A MARKUP MODEL FOR FORECASTING INFLATION FOR THE EURO AREA*

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ABSTRACT

We develop a small model for forecasting inflation for the Euro area using quarterly data over the period June 1973 to March 1999. The model is used to provide inflation forecasts from June 1999 to March 2002. We compare the forecasts from our model with those derived from six competing forecasting models, including autoregressions, vector autoregressions and Phillips-curve based models. A considerable gain in forecasting performance is demonstrated using a relative root mean squared error criterion and the Diebold-Mariano test to make forecast comparisons.

Keywords: Inflation, prices, markup, business cycle, cointegration, forecasting
JEL Classification: C22, C32, C52, D40, E31, E32

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1. INTRODUCTION

Recent work by us (Banerjee, Cockerell and Russell, 2001, and Banerjee and Russell, 2001, 2005) has demonstrated the existence of a long-run relationship between inflation and measures of the markup, where the markup is defined as the ratio of an aggregate measure of price to a measure of cost. These papers proceed from the maintained assumption that both inflation and the markup are integrated of order one, and show that for Australia and for the G7 countries (except Japan), a negative long-run relationship in the sense of Engle and Granger (1987) can be derived. Alternative approaches are given by Henry (1999) and Fagan, Henry and Mestre (2001) and by the multi-country models of De Bondt, Els, and Stokman (1997) and the Deutsche Bundesbank (2000).

Our work formally recognises that monetary policy at times displays discrete shifts and that inflation may therefore be non-stationary. To allow for this possibility one could proceed by treating inflation as either stationary with shifting means or as an integrated variable. We argue in Section 2 that while the former may be the 'true' statistical process, there are good practical reasons to proceed as we do by modelling inflation as an integrated variable.

Our methodology is used here to develop a small inflation-markup model for forecasting inflation for the Euro area. The basic model and our empirical modelling strategy are described in Section 2 and estimated in Section 3 using quarterly Euro-area data for the period March 1973 to March 2002.[1] Important aspects of the model are its simplicity, the stability of the estimated coefficients and its superior forecasting performance compared with a range of competing small models.

Six standard forecasting models are set out in Section 4. In Section 5, these six models plus our inflation-markup model are estimated over the shorter sample period June 1973 to March 1999 to provide out-of-sample forecasts for the twelve quarters between June 1999 and March 2002. A forecast-comparison exercise is then conducted to evaluate the efficacy of the different approaches over forecast horizons of 4, 8 and 12 quarters, using a relative root mean squared error criterion and the Diebold and Mariano (1995) test. We demonstrate the

[1] The data are from Fagan, Henry and Mestre (2001) updated to March 2002. See the data appendix for further details.

superior forecasting performance of our inflation-markup model. In the concluding section, we consider whether the Euro area is at some risk of deflation if the economy enters a recession. The inflation-markup model indicates that if the economy starts in long-run equilibrium with 2 per cent inflation (the stated price stability objective of the European Central Bank), a recession with the equivalent business cycle profile as that experienced in the early 1990s would result in some deflation. Consequently, pursuing a 2 per cent inflation target may raise the risk of the Euro area experiencing deflation at some time in the future.

2. THE INFLATION-MARKUP MODEL

In our earlier papers we investigated the properties of the inflation series for Australia and the G7 countries and argued that inflation could be best characterised as an I(1) process for data starting in the 1970s and ending at the turn of the century. An alternative to assuming I(1) inflation is to model these series as being I(0) with shifting means. Understanding the 'true' statistical process of inflation depends, in part, on how we characterise the behaviour of the monetary authorities in response to inflation shocks and the nature of the shocks themselves.

The choice between the two alternatives can be made on practical and conceptual grounds. If the monetary authorities hold a series of unique inflation targets that are independent of the inflation shocks, inflation will follow a stationary process with shifting mean.[2] If one were able to identify the timing of every shift in the target rate of inflation then a dummy variable could be introduced to capture each shift in the target. The maximum number of dummies would be one less than the number of observations in the sample investigated. In practice one would introduce enough dummies to 'render' inflation a stationary series. Given the well-known low power of unit root tests and tests of breaks in series, it is likely the series would be 'rendered' stationary with the inclusion of a small number of dummies.

However, in our view this approach is unsatisfactory as it is unlikely that the number of dummies is identical to the 'true' number of shifts in the target rate of inflation by the

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[2] The term 'target' is used loosely and does not imply that the monetary authorities explicitly state a target rate of inflation. Instead, the 'target' refers to the revealed preference of the authorities following shocks to the 'general' level of inflation. If the authorities were not satisfied with the 'general' level of inflation, they would have adjusted monetary policy to achieve a 'general' rate of inflation with which they were satisfied.

monetary authorities. On a conceptual level, the lack of economic interpretation of the dummies and the model structure it entails are also unappealing.

Alternatively, we could characterise the monetary authorities as at least partially adjusting their inflation target in response to the inflation shocks in each period. In this case, inflation may follow an integrated process. Given that over most, if not all, of the period in question, the monetary authorities have in general responded to both unemployment and inflation when setting monetary policy, this characterisation of the monetary authorities appears to be the most relevant. Therefore, while acknowledging the possibility that the 'true' statistical process of inflation may be stationary about a frequently (but unknown) shifting mean, we proceed on the stated assumption that inflation is an integrated process.[3]

The Inflation-Markup Model

Banerjee, Cockerell and Russell (2001) develop an imperfect competition macroeconomic model where inflation imposes costs on firms.[4] The costs are due to the difficulties that non-colluding price setting firms face when trying to coordinate price changes in an inflationary environment. The model argues that these costs increase with inflation and lead to a negative relationship between inflation and the markup. Furthermore, it is argued that if the difficulties in coordinating price changes are of a type that is not overcome when inflation is stable then the negative relationship will persist in the steady state.[5] It is this steady state relationship between the markup and inflation that is interpreted as a long-run relationship in the Engle and Granger (1987) sense.

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[3] This argument is made in more detail in Banerjee, Cockerell and Russell (2001).

[4] The model is in the Layard-Nickell tradition and based on Layard, Nickell and Jackman (1991).

[5] The steady state is defined as all nominal variables increasing at the same constant rate. Higher inflation means that non-colluding price setting firms have to either make larger real increases in prices, or increase prices more frequently, or some combination of the two. Higher inflation, therefore, makes it more difficult and increases the cost of changing prices. These costs are unlikely to dissipate if firms observe that the average rate of inflation is stable but high.

The long-run structure of the inflation-markup model is given by:[6]

$$mu = q - \lambda \Delta p \qquad (1)$$

where mu is the markup of price on unit labour costs, q is the 'gross' markup, λ is the parameter that measures the trade-off in the long-run between inflation and the markup (referred to as the inflation cost coefficient), and p is the price level. Lower-case variables denote natural logarithms and Δ is the first change in the variable. The markup is calculated as $p - ulc$, where the price level, p, is the gross domestic product (GDP) implicit price deflator measured at factor costs and ulc is a measure of unit labour costs.[7]

In a standard macroeconomic model, inflation has no impact on the markup in the long run. Thus $\lambda = 0$ and q is the long-run markup. In our more general model $\lambda > 0$. In contrast with the standard model, increases in the general level of inflation now lead to a persistent fall in the gross markup net of the costs of inflation. In this case, q is now the markup that is consistent with zero inflation in the long run. Allowing for $\lambda > 0$ in the long-run relationship distinguishes our work from most empirical studies of inflation and simply reflects the idea that, if inflation can be approximated by an integrated series, it may display persistence at high or low levels of mean inflation over periods of time and is associated with low and high levels of the markup respectively.[8] These persistent shifts in the mean rates of inflation may be due to the nature of the inflation shocks or changes in monetary policy regimes over the years.

This long run relationship is nested within a two dimensional vector autoregressive-error correction model (VAR-ECM) as given below.

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6 We started by specifying the long run as $mu + \delta rer = q - \lambda \Delta p$, where rer is a measure of the real exchange rate. However, the real exchange rate was found to be insignificant in the cointegrating vector and the model performed poorly in the late 1990s. On closer examination, the poor performance could be attributed to a change in the short-run dynamics of rer in the 1990s, possibly due to the steps towards the introduction of a single currency. Ideally we would wish to estimate our model from early in the 1990s but the shortage of quarterly data precludes this.

7 Details concerning the data are provided in the data appendix.

8 See section 2 for why we model inflation as an integrated variable rather than shifts in the mean rate of inflation.

$$\Delta x_t = \mu + \Pi\, x_{t-1} + \sum_{i=1}^{4} \Pi_i \Delta\, x_{t-i} + \Phi\, bc_{t-1} + \varepsilon_t \qquad (2)$$

where $x_t = \begin{pmatrix} mu \\ \Delta\, p \end{pmatrix}_t$, Π is the long-run matrix containing the cointegrating vectors, and Π_i are the short-run matrices. The vector of unrestricted constants is given by μ, which can be written so as to incorporate q from equation (1), and bc_{t-1} is a univariate variable representing the business cycle.[9]

3. ESTIMATES FROM THE INFLATION-MARKUP MODEL

The coefficient estimates using data up to March 2002 are given in Table 1. The results show that we can accept the hypothesis of one negative long-run relationship between inflation and the markup. The estimate of the inflation cost coefficient, λ, is 4.925, implying that an increase of 1 percentage point in annual inflation is associated with around 1 ¼ percent fall in the markup in the long run.[10] The coefficients on the business cycle variable show that the change in the markup is counter-cyclical and the change in inflation is pro-cyclical.

Given the changes in monetary policy regimes over the period, an important question is whether or not the model and the long-run coefficients are stable. Graph 1 reports the recursive estimates of the inflation-markup system and provides evidence of stable long-run coefficients. We have also estimated Chow tests for the inflation-markup model. Graph 2 reports one-step-ahead Chow tests scaled by the 5 percent critical value (so that crossing 1 implies a rejection of the null hypothesis) over the period March 1990 to March 2002 for the markup and inflation equations and the inflation-markup model. There is some evidence of a single model break in March 1998 but this break does not appear in either of the individual equations. The Chow test also indicates a break at the last observation in March 2002. Since this break occurs so late it is most likely due to using 'new' national accounts data to calculate the markup of price on unit labour costs before the improved accuracy derived from subsequent revisions. Formally, the null hypothesis of no structural change would be

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9 Construction of the business cycle variable is explained in the data appendix.

10 This may be compared with the estimate for Germany reported in Banerjee and Russell (2001) of 4.748.

accepted because the Chow statistic is significant only at the very end of the sample. Overall the relationship is remarkably stable given the large shifts in monetary policy over the period and we feel this further justifies our modelling approach which allows for changes in the rate of inflation which are persistent.

The inflation-markup model performs well as an in-sample forecasting tool as shown in Graph 3. This in part reflects the stability of the estimated coefficients over the sample period as demonstrated in Graph 1. The in-sample estimates of inflation use the estimated coefficients from Table 1 and the actual (and not forecast) values for the business cycle. The values for the markup and inflation are those forecast by the model in-sample, starting with the actual values in June 1973. A small-scale sensitivity analysis (not reported here) was undertaken to check the necessity of including variables such as real and nominal short interest rates, world demand, oil and energy prices and these turned out not to be important.

4. THE COMPETING FORECASTING APPROACHES

We now present six competing univariate and multivariate small models for forecasting inflation and compare their forecasting performance with that of the inflation-markup model. These models are often used in forecast comparison exercises for a range of economic variables including inflation.[11] The structural forms of the forecasting models with their estimated coefficients are reported in Appendix A2.[12]

(i) Exponential Smoothing Model

A general univariate exponential model is estimated, allowing for the presence of a linear or an exponential trend as well as additive or multiplicative seasonal components. Our final estimated model chosen by the BIC does not include either a trend or seasonal components. Consequently, the error correction form of the model can be written, $S_t = S_{t-1} + \alpha e_t$, where

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[11] See, for example, Stock and Watson (2002) using data for the United States and Banerjee, Marcellino and Masten (2003) and Marcellino (2004) for the Euro area.

[12] We choose not to look at leading indicator models, given their relatively poor performance and instability for the Euro area as reported in Banerjee, Marcellino and Masten (2005). Our aim in this paper has been to work with small models with few variables in order to show the efficacy of such models in forecasting inflation.

S_t is the smoothed level of the inflation series, e_t is the forecast error in period *t*, and the smoothing constant, α, is chosen to minimise the sum of the squared errors.[13] An advantage of this technique for forecasting is that it is computationally simple with only a small set of sub-models, which makes it relatively easy to choose the 'best' exponential model to fit the data.

(ii) Autoregressive Model (AR)

The univariate autoregressive model given by $\Delta p_t = \delta_0 + \sum_{i=1}^{q} \delta_i \Delta p_{t-i} + \varepsilon_t$, is estimated, with up to 6 lags selected using the BIC. In our case the BIC-choice is unity with an estimated coefficient on lagged inflation of 0.935. Since the estimated coefficient on lagged inflation in the autoregressive model is less than two standard errors from unity, we include in the forecast comparison a random walk model of inflation with and without drift.

(iii) Vector Autoregressive Model (VAR)

We assume that the business cycle is exogenous (as in all the models that we consider) when estimating the model. For this model, defining $\Delta z_t = (\Delta p_t,\ \Delta ulc_t)'$, $c = (c_1, c_2)'$ a vector of constants, bc_{t-1} a univariate variable representing the business cycle as described above, and $\varepsilon_t = (\varepsilon_{it}, \varepsilon_{2t})'$, the vector of i.i.d. errors,

$$\Delta z_t = c + \sum_{i=1}^{4} \Gamma_i \Delta z_{t-i} + \Theta bc_{t-1} + \varepsilon_t ,$$

where $\Gamma_i, i = 1,..,4$ are four matrices of the form $\begin{bmatrix} \gamma_{i11} & \gamma_{i12} \\ \gamma_{i21} & \gamma_{i22} \end{bmatrix}$ and $\Theta = (\theta_1, \theta_2)'$. Starting with a model with 6 lags of both endogenous variables, the lag length is chosen to be 4 by reference to the BIC criterion and this is confirmed by a sequential likelihood ratio test of excluding the last lag.

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13 See Gardener (1985) for further details on forecasting with exponential smoothing models.

(iv) Single Equation Phillips Curve Model

The 'standard' Phillips curve model of inflation is based on the short-run relationship between inflation and unemployment and is a particularly popular model for forecasting United States inflation.[14] However, in this form, the Phillips curve is not an appropriate model of Euro-area inflation since the rate of unemployment is non-stationary. Consequently, the short-run effects on inflation are represented here by our business cycle variable (which is clearly stationary) rather than by the rate of unemployment. The Phillips Curve model used in our paper is of the form: $\Delta p_t = \delta_0 + \sum_{i=1}^{4} \delta_i \, \Delta p_{t-i} + \delta_5 \, bc_{t-1} + \varepsilon_t$. Lag length selection is by the BIC criterion starting at a lag length of 6, resulting with a choice of 4 lags in inflation.

5. COMPARING THE FORECASTS OF THE SEVEN MODELS

The inflation-markup model and the six competing models are estimated on a slighter shorter sample in order to provide twelve out-of-sample forecasts for the period June 1999 to March 2002. The forecasts for inflation and the endogenous variables for June 1999 are calculated using the actual data and the estimated coefficients from the model estimated up to March 1999.[15] In all but the exponential smoothing model, the forecasts for September 1999 use the actual data up to March 1999 and the forecasts for inflation and the endogenous variables for June 1999 derived previously. The coefficient estimates are retained at their original values. The forecasts for December 1999 use the original data and the forecasts for the previous two quarters, and so on. The twelve out-of-sample forecasts are thus derived from the same estimated model and by augmenting the original data up to March 1999 with the forecasts derived from the model at each stage.

For exponential smoothing, the 'best' model does not include a trend or seasonal component and the forecast is then identical to that derived from the random walk model. We therefore compute the forecasts from September 1999 onwards by re-estimating the exponential

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[14] For example, see Gordon (1982, 1997), Fuhrer (1995), and Stock and Watson (2002).

[15] The other endogenous variables are the markup in the inflation-markup model, and unit labour costs in the VAR model.

smoothing model having appended at each stage the forecasts to the data from the original sample.

Before proceeding to report the results of the forecast comparison, it is worth noting that, for the inflation-markup model estimated over the shorter sample, we can again accept the hypothesis of one negative long-run relationship between inflation and the markup. The estimate of the inflation cost coefficient is 5.069 (compared with 4.925 for the longer sample.) The coefficient estimates of the parameters of interest are also substantially unchanged over these two samples, thus justifying our decision not to update the estimates in order to compute the forecasts recursively.

Two related methods of forecast comparison are reported in Table 2. The first is a relative mean squared error comparison (RMSE), where our markup model is taken as the baseline and the ratios of the root mean squared errors (computed as the square root of the average of the squared deviations of the actual values of inflation from their corresponding forecasts each period over the 4, 8 or 12 period forecast horizon) of the competing model to the baseline model are computed. A number in excess of one indicates a forecasting gain from the use of our model. More formally, we also compare the forecasts from the competing models with our forecasts using the unadjusted and adjusted Diebold-Mariano (D-M) tests.[16]

Table 2 demonstrates the superior forecasting performance of the inflation-markup model over the other small models of inflation examined here for all of the forecasting horizons considered in terms of the RMSE criterion. The next most effective models are the AR(1) and the VAR. Given that the inflation-markup model is a VAR-ECM, excluding the highly

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[16] The D-M test statistic is the "t-stat" on a regression of d_t on a constant with HAC standard errors, where $d_t = (\Delta p_A - \Delta p_{IM})_t^2 - (\Delta p_A - \Delta p_{FA})_t^2$ and Δp_A is actual inflation, Δp_{IM} is the forecast from the inflation-markup model and Δp_{FA} is the inflation forecast from the alternative model. Harvey, Leybourne and Newbold (1997) propose a size adjustment to the D-M test statistic of the form, $S_A = \left[\frac{n+1-2h+n^{-1}h(h-1)}{n}\right]^{\frac{1}{2}} S$, where S_A and S are the adjusted and unadjusted D-M test statistics respectively and where the h-steps-ahead forecasts produce n forecast errors. In our case $h = 1$ and therefore the adjustment collapses to $S_A = \left[\frac{n-1}{n}\right]^{\frac{1}{2}} S$ for values of n equal to 4, 8 and 12.

significant ECM term from the simpler VAR forecasting model reduces its forecasting potential as expected. As is often reported in the literature, the very simple AR(1) model also does well and in our case is the second most effective forecasting model over the three forecasting horizons. The autoregressive estimate of the lagged coefficient of inflation is insignificantly different from unity. Therefore, it is surprising that the random walk model for inflation (with or without drift) shows such poor forecasting properties relative to the AR(1) forecasting model. This finding suggests that, for the purposes of forecasting, the coefficient is in fact significantly less than unity. The Phillips curve is also dominated by the inflation-markup model, the VAR and the AR(1), and seems to be in need of variables to capture more complicated business cycle and steady state effects.

When looking at the unadjusted and, more particularly, the adjusted Diebold-Mariano tests, the relative forecasting abilities of the models is less clear cut. The null hypothesis of this test is that the forecasting ability of the inflation-markup model is the same as that of the competing model. The alternative hypotheses are either that the inflation-markup model provides a better forecast than the competing model or the competing model provides a better forecast than the inflation-markup model. A rejection of the null at the 10 percent confidence level against the former alternative would imply a *p*-value of less than 0.10 in Table 2. Similarly a rejection of the null against the latter alternative implies a *p*-value of greater than 0.90. The null hypothesis cannot be rejected if the *p*-value lies in the range 0.10 to 0.90.

We note from Table 2 that the highest *p*-value is 0.271 which is for the comparison between the inflation-markup model and the Phillips curve model at a forecasting horizon of 8 quarters. Therefore, the Diebold-Mariano test results indicate that either the inflation-markup model provides a better forecast than the competing model or cannot distinguish between the two. In no case does the test suggest that the competing model provides better forecasts than the inflation-markup model. Taken in conjunction with the evidence from the RMSE criterion we feel that a strong case can be made that the forecasting ability of the inflation-markup model dominates that of the other small models.

In more detail, the Diebold-Mariano test is more favourable than the RMSE test for the Phillips curve and ranks it closely with the VAR model, although it is still outperformed (at the 10 percent significance level) by the forecasts from the inflation-markup model. The exponential smoothing and AR(1) models are judged to be insignificantly different at the 15 percent significance level, in terms of forecasting efficacy, from the inflation-markup model. This result is somewhat at odds with our finding based on the RMSE criterion but may be explained both by the fact that our estimated root mean squared errors have standard errors and by the power properties of the Diebold-Mariano test. The adjustment to the Diebold-Mariano test makes it more likely that the null hypothesis is accepted since the adjustment is intended to curb the over-sizing observed in the unadjusted version.

The seven inflation forecasts are shown in Graphs 4 and 5 and can be compared visually with actual inflation in the same graphs.

6. DISCUSSION AND CONCLUSION

Given the experience of Japan in the 1990s, a policy issue of some importance is deflation. In particular, if the European Central Bank successfully achieves its target of price stability (defined as 2 per cent annual inflation), is there a risk of deflation in the Euro area if the economy enters a recession? The inflation-markup model indicates that, if the economy starts in long-run equilibrium with 2 per cent inflation and at potential output, then a recession with the equivalent business cycle profile as that experienced in the early 1990s would result in some deflation, as shown in the upper panel of Graph 6. The forecast of negative inflation in this exercise is in contrast with the experience of the early 1990s, where inflation remained at a positive rate throughout the recession. However, in the early 1990s, inflation started at an annual rate of around 3½ per cent instead of our assumed starting rate of 2 per cent. Consequently, the model indicates that successful targeting of inflation by the European Central Bank may simultaneously have undesirable consequences in the face of a downturn caused by unexpected shocks to the economy. Forecasts can easily be constructed under alternative scenarios in order to examine policy options.

Our models are evaluated over 4, 8 and 12-period forecasting horizons starting in June 1999. This could, of course, be replicated over several such horizons (by pushing back the end-point of the first estimation sample to a date earlier in the decade and augmenting this date quarter by quarter). However, both the stability of the underlying model and the quiescent period of the economy over which the re-estimation would occur, lead us to believe that our conclusions would not be altered substantially. Our methodology is fully flexible to allow for any in-sample/out-of-sample partitioning and could be adapted to allow for a simulated real-time forecasting exercise.

To conclude, our results demonstrate the value of the inflation-markup approach to forecasting inflation. The model is stable, captures the in-sample swings and the non-stationarity in the data successfully and forecasts well with an extremely small choice of variables.

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APPENDIX 1: THE DATA

Euro area data seasonally adjusted for the period June 1972 to March 2002 are used. Natural logarithms are taken of all variables before estimation proceeds. The data for the period June 1972 to March 2001 are updated from Fagan *et al.* (2001), where further details may be found. The data was extended to March 2002 using Euro area data from the European Forecasting Network (EFN) data base which, in turn, makes use of data compiled by Eurostat.

The GDP data for the Euro area are aggregated by the following operation on the real and nominal components of GDP for each country, $y_{EA} = \sum_{EA} w_i \, y_i$, where y_{EA} is the Euro-area value of the component, y_i is the component series for country i and w_i is the weight for each country in terms of the share of constant price GDP at PPP of the country in Euro-area GDP in 1995. The weights are provided on page 53 of Fagan *et. al.* (2001). The implicit price deflators are then calculated from the nominal and real aggregated components of Euro-area GDP.

This method of aggregation avoids the difficulties associated with disentangling intra Euro-area trade from trade outside the area for each of the countries. The drawback is that intra Euro-area exports and imports are not allocated to consumption, investment and government expenditures, as they should be. Consequently, if the deflators for intra Euro-area trade diverge from the deflators for trade outside the Euro area then the deflators for each component will not approximate their 'true' component deflators for the Euro area. Given that the composition of intra Euro-area trade differs from trade outside the Euro area, it is unlikely these deflators will move together. We choose to estimate the model using the GDP deflator to avoid this problem.[17]

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[17] While acknowledging the difficulties in constructing the Euro area data, particularly the need to aggregate a lot of widely disparate experiences, the Fagan *et al.* (2001) data remains the most extensive and most frequently used.

A more recent vintage of the data from the Area Wide Model is now available, but appears to us (as a consequence of the revisions that have been undertaken in extending the time span) to contain several anomalies in its unit labour cost and inflation series that makes its use problematic.

Sources and Details of the Data[a]

Variable	*Mnemonics*	*Details*
Price Level	YFD	Gross domestic product (GDP) implicit price deflator at factor cost. The data is extended for the period March 2001 to March 2002 by forward splicing with the 'Deflator GDP' from the EFN data base.
Unit Labour Costs	ULC	Unit labour costs measured as compensation to employees (WIN) divided by constant price gross domestic product (YER). The data is extended for the period March 2001 to March 2002 using the EFN data base where unit labour costs are calculated as 'total nominal hourly labour costs for the whole economy' multiplied by 'employment' and divided by GDP measured at constant 1995 prices.
Business Cycle	YGA	Potential output gap defined as constant price GDP (YER) divided by potential output (YET). Potential output is estimated in Fagan *et al.* (2001) as a function of the level of employment consistent with the NAIRU (LNT), the capital stock (KSR), and trend total factor productivity (TFT). The business cycle is the residuals of the logarithm of the potential output gap (YGA) regressed on a constant and trend. Prior to de-trending, YGA was extended for the period March 2001 to March 2002 by: $YGA_t = YGA_{t-1} + \Delta LYER_t - average \Delta LYER$ where $\Delta LYER$ is the change in the logarithm of constant price GDP and the average is taken for the period of June 1972 to March 2001.

Mnemonics are from Fagan *et. al.* (2001).

APPENDIX 2: THE FORECASTING MODELS

1. Inflation-Markup Model

Normalised Cointegrating Vectors	mu	Δp
Long-run Relationship	1	5.069 (0.314)
Adjustment Coefficients	- 0.164 [- 5.8]	- 0.041 [- 2.1]

Standard errors reported as ( ), *t*-statistics reported as [ ]. The adjustment coefficients are the values with which the long-run relationship enters each equation of the system. The long-run relationship, or dynamic error correction term, is: $ECM_t \equiv mu_t + 5.069\,\Delta p_t$.

Likelihood ratio tests on the long-run relationship (a) test of coefficient on inflation is zero is rejected, $\chi_1^2 = 30.62$, p-value = 0.00, and (b) test of coefficient on the markup is zero is rejected, $\chi_1^2 = 26.82$, p-value = 0.00.

Predetermined Variables: business cycle lagged one period.

Testing for the Number of Cointegrating Vectors

Estimated trace statistic for the null hypothesis $H_0 : r = 0$ is 31.14 {13.31}, $H_0 : r = 1$ is 0.26 {2.71}. Numbers in { } are the relevant 90 per cent critical values from Table 15.3 of Johansen (1995). Statistics computed with 5 lags of the core variables chosen by the significance of the last dynamic terms. The sample is June 1973 to March 1999 and has 104 observations with 92 degrees of freedom.

System Diagnostics for the Model with Linear Homogeneity Imposed

(a) *Tests for Serial Correlation*

Ljung-Box (26) $\chi^2(86)$ = 80.52, p-value = 0.65

LM(1) $\chi^2(4)$ = 3.309, p-value = 0.51

LM(4) $\chi^2(4)$ = 3.305, p-value = 0.51

(b) *Test for Normality:* Doornik-Hansen Test for normality: $\chi^2(4)$ = 0.76, p-value = 0.94

2. Exponential Smoothing Model

$S_t = S_{t-1} + 0.660\varepsilon_t$, where S_t is the smoothed level of the inflation series.

3. Autoregressive Model of Order 1

$$\underset{(2.1)}{\Delta p_t = 0.012} + \underset{(26.0)}{0.935\Delta p_{t-1}} + \varepsilon_t$$

4. Random Walk without Drift

$$\Delta p_t = \varepsilon_t$$

5. Random Walk with Drift

$$\Delta p_t = \underset{(-0.8)}{-0.003} + \varepsilon_t$$

6. Vector Autoregressive Model – Exogenous Business Cycle

$$\begin{aligned}\Delta p_t = {} & \underset{(0.2)}{0.000} + \underset{(5.4)}{0.594\Delta p_{t-1}} + \underset{(1.7)}{0.211\Delta p_{t-2}} + \underset{(0.1)}{0.013\Delta p_{t-3}} + \underset{(1.8)}{0.208\Delta p_{t-4}} \\ & \underset{(-0.8)}{-0.045\Delta ulc_{t-1}} + \underset{(0.1)}{0.008\Delta ulc_{t-2}} \underset{(-0.3)}{-0.020\Delta ulc_{t-3}} + \underset{(0.1)}{0.003\Delta ulc_{t-4}} + \underset{(3.6)}{0.105\,gap_{t-1}}\end{aligned}$$

$$\begin{aligned}\Delta ulc_t = {} & \underset{(-1.4)}{-0.002} + \underset{(2.1)}{0.401\Delta p_{t-1}} + \underset{(1.4)}{0.304\Delta p_{t-2}} + \underset{(0.9)}{0.190\Delta p_{t-3}} + \underset{(0.0)}{0.003\Delta p_{t-4}} \\ & \underset{(-0.5)}{-0.0460\Delta ulc_{t-1}} + \underset{(0.9)}{0.086\Delta ulc_{t-2}} \underset{(-1.0)}{-0.101\Delta ulc_{t-3}} + \underset{(2.3)}{0.231\Delta ulc_{t-4}} + \underset{(6.1)}{0.311\,gap_{t-1}}\end{aligned}$$

7. Single Equation Phillips Curve Model

$$\begin{aligned}\Delta p_t = {} & \underset{(0.4)}{0.000} + \underset{(5.8)}{0.548\Delta p_{t-1}} + \underset{(2.1)}{0.225\Delta p_{t-2}} \underset{(-0.2)}{-0.023\Delta p_{t-3}} \\ & + \underset{(2.2)}{0.215\Delta p_{t-4}} + \underset{(3.6)}{0.101\,gap_{t-1}}\end{aligned}$$

Note: *t*-statistics reported in brackets

Table 1: I(1) Inflation-Markup System Estimates

Long-run Estimates

	$mu = p - ulc$	Δp
Normalised Cointegrating Vector	1	4.925 [0.265]

Short-run Estimates

Variable	**Lag**	**Markup Equation** Δmu	**Inflation Equation** $\Delta^2 p$
Error Correction Term	-1	- 0.177 (- 6.0)	- 0.046 (- 2.4)
Constant		0.109 (6.0)	0.028 (2.3)
Change in Markup	-1	- 0.047 (- 0.6)	0.018 (0.4)
	-2	0.071 (0.9)	- 0.024 (-0.5)
	-3	- 0.090 (- 1.2)	0.026 (0.5)
	-4	0.186 (2.5)	0.000 (0.0)
Change in Inflation	-1	0.914 (5.0)	- 0.349 (- 2.9)
	-2	0.678 (3.7)	- 0.125 (- 1.0)
	-3	0.652 (3.7)	- 0.166 (-1.5
	-4	0.469 (3.2)	- 0.129 (- 1.4)
Business Cycle	-1	- 0.158 (- 3.8)	0.143 (5.3)
R^2		0.426	0.331

Standard errors reported as [ ], *t*-statistics reported as ( ). The implied long-run relationship, or dynamic error correction term, is: $ECM_t \equiv mu_t + 4.925\Delta p_t$.

Likelihood ratio tests on the long-run relationship: (a) test of the coefficient on inflation is zero is rejected, $\chi_1^2 = 32.05$, p-value = 0.00, (b) test of the coefficient on the markup is zero is rejected, $\chi_1^2 = 29.79$, p-value = 0.00; and (c) exclusion of a trend in the cointegrating space is accepted, $\chi_1^2 = 0.42$, p-value = 0.51.

Testing for the number of Cointegrating Vectors

Estimated trace statistics for the null hypothesis $H_0 : r = 0$ is 32.47 {13.31}, and $H_0 : r = 1$ is 0.19 {2.71}. Numbers in { } are the relevant 90 per cent critical values from Table 15.3 of Johansen (1995). Statistics computed with 5 lags of the core variables. The effective sample is June 1973 to March 2002 and has 116 observations with 104 degrees of freedom.

Table 1b: I(1) System Diagnostics

(a) Tests for Serial Correlation	
Ljung-Box (29)	$\chi^2_{98} = 80.92$, p-value 0.89
LM(1)	$\chi^2_4 = 3.175$, p-value 0.53
LM(4)	$\chi^2_4 = 2.287$, p-value 0.68
(b) Test for Normality: Doornik-Hansen Test:	$\chi^2_4 = 1.594$, p-value 0.81

Table 2: Inflation Forecast Comparisons

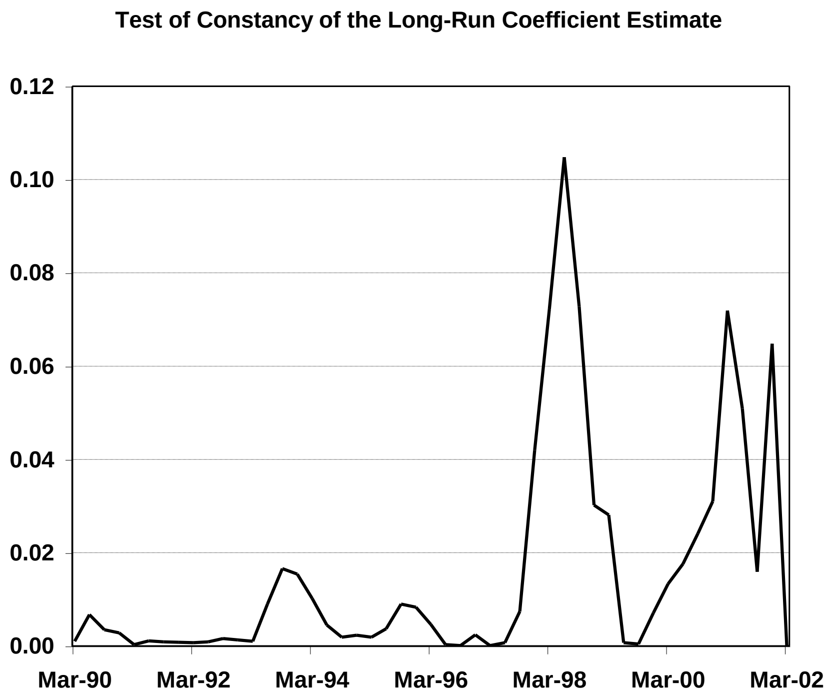
Comparison Criteria ⇒	RMSE[i]			Diebold / Mariano [ii]			Adjusted Diebold Mariano[iii]		
Forecast Horizon in Quarters ⇒	**4**	**8**	**12**	**4**	**8**	**12**	**4**	**8**	**12**
Inflation Forecasting Model ⇓									
1. Inflation-Markup	1.000	1.000	1.000						
2. Exponential	1.997	2.547	1.567	**0.035**	0.104	0.154	**0.058**	0.119	0.164
3. Autoregressive									
AR(1)	1.304	1.397	1.488	**0.091**	0.163	0.146	0.124	0.179	0.157
Random Walk	4.354	6.428	3.881	0.109	**0.030**	**0.022**	0.143	**0.039**	**0.027**
Random Walk With Drift	7.287	10.727	7.370	**0.080**	**0.016**	**0.003**	0.112	**0.022**	**0.004**
4. Vector Autoregressive	2.018	1.212	1.414	**0.049**	**0.092**	**0.067**	**0.076**	0.108	**0.075**
5. Single Equation Phillips Curve	2.180	1.213	1.727	**0.065**	0.258	**0.060**	**0.095**	0.271	**0.068**

i. Ratio of the root mean square errors are reported and calculated as the RMSE of the competing forecasting model divided by the RMSE of the inflation-markup model.

ii. Diebold and Mariano (1995) forecast comparison test. Probability values reported for the null hypothesis that the forecast errors of the inflation-markup model and the competing model are the same versus the alternative hypothesis that the inflation-markup model provides a better forecast than the competing model. Rejections of the null hypothesis at the 10 percent level are indicated in bold.

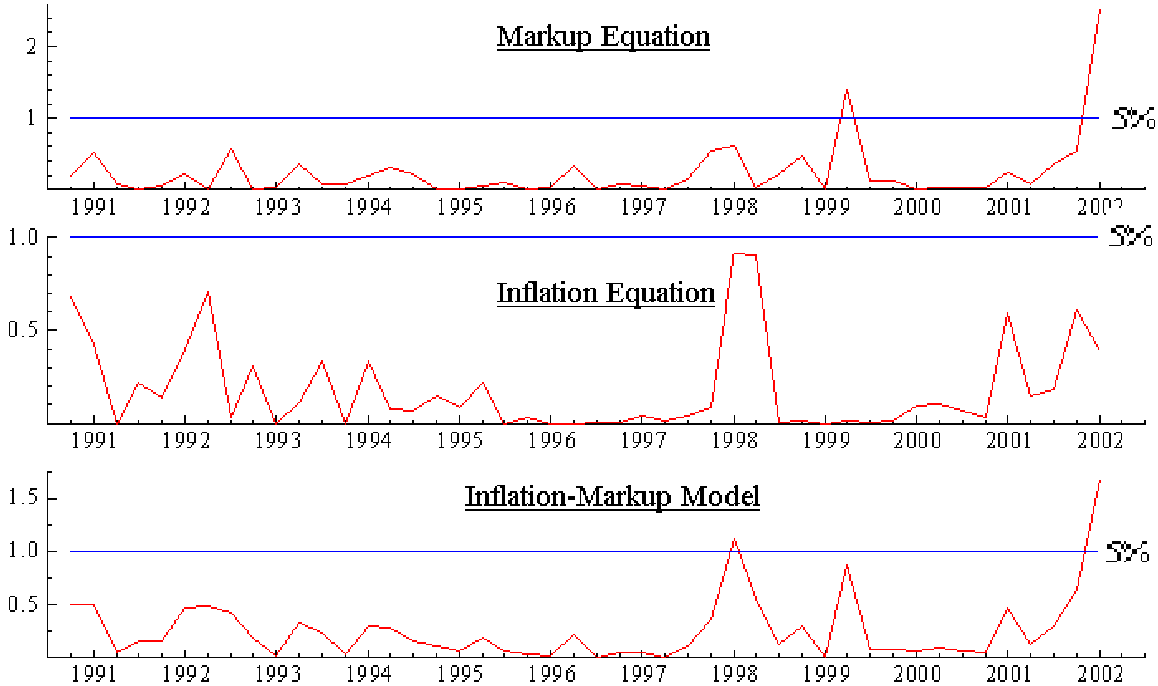
iii. Diebold and Mariano probability values are size adjusted following Harvey, Leybourne and Newbold (1997).

Graph 1

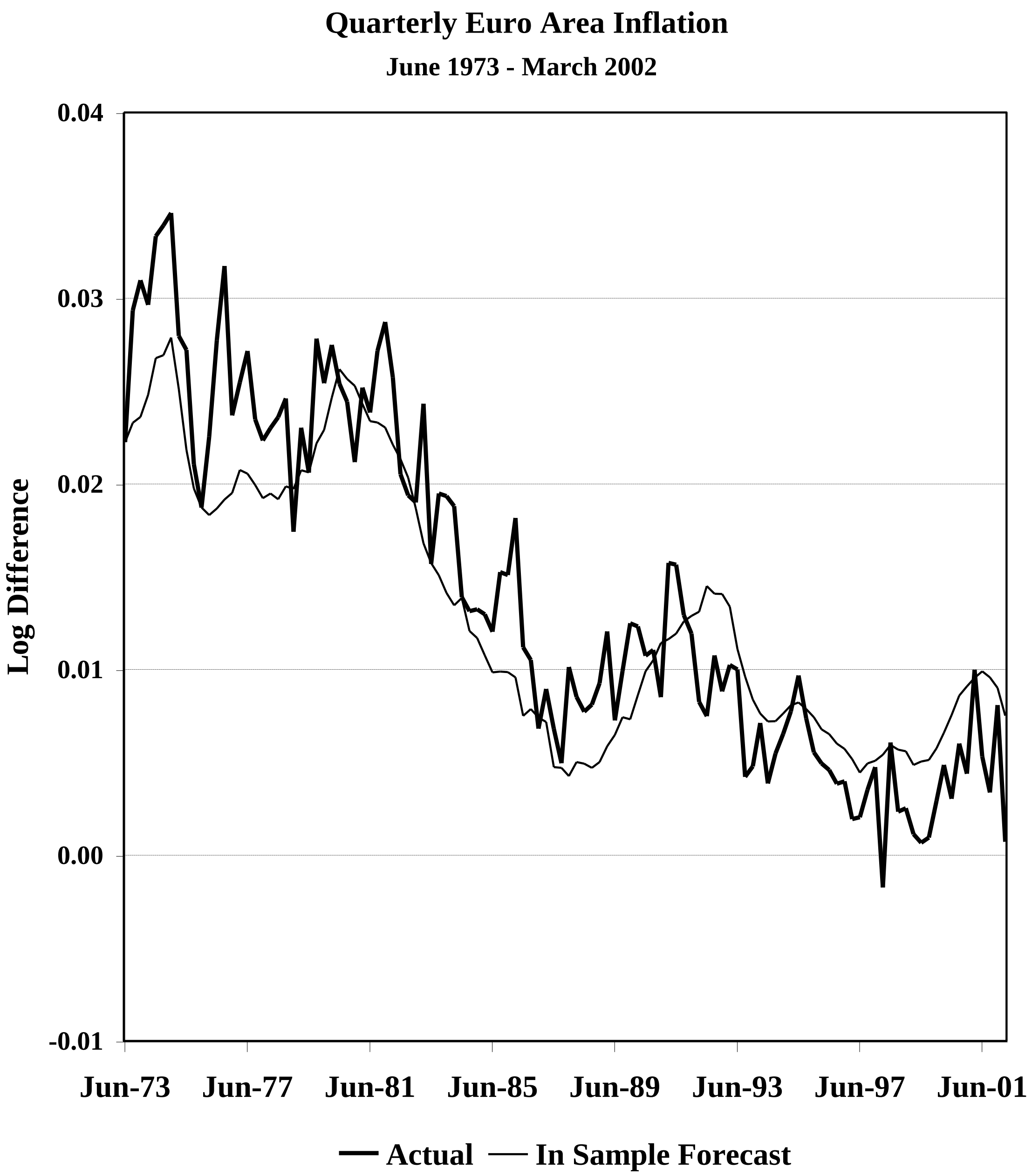


Note: This figure shows the plot of the test for constancy of the cointegrating vector scaled by the 95 per cent quantile of the chi squared distribution with two degrees of freedom such that unity corresponds to a test with a 5 per cent significance level. The null of constancy is, therefore, rejected only if the plot crosses 1.

Graph 2: One-Step-Ahead Chow Test of the Inflation-Markup Model

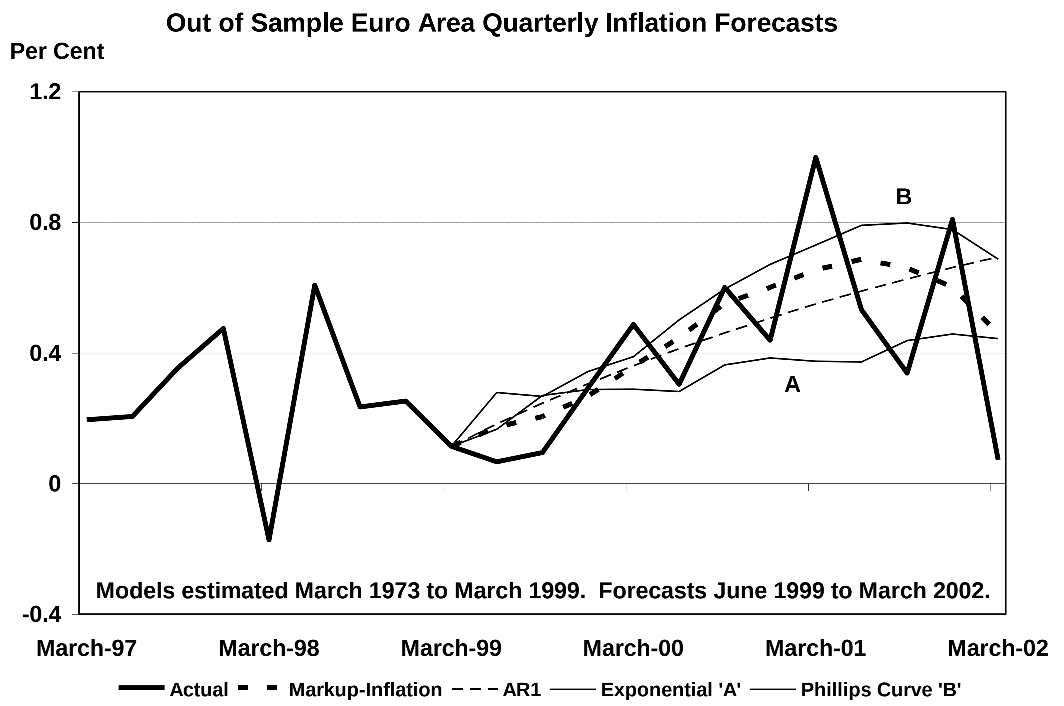


Graph 3

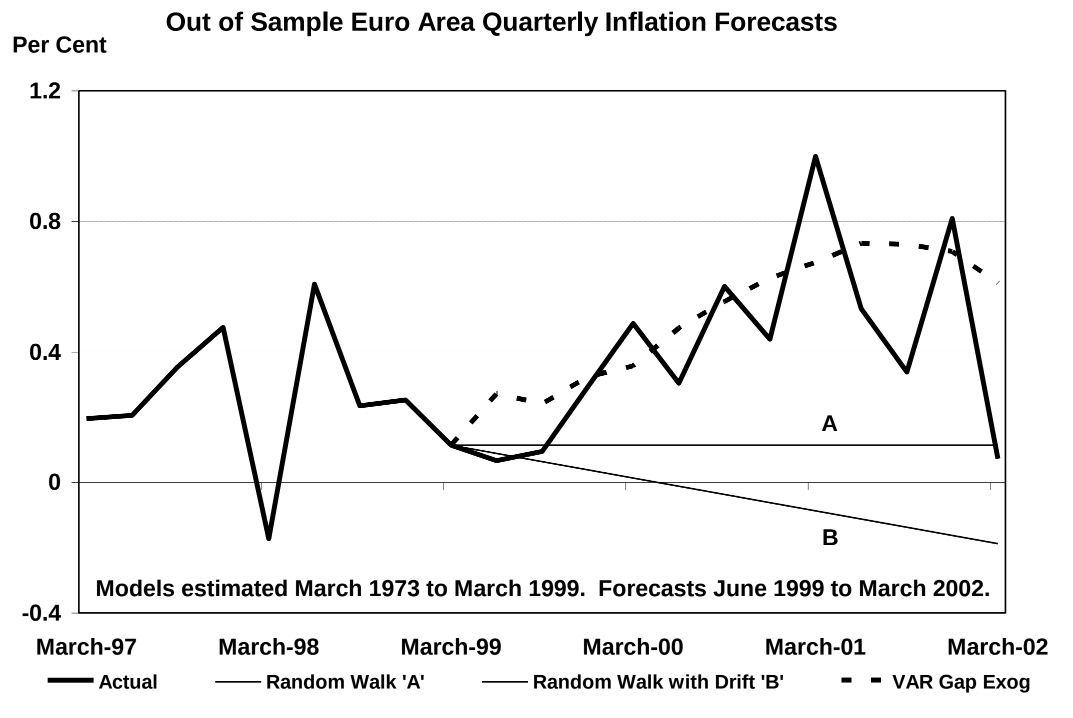


Quarterly Euro Area Inflation
June 1973 - March 2002
0.04
0.03
0.02
0.01
0.00
-0.01
Log Difference
Jun-73
Jun-77
Jun-81
Jun-85
Jun-89
Jun-93
Jun-97
Jun-01
Actual
In Sample Forecast

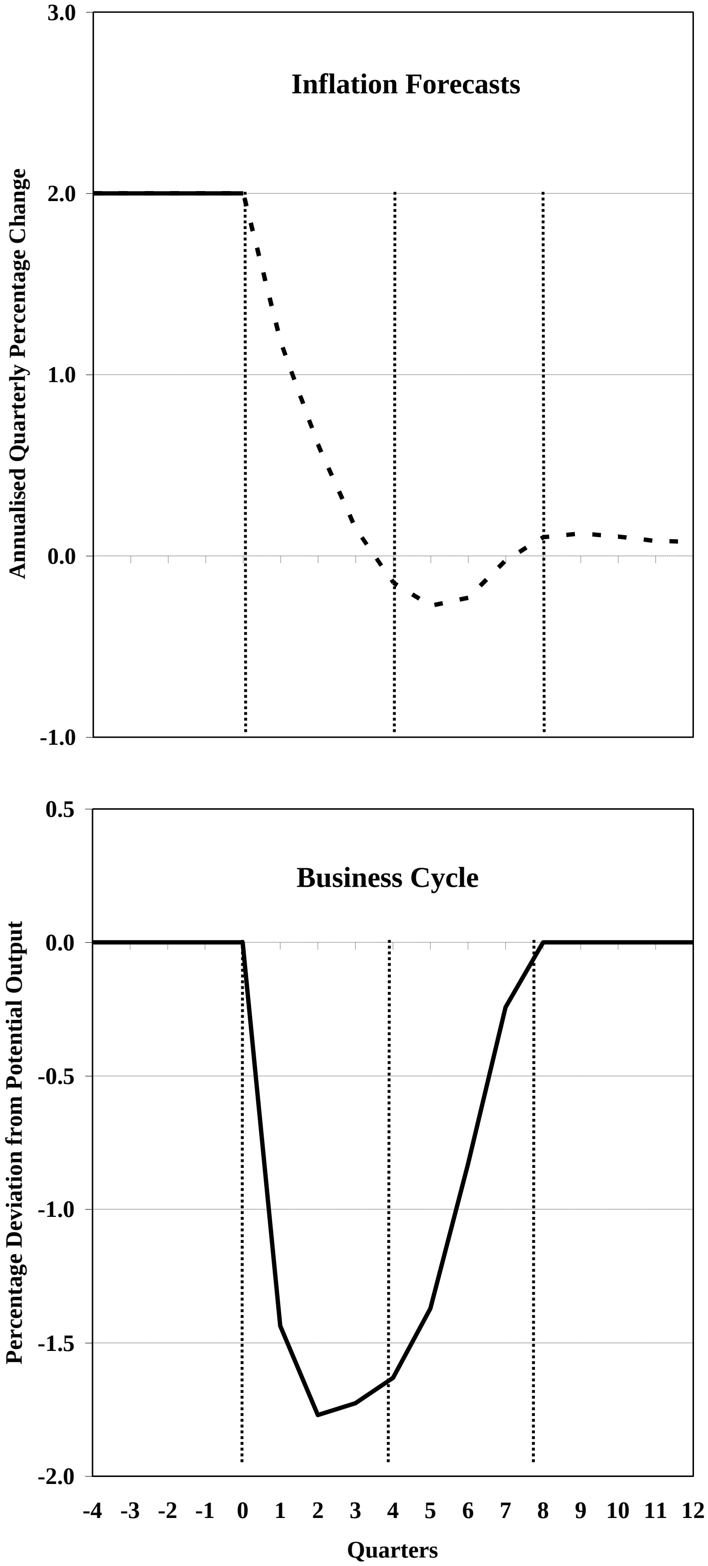
Graph 4



Graph 5



Graph 6



Note: In periods – 4 to 0, inflation is 2 per cent and the output gap is zero. For periods 1 to 12, the output gap (measured as the difference between GDP and potential output) profile is equivalent to the 'recession' between March 1993 and September 1994 before returning to 0 in periods 8 to 12 and is shown in the lower panel of the Graph. Forecast inflation is then computed using the model reported in Table 1 and setting the output gap to the profile in the graph above.