VAR models of inflation[1]

Can movements in some macroeconomic variables give information about future changes in inflation? Here we illustrate the use of Vector Autoregressive (VAR) models as a way of tackling this question. Monthly and quarterly models are estimated, and we show how a small list of inflation indicator variables for each can be selected on statistical grounds. Forecasts for RPIX inflation from the monthly model show inflation rising in 1993 before declining at the end of the year. The quarterly model is used to forecast both 1993 and 1994, and this shows inflation increasing in the second half of 1994 after falling over 1993 and the first half of 1994.

Introduction

Statistical models have been used to forecast the economy for more than twenty years in the United Kingdom. Over much of this period attention has focused on macroeconomic models such as those at the National Institute of Economics and Social Research and the London Business School, as well as those at the Treasury and the Bank. These models are used to provide forecasts of a large number of economic variables, including inflation.

But forecasts of the economy can be produced in a number of ways. This article describes one alternative, using so-called VAR models, and assesses the value of such models in forecasting inflation. Because many things can affect inflation, the advantage of the VAR approach is that their usefulness in forecasting inflation can be directly evaluated. Using this approach it is possible to identify a small selection of economic variables, movements in which appear to have been highly correlated with inflation in the past, and which may then be useful in forecasting future inflation. These variables can be interpreted as indicator variables for inflation [for a related exercise, using US data, see McCallum (1990)].

A Vector Autoregressive (VAR) model is a set of dynamic statistical equations involving a set of variables where every variable is used to determine every other variable in the model. VAR models have increasingly been used in macroeconomic research over the last decade or so, especially in the United States. To a large extent, interest in them has increased because of doubts about the usefulness of 'structural' macroeconomic models for forecasting and the evaluation of policy.

Most macroeconomic models, including forecasting models such as those maintained by the Bank and the Treasury, are structural models. Structural models try to show the main linkages in the economy with each link based on economic theory. In this way theory is used to restrict the number of variables in particular equations and the influence they have. Structural macromodels of this sort are used both for forecasting and to analyse the effects of policy changes. But many economists argue that it is not possible to estimate such structural models. Sims (1980), in a seminal critique of structural models, forcefully argued that the restrictions applied to such models when estimating them were 'incredible', and could not be properly tested. Sims' critique was mainly launched against the use of structural models for policy evaluation. But structural models have also been heavily criticised more recently on the grounds of their poor forecast performance. A VAR model is a 'non-structural' alternative which simply estimates how variables are related to lagged values of other variables over time and without restrictions about which of the variables affect the others.

This article is not concerned with making any judgments about the relative strengths and weaknesses of structural and non-structural models, but simply provides examples of the way VAR models can be estimated and used for forecasting. Its principal focus is the usefulness of these models for forecasting inflation, as measured by changes in RPIX, over a one-year and two-year horizon. Examples using both monthly and quarterly data are discussed.

What is a VAR?

A formal statement of a typical VAR is

$$X_t = B_o + B_1X_{t-1} + \dots B_mX_{t-m} + U_t \qquad (1)$$

where X is a list of macroeconomic variables such as output, employment or inflation. The list of variables on the left hand side is explained by the past values of the same variables on the right hand side (in practice there is a limit on how far back in the past we can go, and on how many variables are used). So, for example, output is explained in terms of the past history of output, employment, inflation etc; and employment is explained in terms of past employment, output and inflation etc etc. The explanation is not perfect, so there is a set of error terms [the Us in

(1) Written by S G B Henry and B Pesaran in the Bank's Economics Division.

equation (1)], which are assumed to be independent of the Xs. The $B_1, \ldots B_m$ terms are sets of coefficients, and in the examples used here these will be treated as fixed when estimated. The VAR is a statistical model which is estimated, and statistical tests are used to decide both on the variables to be included in the model, and on the appropriate length of lags at which they enter. The examples described in Appendix 2 illustrate the application of some of these criteria.

In a VAR model each variable is determined by past values of itself and of other variables in the model. As a result, the model can forecast the complete set of variables one period ahead, and these forecasts are used to predict a further period ahead and so on. In this article the focus is on short-term forecasts. Any forecast using a VAR model is made on the assumption that the estimated form of the model remains unchanged over the forecast. This last assumption can, of course, be challenged. Quantitative models for forecasting—including orthodox macroeconomic models—normally require a similar assumption: that the model estimated on historical data does not change over the forecast period. But one feature of a VAR which distinguishes it from other models used for forecasting is that it does not need further assumptions, such as those made in a typical macromodel about the policy stance or trends in exogenous variables. Instead, in a VAR all variables are forecast within the model.(1)

Sims (1980) and others, argue that unrestricted VARs as exemplified by (1) are not best suited for forecasting. By unrestricted it is meant that the past history of *all* the variables is used to explain each variable. Such VARs are prone to the problem of 'overfitting' and may have a poor forecasting performance. So, although using a large number of variables and their lagged values in a VAR will tend to make it fit historic data well, this fit may be deceptive. Restrictions imposed, either by dropping some of the lags at which variables appear, or even dropping certain variables from some equations in the model altogether, can improve forecast performance.

To avoid this problem of overfitting some researchers limit the number of parameters estimated in the model by limiting the lag structures used in the equations. The so-called BVAR (Bayesian Vector Autoregressive) model simplifies the lag distributions in this way. [See Artis and Zhang (1990) for an application of BVARs to forecasting the world economy, and Bladen-Hovell and Zhang (1992) for an application to the United Kingdom.] In this model beliefs are used to set values of the parameters in the model and to indicate the degrees of confidence with which these beliefs are held. These beliefs may reflect a number of things: economic theory, opinion or previous empirical results. One example in setting parameters is the 'Minnesota prior', where coefficients are set according to the assumption of a random walk, where all lagged values of variables are given a prior coefficient of zero, except the first which is unity. [This is discussed at greater length in Bladen-Hovell and Zhang (1992).] We do not follow the BVAR route here. But we do, as the following section explains, place some limits on the variables included in the VAR model we use for forecasting. We have adopted these limits by testing directly the restrictions we apply in terms of their data fit and their forecasting performance.

Preferred VAR models

To produce a VAR model of inflation, we first considered a large set of variables which may influence RPIX inflation. (See Appendix 1.) The list of variables could not be exhaustive and necessarily involves judgment. So we chose variables which represent domestic demand pressures (such as unemployment, or growth in production), external inflationary pressures (including changes in the nominal exchange rate) and monetary variables. Previous research findings, both in the Bank and elsewhere, had also suggested that some of these variables had, directly or indirectly, influenced inflation.

The initial list included monetary variables for obvious reasons. The aggregates M0 and M4 and several measures of short interest rates were taken as the main monetary factors. Recent research, especially in the United States, has pointed to the usefulness of financial spreads as indicators of activity, so we included the spread between long and short government bonds, and a credit-quality spread (commercial minus government yields). We also investigated the role of indicators of price and cost pressures, including unit labour costs, average earnings, the CBI price expectations series, house prices, and producers' input and output prices. External cost indices included are the nominal exchange rate, world commodity and world consumer prices, and indices of world oil prices. Lastly, we chose a number of measures of overall activity, including GDP and its components, output of production industries, retail sales, unemployment and the Gallup index of consumer confidence.

We built models using monthly data, and models using quarterly data. The sample period for the monthly model is January 1974 to December 1992, and for the quarterly model a sample from 1974 Q1 to 1992 Q4 was used. The data were seasonally unadjusted, unless they were unobtainable in this form. (See Appendix 1.) The monthly model started with twenty-three monthly variables and the quarterly model started with twenty-six quarterly variables. It might be argued that the same set of variables should be used in the empirical work at both monthly and quarterly frequencies. We decided, however, that in this case it was not important given that the aim of the study is to identify the most useful variables for forecasting inflation. So the main influences on inflation at both frequencies have been evaluated independently.

(1) This account emphasises the use of VARs for forecasting. With the addition of further identifying restrictions the policy implications of VARs may be established, although this form of policy analysis is rather different from that normally undertaken in a structural macroeconomic model. The main references on policy analysis in VARs is Sims *(op cit)* and Blanchard and Quah (1989).

We then reduced this list in a series of stages to those variables which appeared both to explain past movements in inflation well, and to produce plausible forecasts. So the final form of the VAR model used, either at quarterly or monthly frequency, uses only some of the initial set of variables.

Choosing the variables and their lags

Once we had chosen the variables for the initial list, the next problem was to select the most useful variables for the relatively small VAR models which are actually used here for forecasting.(1)

Although there are statistical tests which can help to decide which variables should be used, these could not be applied in a straightforward way owing to severe data limitations.(2) Instead we used a procedure which goes some way towards evaluating the alternatives in a systematic way. (See Appendix 2.) First we carried out partial tests to determine the explanatory power of each variable alone on inflation. These tests reduced the number of variables used to seven for both monthly and quarterly data. With the smaller set of variables it was then possible to estimate a VAR in the form given by equation **(1)**. It was also possible to decide on the number of lags in each model using a further statistical procedure which tested for the explanatory power of additional lags.

We then obtained even smaller models by using statistical tests of each *full* model designed to see if any variable could be left out without significantly affecting the fit of the model. It proved possible to derive several models this way, and their forecast performance over a set of different horizons was investigated before a final choice on the preferred model was made.

(a) Monthly

The seven-equation model for the monthly data included inflation, changes in M0, producer input prices, producer output prices, a credit-quality spread, retail sales and output of production industries. Each variable enters every equation with lags from one to thirteen inclusively.

But the evaluation of variables from this point recognises the interconnections between variables in the VAR model. So, although particular variables may have significant *direct* effects upon inflation, it is also possible that others have an important *indirect* effect. In other words, they appear to contribute to the explanation of a variable, which in turn significantly influences inflation, without appearing to affect inflation directly themselves. Another factor which has an important bearing on how well the complete VAR will forecast is the goodness of fit of each equation. So, even if a particular variable, say changes in the exchange rate, is found to have significant effects on inflation, it is not helpful if changes in the exchange rate cannot be forecasted.
To test these general features formally, 'whole-model' tests were used which resulted in a yet further simplification of the model. These tests are so-called tests of exclusion, (see Appendix 2). From these tests a five-variable or 'core' model was derived involving:

- inflation;
- changes in M0;
- producer output prices;
- retail sales; and
- output of production industries.

This version is a model with five equations where each variable enters with thirteen lags. The tests up to this point showed that, apart from past inflation itself, the growth in narrow money, producer output prices, retail sales and output all had significant effects on inflation between 1974 and 1992.

(b) Quarterly

A similar procedure was applied to the quarterly data. The seven-equation model for the quarterly data included inflation, changes in M0, consumer confidence, the FT 500 share price index, producer prices, base rates and the Treasury bill rate. VAR models for the seven variables were then estimated, and formal tests of exclusion of variables were done, again to test which variables could be left out without significantly affecting the overall explanatory power of the model. In this case, tests of the number of lags to be taken into account showed that a lag length of more than nine quarters provides no additional information. The models reported subsequently are restricted accordingly.

The whole-model tests indicated that the FT 500 share price index, producer prices, base rates and the Treasury bill rate could all be dropped without much deterioration in the explanatory power of the resulting model. Moreover, past changes in many of these variables are difficult to explain and, equally, would be difficult to forecast. Hence the quarterly—'core'—model was reduced simply to:

- inflation;
- changes in M0; and
- consumer confidence.

Before settling on this model a further test was carried out to establish whether consumer confidence could be replaced by other macroeconomic variables. Replacing it with, in turn, unemployment, unit labour costs and the exchange rate did not improve the model. So, the basic three-variable model is used for the prediction tests reported below.

(1) Before describing how these selections are made, it should be noticed that a preliminary—so-called pre-fitting—exercise was done on all the variables, to establish their time-series properties. This is an important step which tests whether each variable is stationary or not (broadly speaking, stationary means a variable is mean reverting and has a finite variance). If the variables were not stationary then the statistical tests which are employed later would not be valid. So all variables in the model are first rendered stationary after testing for their orders of integration. Further details are given in Appendix 2. In subsequent applications the variables are used in their stationary form, unless otherwise stated.

(2) Thus in the case of the monthly model there are twenty-three variables used initially and these may be subject to, say, a lag of up to twelve months. To decide whether this was appropriate would require at least 23 x 12 = 276 parameters to be estimated in each regression, which is untenable with 191 usable observations in the sample.

Forecasting performance

Our choice of model is not based only on its fit to past data, but also on its forecasting performance. So the next step is to evaluate the models' forecasts using a set of overlapping sample periods. This next section describes the forecast performance of the models derived above.

In testing the forecast performance of these models we re-introduced certain key variables—the nominal exchange rate, unit labour costs and the rate of unemployment—to see if they resulted in any improvement.

(a) Monthly prediction tests

The forecast tests used a set of predictions between January 1990 and December 1992, each predicting inflation 4, 6 and 12 months ahead. In each case the predictions for inflation were obtained using the full model, so all variables in the VAR, eg RPIX, M0, producer prices, retail sales and output of production industries, were each predicted dynamically in these exercises.

We also tested the effect of using the annual rate of change of prices as the inflation variable. The model to this point has used changes in inflation, on the basis of the results of the pre-fitting exercise given in Appendix 2. But, given that the object of the exercise is ultimately to forecast annual rates of inflation, the model was converted to annual inflation rates, which gave a somewhat improved forecast performance as judged by these summary criteria. It is this version which is reported more fully in Table 1.

The table reports summary statistics for the core model. It then gives the same information on the results from the model with additional variables, taking in turn the nominal exchange rate, the rate of unemployment and unit labour costs.

The summary information in Table 1 for the different models is the Root Mean Square Forecast Error (RMSFE) and the Theil U statistic.(1) The RMSFE is a measure of the *average* forecast accuracy of the model over a number of sample periods. The Theil U statistic compares the prediction from the model with that made by using a model which assumes no change in inflation. A value greater than unity means the forecasts from the VAR model are worse than those made with the 'no change' model.

These results show that, over this set of samples, the core model, using the annual rate of inflation [(a) in the table] produces a reasonably accurate forecast. The tests also show that adding any of the additional variables in the set (b) to (d), does not improve the forecasting ability of the model. Indeed, in the case of the labour market variable [(c) and (d)], the forecasting performance of the model is distinctly worsened. However, there is one exception to this: when the exchange rate is added to the model its predictions over longer periods—6 to 12 months—improve.

(b) Quarterly prediction tests

The tests of the forecasting performance of the quarterly model parallel those already given for monthly data. The

Table 1
Monthly model: summary measures of forecast accuracy for RPIX inflation

Sample: January 1990 to December 1992

	RMSFE percentage points			Theil's U statistic		
Prediction interval	1 month	6 months	12 months	1 month	6 months	12 months
Model:						
(a) Core model	0.41	1.17	1.49	0.91	0.74	0.65
Adding the exchange rate to (a) above						
(b)	0.44	1.15	1.25	0.97	0.73	0.55
Adding the unemployment rate to (a)						
(c)	0.43	1.35	1.70	0.96	0.85	0.74
Adding unit labour costs to (a)						
(d)	0.43	1.28	1.95	0.95	0.81	0.85

Table 2
Quarterly model: summary measures of forecast accuracy for RPIX inflation

Sample: 1988Q1 to 1992Q4

	RMSFE percentage points			Theil's U statistic		
Prediction interval	1Q	4Q	8Q	1Q	4Q	8Q
Model:						
(a) Core model	0.52	1.93	1.96	0.72	0.96	0.67
Adding the exchange rate to (a) above						
(b)	0.61	2.49	1.86	0.84	1.23	0.64
Adding the unemployment rate to (a)						
(c)	0.79	3.45	5.74	1.10	1.73	1.97
Adding unit labour costs to (a)						
(d)	0.67	2.71	2.90	0.93	1.35	0.99

(1) The RMSFE is defined as

$$\sqrt{\left[\frac{1}{N}\sum_{i}^{N}\left(\Delta P_{t+K,i}-\Delta\hat{P}_{t+K,i}\right)^2\right]}$$

Where ΔP is the rate of inflation, and $\Delta\hat{P}$ its value as predicted by the model. Then K is the horizon over which the forecast is made; in the present case 1, 6, and 12 month intervals are used. Finally, N is number of K step-forecasts done. We refer to it as the RMSFE rather than the conventional RMSE because the predicted values are full model forecasts over the different sample periods. The Theil U statistic in turn is

$$\sqrt{\left(\frac{\sum_{i}^{N}\left(\Delta P_{t+K,i}-\Delta\hat{P}_{t+K,i}\right)^2}{\sum_{i}^{N}\Delta P_{t+K,i}^2}\right)}$$

tests consider the forecast accuracy of the core model, which uses the quarterly change in RPIX as its measure of inflation. Table 2 gives the RSME of forecasts and Theil's U statistic for each version.

As with the monthly model, adding the labour market variables to the quarterly model does not appear to improve its forecasts. But adding the nominal exchange rate does lead to a slight improvement.

When comparing the prediction tests for the monthly and quarterly models, the monthly model appears rather better than the quarterly one over the shorter term. In other words, judged purely by its average errors made in prediction, for the samples used here, the monthly model appears somewhat better over the 12-month period than the quarterly one. Even so, this does not provide an absolute measure of the forecast performance of these models. The RMSE of forecasts quoted in Tables 1 and 2 for example are empirical measures which, to some extent, depend on the data period used.

Comparison of quarterly VAR with macromodel forecasts

A further question is how the forecast performance of these VAR models compares with that of the traditional structural macroeconomic models, as judged by these summary measures. Comparisons of this sort are difficult to make, however, because forecasts made with structural macroeconomic models are usually augmented by judgmental factors. The literature on this use of judgment, and its possible advantages, is extensive: discussion and evidence on UK models has been regularly provided in the publications of the Macroeconomic Bureau at Warwick University; and evidence for the United States is given in McNees (1990). But when comparing the forecasting performance of models *per se*, a more valid comparison in judging the usefulness of VAR models is that between a VAR forecast and a forecast produced purely by a macromodel itself. Examples of the latter are less common. Fisher and Wallis (1990) report model-based exercises over 1978–85 for the Bank of England (BE), the National Institute of Economic and Social Research (NIESR) and the London Business School (LBS) models. According to their calculations the RMSE of inflation forecasts given by these models over this sample period ranged from 0.73 percentage points for the Bank model to 1.4 percentage points for the LBS. These estimates refer to predictions made for the consumption price deflator, but only one quarter ahead. So on this—albeit imperfect—comparison, the VAR predictions are at least as good. Internal research on the Bank model estimates that the RMSE of forecasts of annual inflation is 1.48 percentage points for forecasts made one year ahead and 3.28 percentage points for forecasts two years out. Again for this calculation the price used is the consumption price deflator. Also these estimates are for the period 1976–89, a period which includes episodes when inflation was more volatile than the samples used for the tests on the VARs. But, although not strictly comparable, these estimates suggest that predictions from VAR models are at least as accurate as those obtained using structural models.

Forecasts for 1993 and 1994

Lastly, we used the VAR models derived in the previous sections to make forecasts for inflation over the future using the most recent data. Forecasts from each of the VAR models are given in Table 3. The monthly model is used to forecast until the end of the year, and the quarterly model to forecast until the end of 1994.

Table 3
Annual RPIX inflation forecasts from the VARs

Percentage changes on a year earlier

Monthly model	1993	Quarterly model		
April	3.6	1993	Q2	3.6
May	4.1		Q3	3.5
June	4.2		Q4	2.7
July	4.3	1994	Q1	1.9
August	4.3		Q2	1.7
September	4.5		Q3	1.8
October	4.5		Q4	2.6
November	4.3			
December	4.0			

In each case the monthly and quarterly models used are shown as alternative (a) in Tables 1 and 2—the 'core' models. Although there is some evidence from the forecast tests that a model adding the nominal exchange rate could be used for monthly data, taken in conjunction with the results of the earlier tests, the grounds for this change are not strong, and so the core model is used instead.

Forecasts from the monthly model show annual inflation rates rising until the latter part of the year when they fall. Forecasts from the quarterly model show a general tendency for inflation to fall over the two years, but reaching its lowest in the middle of 1994.

Conclusions and interpretations

The empirical results reported above are designed to illustrate how the VAR methodology can be applied when forecasting inflation.

In interpreting these results it is important to be clear about the limited nature of this exercise. It is explicitly intended only to ascertain which economic variables appear, statistically, to explain inflation. We therefore chose the tests to establish which variables have information in this narrow sense and which, like those variables currently used as leading indicators of economic cycles, can be used as leading indicators of inflation. As a result, the models do not have an orthodox—structural—interpretation, unlike the familiar behavioural macroeconomic model. So it would *not* be legitimate to interpret the finding of a significant effect of lagged M0 in the model as showing what would happen to inflation if M0 increased by a certain amount. The estimated parameters in the VAR do not give the marginal effect of, eg a change in M0 on inflation. This is because the model reported here is a 'reduced form' of an underlying structural model, and it is possible to evaluate the policy implications of this structural model only by applying additional identifying restrictions to the reduced form. This sort of evaluation has not been done here, as the purpose is solely that of calculating the usefulness of the estimated models for forecasting inflation over the one and two-year horizon.

What the results show is that fairly simple robust models can be obtained, and that their forecast performance over the short term is, apparently, at least as good as that of structural models. But this can only be a provisional conclusion. The monthly exercise identified a small set of variables which appear useful in predicting inflation. M0, producer output prices, retail sales and output of production industries all appear useful in this sense. In the case of quarterly models, it appears possible to use even fewer indicators: only M0 and the index of consumer confidence appear to be significant, although the resulting quarterly model does not seem to forecast as well as the monthly model over a twelve-month horizon.

Lastly, the reported forecasts obtained from the VARs are, of course, subject to uncertainty. Although we have not reported estimates of this uncertainty, the evidence in Tables 1 and 2 shows that the root mean square of prediction error when using the monthly model for a 12-month prediction was about 1.5 percentage points, as judged by the evidence from 1989–92 [version (a) Table 1]. For the quarterly model when predicting two years ahead the equivalent error was about two percentage points [using version (a) in Table 2].

Appendix 1

Data definitions and sources

List of variables for work on VAR modelling of RPIX

The set of variables below includes those mentioned by the Chancellor in his note to the Treasury and Civil Service Select Committee plus variables which have proved useful in our earlier work in this area.

The data used will generally be from 1974 onwards, although for some series the data cover a shorter period, as is indicated by the list below. All data are *seasonally unadjusted*, unless otherwise stated.

Variable	Comments	Quarterly (q)	Monthly (m)
CONF	Survey data: Gallup consumer confidence indicator	74Q1–92Q4	Jan.74–Feb.93
CONS	Consumers' expenditure, revalued at 1985 prices, only quarterly	54Q4–92Q3	not available
CQS	Credit quality: commercial less government bond yields	65Q1–92Q4	Jan.65–Feb.93
EER	Sterling effective exchange rate index	75Q1–92Q4	Jan.75–Feb.93
ETDE	Average earnings: whole economy (1988=100),*seasonally adjusted*	80Q1–92Q4	Jan.80–Jan.93
GDP	Gross domestic product at factor cost, at 1985 prices, only quarterly, *seasonally adjusted*	55Q1–92Q3	not available
HFAXUK	Halifax house price index (1983=100) is also available not used	not used	Jan.83–Feb.93
INV	Total investment: Total Gross Domestic Fixed Capital Formation, revalued at 1985 prices, only quarterly	55Q1–92Q3	not available
*KM*0	Level of M0, break-adjusted version of **AVAD**	69Q2–92Q4	June69–Jan.93
*KM*4	Level of M4, break-adjusted version of **AUYM**	63Q1–92Q4	June82–Jan.93
OUTP	Output of production industries, (1985=100)	48Q1–92Q4	Jan.68–Jan.93
PAHM	DoE house price index, all dwellings (1985=100), only available quarterly, *seasonally adjusted*	68Q2–92Q4	not available
PE	Survey data: CBI price expectations, forecast of four-month percentage change in manufacturers' domestic prices, calculated series, quarterly only	75Q2–93Q1	not available
PPI	Producers' input prices: manufacturers' input prices (1985=100)	74Q1–92Q4	Jan.74–Feb.93
PPOX	Producers' output prices: output prices for all manufactured products (1985=100)	74Q1–92Q4	Jan.74–Feb.93
PSBR	Public Sector Borrowing Requirement	63Q1–92Q4	Jan.79–Jan.93
RCBR	London clearing banks' base rate, monthly average, (data prior to 1980 for the monthly series relate to the MLR rate rather than the base rate)	74Q4–92Q4	Jan.70–Feb.93
RPIX	RPI excluding mortgage interest payments(1987=100)	74Q1–92Q4	Jan.74–Feb.93
RSALES	Retail sales, all retailers, volume index (1985=100)	71Q1–92Q4	Jan.71–Feb.93
*SPUK*500	FT-500 Industrial share price index (10 April 1962=100)	63Q1–92Q4	Jan.63–Feb.93
TB	Yield on three-month Sterling Treasury Bills,	63Q1–92Q4	Jan.63–Feb.93
ULC	Unit labour costs: unit wage costs for manufacturing industries (1985=100) are available monthly, *seasonally adjusted*	70Q1–92Q4	Jan.70–Jan.93
UMG	Imports of goods, unit value index (1985=100)	63Q1–92Q4	Jan.80–Dec.92
URATE	UK unemployment rate: number of unemployed claimants as a percentage of the estimated total workforce	71Q1–93Q1	Jan.71–Jan.93
*WCP*1	World commodity prices: trade weighted non-oil world commodity price index using UK trade weights (1985=100)	not used	Jan.74–Mar.93
*WCP*2	Foreign prices: trade weighted consumer prices index (1980=100), calculated using Sterling ERI weights	76Q1–92Q3	Jan.76–Sept.92
WPO	Brent crude oil price (US$ per barrel)	not used	Jan.80–Dec.92
*WPO*2	World oil price only available quarterly	63Q1–92Q3	not available
YC	Yield curve: short-dated (five years) gross redemption yield on British Government stock, less three-month Treasury Bill rate	63Q1–92Q4	Jan.63–Feb.93

All data are available on request.

Appendix 2

Methodology of research

In this project we have attempted to apply a systematic search procedure over the contending alternatives. What makes this difficult is the large set of variables used. The question of the seasonal adjustment of the series, and the bearing any decision here might have on later identification of dynamic models, is also an important consideration. In outline, the steps were as follows:

(i) An evaluation of the time series properties of each series

This included the usual tests for orders of integration. In addition we tested for the presence of a seasonal difference, ie for X_t whether

$$(1 - L^{12})\, X_t = \varepsilon_t \tag{1}$$

where L is the lag operator, produced a stationary error term in the monthly series (L^4 is used for the quarterly data).

(ii) Preliminary bivariate models

These models took the form

$$A(L)\, RPIX'_t = B(L)\, X'_{it} \tag{2}$$

where $RPIX'$ is the stationary version of $RPIX$, as dictated by the results from (i) above. $A(.)$ and $B(.)$ are polynomials in the lag operator. Similarly X'_i is the stationary value of the X_i th variable, where X is the set of variables considered in this study. For example, if it was decided that X_i was simply $I(1)$, then X'_{it} is defined as ΔX_{it}.

The tests in (2) were designed to show whether each of the X variables appeared to have explanatory information for inflation once lagged information in inflation itself had been allowed for (the $A(L)$ terms). Tests for this used log-likelihood ratio tests, which are then simple variable exclusion tests,

$$2(LLU - LLR) \sim \chi^2(K) \tag{3}$$

where LLU is the maximised log-likelihood of model (2) and LLR is the value of the log-likelihood when $B(L) = 0$ in (2), and K the degrees of freedom (determined by lag length).

(iii) Tentative VAR models

The results from (ii) are used to exclude variables which appeared uninformative in accounting for inflation. The remaining subset of X variables, including RPIX, were then used to form a VAR. The next set of tests were on this VAR and:

(a) tested for the lag length of the VAR using a likelihood ratio test; and

(b) sequentially eliminated a variable from the VAR model on the basis of block exogeneity tests.

This procedure overall gives a reasonably systematic way of testing the statistical power of each X variable in a VAR model but, as noted in the text, owing to data limitations a fully systematic evaluation of all alternatives did not prove possible.

Further detail in the results of the test of integration noted in the text are given next.

(iv) Integration properties of the data

Table A1 shows the results of a univariate exercise aimed at establishing the time series behaviour of the variables of interest. The alternatives considered are of the general form I(1,1) where the first number refers to the level of zero frequency differencing, the second is the seasonal frequency. Thus, for monthly data, if

(a) $(1\text{-}L)\, X_t$ has a stationary error, this implies the variable is $I(1,0)$

(b) $(1\text{-}L^{12})\, X_t$ implies the variable is $I(0,1)$ ie needs to be differenced at the seasonal frequency (here 12 months) to induce stationarity.

(c) $(1\text{-}L)(1\text{-}L^{12})\, X_t$ implies the variable is $I(1,1)$ so the variable needs to be first differenced, and differenced at the seasonal frequency, to induce stationarity.

The equivalent form for quarterly data is, eg $I(1,1)$ implies that the quarterly operations are $(1\text{-}L)(1\text{-}L^4)$.

The tests used were $ADF(12)$ ($ADF(4)$ for quarterly data) tests, and the results for each of the variables are shown in Table A1, with their assignment.

Table A1
Tests for orders of integration

(A) ADF(12) tests for monthly data

Variable	(1-*L*)	(1-*L*)(1-L^{12})	(1-L^{12})	*I(i, j)*
Log RPIX	-2.1	-5.5	-2.4	I(1,1)
Log (KM0)	-1.9	-5.9	-1.2	I(1,1)
Log (KM4)	1.0	-2.4	0.3	I(1,1)
ΔLog (KM4)	-4.5			I(1,0)
Log (EER)	-4.2			I(1,0)
Log (HFAXUK)	-0.8	-3.0	-0.2	I(1,1)
CQS	-4.5			I(1.0)
YC	-4.0			I(1,0)
Log (ULC)	-3.2			I(1,0)
Log (PPI)	-2.3	-5.5	-2.0	I(1,1)
Log (PPOX)	-2.5	-5.5	-2.5	I(1,1)
Log (WPO)	-3.8			I(1,0)
Log (*SPUK* 500)	-5.4			I(1,0)
Log (*CONF*)	-4.8		-3.1	I(0,1)
Log (*RSALES*)	-3.8	-5.5	-2.8	I(1,1)
Log (*OUTP*)	-3.2	-5.6	-3.7	I(1,1)
Log (*UMG*)	-3.4			I(1,0)
PSBR	-5.2			I(1,0)
Log (*WCP*1)	-4.4			I(1,0)
Log (*WCP*2)	-4.7			I(1,0)
Log (*URATE*)	-10.8	(restricted ADF)with dummy for 88M10		
RCBR	-4.0	(restricted ADF)		I(1,0)
TB	-4.0			
Log (*ETDE*)	-15.4			I(1,0)

(B) *ADF*(4) tests for quarterly data

Variable	*ADF*(4)	*I(i, j)*	Variable	*ADF*(4)	*I(i, j)*
Log(*RPIX*)	-3.72	I(1,0)	Log(*WPO*2)	-4.05	I(1,0)
Log(*KM0*)	-2.66 (a)	I(1,0)	Log(*SPUK* 500)	-5.35	I(1,0)
Log(*KM*4)	-1.42 (a)	I(1,0)	*RCBR*	-4.11	I(1,0)
Log(*EER*)	-4.15	I(1,0)	*TB*	-4.50	I(1.0)
Log(*PAHM*)	-2.35 (a)	I(1,0)	Log(*PE*)	-3.43	I(0,1)
YC	-3.32 (a)	I(1,0)	*CONF*	-4.29	I(1,0)
CQS	-3.23 (a)	I(1,0)	Log(*RSALES*)	-2.32 (a)	I(1,0)
PSBR	-3.66 (b)	I(0,0)	Log(*GDP*)	-3.05 (a)	I(1,0)
Log(*ULC*)	-3.79	I(1,0)	Log(*OUTP*)	-4.65	I(1,0)
Log(*ETDE*)	-2.16 (a)	I(1,0)	log(*INV*)	-2.37 (a)	I(1.0)
Log(*PPI*)	-4.96	I(1,0)	log(*CONS*)	-2.03 (a)	I(1.0)
Log(*PPOX*)	-4.16	I(1,0)	log(*UMG*)	-3.88	I(1,0)
Log(*WCP*2)	-4.87	I(1,0)	log(*URATE*)	-3.50	I(1.0)

(a) By inspection of the spectrum and correlogram.
(b) DF test with quarterly dummies added.

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