DEUTSCHE
BUNDESBANK

Do monetary indicators (still) predict euro area inflation?

Boris Hofmann

Discussion Paper
Series 1: Economic Studies
No 18/2006

Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-1
Telex within Germany 41227, telex from abroad 414431, fax +49 69 5601071

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

ISBN 3–86558–159–5 (Printversion)
ISBN 3–86558–160–9 (Internetversion)

Abstract

This paper assesses the performance of monetary indicators in predicting euro area HICP inflation out-of-sample over the period since the start of EMU considering a wide range of forecasting models, including standard bivariate forecasting models, factor models, simple combination forecasts as well as trivariate two-pillar Phillips Curve type forecasting models. The results suggest that monetary indicators are still useful indicators for inflation 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.

Keywords: euro area, inflation, leading indicators, money

JEL classifications: E31, E40, C32

Non-technical Summary

This paper assesses the performance of monetary indicators in predicting euro area HICP inflation out-of-sample over the period 1999Q1 till 2005Q4 considering standard bivariate forecasting models, factor models, simple combination forecasts as well as trivariate two-pillar Phillips Curve type forecasting models, combining trend M3 growth with other non-monetary indicators. In contrast to the existing studies on inflation forecasting for the euro area, this study employs and compares both direct and iterated forecasting models.

The results suggest that M3, especially its trend or core growth rate, was on average a useful indicator for inflation at medium term horizons, which is consistent with the role of the monetary analysis in the ECB's monetary policy strategy as a tool for the assessment of the medium to long-term risks to price stability. But, a closer look at the forecasting performance reveals that, over the last three years, the forecasting performance of M3 has not been as good anymore as it used to be in the early years of EMU.

The further analysis reveals, however, that it might be premature to neglect monetary indicators on these grounds. We find that a simple combination of all monetary forecasts performs well also over the more recent period. Also, the extremely good and stable performance of an M3 series corrected for the effects of portfolio shifts into and out of M3 since mid 2001 constructed by the ECB suggests that M3 is still a very useful indicator for future price movements once the distorting effects of speculative portfolio flows are identified and removed. These results therefore suggest on the whole that monetary indicators are still useful indicators for inflation 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.

Nicht-technische Zusammenfassung

Dieses Papier untersucht die Güte monetärer Prognosen der HVPI Inflationsrate im Euroraum über den Zeitraum erstes Quartal 1999 bis zum vierten Quartal 2005. Die Analyse stützt sich auf einfache bivariate Prognosemodelle, Faktorenmodelle, Prognosekombinationsverfahren sowie trivariate "Zwei-Säulen" Phillips-Kurven Prognosemodelle, bei denen die Trendwachstumsrate von M3 mit anderen, nicht-monetären Indikatoren kombiniert wird. Im Gegensatz zu anderen Studien zur Inflationsprognose im Euroraum verwendet und vergleicht die vorliegende Studie sowohl direkte als auch iterative Prognosemodelle.

Die Ergebnisse deuten darauf hin, dass vor allem die Trend-, oder Kernwachstumsrate von M3 über den gesamten Betrachtungszeitraum ein nützlicher Indikator für die mittelfristige Inflationsentwicklung im Euroraum war. Dieses Resultat ist konsistent mit der Rolle der monetären Analyse in der geldpolitischen Strategie der EZB als ein Werkzeug zur Einschätzung der mittel- bis langfristigen Risiken für die Preisstabilität. Eine genauere Analyse der Entwicklung der Prognosegüte über die Zeit zeigt allerdings, dass die Güte von monetären Inflationsprognosen in den letzten drei Jahren nicht so gut war wie in den ersten Jahren der Währungsunion.

Die weitere Analyse verdeutlicht jedoch, dass es voreilig wäre, auf Basis dieser Evidenz monetäre Indikatoren zu vernachlässigen. Zum einen liefern einfache Kombinationen monetärer Inflationsprognosen auch in jüngerer Zeit befriedigende Ergebnisse. Zum anderen zeigt sich, dass über den gesamten Erhebungszeitraum sehr gute Inflationsprognosen auf Basis einer von der EZB konstruierten, um die Effekte spekulativer Portfolioumschichtungen bereinigten M3 Reihe erzielt werden können. Diese Ergebnisse legen den Schluss nahe, dass monetäre Indikatoren nach wie vor nützliche Informationen über die zukünftige Inflationsentwicklung im Euroraum liefern, dass allerdings eine sorgfältige und breit angelegt monetäre Analyse notwendig ist, um diese Informationen offenzulegen.

Contents

List of Tables

List of Figures

Do Monetary Indicators (still) Predict Euro Area Inflation? *

1. Introduction

The main elements of the ECB's monetary policy strategy, announced on 13 October 1998 (ECB,1998) and confirmed and clarified on 8 May 2003 (ECB, 2003), 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 (Money Pillar).[1]

The prominent role assigned to money in the ECB's monetary policy strategy was mainly motivated by the conviction that the development of the price level in the medium to long-term is a monetary phenomenon (ECB, 1999), which 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 (e.g. Gerlach and Svensson 2000, Trecroci and Vega 2002 and Nicoletti Altimari 2001).

However, the ECB's special emphasis on the monetary analysis has been subject to intense criticism from the very beginning. Besides theoretically motivated reservations against the

* I thank Jörg Breitung, Claus Greiber, Heinz Herrmann, Christian Schumacher, Jens Weidmann and Andreas Worms for helpful comments and suggestions. The views expressed in this paper are solely my own and do not necessarily represent the views of the Deutsche Bundesbank.

[1] 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." In this context, the ECB has further clarified that these medium to long-term risks to price stability are assessed 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."

money pillar,[2] it has also been argued that money might be an unreliable indicator for inflation because of frequent shifts in velocity.[3] In fact, since the beginning of EMU the annual growth rate of the M3 monetary aggregate was almost continuously above the ECB's reference value of 4.5%, since mid 2001 even substantially so, without showing signs of reversion or triggering a tightening of policy rates or an acceleration in goods price inflation. These developments appear to support the critics' view and have cast doubt on the usefulness of M3 as an indicator of risks to price stability in the euro area.

In this paper we want to assess this issue by testing the performance of monetary indicators in predicting euro area HICP inflation out-of-sample over the period 1999Q1 till 2005Q4.[4] In contrast to the existing studies on inflation forecasting for the euro area, this study employs and compares both direct and iterated forecasting models. Direct forecasts involve regressing an h-period-ahead value of the dependent variable on its own lags and lagged values of other indicators. H-periods ahead out-of-sample forecasts are then calculated as a one-step ahead forecast from the estimated forecasting regression. Iterated forecasts entail estimating a VAR or near-VAR model comprising the variable to be forecast and the other indicator variables taken into account in the forecasting model. H-periods ahead forecasts are then obtained by iterating the estimated VAR h-periods forward. Most empirical forecasting studies rely on the direct approach to forecasting, motivated by theoretical findings that the h-step ahead projection approach reduces the potential impact of specification error. However, the widely accepted view that direct forecasting models are superior has recently been challenged. Marcellino, Stock and Watson (2004) argue that choosing between direct and iterated forecasts involves a trade-off between potential estimation bias and estimation variance.

[2] As Galí (2003) puts it, while the pillar associated with the economic analysis can be related to modern New Keynesian style models, "it is much harder, however, to think of a class of models that would attribute a more direct role to money in the determination of inflation and which central bankers could view as useful."

[3] 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).

[4] 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 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.

While the direct forecasts reduce the impact of model mis-specification bias, the iterated forecasts produce more efficient forecasts when the models are correctly specified. In the following we estimate both direct and iterated forecasting models of euro area HICP inflation in order to see which approach works best for forecasting euro area inflation. This dual approach also serves as a robustness check of the findings on the predictive ability of the indicators considered.

The analysis starts by assessing the forecasting performance of simple bivariate forecasting models considering a large number of aggregate euro area monetary and non-monetary indicators. The forecasting performance of the indicators is evaluated against the forecasts produced by simple autoregressive forecasting models of inflation. By taking a closer look at the forecast errors we assess whether the forecasting performance of monetary indicators has deteriorated over the more recent period. We also consider the performance of factor based forecasts and simple forecast combination methods, which have commonly been found to improve upon single indicator based forecasts.

Besides these more standard forecasting exercises, we further assess the usefulness of trivariate forecasting models, combining the low frequency component of M3 growth with other non-monetary indicators. This exercise is motivated by the recent literature on the role of monetary aggregates in explaining inflation dynamics in the euro area. Gerlach (2003, 2004) has suggested to interpret the ECB's two pillar strategy 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, which can be formalised by a two-pillar Phillips Curve, adding trend or core money growth to an otherwise standard empirical Phillips Curve. 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. In this paper we aim to fill this gap by considering the out-of-sample performance of trivariate two-pillar Phillips curve type forecasting models.

Finally, we assess the relevance of the estimated effect of portfolio shifts on the out-of-sample forecasting performance of M3 based indicators. The ECB has commonly argued that the high

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

growth rates of M3 observed since mid 2001 were driven by portfolio shifts caused by a strong preference of investors for liquid assets in the wake of the exceptional economic and financial uncertainties during this period and that the otherwise close link between M3 and inflation has been temporarily blurred by this effect.[6] The ECB constructs a measure of M3 corrected for the effect of portfolio shifts based on an ARIMA model of M3 augmented with intervention variables to capture the effects of portfolio shifts into and out of M3.[7] In order to assess the effect of the estimated portfolio shift effects on the indicator property of M3 we also assess the forecasting performance of the corrected M3 measure. Clearly, the portfolio shift correction of the M3 aggregate is done based on ex-post information and was not available ex-ante, so that the forecasting exercise is not a real assessment of the out-of-sample performance of the corrected M3 measure. However, analysing the indicator property of the corrected M3 measure is still useful as it gives an indication of whether M3 is in principle still a useful indicator of inflation and whether the corrected M3 measure might be useful for the current assessment of future risks to price stability.

The paper is organised as follows. In section 2 we assess the performance of simple univariate and bivariate forecasting models. Section 3 investigates the performance of forecasts based on factor analysis and simple forecast combination methods. In section 4 we assess the performance of trivariate two-pillar Phillips Curve type forecasting models combining the low frequency component of M3 growth with other non-monetary indicators. In section 5 we investigate whether adjusting the euro area M3 series for the estimated effect of portfolio shifts helps to improve the performance of M3 based indicators in forecasting inflation over the more recent period. Section 6 concludes.

2. Standard autoregressive and bivariate forecasting models

In this section we assess the performance of univariate and bivariate forecasting models in forecasting euro area HICP inflation over the period 1999Q1 till 2005Q4 in a pseudo or simulated out-of-sample set-up. This means that forecasts are calculated using only data prior to the forecasting period in order to most accurately reflect the data limitation faced by

[6] See e.g. ECB (2004).
[7] For details see ECB (2005).

forecasters in real time.[8] The analysis employs both direct and iterated forecasting models and is based on quarterly aggregate euro area data available for the period 1980Q1 till 2005Q4.[9] Unless otherwise indicated, all data are official aggregate euro area data taken from the ECB website, backdated with the corresponding series from the Area Wide Model (AWM) database if necessary. The sample period for the recursive forecasting regressions starts in 1985Q1 in order to insure identical sample periods for all forecasting regressions and also to mitigate the effect of the disinflation of the early 1980s on the results. The range of forecast horizons considered is 1 to 12 quarters.

As a first step we assess simple univariate forecasting models of inflation, modelling the inflation process solely as a function of its own lags. The univariate direct forecasting model takes the form:

$$(1) \qquad \pi_{t+h}^{h} = \beta_0 + \beta_1(L)\pi_t + u_{t+h}^{h},$$

where π_t is the quarterly HICP inflation rate and π_{t+h}^{h} is the h-period ahead rate of change in the HICP, so $\pi_{t+h}^{h} = (400/h)\ln(HICP_{t+h}/HICP_t)$. The lag order was recursively determined based on the Schwarz-Bayes information criterion (SBC) considering up to four lags. Since we consider forecast horizons of 1 to 12 quarters, this means that we estimate at each recursion twelve forecasting models (one for each forecast horizon), compare for each forecasting model four model specifications and calculate one step ahead forecasts based on the model with the best SBC.

The iterated autoregressive forecasting model is given by:

$$(2) \qquad \pi_{t+1} = \beta_0 + \beta_1(L)\pi_t + u_{t+1},$$

where again the lag order of the lagged endogenous variable was recursively selected using the SBC. Here we estimate at each recursion only one forecasting model, compare four specifications and calculate one to twelve steps ahead forecasts based on the model selected

[8] 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. Such a real time database does unfortunately not exist for the euro area.

[9] A possible complementary approach to construct forecasts for euro area aggregates is to aggregate individual country forecasts. See e.g. Marcellino et al. (2001) and Angelini et al. (2001).

by the SBC. Since equation (2) generates forecasts for quarterly inflation we have to obtain the forecast for the h-period ahead inflation rate by calculating at each turn the h-period ahead average of the quarterly inflation forecasts.

In Table 1 we report the Root-Mean-Squared forecast error (RMSE) produced by the univariate forecasting models over the period 1999Q1 till 2005Q4. We also show the RMSE produced by a simple random walk forecast, which takes the last observed inflation rate as the forecast. Finally, we report in the last row of the table the ratio of the Mean squared forecast error (MSE) produced by the direct forecast to the MSE produced by the iterated forecasts with the p-value of the test the ratio is equal to one, i.e. that the forecast performance was not significantly different, in parentheses.[10] The results show that both autoregressive models clearly outperform the random-walk forecast. The iterated forecasts perform slightly better than the direct forecasts, but not significantly so. A look at the absolute forecast errors produced by the two competing models since 1999 (Figure 1) shows that the iterated forecast model also performs better in the majority of periods, though, with few exceptions, only by a small margin.[11]

Table 1: Performance of univariate forecasting models

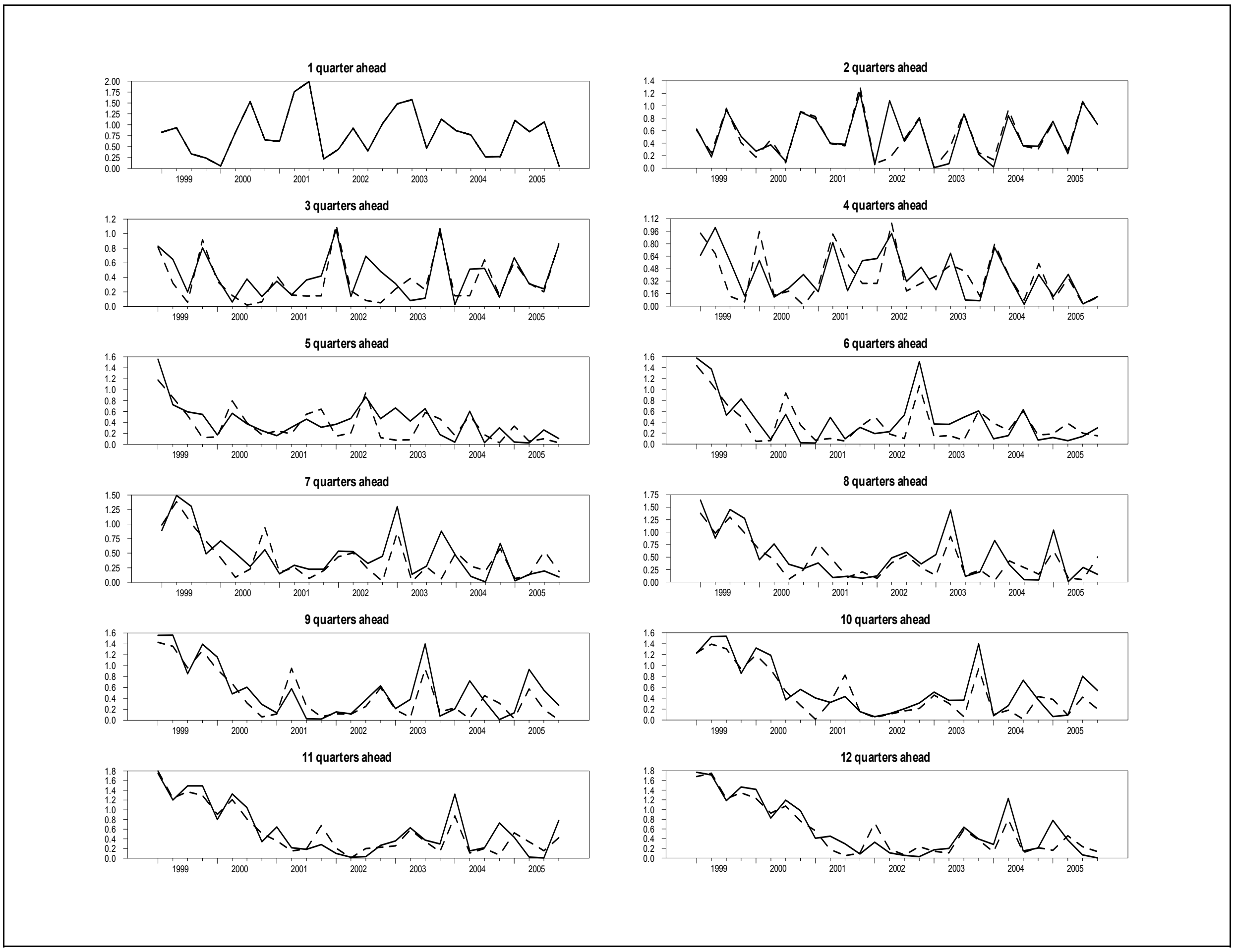
h	1	2	3	4	5	6	7	8	9	10	11	12
RMSE Direct forecast	0.96	0.62	0.52	0.49	0.52	0.61	0.61	0.70	0.72	0.74	0.78	0.81
RMSE Iterated forecast	0.96	0.61	0.47	0.49	0.46	0.53	0.54	0.58	0.62	0.64	0.71	0.75
RMSE Random-walk forecast	1.29	1.08	0.91	0.89	0.90	0.91	0.89	0.94	0.94	0.94	0.94	0.93
Direct vs iterated forecasts	1.00 -	1.05 (0.81)	1.19 (0.58)	0.97 (0.72)	1.25 (0.63)	1.30 (0.75)	1.30 (0.76)	1.43 (0.82)	1.33 (0.88)	1.35 (0.92)	1.20 (0.94)	1.16 (0.97)

Note: The table reports the root mean squared forecast error (RMSE) for the direct, the iterated and the random walk forecasting model over the period 1999Q1 till 2005Q4. The last row reports the ratio of the mean squared forecast error (MSE) generated by the direct forecasting model to the MSE of the iterated forecasting model with p-values of a test that it is equal to one in parentheses. An MSE ratio smaller (larger) than one therefore indicates that the direct model performs better (worse) than the iterated model.

[10] The standard error for the MSE ratio was calculated based on a heteroskedasticity and autocorrelation consistent (HAC) estimate of the variance-covariance (VCV) matrix of the forecast errors using the δ-method. The HAC estimate of the VCV matrix was obtained using a Bartlett kernel with the number of lags equal to the forecast horizon. This approach to forecast evaluation, which has been suggested by West (1996), is applicable in this context since the direct and iterated forecasting models are non-nested at forecast horizons 2 to 12.

[11] The finding that the iterated forecasts perform in general better than the direct forecasts is consistent with the findings by Marcellino et al. (2004) for the US.

Figure 1: Performance of univariate inflation forecasts



Note: The plots show the absolute forecast errors for the autoregressive direct forecasting model (solid line) and the autoregressive iterated forecasting model (dotted line).

Taking the autoregressive forecasts as the benchmark, we assess as the next step bivariate forecasting models of inflation, modelling the inflation process as a function of its own lags and lags of one other indicator variable *x*. The bivariate direct forecasting model is given by:

(3) $$\pi_{t+h}^{h} = \beta_0 + \beta_1(L)\pi_t + \beta_2(L)x_t + u_{t+h}^{h}$$

and the bivariate iterated forecasting model is given by a SUR of the form:

(4) $$\begin{aligned} \pi_{t+1} &= \beta_0 + \beta_1(L)\pi_t + \beta_2(L)x_t + u_{t+1} \\ x_{t+1} &= \lambda_0 + \lambda_1(L)x_t + \lambda_2(L)\pi_t + v_{t+1} \end{aligned}$$

The lag order was again determined based on the SBC, allowing for different lag orders across regressors and also across equations in the case of the iterated forecasting model searching respectively over up to four lags. Forecasts were then computed in the same way as for the univariate forecasting models.

The performance of the single indicator forecasting models is evaluated based on the ratio of the MSE produced by the bivariate models to the MSE produced by the respective univariate model. A caveat is that the evaluation has to be based on the relative MSE number only. Due to the recursive lag order selection, the bivariate and univariate models are at some dates nested and at some dates not, so that neither the forecast evaluation approach suggested by West (1996) for non-nested models nor the approach suggested by Clark and McCracken (2001) for nested models is applicable (Stock and Watson, 2003).[12]

We consider four monetary growth indicators: The quarterly growth rates of the monetary aggregates M1, M2, M3 and of bank loans to the private sector (dm1, dm2, dm3, dloans).[13] Against the background of the recent literature which has stressed that it is only the low frequency movements in M3 which are relevant for inflation[14] we also consider the trend, or core growth rate of the M3 aggregate (dm3t), calculated using a one side Hodrick-Prescott (HP) filter with a smoothing parameter of 1600.[15] We further consider three M3 indicators derived from the long-run money demand model: the change in p-star (dpstar), the real money gap (mgap) and the monetary overhang (mov). These indicators are derived from a recursively estimated long-run M3 demand function using the current consensus specification proposed by Calza et al (2001)[16] given by $(m-p)_t = a_0 + a_1 y_t + a_2 oc_t + u_t$, where m is the (log) M3, p is the (log) GDP deflator, y is (log) real GDP and oc is the opportunity cost of

[12] 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.

[13] The seasonally adjusted series for private sector loans from the ECB website was spliced with the series constructed by Calza et al. (2001) in 1991Q1. All quarterly monetary series are monthly averages.

[14] See e.g. Gerlach (2003, 2004), Neumann and Greiber (2005) and, more recently, Assenmacher-Wesche and Gerlach (2006).

[15] We 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.

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

holding M3, measured as the spread of the three months money market rate over M3's own rate of return.[17] 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 variables which was calculated using a one sided HP filter with a smoothing value of 1600. 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 $u_t = (m_t - p_t) - a_0 - a_1 y_t - a_2 oc_t$.

Besides these eight monetary indicators we further consider a number of non-monetary indicators: quarterly real GDP growth (dgdpr), the level and first difference of the output gap[18] (ygap and dygap), the level and first difference of the unemployment rate (unr and dunr), the log level and quarterly growth rate of total employment (emp and demp), the level and first difference of the short-term interest rate (irs and dirs), level and first difference of the long-term interest rate (irl and dirl), the yield spread (long-term rate less short-term rate), the quarterly rate of change in the share price index (dsp), the quarterly rate of change in the producer price index (dppi), the log level and quarterly growth rate of real unit labour costs[19] (rulc and drulc), the quarterly rate of change in nominal unit labour costs (dulc), quarterly nominal wage inflation (dwage), quarterly import price inflation (dimpp), the quarterly rate of change in the nominal effective exchange rate (dexr), the quarterly rate of change in the euro based commodity price index[20] (dcom) and the quarterly rate of change the euro based world oil price index[21] (doil).

Tables 2 and 3 present the results. An MSE ratio less (larger) than one means that the bivariate model has produced a lower (larger) MSE than the autoregressive model. The results suggest that the M3 growth indicators improve upon the autoregressive forecast at forecast horizons beyond six to eight quarters, while the M3-demand based indicators as well as the other monetary growth indicators do in general not outperform the autoregressive forecast. In

[17] The data for the own rate of M3 were taken from Calza et al (2001) and extended by own calculations using Bundesbank data.

[18] The output gap is calculated as the percent deviation of real GDP from its long-run trend obtained using a one sided HP filter with smoothing parameter 1600.

[19] Nominal unit labour cost deflated with the GDP deflator.

[20] The commodity price index is the HWWA US-$ based commodity price index converted to € using the historical €-$ exchange rate from the OECD Economic Outlook database.

[21] The oil price index is the US-$ average price of crude petroleum from the IMF International Financial Statistics database also converted to € using the historical €-$ exchange rate series.

accordance with the findings of the recent literature on the information content of low frequency movements in money for inflation already referred to above, we find that the best performing monetary indicator is the one sided HP-filtered M3 growth rate. In the group of non-monetary indicators, only the change in nominal wages and, to a lesser extent, the change in nominal unit labour costs, generate better forecasts than the autoregressive forecasting models. In fact, nominal wage inflation is the best performing single indicator at forecast horizons beyond four quarters, except for direct forecasts beyond the two year horizon, where the M3 growth indicators perform better. A more detailed assessment of the relative performance of the direct and the iterated forecasting approach is provided in the appendix.

On the whole, the results suggest that M3 growth contains useful information about future HICP inflation in the euro area at least at longer prediction horizons. This finding is consistent with the results reported by Nicoletti Altimari (2001). However, as we have already discussed in the introduction, since 2001 euro area M3 growth has been well above the ECB's reference value, without triggering an acceleration of inflation or an increase in ECB policy rates. This suggests that the usefulness of M3 growth as an inflation indicator may have deteriorated over the more recent time period.

In order to assess this point we take a closer look at the forecast errors produced by the M3 growth indicator models over time. Figures 2 and 3 show the absolute forecast errors produced by the quarterly M3 growth model and the trend M3 growth model respectively together with the absolute forecast error produced by the autoregressive forecasting model. The graphs reveal that the good average forecasting performance of the M3 growth indicators for longer forecast horizons over the sample period is mainly driven by the very good performance of these indicators, especially for the direct forecasting models, over the first two years of EMU. Since 2003, however, the money growth indicators cannot outperform the autoregressive forecasts anymore. Compared to this, the forecasting performance of wage inflation, which we show in Figure 4, has been more stable. The wage inflation based forecasts did not perform as well as the direct money growth forecasts in 1999 and 2000, but continuously outperform the autoregressive forecasts over the full sample period.

Table 2: Bivariate direct forecasting models

h	1	2	3	4	5	6	7	8	9	10	11	12
					Monetary indicators							
dm3	1.05	1.11	1.13	1.28	1.11	1.06	1.10	0.95	0.76	0.61	0.48	0.43
dm3t	0.99	1.06	1.27	1.40	1.24	0.86	0.78	0.61	0.47	0.48	0.49	0.42
dpstar	1.09	1.08	1.03	1.02	1.01	1.01	1.00	0.97	0.93	0.92	0.91	0.89
mgap	1.17	1.49	1.71	2.20	1.91	1.53	1.26	1.01	1.00	0.96	0.94	1.03
movc	1.17	1.49	1.95	2.78	2.73	2.18	1.86	1.27	1.04	0.96	0.79	0.71
dm1	1.03	0.93	1.03	1.14	1.03	1.05	1.07	1.09	1.17	1.28	1.35	1.30
dm2	1.03	1.01	1.01	1.05	1.00	0.86	0.97	0.95	0.94	0.95	0.95	0.92
dloans	0.94	0.89	1.08	1.35	1.84	1.47	1.85	1.88	1.59	1.50	1.32	1.28
					Non-monetary indicators							
dgdpr	1.06	1.09	1.05	1.01	1.27	1.24	1.10	1.00	0.98	0.98	0.97	0.97
ygap	1.11	1.09	1.01	1.06	1.10	1.16	1.16	1.12	1.11	1.11	1.08	1.09
dygap	1.14	1.15	1.06	1.05	1.01	0.90	1.01	1.00	1.00	1.00	1.01	1.01
unr	1.05	1.23	1.76	2.69	2.49	2.18	2.43	2.27	2.22	2.31	2.21	2.07
dunr	1.00	0.91	0.92	0.93	1.02	0.97	1.12	0.99	1.00	1.02	1.05	1.06
demp	1.02	1.02	1.03	1.09	1.19	1.12	1.30	1.09	1.11	1.11	1.17	1.18
irs	1.19	1.61	1.90	2.23	2.09	1.45	1.45	1.21	1.11	1.10	1.07	1.14
dirs	0.96	0.93	0.84	0.88	1.08	0.97	1.12	0.98	0.95	1.02	1.01	1.02
irl	1.21	1.59	2.04	2.35	2.12	1.48	1.31	1.24	1.09	1.04	0.96	0.99
dirl	0.99	0.93	0.92	0.82	0.93	1.00	1.03	1.00	0.95	1.01	0.94	0.92
ys	0.99	1.06	1.01	1.18	1.04	0.95	0.94	0.93	0.96	1.04	1.09	1.14
dsp	1.06	1.28	1.31	1.54	1.55	1.22	1.08	1.06	1.05	1.04	1.01	0.96
dppi	0.97	0.85	0.93	0.97	1.01	1.03	1.01	0.99	1.00	1.01	1.01	1.02
lnrulc	1.21	1.32	1.34	1.47	1.30	1.02	1.07	1.00	0.99	1.02	1.01	1.06
drulc	1.17	1.19	1.05	1.11	0.98	0.87	1.02	0.98	0.96	1.02	1.01	1.00
dulc	1.20	1.27	1.01	1.09	0.94	0.90	0.85	0.86	0.79	0.80	0.78	0.76
dwage	1.04	1.13	0.95	1.10	0.88	0.67	0.62	0.57	0.58	0.61	0.59	0.67
dimpp	1.06	0.80	1.04	1.03	1.03	1.08	1.09	1.03	1.03	1.06	1.00	0.95
dexr	0.97	1.02	1.02	1.08	1.04	1.33	1.33	1.26	1.02	1.12	1.00	1.09
dcomeur	0.96	0.88	0.95	1.24	1.02	0.92	1.05	0.99	0.97	0.98	0.99	0.96
doileur	0.94	0.96	0.92	1.33	1.13	1.05	1.00	0.98	0.95	0.96	0.96	0.93

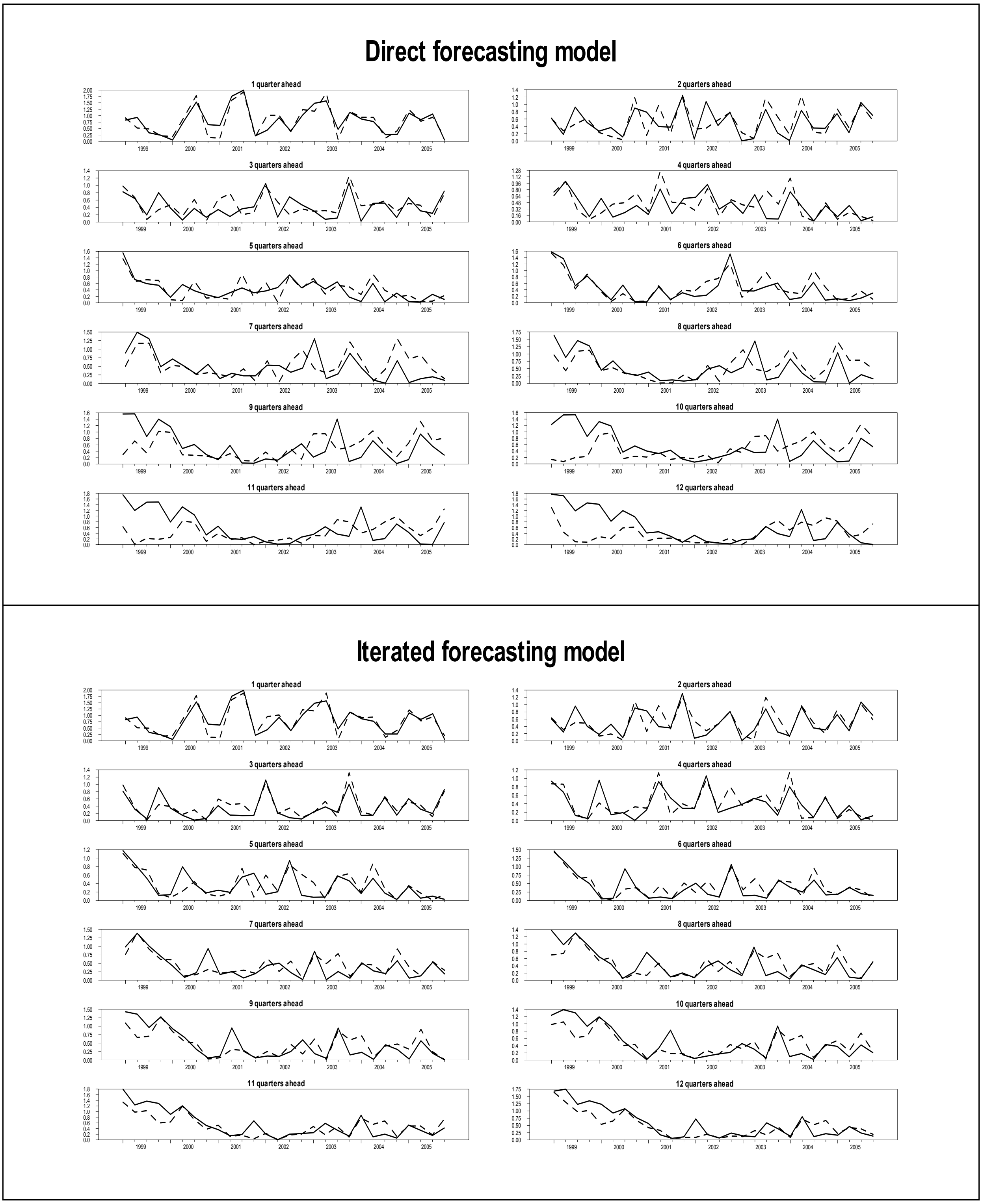
Note: The table reports the ratio of the mean squared forecast error (MSE) generated by the respective bivariate forecasting model to the MSE of the autoregressive forecasting model. An MSE ratio smaller (larger) than one therefore indicates that the model performs better (worse) than the autoregressive model.

Table 3: Bivariate iterated forecasting models

h	1	2	3	4	5	6	7	8	9	10	11	12
Monetary indicators												
dm3	1.03	1.10	1.19	1.13	1.11	1.10	1.08	0.91	0.81	0.77	0.70	0.69
dm3t	0.97	1.03	1.13	1.12	1.18	1.09	1.06	0.89	0.81	0.72	0.59	0.61
dpstar	1.09	1.16	1.23	1.22	1.08	1.05	1.03	0.94	0.89	0.87	0.86	0.83
mgap	1.18	1.49	1.84	1.83	1.96	1.67	1.75	1.59	1.27	1.21	0.96	0.93
mov	1.18	1.45	1.76	1.79	1.84	1.59	1.64	1.47	1.18	1.13	0.83	0.80
dm1	1.03	1.01	1.02	1.03	1.03	1.07	1.07	1.07	1.09	1.10	1.08	1.07
dm2	1.04	1.01	1.01	1.01	1.01	1.00	0.94	0.94	0.93	0.94	0.96	0.94
dloans	0.94	0.99	1.07	1.21	1.42	1.42	1.52	1.50	1.43	1.42	1.28	1.23
Non-monetary indicators												
dgdpr	1.05	1.08	1.07	1.12	1.04	1.02	0.98	0.97	0.99	0.98	0.98	0.99
ygap	1.11	1.17	1.18	1.31	1.31	1.28	1.27	1.23	1.23	1.22	1.19	1.18
dygap	1.14	1.22	1.21	1.29	1.18	1.12	1.07	1.02	1.03	1.01	1.00	1.00
unr	1.05	1.28	1.64	1.90	2.30	2.13	2.20	2.04	1.94	1.86	1.66	1.55
dunr	1.00	1.04	1.05	1.05	1.04	1.01	1.02	1.01	0.99	0.99	0.99	0.99
demp	1.03	1.10	1.15	1.19	1.35	1.32	1.34	1.29	1.25	1.24	1.19	1.16
irs	1.14	1.48	1.79	1.69	1.90	1.50	1.55	1.40	1.11	1.09	0.87	0.82
dirs	0.94	0.98	0.97	0.97	1.11	1.10	1.11	1.12	1.08	1.07	1.02	1.00
irl	1.14	1.52	1.90	1.76	1.89	1.55	1.61	1.47	1.26	1.29	1.14	1.11
dirl	0.95	0.98	0.98	0.95	0.99	0.98	0.98	0.99	1.01	1.01	1.01	1.01
ys	0.99	1.02	1.06	1.09	1.19	1.10	1.08	1.03	0.96	0.91	0.85	0.84
dsp	1.07	1.11	1.11	1.08	1.12	1.05	1.03	0.99	1.00	1.01	1.00	1.00
dppi	0.92	0.93	0.96	0.96	0.99	0.94	0.96	1.00	1.03	1.06	1.00	0.94
lnrulc	1.22	1.37	1.40	1.29	1.11	0.98	0.99	0.96	0.89	0.92	0.87	0.94
drulc	1.17	1.26	1.27	1.29	1.19	1.18	1.17	1.18	1.21	1.24	1.18	1.18
dulc	1.20	1.27	1.27	1.20	0.94	0.88	0.82	0.74	0.74	0.78	0.80	0.84
dwage	1.05	1.01	0.95	0.89	0.72	0.69	0.67	0.64	0.65	0.66	0.62	0.64
dimpp	1.01	0.90	0.92	1.04	1.02	1.00	1.09	1.18	1.22	1.27	1.19	1.17
dexr	0.98	0.89	0.88	0.92	0.90	0.93	0.96	1.03	1.03	1.04	1.04	1.05
dcomeur	0.94	0.85	0.87	0.83	0.81	0.74	0.73	0.78	0.94	1.07	1.01	1.03
doileur	0.93	0.97	0.95	0.93	1.05	1.15	1.24	1.37	1.46	1.53	1.45	1.43

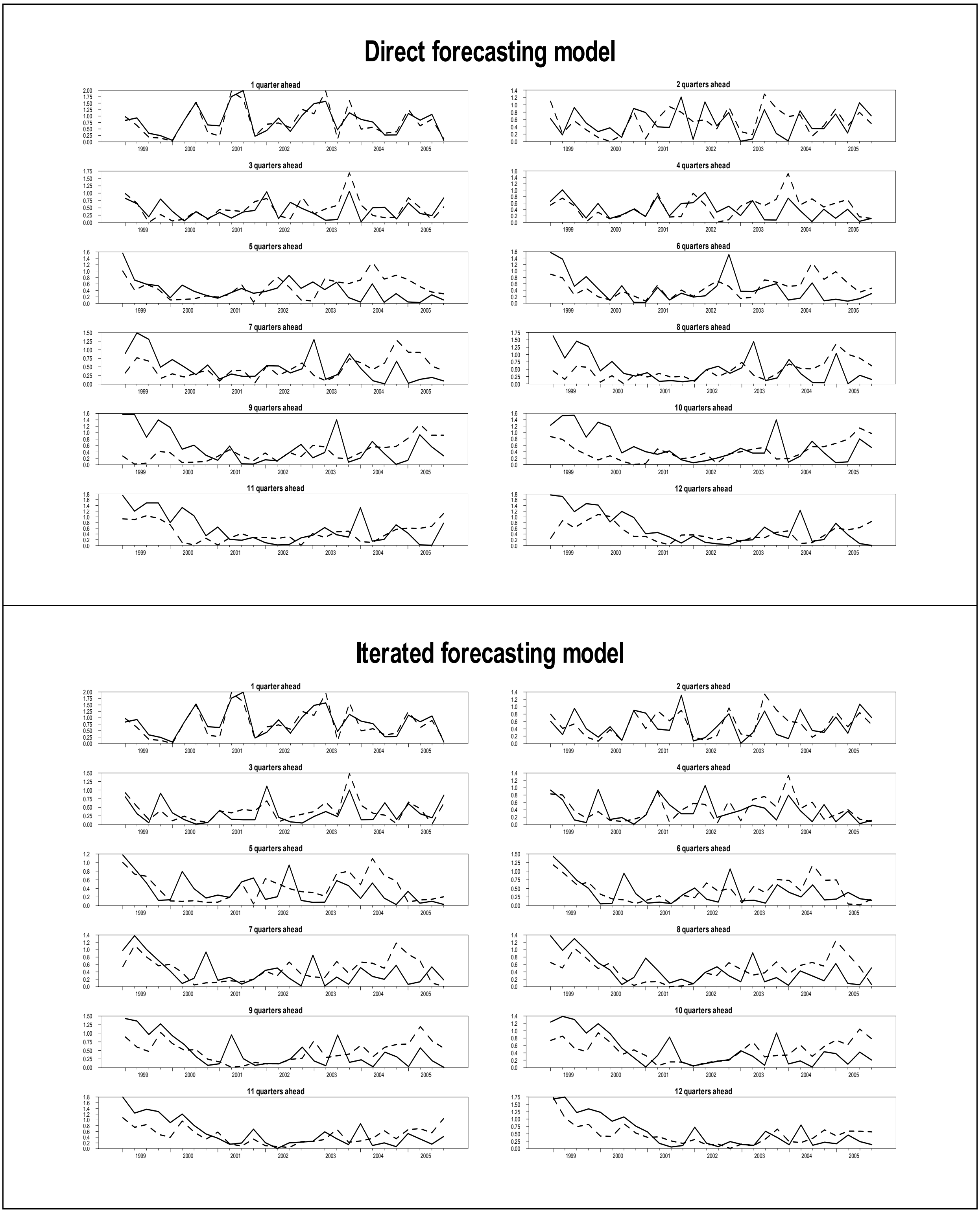
Note: The table reports the ratio of the mean squared forecast error (MSE) generated by the respective bivariate forecasting model to the MSE of the autoregressive forecasting model. An MSE ratio smaller (larger) than one therefore indicates that the model performs better (worse) than the autoregressive model.

Figure 2: Quarterly M3 growth forecasts vs autoregressive forecasts



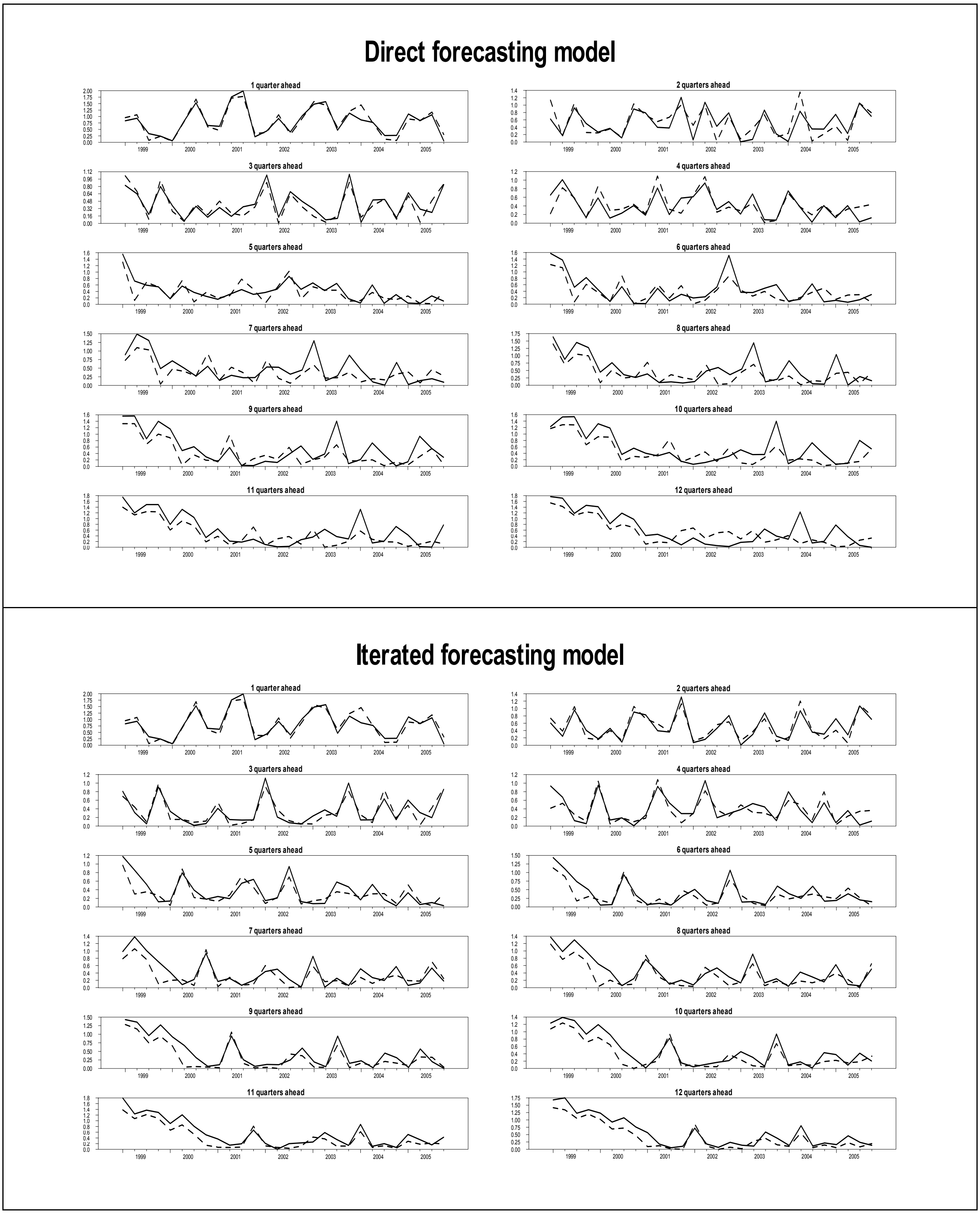
Note: The plots show the absolute forecast error of the bivariate forecasting model with quarterly M3 growth (dotted line) and of the autoregressive forecasting model (solid line).

Figure 3: Trend M3 growth forecasts vs autoregressive forecasts



Note: The plots show the absolute forecast error of the bivariate forecasting model with trend M3 growth (dotted line) and of the autoregressive forecasting model (solid line).

Figure 4: Wage inflation forecasts vs autoregressive forecasts



Note: The plots show the absolute forecast error of the bivariate forecasting model with wage inflation (dotted line) and of the autoregressive forecasting model (solid line).

3. 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 autoregressive or single indicator models considered in the previous section. The disadvantage of this approach is that when the information content of one or a group of indicators is considered, the information contained in the other available indicators is not taken into account. 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.[22] 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 observable indicators and Λ is an *nxr* matrix of eigenvectors corresponding to the *r* largest eigenvalues of the sample variance-covariance matrix of the indicator variables. In order to assess the performance of factor based forecasts we first recursively determine the number of factors using the IC_{P2} criterion of Bai and Ng (2002)[23] and then estimate based on the thus determined number of factors direct and iterated forecasting models. We perform the principal component analysis separately for the group of monetary indicators and the group of non-monetary indicators and also for the group of all indicators together, considering one factor for the group of monetary indicators, up to two factors for the group of non-monetary

[22] Recently, 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.

[23] The criterion function is given by $IC_{P2}(r) = \ln((1/NT)\sum_{i=1}^{N}\sum_{t=1}^{T}(X_{it} - C_i F_t)) + r((N+T)/NT)\ln(\min\{N,T\})$, where *r* is the number of factors, *N* is the number of indicators, *T* is the size of the sample period and C_i is a *nxr* matrix of factor loadings which is estimated by applying OLS to each equation (Bai and Ng, 2002). The number of factors is determined by minimising the criterion function.

indicators and up to three factors for the group of all indicators. For each recursion the forecasting model is specified according to the number of common factors selected by the IC_{P2} criterion. The dynamic specification is then chosen based on the SBC criterion as in the previous section considering up to four lags for each regressor and allowing lag orders to differ across regressors and across equations.[24]

An alternative to constructing composite indicators based on principal component analysis is to first estimate the forecasting models for the individual indicator variables and then to combine the forecasts using forecast combination techniques.[25] The combination forecast is given by $f_t^c = \sum_{i=1}^{n} \omega_{it} f_{it}$, 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 mean and the median of the forecasts produced by the bivariate models estimated in the previous section.[26] We again recursively perform the analysis separately for the group of monetary indicators and the group of non-monetary indicators and also for all indicators together.

Table 4 reports the relative MSEs of the factor based forecasts and of the forecast combinations with respect to the autoregressive forecast.[27] The results suggest that the forecast combination methods perform better than the factor based forecasts, which is consistent with the findings of Stock and Watson (2004). The mean forecast, in particular for the group of monetary indicators, can clearly improve upon the autoregressive forecast and on average also tends to perform better than the bivariate forecasts of the previous section.

[24] This means, for example, that if at one of the recursions three factors were selected for the whole group of indicators, four dimensional forecasting models had to be estimated. In the case of the direct forecasting model this entailed regressing h-period ahead inflation on its own lags and lags of the three factors selecting the lag order of the regressors based on the SBC, which means comparing for each forecasting horizon 256 models and selecting the one with the best SBC. For the iterated forecasting models a four equation SUR had to be estimated with lag orders of the four equations determined by the SBC, which means that 256 models had to be compared for each equation of the SUR.

[25] For surveys of the forecast combination literature see Diebold and Lopez (1996), Newbold and Harvey (2002) and Hendry and Clements (2002).

[26] More sophisticated forecast combination methods base the forecast weights in some way on previous forecast performance. Due to the small sample period we do not have sufficient forecast observations to apply such more sophisticated combination methods. However, in their comparison of the forecast performance of various forecast combination methods, Stock and Watson (2004) find that simple forecast combinations, like the mean, tend to perform better than more sophisticated methods.

[27] A comparison of the performance of the direct and the iterated forecasts shows that, as in the case of the autoregressive and single indicator models, the iterated forecasts tend to perform somewhat better than the direct forecast, except for the longest forecast horizons. But the MSE ratios are again never significantly different from one. We do not report the results here for brevity, but they are available upon request.

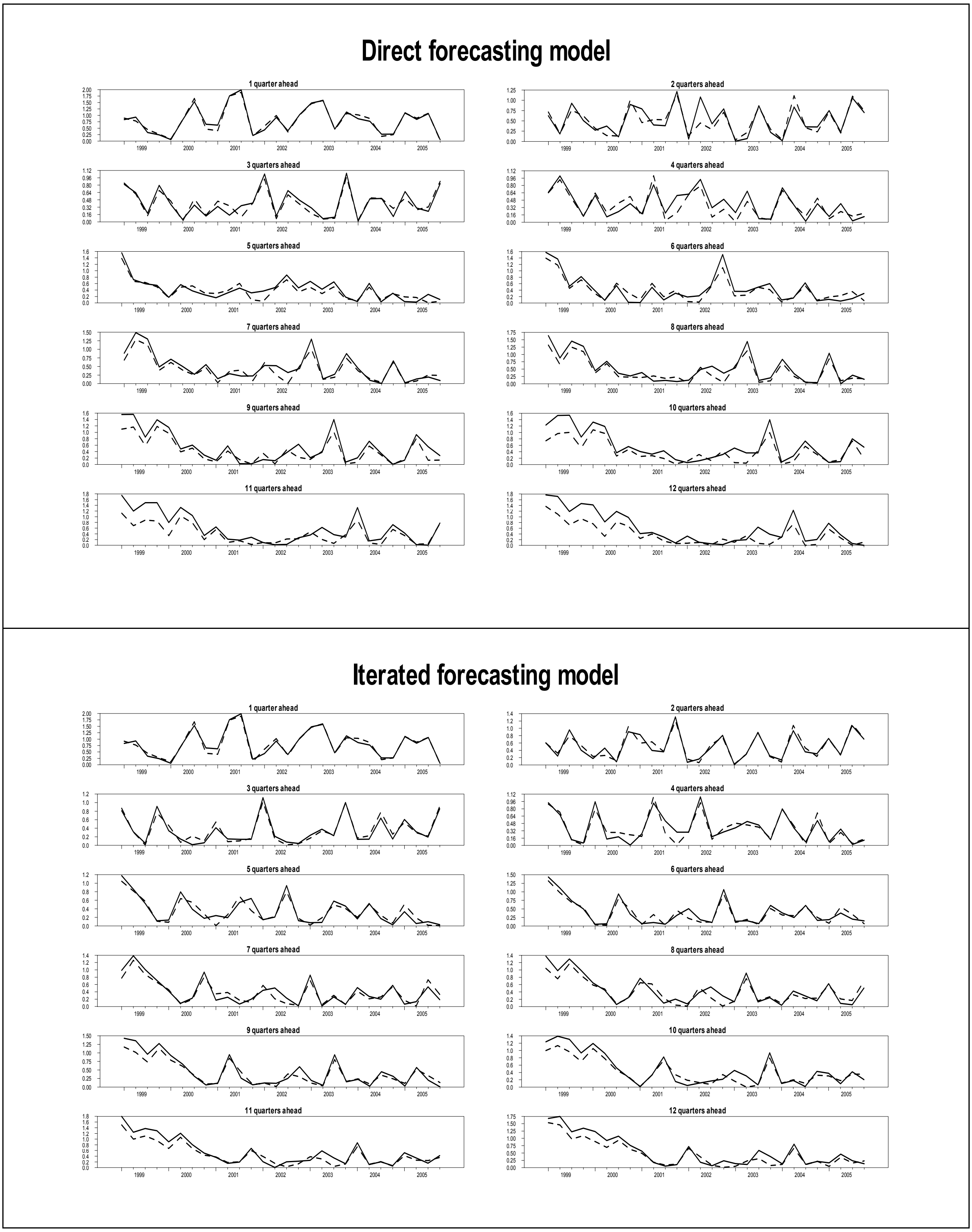
Table 4: Factor forecasts and forecast combinations

h	1	2	3	4	5	6	7	8	9	10	11	12
Direct forecasting models												
M-factor	1.00	0.89	0.95	1.11	1.07	1.00	1.06	1.09	0.88	0.89	0.72	0.62
NM-factor	1.04	1.46	1.71	2.26	2.22	1.27	1.53	1.42	1.29	1.40	1.28	1.16
T-factor	1.07	1.46	1.38	2.03	1.89	1.21	1.28	0.81	0.84	0.68	0.80	0.68
M-mean	1.01	0.94	0.93	0.93	0.82	0.78	0.75	0.69	0.60	0.52	0.46	0.43
NM-mean	1.02	0.95	0.93	0.93	0.89	0.85	0.86	0.82	0.80	0.81	0.80	0.79
T-mean	1.02	0.94	0.93	0.92	0.87	0.82	0.83	0.78	0.74	0.72	0.69	0.68
M-median	1.03	1.00	1.00	0.94	0.87	0.85	0.81	0.77	0.73	0.73	0.71	0.66
NM-median	1.00	0.92	0.94	0.99	0.97	0.98	0.98	0.94	0.93	0.96	0.96	0.94
T-median	1.00	0.92	0.96	0.98	0.95	0.91	0.97	0.92	0.90	0.92	0.91	0.90
Iterated forecasting models												
M-factor	1.00	0.93	0.96	1.00	1.07	1.12	1.10	1.08	1.07	1.06	1.01	0.96
NM-factor	1.01	1.17	1.20	1.24	1.61	1.43	1.43	1.47	1.50	1.55	1.45	1.41
T-factor	1.05	1.20	1.15	1.17	1.41	1.13	1.04	0.96	0.95	1.04	1.03	1.02
M-mean	1.01	1.01	1.01	0.97	0.90	0.88	0.85	0.78	0.72	0.69	0.68	0.69
NM-mean	1.01	1.01	0.99	0.96	0.91	0.88	0.87	0.87	0.87	0.87	0.86	0.87
T-mean	1.00	1.00	0.99	0.95	0.89	0.87	0.85	0.83	0.82	0.82	0.80	0.81
M-median	1.03	1.00	1.00	0.97	0.89	0.92	0.87	0.79	0.75	0.73	0.73	0.75
NM-median	0.99	1.03	1.01	1.01	1.00	0.99	0.97	0.96	0.97	0.97	0.96	0.97
T-median	1.00	1.00	1.00	0.98	0.97	0.96	0.92	0.91	0.92	0.93	0.92	0.93

Note: The table reports the ratio of the mean squared forecast error (MSE) generated by the respective forecasting model to the MSE of the autoregressive forecasting model. M refers to the group of monetary indicators, NM to the group of non-monetary indicators and T to the total group of monetary and non-monetary indicators. An MSE ratio smaller (larger) than one therefore indicates that the model performs better (worse) than the autoregressive model.

Figure 5 takes a closer look at the forecasting performance of the mean forecast of the monetary indicators over time. The graphs reveal that the mean monetary forecast not only performed very well on average, but that the performance was also very stable over time. The finding that simple combination forecasts may improve upon autoregressive forecasts even when the forecasts based on individual predictors are unstable over time and on average perform worse than an autoregressive benchmark is consistent with findings reported by Stock and Watson (2003) who study the performance of forecast combination techniques in forecasting GDP growth in the G7 countries. An implication of this result is that a broader based monetary analysis, taking into account the information content of a larger group of monetary indicators, may yield a more reliable and more robust assessment of inflation trends than focusing on a single monetary indicator.

Figure 5: Mean forecast of monetary indicators vs autoregressive forecasts



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

4. A two-pillar Phillips Curve forecasting model

In the evaluation of its monetary policy strategy, the ECB (2003) has emphasised that the economic analysis within the framework of its non-monetary pillar serves to "identify short to medium term risks to price stability", while the monetary analysis in the framework of its money pillar assesses the "medium to long-term trends in inflation". This phrasing suggests that the ECB's two pillar strategy may be interpreted as a combination of two separate forecasting models for inflation, the non-monetary pillar for the short to medium-run and the money pillar for the medium to long-run (Gerlach 2003, 2004). As a way to formalise this view of the inflation process, several studies have adopted a two-pillar Phillips Curve model, specifying the euro area inflation process as a function of trend or core money growth and some measure of the output gap. [28] While these studies have shown that such a two-pillar Phillips Curve model provides a good in-sample fit for euro area inflation, the usefulness of the concept for forecasting inflation out-of-sample has not yet been explored.

In this section we proceed to forecast euro area inflation based on trivariate, two-pillar Phillips Curve type forecasting models, modelling 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). The trivariate direct and iterated forecasting models are respectively given by

$$\pi_{t+h}^h = \beta_0 + \beta_1(L)\pi_t + \beta_2(L)\Delta m_t^T + \beta_3(L)x_t + u_{t+h}^h \tag{5}$$

$$\begin{aligned} \pi_{t+1} &= \beta_0 + \beta_1(L)\pi_t + \beta_2(L)\Delta m_t^T + \beta_3(L)x_t + u_{t+1} \\ \Delta m_{t+1}^T &= \gamma_0 + \gamma_1(L)\pi_t + \gamma_2(L)\Delta m_t^T + \gamma_3(L)x_t + \varepsilon_{t+1} \\ x_{t+1} &= \lambda_0 + \lambda_1(L)\pi_t + \lambda_2(L)\Delta m_t^T + \lambda_3(L)x_t + v_{t+1} \end{aligned} \tag{6}$$

Lag orders were selected and forecasts computed recursively in the same way as for the univariate and bivariate models, allowing for different lag orders across regressors and also across equations in the case of the iterated forecasting model searching over up to four lags respectively.

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

Tables 5 and 6 report the ratio of the MSE produced by the trivariate forecasting models to the MSE produced by the respective univariate model. For comparison we also report in the first row of the tables the relative MSE for the bivariate model including trend M3 growth. Besides considering each non-monetary indicator separately, we also consider a factor based forecast[29] and the mean and median of the trivariate forecasts. The results suggest that the trivariate models perform very well, on the whole clearly outperforming the autoregressive forecast over the full sample period. Some of the trivariate models also outperform the best bivariate forecasting models and also the forecast combinations considered in the previous section. For the direct forecasting model, a true two-pillar Phillips Curve model comprising trend money growth and the output gap performs best on average, while for the iterated forecasts a trivariate model comprising wage inflation is the best performer. A more detailed assessment of the relative performance of the direct and the iterated forecasting approach is again provided in the appendix.

On the whole, the results suggest that the two-pillar Phillips Curve forecasting model is a useful tool for forecasting inflation. However, a closer look at the performance of the models over time reveals that also the trivariate models were not able to outperform the autoregressive models over the more recent time period. Figure 6 shows as an example the performance of the trivariate model with the output gap as the non-monetary indicator. The graphs show that while the model performs better than the bivariate model with M3 growth, its predictive ability relative to the simple autoregressive forecasting model has also deteriorated since 2003.[30]

[29] The factor analysis is performed in the same way as in the previous section, considering up to two factors.

[30] For the other non-monetary indicators we obtain a very similar picture. The results are available upon request.

Table 5: Trivariate direct forecasting models

h	1	2	3	4	5	6	7	8	9	10	11	12
Bivariate model	0.99	1.06	1.27	1.40	1.24	0.86	0.78	0.61	0.47	0.48	0.49	0.42
dgdpr	1.06	1.16	1.23	1.28	1.11	0.89	0.70	0.51	0.38	0.43	0.45	0.39
ygap	1.00	1.01	1.13	1.15	1.00	0.70	0.60	0.44	0.31	0.30	0.31	0.29
dygap	1.09	1.04	1.28	1.41	1.25	0.99	0.79	0.61	0.48	0.51	0.52	0.43
unr	1.06	1.07	1.33	1.70	1.54	1.16	1.09	0.84	0.68	0.73	0.76	0.75
dunr	0.98	0.92	1.07	1.21	1.04	0.76	0.64	0.48	0.36	0.36	0.37	0.31
demp	1.03	1.02	1.18	1.35	1.26	0.87	0.74	0.55	0.40	0.36	0.34	0.28
irs	1.05	1.09	1.07	1.13	1.09	0.87	0.93	0.90	0.83	0.82	0.70	0.56
dirs	0.95	1.03	1.23	1.29	1.23	0.85	0.75	0.58	0.43	0.44	0.46	0.28
irl	1.07	1.38	1.20	1.34	1.04	0.64	0.74	0.67	0.60	0.64	0.67	0.50
dirl	1.00	1.09	1.24	1.36	1.10	0.77	0.73	0.58	0.48	0.49	0.49	0.43
ys	1.01	1.19	1.46	1.70	1.60	1.11	1.08	0.89	0.73	0.72	0.75	0.40
dsp	1.04	1.22	1.60	1.77	1.61	1.02	0.86	0.66	0.53	0.56	0.58	0.49
dppi	1.05	1.35	1.61	2.12	1.82	1.06	0.92	0.66	0.50	0.61	0.66	0.44
lnrulc	1.16	1.18	1.53	1.81	1.78	1.25	1.10	0.86	0.64	2.29	4.79	2.40
drulc	1.13	1.13	1.19	1.41	1.24	0.86	0.78	0.61	0.48	0.68	1.25	0.48
dulc	1.14	1.09	1.25	1.39	1.28	0.86	0.77	0.61	0.47	0.49	0.49	0.40
dwage	1.00	1.03	1.20	1.22	1.05	0.72	0.63	0.50	0.42	0.44	0.46	0.37
dimpp	0.91	0.85	1.03	1.25	1.28	0.99	0.91	0.66	0.49	0.47	0.48	0.39
dexr	0.96	1.00	1.13	1.37	1.18	0.86	0.77	0.60	0.44	0.46	0.51	0.41
dcomeur	0.98	1.12	1.15	1.36	1.20	0.89	0.89	0.65	0.49	0.50	0.53	0.43
doileur	0.98	1.08	1.19	1.40	1.21	0.89	0.82	0.62	0.48	0.48	0.50	0.31
fac	1.08	1.26	1.44	2.13	1.67	1.04	0.89	0.67	0.52	0.54	0.58	0.38
mean	0.99	0.96	1.12	1.26	1.14	0.84	0.76	0.60	0.47	0.52	0.59	0.38
median	0.99	1.03	1.18	1.31	1.16	0.84	0.77	0.60	0.46	0.47	0.48	0.38

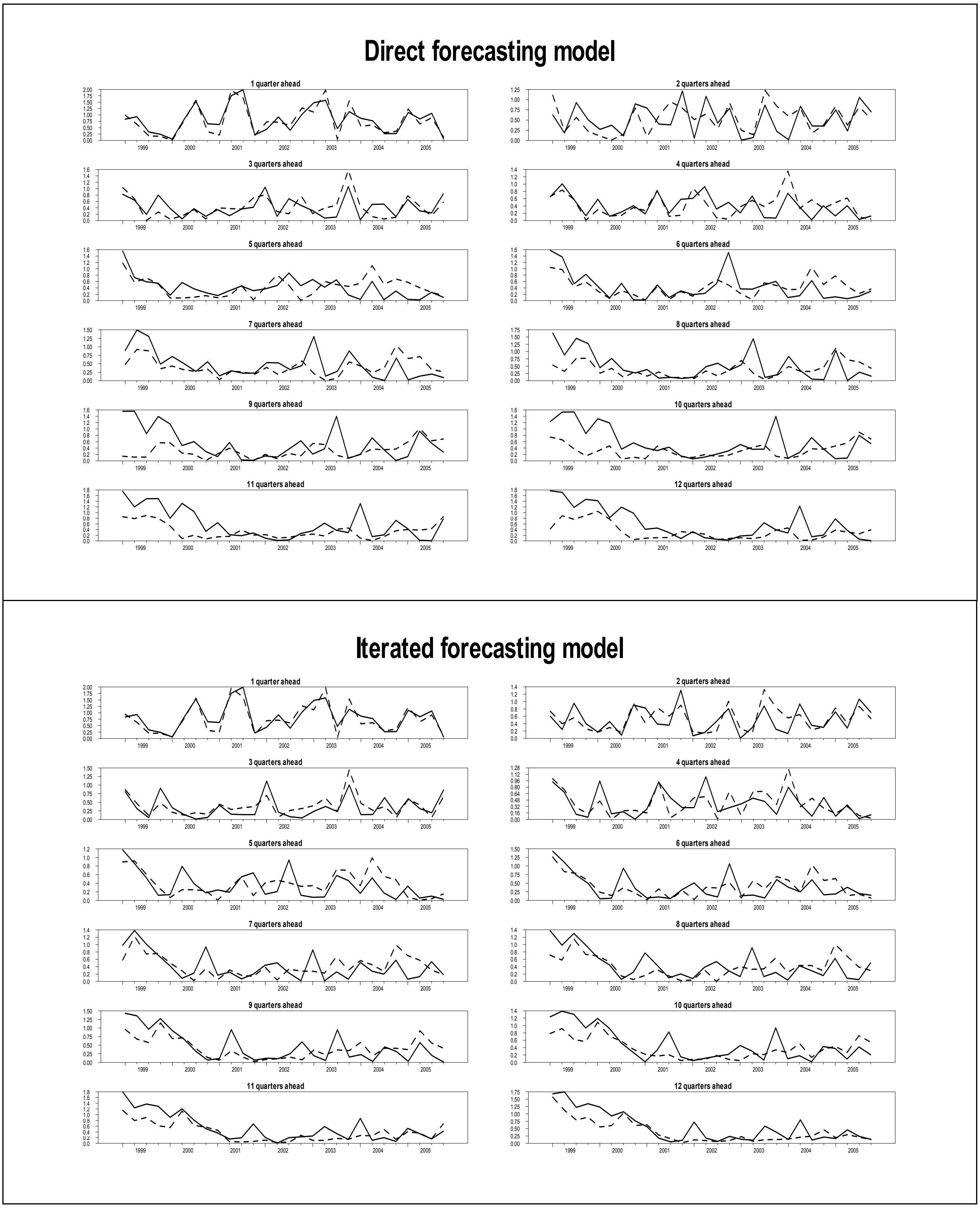
Note: The table reports the ratio of the mean squared forecast error (MSE) generated by the trivariate forecasting model comprising trend M3 growth and the respective non-monetary indicator to the MSE of the autoregressive forecasting model. An MSE ratio smaller (larger) than one therefore indicates that the model performs better (worse) than the autoregressive model. Bivariate model refers to the bivariate forecasting model with trend M3 growth only.

Table 6: Trivariate iterated forecasting models

h	1	2	3	4	5	6	7	8	9	10	11	12
Bivariate benchmark	0.97	1.03	1.13	1.12	1.18	1.09	1.06	0.89	0.81	0.72	0.59	0.61
dgdpr	1.04	1.11	1.19	1.22	1.21	1.12	1.08	0.91	0.83	0.74	0.61	0.61
ygap	0.98	1.02	1.06	1.07	1.02	0.95	0.89	0.72	0.64	0.55	0.49	0.53
dygap	1.08	1.14	1.21	1.24	1.21	1.10	1.04	0.86	0.79	0.69	0.56	0.56
unr	1.05	1.16	1.33	1.45	1.59	1.47	1.46	1.29	1.20	1.08	0.92	0.86
dunr	0.97	1.02	1.08	1.05	1.03	0.96	0.91	0.78	0.72	0.64	0.59	0.60
demp	1.04	1.09	1.20	1.18	1.26	1.16	1.11	0.93	0.83	0.73	0.61	0.60
irs	1.00	1.09	1.14	1.02	1.01	0.89	0.86	0.72	0.59	0.54	0.43	0.42
dirs	0.92	0.96	1.04	1.01	1.13	1.06	1.01	0.87	0.78	0.70	0.58	0.56
irl	1.01	1.17	1.32	1.17	1.20	1.06	1.05	0.90	0.78	0.73	0.59	0.54
dirl	0.94	1.01	1.12	1.10	1.16	1.09	1.03	0.88	0.80	0.69	0.57	0.57
ys	1.00	1.06	1.16	1.14	1.16	1.04	0.98	0.82	0.75	0.69	0.55	0.53
dsp	1.03	1.10	1.22	1.21	1.29	1.18	1.13	0.97	0.88	0.78	0.65	0.65
dppi	0.99	1.22	1.58	1.54	1.62	1.39	1.35	1.13	1.02	0.91	0.68	0.57
lnrulc	1.14	1.30	1.56	1.58	1.77	1.74	1.73	1.52	1.42	1.35	1.18	1.25
drulc	1.12	1.22	1.29	1.28	1.24	1.12	1.06	0.90	0.82	0.73	0.58	0.57
dulc	1.11	1.19	1.26	1.23	1.18	1.10	1.06	0.90	0.84	0.74	0.59	0.58
dwage	0.99	0.98	0.99	0.93	0.86	0.81	0.76	0.63	0.58	0.50	0.37	0.34
dimpp	0.89	0.90	1.09	1.14	1.27	1.20	1.21	1.07	0.99	0.89	0.70	0.72
dexr	0.95	0.88	0.97	0.95	0.92	0.93	0.90	0.82	0.75	0.67	0.56	0.62
dcomeur	0.92	0.94	1.07	1.00	1.14	1.06	1.06	0.96	0.88	0.83	0.67	0.68
doileur	0.96	1.12	1.35	1.34	1.53	1.37	1.35	1.18	1.09	1.01	0.83	0.84
fac	1.03	1.20	1.37	1.40	1.57	1.38	1.37	1.22	1.11	1.02	0.84	0.83
mean	0.96	1.00	1.08	1.05	1.07	1.02	0.97	0.83	0.76	0.68	0.55	0.55
median	0.97	1.01	1.11	1.08	1.12	1.04	1.01	0.87	0.80	0.71	0.58	0.58

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 autoregressive forecasting model. An MSE ratio smaller (larger) than one therefore indicates that the model performs better (worse) than the autoregressive model. Bivariate model refers to the bivariate forecasting model with trend M3 growth only.

Figure 6: Two-pillar Phillips Curve forecasts vs autoregressive forecasts



Note: The plots show the absolute forecast error of the trivariate forecasting model comprising trend M3 growth and the output gap (dotted line) and of the autoregressive forecasting model (solid line).

5. Portfolio shift effects

The ECB has commonly argued that the high growth rates of M3 since 2001 have been driven by transitory portfolio shifts caused by a strong preference of investors for liquid assets in the wake of the exceptional economic and financial uncertainties during this period.[31] This would imply that the information content of M3 indicators for inflation has only temporarily been blurred and that a correction of M3 for the effect of portfolio shifts would restore the indicator property of M3 for inflation trends.

The ECB constructs a measure of M3 corrected for the effect of portfolio shifts 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 (ECB, 2005). 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.[32] For the stochastic part of the model an ARIMA (0,1,1) [0,1,1] model is used.[33]

In order to assess the effect of the estimated portfolio shift effects on the indicator property of M3 we analyse the out-of sample forecasting performance of the ECB portfolio shift corrected M3 series. An obvious objection is that the portfolio shift correction of the M3 aggregate is done based on ex-post information and was not available ex-ante, so that the forecasting exercise is not a real assessment of the out-of-sample performance of the corrected M3 measure. However, analysing the indicator property of the corrected M3 measure is still useful as it gives an indication of whether M3 is in principle still a useful indicator of inflation and whether the corrected M3 measure might be of use for the current assessment of future risks to price stability.

---

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

[32] An alternative approach has been proposed by Greiber and Lemke (2005), who 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.

[33] The parenthesis term refers to the specification of the regular part and the bracket term refers to the specification of the seasonal part of the model. The chosen specification states that for both parts a specification with no AR components, first order differencing and a first order moving average was chosen.

Table 7 shows the relative MSEs with respect to the autoregressive forecasts for the bivariate forecasting model with portfolio shift corrected M3 indicators. We consider again the quarterly growth and the trend M3 growth rate[34] as well as recursively calculated M3 demand based indicators, namely the change in p-star (dpstar), the real money gap (mgap) and the monetary overhang (mov). The results suggest that the portfolio shift corrected M3 growth indicators deliver for all forecast horizons on average better forecasts than the unadjusted M3 series. In fact, the bivariate models for the adjusted M3 growth indicators deliver lower MSE ratios than all the bivariate models, forecast combinations and trivariate models we have considered in the previous sections. A look at the forecasting performance of the corrected M3 growth indicators over time, shown in Figures 7 and 8, reveal that when M3 is cleansed from the estimated effects of portfolio shifts, it outperforms the autoregressive forecast also over the more recent time period.

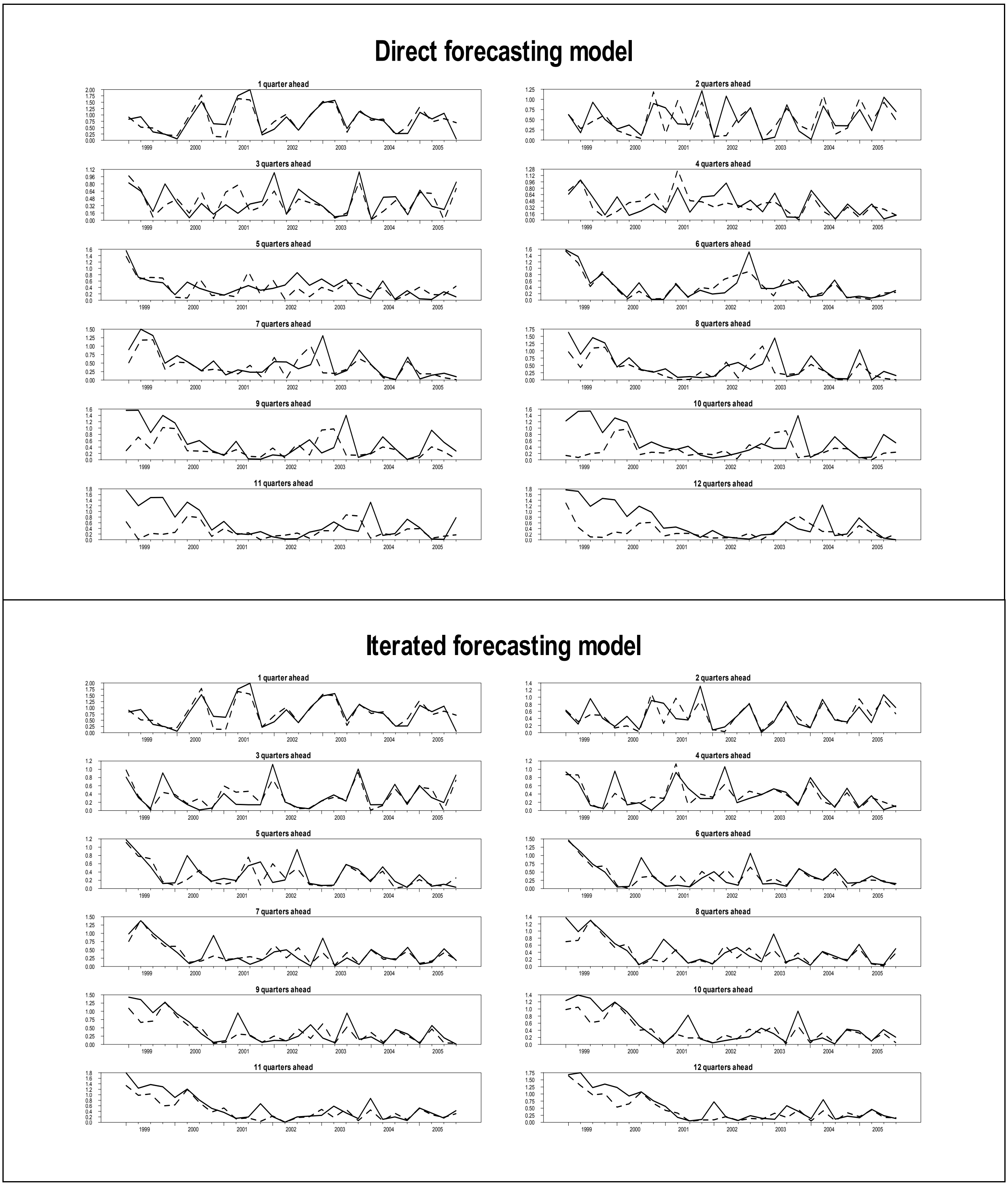
Table 7: Forecasting performance of the portfolio shift corrected M3 series

h	1	2	3	4	5	6	7	8	9	10	11	12
					Direct forecasting model							
DM3	0.97	0.91	0.86	0.98	0.89	0.85	0.68	0.55	0.40	0.31	0.25	0.27
DM3T	0.93	0.83	0.80	0.74	0.59	0.42	0.32	0.22	0.15	0.23	0.34	0.34
dpstar	1.07	1.02	0.98	1.00	0.99	0.99	0.97	0.92	0.86	0.84	0.85	0.86
mgap	1.14	1.50	1.65	1.98	1.66	1.39	1.17	1.00	0.99	0.96	0.95	1.02
mov	1.13	1.43	1.72	2.16	1.87	1.53	1.32	1.01	0.94	0.86	0.74	0.65
					Iterated forecasting model							
DM3	0.96	0.89	0.89	0.84	0.79	0.86	0.81	0.67	0.62	0.61	0.59	0.62
DM3T	0.92	0.80	0.73	0.69	0.64	0.64	0.58	0.47	0.44	0.42	0.41	0.51
dpstar	1.07	1.09	1.11	1.10	0.95	0.95	0.93	0.83	0.81	0.81	0.81	0.81
mgap	1.15	1.40	1.63	1.56	1.61	1.37	1.41	1.29	1.09	1.03	0.93	0.91
mov	1.14	1.34	1.54	1.48	1.45	1.25	1.28	1.14	0.94	0.89	0.75	0.74

Note: The table reports the ratio of the mean squared forecast error (MSE) generated by the respective forecasting model to the MSE of the autoregressive forecasting model. An MSE ratio smaller (larger) than one therefore indicates that the model performs better (worse) than the autoregressive model.

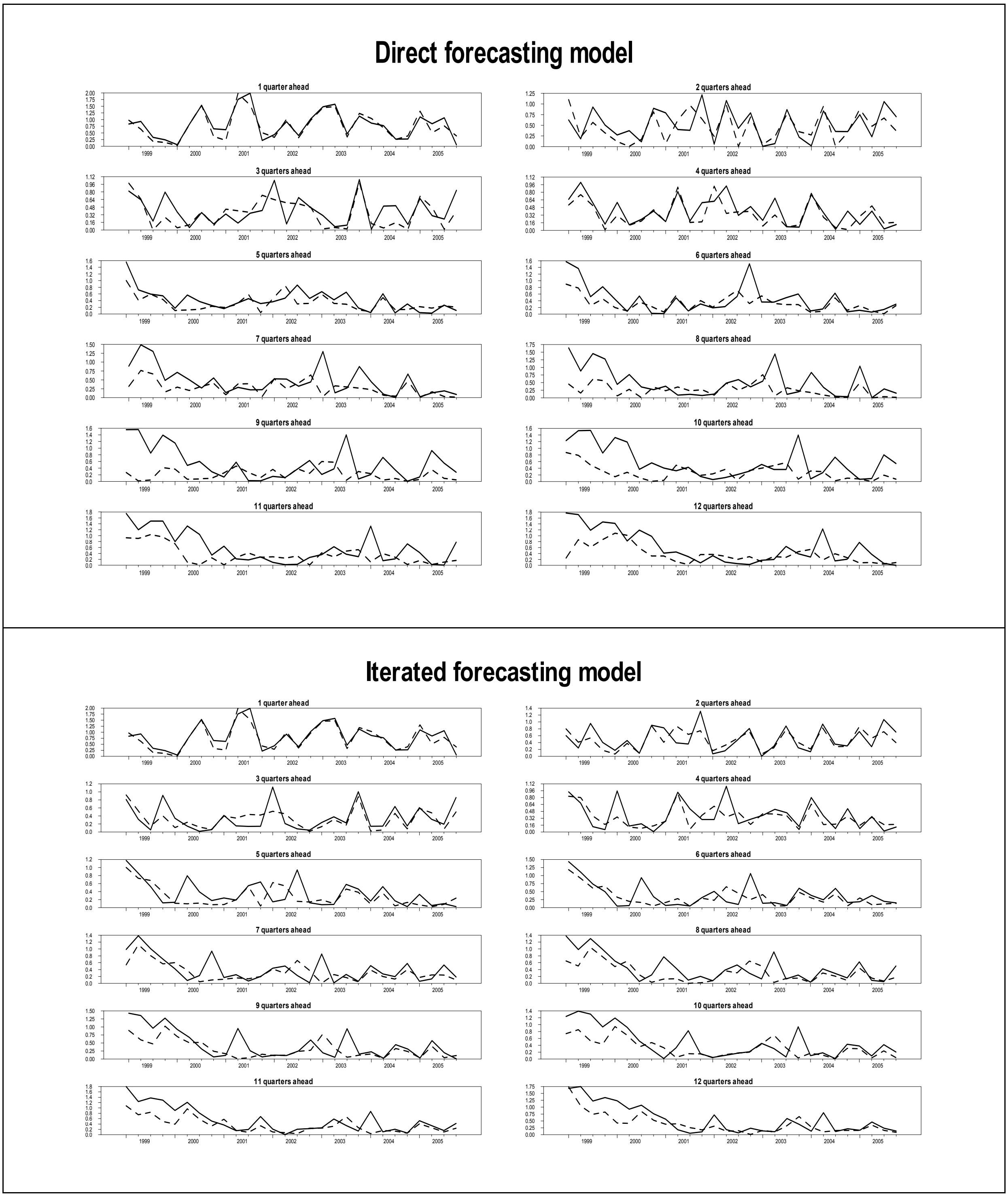
[34] The trend growth rate is again calculated based on a one-sided HP filter using a smoothing parameter of 1600.

Figure 7: Portfolio shift corrected quarterly M3 growth forecasts vs autoregressive forecasts



Note: The plots show the absolute forecast error of the bivariate forecasting model with portfolio shift adjusted quarterly M3 growth (dotted line) and of the autoregressive forecasting model (solid line).

Figure 8: Portfolio shift corrected trend M3 growth forecasts vs autoregressive forecasts



Note: The plots show the absolute forecast error of the bivariate forecasting model with portfolio shift adjusted trend M3 growth (dotted line) and of the autoregressive forecasting model (solid line).

6. 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 medium to long-run risks to price stability, has been subject to intense criticism from the very beginning. The continued brisk growth of M3 since mid 2001, which did not trigger a tightening of policy rates or 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.

In this paper we assess this issue by testing the performance of monetary indicators in predicting euro area HICP inflation out-of-sample over the period 1999Q1 till 2005Q4. In contrast to the existing studies on inflation forecasting for the euro area, this study employs and compares both direct and iterated forecasting models. The paper further contributes to the literature by assessing the out-of-sample forecasting performance of trivariate two-pillar Phillips Curve type forecasting models, combining trend M3 growth with other non-monetary indicators, which have so far only been shown to provide a good in-sample fit of euro area inflation dynamics.

The results suggest that M3, especially its trend or core growth rate, was over the EMU period on average a useful indicator for inflation at medium term horizons, which is consistent with the role of the monetary analysis in the ECB's monetary policy strategy as a tool for the assessment of the medium to long-term risks to price stability. However, a closer look at the forecasting performance reveals that M3 has become less useful as an inflation indicator over recent years. Since 2003, even the on average best performing trend M3 growth indicator cannot outperform simple autoregressive forecasting models of inflation. The further analysis suggests, however, that it might be premature to discard monetary indicators on these grounds. In particular, we find that a simple combination of all monetary forecasts performs well also over the more recent period. Also, the extremely good and stable performance of an M3 series corrected for the effects of portfolio shifts into and out of M3 since mid 2001 constructed by the ECB suggests that M3 is still a very useful indicator for future price movements once the distorting effects of speculative portfolio flows are identified and removed. Taken all together, the answer to the question of whether monetary indicators still predict inflation in the euro area is probably yes, but a thorough and broad based monetary analysis appears to be needed to extract the information content of monetary developments for future inflation.

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 frequency, mimeo, University of Basel.

Brand, C. and N. Cassola (2000), A money demand system for the euro area M3, ECB Working Paper No. 39.

Bai, J. and S. Ng (2002), Determining the number of factors in approximate factor models, *Econometrica*, 70, 191–221.

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.

Clark T. and M. McCracken (2001), Tests of equal forecast accuracy and encompassing for nested models, *Journal of Econometrics,* 105, 85–100.

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 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, 43-66.

ECB (2005), Approaches to identifying and estimating portfolio shifts into and out of M3, ECB Monthly Bulletin January 2005, 13-16.

Estrella, A., and F. Mishkin (1997), Is there a role for money in monetary policy? *Journal of Monetary Economics* 40, 279-304

Galí, J. (2003), Monetary Policy in the early years of EMU, in: M. Buti and A. Sapir (eds.), EMU and Economic Policy in Europe: the Challenges of the Early Years, Edward Elgar.

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.

Gerlach, S. And L. Svensson (2003), Money and inflation in the euro area: A case for monetary indicators?, *Journal of Monetary Economics*, 50, 1649-1672.

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

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.

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.

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

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.

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 in 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.

Appendix

Comparing the performance of direct and iterated forecasting models

In Appendix-Tables 1 and 2 we assess respectively the relative performance of the two competing forecasting approaches, the direct and the iterated approach, for the bivariate and the trivariate forecasting models. We compare for each indicator variable the ratio of the MSE from the direct forecast to that of the iterated forecast. For the bivariate models the results suggest that, on the whole, the iterated forecasting models deliver lower MSEs than the direct forecasting models except maybe for the M3 growth based indicators at longer forecasting horizons.[35] The results for the trivariate models suggest that the iterated method works better for shorter forecast horizons, while the direct forecasting approach appears to perform better at longer horizons. Since the direct and the iterated forecasting models are non-nested for forecast horizons 2 to 12 we also performed a test of the statistical significance of the MSE ratio as we have done for the autoregressive forecasts below following the approach suggested by West (1996), i.e. we calculate the standard error for the MSE ratio based on a heteroskedasticity and autocorrelation consistent (HAC) estimate of the variance-covariance (VCV) matrix of the forecast errors using the δ-method.[36] The results of this test, which we do not report for brevity, reveal that the MSE ratios are never significantly different from one, implying that the forecasting performance of the direct and iterated models is not significantly different.[37]

[35] Note that, although the specification of the forecasting equation for the inflation rate in the direct and the iterated forecasting model are identical, the MSE ratio is not equal to one as has been the case in the autoregressive forecasting model because the iterated forecasting model here also comprises a forecasting equation for the indicator variable which is estimated jointly with the inflation equation by SUR, which also affects the coefficient estimates in the inflation equation.

[36] The HAC estimate of the VCV matrix was obtained using a Bartlett kernel with the number of lags equal to the forecast horizon.

[37] The p-values of the tests are available upon request.

Appendix-Table 1: Bivariate model, direct vs iterated forecasts

h	1	2	3	4	5	6	7	8	9	10	11	12
					Monetary indicators							
dm3	1.01	1.06	1.13	1.10	1.24	1.26	1.33	1.48	1.24	1.06	0.82	0.71
dm3t	1.02	1.09	1.34	1.21	1.32	1.02	0.97	0.97	0.78	0.90	1.00	0.81
dpstar	1.00	0.98	0.99	0.81	1.16	1.25	1.26	1.49	1.39	1.42	1.28	1.24
mgap	0.99	1.05	1.11	1.16	1.21	1.19	0.93	0.91	1.05	1.07	1.17	1.28
mov	0.99	1.08	1.32	1.51	1.85	1.78	1.47	1.24	1.17	1.15	1.14	1.02
dm1	1.00	0.97	1.20	1.06	1.25	1.27	1.30	1.47	1.43	1.58	1.49	1.41
dm2	1.00	1.05	1.18	1.01	1.24	1.12	1.34	1.45	1.36	1.37	1.19	1.13
dloans	1.00	0.94	1.21	1.09	1.62	1.34	1.59	1.79	1.48	1.43	1.24	1.20
					Non-monetary indicators							
dgdpr	1.00	1.06	1.17	0.87	1.51	1.59	1.46	1.47	1.31	1.35	1.19	1.13
ygap	1.00	0.98	1.02	0.79	1.05	1.18	1.20	1.31	1.21	1.22	1.09	1.07
dygap	1.00	0.98	1.04	0.79	1.07	1.04	1.23	1.41	1.29	1.34	1.22	1.17
unr	1.00	1.01	1.28	1.37	1.35	1.33	1.44	1.59	1.52	1.68	1.60	1.54
dunr	1.00	0.92	1.05	0.86	1.22	1.25	1.44	1.40	1.35	1.39	1.27	1.24
demp	0.99	0.98	1.07	0.89	1.10	1.10	1.27	1.22	1.19	1.21	1.18	1.18
irs	1.05	1.14	1.26	1.28	1.37	1.25	1.22	1.24	1.33	1.37	1.48	1.61
dirs	1.02	1.00	1.03	0.88	1.21	1.14	1.31	1.26	1.18	1.30	1.19	1.19
irl	1.07	1.10	1.28	1.30	1.39	1.24	1.06	1.21	1.16	1.09	1.01	1.03
dirl	1.04	1.00	1.12	0.84	1.17	1.34	1.38	1.44	1.26	1.35	1.12	1.05
ys	1.00	1.09	1.14	1.05	1.09	1.12	1.14	1.29	1.34	1.56	1.54	1.57
dsp	1.00	1.22	1.41	1.39	1.72	1.51	1.37	1.53	1.39	1.40	1.21	1.11
dppi	1.05	0.96	1.16	0.98	1.27	1.42	1.37	1.42	1.29	1.30	1.21	1.26
lnrulc	1.00	1.02	1.14	1.11	1.45	1.35	1.41	1.49	1.48	1.50	1.39	1.30
drulc	1.00	0.99	0.98	0.83	1.02	0.96	1.13	1.19	1.05	1.12	1.02	0.98
dulc	1.00	1.05	0.95	0.89	1.24	1.33	1.35	1.65	1.42	1.39	1.18	1.05
dwage	0.99	1.17	1.19	1.21	1.52	1.27	1.20	1.28	1.19	1.25	1.14	1.22
dimpp	1.05	0.93	1.34	0.96	1.26	1.40	1.30	1.25	1.12	1.14	1.00	0.94
dexr	0.99	1.20	1.38	1.14	1.45	1.85	1.81	1.75	1.33	1.46	1.16	1.20
dcomeur	1.03	1.09	1.30	1.45	1.57	1.62	1.87	1.82	1.38	1.24	1.18	1.07
doileur	1.01	1.04	1.15	1.39	1.34	1.18	1.05	1.02	0.87	0.85	0.79	0.76

Note: The table reports the ratio of the mean squared forecast error (MSE) generated by the respective direct forecasting model to the MSE of the iterated forecasting model. An MSE ratio smaller (larger) than one therefore indicates that the direct model performs better (worse) than the iterated model.

Appendix-Table 2: Trivariate model, direct vs iterated forecasts

	1	2	3	4	5	6	7	8	9	10	11	12
Bivariate benchmark	1.02	1.09	1.34	1.21	1.32	1.02	0.97	0.97	0.78	0.90	1.00	0.81
dgdpr	1.02	1.09	1.23	1.02	1.14	1.03	0.85	0.80	0.61	0.78	0.90	0.75
ygap	1.02	1.04	1.27	1.03	1.22	0.96	0.88	0.87	0.64	0.73	0.76	0.63
dygap	1.02	0.95	1.25	1.10	1.28	1.17	1.00	1.02	0.81	0.99	1.12	0.89
unr	1.01	0.97	1.20	1.14	1.21	1.02	0.98	0.94	0.75	0.91	0.99	1.01
dunr	1.01	0.95	1.18	1.12	1.26	1.03	0.91	0.89	0.67	0.76	0.75	0.59
demp	0.99	0.98	1.18	1.11	1.25	0.98	0.87	0.86	0.64	0.67	0.67	0.55
irs	1.05	1.05	1.13	1.08	1.35	1.27	1.41	1.79	1.86	2.08	1.95	1.56
dirs	1.03	1.12	1.41	1.24	1.36	1.05	0.97	0.95	0.74	0.85	0.95	0.57
irl	1.06	1.24	1.08	1.11	1.08	0.78	0.93	1.07	1.04	1.18	1.36	1.07
dirl	1.06	1.13	1.32	1.20	1.18	0.92	0.92	0.95	0.80	0.95	1.03	0.88
ys	1.01	1.18	1.49	1.44	1.72	1.40	1.44	1.54	1.29	1.42	1.61	0.88
dsp	1.01	1.16	1.57	1.42	1.55	1.13	0.99	0.99	0.80	0.97	1.08	0.87
dppi	1.06	1.17	1.22	1.33	1.40	0.99	0.89	0.84	0.65	0.90	1.17	0.89
lnrulc	1.02	0.95	1.17	1.11	1.25	0.93	0.83	0.81	0.60	2.29	4.87	2.22
drulc	1.01	0.97	1.10	1.07	1.25	1.00	0.97	0.97	0.77	1.27	2.58	0.96
dulc	1.02	0.96	1.18	1.10	1.35	1.02	0.94	0.98	0.76	0.89	0.99	0.80
dwage	1.01	1.10	1.44	1.27	1.51	1.16	1.08	1.14	0.96	1.20	1.49	1.28
dimpp	1.02	0.99	1.13	1.06	1.26	1.08	0.98	0.88	0.66	0.72	0.83	0.63
dexr	1.01	1.19	1.38	1.39	1.60	1.20	1.12	1.06	0.79	0.94	1.09	0.77
dcomeur	1.07	1.24	1.29	1.32	1.31	1.10	1.10	0.97	0.75	0.82	0.95	0.73
doileur	1.01	1.01	1.05	1.01	0.98	0.84	0.79	0.75	0.59	0.64	0.72	0.43
fac	1.05	1.10	1.26	1.47	1.33	0.98	0.84	0.79	0.63	0.72	0.83	0.53
mean	1.03	1.01	1.23	1.16	1.32	1.07	1.01	1.04	0.82	1.04	1.28	0.80
median	1.02	1.06	1.27	1.17	1.29	1.04	0.99	0.99	0.76	0.89	0.99	0.75

Note: The table reports the ratio of the mean squared forecast error (MSE) generated by the respective direct forecasting model to the MSE of the iterated forecasting model. An MSE ratio smaller (larger) than one therefore indicates that the direct model performs better (worse) than the iterated model.

The following Discussion Papers have been published since 2005:

Series 1: Economic Studies

1	2005	Financial constraints and capacity adjustment in the United Kingdom – Evidence from a large panel of survey data	Ulf von Kalckreuth Emma Murphy
2	2005	Common stationary and non-stationary factors in the euro area analyzed in a large-scale factor model	Sandra Eickmeier
3	2005	Financial intermediaries, markets, and growth	F. Fecht, K. Huang, A. Martin
4	2005	The New Keynesian Phillips Curve in Europe: does it fit or does it fail?	Peter Tillmann
5	2005	Taxes and the financial structure of German inward FDI	Fred Ramb A. J. Weichenrieder
6	2005	International diversification at home and abroad	Fang Cai Francis E. Warnock
7	2005	Multinational enterprises, international trade, and productivity growth: Firm-level evidence from the United States	Wolfgang Keller Steven R. Yeaple
8	2005	Location choice and employment decisions: a comparison of German and Swedish multinationals	S. O. Becker, K. Ekholm, R. Jäckle, M.-A. Muendler
9	2005	Business cycles and FDI: evidence from German sectoral data	Claudia M. Buch Alexander Lipponer
10	2005	Multinational firms, exclusivity, and the degree of backward linkages	Ping Lin Kamal Saggi

11	2005	Firm-level evidence on international stock market comovement	Robin Brooks Marco Del Negro
12	2005	The determinants of intra-firm trade: in search for export-import magnification effects	Peter Egger Michael Pfaffermayr
13	2005	Foreign direct investment, spillovers and absorptive capacity: evidence from quantile regressions	Sourafel Girma Holger Görg
14	2005	Learning on the quick and cheap: gains from trade through imported expertise	James R. Markusen Thomas F. Rutherford
15	2005	Discriminatory auctions with seller discretion: evidence from German treasury auctions	Jörg Rocholl
16	2005	Consumption, wealth and business cycles: why is Germany different?	B. Hamburg, M. Hoffmann, J. Keller
17	2005	Tax incentives and the location of FDI: evidence from a panel of German multinationals	Thiess Buettner Martin Ruf
18	2005	Monetary Disequilibria and the Euro/Dollar Exchange Rate	Dieter Nautz Karsten Ruth
19	2005	Berechnung trendbereinigter Indikatoren für Deutschland mit Hilfe von Filterverfahren	Stefan Stamfort
20	2005	How synchronized are central and east European economies with the euro area? Evidence from a structural factor model	Sandra Eickmeier Jörg Breitung
21	2005	Asymptotic distribution of linear unbiased estimators in the presence of heavy-tailed stochastic regressors and residuals	J.-R. Kurz-Kim S.T. Rachev G. Samorodnitsky

22	2005	The Role of Contracting Schemes for the Welfare Costs of Nominal Rigidities over the Business Cycle	Matthias Paustian
23	2005	The cross-sectional dynamics of German business cycles: a bird's eye view	J. Döpke, M. Funke S. Holly, S. Weber
24	2005	Forecasting German GDP using alternative factor models based on large datasets	Christian Schumacher
25	2005	Time-dependent or state-dependent price setting? – micro-evidence from German metal-working industries –	Harald Stahl
26	2005	Money demand and macroeconomic uncertainty	Claus Greiber Wolfgang Lemke
27	2005	In search of distress risk	J. Y. Campbell, J. Hilscher, J. Szilagyi
28	2005	Recursive robust estimation and control without commitment	Lars Peter Hansen Thomas J. Sargent
29	2005	Asset pricing implications of Pareto optimality with private information	N. R. Kocherlakota Luigi Pistaferri
30	2005	Ultra high frequency volatility estimation with dependent microstructure noise	Y. Aït-Sahalia, P. A. Mykland, L. Zhang
31	2005	Umstellung der deutschen VGR auf Vorjahres-preisbasis – Konzept und Konsequenzen für die aktuelle Wirtschaftsanalyse sowie die ökonometrische Modellierung	Karl-Heinz Tödter

32	2005	Determinants of current account developments in the central and east European EU member states – consequences for the enlargement of the euro erea	Sabine Herrmann Axel Jochem
33	2005	An estimated DSGE model for the German economy within the euro area	Ernest Pytlarczyk
34	2005	Rational inattention: a research agenda	Christopher A. Sims
35	2005	Monetary policy with model uncertainty: distribution forecast targeting	Lars E.O. Svensson Noah Williams
36	2005	Comparing the value revelance of R&D reporting in Germany: standard and selection effects	Fred Ramb Markus Reitzig
37	2005	European inflation expectations dynamics	J. Döpke, J. Dovern U. Fritsche, J. Slacalek
38	2005	Dynamic factor models	Sandra Eickmeier Jörg Breitung
39	2005	Short-run and long-run comovement of GDP and some expenditure aggregates in Germany, France and Italy	Thomas A. Knetsch
40	2005	A“wreckers theory” of financial distress	Ulf von Kalckreuth
41	2005	Trade balances of the central and east European EU member states and the role of foreign direct investment	Sabine Herrmann Axel Jochem
42	2005	Unit roots and cointegration in panels	Jörg Breitung M. Hashem Pesaran
43	2005	Price setting in German manufacturing: new evidence from new survey data	Harald Stahl

1	2006	The dynamic relationship between the Euro overnight rate, the ECB's policy rate and the term spread	Dieter Nautz Christian J. Offermanns
2	2006	Sticky prices in the euro area: a summary of new micro evidence	Álvarez, Dhyne, Hoeberichts Kwapil, Le Bihan, Lünnemann Martins, Sabbatini, Stahl Vermeulen, Vilmunen
3	2006	Going multinational: What are the effects on home market performance?	Robert Jäckle
4	2006	Exports versus FDI in German manufacturing: firm performance and participation in international markets	Jens Matthias Arnold Katrin Hussinger
5	2006	A disaggregated framework for the analysis of structural developments in public finances	Kremer, Braz, Brosens Langenus, Momigliano Spolander
6	2006	Bond pricing when the short term interest rate follows a threshold process	Wolfgang Lemke Theofanis Archontakis
7	2006	Has the impact of key determinants of German exports changed? Results from estimations of Germany's intra euro-area and extra euro-area exports	Kerstin Stahn
8	2006	The coordination channel of foreign exchange intervention: a nonlinear microstructural analysis	Stefan Reitz Mark P. Taylor
9	2006	Capital, labour and productivity: What role do they play in the potential GDP weakness of France, Germany and Italy?	Antonio Bassanetti Jörg Döpke, Roberto Torrini Roberta Zizza
10	2006	Real-time macroeconomic data and ex ante predictability of stock returns	J. Döpke, D. Hartmann C. Pierdzioch

11	2006	The role of real wage rigidity and labor market frictions for unemployment and inflation dynamics	Kai Christoffel Tobias Linzert
12	2006	Forecasting the price of crude oil via convenience yield predictions	Thomas A. Knetsch
13	2006	Foreign direct investment in the enlarged EU: do taxes matter and to what extent?	Guntram B. Wolff
14	2006	Inflation and relative price variability in the euro area: evidence from a panel threshold model	Dieter Nautz Juliane Scharff
15	2006	Internalization and internationalization under competing real options	Jan Hendrik Fisch
16	2006	Consumer price adjustment under the microscope: Germany in a period of low inflation	Johannes Hoffmann Jeong-Ryeol Kurz-Kim
17	2006	Identifying the role of labor markets for monetary policy in an estimated DSGE model	Kai Christoffel Keith Küster Tobias Linzert
18	2006	Do monetary indicators (still) predict euro area inflation?	Boris Hofmann

Series 2: Banking and Financial Studies

1	2005	Measurement matters – Input price proxies and bank efficiency in Germany	Michael Koetter
2	2005	The supervisor's portfolio: the market price risk of German banks from 2001 to 2003 – Analysis and models for risk aggregation	Christoph Memmel Carsten Wehn
3	2005	Do banks diversify loan portfolios? A tentative answer based on individual bank loan portfolios	Andreas Kamp Andreas Pfingsten Daniel Porath
4	2005	Banks, markets, and efficiency	F. Fecht, A. Martin
5	2005	The forecast ability of risk-neutral densities of foreign exchange	Ben Craig Joachim Keller
6	2005	Cyclical implications of minimum capital requirements	Frank Heid
7	2005	Banks' regulatory capital buffer and the business cycle: evidence for German savings and cooperative banks	Stéphanie Stolz Michael Wedow
8	2005	German bank lending to industrial and non-industrial countries: driven by fundamentals or different treatment?	Thorsten Nestmann
9	2005	Accounting for distress in bank mergers	M. Koetter, J. Bos, F. Heid C. Kool, J. Kolari, D. Porath
10	2005	The eurosystem money market auctions: a banking perspective	Nikolaus Bartzsch Ben Craig, Falko Fecht
11	2005	Financial integration and systemic risk	Falko Fecht Hans Peter Grüner

12	2005	Evaluating the German bank merger wave	Michael Koetter
13	2005	Incorporating prediction and estimation risk in point-in-time credit portfolio models	A. Hamerle, M. Knapp, T. Liebig, N. Wildenauer
14	2005	Time series properties of a rating system based on financial ratios	U. Krüger, M. Stötzel, S. Trück
15	2005	Inefficient or just different? Effects of heterogeneity on bank efficiency scores	J. Bos, F. Heid, M. Koetter, J. Kolatri, C. Kool
01	2006	Forecasting stock market volatility with macroeconomic variables in real time	J. Döpke, D. Hartmann C. Pierdzioch
02	2006	Finance and growth in a bank-based economy: is it quantity or quality that matters?	Michael Koetter Michael Wedow
03	2006	Measuring business sector concentration by an infection model	Klaus Düllmann

Visiting researcher at the Deutsche Bundesbank

The Deutsche Bundesbank in Frankfurt is looking for a visiting researcher. Among others under certain conditions visiting researchers have access to a wide range of data in the Bundesbank. They include micro data on firms and banks not available in the public. Visitors should prepare a research project during their stay at the Bundesbank. Candidates must hold a Ph D and be engaged in the field of either macroeconomics and monetary economics, financial markets or international economics. Proposed research projects should be from these fields. The visiting term will be from 3 to 6 months. Salary is commensurate with experience.

Applicants are requested to send a CV, copies of recent papers, letters of reference and a proposal for a research project to:

Deutsche Bundesbank
Personalabteilung
Wilhelm-Epstein-Str. 14

D - 60431 Frankfurt
GERMANY