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# Measures of Underlying Inflation in the Euro Area: Assessment and Role for Informing Monetary Policy

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## Measures of Underlying Inflation in the Euro Area: Assessment and Role for Informing Monetary Policy

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## Abstract



The paper evaluates the 24-month ahead inflation forecasting performance of various indicators of underlying inflation and structural models. The inflation forecast errors resulting from model misspecification are larger than the errors resulting from forecasting of exogenous variables. Also, measures derived using the generalized dynamic factor model (GDFM) overperform other measures over the monetary policy horizon and are leading indicators of headline inflation. Trimmed means, although weaker than GDFM indicators, have good forecasting performance, while indicators by permanent exclusion underperform but provide useful information about short-term dynamics. The forecasting performance of theoretically-founded models that relate monetary aggregates, the output gap, and inflation improves with the time horizon but generally falls short of that of the GDFM. A composite measure of underlying inflation, derived by averaging the statistical indicators and the model-based estimates, improves forecast accuracy by eliminating bias and offers valuable insight about the distribution of risks.

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## I. Introduction

Headline and core inflation in the euro area have been sending divergent signals about underlying inflation over the past couple of years. On an annual basis, headline inflation has remained above the European Central Bank's (ECB) "close to but below" 2 percent target since 2000 and is forecast to continue to do so through 2007 (Figure 1). Over the past several years various shocks such as increases in energy and administrative prices as well as hikes in indirect taxes have pushed headline inflation above the target. However, various core inflation measures (excluding energy and unprocessed food) have declined since 2004—to around 1½ percent in the spring of 2006—suggesting subdued inflationary pressures. Other indicators such as mild wage and unit labor cost growth also indicate little inflationary pressure in the near future, and, notably, no second-round effects from rising oil prices.

For monetary policy, one key issues is what different indicators suggest about current underlying and future headline inflation.[1] Specifically, how useful are indicators of underlying inflation in forecasting future inflation? Are there gains to be made in forecasting future inflation by utilizing information from a large set of underlying inflation indicators and using different modeling approaches? Finally, where is inflation headed over the medium-term—that is, the ECB's monetary policy horizon?

Answering these questions requires an evaluation of the predictive performance and leading indicator properties of a broad range of underlying inflation measures using various methods. Based on the results, the indicators' relative usefulness in informing monetary policy can be assessed. Furthermore, a composite indicator can be constructed that exploits the information content embedded in the large number of different measures of underlying inflation and modeling approaches. This indicator is used to produce a baseline forecast for headline inflation, using information available as of spring 2006. The paper is organized follows: Section II discusses theoretical foundations and the purpose of various indicators of underlying inflation. Section III discusses the properties of these indicators. Section IV describes the forecasting methodology and discusses forecasting performance of the indicators of underlying inflation; and Section V concludes.

The main findings are:

- Inflation forecast errors over a 24-month horizon resulting from model misspecification are larger than errors resulting from forecasting of exogenous variables.

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[1] In this paper core inflation denotes indicators by permanent exclusion, while underlying inflation stands for the unobservable component of inflation driven by fundamental factors.

- Measures derived using the generalized dynamic factor model (GDFM) overperform other measures over the monetary policy horizon and are leading indicators of headline inflation. Although weaker than GDFM indicators, trimmed means have good forecasting performance over a 24-month horizon. Indicators by permanent exclusion (notably core inflation) underperform but provide useful information about short-term dynamics. The forecasting performance of theoretically-founded models that relate monetary aggregates, the output gap, and inflation improves with the time horizon but generally falls short of that of the GDFM.

- A composite measure of underlying inflation, derived by averaging the statistical indicators and the model-based estimates, improves forecast accuracy by eliminating bias, and offers valuable insight about the distribution of risks.

## II. Taxonomy of Underlying Inflation Indicators

The rationale behind indicators of underlying inflation is to facilitate disentangling the effects of idiosyncratic/temporary and policy-related/persistent forces that drive the inflation process. Some factors have a more permanent effect, while others have a more temporary one. The permanent component is related to the fundamental driving forces of inflation such as excess demand for goods and services and ultimately the macroeconomic policy mix. The transitory component can be a result of temporary shocks such as one-off indirect tax changes, changes in relative prices, unusual seasonal patterns, or measurement errors. Transitory shocks, however, can have more lasting effects on inflation, if they trigger second-round effects.

Monetary policy is known to affect inflation with long and variable lags, and cannot offset short-term, temporary shocks to inflation. However, it can affect the persistent component of inflation, notably through anchoring inflation expectations, and thus needs to be focused on stabilizing inflation over the medium term. Therefore, separating inflation in a persistent "common" component, driven by fundamental forces, and transient "noise," due to mostly idiosyncratic shocks, is a useful exercise from a monetary policy standpoint. This is what indicators of underlying inflation are trying to achieve with a view to providing reliable information on current and future inflation dynamics.

Measures of underlying inflation can be separated into two main groups—statistical indicators and theoretical/structural measures (Table 1).

- *Statistical indicators are derived using pure econometric methods*. They can be further divided into three subcategories—employing time series, cross-section distribution of prices, and panel data. Examples include various univariate filters (time series), indicators by permanent exclusion such as core inflation or variable exclusion such as trimmed means (cross-section), and the generalized dynamic factor model, GDFM, (panel data).

- *Theoretical measures are based on economic theory*. The two most common theoretical frameworks used to estimate underlying inflation build on the long-run Phillips curve and the quantity theory of money. Vector autoregressive models (SVAR), as in Quah and Vahey (1995) and Blix (1995), and reduced form Phillips curve equations are the most common examples of the first group; money demand equations and P* models, as in Nicoletti Altimari (2001), are the most widespread examples of the second group.

## III. Features of the Indicators

All measures of underlying inflation have pros and cons.

- *A common advantage of the statistical indicators is that they are less volatile than headline inflation and thus, presumably, capture better fundamental price changes*. To achieve this, core inflation excludes presumed idiosyncratic shocks from headline inflation (e.g., energy prices, unprocessed food); trimmed means apply objective statistical criteria to achieve the same (Bryan and Cecchetti, 1994, 1996); while GDFM measures do so by filtering idiosyncratic shocks with the help of both the cross-section and time series dimension of the data.[2] *A general disadvantage of the statistical indicators is that they are not backed by economic theory*.[3]

- *The main advantage of the theoretical measures is that they have macroeconomic foundations*. Consequently, they allow for an economic interpretation of the results by linking inflation developments to the macroeconomic variables relevant from a policy perspective. *The main disadvantage of the theoretical measures is that it is difficult to identify structural shocks and estimate the parameters*. Also, they suffer from behavioral invariance in that structural parameters remain constant, despite possible structural changes in the future (Lucas critique).

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[2] Each indicator has specific advantages. In particular, GDFM measures are good coincident and leading indicators—see, for example, Cristadoro and others (2001), Hahn (2002), and Forni and others (2003); core inflation and trimmed means can be computed in real time; and trimmed means are superior estimators of the central tendency if excess kurtosis of the sectoral distribution of prices is an issue—see Bryan and Cecchetti (1997).

[3] There are indicator-specific disadvantages. For example, the static nature of both permanent and variable exclusion indicators is a drawback, as their leading indicator properties could vary over time, depending on the nature of the shocks. Also, the exclusions in deriving core inflation are significantly based on subjective criteria—the results in Table 2 as well as several other studies, among them Vega and Wynne (2002), show that the excluded components are not always the most volatile ones.

To gauge uncertainty and provide a comparative perspective, a wide set of statistical indicators and economic models are used to estimate underlying inflation. Representatives of all standard statistical indicators are included here—specifically, a univariate spectral density filter, permanent and variable exclusion indicators, and panel methods. Theoretically-founded models are represented by a bivariate SVAR model, a reduced form Phillips curve model that controls for oil prices and the exchange rate, and a P* model. The use of a large number of measures is intended to deal with single forecast uncertainty and provide the basis for risk assessment. At the same time, it allows an evaluation of the relative usefulness of each measure in forecasting future inflation over the medium term.

The analysis of the indicators' statistical properties provides insights into two main features—volatility and bias. Regarding volatility (Table 3), all indicators but core inflation excluding energy perform well in filtering noise—they have smaller variances than harmonized index for consumer prices (HICP) inflation. However, indicators differ substantially in the degree of noise reduction. GDFM measures outperform other measures according to this criterion, with their standard deviation ranging from 32 to 77 percent of HICP standard deviation for indicators with 1 and 2 dynamic factors, respectively. Theoretically-based (Quah and Vahey and Phillips curve) measures follow, with standard deviations of 38 percent and 54 percent, respectively. Trimmed mean indicators rank third, with their variability declining as the share of excluded goods increases. Core inflation indicators rank last. Regarding bias, GDFM and model-based indicators are unbiased, trimmed means have a small (0.1 percentage points) but statistically significant downward bias, while core measures again underperform, displaying the highest downward bias (0.2 percentage points in the sample).

A visual inspection of headline inflation and the indicators gives a sense about the indicators' performance in signaling inflationary pressure over the sample (Figures 2-5). *Qualitatively*, GDFM measures seem to have good leading indicator properties, as they signaled the inflation pickup that started in 1999. They suggest that underlying inflation has remained stable since 2002. Both core and trimmed mean indicators performed well over 1997–99, lagged headline inflation during 1999–2001, and have implied declining (core indicators) or stable underlying inflation (trimmed means) since 2004. Model-based estimates (Quah and Vahey and Phillips curve) anticipated the 1999 pickup in inflation and indicate roughly stable underlying inflation over the past few years; only the Phillips curve indicator points to a slight increase of inflation since mid-2004, driven by high energy prices. *Quantitatively*, the indicators suggest that underlying inflation has been moving broadly sideways over the past year and is currently in a range of 1½ to 2¼ percent, with most indicators pointing to a figure under 2 percent.

# IV. Forecasting Methodology and Assessment of Forecasting Performance

## A. Forecasting Methodology

Forecasting performance of the statistical indicators is assessed using several methods based on simulated out-of-sample forecasts.[4,5] Specifically, for the statistical indicators (core, trimmed means, and GDFM) univariate, bivariate, and multivariate specifications are used to forecast headline inflation. In addition, inflation forecasts are produced with non-price variables (industrial production, monetary aggregates, wages, unit labor cost, unemployment, and interest rates). Simulated out-of-sample 24-month ahead forecasts start in November 2000. The equations are re-estimated each time a new month is added.

The 24-month ahead forecasts are made using two approaches—first, with 1-month lag equations and, second, with 24-month lag equations. Each of the two methods has pros and cons. An advantage of the first is that the estimated equations have better goodness of fit statistics and smaller standard errors compared to the second approach. A disadvantage, however, is that the indicators have to be forecast 24 months ahead in order to forecast inflation over that horizon, thereby adding exogenous variable forecast error to the model forecast error. For the forecast performance of the two approaches it is, therefore, important which forecast error is smaller—the one from model misspecification or the one from exogenous variable forecast. The semi-structural, distributed lag, and gap equations were estimated both with the indicator lagged one month (based on lag selection tests) and 24 months. At the time of the forecast, all right-hand side variables, (including the indicator for the models where the indicator is lagged one month) are assumed to be unknown and are projected using a nonparametric spectral density filter. A brief description of the equations used in the paper follows.

- **Static equation**

  The static equation is used to forecast headline inflation with both the statistical and theoretically-founded indicators. The equation is defined as $\pi_t = x_{t-h} + \varepsilon_t$, where $\pi_t$ is headline inflation, $x_{t-h}$ is the indicator of underlying inflation, and $\varepsilon_t$ is an error

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[4] Two estimation methods were used: (i) an expanding window—the initial point of the sample remains fixed, while the end point is extended each time by one month, and, (ii) a 4-year rolling window—both the initial and the end points are moved forward by one month each time a new observation is added. The results from both methods are similar.

[5] The sample period is January 1997–November 2005 for the estimates with year-on-year data. To eliminate the effect of the sample period on forecast evaluation, the forecasting performance of the measures was assessed over a common sample. As a result, the length of the sample period was restricted by the GDFM, as 4-digit disaggregated HICP data used to estimate the model are available only since January 1996.

term. Headline inflation at time $t$ is simply equal to the value of the indicator of underlying inflation $x$ at time $t\text{-}h$.

- **Spectral density filter**

  The spectral density filter is similar in nature to the Box-Jenkins autoregressive moving average model (ARMA). However, there are some key differences. First, this is a nonparametric technique, which does not depend on the lag selection procedure, and, second, the model is estimated in the frequency domain instead of the time domain (see Hamilton, 1994).

- **Semi-structural equation controlling for oil and exchange rate**

  This equation is an unrestricted version (the coefficient on $x_{t-1}$ ($x_{t-24}$) is estimated instead of being restricted to 1) of the static equation extended with oil prices and the exchange rate to control for these shocks. From a practical perspective, the semi-structural equation is attractive because forecasts are typically made conditional on certain exchange rate and oil price assumptions. Formally: $\pi_t = \alpha + \beta x_{t-1} + \gamma oil_{t-1} + \delta z_{t-1} + \varepsilon_t$ ($\pi_t = \alpha + \beta x_{t-24} + \gamma oil_{t-1} + \delta z_{t-1} + \varepsilon_t$), where $oil_{t-1}$ is oil prices in euros, and $z_{t-1}$ is the exchange rate. As noted above, the 24-month ahead simulated out-of-sample forecast with this equation (and all equations described below) is done in two steps: first, the right-hand side variables ($x_{t-1}$, $oil_{t-1}$, and $z_{t-1}$) are forecast with the spectral density filter, and, second, the equation is solved for the headline inflation $\pi_t$.

- **Distributed lag equation**

  The distributed lag equation has the following form: $\pi_t = \alpha + A(L)\pi_{t-1} + B(L)x_{t-1} + \varepsilon_t$, ($\pi_t = \alpha + A(L)\pi_{t-24} + B(L)x_{t-24} + \varepsilon_t$) where $A(L)$ and $B(L)$ are lag polynomials (the lag selection is determined by the Akaike and Schwartz information criteria), and $x_{t-1}$($x_{t-24}$) stands for the indicator of underlying inflation or the non-price variables (this model is also estimated with the non price variables).

- **Gap equation**

  Depending on the indicators, two forms of the gap equation are estimated. For the *statistical indicators*, it has the following form: $\pi_t - \pi_{t-1} = \alpha + \beta(x_{t-1} - \pi_{t-1}) + \varepsilon_t$ ($\pi_t - \pi_{t-24} = \alpha + \beta(x_{t-24} - \pi_{t-24}) + \varepsilon_t$), where $\pi_t$ is headline inflation and $x_{t-1}$($x_{t-24}$) is one of the statistical indicators (GDFM, core, or trimmed means). The equation allows to assess whether there is a tendency for headline inflation to converge to the estimate of underlying inflation over the medium term. If underlying inflation is leading the headline number, the coefficient $\beta$ should be positive. For the *non-price variables* $c_t$, (wages, monetary aggregates, etc.) the above equation is estimated in deviation from the means, namely: $\pi_t - \bar{\pi} = \alpha + \beta(c_{t-1} - \bar{c}) + \varepsilon_t$ ($\pi_t - \bar{\pi} = \alpha + \beta(c_{t-24} - \bar{c}) + \varepsilon_t$), where $\bar{\pi}$ is headline inflation mean and $\bar{c}$ stands for the mean of the non-price variables.

The forecast with the theoretically-founded models is done with the estimated equations for each model. A short description of each model follows below.

- **Reduced form Phillips curve model**

  This model is a version of the traditional Phillips curve, with inflation depending on the deviation of output from its potential instead of unemployment from its non-accelerating inflation rate (NAIRU). Similar models have been used to describe inflation dynamics in the forecasting and policy analysis models in several central banks—see, for example, Coletti and others (1996) and Coats (2000). Inflation dynamics are specified as: $\pi_t = \alpha + \beta\pi_{t-1} + \gamma gap_{t-1} + \delta z_{t-1} + \eta oil_{t-1} + \varepsilon_t$, where $gap_{t-1}$ is output gap, $z_t$ is the change in the exchange rate, and $oil_{t-1}$ is the change in oil prices.[6]

- **P* model**

  Following Nicoletti Altimari (2001), the quantity equation of money gives the P* indicator as: $p_t^* = m_t + v_t^* - y_t^*$, where $y_t^*$ denotes potential output, $m_t$ is the current money stock and $v_t^*$ is equilibrium velocity; all variables are in natural logarithms. Inflation dynamics are given by the following equation: $\pi_t = (1-\lambda)\pi_{t-1} + \lambda\Delta p_{t-1}^* - \alpha(p_{t-1} - p_{t-1}^*) + \varepsilon_t$, which implies that after the shocks disappear the price level returns to its long-run equilibrium P*.

- **Bivariate SVAR**

  In this model, it is assumed that two types of exogenous shocks affect headline inflation—one that has no impact on output beyond the short term,[7] and, the other that might have significant medium- to long-run effects on output (a supply shock that

[6] The output gap, the exchange rate, and the oil prices are forecast with the spectral density filter.

[7] This assumption implies a vertical long-run Phillips curve and provides the necessary identification restriction for the SVAR coefficients (see Quah and Vahey, 1995, for further details).

shifts potential output for instance). Underlying inflation is, therefore, defined as the unobserved component of headline inflation that is driven by the first type of shocks. Given the above assumptions, the bivariate SVAR can be written as:

$$\begin{pmatrix} \Delta y_t \\ \pi_t \end{pmatrix} = D(L) \begin{pmatrix} \varepsilon_t^1 \\ \varepsilon_t^2 \end{pmatrix},$$

where $\Delta y_t$ is the change in industrial production, $\pi_t$ is headline inflation, and $\varepsilon_t^1$, $\varepsilon_t^2$ are the two disturbances. This presentation implies that inflation can be decomposed as:

$$\pi_t = \sum_{j=0}^{\infty} d_{21}(j)\varepsilon_{t-j}^1 + \sum_{j=0}^{\infty} d_{22}(j)\varepsilon_{t-j}^2 \ ,$$

with underlying inflation defined as:

$$x_t = \sum_{j=0}^{\infty} d_{21}(j)\varepsilon_{t-j}^1 \ .$$

### B. Assessment of Forecasting Performance

Forecasting performance is evaluated by two statistics—root mean square error (RMSE) and bias. These two statistics are estimated for forecast horizons of 6, 12, 18, and 24 months. Given that the simulated out-of-sample forecasts start in November 2000 and the sample ends in November 2005, there are 61 forecast rounds. The number of observations available to estimate the RMSE and the bias are equal to the number of forecast rounds minus the length of the forecast horizon (i.e., there are 37, 43, 49, and 55 observations for the 24-, 18-, 12-, and 6-month horizons, respectively). The RMSE and the bias are calculated as follows:

$$RMSE_h = \sqrt{\sum (\pi_{t+h} - \hat{\pi}_{t+h})^2 / T} \text{ , and}$$

$$Bias_h = \sum (\pi_{t+h} - \hat{\pi}_{t+h}) / T \ ,$$

where $T$ is the number of observations.

The forecasts with a 1-month lag overperform those with a 24-month lag, suggesting that errors due to model specification are larger than exogenous variables forecast errors (Tables 4, 5, and 6). Exceptions are trimmed means and M2, which perform better with the 24-month lag distributed lag equation, and 5 and 10 percent trimmed means and M3, which perform better with the 24-month lag gap equation. However, the RMSE of the best performing indicators with the 24-month lag equations are larger than the best performing indicators with the 1-month lag equations. This implies that the errors resulting from model misspecification are larger than the forecast errors of exogenous variables with the spectral density filter. Therefore, in what follows, the forecast performance across models and indicators is assessed based on the forecasts with the 1-month lag equations.

The measures can be compared across two dimensions—forecast horizons and models. The benchmark for comparison is the random walk forecast of headline inflation, in which future inflation is simply equal to current inflation. In addition to the random walk forecast, two spectral density forecasts (in levels and first differences) are produced with headline inflation. The GDFM, core, and trimmed mean indicators are used for two types of forecasts—a static one, in which headline inflation is forecast as the current value of the indicator; and a model-based one, in which distributed lag, gap, and semi-structural equations are used (bivariate model-based forecasts are done also with the non-price variables). Finally, structural forecasts are done the SVAR, Phillips curve, and P* models.

GDFM measures outperform other statistical measures, including the random walk forecast, across time and models (Table 4).[8] GDFM performance is superior according to both assessment statistics—the RMSE and the bias.[9] Trimmed means come second, although they are performing slightly worse than the random walk by the RMSE statistic. The trimmed means, however, are the best indicators for the short run—6 to 12 months. Core indicators have the worst performance. Labor market variables (wages, unit labor cost, and unemployment) perform on average better than the three monetary aggregates (M1-M3) by the RMSE statistics; however, they are somewhat worse than the monetary aggregates by the bias criterion.

The static equation overperforms all other specifications at the 24-month horizon. The gap equation comes second—it has a good performance with labor market variables (and monetary aggregates less M3) over the long run. The RMSE of the gap equation with these variables improves significantly with the forecast horizon. This result is in line with theoretical findings that the forecast performance of labor market variables and monetary aggregates should improve with the length of the forecast horizon. The semi-structural

[8] The results in Table 4 are for estimates using year-on-year data. In that case, a central estimate of 2 percent and a RMSE of 0.4 percentage points suggest that with 70 percent probability year-on-year inflation is forecast to be in the range of 1.6 to 2.4 percent.

[9] The large amount of disaggregate information used in the GDFM could be behind its superior performance over the sample period used here—as Hendry and Hubrich (2006) show, disaggregate information should, in theory, help forecasting the aggregate. However, they also find that including disaggregate information does not always improve forecasts of the aggregate inflation for the euro area, in particular at longer forecast horizons, as changing collinearity among the components undermines the performance of disaggregated models.

equation controlling for oil and exchange rate has a good performance with GDFM and trimmed means. The distributed lag model has acceptable performance over the short run (6 to 12 months); however, its performance deteriorates significantly towards the medium term across all indicators.

The measures derived from the theoretical models, particularly the Phillips curve, provide valuable insights into the driving forces of inflation. The Phillips curve-based models outperform the P* model at the 24-month horizon, ranked by the RMSE criterion.[10] The Phillips curve models have comparable performance to trimmed means and labor market variables, while the P* model performs significantly worse. One explanation for the relatively worse performance of the P* model could be the instability of money velocity over the sample period (see Faruqee, 2005). From a policy standpoint, the Phillips curve model provides useful information about the contribution of the relevant macroeconomic variables to inflation. As shown in Figure 6, the pickup of inflation in 1999 was caused by an inflationary impulse from both domestic and external factors—in particular, excess demand captured by the positive output gap, exchange rate depreciation, and a positive oil price shock. Regarding driving forces of inflation over the past couple of years, the pickup of underlying inflation projected by the model is driven mainly by higher energy prices, with a negligible effect of the output gap, compared to the previous period.[11] Looking ahead, the out-of-sample forecast with the Phillips curve equation suggests declining inflation by 2007. This is driven by oil price and exchange rate stabilization as well as remaining excess capacity (Figure 7).[12]

Combining forecasts improves forecast performance. A simple average of all forecasts results in zero bias and a RMSE similar to the best performing indicators and also has a reasonable in-sample forecasting error for the 24-month ahead forecast (Figure 9). In addition to having better accuracy by practically eliminating the bias, there are several other gains from combining the forecasts. As shown in Hall and Mitchell (2004), the combined forecasts provide a measure of uncertainty surrounding the "central tendency" of the point forecasts. They offer policy makers a fuller picture beyond the uncertainty associated with the individual forecasts, including the distribution of the risks around the central forecast over

[10] The performance of the SVAR model is similar to that of the Phillips curve. However, their usefulness as a tool for monetary policy analysis is questionable, as the probability of measurement error exceeding 0.5 percentage points is in the range of 40 to 60 percent—see Folkertsma and Hubrich (2001) for details.

[11] While providing useful insights about the driving forces of inflation, the reduced form Phillips curve model is missing an important component, namely, monetary policy. To gauge what is its contribution over the sample period, a structural model with monetary policy reaction function would have to be used.

[12] Notice that he exchange rate, oil prices, and the industrial production-based output gap are forecast with an ARMA process (Figure 8). Using March 2006 *World Economic Outlook* (WEO) projections for oil and the exchange rate and replacing the industrial-production based output gap with the WEO output gap for the whole economy would yield a lower inflation forecast.

the forecast horizon. Pooled forecasts, as pointed out in Timmermann (2005), also improve efficiency and, as shown in Aiolfi and Timmermann (2004), perform better in the presence of structural breaks than single model forecasts.

The combined forecast results suggest declining inflationary pressures over the next two years; however, the degree and the speed of the decline are less certain. As Figures 10–12 show, a common feature of all forecasts is that inflation declines towards the end of the forecast horizon. The static equation-based measures and the semi-structural equation controlling for oil and exchange rates predict that inflation will decline to around 1¾ percent by the end of 2007. Including inflation inertia, distributed lag specifications show inflation slightly above 2 percent. Among economic model-based estimates, the Phillips curve and the bivariate SVAR models forecast inflation slightly below 2 percent, while the P* model projects declining inflation, but it remains above 2 percent by 2007. Finally a combination of all forecasts projects inflation declining to slightly above 2 percent.

The projected pace of decline of inflation depends critically on whether the forecast equation features lagged inflation. The coefficient for lagged inflation is high. However, it is unclear to what extent this high coefficient is a result of the repeated hikes in oil and administrative prices since 2001 or because of true persistence, i.e., shocks that trigger indirect and second round effects on wages and therefore have lasting effects on inflation.[13] Firm conclusions require deeper analysis. Findings in the literature on inflation persistence have been mixed. For example, O'Reilly and Whelan (2004) find that the inflation persistence parameter (the sum of the coefficients on the lagged dependent variable) has been quite stable over the post-1970 period, although there is evidence about a break in the mean of the inflation process. Altissimo and others (2005), by contrast, find that at the aggregate level inflation persistence appears to be very high for a long sample period but declines considerably after allowing for time variation in the inflation mean. Also, sectoral inflation is found to be less persistent, mainly due to transitory sector-specific shocks. The empirical models used here do not allow for falling inflation persistence over time.

Assessment of inflation risks over the forecast horizon can be done by analyzing the distribution of the forecasts. Most inflation targeting central banks incorporate judgment in their model-based inflation forecasts to express their assessment of the risks to price stability and the forecasts over the forecast horizon. A common approach for central banks to implement their judgment for the forecast period is to describe the uncertainty and

[13] The estimates from a 4-year rolling AR1 process (Figure 13) suggest a declining coefficient on lagged inflation. Given the persistence of the oil shocks since early 2004, this decline of the coefficient could suggest falling inflation persistence in the euro area over the past several years (perhaps reflecting increased competition due to globalization).

asymmetric risks in the forecast. This is usually done by employing a probability distribution that allows for skewness.[14]

The analysis of the distribution of the forecasts suggests roughly balanced inflation risks over the medium term. The risks assessment in this paper differs from the one explained above in that it does not use judgment but, in a sense, relies entirely on the data, as the parameters of the distribution are estimated. Assuming that these parameters are correctly estimated, if the distribution is skewed to the right (the outliers are to the left of the mean) the risks are considered negative, while the risks are viewed positive if the distribution is skewed to the left. As shown in Figures 14-16, the static equation forecasts lower average inflation but suggests upside risks, while the rest of the models forecast higher average inflation but imply downside risks. Overall, the distribution for all forecasts implies roughly balanced inflation risks, with inflation falling to close to 2 percent in the course of 2007.

## V. Concluding Remarks

The paper has evaluated the 24-month ahead inflation forecasting performance of a large set of underlying inflation measures. The results show that forecasts with 1-month lag overperform those with 24-month lag. This suggests that the errors resulting from model misspecification are larger than the errors due to forecasting of the exogenous variables. Among the static and 1-month lag specifications, the results show that the GDFM indicators overperform all other measures reviewed over the two-year policy horizon and are leading indicators of inflation. Trimmed means rank second, with good predictive power, while standard core indicators underperform.

A simple average of the indicators improves forecasting in two ways. First, it enhances accuracy by eliminating the bias without losing efficiency. Second, the analysis of the distribution of the forecasts allows for a better assessment of inflation risks over the forecast horizon.

Measures derived from theoretically-founded models are valuable assets for policy analysis and forecasting. The reduced form Phillips curve, for example, has a rich theoretical underpinning and good forecasting ability, which is comparable to that of trimmed means according to the RMSE criterion. In general, an important advantage of the theoretical models over the statistical indicators is that they allow a decomposition of driving forces of inflation on domestic demand factors, exogenous supply shocks, and exchange rate effects, offering useful information for monetary policy decision making.

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[14] An example of such a distribution is the two-piece normal distribution, in which the distributions on each side of the mode are proportional to a normal distribution with different standard deviations (for details see Blix and Sellin, 1999).

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Figure 1. Euro Area: Headline and Core Inflation
(In percent)

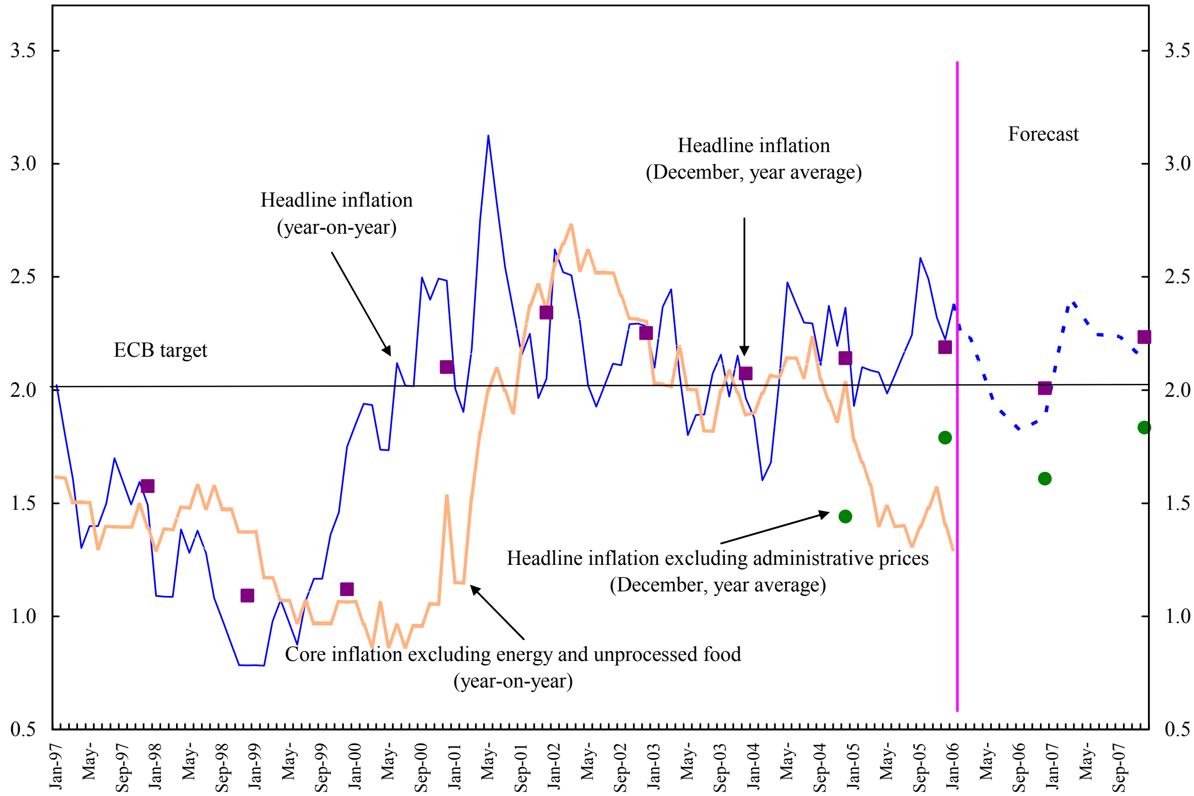
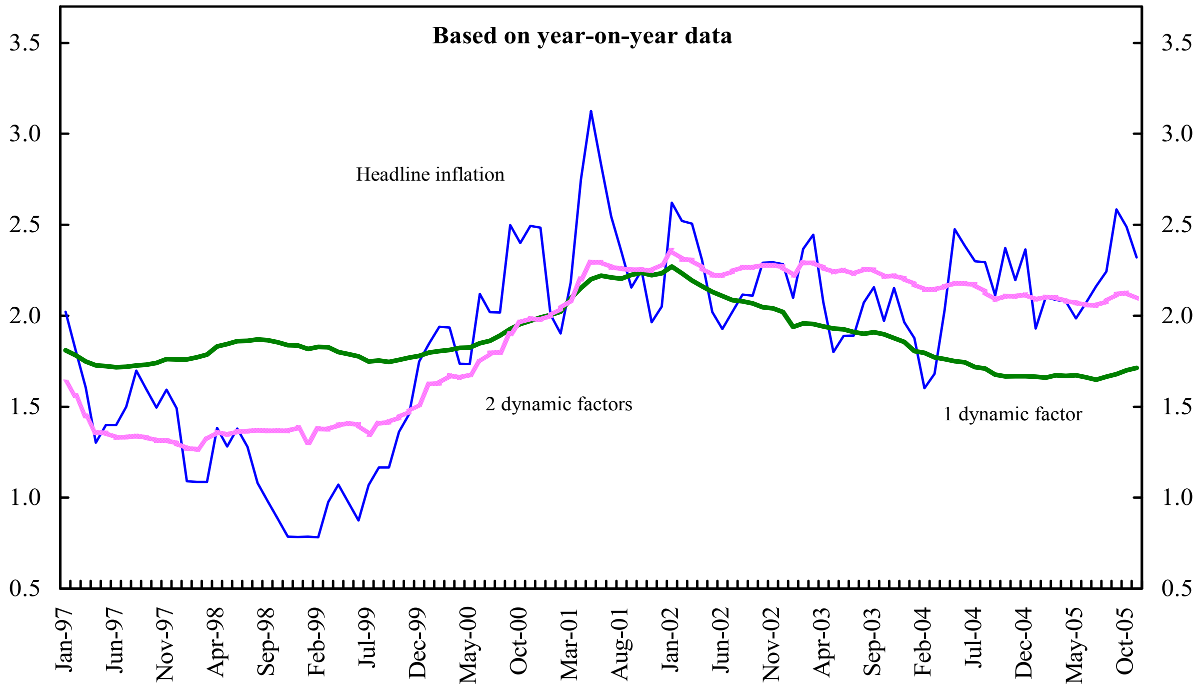
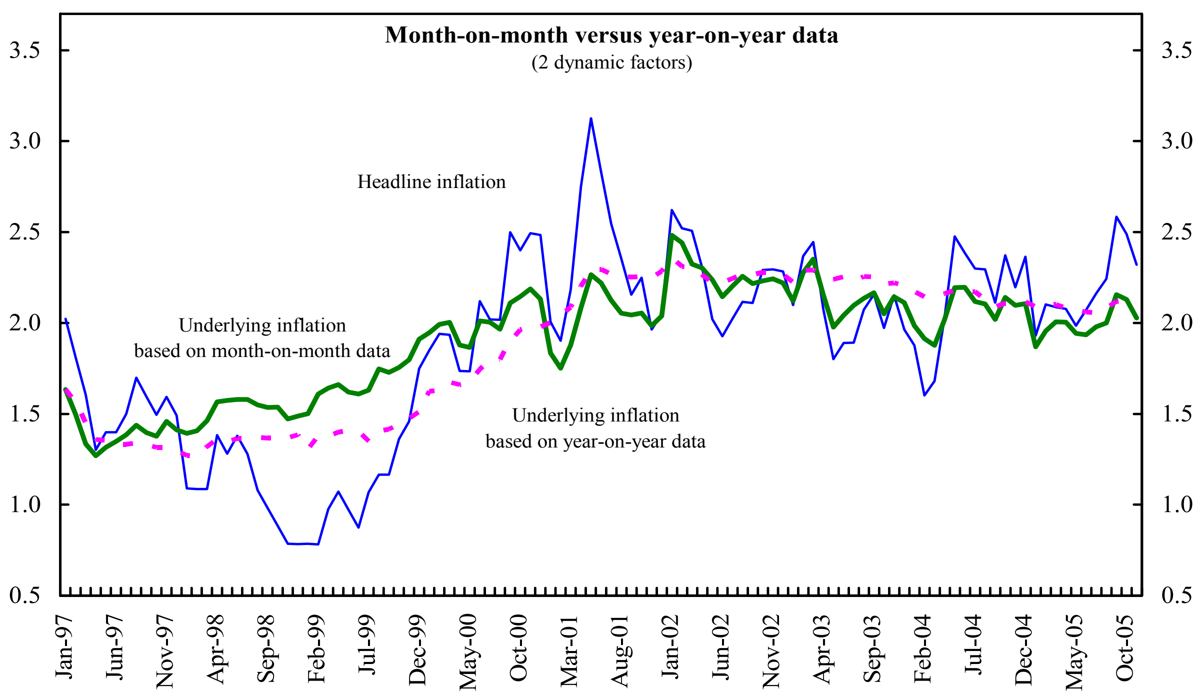


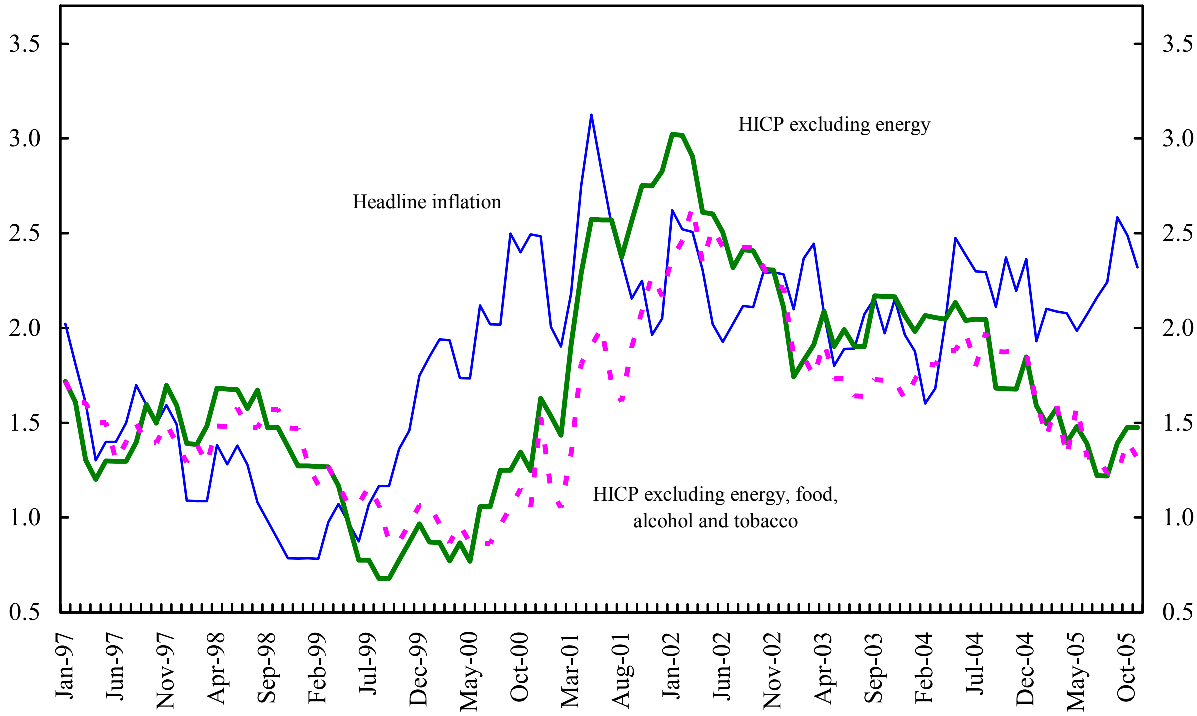
Figure 2. Euro Area: Headline and GDFM Estimates of Underlying Inflation
(In percent)

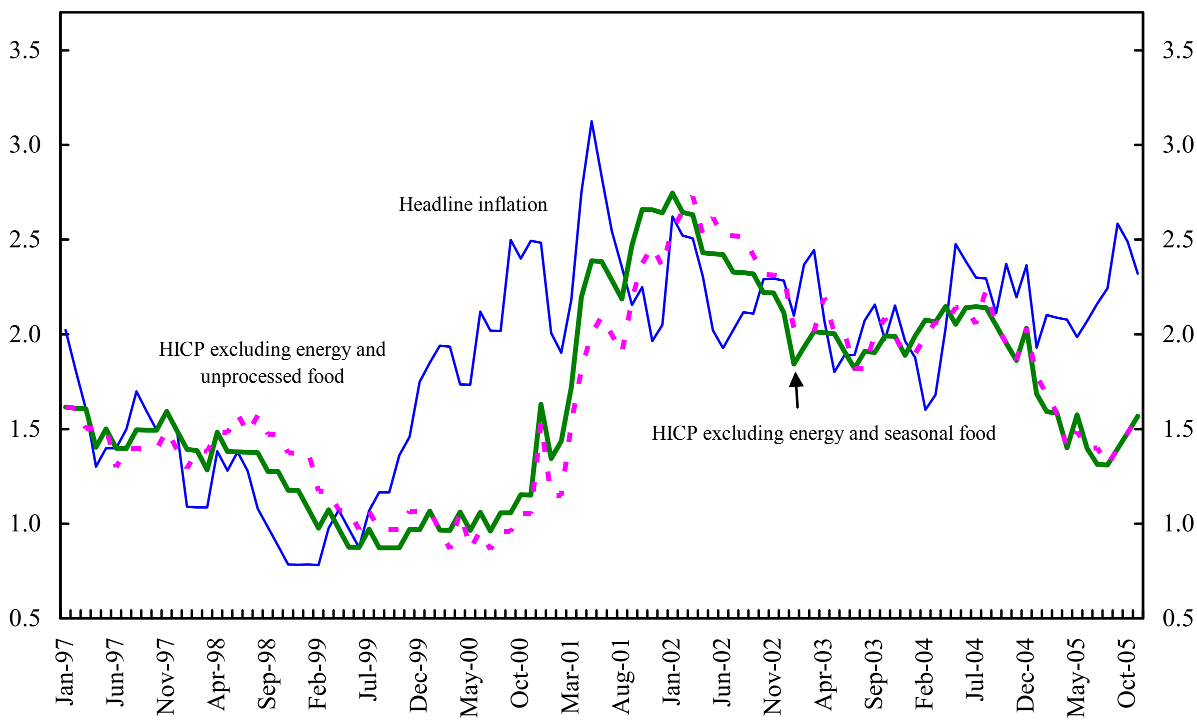



Source: IMF staff estimates.

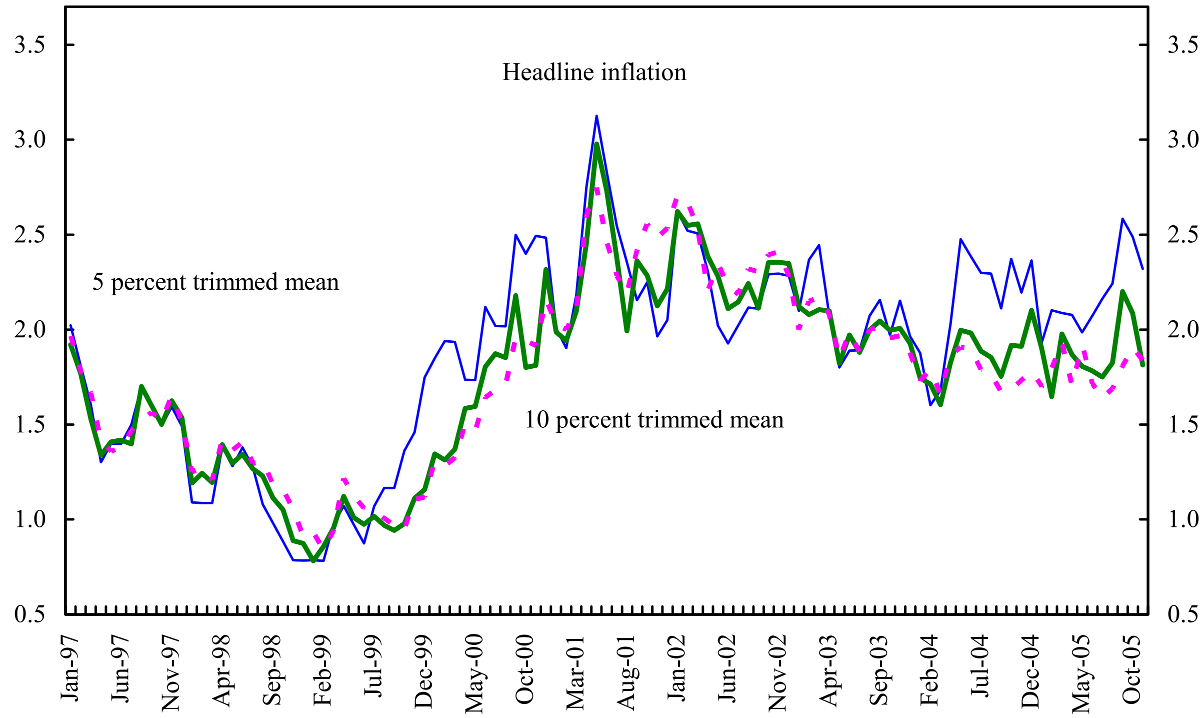
Figure 3. Euro Area: Headline and Permanent Exclusion Core Inflation
(Year-on-year, in percent)

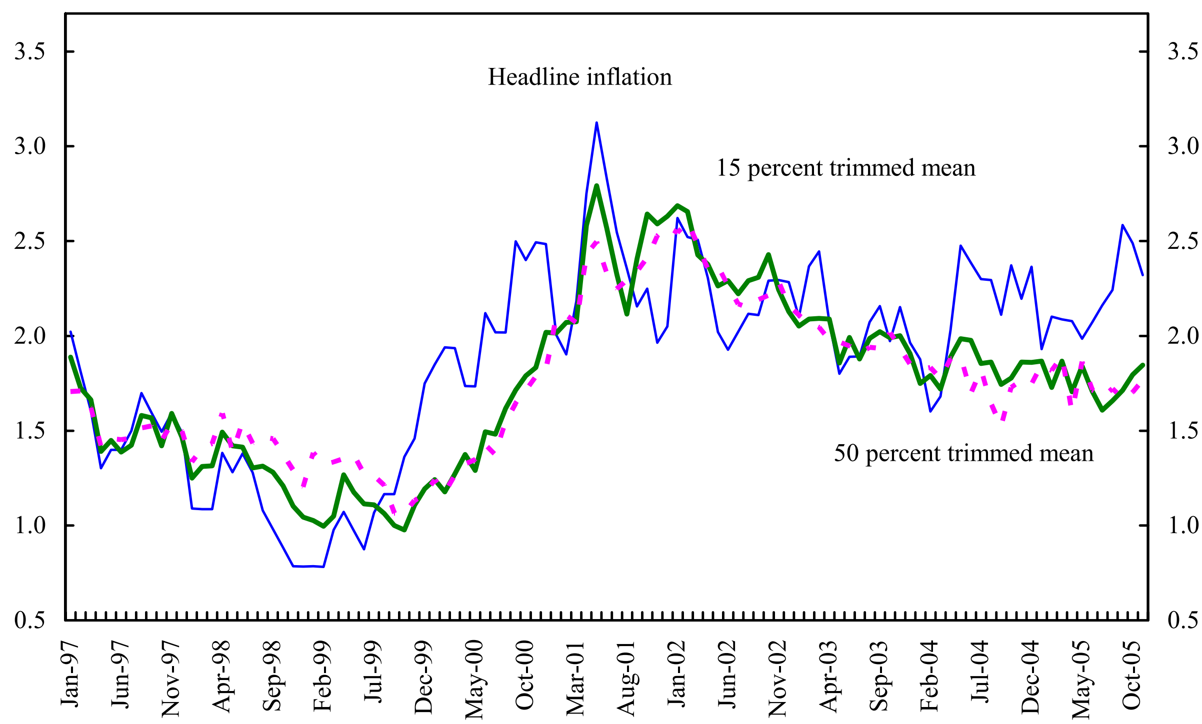



Source: Eurostat.

Figure 4. Euro Area: Headline and Variable Exclusion Core Inflation
(Year-on-year, in percent)




Source: IMF staff estimates.

Figure 5. Euro Area: Headline and Model-based Underlying Inflation
(Year-on-year, in percent)

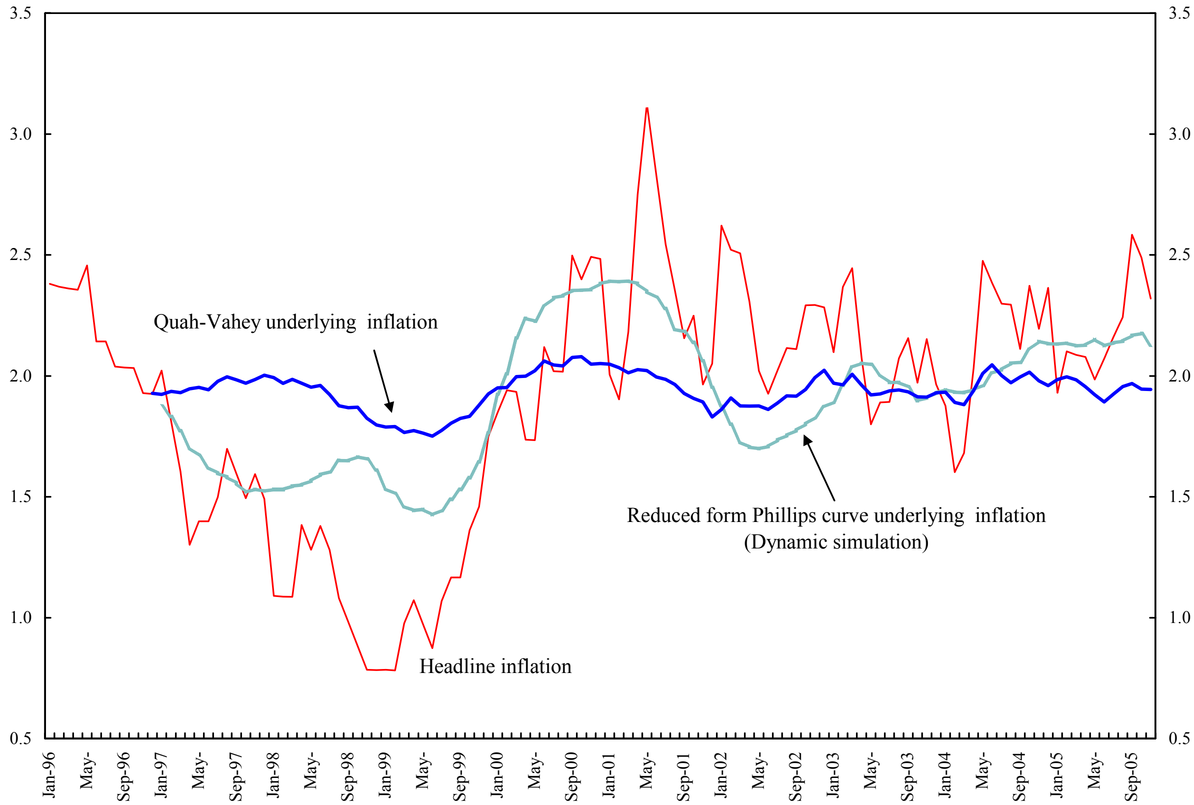
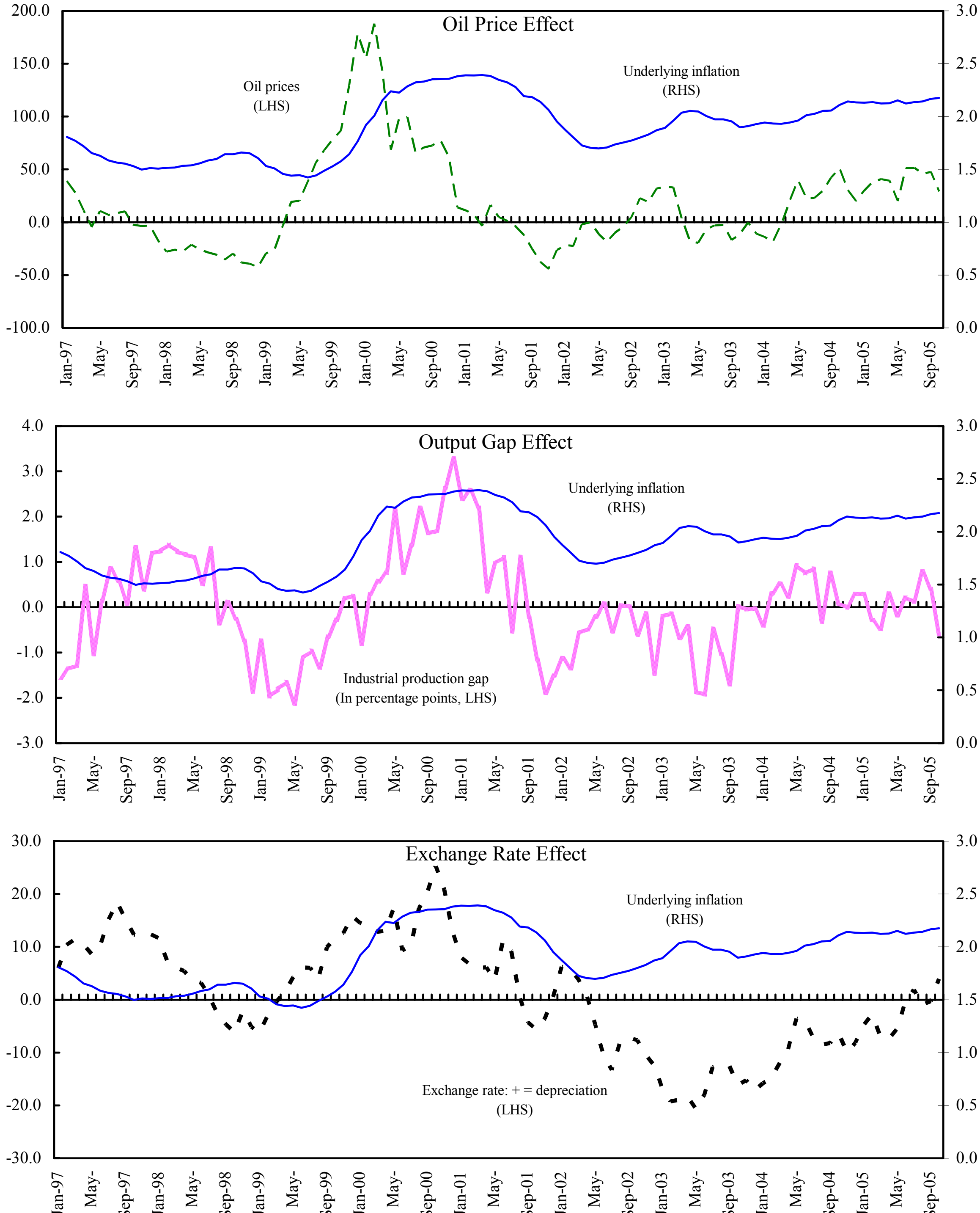


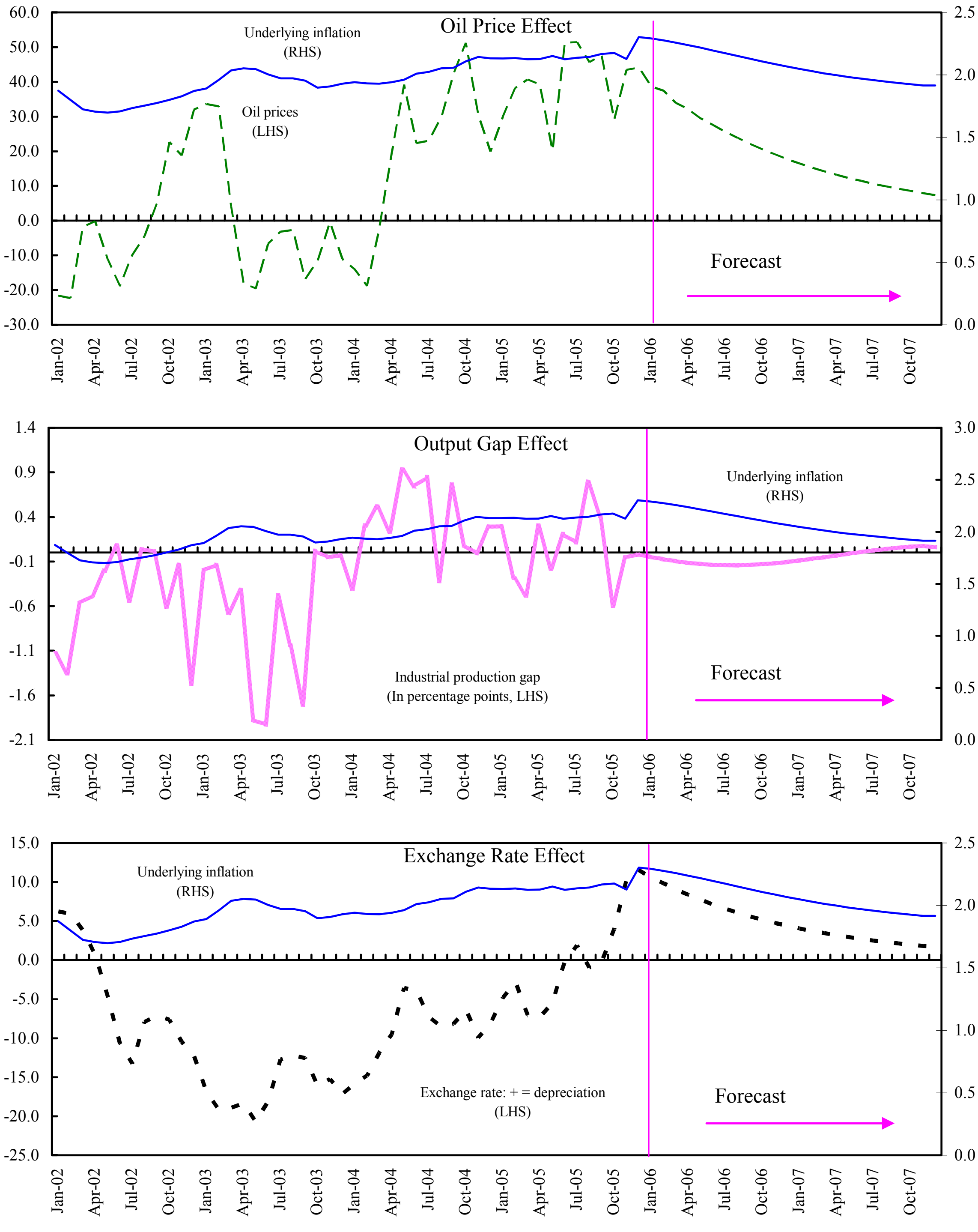
Figure 6. Euro Area: Underlying Inflation and Macroeconomic Factors 1/
(Year-on-year, in percent)




Source: IMF staff estimates.

1/ Dynamic real time forecast with reduced form Phillips curve.

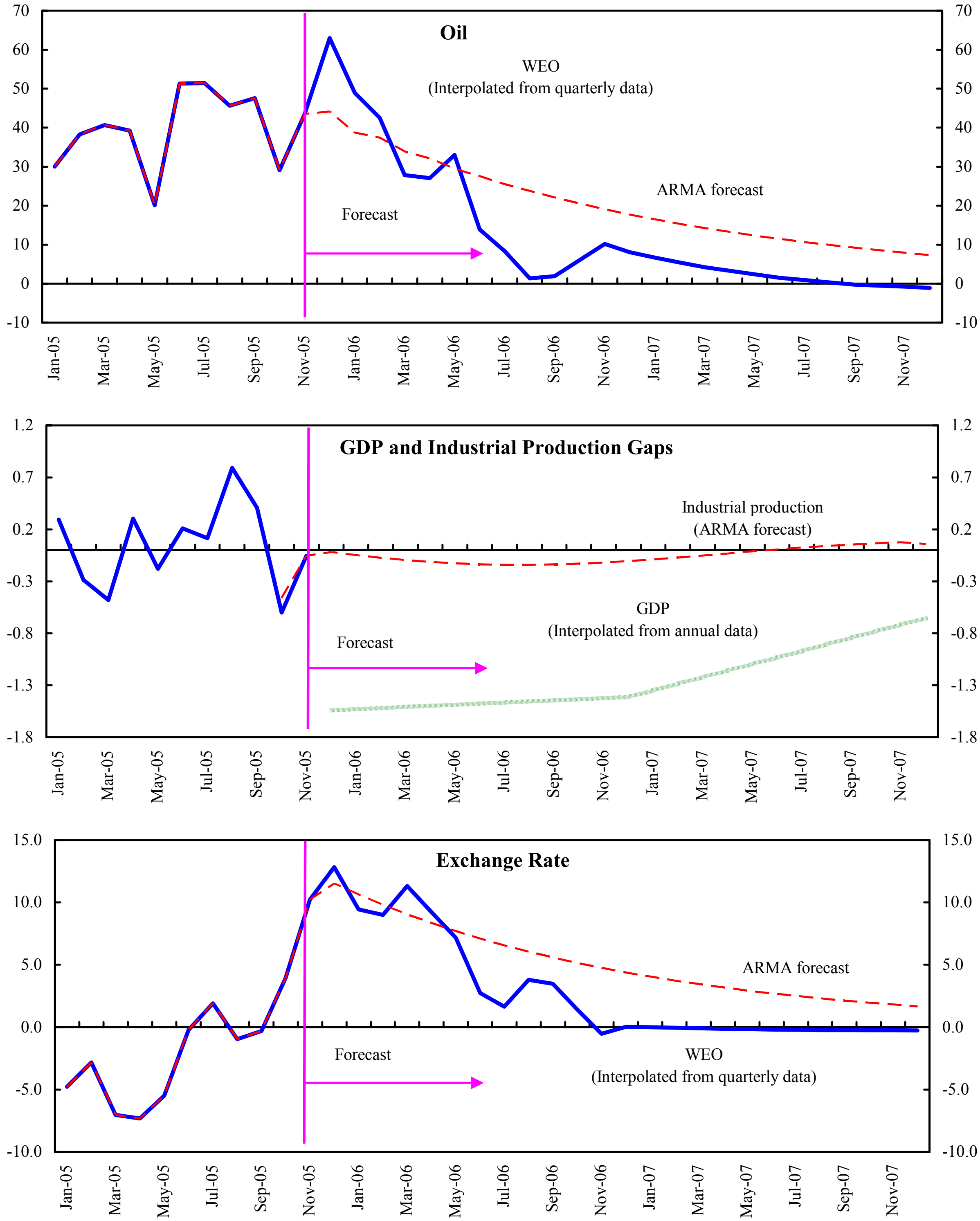
Figure 7. Euro Area: Underlying Inflation and Macroeconomic Factors 1/
(Year-on-year, in percent)




Source: IMF staff estimates.

1/ Out-of-sample forecast with reduced form Phillips curve; oil prices, industrial production gap, and exchange rate are forecast with an ARMA process.

Figure 8. Euro Area: Projection Comparisons
(Year-on-year, in percent)




Source: IMF staff estimates.

Figure 9. Euro Area: 24-month In-sample Forecast with the Composite Indicator
(Year-on-year, in percent, all indicators excluding ARDL)

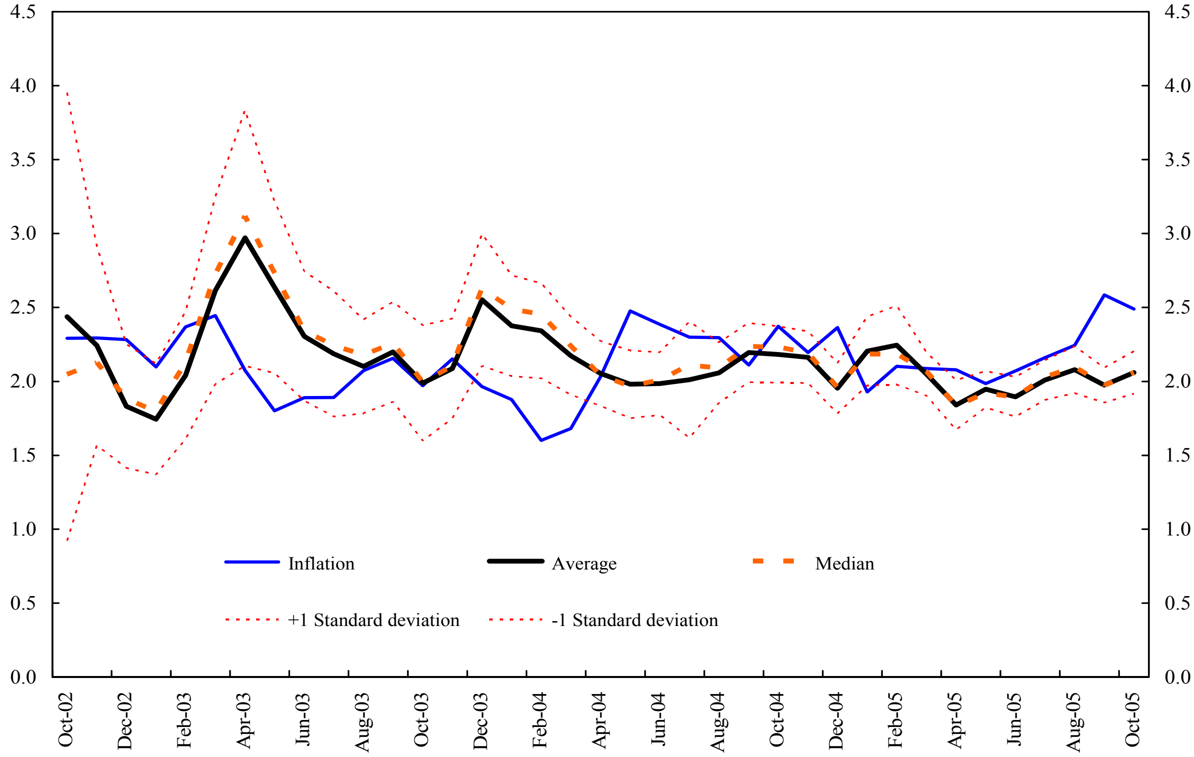
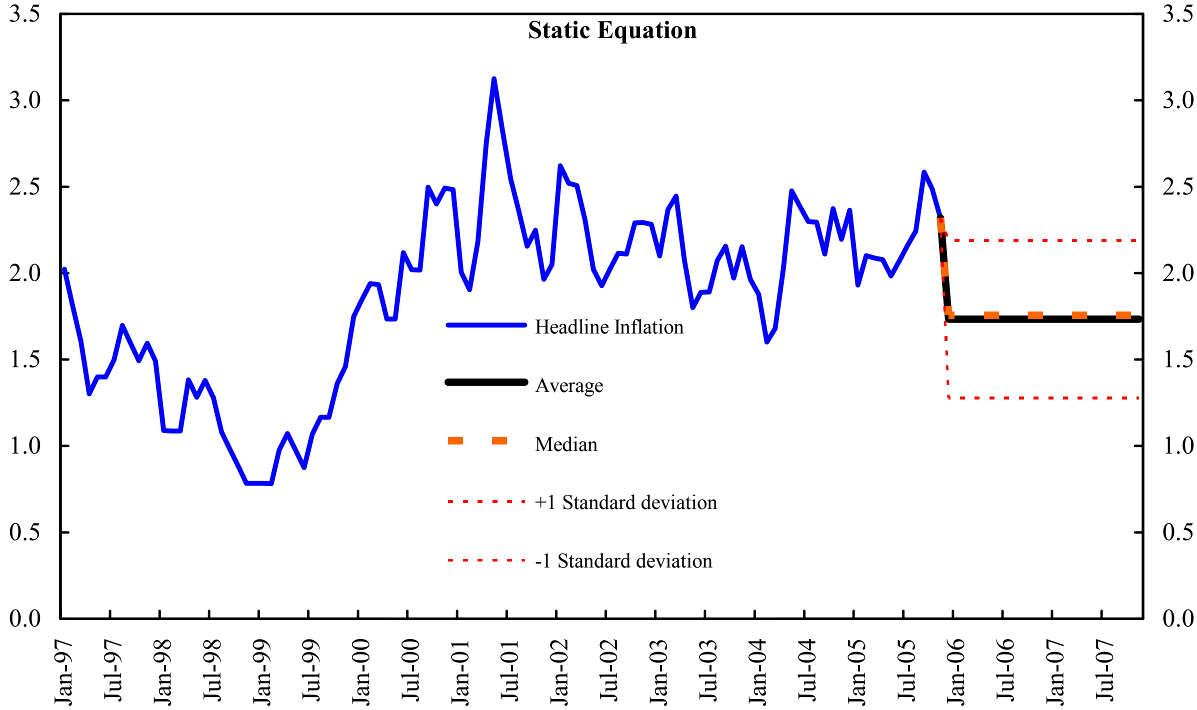
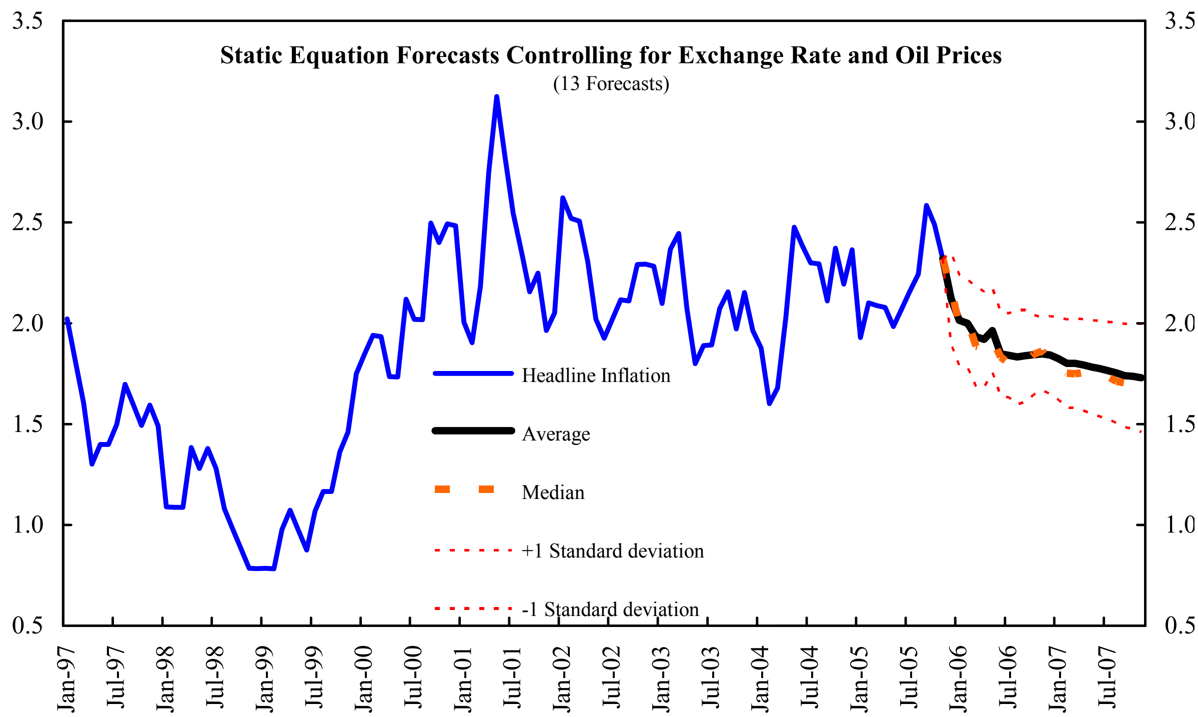


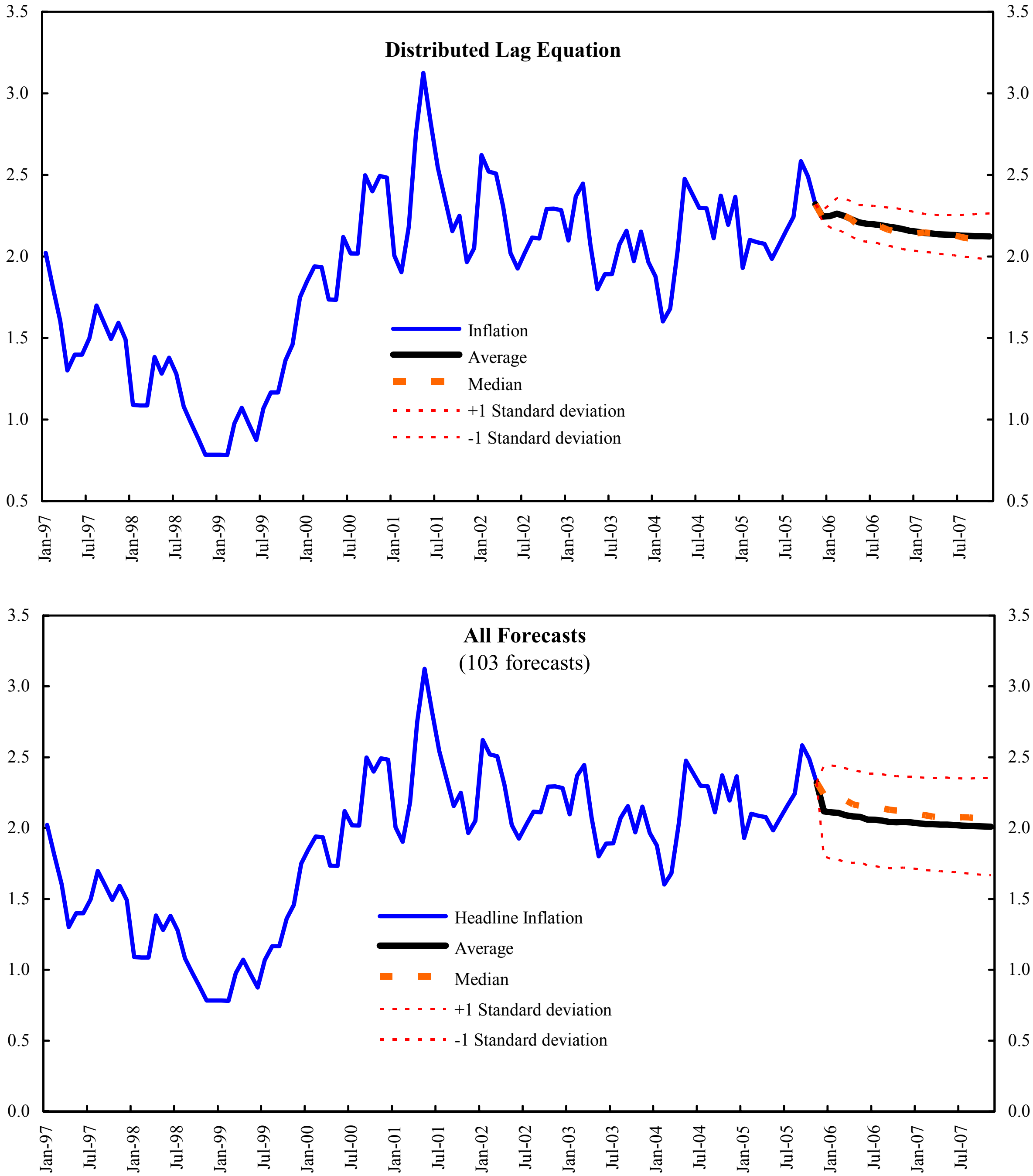
Figure 10. Euro Area: Static Equation Forecasts
(Year-on-year, in percent)




Source: IMF staff estimates.

Figure 11. Euro Area: Time Series Models Forecasts
(Year-on-year, in percent)




Source: IMF staff estimates.

Figure 12. Euro Area: Forecasts with Theoretical Models
(Year-on-year, in percent)

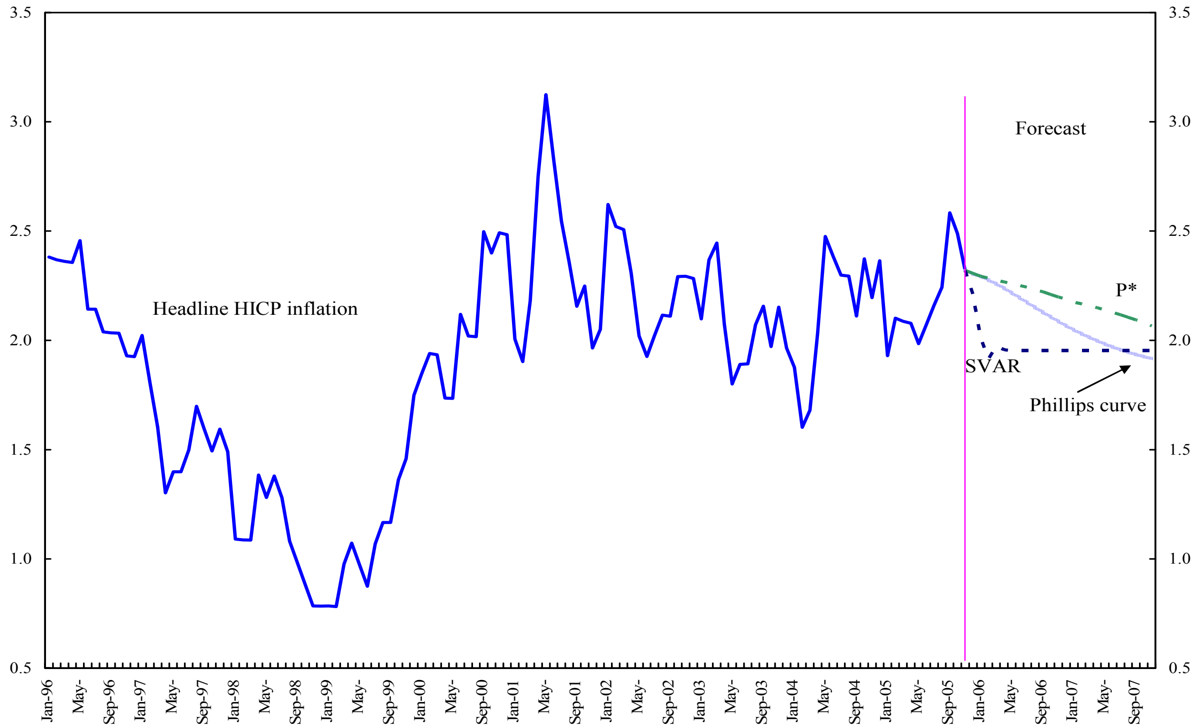



Figure 13. Euro Area: Persistence of Headline Inflation
(Estimates from a 4-year rolling regression)

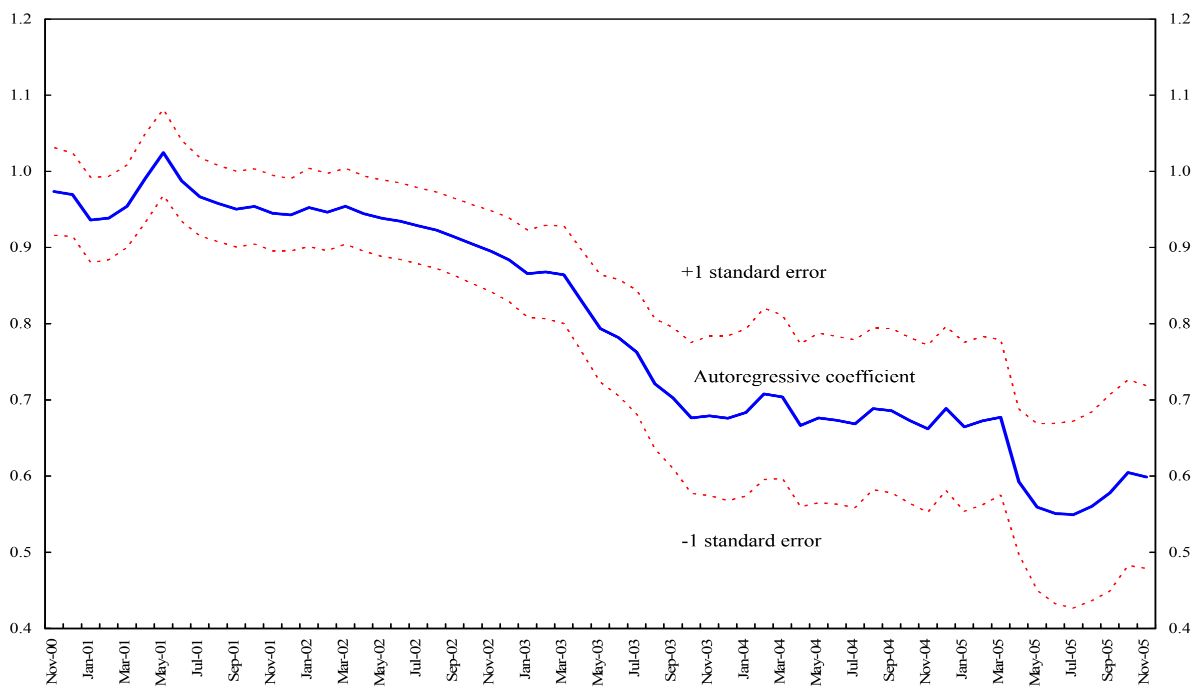


Figure 14. Static Model Forecasts
(Probability Distribution Function and Kernel Density Estimates)

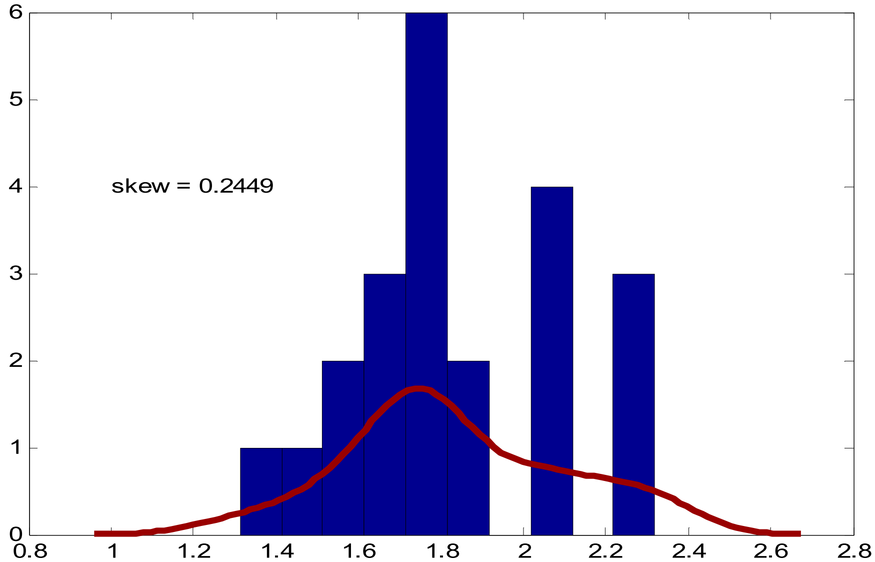



Figure 15. Bivariate and Multivariate Model Forecasts
(Probability Distribution Function and Kernel Density Estimates)

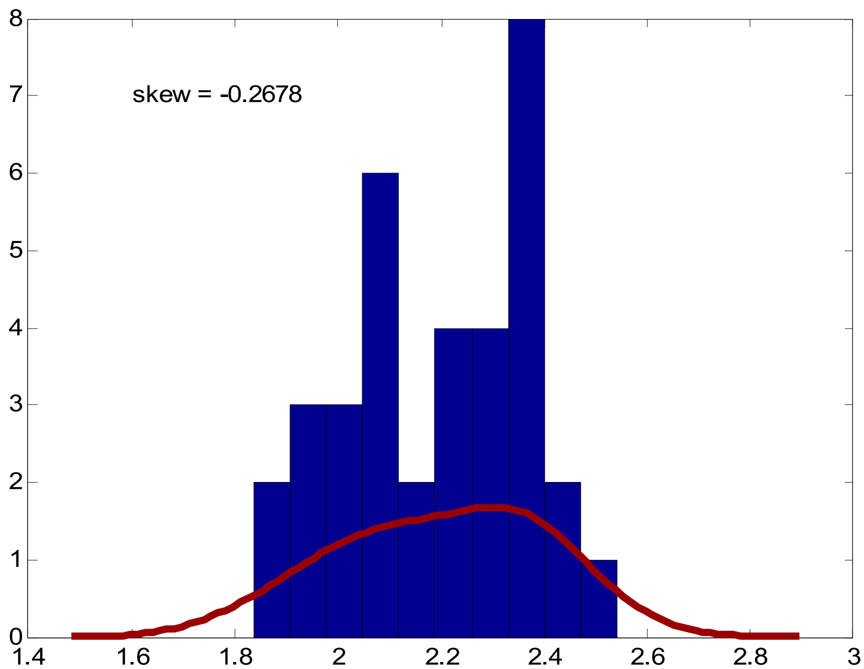


Figure 16. All Forecasts
(Probability Distribution Function and Kernel Density Estimates)

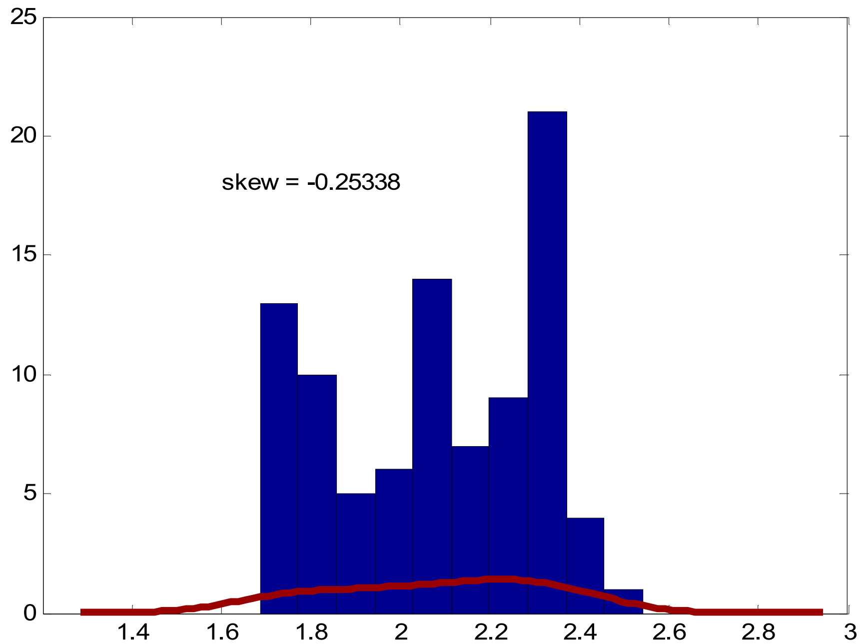



Table 1. Taxonomy of Underlying Inflation Indicators

| | Data set | Theoretical/Structural measures | Statistical indicators | |
|---|---|---|---|---|
| | | Time series | Cross-section | Panel |
| Statistical indicators | HICP components inflation | Bottom up approach: forecast HICP components using various econometric techniques and aggregate them | Exclusion measures: Permanent exclusion excluding energy Variable exclusion: trimmed means | Dynamic factor models Generalized dynamic factor models |
| | Aggregate HICP inflation | Moving averages; Hodrick-Prescott and other univariate filters and smoothing techniques | -- | -- |
| Theoretical/Structural measures | HICP: aggregate or components. Other macroeconomic variables: wages, industrial production, unemployment, exchange rate interest rate, monetary aggregates | Structural VARs Single Phillips curve equations Aggregate supply/demand models Money demand models P* models | -- | Dynamic factor models Generalized dynamic factor models with long-run identifying restrictions |

# Table 2. Euro Area: Descriptive Statistics of HICP Components

| Code | Description | 2005 Weight | Mean m-o-m 1/ | Mean y-o-y | Standard Deviation m-o-m 1/ | Standard Deviation y-o-y |
|---|---|---|---|---|---|---|
| | All-items HICP | 1000.0 | 1.9 | 1.9 | 1.5 | 0.5 |
| **1** | **Food and non-alcoholic beverages** | 154.8 | | | | |
| 1.1 | Food | 142.4 | | | | |
| 01.1.1 | Bread and cereals | 25.2 | 1.2 | 1.2 | 5.1 | 0.8 |
| 01.1.2 | Meat | 37.6 | 2.1 | 2.0 | 3.0 | 1.1 |
| 01.1.3 | Fish | 11.9 | 0.9 | 0.9 | 1.4 | 1.0 |
| 01.1.4 | Milk, cheese and eggs | 21.9 | 2.8 | 2.7 | 2.0 | 0.6 |
| 01.1.5 | Oils and fats | 5.1 | -0.9 | -0.8 | 2.2 | 1.0 |
| 01.1.6 | Fruit | 11.7 | 2.2 | 2.3 | 2.5 | 0.8 |
| 01.1.7 | Vegetables | 15.1 | 1.2 | 1.0 | 2.2 | 1.2 |
| 01.2.1 | Coffee, tea and cocoa | 3.7 | -0.2 | -0.3 | 6.8 | 4.7 |
| **2** | **Alcoholic beverages, tobacco** | 41.5 | | | | |
| 2.2 | Tobacco | 26.3 | 5.7 | 5.8 | 9.2 | 3.1 |
| **3** | **Clothing and footwear** | 74.4 | | | | |
| 3.1 | Clothing | 59.4 | | | | |
| 03.1.1 | Clothing materials | 0.3 | 1.3 | 1.2 | 7.1 | 1.1 |
| 03.1.2 | Garments | 54.8 | 0.8 | 0.8 | 5.1 | 0.9 |
| 03.1.3 | Other articles of clothing and clothing accessories | 2.5 | 1.2 | 1.2 | 5.1 | 0.8 |
| 3.2 | Footwear | 15.0 | | | | |
| 03.2.1/2 | Shoes and other footwear including repair and hire of footwear | 0.0 | 1.6 | 1.6 | 5.4 | 1.0 |
| **4** | **Housing, water, electricity, gas and other fuels** | 150.0 | | | | |
| 04.5.1 | Electricity | 19.5 | 0.8 | 0.7 | 5.1 | 1.9 |
| 04.5.2 | Gas | 13.6 | 4.5 | 4.3 | 9.6 | 6.4 |
| 04.5.3 | Liquid fuels | 7.9 | 8.7 | 9.4 | 50.2 | 19.3 |
| 04.5.4 | Solid fuels | 0.7 | 2.1 | 2.0 | 3.0 | 1.1 |
| 04.5.5 | Heat energy | 4.5 | 4.4 | 4.5 | 9.1 | 7.6 |
| **6** | **Health** | 41.4 | 3.1 | 3.2 | 6.2 | 1.9 |
| **7** | **Transport** | 153.1 | | | | |
| 07.3.3 | Passenger transport by air | 5.2 | 3.1 | 2.9 | 18.1 | 2.7 |
| 07.3.4 | Passenger transport by sea and inland waterway | 1.0 | 2.6 | 2.5 | 20.9 | 3.2 |
| **8** | **Communication** | 28.2 | | | | |
| 8.1 | Postal services | 2.3 | 2.1 | 2.1 | 5.9 | 1.8 |
| 08.2/3 | Telephone and telefax equipment and telephone and telefax services | 26.0 | -2.5 | -2.6 | 6.9 | 2.8 |
| **9** | **Recreation and culture** | 94.6 | | | | |
| 9.1 | Audio-visual, photographic and information processing equipment | 14.9 | | | | |
| 09.1.1 | Equipment for the reception, recording and reproduction of sound and pictures | 5.1 | -4.4 | -4.3 | 2.7 | 1.8 |
| 09.1.2 | Photographic and cinematographic equipment and optical instruments | 1.4 | -4.7 | -4.4 | 3.9 | 3.0 |
| 09.1.3 | Information processing equipment | 3.5 | -14.2 | -13.5 | 8.5 | 5.3 |
| 09.2.3 | Maintenance and repair of other major durables for recreation and culture | 2.4 | 3.3 | 3.5 | 4.9 | 1.9 |
| 09.4.2 | Cultural services | 13.9 | 1.9 | 1.9 | 4.6 | 1.4 |
| 9.6 | Package holidays | 15.2 | 2.6 | 2.4 | 27.4 | 3.1 |
| **11** | **Restaurants and hotels** | 94.6 | | | | |
| 11.2 | Accommodation services | 17.0 | 3.3 | 3.4 | 7.3 | 1.1 |
| **12** | **Miscellaneous goods and services** | 81.6 | | | | |
| 12.5.2 | Insurance connected with the dwelling | 2.3 | 2.1 | 2.0 | 5.9 | 1.7 |
| 12.5.4 | Insurance connected with transport | 7.7 | 1.7 | 1.8 | 8.9 | 3.8 |
| 12.6 | Financial services n.e.c. | 5.9 | 3.6 | 3.5 | 8.7 | 2.0 |

Sources: EUROSTAT; and IMF staff estimates.
1/ Annualized.

Table 3. Euro Area: Headline and Underlying Inflation Indicators: Descriptive Statistics /1
(Year-on-year, in percent)

| | Mean | Median | Maximum | Minimum | Standard Deviation 2/ |
|---|---|---|---|---|---|
| Headline inflation | 1.9 | 2.0 | 3.1 | 0.8 | 1.00 |
| GDFM indicators | | | | | |
| Prices only: 1 dynamic factor | 1.9 | 1.8 | 2.3 | 1.6 | 0.32 |
| Prices only: 2 dynamic factors | 1.9 | 2.1 | 2.3 | 1.2 | 0.77 |
| Price and non-price data: 1 dynamic factor | 1.9 | 1.8 | 2.3 | 1.6 | 0.34 |
| Price and non-price data: 2 dynamic factors | 1.9 | 2.1 | 2.4 | 1.3 | 0.73 |
| Core indicators | | | | | |
| Headline excluding energy | 1.7 | 1.6 | 3.0 | 0.7 | 1.08 |
| Headline excluding energy, food, alcohol and tobacco | 1.6 | 1.6 | 2.6 | 0.9 | 0.83 |
| Headline excluding seasonal food | 1.7 | 1.6 | 2.7 | 0.9 | 0.98 |
| Headline excluding unprocessed food | 1.7 | 1.5 | 2.7 | 0.9 | 0.94 |
| Trimmed means/median | | | | | |
| 5 percent | 1.8 | 1.8 | 3.0 | 0.8 | 0.90 |
| 10 percent | 1.8 | 1.8 | 2.7 | 0.8 | 0.89 |
| 15 percent | 1.8 | 1.8 | 2.8 | 1.0 | 0.87 |
| 20 percent | 1.8 | 1.8 | 2.7 | 1.0 | 0.85 |
| 50 percent | 1.8 | 1.7 | 2.6 | 1.1 | 0.74 |
| Model measures | | | | | |
| Vahey&Quah | 1.9 | 1.9 | 2.4 | 1.5 | 0.38 |
| Phillips curve | 1.9 | 1.9 | 2.4 | 1.4 | 0.54 |

Sources: Eurostat; and IMF staff calculations.

1/ Sample: January, 1997-December, 2005.
2/ Relative to headline inflation.

# Table 4. Euro Area: Forecast Performance of Indicators of Underlying Inflation 1/

(Root mean square error/RMSE/ and bias in percentage points)

**Univariate — Spectral density equation** (Forecast horizon (months))

| | 6 | | 12 | | 18 | | 24 | |
|---|---|---|---|---|---|---|---|---|
| | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias |
| HICP inflation (First difference) | 0.35 | 0.05 | 0.41 | 0.07 | 0.41 | 0.13 | 0.51 | 0.17 |
| HICP inflation (Level) | 0.36 | -0.08 | 0.42 | -0.22 | 0.36 | -0.27 | 0.40 | -0.30 |
| Static equation | | | | | | | | |
| **HICP inflation (Random walk--benchmark)** | **0.32** | **-0.16** | **0.34** | **-0.18** | **0.48** | **0.37** | **0.44** | **-0.05** |
| GDFM estimates of underlying inflation | | | | | | | | |
| HICP components only: 1 factor | 0.48 | 0.31 | 0.41 | 0.23 | 0.35 | 0.17 | 0.38 | 0.14 |
| HICP components only: 2 factors | 0.37 | 0.18 | 0.34 | 0.13 | 0.32 | 0.10 | 0.36 | 0.06 |
| HICP components and non-price data: 1 factor | 0.47 | 0.30 | 0.39 | 0.22 | 0.34 | 0.16 | 0.38 | 0.14 |
| HICP components and non-price data: 2 factors | 0.37 | 0.19 | 0.34 | 0.14 | 0.32 | 0.10 | 0.36 | 0.07 |
| Core inflation measures by exclusion | | | | | | | | |
| Excluding energy | 0.56 | 0.06 | 0.57 | 0.00 | 0.79 | 0.53 | 0.77 | 0.15 |
| Excluding energy, food, alcohol and tobacco | 0.54 | 0.27 | 0.54 | 0.24 | 0.94 | 0.80 | 0.76 | 0.42 |
| Excluding energy and seasonal food | 0.50 | 0.10 | 0.50 | 0.06 | 0.80 | 0.61 | 0.71 | 0.23 |
| Excluding energy and unprocessed food | 0.53 | 0.14 | 0.54 | 0.10 | 0.86 | 0.66 | 0.75 | 0.29 |
| Trimmed means/median | | | | | | | | |
| 5 percent | 0.31 | -0.02 | 0.32 | -0.05 | 0.57 | 0.47 | 0.48 | 0.05 |
| 10 percent | 0.34 | -0.01 | 0.35 | -0.04 | 0.58 | 0.46 | 0.49 | 0.04 |
| 15 percent | 0.36 | 0.00 | 0.37 | -0.03 | 0.62 | 0.48 | 0.53 | 0.07 |
| 20 percent | 0.36 | 0.00 | 0.37 | -0.04 | 0.61 | 0.48 | 0.53 | 0.06 |
| 50 percent | 0.34 | 0.05 | 0.35 | 0.02 | 0.63 | 0.53 | 0.52 | 0.12 |
| Non-price indicators | | | | | | | | |
| M1 | n.a. | | n.a. | | n.a. | | n.a. | |
| M2 | n.a. | | n.a. | | n.a. | | n.a. | |
| M3 | n.a. | | n.a. | | n.a. | | n.a. | |
| Wages | n.a. | | n.a. | | n.a. | | n.a. | |
| ULC | n.a. | | n.a. | | n.a. | | n.a. | |
| Unemployment | n.a. | | n.a. | | n.a. | | n.a. | |
| Industrial production | n.a. | | n.a. | | n.a. | | n.a. | |
| Interest rates | n.a. | | n.a. | | n.a. | | n.a. | |
| Structural measures of underlying inflation | | | | | | | | |
| Quah&Vahey SVAR | 0.53 | 0.37 | 0.55 | 0.36 | 0.49 | 0.34 | 0.50 | 0.35 |
| Reduced form Phillips curve | n.a. | | n.a. | | n.a. | | n.a. | |
| P* model | n.a. | | n.a. | | n.a. | | n.a. | |
| Composite indicators: | | | | | | | | |
| All measures | 0.37 | 0.14 | 0.32 | 0.09 | 0.32 | 0.04 | 0.38 | -0.01 |
| Bivariate equations | 0.36 | 0.12 | 0.33 | 0.07 | 0.34 | 0.02 | 0.42 | -0.04 |

**Bivariate — Distributed lag equation** (Forecast horizon (months))

| | 6 | | 12 | | 18 | | 24 | |
|---|---|---|---|---|---|---|---|---|
| | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias |
| HICP inflation (First difference) | n.a. | | n.a. | | n.a. | | n.a. | |
| HICP inflation (Level) | n.a. | | n.a. | | n.a. | | n.a. | |
| **HICP inflation (Random walk--benchmark)** | n.a. | | n.a. | | n.a. | | n.a. | |
| GDFM estimates of underlying inflation | | | | | | | | |
| HICP components only: 1 factor | 0.41 | 0.10 | 0.48 | 0.05 | 0.51 | -0.07 | 0.64 | -0.23 |
| HICP components only: 2 factors | 0.42 | 0.20 | 0.45 | 0.12 | 0.44 | 0.02 | 0.52 | -0.12 |
| HICP components and non-price data: 1 factor | 0.47 | 0.23 | 0.46 | 0.15 | 0.45 | 0.00 | 0.57 | -0.14 |
| HICP components and non-price data: 2 factors | 0.42 | 0.20 | 0.44 | 0.13 | 0.43 | 0.03 | 0.50 | -0.10 |
| Core inflation measures by exclusion | | | | | | | | |
| Excluding energy | 0.62 | 0.44 | 1.09 | 0.80 | 1.49 | 1.11 | 1.81 | 1.39 |
| Excluding energy, food, alcohol and tobacco | 0.63 | 0.38 | 1.15 | 0.71 | 1.66 | 1.03 | 2.17 | 1.32 |
| Excluding energy and seasonal food | 0.59 | 0.39 | 1.16 | 0.77 | 1.82 | 1.22 | 2.61 | 1.73 |
| Excluding energy and unprocessed food | 0.62 | 0.40 | 1.12 | 0.76 | 1.62 | 1.11 | 2.08 | 1.43 |
| Trimmed means/median | | | | | | | | |
| 5 percent | 0.47 | 0.23 | 1.00 | 0.58 | 2.19 | 1.31 | 4.93 | 2.90 |
| 10 percent | 0.60 | 0.30 | 1.59 | 0.76 | 3.97 | 1.84 | 10.47 | 4.58 |
| 15 percent | 0.58 | 0.31 | 1.20 | 0.65 | 2.15 | 1.18 | 3.95 | 2.06 |
| 20 percent | 0.58 | 0.31 | 1.13 | 0.61 | 1.85 | 1.02 | 3.12 | 1.65 |
| 50 percent | 0.61 | 0.33 | 1.10 | 0.61 | 1.55 | 0.89 | 2.24 | 1.24 |
| Non-price indicators | | | | | | | | |
| M1 | 0.48 | 0.32 | 0.50 | 0.36 | 0.51 | 0.35 | 0.55 | 0.34 |
| M2 | 0.52 | 0.08 | 0.83 | -0.08 | 1.30 | -0.36 | 2.29 | -0.70 |
| M3 | 0.50 | 0.19 | 0.65 | 0.06 | 0.74 | -0.18 | 0.98 | -0.40 |
| Wages | 0.52 | 0.30 | 0.50 | 0.33 | 0.43 | 0.30 | 0.43 | 0.29 |
| ULC | 0.46 | -0.08 | 0.81 | -0.28 | 1.11 | -0.53 | 1.11 | -0.80 |
| Unemployment | 0.43 | 0.22 | 0.54 | 0.36 | 0.59 | 0.47 | 0.64 | 0.53 |
| Industrial production | 0.54 | 0.16 | 0.88 | 0.13 | 1.29 | 0.07 | 2.18 | -0.03 |
| Interest rates | 0.44 | 0.08 | 0.68 | 0.06 | 0.82 | 0.01 | 1.24 | -0.05 |
| Structural measures (bi- or multivariate) | | | | | | | | |
| Quah&Vahey SVAR | 0.47 | 0.36 | 0.47 | 0.36 | 0.42 | 0.34 | 0.43 | 0.34 |
| Reduced form Phillips curve | 0.49 | 0.13 | 0.40 | 0.24 | 0.51 | 0.32 | 0.51 | 0.30 |
| P* model | 0.41 | 0.06 | 0.26 | 0.08 | 0.68 | 0.04 | 0.91 | -0.09 |
| Composite indicators: | | | | | | | | |
| All measures | n.a. | | n.a. | | n.a. | | n.a. | |
| Bivariate equations | n.a. | | n.a. | | n.a. | | n.a. | |

**Bivariate — Gap equation** (Forecast horizon (months))

| | 6 | | 12 | | 18 | | 24 | |
|---|---|---|---|---|---|---|---|---|
| | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias |
| HICP inflation (First difference) | n.a. | | n.a. | | n.a. | | n.a. | |
| HICP inflation (Level) | n.a. | | n.a. | | n.a. | | n.a. | |
| **HICP inflation (Random walk--benchmark)** | n.a. | | n.a. | | n.a. | | n.a. | |
| GDFM estimates of underlying inflation | | | | | | | | |
| HICP components only: 1 factor | 0.41 | 0.21 | 0.41 | 0.21 | 0.38 | 0.13 | 0.41 | 0.01 |
| HICP components only: 2 factors | 0.40 | 0.18 | 0.41 | 0.16 | 0.39 | 0.08 | 0.45 | -0.04 |
| HICP components and non-price data: 1 factor | 0.41 | 0.19 | 0.40 | 0.20 | 0.37 | 0.13 | 0.41 | 0.02 |
| HICP components and non-price data: 2 factors | 0.40 | 0.18 | 0.40 | 0.16 | 0.38 | 0.09 | 0.43 | -0.02 |
| Core inflation measures by exclusion | | | | | | | | |
| Excluding energy | 0.39 | 0.00 | 0.52 | -0.07 | 0.62 | -0.11 | 0.89 | -0.20 |
| Excluding energy, food, alcohol and tobacco | 0.42 | -0.03 | 0.59 | -0.14 | 0.75 | -0.26 | 1.16 | -0.45 |
| Excluding energy and seasonal food | 0.39 | 0.00 | 0.51 | -0.09 | 0.60 | -0.15 | 0.85 | -0.25 |
| Excluding energy and unprocessed food | 0.40 | -0.01 | 0.52 | -0.10 | 0.60 | -0.18 | 0.87 | -0.30 |
| Trimmed means/median | | | | | | | | |
| 5 percent | 0.39 | -0.01 | 0.55 | -0.09 | 0.81 | -0.19 | 1.50 | -0.38 |
| 10 percent | 0.39 | 0.03 | 0.53 | -0.02 | 0.65 | -0.10 | 1.10 | -0.25 |
| 15 percent | 0.37 | 0.03 | 0.45 | -0.01 | 0.48 | -0.06 | 0.64 | -0.12 |
| 20 percent | 0.37 | 0.03 | 0.43 | -0.01 | 0.44 | -0.06 | 0.54 | -0.11 |
| 50 percent | 0.37 | 0.05 | 0.43 | 0.02 | 0.41 | -0.04 | 0.49 | -0.09 |
| Non-price indicators | | | | | | | | |
| M1 | 0.52 | 0.39 | 0.50 | 0.32 | 0.52 | 0.22 | 0.39 | 0.10 |
| M2 | 0.59 | 0.44 | 0.54 | 0.39 | 0.50 | 0.28 | 0.46 | 0.25 |
| M3 | 0.53 | 0.23 | 0.51 | 0.09 | 0.53 | -0.11 | 0.65 | -0.29 |
| Wages | 0.60 | 0.50 | 0.55 | 0.46 | 0.46 | 0.39 | 0.45 | 0.38 |
| ULC | 0.53 | 0.34 | 0.42 | 0.26 | 0.36 | 0.19 | 0.40 | 0.18 |
| Unemployment | 0.58 | 0.46 | 0.54 | 0.44 | 0.50 | 0.43 | 0.50 | 0.45 |
| Industrial production | 0.67 | 0.45 | 0.59 | 0.38 | 0.56 | 0.28 | 0.51 | 0.25 |
| Interest rates | 0.61 | 0.46 | 0.58 | 0.47 | 0.55 | 0.47 | 0.62 | 0.52 |
| Structural measures (bi- or multivariate) | | | | | | | | |
| Quah&Vahey SVAR | n.a. | | n.a. | | n.a. | | n.a. | |
| Reduced form Phillips curve | n.a. | | n.a. | | n.a. | | n.a. | |
| P* model | n.a. | | n.a. | | n.a. | | n.a. | |
| Composite indicators: | | | | | | | | |
| All measures | n.a. | | n.a. | | n.a. | | n.a. | |
| Bivariate equations | n.a. | | n.a. | | n.a. | | n.a. | |

**Multivariate — Semi-structural equation with exchange rate and oil** (Forecast horizon (months))

| | 6 | | 12 | | 18 | | 24 | |
|---|---|---|---|---|---|---|---|---|
| | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias |
| HICP inflation (First difference) | n.a. | | n.a. | | n.a. | | n.a. | |
| HICP inflation (Level) | n.a. | | n.a. | | n.a. | | n.a. | |
| **HICP inflation (Random walk--benchmark)** | n.a. | | n.a. | | n.a. | | n.a. | |
| GDFM estimates of underlying inflation | | | | | | | | |
| HICP components only: 1 factor | 0.54 | 0.30 | 0.50 | 0.34 | 0.57 | 0.29 | 0.47 | 0.12 |
| HICP components only: 2 factors | 0.44 | 0.25 | 0.35 | 0.27 | 0.51 | 0.22 | 0.46 | 0.01 |
| HICP components and non-price data: 1 factor | 0.55 | 0.31 | 0.53 | 0.35 | 0.59 | 0.30 | 0.47 | 0.13 |
| HICP components and non-price data: 2 factors | 0.45 | 0.23 | 0.36 | 0.26 | 0.51 | 0.21 | 0.47 | 0.02 |
| Core inflation measures by exclusion | | | | | | | | |
| Excluding energy | 0.62 | 0.19 | 0.71 | 0.33 | 0.90 | 0.42 | 0.81 | 0.41 |
| Excluding energy, food, alcohol and tobacco | 0.68 | 0.32 | 0.86 | 0.54 | 1.06 | 0.72 | 1.04 | 0.76 |
| Excluding energy and seasonal food | 0.61 | 0.18 | 0.68 | 0.31 | 0.90 | 0.41 | 0.82 | 0.42 |
| Excluding energy and unprocessed food | 0.68 | 0.27 | 0.80 | 0.47 | 0.98 | 0.63 | 0.95 | 0.65 |
| Trimmed means/median | | | | | | | | |
| 5 percent | 0.37 | 0.05 | 0.30 | 0.09 | 0.60 | 0.09 | 0.60 | -0.01 |
| 10 percent | 0.38 | 0.06 | 0.34 | 0.10 | 0.59 | 0.08 | 0.53 | -0.03 |
| 15 percent | 0.44 | 0.05 | 0.44 | 0.10 | 0.67 | 0.09 | 0.57 | 0.01 |
| 20 percent | 0.47 | 0.05 | 0.47 | 0.11 | 0.69 | 0.11 | 0.58 | 0.02 |
| 50 percent | 0.45 | 0.10 | 0.53 | 0.20 | 0.67 | 0.22 | 0.44 | 0.17 |
| Non-price indicators | | | | | | | | |
| M1 | n.a. | | n.a. | | n.a. | | n.a. | |
| M2 | n.a. | | n.a. | | n.a. | | n.a. | |
| M3 | n.a. | | n.a. | | n.a. | | n.a. | |
| Wages | n.a. | | n.a. | | n.a. | | n.a. | |
| ULC | n.a. | | n.a. | | n.a. | | n.a. | |
| Unemployment | n.a. | | n.a. | | n.a. | | n.a. | |
| Industrial production | n.a. | | n.a. | | n.a. | | n.a. | |
| Interest rates | n.a. | | n.a. | | n.a. | | n.a. | |
| Structural measures (bi- or multivariate) | | | | | | | | |
| Quah&Vahey SVAR | n.a. | | n.a. | | n.a. | | n.a. | |
| Reduced form Phillips curve | n.a. | | n.a. | | n.a. | | n.a. | |
| P* model | n.a. | | n.a. | | n.a. | | n.a. | |
| Composite indicators: | | | | | | | | |
| All measures | n.a. | | n.a. | | n.a. | | n.a. | |
| Bivariate equations | n.a. | | n.a. | | n.a. | | n.a. | |

Source: IMF staff estimates.

1/ Forecast evaluation for estimates with year-on-year inflation. Gap and semi-structural equations are estimated with one month lag; lag length of the distributed lag equation is based on Akaike and Schwarz criteria; right-hand side variables in the bivariate and multivariate models are forecast with a spectral density filter.

# Table 5. Euro Area: Forecast Performance of Indicators of Underlying Inflation 1/

(Root mean square error/RMSE/ and bias in percentage points)

| | Univariate | | | | | | | | Bivariate | | | | | | | | | | | | | | | | Multivariate | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Spectral density equation | | | | | | | | Distributed lag equation | | | | | | | | Gap equation | | | | | | | | Semi-structural equation with exchange rate and oil | | | | | | | |
| | Forecast horizon (months) | | | | | | | | Forecast horizon (months) | | | | | | | | Forecast horizon (months) | | | | | | | | Forecast horizon (months) | | | | | | | |
| | 6 | | 12 | | 18 | | 24 | | 6 | | 12 | | 18 | | 24 | | 6 | | 12 | | 18 | | 24 | | 6 | | 12 | | 18 | | 24 | |
| | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias | RMSE | Bias |
| HICP inflation (First difference) | 0.35 | 0.05 | 0.41 | 0.07 | 0.41 | 0.13 | 0.51 | 0.17 | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | |
| HICP inflation (Level) | 0.36 | -0.08 | 0.42 | -0.22 | 0.36 | -0.27 | 0.40 | -0.30 | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | |
| | Static equation | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| **HICP inflation (Random walk--benchmark)** | **0.32** | **-0.16** | **0.34** | **-0.18** | **0.48** | **0.37** | **0.44** | **-0.05** | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | | n.a. | |
| GDFM estimates of underlying inflation | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| HICP components only: 1 factor | 0.48 | 0.31 | 0.41 | 0.23 | 0.35 | 0.17 | 0.38 | 0.14 | 1.05 | -0.15 | 2.31 | -0.39 | 2.97 | -0.32 | 2.77 | -0.05 | 0.55 | 0.19 | 0.46 | 0.05 | 0.51 | 0.08 | 0.68 | 0.46 | 0.96 | -0.21 | 1.79 | -0.39 | 2.54 | -0.43 | 2.42 | -0.25 |
| HICP components only: 2 factors | 0.37 | 0.18 | 0.34 | 0.13 | 0.32 | 0.10 | 0.36 | 0.06 | 0.58 | 0.08 | 1.00 | 0.13 | 1.29 | 0.23 | 1.37 | 0.58 | 0.68 | 0.23 | 0.43 | 0.05 | 0.52 | -0.01 | 0.58 | 0.40 | 0.75 | 0.25 | 1.52 | 0.69 | 2.12 | 1.08 | 2.04 | 1.17 |
| HICP components and non-price data: 1 factor | 0.47 | 0.30 | 0.39 | 0.22 | 0.34 | 0.16 | 0.38 | 0.14 | 1.08 | -0.18 | 2.32 | -0.40 | 2.94 | -0.31 | 2.65 | -0.09 | 0.52 | 0.18 | 0.45 | 0.05 | 0.50 | 0.08 | 0.71 | 0.46 | 1.00 | -0.29 | 1.93 | -0.59 | 2.75 | -0.71 | 2.59 | -0.53 |
| HICP components and non-price data: 2 factors | 0.37 | 0.19 | 0.34 | 0.14 | 0.32 | 0.10 | 0.36 | 0.07 | 0.64 | 0.13 | 1.11 | 0.23 | 1.41 | 0.37 | 1.58 | 0.72 | 0.70 | 0.26 | 0.43 | 0.06 | 0.54 | 0.00 | 0.62 | 0.44 | 0.82 | 0.30 | 1.65 | 0.79 | 2.24 | 1.17 | 2.08 | 1.22 |
| Core inflation measures by exclusion | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Excluding energy | 0.56 | 0.06 | 0.57 | 0.00 | 0.79 | 0.53 | 0.77 | 0.15 | 1.09 | 0.99 | 1.56 | 1.38 | 1.65 | 1.47 | 1.40 | 1.26 | 1.38 | 0.48 | 1.63 | 0.55 | 1.53 | 0.44 | 1.10 | 0.06 | 1.07 | 0.84 | 1.52 | 1.24 | 1.89 | 1.62 | 2.03 | 1.80 |
| Excluding energy, food, alcohol and tobacco | 0.54 | 0.27 | 0.54 | 0.24 | 0.94 | 0.80 | 0.76 | 0.42 | 0.97 | 0.86 | 1.39 | 1.23 | 1.58 | 1.41 | 1.52 | 1.36 | 1.31 | 0.56 | 1.71 | 0.76 | 1.78 | 0.81 | 1.47 | 0.60 | 0.99 | 0.81 | 1.35 | 1.17 | 1.71 | 1.53 | 1.88 | 1.71 |
| Excluding energy and seasonal food | 0.50 | 0.10 | 0.50 | 0.06 | 0.80 | 0.61 | 0.71 | 0.23 | 0.97 | 0.89 | 1.49 | 1.34 | 1.77 | 1.57 | 1.63 | 1.46 | 1.23 | 0.39 | 1.61 | 0.57 | 1.77 | 0.62 | 1.26 | 0.29 | 1.01 | 0.81 | 1.39 | 1.16 | 1.72 | 1.51 | 1.88 | 1.71 |
| Excluding energy and unprocessed food | 0.53 | 0.14 | 0.54 | 0.10 | 0.86 | 0.66 | 0.75 | 0.29 | 0.95 | 0.88 | 1.40 | 1.28 | 1.61 | 1.48 | 1.51 | 1.39 | 1.30 | 0.51 | 1.71 | 0.71 | 1.79 | 0.73 | 1.40 | 0.39 | 1.03 | 0.84 | 1.43 | 1.23 | 1.81 | 1.63 | 2.00 | 1.86 |
| Trimmed means/median | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 5 percent | 0.31 | -0.02 | 0.32 | -0.05 | 0.57 | 0.47 | 0.48 | 0.05 | 1.17 | 0.94 | 1.53 | 1.28 | 1.53 | 1.31 | 1.56 | 1.36 | 0.95 | 0.18 | 0.93 | 0.11 | 0.68 | 0.00 | 0.57 | -0.02 | 0.95 | 0.75 | 1.28 | 1.05 | 1.54 | 1.31 | 1.63 | 1.44 |
| 10 percent | 0.34 | -0.01 | 0.35 | -0.04 | 0.58 | 0.46 | 0.49 | 0.04 | 1.21 | 0.96 | 1.62 | 1.35 | 1.55 | 1.34 | 1.53 | 1.31 | 1.27 | 0.36 | 1.37 | 0.39 | 1.04 | 0.23 | 0.76 | 0.09 | 0.96 | 0.77 | 1.31 | 1.08 | 1.59 | 1.37 | 1.69 | 1.50 |
| 15 percent | 0.36 | 0.00 | 0.37 | -0.03 | 0.62 | 0.48 | 0.53 | 0.07 | 1.05 | 0.86 | 1.42 | 1.22 | 1.41 | 1.24 | 1.32 | 1.17 | 1.18 | 0.35 | 1.28 | 0.40 | 1.04 | 0.25 | 0.65 | 0.02 | 0.98 | 0.78 | 1.34 | 1.10 | 1.63 | 1.40 | 1.73 | 1.53 |
| 20 percent | 0.36 | 0.00 | 0.37 | -0.04 | 0.61 | 0.48 | 0.53 | 0.06 | 1.05 | 0.87 | 1.43 | 1.23 | 1.41 | 1.26 | 1.34 | 1.20 | 1.25 | 0.39 | 1.37 | 0.45 | 1.09 | 0.29 | 0.74 | 0.06 | 0.99 | 0.79 | 1.34 | 1.11 | 1.65 | 1.41 | 1.75 | 1.56 |
| 50 percent | 0.34 | 0.05 | 0.35 | 0.02 | 0.63 | 0.53 | 0.52 | 0.12 | 0.97 | 0.83 | 1.35 | 1.17 | 1.37 | 1.23 | 1.27 | 1.16 | 1.29 | 0.49 | 1.51 | 0.61 | 1.25 | 0.44 | 0.89 | 0.18 | 1.01 | 0.79 | 1.39 | 1.13 | 1.70 | 1.45 | 1.79 | 1.59 |
| Non-price indicators | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| M1 | n.a. | | n.a. | | n.a. | | n.a. | | 0.96 | 0.87 | 1.59 | 1.41 | 2.01 | 1.78 | 2.14 | 1.98 | 0.59 | 0.48 | 0.84 | 0.74 | 1.04 | 0.91 | 1.01 | 0.89 | n.a. | | n.a. | | n.a. | | n.a. | |
| M2 | n.a. | | n.a. | | n.a. | | n.a. | | 0.82 | -0.15 | 1.27 | -0.31 | 1.27 | -0.38 | 1.04 | -0.38 | 0.46 | 0.34 | 0.50 | 0.33 | 0.51 | 0.29 | 0.52 | 0.22 | n.a. | | n.a. | | n.a. | | n.a. | |
| M3 | n.a. | | n.a. | | n.a. | | n.a. | | 0.84 | -0.30 | 1.53 | -0.86 | 1.86 | -1.28 | 1.85 | -1.36 | 0.56 | 0.44 | 0.46 | 0.39 | 0.41 | 0.36 | 0.45 | 0.37 | n.a. | | n.a. | | n.a. | | n.a. | |
| Wages | n.a. | | n.a. | | n.a. | | n.a. | | 0.73 | 0.39 | 1.12 | 0.46 | 1.11 | 0.51 | 1.07 | 0.60 | 0.55 | 0.41 | 0.53 | 0.43 | 0.50 | 0.43 | 0.50 | 0.44 | n.a. | | n.a. | | n.a. | | n.a. | |
| ULC | n.a. | | n.a. | | n.a. | | n.a. | | 0.71 | 0.37 | 1.04 | 0.58 | 1.28 | 0.80 | 1.42 | 0.98 | 0.59 | 0.45 | 0.48 | 0.39 | 0.43 | 0.37 | 0.49 | 0.38 | n.a. | | n.a. | | n.a. | | n.a. | |
| Unemployment | n.a. | | n.a. | | n.a. | | n.a. | | 0.86 | 0.55 | 1.50 | 0.86 | 1.71 | 1.10 | 1.62 | 1.27 | 0.62 | 0.52 | 0.66 | 0.59 | 0.69 | 0.64 | 0.73 | 0.70 | n.a. | | n.a. | | n.a. | | n.a. | |
| Industrial production | n.a. | | n.a. | | n.a. | | n.a. | | 0.88 | 0.09 | 1.47 | -0.01 | 1.50 | -0.13 | 1.26 | -0.24 | 0.56 | 0.49 | 0.66 | 0.58 | 0.63 | 0.49 | 0.68 | 0.22 | n.a. | | n.a. | | n.a. | | n.a. | |
| Interest rates | n.a. | | n.a. | | n.a. | | n.a. | | 0.86 | -0.26 | 1.29 | -0.57 | 1.32 | -0.73 | 1.13 | -0.72 | 0.57 | 0.44 | 0.55 | 0.36 | 0.49 | 0.27 | 0.45 | 0.25 | n.a. | | n.a. | | n.a. | | n.a. | |

Source: IMF staff estimates.

1/ Forecast evaluation for estimates with year-on-year inflation. Bivariate and multivariate models are estimated using 24-month lag.

## Table 6. Euro Area: 1-month Lag versus 24-month Lag Model Forecast Performance 1/

(Root mean square error/RMSE/ and bias in percentage points)

| | Bivariate | | | | Multivariate | |
|---|---|---|---|---|---|---|
| | Distributed lag equation | | Gap equation | | Semi-structural equation with exchange rate and oil | |
| | 24-month forecast horizon | | | | | |
| | RMSE | Bias | RMSE | Bias | RMSE | Bias |
| GDFM estimates of underlying inflation | | | | | | |
| HICP components only: 1 factor | -2.14 | 0.18 | -0.26 | -0.44 | -1.95 | -0.14 |
| HICP components only: 2 factors | -0.85 | -0.46 | -0.13 | -0.36 | -1.58 | -1.15 |
| HICP components and non-price data: 1 factor | -2.09 | 0.06 | -0.30 | -0.44 | -2.12 | -0.40 |
| HICP components and non-price data: 2 factors | -1.07 | -0.62 | -0.18 | -0.42 | -1.62 | -1.20 |
| Core inflation measures by exclusion | | | | | | |
| Excluding energy | 0.41 | 0.12 | -0.21 | 0.14 | -1.22 | -1.39 |
| Excluding energy, food, alcohol and tobacco | 0.65 | -0.04 | -0.32 | -0.15 | -0.84 | -0.95 |
| Excluding energy and seasonal food | 0.97 | 0.27 | -0.41 | -0.04 | -1.06 | -1.29 |
| Excluding energy and unprocessed food | 0.57 | 0.05 | -0.53 | -0.09 | -1.05 | -1.20 |
| Trimmed means/median | | | | | | |
| 5 percent | 3.37 | 1.54 | 0.93 | 0.35 | -1.03 | -1.42 |
| 10 percent | 8.94 | 3.27 | 0.34 | 0.16 | -1.16 | -1.47 |
| 15 percent | 2.63 | 0.89 | -0.02 | 0.10 | -1.16 | -1.52 |
| 20 percent | 1.79 | 0.45 | -0.20 | 0.04 | -1.17 | -1.54 |
| 50 percent | 0.97 | 0.08 | -0.39 | -0.09 | -1.35 | -1.42 |
| Non-price indicators | | | | | | |
| M1 | -1.59 | -1.64 | -0.62 | -0.79 | n.a. | |
| M2 | 1.26 | 0.32 | -0.06 | 0.03 | n.a. | |
| M3 | -0.87 | -0.96 | 0.21 | -0.08 | n.a. | |
| Wages | -0.64 | -0.32 | -0.05 | -0.05 | n.a. | |
| ULC | -0.31 | -0.18 | -0.09 | -0.20 | n.a. | |
| Unemployment | -0.98 | -0.74 | -0.23 | -0.24 | n.a. | |
| Industrial production | 0.92 | -0.22 | -0.17 | 0.03 | n.a. | |
| Interest rates | 0.10 | -0.67 | 0.17 | 0.28 | n.a. | |

Source: IMF staff estimates.

1/ Forecast evaluation for estimates with year-on-year inflation; 1-month lag minus 24-month lag.