-EXP	RLONG-RSHORT deterministic trend	1 to 2 and 12 to 13

Note that the inclusion of identical variables in different VARs, for instance the wage rate index, wholesale prices and German consumer prices, produces a possible inconsistency since more than a single forecast is generated for these variables. Furthermore, degrees of freedom diminish by the estimation of the additional parameters.[9] Since it seems plausible that several subindices are influenced by the same factors, including identical variables in different systems can account for this situation. Alternatively, one could explicitly model the comovements in the subindexes.

[9]However, this appears to be a minor problem due to the low number of included lags. Nevertheless, the inconsistent forecasts of endogenous variables remain a weakness of our approach. A possible solution that could be considered in future work is to use exogenous forecasts for these variables instead of predicting them within the respective systems.

The energy price index is modelled differently from the others in that the world energy price index is specified as an exogenous variable. This means that there is no equation for this variable in the system, implying that "outside forecasts" must be provided as an input in the forecasting process. One possibility is to use prices of forward contracts on crude oil.

3 Forecast performance and evaluation

In order to evaluate our forecasts of the Austrian HICP and its components we used the root mean square error (RMSE) criterion as defined in appendix A.3. Forecasts where generated for all subindexes using the optimal VAR and optimal ARIMA models described above. Since in-sample forecasts largely resemble the fit of the chosen model, which may be a poor proxy for the forecasting performance of the model, we used the procedure for generating out-of-sample forecasts as described in section 2.1 and 2.3.[10] The evaluation period ends in 2000:12 yielding a total of 47 twelve-months out-of-sample forecasts.

In the next step we used the forecasts generated by the VAR-models (plus the ARIMA model forecasts of the non-energy index) and all ARIMA models to aggregate them up to forecasts for the HICP according to the weights they have in the HICP index.[11]

In table 6 forecasting accuracy of the optimal aggregated models and optimal models for HICP inflation are presented:

The general conclusion is that ARIMAs have smaller forecasting errors over a shorter horizon while VARs perform better over longer forecasting horizons (8 to 12 months ahead). ARIMA models on the other hand outperformed the VAR approach up to 6-months ahead. However, the difference to the headline HICP VAR is rather small. Interestingly there is apparently no loss of information when considering the headline HICP VAR compared to the aggregate of optimised subcomponents up to 8 months ahead. Only over the longer horizon (10 to 12 months ahead) the aggregated VAR forecasts of the optimised subcomponents do outperform the VAR for headline inflation. Especially noteworthy is the almost perfect performance of the ARIMA model of headline HICP for the one month-ahead forecast.

[10]For VARs we use data starting at 1987:01 and for ARIMAs we use data starting at 1990:01.

[11]As of January 2001 the respective weights are 10.8% for processed food, 5.5% for unprocessed food, 31.3% for non-enery industrial goods, 7.9% for energy and 44.5% for services.

Table 6: Root Mean Squared Forecast Errors

Forecast Months	aggregated VARs for subcomponents	Headline HICP VAR	aggregated ARIMAs for subcomponents	Headline HICP ARIMA
1	0.39	0.28	0.20	almost 0
2	0.51	0.35	0.31	0.35
3	0.58	0.42	0.38	0.49
4	0.63	0.49	0.44	0.62
5	0.66	0.54	0.50	0.72
6	0.70	0.59	0.55	0.80
7	0.72	0.62	0.62	0.87
8	0.74	0.65	0.69	0.95
9	0.70	0.67	0.75	1.00
10	0.71	0.72	0.80	1.04
11	0.72	0.76	0.87	1.10
12	0.74	0.80	0.90	1.16

Note: The selection criterion was the 12-months ahead root mean square error.

4 Conclusions and directions for further research

This paper provides a comparative assessment of VAR and ARIMA models to forecast Austrian HICP inflation over the short term. We consider generating forecasts of five sub-components and aggregating them up to the HICP forecast. In addition we consider forecasts for headline HICP itself. The model selection procedure is automatic in the sense that it involves the estimation of all possible ARMA models that encompass (11,11)x(1,1) (i.e. $12 \times 12 \times 4 = 576$) specifications and most lag specifications for VARs that encompass a maximum lag order of 14 and a minimum lag order of 4 in a first step. The second step consists of selecting the model with the smallest 12-months out-of sample root mean squared forecasting error.

The evaluation of the forecasting performance reveals that VAR models predict the HICP inflation more accurately than ARIMA specifications over a longer forecasting horizon (8 to 12 months ahead). The "bottom-up approach" (i.e. aggregating forecasts of subcomponents to the HICP inflation forecast) improves forecasting accuracy substantially in comparison to the forecast of overall HICP inflation in case of the ARIMA models. In case of the VARs the (slight) superiority of the "bottom-up approach" is demonstrated only over the longer forecasting period (10 to 12 months ahead). One reason for this result might be that the positive correlation of the indices is not fully captured by common explanatory variables of the VARs for the subcomponents. Therefore we expect that one promising direction for future research is a further investigation of the variable selection based on the prefitting regressions.

A Appendix: Forecasting inflation with time series models

A.1 Introductory comments on ARIMA processes

A general class of univariate time series models is the Autoregressive Integrated Moving Average (ARIMA) model. An ARIMA model represents current values of a time series by past values of itself (the autoregressive component) and past values of the stochastic error term (the moving average term). The acronym 'I' stands for integrated and refers to the number of times a series must be differenced to achieve stationarity. The ARIMA (p,d,q) process of a variable y_t can be written as

$$\phi(L)(1-L)^d y_t = \delta + \theta(L)\epsilon_t \tag{1}$$

where ϵ_t is independent and normally distributed with zero mean and constant variance σ_ϵ. Furthermore, δ is a constant, $\phi(L)$ and $\theta(L)$ are the autoregressive (AR) and moving average (MA) polynomials, respectively, with orders p and q, so that:

$$\phi(L) = 1 - \phi_1 L - \ldots - \phi_p L^p,\ \theta(L) = 1 - \theta_1 L - \ldots - \theta_q L^q \tag{2}$$

If the series is seasonal, with s time periods per year, then a seasonal ARIMA model may be obtained as a generalization of equation 1. Let L^s denote the operator such that $L^s y_t = y_{t-s}$. A seasonal ARIMA model with non-seasonal terms of order (p,d,q) and seasonal terms of order (P,D,Q) is abbreviated to a seasonal ARIMA$(p,d,q) \times (P,D,Q)$ model and may be written

$$\phi(L)\Phi(L^s)(1-L)^d(1-L^s)^D y_t = \delta + \theta(L)\Theta(L^s)\epsilon_t \tag{3}$$

where Φ, Θ denote polynomials in L^s of orders P, Q, respectively.

This highlights the two main problems inherent in ARIMA modelling. First, it is vital for correct statistical inference to choose suitable values for the two orders of differencing, both seasonal (D) and non-seasonal (d), so as to make the series stationary and remove (most of) the seasonality. Second, the correct orders of the $\phi(L)$, $\theta(L)$, Φ and Θ polynomials have to be determined. Hence there may be AR and MA terms at lags which are a multiple of the season lag s.

There are important differences between stationary and non-stationary time series. Innovations to a stationary series die out over time and the process returns to its long run mean while in a non-stationary series shocks are accumulated, i.e. a non-stationary series does not exhibit mean reversion. A second difference is that the variance of a non-stationary process goes to infinity as time goes to infinity, while the variance of a stationary process is time invariant.

Another difference between stationary and non-stationary time series can be exploited as a first guess towards identification of the degree of integration of the series. This difference lies in the behaviour of the autocorrelation function. If inspection of the plot of this function shows that it dies out slowly, this is some evidence that the series is non-stationary. If it goes to zero immediately, it will be stationary. Visual inspection can give only a first approximation of the degree of integration. What is really required is a formal test. The most widely used test for this purpose is the Dickey-Fuller (DF) test [6]. The DF test is based on the estimation of the following regression equation:

$$\Delta y_t = \gamma y_{t-1} + v_t \tag{4}$$

and testing the null hypothesis of non-stationarity ($\gamma = 0$) against the alternative of $\gamma < 0$. If it cannot be rejected, the series must be integrated and therefore requires some form of differencing to achieve stationarity (which may also be seasonal). If the variable is generated by a stochastic and/or deterministic trend, it will be necessary to augment the equation with a drift and/or a deterministic trend. In case the process $\{v_t\}$ is autocorrelated, equation 4 must be augmented with additional lagged left-hand variables.

Having determined the correct order of differencing to render the series stationary, the next step is to find the appropriate ARMA specification to model the stationary series. The traditional approach to this problem goes back to Box and Jenkins [2]. Their identification procedure involves examining plots of the sample autocorrelation and the partial autocorrelation and inferring from patterns observed in these functions the correct form of the ARMA model. The autocorrelation between y_t and lag k of the series, i.e. y_{t-k}, is defined as the covariance between y_t and y_{t-k}, scaled by the variance of the y_t series. The autocorrelation function shows all the autocorrelations for different time horizons. The partial autocorrelation measures the "direct" correlation between y_t and y_{t-k} and hence eliminates the effects of intervening values $y_{t-1}, \ldots, y_{t-k+1}$. In regressing y_t on all lags up to y_{t-k} the partial autocorrelation between y_t and y_{t-k} is equal to the estimated regression coefficient on y_{t-k}. The partial autocorrelation function shows all the partial autocorrelations for different time horizons.

When the data are generated by pure MA or AR processes, identification using the autocorrelation function and the partial autocorrelation function is a relatively straightforward matter. If there is a pure AR(p) process, the partial autocorrelation function will cut off after p lags (since at lag p+1 there is no correlation between y_t and y_{t-p-1}) while its autocorrelation function will die out smoothly. Given a MA(q) process its autocorrelation function cuts off after q lags while its partial autocorrelation function decays smoothly.

Things get more difficult when the data cannot be represented by pure AR or MA processes, which implies that a mixed process (ARMA) is required. In that case it is very probable that different users of the Box-Jenkins method will specify different models when confronted with the same data.

A natural measure of the quality of an ARMA model is the "fit", i.e. the amount of variation of the series under investigation which is explained by the autoregressive and moving-average terms of the process. This fit will always improve when more AR and MA terms are added. However, the inclusion of more terms entails a loss of degrees of freedom, which increases the variance of the single coefficients in the model and hence reduces the forecasting performance. A parsimonious model takes account of this trade-off. The procedure to arrive at a specification which has a good fit as well as a high number of degrees of freedom is to minimise a penalty function of the form

$$P(p,q) = \ln \hat{\sigma}^2_{p,q} + (p+q)\frac{C(T)}{T} \tag{5}$$

where $\hat{\sigma}^2_{p,q}$ is the maximum likelihood estimate of the variance of the white noise error process for an ARMA specification of order (p,q), $C(T)$ is some function of the number of observations T. The penalty term $(p+q)\frac{C(T)}{T}$ counterbalances the fact that $\hat{\sigma}^2_{p,q}$ decreases the higher the order (p,q) of the ARMA model. Equation 5 thus expresses the trade-off between the fit and the simplicity of the model. For $C(T) = 2$, we obtain the Akaike Information Criterion (AIC), for $C(T) = \ln(T)$ the Bayesian Information Criterion of Schwarz (SIC), and for $C(T) = 2\ln(\ln(T))$ the Hannan-Quinn (HQ) Information Criterion. The fundamental difference between the AIC and the SIC is that the former is essentially an estimate of the ability of a model to predict future data. The SIC criterion focuses less on predictive accuracy but more on the probability that the model is correct. However, extra parameters may reduce predictive accuracy if the better fit is due to the purely random variation of new data. The HQ Information Criterion lies somewhere in the middle between AIC and SIC. Another difference between AIC and SIC is that the latter is a consistent estimator of the order of an ARMA process whereas the former is not.[12]

[12]Some authors (see [9]) argue that they had better experience with the SIC in practical

The second criterion for the quality of the model is the behaviour of the residuals. The plot of the residuals should be free from outliers (which could influence parameter estimates) and from any autocorrelation. If the model is specified correctly, the acf of the residuals should resemble the autocorrelation function of a white noise process, i.e. it should decay immediately to zero and remain there.

A formal test for the presence of autocorrelation is the Ljung-Box statistic. This test sums up the squared autocorrelations up to lag p and therefore tests whether any of the autocorrelations up to lag p are nonzero. If this sum is large the hypothesis of autocorrelation cannot be rejected.

Another essential check is to assess the robustness of a selected model by estimating it over different time periods. If the parameter estimates are not stable over time this indicates that further considerations will have to be given to the model. This non-constancy could indicate breaks in the series under investigation. If this is the case, which can be determined with tests for structural breaks, the model should only be estimated with the data after the break, as these observations give a better description of the data generation process.

A.2 VAR(X) models

The starting point of modelling a VAR is the formulation of a general (unrestricted) vector autoregressive model. A VARX model consists of regressing each current endogenous variable in the model on all the lagged endogenous **and** exogenous variables (hence VARX). Compactly this can be written as:

$$\Psi(L)Y_t = \Omega X_t + Z_t \tag{6}$$

where Y_t is a $m \times 1$ vector of endogenous variables, X_t an $n \times 1$ vector of exogenous variables[13] included in the system, Ω a $m \times m$ matrix of parameters and Z_t a $m \times 1$ vector of random disturbances which may be correlated contemporaneously (i.e. between equations) but not autocorrelated. $\Psi(L)$ is a matrix of polynomials in the lag operator of order p, so that:

$$\Psi(L) = I - \Psi_1 L - \ldots - \Psi_p L^p \tag{7}$$

with Ψ_i matrices of dimension $m \times m$. Due to the fact that Austria is a small and open economy price dynamics depend to a large extent on developments from abroad. In our analysis variables such as interest rates,

applications.

[13]In our analysis we used only contemporaneous exogenous variables.

exchange rates and the oil price enter the VAR system exogenously, yielding a VARX model.[14] Since a VAR model involves only lagged variables, and since these variables are not correlated with the error term (given there is no autocorrelation) and all equations carry the same explanatory variables, an efficient estimation procedure consists of estimating each equation separately using ordinary least squares.

There are two noteworthy features in the application of a VAR model for forecasting purposes. First, as long as no restrictions are introduced into the model no account is taken of economic theory (as soon as the variables which enter the system are determined). Second, usually the variables are endogenous[15] in the system. For these variables it is not necessary to provide any future values in the forecasting process. Generating forecasts for all the variables in the system simply consists of using the set of linear equations which incorporate the estimated parameters and the data points up to lag p, yielding a one-step forecast conditional on the realisation of the past values of the variables in the system. This forecasted vector is then used as the last data vector in calculating the two-months forecast. Forecasts with a longer horizon are calculated in a similar way.

Using VARs to model economic time series requires the selection of variables to be included in the system. At this stage economic theory plays an important role. But if the focus is on forecasting performance it may be optimal to supplement the theoretical with statistical information. One possibility is to conduct a "leading indicator" analysis (described below), which determines which of the variables suggested by theory contain information about the future course of the variable of interest (in our case inflation). It is important that all variables which appear relevant according to the leading indicator analysis can be forecast with reasonable accuracy. Otherwise inaccurate forecasts of one variable are transmitted to all equations and reduce the forecasting precision of all variables (given that the variable which is difficult to forecast enters all equations together with non-zero coefficients). This points to the main advantage of the VAR analysis against ARIMA models. Since the course of future inflation will usually be influenced by some other variables forecasts conditional on these variables are likely to be more precise. In the VAR model the advantages of conditional forecasting are magnified by the fact that even such variables which do not explain future movements of inflation may improve its forecast since they can help to improve the pro-

[14]A further reason for VAR models with exogenous variables is the common assumption of "no change" in interest rates in forecasting exercises for monetary policy purposes.

[15]The exceptions are variables which are mostly controlled by monetary authorities (interest rates,...) or variables which are external assumptions (oil price,...). These variables are exogenous in the VAR forecasts.

jection of other variables in the system which do influence future inflation.

Given that the vector of endogenous variables is determined the next step in a VAR analysis is the determination of the appropriate lag length. As mentioned above this is important since adding more lags tends to clear the residuals of autocorrelation, which is essential for consistent estimation of the parameters of the model. But if too many lags are included there will be a loss of degrees of freedom, which reduces the preciseness of the estimators. Criteria which take account of this problem are the Akaike Information Criterion, the Bayesian Information Criterion and the Hannan-Quinn Information criterion (defined in equation 5), applied to the covariance matrix of the system, yielding an optimal average lag length for all equations. In our choice of the lag length we rely on the one that maximises the forecasting accuracy.[16] As Lütkepohl [18] states "For instance, a VAR model is often used for forecasting. In such a case we are not so much interested in the correct order of the DGP but in obtainig a good model for prediction. Hence it seems useful to take the objective of the analysis into account when choosing the VAR order".

The number of degrees of freedom with the implied accuracy of estimated parameters is of particular interest if the goal of the estimation exercise is forecasting. This constitutes a main disadvantage of VAR models when employed for this goal: since all variables are included in all equations a large number of parameters has to be estimated (if the number of endogenous variables is k and the number of lags p then every equation will carry $k \times p$ variables and parameters). It would therefore be desirable to exclude those explanatory variables in the system whose estimated coefficient is zero, which leaves the model well specified and reduces the number of parameters. However, this is difficult for two reasons: First, in such cases the equations do not carry the same variables in every equation, which makes it impossible to estimate each equation separately, with the associated high computational cost of the then required systems estimator (for instance Full Information Maximum Likelihood estimation). Second, since the explanatory variables are autoregressive it is very likely that some degree of multicollinearity is present, i.e. there exists linear dependence between the explanatory variables. The effect of multicollinearity will be similar to a lack of degrees of freedom - high parameter variances. Furthermore the presence of multicollinearity biases t- and F-statistics towards the type II error, making exclusion tests unreliable.

An additional problem arises if some or all of the variables in the system are integrated of a degree greater than 0. In this case it has to be decided whether the variables should be differenced or not. The main point in this

[16]The specification which minimised the root mean squared error was selected.

issue is that the variables in the system may be cointegrated, i.e. there exists a linear combination of the non-stationary variables in the system which is stationary. In this case differencing of the variables ignores important interrelationships between the variables in the levels, which induces misspecification and consequently reduces the forecasting performance of the model.

Before the actual VARs are estimated, it is necessary to select the variables to be included in the model. A wide variety of sources might be responsible for movements in the price level. Hence, as a first step in determining the relevance of various indicators (e.g. monetary aggregates, indicators of aggregate activity, wages, exchange rates) we fit the following regression

$$\pi_{t+k}^{j} = \sum_{i=1}^{13} \alpha_i \pi_{t+k-i}^{j} + \sum_{i=0}^{13} \beta_i Y_{t-i} + \epsilon_t^{j} \qquad j = 1, ..., 5 \tag{8}$$

where π_{t+k}^{j} is the inflation rate in period $t+k$ for subindex j (four subcomponents and headline HICP) on a monthly basis, Y_t is the indicator variable to be tested (both are made stationary by differencing). The equations are estimated over the full sample from 1987:01 to 2001:05. Since it appears natural that different variables might be helpful predictors at different forecast horizons, we estimated the equations for several leads ($k = 1, 3, 6, 12$).

The relevance of indicator variables is determined by testing the joint hypothesis that all the β_i are simultaneously zero. Although a statistical test is employed, the selection of the variables still involves a substantial amount of judgement. This is true especially in cases where the significance depends crucially on the forecast horizon. It should be noted that determining the importance of various indicators on the basis of the estimated regressions and the Wald test statistics can act only as a preliminary tool for sorting out relevant variables. It is possible that variables which are significant in the regression do not improve the forecasts of the multi-equation model. It is also known that the predictive power of inflation indicators is not very stable over time. Hence, one should expect that estimation of regressions over different subsamples might lead to different results.

A.3 Appendix: Measuring forecast accuracy

In general there are a few factors that need to be considered when choosing a forecasting method. The most important include forecasting accuracy, cost, properties of the series being forecasted and available computer software. We have used forecasting accuracy as a benchmark in our comparison. Measuring forecasting accuracy is, however, not a trivial task.

Let $e_{t+n|I_t} = x_{t+n} - \hat{x}_{t+n|I_t}$ be the n months ahead forecast error given Information I_t available at time t, x_{t+n} the realised value at time $t+n$ and $\hat{x}_{t+n|I_t}$ the forecast of x_{t+n} with information set I_t.

Four commonly used accuracy statistics for n months ahead forecasts can be defined as

$$
\begin{array}{lll}
MAE(n) & = T^{-1} \sum_{t=1}^{T} |e_{t+n|I_t}| & \text{mean absolute error} \\
MSE(n) & = T^{-1} \sum_{t=1}^{T} e_{t+n|I_t}^2 & \text{mean square error} \\
RMSE(n) & = \sqrt{T^{-1} \sum_{t=1}^{T} e_{t+n|I_t}^2} & \text{root mean square error} \\
U_2(n) & = \dfrac{\sqrt{\sum_{t=1}^{T} e_{t+n|I_t}^2(n)}}{\sqrt{\sum_{t=1}^{T} x_{t+n}^2}} & \text{Theil's U}
\end{array}
$$

Which of those measures to choose for the evaluation of forecasting accuracy? The inherent difficulty in choosing one of those measures lies in the fact that it depends on the characteristics of the loss function of the forecaster. Among the most important characteristics are its functional form (linear or nonlinear) and the degree of symmetry. With a symmetric loss function overestimation is as bad as underestimation. An asymmetric shape, however, implies that an amount of overestimation is not as bad as an equal amount of underestimation. What accuracy measure should be chosen given the loss function of a central bank?

The MAE obviously implies a linear loss function of the forecaster as this measure doubles if the forecasting error doubles. In contrast, the MSE as well as the RMSE and Theil's U[17] imply quadratic and hence symmetric loss functions as an increase in the forecasting error is penalised quadratically. The MAE in contrast implies an asymmetric loss function. An additional

[17] There are two variants of Theil's inequality coefficient labelled U_1 and U_2. U_1 was the original form of Theil's accuracy statistic (see [23]). The definition in appendix A.3 refers to U_2 originally published in [24]. U_1 suffers from the deficiency of not being a monotonic function of the forecasting error $e_t(n)$. Granger and Newbold [10] have shown that minimizing U_1 might fail to yield the optimal predictor.

feature is the scale dependence of the MAE, MSE and RMSE. Theil's U instead is scale independent and hence the preferable measure if comparisons are made across series.

In our empirical application in section 3 we use the RMSE as we are of the opinion that the central bank's loss function is better described by a quadratic function or some transformation of it so as to penalised large deviations from an objective stronger than small deviations. Furthermore, as we are not comparing forecasting accuracy across series the application of the RMSE appears to be an appropriate measure.

B APPENDIX: List of variables

Variable	Comments	Databank Code
ip	Industrial production, total exclusive construction, 1990=100; from January 1996 according to NACE-system	SBBAAT11*
ipexe	Industrial production, mining and manufacturing, 1990 = 100; as of January 1996 according to NACE-system	SBEAAT11*
ipe	Industrial production, energy, 1991 = 100; as of January 1996 according to NACE-system	SCHAAT01*
orders	Orders in Industry, total inflow, value, as of January 1996 according to NACE-system	TBHAAT01*
rshort	Money market rate, 3-months, moving average	HEEAAT02
rlong	Secondary market yield, central government bonds (9 to 10 years), end of month	HGCAAT01*
realex	Effective exchange rate, real, CPI based, moving average	QSHAAT02*
ex$	Exchange rate, AT Schillings/US Dollar, moving average	QBCAAT01*
vpide	Cost of living index for Germany, all items, West and East (before 1991 West Germany) Germany	VEBADE01 (VEBA DE51)*
epupf	Producers' price index for pigs exclusive VAT, weighted price for average quality	PLESHN**
tl	Negotiated standard wage rate index, overall index exclusive public sector employees, 1986 = 100	Y8PBBS**
p-exp	Sales price expectations, balance in percent, EU DG2	TEIATVP3**
pworld	World market price index, HWWA, 1975 = 100, $ basis	WPNGGS**
tl-upf	Negotiated standard wage rate index. agriculture and forestry, 1976 = 100	YNLBBS**
ghpupf	Wholesale price index, agricultural products	PJLANS**
tl-neig	Negotiated standard wage rate index, industry, 1976 = 100	YNIBBS**
pworld-ne	World market prices, HWWA Index, total exclusive energy	WPNOES**
pworld-e	World market prices, HWWA Index, energy, $ basis	WPNERS**
pworld-o	World market prices, HWWA Index, crude oil, $ basis	WPNROS**
tl-fv	Negotiated standard wage rate index, tourism, 1966 = 100	YTFBBS**
tl-ha	Negotiated standard wage rate index, trades, 1966 = 100	YTHBBS**
tl-ba	Negotiated standard wage rate index, banking and insurance, 1966 = 100	YTKNNS**
r$3m	3-month interest rate on the Euro-$ market, average of daily quotes	WREU3N**
emp	Employees, total number in persons	ABSEGM**
ghp-e	Wholesale price index, mineral oil exclusive VAT, 1986 = 100	PJMOES**
pkw	Registrations of new vehicles, total	DPSPUM**
realwk	Index of Austria's Price Competitiveness (until December 1998 Index of Effective Exchange Rates of the Schilling)	FTRTTS**
naecht	Tourism, total overnight stays.	DFJGGM**
m1	Monetary aggregate M1; from January 1999 exclusive euro area currencies	OeNB data
m3	Monetary aggregate M3, from January 1999 exclusive euro area currencies	OeNB data
credit	Loans to private sector	OeNB data

* Bank of International Settlements Databank

** Austrian Institute of Economic Research Databank

C APPENDIX: Results of the leading indicator analysis

The tables below show the results of the prefitting regressions (see equation 8in appendix A) for various forecasting horizons. The F-statistic is the result of comparing the residual sum of squares of a regression with and without the indicator variable. If the corresponding probability of type 1 error is small the hypothesis of explanatory power of the indicator variable for the subindexes is not rejected.

The numbers in parenthesis in the tables below indicate the order of differencing. For instance, (1,12) indicates first order differencing and seasonal differencing at lag 12. The indicator variables for the other price indices required unit and seasonal differencing at lag 12 except for the spread, the long term and short term interest rates, the real exchange rate and price expectations, which were integrated of order 1.

Table 7: Energy Index

Indicator	F-statistic	p-value	F-statistic	p-value
	1 lead		3 leads	
ghp-e(1,12)	2.12	0.13	2.87	0.06
vpide(1,12)	2.64	0.08	2.09	0.13
orders(1,12)	2.43	0.09	2.04	0.13
p-world-e(1,0)	3.16	0.05	1.38	0.25
spread(1,0)	1.55	0.22	1.86	0.16
credit(1,12)	1.05	0.35	1.4	0.25
tl(1,12)	3.24	0.04	2.95	0.06
emp(1,12)	3.19	0.04	2.69	0.07
m1(1,12)	3.97	0.02	2.48	0.09
realex(1,0)	2.79	0.07	1.97	0.14
rlong(1,0)	3.33	0.04	3.66	0.03
rshort(1,0)	1.21	0.3	1.21	0.3
ip(1,12)	1.21	0.3	0.68	0.51
ex(1,0)	1.98	0.14	1.53	0.22

Table 8: Energy Index

Indicator	F-statistic	p-value	F-statistic	p-value
	6 leads		12 leads	
ghp-e(1,12)	3.35	0.04	0.72	0.49
vpide(1,12)	1.14	0.32	1.17	0.31
orders(1,12)	1.65	0.2	1.69	0.19
p-world-e(1,0)	2.01	0.14	3.08	0.05
spread(1,0)	2.19	0.12	1.61	0.2
credit(1,12)	1.4	0.25	1.14	0.32
tl(1,12)	2.16	0.12	1.8	0.17
emp(1,12)	2.5	0.09	2.77	0.07
m1(1,12)	1.93	0.15	2.1	0.13
realex(1,0)	1.78	0.17	2.07	0.13
rlong(1,0)	3.84	0.02	3.18	0.05
rshort(1,0)	2.82	0.06	2.84	0.06
ip(1,12)	1.46	0.24	0.57	0.57
ex(1,0)	1.12	0.33	1.9	0.15

Table 9: Services Index

Indicator	F-statistic	p-value	F-statistic	p-value
	1 lead		3 leads	
vpide(1,12)	0.49	0.61	1.02	0.36
p-world-e(1,0)	1.00	0.37	0.75	0.47
spread(1,0)	2.49	0.09	1.89	0.16
credit(1,12)	1.09	0.34	1.11	0.33
tl(1,12)	1.45	0.24	0.86	0.43
m1(1,12)	0.54	0.58	2.09	0.13
realex(1,0)	0.89	0.41	1.83	0.17
rlong(1,0)	1.80	0.17	1.18	0.31
rshort(1,0)	1.89	0.16	0.80	0.45
ip(1,12)	3.12	0.05	3.98	0.02
ex(1,0)	1.27	0.28	1.46	0.24
naecht(1,12)	2.88	0.06	0.67	0.51

Table 10: Services Index

Indicator	F-statistic	p-value	F-statistic	p-value
	6 leads		12 leads	
vpide(1,12)	1.50	0.23	0.41	0.66
p-world-e(1,0)	0.96	0.39	0.23	0.79
spread(1,0)	2.47	0.09	2.33	0.10
credit(1,12)	0.75	0.47	0.13	0.88
tl(1,12)	2.11	0.13	0.93	0.40
m1(1,12)	0.58	0.56	0.07	0.94
realex(1,0)	2.34	0.10	2.58	0.08
rlong(1,0)	1.46	0.24	2.58	0.08
rshort(1,0)	1.02	0.36	1.21	0.30
ip(1,12)	1.41	0.25	0.61	0.55
ex(1,0)	1.92	0.15	2.59	0.08
naecht(1,12)	0.25	0.78	1.22	0.30

Table 11: Unprocessed Food Index

Indicator	F-statistic	p-value	F-statistic	p-value
	1 lead		3 leads	
vpide(1,12)	1.38	0.26	2.66	0.07
spread(1,0)	0.86	0.42	1.58	0.21
credit(1,12)	1.29	0.28	1.48	0.23
tl(1,12)	0.77	0.47	0.30	0.74
m1(1,12)	1.62	0.20	1.30	0.28
realex(1,0)	0.60	0.55	1.10	0.34
rlong(1,0)	0.22	0.80	2.15	0.12
rshort(1,0)	0.86	0.42	0.84	0.43
ip(1,12)	0.84	0.44	1.26	0.29
ex(1,0)	0.93	0.40	0.37	0.69
dsdlm3	1.66	0.19	1.29	0.28
ghpupf(1,12)	0.95	0.39	1.10	0.34

Table 12: Unprocessed Food Index

Indicator	F-statistic	p-value	F-statistic	p-value
	6 leads		12 leads	
vpide(1,12)	3.29	0.04	4.96	0.01
spread(1,0)	0.63	0.53	0.54	0.58
credit(1,12)	3.92	0.02	3.12	0.05
tl(1,12)	1.18	0.31	1.88	0.16
m1(1,12)	1.36	0.26	1.74	0.18
realex(1,0)	1.00	0.37	0.50	0.61
rlong(1,0)	0.28	0.76	0.19	0.83
rshort(1,0)	0.96	0.39	1.95	0.15
ip(1,12)	2.40	0.10	2.48	0.09
ex(1,0)	0.52	0.60	0.53	0.59
m3(1,12)	4.00	0.02	1.61	0.21
ghpupf(1,12)	3.25	0.04	3.84	0.02

Table 13: Processed Food Index

Indicator	F-statistic	p-value	F-statistic	p-value
	1 lead		3 leads	
credit(1,12)	1.89	0.16	1.98	0.14
vpide(1,12)	0.65	0.52	3.21	0.04
tl(1,12)	1.86	0.16	2.02	0.14
m1(1,12)	3.39	0.04	2.90	0.06
realex(1,0)	0.84	0.43	1.47	0.23
rlong(1,0)	0.12	0.89	1.68	0.19
spread(1,0)	0.86	0.43	1.94	0.15
ip(1,12)	1.12	0.33	2.86	0.06
ex(1,0)	0.50	0.61	1.88	0.16
rshort(1,0)	1.20	0.31	2.93	0.06
ghpupf(1,12)	2.00	0.14	1.21	0.30
m3(1,12)	1.18	0.31	2.42	0.09
pexp(1,0)	1.82	0.17	4.25	0.02

Table 14: Processed Food Index

Indicator	F-statistic	p-value	F-statistic	p-value
	6 leads		12 leads	
credit(1,12)	2.82	0.06	2.06	0.13
vpide(1,12)	4.65	0.01	2.73	0.07
tl(1,12)	2.50	0.09	2.63	0.08
m1(1,12)	4.80	0.01	2.79	0.07
realex(1,0)	2.02	0.14	2.69	0.07
rlong(1,0)	2.67	0.07	3.12	0.05
spread(1,0)	2.87	0.06	2.74	0.07
ip(1,12)	3.50	0.03	4.34	0.02
ex(1,0)	2.38	0.10	2.31	0.10
rshort(1,0)	3.40	0.04	6.94	0.00
ghpupf(1,12)	1.66	0.19	2.53	0.08
m3(1,12)	3.39	0.04	3.14	0.05
pexp(1,0)	5.44	0.01	3.31	0.04

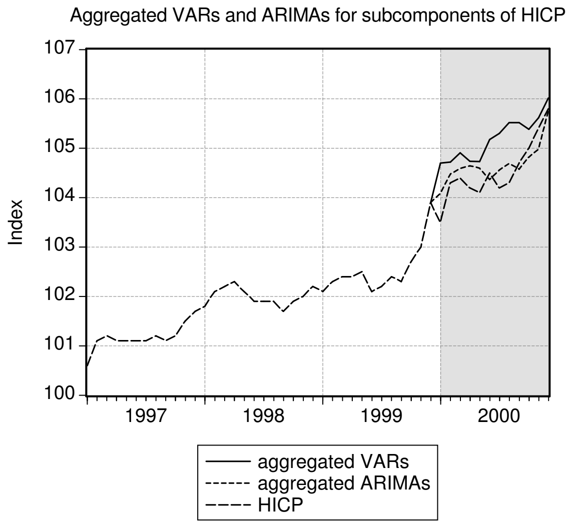
Table 15: Headline HICP

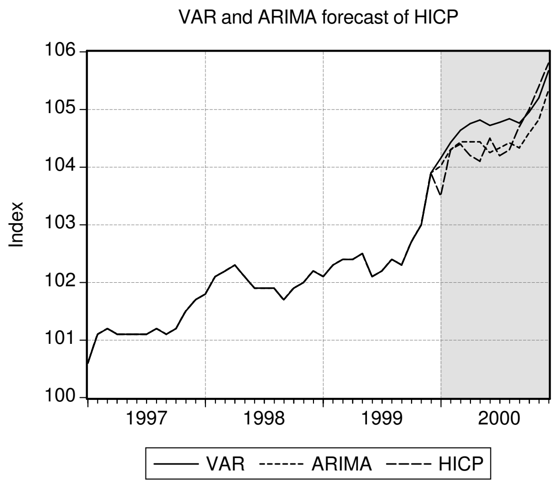
Indicator	F-statistic	p-value	F-statistic	p-value
	1 lead		3 leads	
vpide(1,12)	1.52	0.22	1.62	0.20
spread(1,0)	0.41	0.67	0.66	0.52
credit(1,12)	2.47	0.09	2.74	0.07
tl(1,12)	1.33	0.27	1.42	0.25
m1(1,12)	1.22	0.30	3.40	0.04
m3(1,12)	0.79	0.46	2.12	0.12
realex(1,0)	1.27	0.28	0.88	0.42
ip(1,12)	0.47	0.63	0.68	0.51
ex(1,0)	1.92	0.15	1.56	0.21
pexp(1,0)	1.53	0.22	1.34	0.27
emp(1,12)	1.57	0.21	2.37	0.10
ghp-e(1,12)	0.93	0.40	1.40	0.25
naecht(1,12)	0.40	0.67	0.66	0.52
orders(1,12)	0.75	0.47	0.94	0.40
p-world-e(1,0)	1.02	0.36	0.80	0.45
pkw(1,12)	1.58	0.21	1.38	0.26

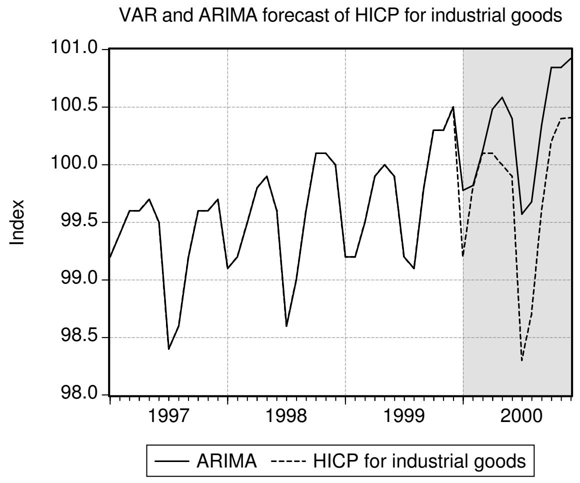
Table 16: Headline HICP

Indicator	F-statistic	p-value	F-statistic	p-value
	6 leads		12 leads	
vpide(1,12)	1.57	0.21	1.74	0.18
spread(1,0)	1.25	0.29	0.98	0.38
credit(1,12)	2.03	0.14	1.19	0.31
tl(1,12)	1.34	0.27	1.43	0.24
m1(1,12)	1.78	0.17	0.59	0.55
m3(1,12)	2.05	0.13	0.56	0.57
realex(1,0)	0.82	0.44	1.40	0.25
ip(1,12)	1.21	0.30	1.10	0.34
ex(1,0)	1.56	0.22	1.16	0.32
pexp(1,0)	1.11	0.33	1.37	0.26
emp(1,12)	1.66	0.19	1.50	0.23
ghp-e(1,12)	2.44	0.09	1.17	0.32
naecht(1,12)	0.80	0.45	0.49	0.61
orders(1,12)	0.75	0.48	1.11	0.33
p-world-e(1,0)	3.00	0.05	2.07	0.13
pkw(1,12)	0.78	0.46	2.52	0.09

D APPENDIX: Figures






VAR and ARIMA forecast of HICP for industrial goods
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98.0
1997
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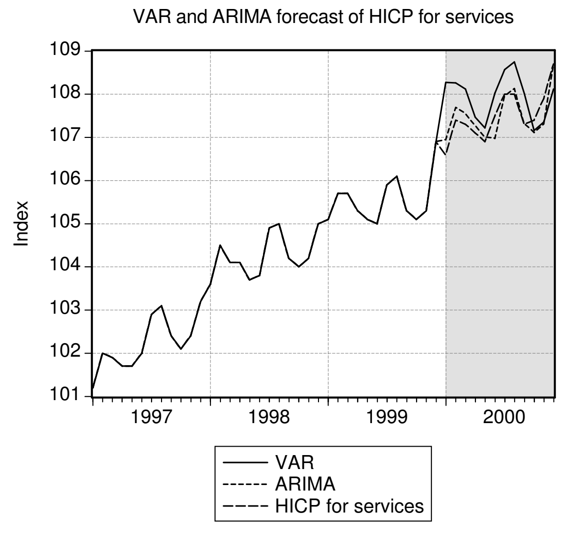
1999
2000
ARIMA
HICP for industrial goods


VAR and ARIMA forecast of HICP for services
Index
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108
107
106
105
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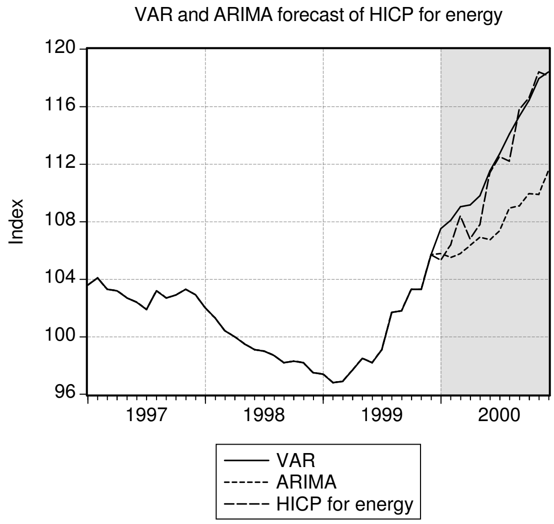
103
102
101
1997
1998
1999
2000
VAR
ARIMA
HICP for services


VAR and ARIMA forecast of HICP for energy
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116
112
108
104
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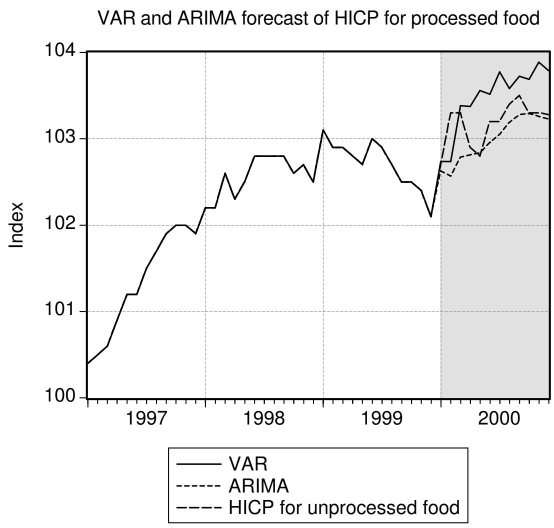
96
1997
1998
1999
2000
VAR
ARIMA
HICP for energy


VAR and ARIMA forecast of HICP for processed food
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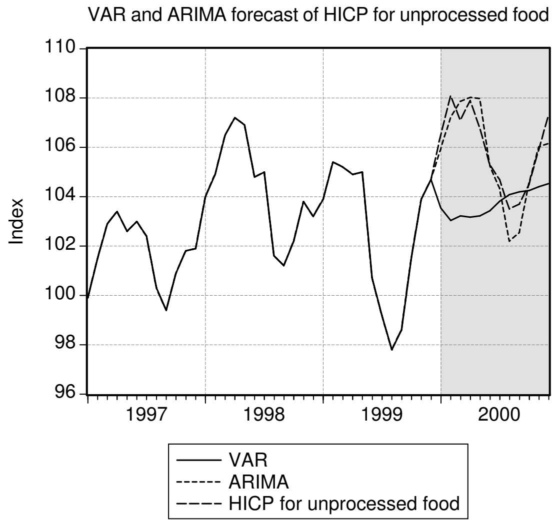
104
103
102
101
100
1997
1998
1999
2000
VAR
ARIMA
HICP for unprocessed food


VAR and ARIMA forecast of HICP for unprocessed food
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104
102
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98
96
1997
1998
1999
2000
VAR
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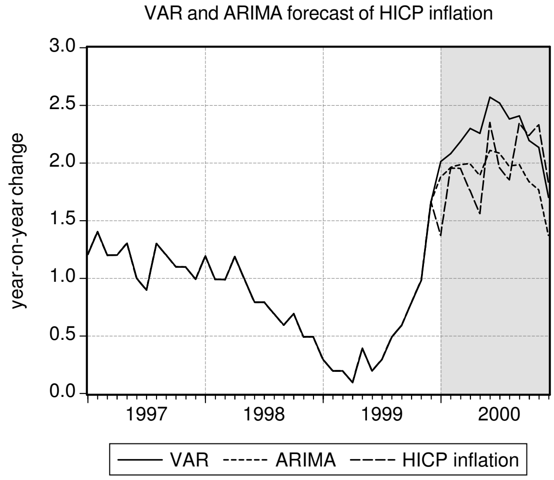
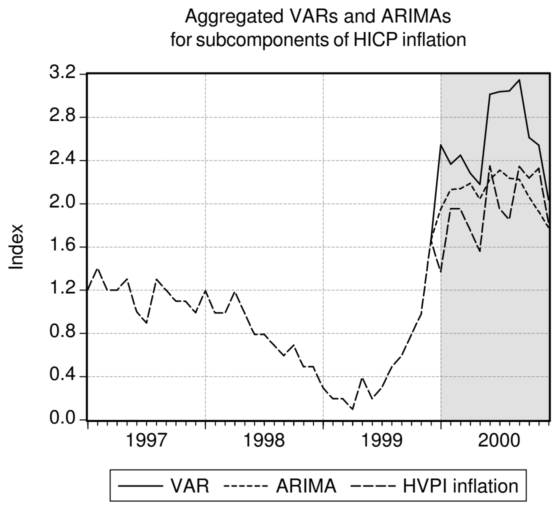
HICP for unprocessed food


VAR and ARIMA forecast of HICP inflation
year-on-year change
3.0
2.5
2.0
1.5
1.0
0.5
0.0
1997
1998
1999
2000
VAR
ARIMA
HICP inflation



Aggregated VARs and ARIMAs
for subcomponents of HICP inflation
Index
3.2
2.8
2.4
2.0
1.6
1.2
0.8
0.4
0.0
1997
1998
1999
2000
VAR
ARIMA
HVPI inflation

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