EUROPEAN CENTRAL BANK

EUROSYSTEM

WORKING PAPER SERIES

NO 867 / FEBRUARY 2008

DO MONETARY INDICATORS LEAD EURO AREA INFLATION?

by Boris Hofmann

EUROPEAN CENTRAL BANK

EUROSYSTEM

WORKING PAPER SERIES

NO 867 / FEBRUARY 2008

DO MONETARY INDICATORS LEAD EURO AREA INFLATION?[1]

Boris Hofmann[2]

In 2008 all ECB publications feature a motif taken from the €10 banknote.

1 I thank Jörg Breitung, Michael Ehrmann, Stefan Gerlach, Claus Greiber, Heinz Herrmann, Huw Pill, Julian Reischle, Christian Schumacher, Frank Smets, Jens Weidmann, Andreas Worms and two anonymous referees for helpful comments and suggestions. I also thank Björn Fischer for providing me with the real-time data for M3 corrected for portfolio shifts and for M3 adjusted for special factors. The views expressed in this paper are solely my own and do not necessarily represent the views of the ECB or the Eurosystem.
2 European Central Bank, Kaiserstrasse 29, 60311 Frankfurt am Main, Germany; e-mail: boris.hofmann@ecb.int

Address
Kaiserstrasse 29
60311 Frankfurt am Main, Germany

Postal address
Postfach 16 03 19
60066 Frankfurt am Main, Germany

Telephone
+49 69 1344 0

Website
http://www.ecb.europa.eu

Fax
+49 69 1344 6000

ISSN 1561-0810 (print)
ISSN 1725-2806 (online)

CONTENTS

ABSTRACT

This paper assesses the performance of monetary indicators as well as of a large range of economic and financial indicators in predicting euro area HICP inflation out-of-sample over the period first quarter 1999 till third quarter 2006 considering standard bivariate forecasting models, factor models, simple combination forecasts as well as trivariate two-pillar Phillips Curve forecasting models using both ex-post revised and real-time data. The results suggest that the predictive ability of money-based forecasts relative to a simple random walk benchmark model was high at medium-term forecasting horizons in the early years of EMU, but has substantially deteriorated recently. A significantly improved forecasting performance vis-à-vis the random walk can, however, be achieved based on the ECB's internal M3 series corrected for the effects of portfolio shifts and by combining monetary and economic indicators.

Keywords: euro area, inflation, leading indicators, money

JEL classifications: E31, E40, C32

NON-TECHNICAL SUMMARY

This paper assesses the performance of monetary indicators as well as of a large range of economic and financial indicators in predicting euro area HICP inflation over the coming one, two and three years out-of-sample over the period first quarter 1999 till third quarter 2006 considering standard bivariate forecasting models, factor models, simple combination forecasts as well as trivariate two-pillar Phillips Curve forecasting models using both ex-post revised and real-time data.

The analysis of the performance of bivariate forecasting models and trivariate two-pillar Phillips Curve-type forecasting models suggests that forecasting models comprising headline quarter-on-quarter or trend M3 growth produced on average lower forecast errors than a naive random walk model at longer forecasting horizons of two and three years, but tests of equal predictive ability suggest that the M3-based indicator models could not significantly improve over the simple benchmark model, with the exception of very few two-pillar Phillips Curve type forecasting models at the three year forecast horizon. The analysis also reveals that similarly disappointing results are obtained for all other indicators considered. None of the 96 bivariate forecasting models and only 7 out of 88 trivariate forecasting models that were analysed produce a mean squared forecast error that is significantly smaller than that of the random walk model at any forecast horizon, in most cases the mean squared error is even larger. This result echoes the finding of Stock and Watson (2005) for the US that it has become more difficult to beat simple univariate forecasts of inflation in the environment of low inflation that has prevailed since the mid 1980s.

A closer look at the forecasting performance over time reveals that the predictive power of the forecasting models including headline M3 growth has substantially deteriorated in recent years, producing systematically higher forecast errors than the benchmark since 2001. This deterioration of forecasting performance is apparently related to the effects of portfolio shifts into M3 over the 2001 to 2003 period, since a forecasting model including an internal ECB series of M3 corrected for the effects of portfolio shifts significantly improves over the random walk on average at medium-term forecasting horizons and continues to produce accurate forecasts until very recently. These findings also obtain when real-time rather than ex-post revised data are used in the forecasting exercise. Overall, these results suggest that M3 growth continues to be a useful indicator for future price developments in the euro area, but that a thorough and broad based monetary analysis is needed to extract the information content of monetary developments for future inflation.

The analysis further suggests that a considerably improved forecasting performance vis-à-vis the random walk benchmark is obtained when the information from the monetary and the economic analysis are combined. A simple factor forecasting model combining monetary and economic indicators produced on average significantly smaller forecast errors at medium-term forecasting horizons than the random walk and has also recently produced relatively accurate out-of-sample forecasts. The forecasting exercise using real-time data yields a very similar result. Here the average of the forecasts from the monetary analysis, in the form of the forecasts from a bivariate model with the growth rate of portfolio-shift corrected M3, and the forecasts from the economic analysis, in the form of the inflation projections from the ECB/Eurosystem Broad Macroeconomic Projections Exercise (BMPE), produces a significantly lower mean squared forecast error than the random walk benchmark at the one and two year forecast horizon. These findings suggest that the integrated assessment of monetary and economic indicators may help to improve euro area inflation forecasts and confirms that the two pillars of the ECB's strategy cannot be viewed as fully independent from each other.

1. Introduction

The main elements of the ECB's monetary policy strategy are a quantitative definition of price stability and a so-called "two-pillar" framework for the assessment of the outlook for price developments and the current risks to price stability. The ECB's definition of price stability is an annual increase in the Harmonized Index of Consumer Prices (HICP) of below, but close to two percent. The two-pillar framework for the assessment of the risks to price stability combines a ''broadly based assessment of the outlook for the future price developments'' based on a "wide range of economic and financial variables" (economic analysis) and a "prominent role for money" with a reference value for the growth rate of the broad monetary aggregate M3 (monetary analysis). While the two pillars were originally described as two parallel analytical perspectives, the ECB (2003) has clarified in the evaluation of its monetary policy strategy that the money pillar "mainly serves as a means of cross-checking, from a medium to long-term perspective, the short to medium term indications coming from economic analysis."

The prominent role assigned to money in the ECB's monetary policy strategy was motivated by the notion that the development of the price level in the medium to longer term is a monetary phenomenon (ECB, 1999). This view was supported by a number of empirical studies showing that the long-run euro area M3 demand function was stable (Brand and Cassola, 2000, Coenen and Vega, 1999 and Calza et al. 2001) and that M3 based indicators were leading euro area inflation at medium-term horizons (Nicoletti Altimari, 2001, Trecroci and Vega, 2002). However, the ECB's special emphasis on monetary analysis has been exposed to intense criticism from the very beginning. Besides theoretically motivated reservations against the money pillar,[1] it has also been argued that money is an unreliable indicator for inflation because of frequent shifts in velocity.[2] In fact, since 2001 euro area M3 has been growing at rates well above its reference value of 4.5%, while HICP inflation has remained broadly stable at rates around 2%. This observation seems to confirm the view that M3 growth has not been a reliable indicator for future price developments in the euro area recently.

This paper explores the performance of monetary indicators in predicting euro area HICP inflation over the coming one, two and three years out-of-sample[3] over the period 1999Q1 till

---

[1] For a rigorous discussion of the (lack of a) theoretical foundation of the money pillar from the perspective of modern-style New Keynesian models see Woodford (2006).

[2] Estrella and Mishkin (1997) have argued that volatility in money demand dominates movements in money growth in an environment of subdued inflation and money growth, giving rise to a low signal-to-noise ratio of money growth with respect to inflation. The same line of reasoning has also been brought forward by Begg et al (2002) and De Grauwe and Polan (2005).

[3] Out-of-sample performance tests are commonly regarded as being superior to in-sample tests, as the latter are commonly held to generate spurious rejections of the null of no predictability because of size distortions arising from data mining (e.g. Granger, 1990). Other compelling reasons to rather rely on out-of-sample tests is that they more accurately reflect the data and information constraints faced by forecasters and policymakers in real-time

2006Q3. Following Nicoletti Altimari (2001) and Hofmann (2006), the h-quarter change in the HICP (h-quarter average HICP inflation) is forecast based on direct forecasting models. This direct forecasting approach, which was originally proposed by Stock and Watson (1999, 2003), involves regressing the *h*-quarter change in the HICP on h-quarters lagged inflation and h-quarters lagged values of one or more other indicators. *H*-quarter out-of-sample forecasts are then calculated as a one-step ahead forecast from the estimated forecasting regression. This is also the approach followed by the ECB to derive money-based inflation forecasts as one of the tools of its internal monetary analysis, as described in ECB (2006) and Fischer et al. (2006).[4]

The analysis starts by assessing the forecasting performance of simple bivariate forecasting models considering a large number of aggregate euro area monetary, economic and financial indicators. The forecasting performance of the indicators is evaluated against the forecasts produced by a smooth random walk, which forecasts h-period ahead inflation simply by taking the last observable h-period average inflation rate. We further consider the performance of factor based forecasts and simple forecast combination methods. After the evaluation of its monetary policy strategy, the ECB (2003) has clarified that its money pillar is based on a broad based monetary analysis, which "will take into account developments in a wide range of monetary indicators, including M3, its components and counterparts, notably credit, and various measures of excess liquidity." A monetary factor forecasting model and simple combinations of monetary inflation forecasts can be seen as a simple and tractable way to operationalise such a broad based monetary analysis in a forecasting context. We also analyse the performance of a factor forecasting model and forecast combinations for the group of economic and financial indicators as a simple approximation of a broad based economic analysis. Finally, we also analyse a factor forecasting model and forecast combinations for the combined group of monetary and economic indicators in order to asses the potential gains from combining the information from the monetary and economic analysis.

As an alternative way to combine monetary and economic and financial indicators we also consider the usefulness of trivariate forecasting models combining the low frequency component of M3 growth with other non-monetary indicators Gerlach (2003, 2004) has argued that the ECB's two pillar strategy can be interpreted as a combination of two different models of the inflation process, the money pillar as a model of the longer-term inflation trends and the economic analysis as a model of the short to medium-run determinants of inflation. He suggests a two-pillar Phillips Curve, adding trend or core money growth to an otherwise

---

and that in-sample tests may be misleading if there is a structural break in the forecasting model (Stock and Watson, 2003). In the light of the recent discussion of the potential instability of the link between M3 indicators and inflation in the euro area, the last point is of particular relevance in the present context.

[4] This is, however, not common practice in all forecasting studies. For example, in their assessment of the forecasting performance of inflation indicators in the US, Stock and Watson (1999) forecast the *change* in inflation over the coming h-quarters. In another recent study for the euro area, Lenza (2006) forecasts the year-on-year change in the HICP *h* quarters ahead.

standard empirical Phillips Curve as a simple formalisation of this view of the inflation process. While several studies have shown that such a two-pillar Phillips Curve provides a good in-sample fit for euro area inflation[5], the usefulness of the concept for forecasting inflation out-of-sample has not yet been explored.

While these forecasting exercises are fairly comprehensive, they do miss out one important element of the ECB's monetary analysis, namely the role of judgement and interpretation in the assessment of the implications of observable monetary trends for future price stability. We further assess the implications of judgemental corrections to M3 performed by ECB staff in the ECB's internal monetary analysis for the out-of-sample forecasting performance of M3-based indicators. The above mentioned caveat that headline monetary data may at times be distorted by temporary shifts in velocity has been well recognized at the ECB (see Fischer et al. 2006). For this reason, the ECB's internal assessment of monetary risks to price stability is not based on headline monetary data alone, but also involves a broad based judgemental analysis of the determinants of the underlying monetary trends. The outcome of this judgemental analysis has been quantified in an internal ECB series for M3 corrected for the effects of special developments that are deemed not to signal risks to medium-term price stability. In particular, a judgemental adjustment is made for portfolio-shift effects on M3 caused by the strong preference of investors for liquid assets in the wake of the exceptional economic and financial uncertainties over the period 2001-2003. In order to assess the implications of the estimated portfolio shift effects for the indicator property of M3 we perform a simulated out-of-sample forecasting exercise based on the portfolio-shift corrected M3 series.

A potential objection to this exercise is that the portfolio-shift adjustments were performed ex-post in order to re-establish the indicator property of M3 and would therefore not have been of any use for forecasting in real time. In order to address this point we also carry out a simulated out-of-sample forecasting exercise using real-time data for corrected M3 as well as for headline M3. In this context we also assess the performance of the real-time inflation projections from the ECB/Eurosystem Broad Macroeconomic Projection Exercise (BMPE), which is an important element of the ECB's economic analysis.

The paper contributes to the literature in various ways. It is the first paper to analyse the performance of money-based forecasts using both ex-post revised and real-time data. In the part of the analysis which is based on ex-post revised data, the paper explores the performance of a large set of monetary and economic indicators based on a large range of forecasting models, including bivariate models, trivariate two-pillar Phillips Curve models as well as factor models and forecast combinations. Other recent studies on the performance of

---

[5] See Gerlach (2003, 2004), Neumann (2003), Neumann and Greiber (2005) and von Hagen and Hofmann (2003).

monetary indictors using ex-post revised data have instead focused on the performance of monetary forecasts obtained from bivariate or trivariate models (Hofmann, 2006) or on the usefulness of monetary variables in large scale factor forecasting models (Lenza, 2006). Regarding the part of the paper that is based on real-time data, there is some similarity with the paper by Fischer et al (2006) in the sense that the performance of the same set of indicators is investigated using real-time data. There are, however, also a number of important differences between that paper and the present one. First, the forecast evaluation sample is different. In Fischer et al. the forecast evaluation sample is determined by the availability of money-based inflation forecasts in the ECB's QMA, which is from 2000Q4 onwards, while in the present paper the forecast evaluation sample is determined by the availability of ECB internal real-time data series for monetary analysis, which is from 1998Q4 onwards. This difference in forecast evaluation samples matters, since, as will be shown in the following sections, the forecast performance of monetary indicators vis-à-vis a simple random walk benchmark has been unstable since the start of EMU, which can only be documented based on a longer forecast evaluation sample. The second important difference between the present paper and the paper by Fischer et al is that, because of the relatively short forecast evaluation sample, the latter paper focuses on the six quarter forecast horizon, while the present paper also investigates the real-time performance of money-based forecasts over the eight and twelve quarter horizon. Previous studies using ex-post revised data (Nicoletti Altimari, 2006 and Hofmann, 2006) have concluded that money-based forecasts outperform univariate benchmarks only at longer forecast horizons beyond two years, a result that is also confirmed by the analysis with ex-post revised data in this paper. The real-time analysis here therefore also adds to the literature by exploring whether this result also holds when real-time data are used.

The paper is organised as follows. Section 2 describes the data. In section 3 we discuss the forecasting models and the methodology for the forecast evaluation. Section 4 presents the empirical results. The performance of the M3 series corrected for the effects of portfolio shifts is discussed in section 5. Section 6 reports the results of the real-time forecasting exercise. Section 7 concludes.

2. Data

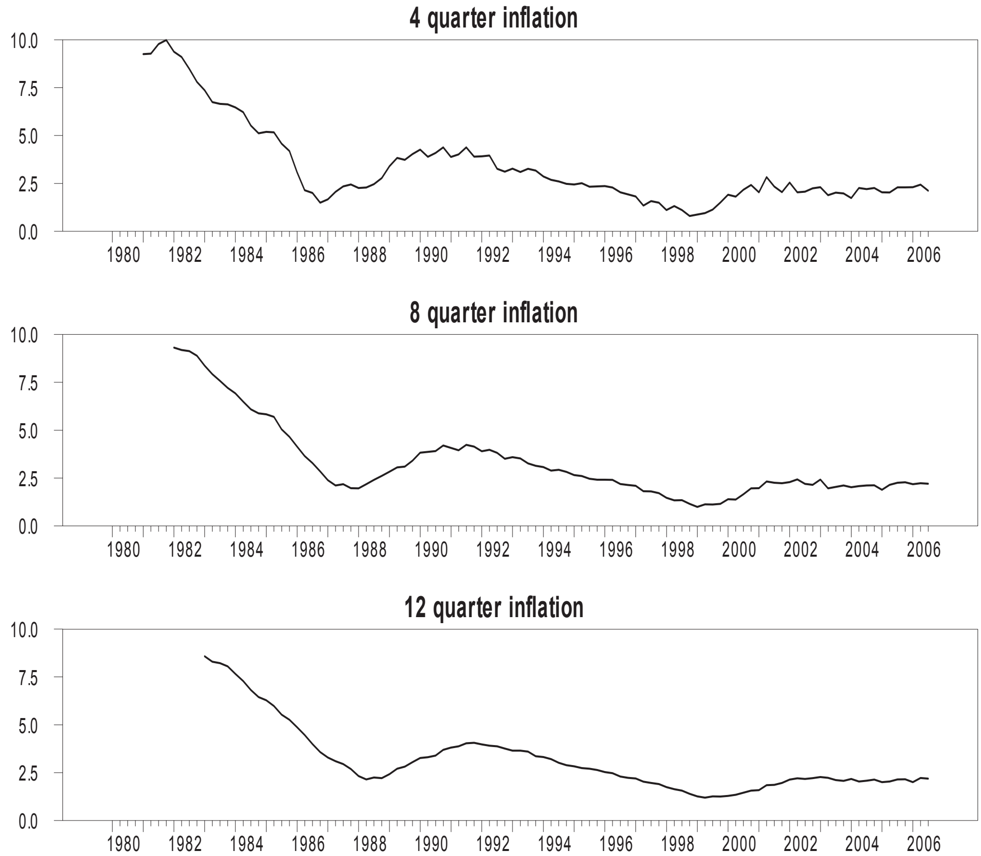
The analysis is based on quarterly aggregate euro area data available for the period 1980Q1 till 2006Q3.[6] Unless otherwise indicated, all data are official, seasonally adjusted aggregate euro area data taken from the ECB databases. Data which are originally available in monthly

[6] A possible complementary approach to construct forecasts for euro area aggregates is to aggregate individual country forecasts (e.g. Marcellino et al., 2001 and Angelini et al., 2001), which is, however, beyond the scope of this paper.

frequency were converted to quarterly frequency by taking monthly averages. A short description of the data and their original sources is provided in the appendix.

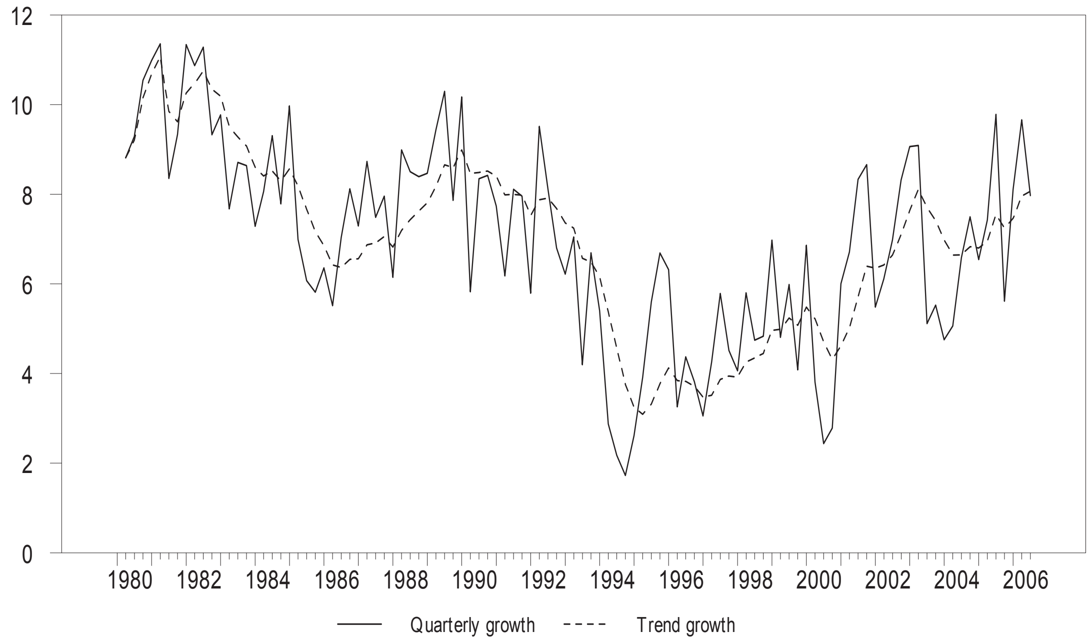
Following Nicoletti Altimari (2001) and the ECB's practice in its internal monetary analysis (ECB, 2006, Fischer et al., 2006) the forecast variable in the following forecasting exercises is the annualised change in the HICP, or annualised average inflation over the coming h quarters, given by $\pi^h_{t+h} = (400/h)\ln(HICP_{t+h}/HICP_t)$. This implies that the smoothness of the forecast variable increases with the forecast horizon, as is visualised in Figure 1, which shows π^h_t for h = 4, 8, 12.

Figure 1: HICP inflation in the euro area



The growth rate of the monetary aggregate M3 is the most prominent single monetary indicator in the ECB's monetary analysis. For this reason we will pay particular attention to the forecasting performance of this indicator. The M3 growth rate is calculated based on the seasonally adjusted monthly average index of notional stocks, which corrects the outstanding stock of M3 for the effects of reclassifications, exchange rate revaluations and other revaluations.[7] Against the background of the recent literature already referred to below which has stressed that it is mainly the low frequency movements in M3 which contains relevant information for future inflation we also consider the trend, or core growth rate of the M3 aggregate, calculated using a one-sided Hodrick-Prescott (HP) filter with a smoothing parameter of 1,600.[8] As explained in more detail in Stock and Watson (1999), who also use a one-sided HP filter to calculate trend output measures, the one-sided HP trend estimate is calculated using the Kalman filter and is the optimal one-sided analogue to the standard two-sided HP trend filter. The one-sided HP filter uses for each period in the sample only information up to that period, so that recursive estimation of the trend yields the same trend estimate as the full sample estimate. Figure 2 shows the quarterly and the trend growth rate of M3 over the sample period.

Figure 2: Euro area M3 growth



[7] For more details see http://www.ecb.int/stats/money/aggregates/aggr/html/index.en.html on the ECB website and Fischer et al. (2006, Appendix C).
[8] I also experimented with other values of the smoothing parameter. The lower the smoothing parameter the more closely the filtered series adjusts to the actual series, so that the results become increasingly similar to the ones obtained from the quarterly M3 growth rate. Higher values of the smoothing parameter delivered worse forecasts. Furthermore, I also experimented with a recursively calculated two-sided HP filter, which yields a substantially smoother estimate of trend M3 growth than the one-sided HP filter. In the forecasting exercise the recursively two-sided filtered M3 growth indicator performed much worse than the one obtained from the one-sided filter, so that I decided not to report the results for this filter, but they are available upon request.

We further consider three indicators, the change in p-star, the real money gap and the monetary overhang, derived from a recursively estimated long-run M3 demand function using the current consensus specification proposed by Calza et al (2001).[9] The money demand function is given by $(m-p)_t = a_0 + a_1 y_t + a_2 oc_t + u_t$, where m is (log) M3, p is the (log) GDP deflator, y is (log) real GDP and oc is the opportunity cost of holding M3, measured as the spread of the three months money market rate over M3's own rate of return. From the estimated long-run money demand function we obtain the long-run trend price level p-star $p_t^* = m_t - a_0 - a_1 y_t^* - a_2 oc_t^*$, where an asterisk denotes the long-run trend level of a variable estimated using again a one-sided HP filter with a smoothing value of 1,600. The change in p-star is then given by $\Delta p_t^* = \Delta m_t - a_0 - a_1 \Delta y_t^* - a_2 \Delta oc_t^*$, the real money gap is given by $(m_t - p_t) - (m_t - p_t^*) = -(p_t - p_t^*) = (m_t - p_t) - (a_0 + a_1 y_t^* + a_2 oc_t^*)$ and the monetary overhang is simply the long-run residual given by $u_t = (m_t - p_t) - a_0 - a_1 y_t - a_2 oc_t$. Finally, we also consider three monetary indicators which are not M3 related, namely the quarterly growth rates of M1, M2 and MFI loans to the private sector. The growth rates are again calculated based on seasonally adjusted monthly average indices of notional stocks.

We further consider a set of 85 economic and financial indicators which are available back to 1980 comprising data series for volume and deflator of GDP and its components, wages, unit labour costs, industrial production, the unemployment rate, retail sales, short-term and longer term market interest rates, stock prices, commodity prices, producer prices as well as surveys from the manufacturing and construction sector. The dataset also includes a number of gap measures, i.e deviations of a variable from its trend level, such as output gap measures for real GDP and industrial production. The gap measures were also calculated as deviations from a one-sided HP trend using the standard smoothing parameter. For a complete list of the indicator variables see the appendix.

3. Methodology

Bivariate forecasting models

The performance of the monetary and the economic and financial leading indicators in predicting inflation in the euro area over the EMU period first quarter 1999 till third quarter 2006 is evaluated based on a simulated out-of-sample forecasting exercise, following closely the methodology proposed by Stock and Watson (1999). Forecasts of euro area HICP inflation are constructed based on the following bivariate direct forecasting model:

(1) $$\pi_{t+h}^h = \beta_0 + \beta(L)\pi_t + \gamma(L)x_t + u_{t+h} \qquad h = 4, 8, 12$$

[9] Alternative specifications of the long-run M3 demand function have been proposed by Brand and Cassola (1999) and Coenen and Vega (2000).

where π_t is the quarterly HICP inflation rate and x is another indicator. The dependent variable is the annualised h-periods ahead average HICP inflation rate, which is given by $\pi_{t+h}^{h} = 400 / h \cdot \ln(HICP_{t+h} / HICP_t)$. For brevity we consider only the forecast horizons 4, 8 and 12 quarters ahead. The results for the remaining forecast horizons are available upon request.

In the simulated out-of-sample forecasting exercise, model (1) is estimated and an h-period ahead forecast of inflation is derived using only data prior to the forecasting period in order to most accurately reflect the data limitations faced by forecasters in real time.[10] To be more specific, consider the forecast of the two years ahead inflation rate (h=8) constructed in the first quarter 1999. To compute the forecast, all models are estimated using data from first quarter 1980 through the fourth quarter 1998. A forecast for the (annualized average) inflation rate from first quarter 1999 to first quarter 2001 is then made using the selected model. Moving forward one quarter, all models are re-estimated using data through first quarter 1999, and a new forecast of inflation over the period second quarter 1999 to second quarter 2001 is calculated, and so on until the end of the sample period (third quarter 2006). For each indicator x_t and each forecast horizon this produces a single series of forecasts based on simulated out-of-sample forecasting with recursive estimation and model selection. It is important to note that for each forecast horizon h the first out-of-sample forecast is constructed in period 1999Q1-h so that we have for each forecast horizon a series of simulated out-of-sample forecasts of equal length over the period first quarter 1999 till third quarter 2006.

The lag order of the forecasting model is recursively determined based on the Schwarz-Bayes information criterion ($SBC = ln(RSS/T) + kln(T)/T$ where ln is the natural logarithm, RSS is the residual sum of squared errors of the estimated forecasting model, k is the number of estimated parameters and T is the number of observations) considering up to four lags of each right-hand side variable and comparing all possible lag order combinations. The sample period for the recursive forecasting regressions always starts in 1985Q1 in order to ensure identical sample periods for all forecasting regressions and also to mitigate the effect of the disinflation of the early 1980s on the results.

Factor-based forecasts and forecast combinations

In order to avoid over-parameterisation of the forecasting models, time series forecasting of economic variables usually focuses on low-dimensional models like the bivariate indicator

---

[10] Of course, in order to perform a "real" real time exercise one would need to use unrevised real time data as they were available at the time the forecast was made. A very comprehensive real-time database for the euro area has recently been launched by the Euro Area Business Cycle Research Network (see Ciccarelli et al. 2006). The data series that are available from this database are, however, too short for the analysis of this paper since the series only start in 2001and are sometimes available only back to the early 1990s. An assessment of the real-time forecasting performance of all indicators is therefore not possible, but in Section 6 I investigate the real-time performance of M3-based inflation forecasts based on internal ECB series.

models considered in the previous section. The disadvantage of such bivariate indicator models is that forecasts are respectively constructed based on information from only one indicator, while the information content of all other indicators is ignored. In order to combine and condense the information contained in a large group of indicators, two approaches have been suggested in the literature: the use of diffusion indices or factors, which extract the main common driving forces (factors) of a group of indicators before estimating the forecasting model, and the use of forecast combination methods, which combine the forecasts produced by the single indicator models.

Factor models suppose that a group of indicator variables is driven by a few common factors which may summarise their information content for forecasting purposes. Stock and Watson (2002) propose to use static principal components analysis to derive the common factors.[11] In this framework, we obtain the first r static factors for a group of n indicators over a sample period of size T from $F_t = X_t \Lambda$, where F is a Txr matrix of static factors, X is a Txn matrix of standardised indicators and Λ is an nxr matrix of eigenvectors corresponding to the r largest eigenvalues of the sample variance-covariance matrix of the standardised indicator variables. Based on prior unit root tests it was confirmed that the considered indicators are stationary. The only exception was the real money gap and the monetary overhang, which were therefore excluded from the factor analysis and also from the forecast combination analysis.

We construct factor based forecasts separately for the group of monetary indicators and the group of economic and financial indicators and also for the group of all indicators combined, considering up to two factors for the money factor forecasting model, up to three factors for non-monetary factor forecasting model and up to five factors for the factor forecasting model comprising all indicators.[12] The factor analysis is performed recursively using only data up to the period in which the forecast is made. Following Stock and Watson (1999), the factors are computed recursively and the factor forecasting models are recursively determined by selecting the combination of factors with the highest explanatory power for h-quarter inflation in a multivariate extension of the forecasting regression (1). The forecasting model was selected based on the Schwarz-Bayes information criterion considering all possible factor

[11] A number of recent contributions, e.g. Forni et al. (2003) and Kapetanios and Marcellino (2004), have extended the static framework developed by Stock and Watson to also allow for dynamic relationships between the variables in the model. However, these extensions impose a certain structure on the dynamics of the system which may not be consistent with the data and also have a more complicated structure, so that that they are more prone to misspecification in empirical applications. Boivin and Ng (2005) investigate the forecasting performance of the different approaches to factor derivation and conclude that the Stock and Watson approach outperforms the other approaches just because of these caveats. For these reasons we rely on the Stock and Watson approach to derive the factors.

[12] We also considered a larger maximum number of factors for the group of non-monetary indicators (up to four) and full set of indicators (up to six), which we found not to lead to better forecasting performance however. The results are available upon request.

combinations and all possible lag order combinations allowing for up to four lags of each regressor.[13]

An alternative to constructing composite indicators based on principal components analysis is using forecast combination techniques.[14] The combination forecast is given by $f_t^c = \sum_{i=1}^{n} \omega_{i,t} f_{i,t}$, where f_{it} is the forecast produced by indicator i in period t and ω_{it} is the weight given to this forecast. The combination forecasts we consider here are the sample mean and the sample median of the forecasts produced by the bivariate models estimated in the previous section. We also consider an approximate Bayesian model averaging approach where the models are weighted based on the Schwarz-Bayes information criterion of the forecasting regression (Pesaran and Zaffaroni, 2006). The forecast weights are given by $\omega_{i,t} = \exp(\Delta_{i,t}) / \sum_{j=1}^{n} \exp(\Delta_{j,t})$ with $\Delta_{i,t} = Min_j(SBC_{j,t-h}) - SBC_{i,t-h}$, where *exp* is the exponential function and $SBC_{i,t-h}$ is the SBC of the forecasting regression for the h-quarter ahead forecast based on indicator *i*. We again perform the analysis separately for the group of monetary indicators and the group of non-monetary indicators and also for all indicators together.

Trivariate two-pillar Phillips Curve forecasting models

As an alternative way to combine monetary and economic and financial indicators we also consider the usefulness of trivariate two-pillar Phillips Curve models that have been recently proposed in the academic literature as a potential formalisation of the ECB's view of the inflation process (Gerlach 2003, 2004). Such trivariate forecasting models model h-quarter average inflation as a function of its own lags, lags of trend money growth measured as the growth rate of one-sided HP filtered M3 (Δm_t^T), and lags of a non-monetary indicator (x):

(2) $$\pi_{t+h}^h = \beta_0 + \beta_1(L)\pi_t + \beta_2(L)\Delta m_t^T + \beta_3(L)x_t + u_{t+h}^h .$$

Lag orders were selected and forecasts computed recursively in the same way as for the bivariate models, allowing for different lag orders of the regressors searching over up to four lags respectively.

Besides estimating a forecasting model for each economic indicator separately, we also consider in the same way as described in the previous sub-section a factor forecasting model considering up to three common factors. The factors are again computed recursively and the

[13] This means that at each recursion for the monetary, the non-monetary and the combined factor model 96, 496 and 8,400 models were respectively compared and the best model according to the SBC was respectively selected to compute the forecast.
[14] For surveys of the forecast combination literature see Diebold and Lopez (1996), Newbold and Harvey (2002), Hendry and Clements (2002) and Stock and Watson (2004). Due to the small sample period we do not have sufficient forecast observations to apply such combination methods that require a forecasting track record, such as discounted MSE forecast where the forecasts are weighted according to their past out-of-sample forecasting performance.

factor forecasting models are recursively determined by selecting the specification with the highest explanatory power for h-period ahead inflation based on the Schwarz-Bayes information criterion considering all possible factor combinations and all possible combinations of lag orders respectively allowing for up to four lags.[15] We also consider the mean and the median of the trivariate forecasts as well as a combination forecast obtained from approximate Bayesian model averaging as described in the previous sub-section.

Forecast evaluation

Following Atkenson and Ohanian (2001), the benchmark for the assessment of the forecasting performance of the various forecasting models described above is a "naïve" random walk. Future h-quarter inflation is forecast by taking the last observed h-quarter inflation rate:

$$(3) \quad \hat{\pi}^{h}_{RW,t+h|t} = \pi^{h}_{t} .$$

This benchmark was chosen because it produced lower forecast errors over the forecast evaluation sample than an alternative benchmark autoregressive benchmark model, which is given by:

$$(4) \qquad \pi^{h}_{t+h} = \beta_0 + \beta_1(L)\pi_t + u^{h}_{t+h} ,$$

Table 1 reports the root mean squared error (MSE), i.e. the square root of the MSE, produced by these two alternative benchmark models over the period first quarter 1999 to third quarter 2006. The forecasts from the autoregressive model were constructed by means of recursive estimation, recursively determining the lag order of the model based on the SBC considering up to four lags. The results suggest that the autoregressive forecast model performed marginally better at the four quarter forecast horizon, while the random walk model clearly performed better at the longer forecast horizons, which are of most relevance in the context of this study.

Table 1: Root mean squared errors of the univariate forecasting models

	4 quarters ahead	8 quarters ahead	12 quarters ahead
Root MSE autoregressive model	0.47	0.66	0.79
Root MSE random walk model	0.50	0.61	0.67

The forecasting performance of each forecasting model *M* is assessed based on the relative mean squared forecast error, which is given by the ratio of the mean squared forecast error

[15] This means that at each recursion 1,984 models were compared and the best model according to the SBC was selected to compute the forecast.

produced by the forecasting model M to the mean squared forecast error produced by the "naïve" random walk model RW at the respective forecasting horizon:

$$(5) \qquad \Re = \frac{MSE_M}{MSE_{RW}} = \frac{\frac{1}{T_2 - T_1}\sum_{t=T_1}^{T_2}\left(\pi_t^h - \hat{\pi}_{M,t+h|t}^h\right)^2}{\frac{1}{T_2 - T_1}\sum_{t=T_1}^{T_2}\left(\pi_t^h - \hat{\pi}_{RW,t+h|t}^h\right)^2},$$

where $\hat{\pi}_{M,t+h|t}^h$ is the h-period ahead forecast obtained from forecasting model M and $\hat{\pi}_{RW,t+h|t}^h$ is the h-period ahead forecast obtained from the random walk model. T_1 and T_2 are respectively the first and the last period of the forecast evaluation sample. In this application we have T_1 = first quarter 1999 and T_2 = third quarter 2006.

An indicator model would be regarded as containing useful additional information compared to the benchmark if it produces smaller forecast errors than the benchmark model over the forecast evaluation sample. This implies that the relative MSE should be less than one. For the improvement in forecast accuracy to be statistically significant, the mean squared forecast error of the indicator model should be significantly smaller than that produced by the benchmark model. Diebold and Mariano (1995) and West (1996) have proposed tests for equal predictive ability for the case that the forecasting models are non-nested, i.e. that the benchmark model is not a special case of the indicator model.[16] Under conventional assumptions these test statistics have a standard normal distribution so that standard critical values can be used. Clark and McCracken (2001, 2005) have shown that the statistics of tests of equal predictive ability have non-standard distributions in nested frameworks when the benchmark model is a special case of the indicator model and propose a bootstrap procedure to derive critical values in this case.[17]

In many empirical applications it occurs that the indicator and the benchmark model are sometimes nested and sometimes non-nested as the forecasting exercise proceeds through the sample because of recursive lag-order selection. For this reason, Stock and Watson (2003) do not perform tests of equal predictive ability for the forecasts derived from recursively re-specified forecasting models and perform the test for models with fixed lag length instead. A drawback of this approach is that it involves comparison of potentially overparameterised models, so that the test is potentially not based on the best forecasts that could have been obtained from the models. In a more recent forecasting study, Stock and Watson (2004) do not perform any test of the statistical significance of relative MSE on the grounds that

[16] Diebold and Mariano (1995) propose procedures for the case that the forecasts do not rely on regression estimates while West (1996) considers the case of forecasts derived from non-nested regression models.

[17] Giacomini and White (2004) have recently suggested a test which is applicable to both nested and non-nested models. However, the test requires moving window estimation of the forecasting regressions, while we perform recursive estimation throughout. We also experimented with moving window estimation of the forecasting regressions but found these forecasting models to perform much worse than the recursively estimated models.

"because of the recursive lag length selection, at some dates the two models are nested but at other dates they are not, and the null distribution of the relative MSE is unknown."

In this application we do not encounter this problem for the forecast horizons considered because the indicator models and the benchmark random walk model are non-nested, so that the standard tests of equal predictive ability proposed by Diebold and Mariano (1995) and West (1996) can be used. This is because the benchmark model is the last h-period average inflation rate, while the indicator models always consider up to four autoregressive lags. This means that for forecast horizons beyond four quarters the benchmark model involves at least h-4 lags of inflation more than the indicator model, so that the benchmark model is not a special case of the indicator model and the two models are therefore non-nested. For the four quarter horizon, the indicator and the benchmark model would be nested if the indicator model would select the largest possible lag order of four for the autoregressive terms. It turned out, however, that this case never occurred in the course of the recursive estimation. The SBC always selected a lag order of three or lower for the autoregressive terms, so that the indicator and the benchmark models were also non-nested for this horizon.

We test equal predictive ability by testing whether the relative MSE in (5) is significantly smaller than one. We therefore perform a one-sided test of the hypothesis that the relative MSE is equal to one using the standard normal distribution a proposed by West (1996). The test is based on heteroskedasticity and autocorrelation (HAC) corrected standard errors of the relative MSE, which were calculated using the delta method as:

(6) $Std.error(\Re) = \sqrt{(d\Re/dX)^T \widehat{V}(X)(d\Re/dX)}, \quad X = (MSE_x, MSE_{RW})^T$

where $\widehat{V}(X)$ is a the Newey-West HAC robust estimator of the long-run variance-covariance matrix of X obtained using a Bartlett kernel with a lag truncation length of h-1.

4. Empirical results

Bivariate forecasting models

Table 2 presents the results for the bivariate forecasting models. The Table reports the relative MSE and the p-value of the test that the relative MSE is equal to one.[18] The first row reports the relative MSE from the autoregressive model. The results suggest that the M3 growth indicators perform better than the random walk forecast at the twelve quarter forecast horizon, while the M3-demand based indicators as well as the other monetary growth indicators perform worse than the random walk benchmark at all forecast horizons. In accordance with the findings of the recent literature on the information content of low frequency movements in

[18] Since the test is one-sided the p-value is equal to one when the relative MSE is equal to or larger than one.

money for inflation already referred to above, we find that the best performing monetary indicator is the M3 trend growth rate. But although the MSE of the bivariate model with trend M3 growth is almost 30% lower than that of the random walk benchmark at the 12 quarter horizon, the reported p-values reveal that the relative MSEs from the forecasting models with M3 growth are never significantly smaller than one.

These results are only partly in line with those reported by Nicoletti Altimari (2001), who found a significantly better performance of money-based forecasts compared to a univariate benchmark model. A closer look at the forecast errors produced by the M3 growth indicator models over time, shown in Figure 3 together with the absolute forecast errors produced by the random walk model, reveals that this discrepancy is due to a substantial deterioration in the predictive ability of M3 growth in recent years. The graphs show that the M3 growth indicators produced lower forecast errors than the random walk in the first half of the forecast evaluation sample. But since 2003/2004 the M3-based forecasting models produced substantially larger forecast errors than the random walk benchmark.

The results reported in Table 2 also reveal, however, that not a single bivariate forecasting model was able to significantly outperform the random walk model over the forecast evaluation sample 1999-2006. A number of indicators produced lower MSEs than the random walk model at the four quarter forecast horizon, but the relative MSE is never significantly smaller than one and in most cases also not smaller than that of the autoregressive model. At the longer forecast horizons only very few indicators, including the price deflator of GDP, investment and government consumption, wage inflation and some of the survey indicators, are able to outperform the random walk model, but again the relative MSE is never significantly smaller than one at conventional significance levels.

Thus, none of the bivariate models is able to significantly outperform the random walk forecast of euro area inflation. This result echoes the finding of Stock and Watson (2005) for the US that it has become more difficult to beat simple univariate forecasts of inflation in the environment of low inflation that has prevailed since the mid 1980s.

Table 2: Relative mean squared errors of bivariate forecasting models

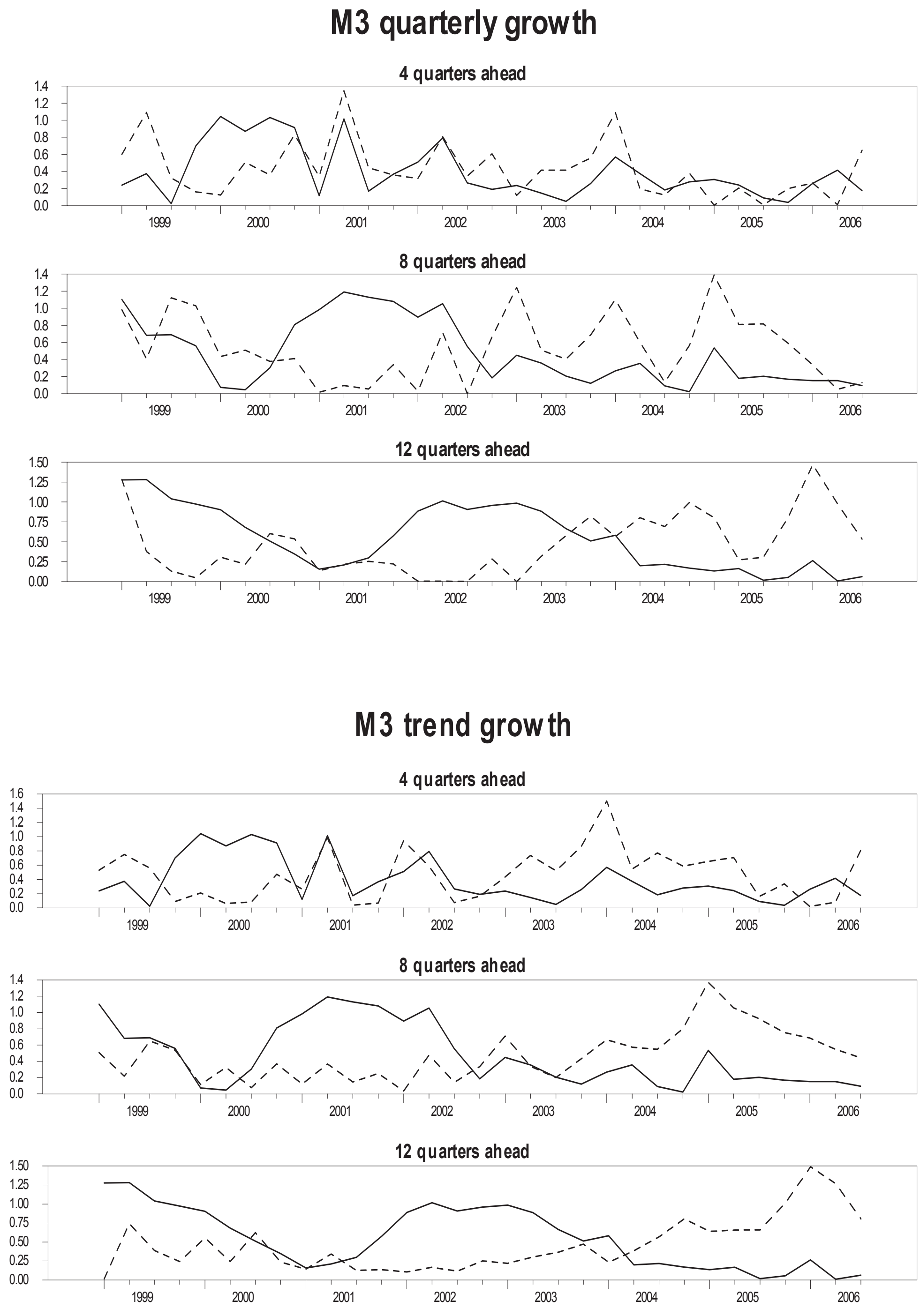
	4 quarters ahead		8 quarters ahead		12 quarters ahead	
Autoregressive model	0.89	(0.38)	1.19	(1.0)	1.37	(1.0)
Monetary indicators						
Δ M3	1.14	(1.00)	1.18	(1.00)	0.80	(0.35)
Δ trend M3 (one-sided)	1.37	(1.00)	0.87	(0.42)	0.73	(0.32)
Δ P-star (M3)	1.13	(1.00)	1.23	(1.00)	1.30	(1.00)
Real money gap (M3)	2.08	(1.00)	1.52	(1.00)	1.65	(1.00)
Monetary overhang (M3)	2.00	(1.00)	1.71	(1.00)	1.37	(1.00)
Δ M1	1.00	(0.50)	1.38	(1.00)	1.82	(1.00)
Δ M2	1.00	(1.00)	1.20	(1.00)	1.34	(1.00)
Δ Loans	1.42	(1.00)	2.19	(1.00)	1.97	(1.00)
Economic and financial indicators						
Δ nominal GDP	1.24	(1.00)	0.96	(0.47)	1.00	(1.00)
Δ real GDP	0.89	(0.39)	1.19	(1.00)	1.32	(1.00)
Real GDP gap	0.92	(0.42)	1.33	(1.00)	1.50	(1.00)
Δ GDP deflator	1.12	(1.00)	0.85	(0.33)	0.80	(0.23)
Δ nominal consumption	1.08	(1.00)	1.18	(1.00)	1.42	(1.00)
Δ real consumption	1.31	(1.00)	1.41	(1.00)	2.07	(1.00)
Real consumption gap	1.68	(1.00)	3.01	(1.00)	5.47	(1.00)
Δ consumption deflator	1.08	(1.00)	0.94	(0.45)	1.14	(1.00)
Δ nominal investment	0.90	(0.39)	1.03	(1.00)	1.31	(1.00)
Δ real investment	0.92	(0.41)	1.20	(1.00)	1.36	(1.00)
Real investment gap	0.92	(0.41)	1.26	(1.00)	1.52	(1.00)
Δ investment deflator	1.01	(1.00)	0.77	(0.28)	0.74	(0.15)
Δ nominal government consumption	1.16	(1.00)	0.77	(0.30)	0.82	(0.31)
Δ real government consumption	0.92	(0.42)	1.15	(1.00)	1.29	(1.00)
Δ government consumption deflator	0.95	(0.45)	0.68	(0.20)	0.83	(0.34)
Δ nominal exports	0.87	(0.36)	1.30	(1.00)	1.35	(1.00)
Δ real exports	0.88	(0.37)	1.27	(1.00)	1.32	(1.00)
Δ export deflator	0.84	(0.32)	1.28	(1.00)	1.47	(1.00)
Δ nominal imports	0.90	(0.39)	1.29	(1.00)	1.39	(1.00)
Δ real imports	1.00	(0.50)	1.23	(1.00)	1.40	(1.00)
Δ import deflator	1.00	(0.50)	1.27	(1.00)	1.30	(1.00)
Δ extra euro area exports (value)	0.91	(0.40)	1.22	(1.00)	1.40	(1.00)
Δ extra euro area imports (value)	0.93	(0.43)	1.23	(1.00)	1.31	(1.00)
Δ intra euro area exports (value)	0.96	(0.46)	1.22	(1.00)	1.42	(1.00)
Δ intra euro area imports (value)	0.88	(0.38)	1.28	(1.00)	1.33	(1.00)
d employment	0.94	(0.45)	1.23	(1.00)	1.45	(1.00)
Employment gap	1.06	(1.00)	1.27	(1.00)	1.82	(1.00)
d unemployment rate	0.88	(0.39)	1.06	(1.00)	1.41	(1.00)
Unemployment rate gap	0.93	(0.43)	1.28	(1.00)	1.55	(1.00)
Δ wages	1.14	(1.00)	0.71	(0.21)	0.75	(0.19)
Δ labour productivity	0.91	(0.41)	1.15	(1.00)	1.36	(1.00)
Δ unit labour costs	1.00	(0.50)	1.02	(1.00)	1.00	(0.50)
Δ share prices	1.23	(1.00)	1.22	(1.00)	1.42	(1.00)
Price earnings ratio	1.45	(1.00)	1.20	(1.00)	1.20	(1.00)
Δ commodity prices (€ basis)	1.14	(1.00)	1.21	(1.00)	1.32	(1.00)
Δ oil prices (€ basis)	1.10	(1.00)	1.20	(1.00)	1.25	(1.00)
Δ gold price (€ basis)	0.94	(0.45)	1.17	(1.00)	1.39	(1.00)
Δ industrial production	0.89	(0.39)	1.33	(1.00)	1.36	(1.00)
Δ manufacturing production	0.93	(0.42)	1.30	(1.00)	1.36	(1.00)

Table 2, continued

	4 quarters ahead		8 quarters ahead		12 quarters ahead	
Δ capital goods production	0.93	(0.42)	1.21	(1.00)	1.36	(1.00)
Δ intermediate goods production	0.88	(0.38)	1.41	(1.00)	1.37	(1.00)
Δ electrical machinery production	0.94	(0.43)	1.25	(1.00)	1.38	(1.00)
Industrial production gap	0.95	(0.45)	1.26	(1.00)	1.45	(1.00)
Manufacturing production gap	0.95	(0.45)	1.24	(1.00)	1.43	(1.00)
Capital goods production gap	0.98	(0.48)	1.25	(1.00)	1.47	(1.00)
Intermediate goods production gap	0.95	(0.45)	1.25	(1.00)	1.40	(1.00)
Electr. machinery production gap	1.10	(1.00)	1.10	(1.00)	1.38	(1.00)
Δ retail sales	0.89	(0.38)	1.15	(1.00)	1.03	(1.00)
d short-term interest rate	0.77	(0.17)	1.18	(1.00)	1.39	(1.00)
d 10-year bond yield	0.75	(0.18)	1.21	(1.00)	1.25	(1.00)
10-year bond spread	0.93	(0.43)	1.10	(1.00)	1.52	(1.00)
d 5-year bond yield	0.88	(0.36)	1.21	(1.00)	1.39	(1.00)
5-year bond spread	1.08	(1.00)	1.06	(1.00)	1.10	(1.00)
d 2-year bond yield	0.76	(0.20)	1.16	(1.00)	1.37	(1.00)
2-year bond spread	1.04	(1.00)	1.09	(1.00)	1.39	(1.00)
Δ industrial producer prices	0.91	(0.40)	1.19	(1.00)	1.39	(1.00)
Δ manufacturing producer prices	0.91	(0.41)	1.20	(1.00)	1.47	(1.00)
Δ nominal effective exchange rate	0.92	(0.42)	1.28	(1.00)	1.47	(1.00)
Δ nominal exchange rate $/€	0.93	(0.43)	1.30	(1.00)	1.46	(1.00)
Δ nominal exchange rate ¥/€	0.93	(0.44)	1.17	(1.00)	1.47	(1.00)
Δ nominal exchange rate £/€	1.00	(1.00)	1.23	(1.00)	1.42	(1.00)
Industry confidence	1.08	(1.00)	1.20	(1.00)	1.36	(1.00)
Δ Industry confidence	0.89	(0.39)	1.25	(1.00)	1.29	(1.00)
Industry production trend	1.09	(1.00)	1.20	(1.00)	1.28	(1.00)
Δ Industry production trend	0.90	(0.39)	1.23	(1.00)	1.33	(1.00)
Industry order-book levels	1.03	(1.00)	1.07	(1.00)	1.18	(1.00)
Δ Industry order-book levels	0.89	(0.39)	1.21	(1.00)	1.28	(1.00)
Industry export order-book levels	1.10	(1.00)	1.24	(1.00)	1.41	(1.00)
Δ Industry export order-book levels	0.93	(0.42)	1.23	(1.00)	1.30	(1.00)
Industry stocks of finished products	1.01	(1.00)	1.03	(1.00)	1.11	(1.00)
d Industry stocks of finished products	0.93	(0.42)	1.23	(1.00)	1.32	(1.00)
Industry production expectations	1.07	(1.00)	1.27	(1.00)	1.36	(1.00)
d Industry production expectations	0.90	(0.39)	1.27	(1.00)	1.32	(1.00)
Industry selling price expectations	1.06	(1.00)	0.98	(0.48)	0.93	(0.41)
d Industry selling price expectations	0.89	(0.38)	1.23	(1.00)	1.36	(1.00)
Construction confidence	1.10	(1.00)	1.05	(1.00)	1.06	(1.00)
d Construction confidence	0.97	(0.46)	1.23	(1.00)	1.34	(1.00)
Construction trend of activity	1.04	(1.00)	0.93	(0.44)	0.80	(0.14)
d Construction trend of activity	0.95	(0.44)	1.20	(1.00)	1.36	(1.00)
Construction order books	1.03	(1.00)	1.08	(1.00)	1.16	(1.00)
d Construction order books	0.92	(0.42)	1.21	(1.00)	1.36	(1.00)
Construction employment expectations	1.02	(1.00)	0.95	(0.46)	0.94	(0.42)
d Construction employment expectations	0.95	(0.44)	1.23	(1.00)	1.34	(1.00)
Construction price expectations	0.92	(0.44)	0.99	(0.49)	0.81	(0.30)
d Construction price expectations	0.92	(0.40)	1.21	(1.00)	1.27	(1.00)

Note: The table reports the ratio of the mean squared forecast error (MSE) generated by the respective bivariate forecasting model to the MSE of the random walk forecasting model. P-values of the tests of the hypothesis that the relative MSE is equal to one are in parentheses. 'Δ' denotes the quarterly growth rate, 'd' denotes the first difference and 'gap' denotes the deviation from a one-sided HP trend.

Figure 3: M3-based forecasts vs random walk forecasts



Note: The graphs show the absolute forecast error of the bivariate forecasting model with M3 growth (dotted line) and of the smooth random walk forecast (solid line).

Factor forecasts and forecast combinations

Table 3 reports the relative MSEs of the forecast combinations and the factor forecasting models. With regard to the forecast combinations, the mean and the SBC weighted mean (approximate Bayesian model averaging) of the monetary forecasts yields relative MSEs which are smaller than one, but only marginally significantly so at the twelve quarter horizon. The combination forecasts for the group of economic and financial indicators and for the full group of indicators do not perform better than the random walk forecast. On the whole, the approximate Bayesian model averaging procedure produces only marginally smaller forecast errors than the simple mean. This might be explained by the fact that all forecasting models have a common, highly significant autoregressive component, which makes the SBC weights used to compute the approximate Bayesian average forecast not differ substantially from the uniform weight used to compute the simple mean forecast.

The monetary factor model performs better than the random walk only at the twelve quarter horizon, but not significantly so. The factor model for the economic and financial indicators outperforms the random walk model at the four and eight quarter horizon, but the relative MSEs are also not significantly smaller than one. A clear improvement in forecast performance is obtained based on the factor model for the combined set of monetary and economic indicators. The relative MSE of this forecasting model is smaller than one for all three forecast horizons. At the two and three year horizon the MSE produced by this model is respectively 80% and 60% lower than that produced by the random walk model and the hypothesis of equal predictive ability vis-à-vis the random walk is respectively rejected at the 1% level.[19]

A look at the forecasting performance over time (Figure 4) reveals that the performance of this model was also quite stable over time. In particular at the longer forecasting horizon the model clearly outperformed the random walk model until about 2004 and since then produced forecast errors of similar (small) magnitude. These results strongly suggest that combining information from the economic and the monetary analysis yields significantly improved forecasts of euro area HICP inflation.

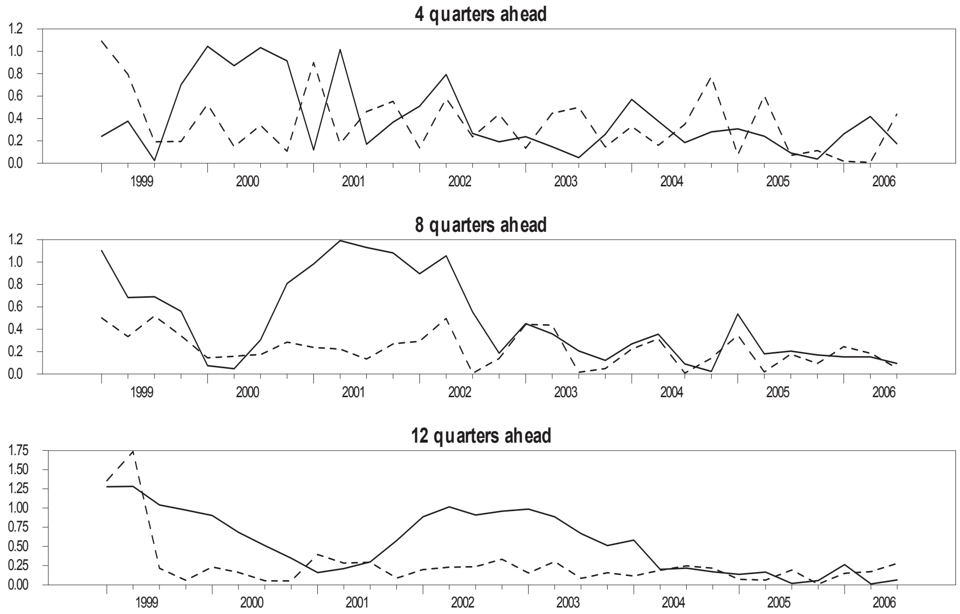
[19] This result contrasts somewhat with Lenza (2006), who finds that a factor model comprising both monetary and economic indictors outperforms the random walk forecast only marginally and not significantly. There are a number of potential explanations for this discrepancy. First, while this paper uses the h-quarter change in the HICP as the forecast variable, Lenza forecasts the year-on-year change in the HICP *h* quarters ahead. Second, Lenza uses monthly data while the present paper uses quarterly data. Third, the forecast evaluation sample is different (1997-2005 in Lenza, 1999-2006 here). Finally, the indicators included in the factor model are also different. Lenza's model also comprises euro area country-level data while this paper uses exclusively euro area data. Due to the use of monthly data, Lenza's factor model does not comprise national accounts aggregates while they are included in the factor model of the present paper.

Table 3: Forecast combinations and factor forecasts

	4 quarters ahead		8 quarters ahead		12 quarters ahead	
Mean						
Monetary indicators	0.85	(0.31)	0.83	(0.35)	**0.67**	**(0.08)**
Economic and financial indicators	0.88	(0.37)	1.09	(1.00)	1.23	(1.00)
All indicators	0.87	(0.35)	1.06	(1.00)	1.17	(1.00)
Median						
Monetary indicators	0.89	(0.37)	0.95	(0.46)	0.93	(0.43)
Economic and financial indicators	0.91	(0.40)	1.18	(1.00)	1.33	(1.00)
All indicators	0.91	(0.40)	1.17	(1.00)	1.33	(1.00)
Approx. Bayesian model averaging						
Monetary indicators	0.85	(0.31)	0.82	(0.35)	**0.63**	**(0.05)**
Economic and financial indicators	0.88	(0.36)	1.08	(1.00)	1.24	(1.00)
All indicators	0.87	(0.35)	1.04	(1.00)	1.15	(1.00)
Factor model						
Monetary indicators	1.28	(1.00)	0.97	(0.48)	0.55	(0.11)
Economic and financial indicators	0.77	(0.17)	0.87	(0.40)	0.97	(0.46)
All indicators	0.79	(0.28)	**0.20**	**(0.00)**	**0.43**	**(0.01)**

Note: The table reports the ratio of the mean squared forecast error (MSE) generated by the respective forecasting model to the MSE of the random walk forecasting model. P-values of the tests of the hypothesis that the relative MSE is equal to one are in parentheses. Relative MSEs significantly smaller than one at least at the 10% level are in bold.

Figure 4: Forecasts from factor model comprising all indicators vs random walk



Note: The graphs show the absolute forecast errors of the mean forecasts of the bivariate forecasting models of monetary indicators (dotted line) and of the random walk forecasting model (solid line).

Two-pillar Phillips Curve forecasting model

Table 4 reports the relative MSEs produced by the trivariate two-pillar Phillips Curve forecasting models. For comparison we also report in the first row of the table the relative MSE for the bivariate model including trend M3 growth and again the relative MSE of the autoregressive model. The results suggest that the trivariate models in general do not produce lower relative MSEs than the bivariate model including trend M3 growth alone. Also the factor model and the forecast combinations do not perform better than the bivariate model. There are, however, a few trivariate models that yield considerable better forecast performances than the bivariate model. These include the models with nominal GDP growth, the GDP gap, the investment gap, the change in employment, the employment gap, the unemployment rate gap and wage inflation. These models yield lower relative MSE than the bivariate model with trend M3 growth at all forecast horizons. At the twelve quarter forecast horizon the relative MSE is even significantly smaller than one.

This result may look surprising at first sight since it might rather have been expected that measures of economic slack, such as the output or the unemployment rate gap, are most useful for forecasting at the shorter horizons. However, the empirical evidence reported in Assenmacher-Wesche and Gerlach (2006) suggests that, in the euro area, the output gap displays significant correlation with the inflation rate at the business cycle frequency including frequency bands up to eight years, but not at higher frequency bands of 0.5 – 2 years. An h-quarter moving average of inflation essentially filters out fluctuations below h-quarters. This means that the twelve quarter average inflation rate includes movements in the inflation rate at all frequencies beyond three years, i.e the part of the business cycle frequency band beyond three years and the low frequency movements beyond the business cycle frequency. From that perspective and against the background of the results reported in Assenmacher-Wesche and Gerlach (2006), it rather seems that the result that some of the two pillar Phillips Curve forecasting models perform best at the twelve quarter horizon where the correlation of the output gap with inflation at the lower end of the business cycle frequency and of trend money growth with the low frequency movements of inflation are combined is just what one should expect.

However, a closer look at the performance of the best performing trivariate models over time reveals that they were also not able to outperform the random walk over the more recent time period. Figure 5 shows as an example the performance of the trivariate model with the unemployment rate gap. The graphs show that while the model performs better than the bivariate model with M3 growth, its predictive ability relative to the simple random walk forecasting model has also deteriorated since 2003/2004. For the other trivariate models we obtain a very similar picture. The results are available upon request.

Table 4: Relative mean squared errors of trivariate forecasting models

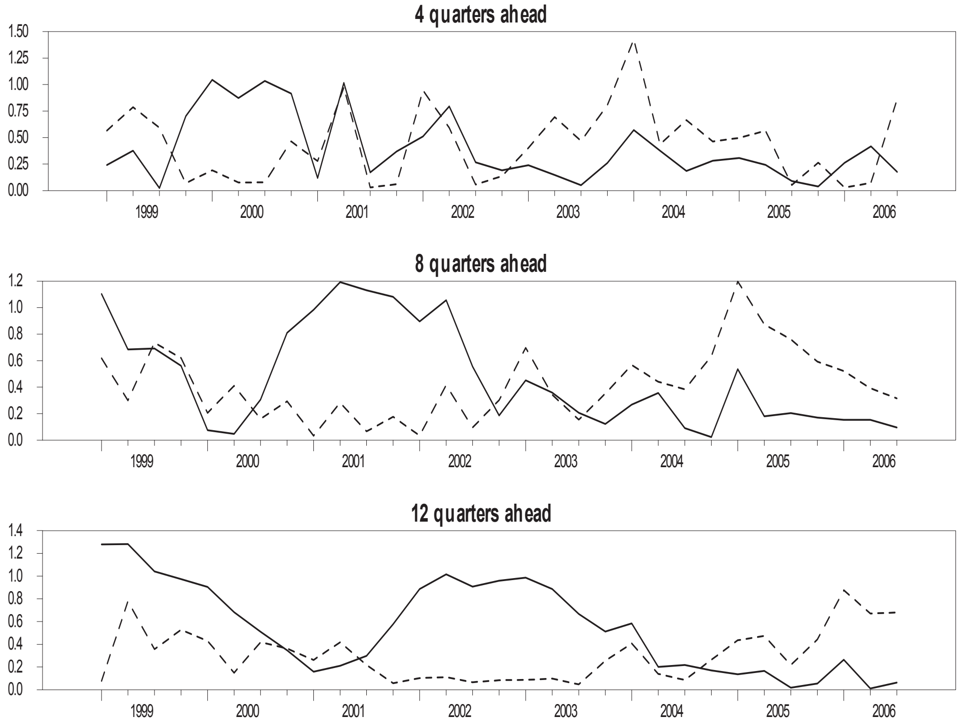
	4 quarters ahead		8 quarters ahead		12 quarters ahead	
Autoregressive model	0.89	(0.38)	1.19	(1.0)	1.37	(1.0)
Bivariate Δ trend M3	1.37	(1.0)	0.87	(0.42)	0.73	(0.32)
Trivariate models						
Δ nominal GDP	1.13	(1.00)	0.58	(0.14)	**0.51**	**(0.03)**
Δ real GDP	1.19	(1.00)	0.71	(0.29)	0.68	(0.25)
Real GDP gap	1.17	(1.00)	0.63	(0.19)	**0.48**	**(0.05)**
Δ GDP deflator	1.36	(1.00)	0.81	(0.37)	1.06	(1.00)
Δ nominal consumption	1.70	(1.00)	0.75	(0.32)	0.89	(0.38)
Δ real consumption	1.73	(1.00)	0.94	(0.47)	0.94	(0.43)
Real consumption gap	1.91	(1.00)	1.70	(1.00)	1.73	(1.00)
Δ consumption deflator	1.11	(1.00)	0.73	(0.31)	0.84	(0.37)
Δ nominal investment	1.35	(1.00)	0.65	(0.22)	0.66	(0.21)
Δ real investment	1.37	(1.00)	0.76	(0.33)	0.72	(0.28)
Real investment gap	1.32	(1.00)	0.66	(0.22)	**0.36**	**(0.00)**
Δ investment deflator	1.19	(1.00)	0.67	(0.24)	0.85	(0.34)
Δ nominal government consumption	1.27	(1.00)	0.78	(0.35)	0.69	(0.28)
Δ real government consumption	1.46	(1.00)	0.91	(0.45)	0.74	(0.34)
Δ government consumption deflator	1.16	(1.00)	0.71	(0.29)	0.76	(0.32)
Δ nominal exports	1.40	(1.00)	0.87	(0.42)	0.72	(0.31)
Δ real exports	1.68	(1.00)	0.87	(0.42)	0.74	(0.33)
Δ export deflator	1.30	(1.00)	0.87	(0.42)	0.71	(0.29)
Δ nominal imports	1.45	(1.00)	0.93	(0.46)	0.76	(0.32)
Δ real imports	1.44	(1.00)	0.83	(0.39)	0.68	(0.25)
Δ import deflator	1.46	(1.00)	1.00	(0.50)	0.77	(0.35)
Δ extra euro area exports (value)	1.32	(1.00)	0.82	(0.39)	0.65	(0.26)
Δ extra euro area imports (value)	1.34	(1.00)	0.87	(0.43)	0.83	(0.39)
Δ intra euro area exports (value)	1.41	(1.00)	0.85	(0.41)	0.73	(0.31)
Δ intra euro area imports (value)	1.38	(1.00)	0.99	(0.49)	0.76	(0.34)
d employment	1.32	(1.00)	0.80	(0.37)	**0.49**	**(0.06)**
Employment gap	1.34	(1.00)	0.76	(0.33)	**0.36**	**(0.00)**
d unemployment rate	1.21	(1.00)	0.70	(0.28)	0.59	(0.18)
Unemployment rate gap	1.23	(1.00)	0.67	(0.24)	**0.32**	**(0.00)**
Δ wages	1.11	(1.00)	0.53	(0.11)	0.56	(0.13)
Δ labour productivity	1.29	(1.00)	0.79	(0.36)	0.70	(0.29)
Δ unit labour costs	1.34	(1.00)	0.87	(0.43)	0.74	(0.32)
Δ share prices	1.83	(1.00)	1.06	(1.00)	0.84	(0.41)
Price earnings ratio	1.92	(1.00)	0.94	(0.46)	0.78	(0.34)
Δ commodity prices (€ basis)	1.36	(1.00)	0.96	(0.48)	0.74	(0.33)
Δ oil prices (€ basis)	1.43	(1.00)	0.90	(0.44)	0.97	(0.48)
Δ gold price (€ basis)	1.39	(1.00)	0.86	(0.42)	0.73	(0.32)
Δ industrial production	1.37	(1.00)	0.85	(0.40)	0.70	(0.29)
Δ manufacturing production	1.33	(1.00)	0.84	(0.40)	0.74	(0.32)
Δ capital goods production	1.37	(1.00)	0.84	(0.40)	0.76	(0.34)
Δ intermediate goods production	1.60	(1.00)	0.90	(0.44)	0.76	(0.33)
Δ electrical machinery production	1.39	(1.00)	0.86	(0.42)	0.85	(0.41)
Industrial production gap	1.30	(1.00)	0.75	(0.32)	0.66	(0.22)
Manufacturing production gap	1.33	(1.00)	0.78	(0.35)	0.70	(0.27)
Capital goods production gap	1.41	(1.00)	0.86	(0.42)	0.69	(0.27)
Intermediate goods production gap	1.30	(1.00)	0.76	(0.32)	0.69	(0.25)
Electr. machinery production gap	1.48	(1.00)	0.99	(0.50)	0.82	(0.40)

Table 4, continued

	4 quarters ahead		8 quarters ahead		12 quarters ahead	
Δ retail sales	1.38	(1.00)	0.84	(0.40)	**0.47**	**(0.04)**
d short-term interest rate	1.23	(1.00)	0.84	(0.40)	0.83	(0.38)
d 10-year bond yield	1.26	(1.00)	0.89	(0.43)	0.72	(0.33)
10-year bond spread	1.55	(1.00)	1.15	(1.00)	1.21	(1.00)
d 5-year bond yield	1.35	(1.00)	0.88	(0.43)	0.69	(0.29)
5-year bond spread	1.56	(1.00)	0.86	(0.42)	0.69	(0.26)
d 2-year bond yield	1.30	(1.00)	0.89	(0.43)	0.72	(0.31)
2-year bond spread	1.55	(1.00)	1.10	(1.00)	1.14	(1.00)
Δ industrial producer prices	2.02	(1.00)	1.09	(1.00)	0.76	(0.36)
Δ manufacturing producer prices	1.80	(1.00)	1.08	(1.00)	0.83	(0.40)
Δ nominal effective exchange rate	1.33	(1.00)	0.88	(0.43)	0.74	(0.32)
Δ nominal exchange rate $/€	1.35	(1.00)	0.88	(0.43)	0.86	(0.41)
Δ nominal exchange rate ¥/€	1.37	(1.00)	0.85	(0.41)	0.84	(0.39)
Δ nominal exchange rate £/€	1.39	(1.00)	0.89	(0.43)	0.70	(0.30)
Industry confidence	1.32	(1.00)	0.80	(0.37)	0.62	(0.22)
d Industry confidence	1.46	(1.00)	0.94	(0.46)	0.85	(0.41)
Industry production trend	1.30	(1.00)	0.73	(0.30)	0.60	(0.15)
d Industry production trend	1.37	(1.00)	0.91	(0.45)	0.86	(0.41)
Industry order-book levels	1.27	(1.00)	0.76	(0.33)	0.63	(0.20)
d Industry order-book levels	1.51	(1.00)	0.93	(0.46)	1.00	(0.50)
Industry export order-book levels	1.53	(1.00)	0.87	(0.42)	0.65	(0.25)
d Industry export order-book levels	1.49	(1.00)	0.95	(0.47)	0.86	(0.40)
Industry stocks of finished products	1.34	(1.00)	0.85	(0.41)	1.89	(1.00)
d Industry stocks of finished products	1.37	(1.00)	0.90	(0.44)	0.97	(0.48)
Industry production expectations	1.47	(1.00)	0.87	(0.42)	1.19	(1.00)
d Industry production expectations	1.37	(1.00)	0.95	(0.47)	0.81	(0.37)
Industry selling price expectations	0.81	(0.30)	0.54	(0.10)	0.60	(0.15)
d Industry selling price expectations	1.68	(1.00)	1.03	(1.00)	0.96	(0.47)
Construction confidence	1.15	(1.00)	0.95	(0.47)	0.70	(0.26)
d Construction confidence	1.38	(1.00)	0.86	(0.42)	0.70	(0.29)
Construction trend of activity	1.13	(1.00)	0.86	(0.42)	0.62	(0.15)
d Construction trend of activity	1.37	(1.00)	0.87	(0.42)	0.75	(0.33)
Construction order books	1.19	(1.00)	0.96	(0.48)	0.66	(0.27)
d Construction order books	1.38	(1.00)	0.85	(0.41)	0.72	(0.31)
Construction employment expectations	1.05	(1.00)	0.92	(0.46)	0.80	(0.33)
d Construction employment expectations	1.37	(1.00)	0.87	(0.42)	0.70	(0.30)
Construction price expectations	0.95	(0.46)	0.55	(0.10)	0.92	(0.41)
d Construction price expectations	1.33	(1.00)	0.87	(0.42)	0.63	(0.15)
Forecast combinations and factor model						
Mean	1.29	(1.00)	0.81	(0.38)	0.63	(0.22)
Median	1.33	(1.00)	0.84	(0.40)	0.68	(0.28)
Approx. Bayesian model averaging	1.29	(1.00)	0.81	(0.38)	0.62	(0.22)
Factor model	1.16	(1.00)	0.82	(0.38)	0.64	(0.20)

Note: The table reports the ratio of the mean squared forecast error (MSE) generated by the trivariate forecasting model comprising trend M3 growth and the respective non-monetary indicator to the MSE of the random walk forecasting model. P-values of the tests of the hypothesis that the relative MSE is equal to one are in parentheses. Relative MSEs significantly smaller than one at least at the 10% level are boldface. 'Δ' denotes the quarterly growth rate, 'd' denotes the first difference and 'gap' denotes the deviation from a one-sided HP trend.

Figure 5: Two-pillar Phillips Curve forecasting model vs random walk forecasts



Note: The graphs show the absolute forecast error of the trivariate forecasting model comprising trend M3 growth and the unemployment rate gap (dotted line) and of the random walk forecasting model (solid line).

5. Portfolio shift effects

The evidence presented in the previous section has shown that the information content of M3 growth has substantially deteriorated over recent years. Bivariate and trivariate forecasting models including M3 growth have produced larger forecast errors than the random walk benchmark model since 2003 (2004) for the two (three) year forecasting horizon. This result reflects the fact that the acceleration in M3 growth since 2001 was not followed by an upsurge in inflation. The ECB attributes the high growth rates of M3 over the period 2001 to 2003 to transitory, but persistent portfolio shifts caused by a strong preference of investors for liquid assets in the wake of the exceptional economic and financial uncertainties over this period.[20] This would imply that the information content of M3 indicators for inflation has been blurred only temporarily and that a correction of M3 for the effects of these portfolio shifts might restore the indicator property of M3 for inflation trends.

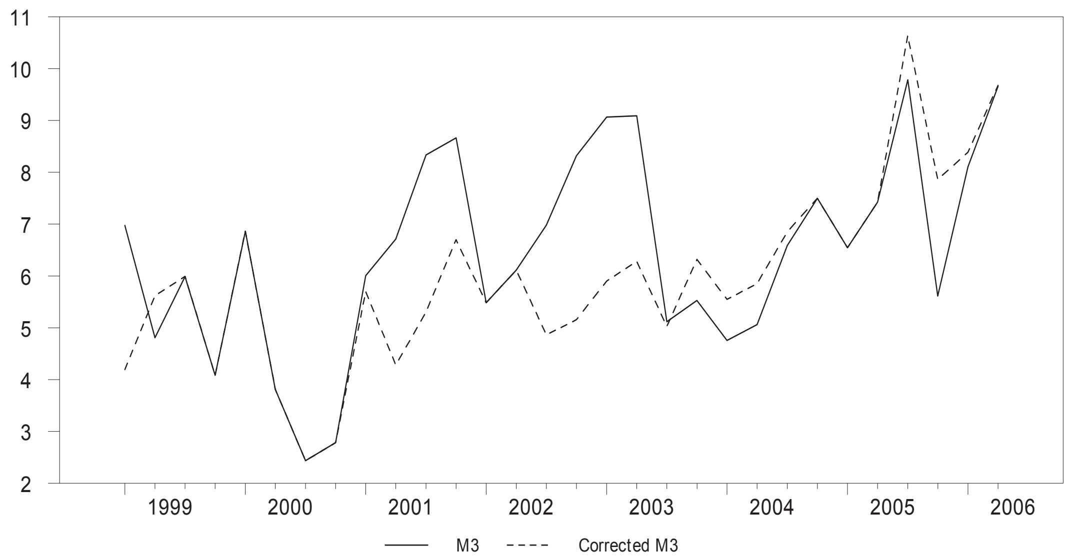
The ECB has constructed an M3 series that is corrected for the effects of portfolio shifts which plays an important role in the internal monetary analysis (Fischer et al. 2006). The M3

[20] See e.g. ECB (2004).

series corrected for the effects of portfolio shifts is constructed based on a seasonal reg-ARIMA model (regression model with seasonal ARIMA errors) of the log-transformed index of adjusted stocks of euro area M3, which captures the portfolio shift effects since 2001 by means of intervention variables. The specification of the intervention variables is determined in a judgemental way, involving a prior broad based analysis of monetary developments and their potential driving forces. The portfolio shifts between March and October 2001 and between September 2002 and May 2003 are respectively modelled by a linear trend. The gradual unwinding of past portfolio shifts in the period from mid-2003 to mid-2004 is assumed to proceed linearly at a quarter of the pace observed for the earlier shifts into M3.[21] The historical portfolio shift corrected M3 series further incorporates adjustments for distortions related to a new balance sheet reporting scheme for MFIs and the introduction of a remunerated minimum reserve system in 1999, for the ERM crisis in 1992/93 as well as for a number of seasonal and calendar effects. For the stochastic part of the model an ARIMA model is used. A more detailed exposition of the technical details of the model and the adjustments is provided in Appendix C in Fischer et al. (2006).

Figure 6 shows the quarterly growth rate of headline M3 and of portfolio-shift corrected M3 since 1999. The graph shows that as a consequence of the adjustments the corrected M3 series has been growing at a much lower rate than headline M3 over the period 2001 to mid-2003. Since end 2003 the portfolio shift corrected series has been growing at a higher rate than the headline series as a consequence of the estimated unwinding of the earlier portfolio inflows.

Figure 6: Headline and portfolio-shift corrected M3 quarterly growth in the euro area



[21] Greiber and Lemke (2005) capture the effect of portfolio shifts on the demand for M3 by including measures of aggregate risk to an otherwise standard specification of the M3 demand function. They show that including these measures substantially reduces the estimated monetary overhang at the end of the sample period.

Table 5 shows the relative MSEs with respect to the random walk forecasts for the bivariate forecasting model with portfolio-shift corrected M3 indicators. We consider again the quarterly and the trend growth rate of corrected M3[22] as well as recursively calculated money demand based indicators, the change in p-star, the real money gap and the monetary overhang. The results suggest that the relative MSEs obtained from the forecasting models with portfolio shift corrected M3 are in general smaller that those obtained from the models with headline M3. While the money demand based indicators are still not able to significantly outperform the random walk model, the forecasting model including corrected M3 quarterly growth yields smaller MSEs than the random walk model at the eight and twelve quarter forecast horizon. At the twelve quarter horizon the relative MSE is even significantly smaller than one at the 1% level. The best performing model is the forecasting model including corrected M3 trend growth, which produces smaller MSEs than the random walk benchmark at all three forecast horizons. At the two and three year horizon the MSE of this model is respectively 70% and 80% lower than that of the random walk model and the relative MSE is in both cases significantly smaller than one at the 1% level.

Table 5: Forecasting performance of the portfolio-shift-corrected M3 series

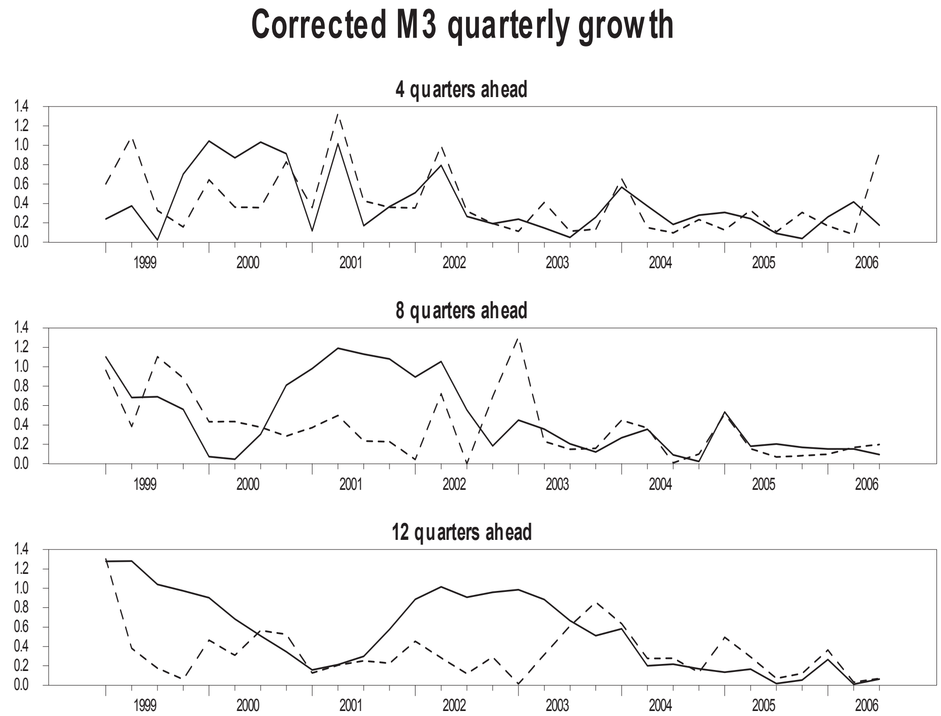
	4 quarters ahead		8 quarters ahead		12 quarters ahead	
Δ M3 corrected	1.07	(1.00)	0.68	(0.15)	**0.40**	**(0.00)**
Δ trend M3 corrected	0.89	(0.39)	**0.32**	**(0.00)**	**0.21**	**(0.00)**
Δ P-star (M3 corrected)	1.41	(1.00)	1.03	(1.00)	0.84	(0.22)
Real money gap (M3 corrected)	1.73	(1.00)	1.57	(1.00)	1.43	(1.00)
Monetary overhang (M3 corrected)	1.79	(1.00)	1.35	(1.00)	1.10	(1.00)

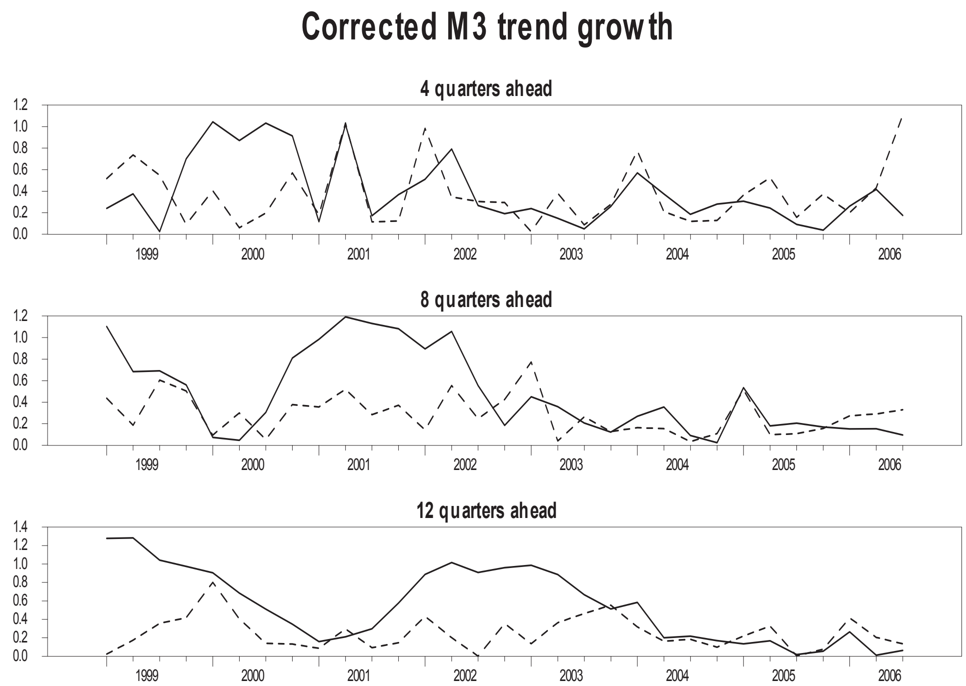
Note: The table reports the ratio of the mean squared forecast error (MSE) generated by the respective forecasting model to the MSE of the random walk forecasting model. P-values of the tests of the hypothesis that the relative MSE is equal to one are in parentheses. Relative MSEs significantly smaller than one at least at the 10% level are in bold.

A look at the forecasting performance of the corrected M3 growth indicator models over time, shown in Figure 7, reveals that these models have not produced systematically larger forecast errors than the random walk over recent years, like the headline M3 based forecasting models. This result supports the view that the signal contained in M3 for medium term risks to price stability has been blurred by portfolio shifts and that accurate out-of-sample forecasts can be obtained when a judgemental correction for these effects is applied to headline M3.

[22] The trend growth rate is again calculated based on a one-sided HP filter using a smoothing parameter of 1,600.

Figure 7: Portfolio shift corrected M3 growth forecasts vs. random walk forecasts





Note: The graphs show the absolute forecast error of the bivariate forecasting model with portfolio shift adjusted M3 growth (dotted line) and of the smooth random walk forecast (solid line).

6. Real-time inflation forecasts

An obvious objection to the analysis of the previous section is that the portfolio shift correction of the M3 aggregate is done based on ex-post information which was not available ex-ante, so that the forecasting exercise is not a proper assessment of the usefulness of the corrected M3 measure for out-of-sample forecasting. In order to address this issue we assess in this section the forecasting performance of corrected M3 as well as of headline M3 using real-time data. As an additional interesting exercise we also assess the performance of the HICP inflation projections from the Broad Macroeconomic Projection Exercise (BMPE)[23], which play an important role in the ECB's economic analysis for the assessment of the short- to medium run risks to price stability. We also consider the unweighted mean of the forecast from the BMPE and from the bivariate model with corrected M3 as a simple way to combine or cross check the signals coming from the monetary and the economic analysis.

Real-time data series for euro area HICP, headline M3, corrected M3 as well as real-time inflation projections from the BMPE were obtained from internal ECB sources. The time series for the real-time adjusted M3 comprise the real-time series for M3 for the effects of the increased preference of investors for liquid assets over the period and the following unwinding of these effects thereafter over the period since 2001Q3 (referred to as M3 corrected for portfolio-shifts) as well as real-time series for M3 incorporating judgemental adjustments made for the non-resident holdings of marketable instruments issued by Monetary Financial Institutions (MFIs) for the period 2000Q3 till 2001Q2 (referred to as M3 adjusted for special factors).[24] The real-time corrected M3 series therefore comprise the real-time series for portfolio-shift corrected M3 for the period 2001Q3 till 2006Q3 and the real-time series for M3 adjusted for special factors for the period 2000Q3 till 2001Q2. For the period 1998Q4 till 2000Q2 the real-time series for headline M3 were used.

With regard to the BMPE projections it should be noted that the projections are for year-on-year inflation h quarters ahead. In order to obtain a projection for the h-quarter ahead average inflation rate we first calculated a projected path for the HICP level based on the projections for the year-on-year inflation rate and then compute the h-quarter ahead change in the HICP. Consistent runs of BMPE projections are not available for the 12 quarter horizon, so that the evaluation of the BMPE projections could only be performed for the 4 and 8 quarter horizon.

[23] The BMPE is a quarterly projection exercise, conducted by Eurosystem staff for the second and the fourth quarter of the year and by ECB staff for the first and third quarter. It is based on a portfolio of area wide and country-specific models but also involves judgmental input of ECB and Eurosystem staff. For the assessment of forecast performance we use the mid-points of the BMPE inflation projection ranges

[24] Non-resident holdings of MFI marketable instruments were excluded from the official revised M3 series in 2001Q3.

The real-time simulated out-of-sample forecasting analysis is performed in the same way as described in Section 3. Since we are using real-time data this involves now recursively estimating the forecasting equation (1) using at each step the real-time series for the respective quarter. For both headline and corrected M3 we consider the quarterly growth rate and the trend growth rate constructed as in the previous sections using a one-sided HP filter with a smoothing parameter of 1,600. Since the real-time data are available only from 1998Q4, the first set of simulated out-of-sample forecasts can only be constructed in this quarter. Simulated out-of-sample forecasts for the 4, 8 and 12 quarter forecast horizon are therefore only available starting in 1999Q4, 2000Q4 and 2001Q4 respectively until 2006Q3. In the previous sections the forecast evaluation sample was always 1999Q1 till 2006Q3. Differences to the results reported in the previous sections can therefore not only arise because of the use of real-time rather than ex-post data, but also because of unavoidable differences in the forecast evaluation sample.

Table 6 reports the relative MSEs with respect to the real-time random walk forecast (calculated using the real-time HICP) for the bivariate real-time forecasting models with headline M3 quarterly and trend growth, corrected M3 quarterly and trend growth and the BMPE inflation projections. The last two rows report the relative MSEs obtained when taking the unweighted average of the BMPE projections and the forecast from the model with corrected M3 quarterly growth or trend growth.

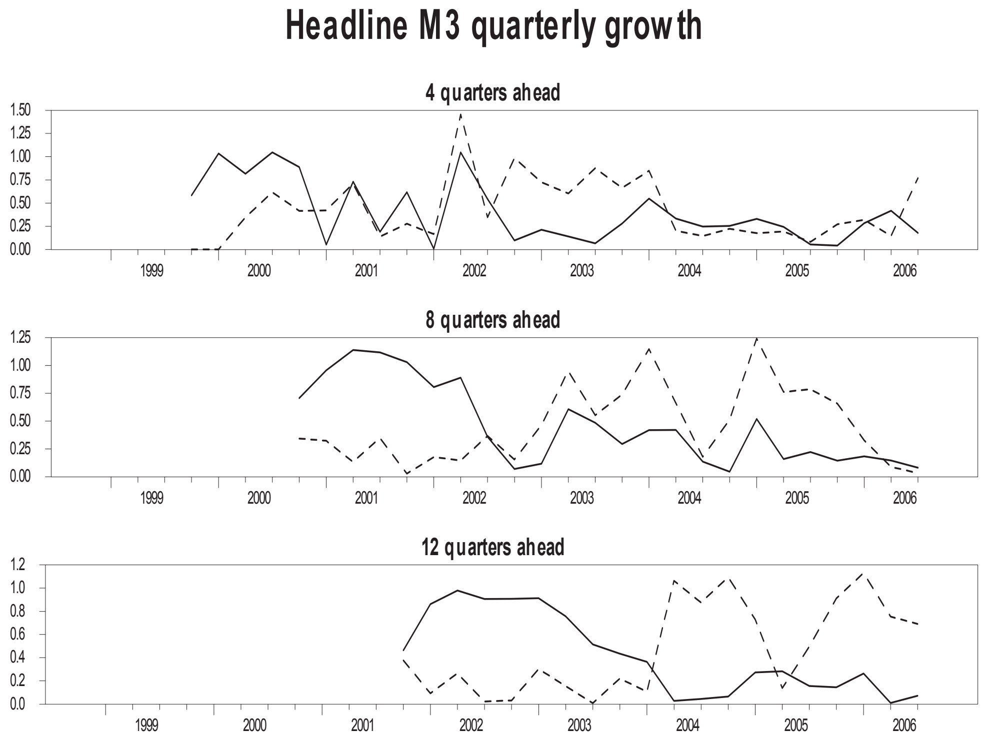
Table 6: Relative MSEs from real-time forecasts

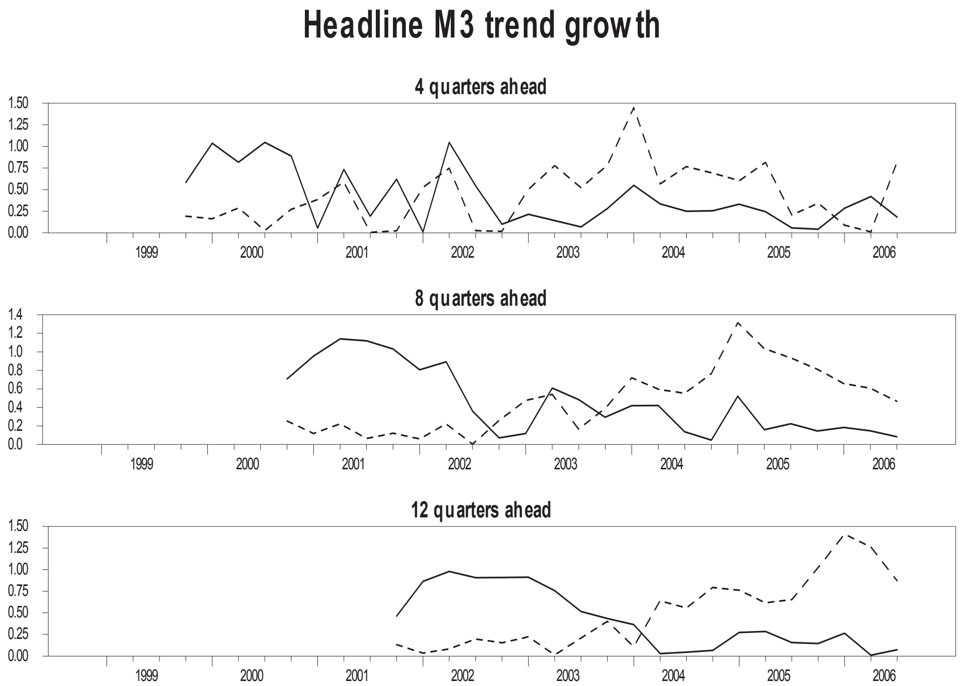
	4 quarters ahead		8 quarters ahead		12 quarters ahead	
Δ M3	1.14	(1.00)	0.97	(0.49)	1.28	(1.00)
Δ trend M3	1.16	(1.00)	1.00	(0.50)	1.45	(1.00)
Δ corrected M3	0.75	(0.21)	**0.39**	**(0.01)**	**0.46**	**(0.06)**
Δ trend corrected M3	0.63	(0.11)	**0.21**	**(0.00)**	**0.23**	**(0.00)**
BMPE	0.93	(0.40)	0.87	(0.36)	-	
Average of BMPE and Δ corrected M3	**0.46**	**(0.00)**	**0.31**	**(0.00)**	-	
Average of BMPE and Δ trend corrected M3	**0.35**	**(0.00)**	**0.28**	**(0.00)**	-	

Note: P-values of the tests of the hypothesis that the relative MSE is equal to one are in parentheses. Relative MSEs significantly smaller than one at least at the 10% level are boldface. BMPE projections are not available for the 12 quarter horizon.

The results reveal that in real-time the headline M3 growth based forecasts did on average not perform better than the random walk forecasts across all three forecast horizons. This result contrasts with the results obtained based on the ex-post data, where a relative MSE smaller than one was obtained at the longer forecast horizons. This discrepancy is mainly due to differences in the forecast evaluation sample. As Figure 8 shows, the forecast errors look similar to those obtained based on the ex-post data, but because of the shorter forecast evaluation sample the period where the headline M3-based forecasts produced larger forecast errors than the random walk now dominates the forecast evaluation sample.

Figure 8: Headline M3-based forecasts vs random walk forecasts





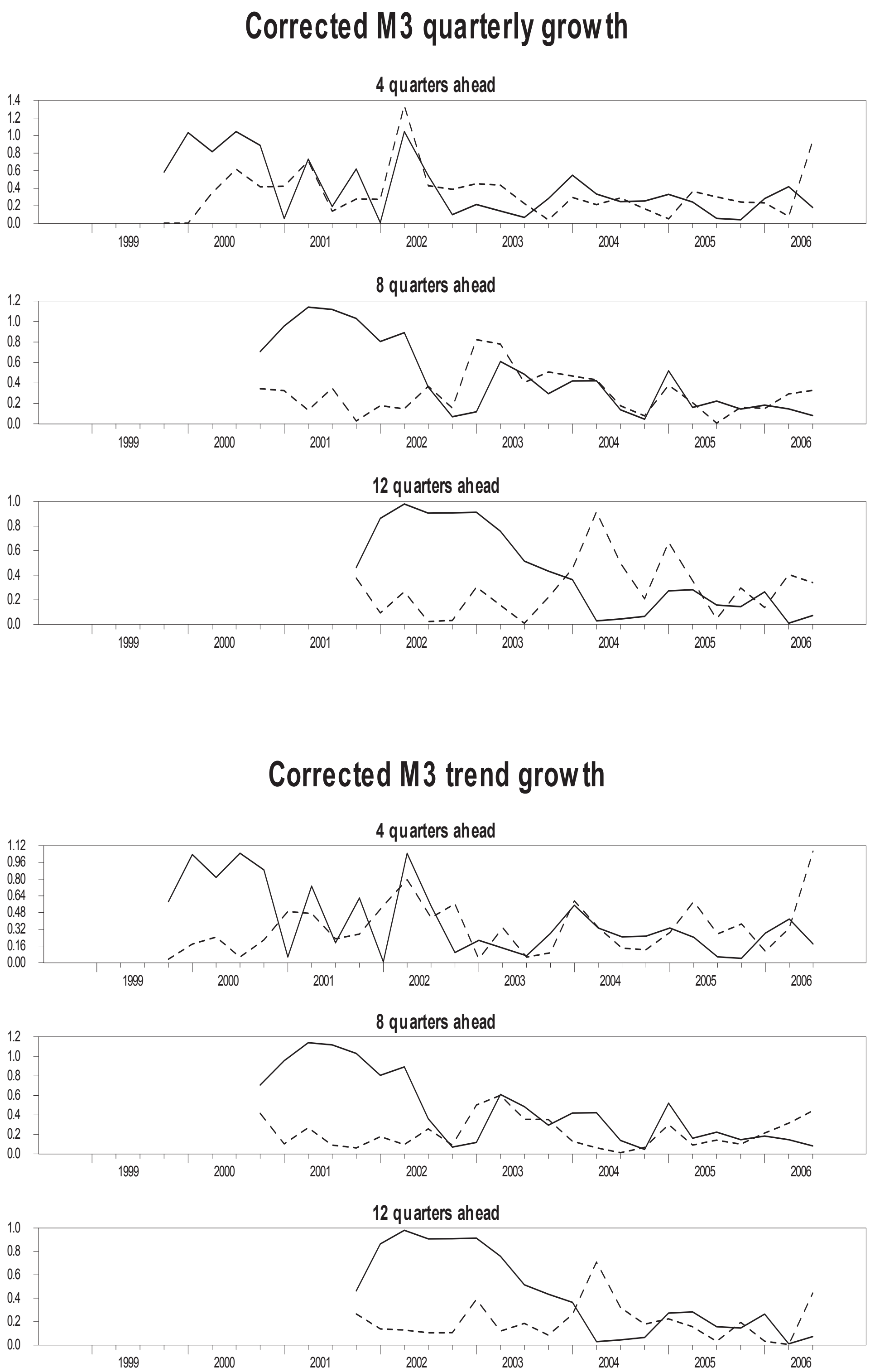
Note: The graphs show the absolute forecast error of the bivariate forecasting model with portfolio shift adjusted M3 growth (dotted line) and of the smooth random walk forecast (solid line).

The real-time forecasts obtained from the model with corrected M3 yield relative MSEs significantly smaller than one at the eight and twelve quarter forecast horizon. The best performing model is the model with the trend growth rate of corrected M3 with an MSE almost 40% lower than that of the random walk model at the 4 quarter forecast horizon and almost 80% lower at the eight and twelve quarter horizon. These results are fully consistent with those obtained based on ex-post data in the previous section. Figure 9 shows the absolute real-time forecast errors of the model with corrected M3 compared to the random walk model. The picture of the performance of the models over time is broadly similar to that obtained with the ex-post data. Except for a large forecast error at the 12 quarter forecast horizon in 2004, the corrected M3-based models produced fairly accurate inflation forecasts also in real-time, but the performance of this indicator relative to the random walk benchmark has also deteriorated recently as a result of the very low forecast errors produced by the benchmark model.

The BMPE projections, which are not available for the twelve quarter horizon, performed slightly better than the random walk, but the relative MSEs are not significantly different from one. However, combining the BMPE projections and the forecasts obtained from the forecasting models with corrected M3 growth by taking the unweighted average of the forecasts yields relative MSEs significantly smaller than one at both the four and the eight quarter forecasting horizon. Figure 10, which shows the absolute forecast errors, reveals that the performance of this forecast combination was also very stable over the forecast evaluation sample.

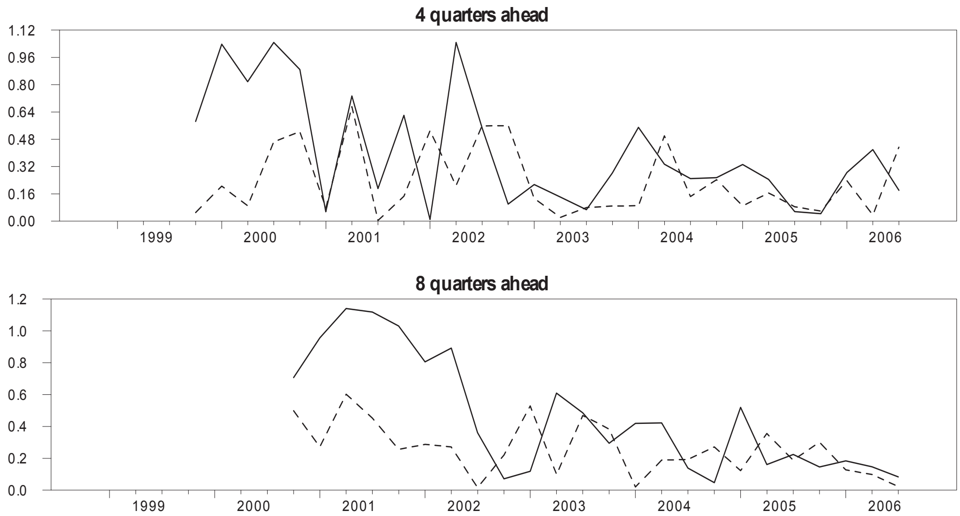
Fischer et al. (2006) also find that the best forecast performance at the six quarter horizon is obtained by means of a simple combination of BMPE projections and M3-based forecasts. The results reported here show that this also holds true for the four and the eight quarter forecast horizon. Besides confirming this result, the evidence reported in this section offers a number of additional interesting insights for the longer forecast horizons of eight and twelve quarters ahead. First, the pattern that the M3-based forecasts outperformed a simple random walk benchmark in the early years of EMU but performed substantially worse than this benchmark in recent years is also found when real-time instead of ex-post revised data are used. Second, the result that the forecasting performance of M3 is restored when a judgementally corrected M3 series is used also holds with real-time data.

Figure 9: Corrected M3-based forecasts vs random walk forecasts



Note: The graphs show the absolute forecast error of the bivariate forecasting model with portfolio shift adjusted M3 growth (dotted line) and of the smooth random walk forecast (solid line).

Figure 10: BMPE and corrected M3 trend growth combined vs random walk forecasts



Note: The graphs show the absolute forecast error of the bivariate forecasting model with portfolio shift adjusted M3 growth (dotted line) and of the smooth random walk forecast (solid line).

7. Conclusions

The money pillar of the ECB's monetary policy strategy, which stresses the importance of monetary indicators, in particular of the broad monetary aggregate M3, for the assessment of medium to long-run risks to price stability, has been exposed to intense criticism from the very beginning. The brisk growth of headline M3 over the period 2001 to 2003, which has not been followed by an acceleration in goods price inflation, appears to support the critics' view and has cast doubt on the usefulness of M3 as an indicator of risks to price stability in the euro area.

This paper assesses the performance of monetary indicators as well as of a large range of economic and financial indicators in predicting euro area HICP inflation over the coming one, two and three years out-of-sample over the period first quarter 1999 till third quarter 2006 considering standard bivariate forecasting models, factor models, simple combination forecasts as well as trivariate two-pillar Phillips Curve forecasting models using both ex-post revised and real-time data.

The analysis of the performance of bivariate forecasting models and trivariate two-pillar Phillips Curve-type forecasting models suggests that forecasting models comprising headline quarter-on-quarter or trend M3 growth produced on average lower forecast errors than a naive random walk model at longer forecasting horizons of two and three years, but tests of equal predictive ability suggest that the M3-based indicator models could not significantly improve over the simple benchmark model, with the exception of very few two-pillar Phillips Curve type forecasting models at the three year forecast horizon. The analysis also reveals that similarly disappointing results are obtained for all other indicators considered. None of the 96 bivariate forecasting models and only 7 out of 88 trivariate forecasting models that were analysed produce a mean squared forecast error that is significantly smaller than that of the random walk model at any forecast horizon, in most cases the mean squared error is even larger. This result echoes the finding of Stock and Watson (2005) for the US that it has become more difficult to beat simple univariate forecasts of inflation in the environment of low inflation that has prevailed since the mid 1980s.

A closer look at the forecasting performance over time reveals that the predictive power of the forecasting models including headline M3 growth has substantially deteriorated in recent years, producing systematically higher forecast errors than the benchmark since 2001. This deterioration of forecasting performance is apparently related to the effects of portfolio shifts into M3 over the 2001 to 2003 period, since a forecasting model including an internal ECB series of M3 corrected for the effects of portfolio shifts significantly improves over the random walk on average at medium-term forecasting horizons and continues to produce accurate forecasts until very recently. These findings also obtain when real-time rather than ex-post revised data are used in the forecasting exercise. Overall, these results suggest that M3 growth continues to be a useful indicator for future price developments in the euro area, but that a thorough and broad based monetary analysis is needed to extract the information content of monetary developments for future inflation.

The analysis further suggests that a considerably improved forecasting performance vis-à-vis the random walk benchmark is obtained when the information from the monetary and the economic analysis are combined. A simple factor forecasting model combining monetary and economic indicators produced on average significantly smaller forecast errors at medium-term forecasting horizons than the random walk and has also recently produced relatively accurate out-of-sample forecasts. The forecasting exercise using real-time data yields a very similar result. Here the average of the forecasts from the monetary analysis, in the form of the forecasts from a bivariate model with the growth rate of portfolio-shift corrected M3, and the forecasts from the economic analysis, in the form of the inflation projections from the ECB/Eurosystem Broad Macroeconomic Projections Exercise (BMPE), produces a significantly lower mean squared forecast error than the random walk benchmark at the one and two year forecast horizon. These findings suggest that the integrated assessment of monetary and economic indicators may help to improve euro area inflation forecasts and confirms that the two pillars of the ECB's strategy cannot be viewed as fully independent from each other.

References

Angelini, E., J. Henry and R. Mestre (2001), Diffusion Index-Based Inflation Forecasts for the Euro Area, ECB Working Paper No. 61.

Assenmacher-Wesche, K. and S. Gerlach (2006), Interpreting Euro Area Inflation at High and Low Frequencies, mimeo, University of Basel.

Atkenson, A. and L. Ohanian (2001), Are Phillips Curves Useful for Forecasting Inflation?, Federal Reserve Bank of Minneapolis Quarterly Review, 25, 2-11.

Begg, D., F. Canova, P. De Grauwe, A.. Fatás, P. Lane (2002), Surviving the Slowdown, Monitoring the European Central Bank 4, CEPR, 2002.

Brand, C. and N. Cassola (2000), A Money Demand System for the Euro Area M3, ECB Working Paper No. 39.

Boivin, J. and S. Ng (2005), Understanding and Comparing Factor Based Forecasts, *International Journal of Central Banking*, 1, 117-151.

Calza, A., C. Gartner and J. Sousa (2001). Modeling the Demand for Loans to the Private Sector in the Euro Area. ECB Working Paper No. 55.

Calza, A., D. Gerdesmeier and J. Levy (2001). Euro Area Money Demand: Measuring the Opportunity Costs Appropriately, IMF Working Paper No.01/179.

Ciccarelli, M., G. Coenen and J. Henry (2006), A real-time database for the euro area, ECB Research Bulletin No 5, 6-8.

Clark T. and M. McCracken (2001), Tests of Equal Forecast Accuracy and Encompassing for Nested Models. *Journal of Econometrics,* 105, 85–100.

Clark T. and M. McCracken (2005), Evaluating Direct Multi-step Forecasts, *Econometrics Review,* 24, 369-404.

Coenen, G. and J.L. Vega (1999), The Demand for M3 in the Euro Area, ECB Working Paper Series No. 6.

De Grauwe P. and M. Polan (2005), Is Inflation Always and Everywhere a Monetary Phenomenon, *Scandinavian Journal of Economics*, 107, 239 - 259.

Diebold, F. and R. Mariano (1995), Comparing Predictive Accuracy, *Journal of Business and Economics Statistics*, 13, 253–263.

Diebold F. and J. Lopez (1996). Forecast Evaluation and Combination, in: G. Maddala and C. Rao (eds.), Handbook of Statistics, North-Holland: Amsterdam.

ECB (1998), A Stability-oriented Monetary Policy Strategy for the ESCB , Press Statement, European Central Bank, October 1998.

ECB (1999), Euro Area Monetary Aggregates and Their Role in the Eurosystem's Monetary Policy Strategy, ECB Monthly Bulletin February 1999, 29-46.

ECB (2003), The ECB's Monetary Policy Strategy, Press Statement, European Central Bank, May 2003

ECB (2004), Monetary Analysis in Real-time, ECB Monthly Bulletin October 2004, 43-63.

ECB (2005), Approaches to Identifying and Estimating Portfolio Shifts into and out of M3, ECB Monthly Bulletin January 2005, 13-16.

ECB (2006), Inflation Forecasts Derived From Monetary Indicators, ECB Monthly Bulletin June 2006, 22-25

Estrella, A., and F. Mishkin (1997), Is There a Role for Money in Monetary Policy? *Journal of Monetary Economics* 40, 279-304

Fischer, B., M. Lenza, H. Pill and L. Reichlin (2006), Money and Monetary Policy: ECB 1999-2006, paper presented at the 4th ECB Central Banking Conference, 10-11 November 2006.

Forni, M., M. Hallin, M. Lippi, and L. Reichlin (2003), Do Financial Variables Help Forecasting Inflation and Real Activity in the Euro Area?, *Journal of Monetary Economics* 50, 1243-1255.

Galí, J., S. Gerlach, J. Rotemberg, H. Uhlig and M. Woodford (2004), The Monetary Policy Strategy of the ECB Reconsidered: Monitoring the European Central Bank 5. London, Centre for Economic Policy Research.

Gerlach, S. (2003), The ECB's Two Pillars. CEPR Discussion Paper No 3689.

Gerlach, S. (2004), The Two Pillars of the European Central Bank, *Economic Policy*, 40, 389-439.

Giacomini, R. and H. White (2004), Tests of Conditional Predictive Ability, mimeo, Boston College.

Greiber, C. and W. Lemke (2005), Money Demand and Macroeconomic Uncertainty Deutsche Bundesbank Discussion Paper No. 26/2005.

Granger, C. (1990), Modelling Economic Time Series: Readings in Econometric Methodology, Oxford University Press: Oxford, UK.

Hendry D. and M. Clements (2002), Pooling of Forecasts, *Econometrics Journal* 5, 1–26

Hofmann, B. (2006), Do monetary indicators (still) predict inflation in the euro area?, Deutsche Bundesbank Discussion Paper No. 18/2006.

Kapetanios, G. and M. Marcellino (2004), A Parametric Estimation Method for Dynamic Factor Models of Large Dimensions, Queen Mary University of London, Working Paper 489.

Lenza, M. (2006), Does money help to forecast inflation in the euro area?, mimeo, European Central Bank.

Marcellino, M., J. Stock and M. Watson (2001), Macroeconomic Forecasting in the Euro Area: Country Specific versus Area-Wide Information, IGIER Working Paper No.201, Bocconi University.

Marcellino, M., J. Stock and M. Watson (2004), A Comparison of Direct and Iterated Multistep AR Methods for Forecasting Macroeconomic Time Series, mimeo, Harvard University.

Neumann, M. J. M. (2003). The European Central Bank's First Pillar Reassessed , *Working Paper* March 03, IIW Bonn University.

Neumann, M. J.M. and C. Greiber (2004), Inflation and Core Money Growth in the Euro Area. Discussion Paper 36/2004, Deutsche Bundesbank.

Newbold, P. and D. Harvey (2002), Forecast Combination and Encompassing, in: M. Clements and D. Hendry (eds.), *A Companion to Economic Forecasting*,; Blackwell Press: Oxford, 268–283.

Nicoletti Altimari, S. (2001), Does Money Lead Inflation in the Euro Area? ECB Working Paper 63

Pesaran, H. and P. Zaffaroni (2006), Model Averaging and Value-at-Risk Based Evaluation of Large Multi Asset Volatility Models for Risk Management, mimeo, University of Cambridge.

Stock, J. and M. Watson (1999), Forecasting Inflation. *Journal of Monetary Economics* 44, 293–335.

Stock, J. and M. Watson. (2002a), Macroeconomic Forecasting Using Diffusion Indexes. *Journal of Business and Economic Statistics* 20, 147-162.

Stock, J. and M. Watson. (2002b), Forecasting Using Principal Components from a Large Number of Predictors. *Journal of the American Statistical Association* 97, 1167–1179.

Stock, J. and M. Watson. (2003), Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature* 41, 788-829

Stock, J. and M. Watson (2004), Combination Forecasts of Output Growth in a Seven-Country Data Set, mimeo, Harvard University.

Stock, J. and M. Watson (2005), Has Inflation Become Harder to Forecast?, mimeo, Harvard University.

Trecroci, C., und J. L. Vega (2002), The Information Content of M3 for Future Inflation. *Weltwirtschaftliches Archiv* 138, 22-53

von Hagen, J. and B. Hofmann (2003), Monetary Policy Orientation in Times of Low Inflation, paper presented at the conference on 'Monetary policy under low inflation, Federal Reserve Bank of Cleveland, November 2003, forthcoming in conference proceedings.

West, K. (1996), Asymptotic Inference About Predictive Ability. *Econometrica* 64, 1067 – 1084.

Woodford, M. (2006), Is Money Important for Monetary Policy?, paper presented at the 4th ECB Central Banking Conference, 10-11 November 2006.

Appendix

List of data series used in the empirical analysis in Section 4

Variable	Source
Harmonised index of consumer prices (HICP)	Eurostat, ECB
Monetary aggregate M1 (index)	ECB
Monetary aggregate M2 (index)	ECB
Monetary aggregate M3 (index)	ECB
M3's own rate of return	ECB
MFI loans to the private sector (index)	ECB
Nominal Gross Domestic Product	Eurostat, ECB
Real Gross Domestic Product	Eurostat, ECB
Deflator Gross Domestic Product	Eurostat, ECB
Nominal Private Consumption	Eurostat, ECB
Real Private Consumption	Eurostat, ECB
Deflator Private Consumption	Eurostat, ECB
Nominal Fixed Capital Formation (investment)	Eurostat, ECB
Real Fixed Capital Formation (investment)	Eurostat, ECB
Deflator Fixed Capital Formation (investment)	Eurostat, ECB
Nominal Government Consumption	Eurostat, ECB
Real Government Consumption	Eurostat, ECB
Deflator Government Consumption	Eurostat, ECB
Nominal Exports	Eurostat, ECB
Real Exports	Eurostat, ECB
Deflator Exports	Eurostat, ECB
Nominal Imports	Eurostat, ECB
Real Imports	Eurostat, ECB
Deflator Imports	Eurostat, ECB
Euro area trade, Extra euro area exports, value	Eurostat, ECB
Euro area trade , Extra euro area imports, value	Eurostat, ECB
Euro area trade, Intra euro area exports, value	Eurostat, ECB

Euro area trade , Intra euro area imports, value	Eurostat, ECB
Employment	Eurostat, ECB
Unemployment rate	Eurostat, ECB
Compensation to employees (wages)	Eurostat, ECB
Labour productivity	Eurostat, ECB
Unit labour costs	Eurostat, ECB
Industrial production, Total industry (excl. construction	Eurostat, ECB
Industrial production, Manufacturing	Eurostat, ECB
Industrial production, Capital goods industry	Eurostat, ECB
Industrial production, Intermediate goods industry	Eurostat, ECB
Industrial production, Manufacture of electrical machinery	Eurostat, ECB
Producer price index, Total industry (excl. construction)	Eurostat, ECB
Producer price index, Manufacturing	Eurostat, ECB
Industry Survey: Industrial Confidence Indicator-Balances	EU Commission
Industry Survey: Production trend observed in recent months – Balances	EU Commission
Industry Survey: Assessment of order-book levels - Balances	EU Commission
Industry Survey: Assessment of export order-book levels – Balances	EU Commission
Industry Survey: Assessment of stocks of finished products – Balances	EU Commission
Industry Survey: Production expectations for the months ahead – Balances	EU Commission
Industry Survey: Selling price expectations for the months ahead – Balances	EU Commission
Construction Survey: Construction Confidence Indicator – Balances	EU Commission
Construction Survey: Trend of activity compared with preceding months – Balances	EU Commission
Construction Survey: Assessment of order books – Balances	EU Commission
Construction Survey: Employment expectations for the months ahead – Balances	EU Commission
Construction Survey: Price expectations for the months ahead – Balances	EU Commission
Retail trade, except of motor vehicles and motorcycles	Eurostat, ECB
Effective nominal exchange rate, core group of currencies against Euro	ECB
Nominal exchange rate $/€	ECB
Nominal exchange rate ¥/€	ECB

Nominal exchange rate £/€	ECB
World market prices of raw materials, € basis	HWWA, ECB
World market prices of crude oil, € basis	ECB
Gold price /fine ounce, € basis	ECB
3 months money market rate	Reuters, ECB
2 year government bond yield	Reuters, ECB
5 year government bond yield	Reuters, ECB
10 year government bond yield	Reuters, ECB
Share price index	Global Financial Data
Price-earnings ratio	Global Financial Data

European Central Bank Working Paper Series

For a complete list of Working Papers published by the ECB, please visit the ECB's website (http://www.ecb.europa.eu).

827 "How is real convergence driving nominal convergence in the new EU Member States?" by S. M. Lein-Rupprecht, M. A. León-Ledesma, and C. Nerlich, November 2007.

828 "Potential output growth in several industrialised countries: a comparison" by C. Cahn and A. Saint-Guilhem, November 2007.

829 "Modelling inflation in China: a regional perspective" by A. Mehrotra, T. Peltonen and A. Santos Rivera, November 2007.

830 "The term structure of euro area break-even inflation rates: the impact of seasonality" by J. Ejsing, J. A. García and T. Werner, November 2007.

831 "Hierarchical Markov normal mixture models with applications to financial asset returns" by J. Geweke and G. Amisano, November 2007.

832 "The yield curve and macroeconomic dynamics" by P. Hördahl, O. Tristani and D. Vestin, November 2007.

833 "Explaining and forecasting euro area exports: which competitiveness indicator performs best?" by M. Ca' Zorzi and B. Schnatz, November 2007.

834 "International frictions and optimal monetary policy cooperation: analytical solutions" by M. Darracq Pariès, November 2007.

835 "US shocks and global exchange rate configurations" by M. Fratzscher, November 2007.

836 "Reporting biases and survey results: evidence from European professional forecasters" by J. A. García and A. Manzanares, December 2007.

837 "Monetary policy and core inflation" by M. Lenza, December 2007.

838 "Securitisation and the bank lending channel" by Y. Altunbas, L. Gambacorta and D. Marqués, December 2007.

839 "Are there oil currencies? The real exchange rate of oil exporting countries" by M. M. Habib and M. Manolova Kalamova, December 2007.

840 "Downward wage rigidity for different workers and firms: an evaluation for Belgium using the IWFP procedure" by P. Du Caju, C. Fuss and L. Wintr, December 2007.

841 "Should we take inside money seriously?" by L. Stracca, December 2007.

842 "Saving behaviour and global imbalances: the role of emerging market economies" by G. Ferrucci and C. Miralles, December 2007.

843 "Fiscal forecasting: lessons from the literature and challenges" by T. Leal, J. J. Pérez, M. Tujula and J.-P. Vidal, December 2007.

844 "Business cycle synchronization and insurance mechanisms in the EU" by A. Afonso and D. Furceri, December 2007.

845 "Run-prone banking and asset markets" by M. Hoerova, December 2007.

846 "Information combination and forecast (st)ability. Evidence from vintages of time-series data" by C. Altavilla and M. Ciccarelli, December 2007.

847 "Deeper, wider and more competitive? Monetary integration, Eastern enlargement and competitiveness in the European Union" by G. Ottaviano, D. Taglioni and F. di Mauro, December 2007.

848 "Economic growth and budgetary components: a panel assessment for the EU" by A. Afonso and J. González Alegre, January 2008.

849 "Government size, composition, volatility and economic growth" by A. Afonso and D. Furceri, January 2008.

850 "Statistical tests and estimators of the rank of a matrix and their applications in econometric modelling" by G. Camba-Méndez and G. Kapetanios, January 2008.

851 "Investigating inflation persistence across monetary regimes" by L. Benati, January 2008.

852 "Determinants of economic growth: will data tell?" by A. Ciccone and M. Jarocinski, January 2008.

853 "The cyclical behavior of equilibrium unemployment and vacancies revisited" by M. Hagedorn and I. Manovskii, January 2008.

854 "How do firms adjust their wage bill in Belgium? A decomposition along the intensive and extensive margins" by C. Fuss, January 2008.

855 "Assessing the factors behind oil price changes" by S. Dées, A. Gasteuil, R. K. Kaufmann and M. Mann, January 2008.

856 "Markups in the euro area and the US over the period 1981-2004: a comparison of 50 sectors" by R. Christopoulou and P. Vermeulen, January 2008.

857 "Housing and equity wealth effects of Italian households" by C. Grant and T. Peltonen, January 2008.

858 "International transmission and monetary policy cooperation" by G. Coenen, G. Lombardo, F. Smets and R. Straub, January 2008.

859 "Assessing the compensation for volatility risk implicit in interest rate derivatives" by F. Fornari, January 2008.

860 "Oil shocks and endogenous markups: results from an estimated euro area DSGE model" by M. Sánchez, January 2008.

861 "Income distribution determinants and public spending efficiency" by A. Afonso, L. Schuknecht and V. Tanzi, January 2008.

862 "Stock market volatility and learning" by K. Adam, A. Marcet and J. P. Nicolini, February 2008.

863 "Population ageing and public pension reforms in a small open economy" by C. Nickel, P. Rother and A. Theophilopoulou, February 2008.

864 "Macroeconomic rates of return of public and private investment: crowding-in and crowding-out effects" by A. Afonso and M. St. Aubyn, February 2008.

865 "Explaining the Great Moderation: it is not the shocks" by D. Giannone, M. Lenza and L. Reichlin, February 2008.

866 "VAR analysis and the Great Moderation" by L. Benati and P. Surico, February 2008.

867 “Do monetary indicators lead euro area inflation?” by B. Hofmann, February 2008.

ISSN 1561-0810