WP/08/53

IMF Working Paper

Does Money Growth Granger-Cause Inflation in the Euro Area? Evidence from Out-of-Sample Forecasts Using Bayesian VARs

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INTERNATIONAL MONETARY FUND

 WP/08/53

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European Department

Does Money Growth Granger-Cause Inflation in the Euro Area? Evidence from Out-of-Sample Forecasts Using Bayesian VARs[1]

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Authorized for distribution by Jörg Decressin

March 2008

Abstract

We use a mean-adjusted Bayesian VAR model as an out-of-sample forecasting tool to test whether money growth Granger-causes inflation in the euro area. Based on data from 1970 to 2006 and forecasting horizons of up to 12 quarters, there is surprisingly strong evidence that including money improves forecasting accuracy. The results are very robust with regard to alternative treatments of priors and sample periods. That said, there is also reason not to overemphasize the role of money. The predictive power of money growth for inflation is substantially lower in more recent sample periods compared to the 1970s and 1980s. This cautions against using money-based inflation models anchored in very long samples for policy advice.

JEL Classification Numbers: *E47, E52, E58*

Keywords: Bayesian VAR, Out-of-sample Forecasting, Granger Causality, Monetary Aggregates, Inflation, Monetary Policy, European Central Bank.

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[1] Both authors thank the IMF for its hospitality. Österholm gratefully acknowledges financial support from Jan Wallander's and Tom Hedelius' Foundation. Katrin Assenmacher-Wesche, Martin Cihak, Michael Ehrmann, Emil Stavrev, Henning Weber, as well as seminar participants at the IMF gave helpful comments and suggestions. The views expressed in this paper are those of the authors and do not necessarily represent those of the IMF or IMF policy.

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I. INTRODUCTION

There is an interesting debate on the role of money in monetary policy. While it would seem natural that central banks charged with keeping inflation at bay should be concerned with controlling money growth, Woodford (2003, 2007a) makes a strong theoretical argument for focusing on interest rate setting alone.[2] On the other hand, McCallum (2001, p. 4) stresses that "*it would be wrong to view [models] without any monetary aggregate… as representing a non-monetary model*." Moreover, Nelson (2003) and Gerlach (2004) argue that money contributes theoretically and empirically to our understanding of inflation dynamics and should, thus, remain an integral part of modern monetary policy. The debate has considerable policy implications because of the European Central Bank's (ECB) strong focus on monetary analysis in its policy framework (ECB 2003).

The case for a cashless economy is based on the current generation of New Keynesian (or Wicksellian) dynamic general equilibrium models, which have become the workhorse of modern monetary economics. In these models, money plays little or no role, being introduced almost as an afterthought to provide a unit of account (Woodford 2003, Galí and Gertler 2007). In a fully separable money-in-utility framework, households will demand real balances along the lines of a standard money demand function, but monetary developments have no short-run effects on the output gap or inflation. Monetary policy influences the economy through the interest rate and its impact on consumption and investment decisions alone. And while interest rate control presupposes control of the money supply, the central bank will supply money elastically at the set rate. As a consequence, changes in real balances will be independent of aggregate demand. In short, as Woodford (2007a) concludes, in this class of models there is "*no compelling reason to assign a prominent role to monetary aggregates in the conduct of monetary policy*."

Those arguing in favor of a more prominent role of money stress the lack of generality of the New Keynesian model. For instance, Christiano and Rostagno (2002) and Goodfriend and McCallum (2007) develop extensions of the Wicksellian model including a banking sector that suggest a more explicit role of money in the monetary policy process. And Nelson (2002), Ireland (2004), and Andrés *et al*. (2006) all stress that non-separability of money in the utility function of households will introduce a causal link (however large) from monetary aggregates to the output gap and inflation.[3] Finally, money would be a leading indicator variable for central banks if money demand was forward-looking and, thus, leading output and inflation developments. As Andrés *et al*. (2007) show, this will be the case in the presence of adjustment costs for real balances and/or if money enters the utility function non-separable and consumption is habit-persistent.[4]

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[2] See also Galí *et al*. (2004).

[3] Money influences inflation through two channels. Non-separability introduces money as an argument into the dynamic AD equation because it enters the consumption Euler equation. For the same reason, money may enter the stochastic discount factor of price-setting firms and, thus, the dynamic AS equation. McCallum (2000) argues, however, that these effects tend to be small under plausible specifications of the utility function. Similarly, in his discussion of the cashless limiting economy, Woodford (2003) argues that money is required for only a small fraction of transactions and these effects can be neglected in the limit.

[4] Orphanides (2003), among others, argues that money could also be relevant for informational reasons, for instance, if monetary developments reflect unobservable output movements. However, since any

With something to be said for both sides of the argument, there is an increased interest in empirical research—with distinctively mixed results. For instance, Kremer *et al*. (2003) find evidence for the non-separability of money and consumption in an estimated New Keynesian model for German data, while Ireland (2004) for the US and Andrés *et al*. (2006) reject the assumption for the euro area.[5] Jones and Stracca (2006, p. 9), using a non-parametric approach for the euro area, conclude that additive separability seems to hold "*most of the time*", even though non-separability cannot be rejected for their full sample period.[6] There is, however, some evidence supporting the idea of a forward-looking money demand in the UK, US, and euro area (Andrés *et al*. 2007). Turning to non-structural approaches, Assenmacher-Wesche and Gerlach (2006, 2007), among others, argue that longer-run movements in money growth (appropriately filtered) influence euro area inflation in a Phillips-curve framework.[7] However, the tight correlations between money and inflation found in this strand of the literature usually require data smoothing over long periods (OECD 2007).[8] Finally, de Grauwe and Polan (2005) have raised some doubts concerning the robustness of the long-run relation between money and prices in low inflation environments.

In more than one way, however, the most interesting empirical question may be whether money improves out-of-sample forecasts of inflation other than in the very long run. From a theoretical perspective, out-of-sample forecasts have been called the "*sound and natural approach*" to causality testing in a multivariate environment (Ashley *et al*. 1980, p. 1149), where more traditional Granger tests are difficult to administer. In addition, out-of sample forecasting is undoubtedly the relevant approach from an applied policy perspective. Central banks are ultimately interested in whether money contributes to their ability to predict inflation at horizons of roughly up to two or three years. And while the within-sample properties of an empirical model will help uncovering, for instance, the various channels through which money may influence inflation, its out-of-sample properties will help monetary policy to predict future inflation.

In this paper, we employ a state-of-the-art forecasting tool to test whether money Granger causes inflation. Using a mean-adjusted Bayesian vector autoregressive (BVAR) approach—which, to our knowledge, has not previously been applied to the problem—we find that money contributes at a relevant scale and robustly to the simulated out-of-sample forecast of euro area inflation.[9] The result is somewhat

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impact money may have on inflation would be through the interest rate reaction of the central bank, there may be less room for an independent empirical relation between money and inflation in this case.

[5] While all three papers use a similar methodology, Kremer *et al*.'s (2003) solution techniques deviates from Ireland (2004) and Andrés *et al*. (2006) in that it does not force a non-explosive, stable solution, but freely estimates the inflation coefficient in the Taylor rule.

[6] The full sample period runs 1991-2005.

[7] Their results mirror earlier findings, including for other currency areas, going back to Lucas (1980). See, for example, Benati (2005), Gerlach (2003), Jaeger (2003), Neumann (2003), Christiano and Fitzgerald (2003), or Backhus and Kehoe (1992).

[8] In addition, Nelson (2002), Ireland (2004), and Woodford (2007b) argue that, from a theoretical point of view, these long-run correlations are well compatible with the implications of the standard New Keynesian model, which, however, rejects a causal or forward-looking role of money growth for output and inflation.

[9] No extensive real-time data set is available for the euro area for our sample period. Lacking such a data set, our out-of-sample framework (only) simulates real-time forecasting conditions. This is, however, not likely to matter much since revisions to money growth and inflation—in the cases when they even exist—tend to be minor; see, for example, Orphanides (2001). However, not even when output growth is used in models in this paper do we believe that our results are likely to be misleading, since the models that are being compared will have the same kind of "misspecification" with respect to this issue.

surprising given the ambivalence of some of the existing empirical findings (as well as the strength of some of the theoretical positions). There is a positive marginal contribution of money both to the out-of-sample forecasting accuracy of univariate inflation models and to trivariate models comprising inflation, output, and interest rates. Quantitatively, however, the improvements in forecasting accuracy tend to be small, in particular in more recent subperiods and compared to the trivariate model. All results are robust to changes in the sample period and do not depend on particular assumptions about priors. Finally, we find that the question of whether fourvariate forecasting model or bivariate models (both including money) should be preferred depends on the sample and the time horizon of the inflation forecast.

The rest of the paper is organized as follows. Section 2 briefly reviews the empirical literature closest to our own approach. Section 3 elaborates on the principles of establishing Granger causality in an out-of-sample framework. Section 4 discusses the BVAR model as well as our main empirical results, including various robustness checks. Section 5 compares the forecasting performance of the various models in a horserace. Section 6 concludes.

II. Related Literature

Our out-of-sample approach based on BVAR models is most closely related to the literature that explores the links between money and inflation from a causality or forecasting perspective. As to within-sample exercises, for instance, Assenmacher-Wesche and Gerlach (2006) investigate Granger causality between money and inflation in the euro area at different frequencies. They find that their measure of causality running from money to inflation peaks at frequencies lower than 5 years.

There are a number of recent papers looking at the importance of monetary aggregates in simulated out-of-sample inflation forecasts. For example, Hofmann (2006) performs a forecasting horserace with a number of inflation models, including conventional bivariate VARs with various monetary indicators. His results—broadly in line with Nicoletti-Altimari (2001)—suggest a rather limited contribution of money to inflation forecasts at horizons shorter than two years, but forecasting improvements over a simple univariate AR model at longer horizons.[10] This is compatible with results for the US in Bachmeier and Swanson (2005), who report that money marginally improves forecasting performance of a bivariate VAR model for horizons exceeding one year over the univariate model. However, Hale and Jordà (2007), in a recent note, come to different conclusions comparing the contribution of monetary aggregates to out-of-sample inflation forecasts in the US and the euro area. They find that the forecast gains of including money in a simple forecasting equation, to the extent that they exist, are toward the very short-term of two quarters or less.[11]

[10] Hofmann (2006) also reports that forecasting performance of a combination of monetary models or indicators is somewhat better (at shorter horizons). Scharnagl and Schumacher (2007) come to broadly similar results using Bayesian model averaging techniques. The interpretation of these findings is complicated somewhat by the combination of a large number of overlapping approaches, including, for instance, various monetary aggregates, the so-called p-star model, trend variables and low-frequency indicators.

[11] The sample considered are: Nicoletti-Altimari (2001): 1980-2000, with forecasts evaluated over 1992-2000; Hofmann (2006) 1980 (1985 for some)-2005, with the forecasting period restricted to 1999-2005; Bachmeier and Swanson (2005): 1979-1992 and 1993-2003, without an explicit restriction of the testing period; Hale and Jordà (2007): euro area 1977-2006, US 1984-2007, also without a discussed restriction.

There is also some discussion about the appropriate way to model the VARs dominating the recent empirical literature. As, among others, Adolfson *et al*. (2007) have pointed out, a problem of conventional VARs is over-parameterization. As a rule, a large number of parameters needs to be estimated, which is likely to deteriorate forecasting performance. At the same time, VARs are appealing as their flexibility provide for a good description of the data generating process. One way out of the dilemma is to use BVARs, which shrink parameters using priors, thereby reducing the problem of over-parameterization (see, for example, Doan *et al*. 1984, Litterman 1986). Another problem shared by VAR and (to a lesser degree) BVAR models, especially at longer horizons, is that forecasts sometimes converge at implausible levels. This issue was recently addressed by Villani (2005), who suggests a BVAR specification which allows an informative prior distribution to be specified for the steady state of the variables in the system. This methodology has been shown to improve forecasts relative to traditional BVARs (see, for example, Adolfson *et al*. 2007, Österholm 2007) and will be used as a forecasting tool in this paper.

III. ESTABLISHING GRANGER CAUSALITY

There are two ways to test whether monetary aggregates have a meaningful predictive power for inflation within a VAR or BVAR setup. Within-sample, Granger causality of money growth for inflation in a bivariate framework can be inferred when lags of money growth are found significant in a regression of inflation on its own lags and lags of money growth—for instance, according to a simple *F*- or Wald-test. If, however, money growth does not add to the explanation of inflation, we would infer Granger non-causality.[12] Equivalently, the significance of responses of inflation to impulses in money could in the bivariate (B)VAR be used as a criterion for Granger causality (see Appendix 1).[13]

Out-of-sample causality tests based on forecasting performance may be the more attractive alternative compared to the within-sample approach. While within-sample tests are widely used, out-of-sample tests are closer to Granger's original idea (Ashley *et al*. 1980). In addition, at a practical level, within-sample tests can be difficult to implement in a multivariate framework. Also, from a policy perspective, monetary policy makers are most interested in the ability of money to add to their forecast of inflation. Finally, out-of-sample forecasting performance presents a somewhat higher hurdle for well-parameterized (B)VAR models than within-sample test, which adds some welcome additional prudence to the empirical exercise.

Picking up the earlier bivariate example, out-of-sample Granger causality will be present when the forecasting performance of a univariate (B)AR model of inflation can be improved at different forecasting horizons—for instance, as measured by the root mean squared error (*RMSE*)—by using a bivariate (B)VAR model with inflation and money. Non-causality is present if the forecasting performance of the bivariate (B)VAR is worse than that of the univariate (B)AR model. In the absence of an applicable

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[12] See, for example, the discussion in Hamilton (1994).

[13] The latter approach seems less popular in the literature, perhaps because standard errors for impulse response functions are reasonably complicated to calculate. See Lütkepohl (1989) for a description of a simple case.

statistical test, we will, in addition, discuss the quantitative dimension of the possible contribution of money to inflation forecasting performance.[14]

IV. Empirical Results

Our empirical application focuses on seasonally adjusted data for quarterly euro area CPI inflation, money growth, real GDP growth, and short-term (three month treasury bill) interest rate spanning the period between 1970Q3 and 2006Q4. Data are shown in Figure 1. Money growth is computed based on M2.[15] The data have been compiled using the historical time series provided by the ECB, extended, where necessary, using the corresponding series from the Area Wide Model (AWM) database. Both the ECB and the AWM data are available online.[16] To take into account the disinflation during the 1980s, we provide results for the full sample as well as for appropriately selected subsamples.

Our forecasting model is a flexible mean-adjusted BVAR model, which allows incorporating information regarding the steady-state values of the variables in the system (Villani 2005). More specifically, the model is given by

$$\mathbf{G}(L)(\mathbf{x}_t - \boldsymbol{\mu}) = \boldsymbol{\eta}_t, \qquad (2)$$

where $\mathbf{G}(L) = \mathbf{I} - \mathbf{G}_1 L - \ldots - \mathbf{G}_p L^p$ is a lag polynomial of order p, $\mathbf{x}_t$ is an nx1 vector containing the variables of interest, $\boldsymbol{\mu}$ is the corresponding vector of time-invariant steady-state values (discussed below), and $\boldsymbol{\eta}_t$ is an nx1 vector of *iid* error terms fulfilling $E(\boldsymbol{\eta}_t) = \mathbf{0}$ and $E(\boldsymbol{\eta}_t \boldsymbol{\eta}_t') = \boldsymbol{\Sigma}$. Priors on dynamics are given by a modified Minnesota prior in which the first own lag of variables in first differences has a prior mean of zero whereas it is set to 0.9 for variables in levels. The prior for the covariance matrix is a mainstream diffuse prior.[17] As to the data, for example, in the fourvariate BVAR, we would have $\mathbf{x}_t = (\Delta p_t \quad \Delta m_t \quad \Delta y_t \quad i_t)'$, with Δp_t, Δm_t, Δy_t, and i_t representing inflation, money growth, real GDP growth, and short-term interest rates, respectively. Growth rates are computed as quarter-on-quarter logarithmic changes (or first differences) of the original series in levels, and all variables are measured in percent. In all models, the lag length is set to $p = 4$.

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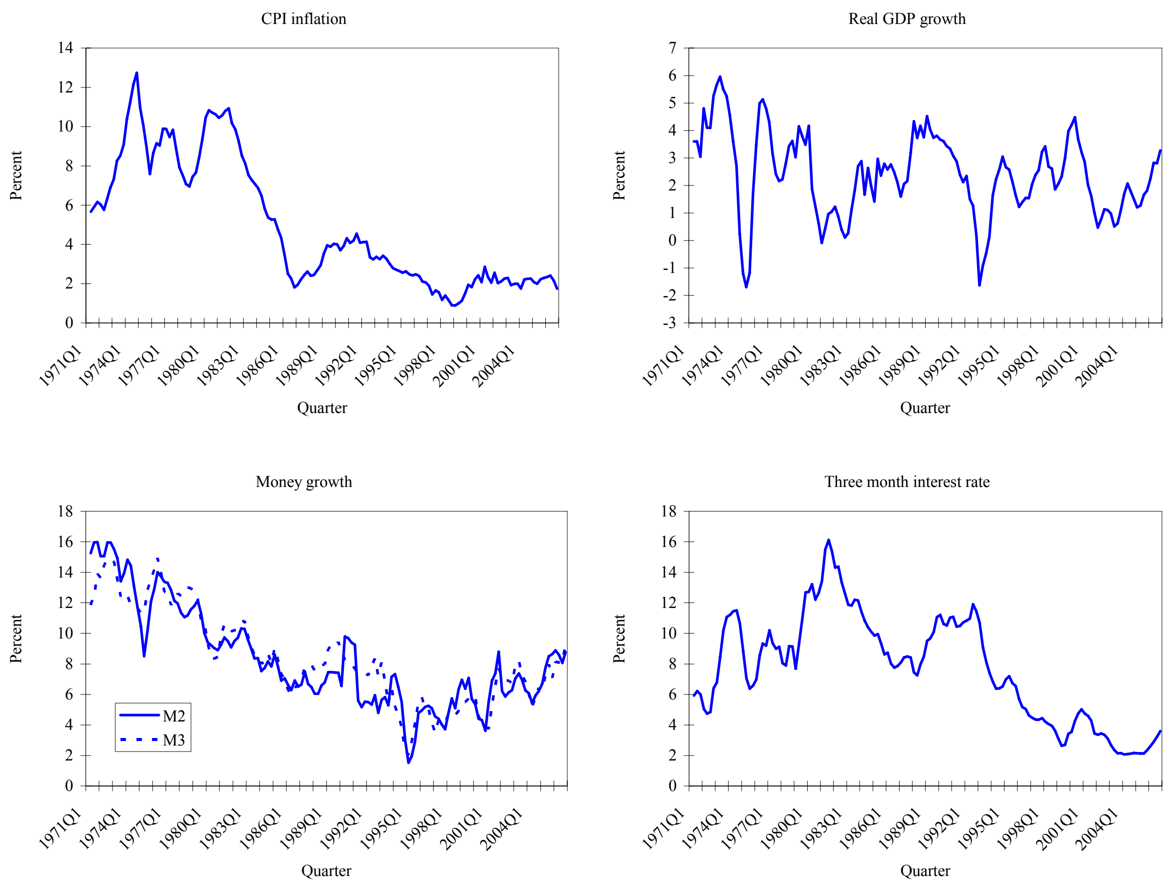
[14] The Diebold and Mariano (1995) test is often used to test whether the difference in forecasting performance is statistically significant. However, the test does not take into account the non-linearity and recursiveness of our models and that the forecasting horizon is larger than one (Clark and McCracken 2001, 2005). There is also the argument that in forecasting, significance tests are of little value in addition to the *RMSE* criterion (Armstrong 2007). Nevertheless, we will, in addition and without further comment, report DM tests as a tentative indicator of statistical significance in the Appendix.

[15] There is no general consensus in the literature about which monetary aggregate is to be preferred. We follow Reynard (2007), among others, who argues in favor of M2 on grounds of its empirical link to inflation and greater stability to portfolio shifts. We will, in addition, discuss results using M3.

[16] For more information consult `www.ecb.int` and `www.eabcn.org`.

[17] See Villani (2005) for details.

Figure 1. Data.



Note: Growth rates are given as changes with respect to the same quarter in the preceding year (annual growth rates) in percent.[18]

A. Univariate and Bivariate Models

We start by comparing the univariate BAR model of inflation with the bivariate BVAR including money growth. That is, we set $\mathbf{x}_t = (\Delta p_t)$ in the univariate and

$\mathbf{x}_t = (\Delta p_t \quad \Delta m_t)'$ in the bivariate case.

The priors for the steady-state values of inflation and money growth are given in Table 1 as the 95 percent probability interval for a normal distribution and seem fairly uncontroversial. For inflation, the prior is based on the ECB's officially stated inflation target of "*below but close to two percent over the medium term*" (ECB 2004, p. 51). For money growth, we combine the inflation target with the assumptions of potential real GDP growth of 2.5 percent and constant velocity, yielding a steady-state value for money growth of roughly 4.5 percent based on the quantity theory. Note that the priors have been converted from quarterly to annual growth, which are slightly more intuitive.

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[18] Like in Figure 1, we will also use annual growth rates in percent to evaluate the inflation forecasts produced in the main part of the paper. Note, however, that the empirical estimates underlying the forecasts will be based on first differences (that is, quarter-on-quarter growth rates).

Table 1. 95 percent prior probability intervals for parameters determining the annual steady-state growth rates.

	Δp_t	Δm_t
95 percent prior probability interval	(1.0, 3.0)	(3.5, 5.5)

The out-of-sample forecast exercise is quite straightforward. For the full sample, we estimate both BVAR models—that is, the univariate and bivariate versions of equation (2)—using data from 1970Q3 to 1975Q2 and use the estimated models to generate forecasts of the four-quarter ended values up to 1978Q2, that is, up to twelve quarters ahead.[19] The sample is then extended one period, the models are re-estimated, and new forecasts of four-quarter ended values up to twelve periods ahead are generated, This continues until we reach 2006Q3. The procedure generates, for instance, 126 one-step-ahead forecasts and 115 twelve-step-ahead forecasts to evaluate.

As a robustness test, we in addition apply the described forecasting exercise to two subsamples, which allows the models to differentiate between the more inflationary period in the earlier part of the sample and the later low-inflation period. The first subsample starts in 1970Q3 and ends in 1988Q2, halfway into the full sample period; it also corresponds to a point in time when the high inflation numbers of the 1970's and 1980's—and the following disinflation—had been left behind. This generates 53 one- to twelve-step-ahead forecasts to evaluate.[20] For the second subsample, the first forecast is generated based on models using data from 1988Q3 to 1993Q2. As our sample ends in 2006Q4, we have a different number of out-of-sample forecasts to evaluate, ranging from 54 for the one-step-ahead forecasts to 43 for the twelve-step-ahead forecasts.[21].

[19] The forecasts from the model are generated in a standard fashion. For every draw from the posterior distribution of the coefficients, a sequence of shocks are drawn and used to generate future data, that is, forecasts from one up to twelve quarters ahead. We hence get as many paths for each variable as we have iterations in the Gibbs sampling algorithm—that is, 10 000—and the evaluation is conducted using the median forecast from the predictive density generated.

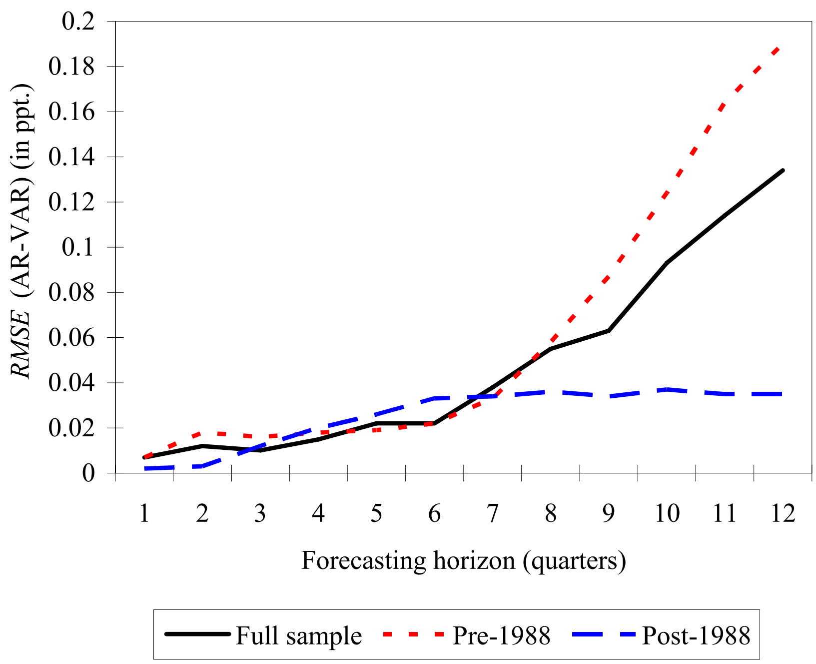
[20] This means that not all forecasts will be evaluated against actual values that also are from the first subsample. One (of the 53) one-step-ahead forecast will accordingly be evaluated against an observation from the second subsample; as the forecast horizon increases, so does this number. This seems to be a minor issue for the analysis, and we would argue that this approach is preferable to throwing away observations—not least because the exact breakpoint between the two samples can be varied without qualitative implications for the results.

[21] The steady-state priors are kept the same regardless of the sample period in order to facilitate straightforward comparisons. Note, however, that the higher average inflation of the 1970's and 1980's is not in itself a reason to choose a higher steady-state prior for inflation. As pointed out by Beechey and Österholm (2007), high inflation outcomes may well be an outcome of a central bank with a strong relative preference for output stability combined with a low inflation target. As a sensitivity analysis, we also changed the priors for the first subsample, centering them on values close to the arithmetic mean over the same period. Doing this does not change the results qualitatively in any meaningful way. (Results are not reported but are available upon request.)

Findings

Figure 1 depicts the results, in terms of the difference in *RMSE* between the univariate and bivariate models, for the full sample as well as the two subsamples. A number of results are worthwhile pointing out. First, money growth clearly improves inflation forecasts across all time horizons. As can be seen, the *RMSE* of the bivariate BVAR model is consistently below that of the univariate BAR model. This suggests that money impacts inflation in the sense of Granger-causality, and that this result holds not only in the long-run but also over the short- and medium-term.[22]

Figure 2. Difference in RMSE at different forecasting horizon between univariate and bivariate model.



Second, the absolute marginal contribution of money to inflation forecasting accuracy is between about 0.002 and 0.2 percentage points, with larger improvements tending to occur at horizons of half a year or longer. While not dramatic, these improvements seem quite remarkable given the simplicity of the underlying models. This impression is tentatively supported by the DM test statistics, which indicate, depending on the time horizon of the forecast and sample, that some of the observed *RMSE* differences are also statistically large (see Tables A1 and A2 in Appendix 2).

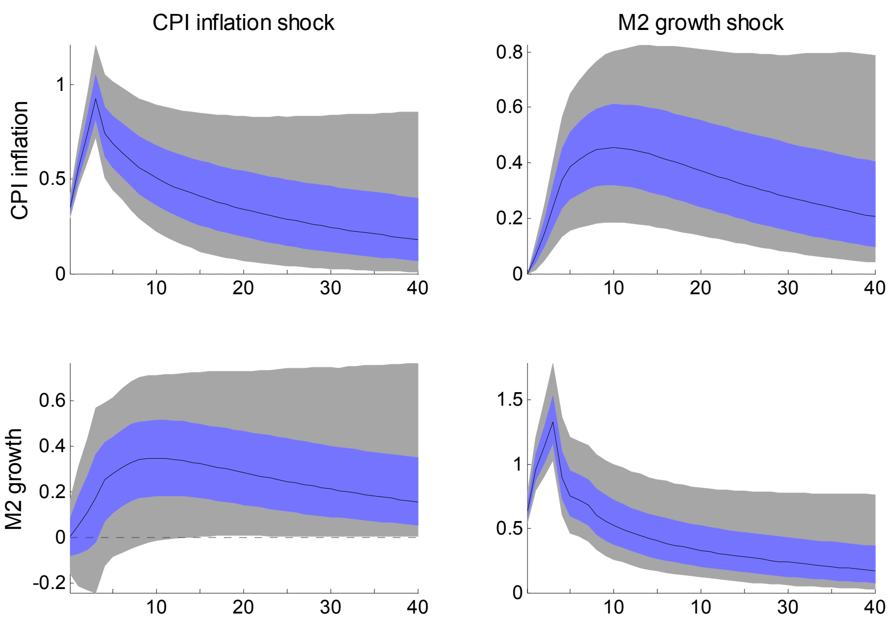
Third, the univariate model without money and the bivariate model with money compare differently in the early and the late subsample. In particular, the improvement from using the bivariate model appears to have been substantially larger in the first subsample.

[22] Table A1 in Appendix 2 reports the *RMSE* at different forecasting horizons for the univariate BVAR and bivariate BVAR model separately. Table A2 shows the DM test statistic for the differences between the univariate and the bivariate model, with a positive number indicating a lower *RMSE* for the bivariate model. A positive number suggests a positive marginal contribution of money growth to forecasting and, thus, suggests that money growth Granger-causes inflation.

The difference in the inflation-impact of money growth across subsamples is also present in within-sample causality tests. Figures 3 and 4 show the responses of inflation and money growth to shocks in either variable based on the bivariate BVAR models for the pre-1988 and post-1988 subsamples, respectively.[23] The figures also depict the 68 and 95 percent confidence intervals around the impulse response functions. Comparing the reaction to shocks in general, it is clear that both inflation and money growth were more persistent in the earlier subsample than in the later. As to the reaction of inflation to money growth shocks, money matters in both subsamples (at least at the more generous significance level). Where the subperiods differ, however, is the degree to which money growth accommodates shocks to inflation. While the pre-1988 period is characterized by a positive reaction of money growth to inflation, money growth did not react, or reacted negatively, to inflationary surprises after 1988.

One way to interpret the within-sample results would be that aggregate monetary policy in the euro area stopped accommodating inflation in the 1980s. This is in line with the policy-oriented explanation of the secular decline in US inflation ("Volcker disinflation") occurring around that period.[24]

Figure 3. Impulse response Euro area pre-1988 (1970Q3-1988Q2).



Note: Median impulse response shown with 68 and 95 percent confidence bands. Horizon in quarters.

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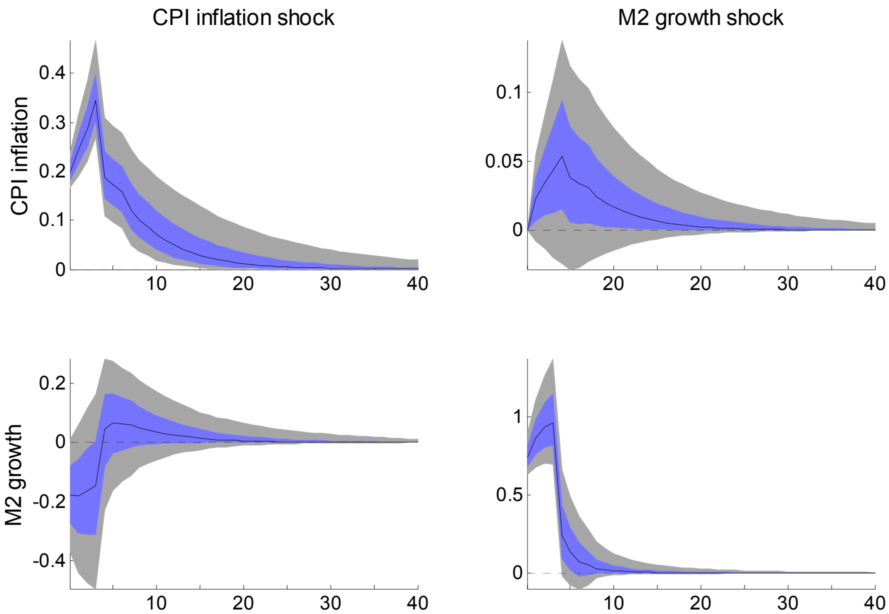
[23] The impulse response functions were calculated using a standard Cholesky decomposition of the covariance matrix, where CPI inflation was ordered ahead of money growth.

[24] See, for example, Goodfriend and King (2005) for a discussion.

Figure 4. Impulse response Euro area post-1988 (1988Q3-12006Q4).



Note: Median impulse response shown with 68 and 95 percent confidence bands. Horizon in quarters.

Extensions and robustness

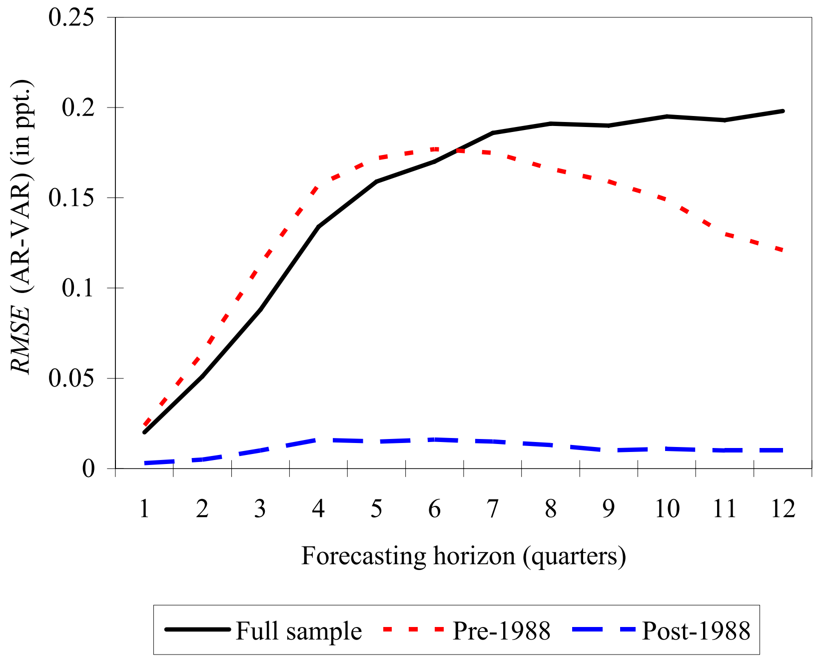
We conduct a number of sensitivity tests, starting with a less restrictive set of priors for the steady state growth rates on inflation and money growth. Instead of using the model in equation (2) and the assumptions given in Table 1, we employ the traditional specification. That is, we estimate univariate BAR and bivariate BVAR models of the form

$$\mathbf{G}(L)\mathbf{x}_t = \boldsymbol{\delta} + \boldsymbol{\eta}_t, \qquad (3)$$

where $\mathbf{G}(L)$, $\mathbf{x}_t$ and $\boldsymbol{\eta}_t$ all are defined as in equation (2). The difference between this model and the BVAR in equation (2) is that the model in equation (3) is not expressed in deviations from the long-run means. It is therefore difficult to specify an informative prior for $\boldsymbol{\delta}$ and we accordingly follow the literature and employ a **diffuse prior**. This—in essence—lets the data more freely decide on the steady-state values. The priors on the dynamic coefficients and the covariance matrix are not changed relative to the previous specification.

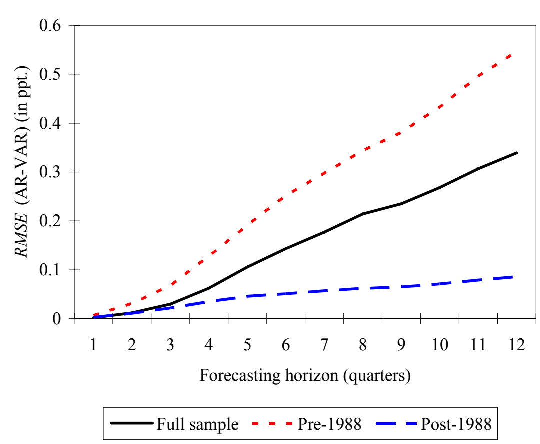
The results using the model in equation (3), reported in Figure 5 and Tables A3 and A4 in Appendix 2, are fairly similar to our earlier findings. We still find that money makes a positive marginal contribution to forecasting inflation across all subsamples and time horizons. If anything, the DM test statistics indicate that the degree to which the bivariate BVAR including money growth outperforms the univariate BAR model without inflation increase when diffuse priors are used. The effect is especially pronounced in the pre-1988 period.

Figure 5. Difference in RMSE at different forecasting horizon between univariate and bivariate model (diffuse priors).



Another robustness test is substituting **M3** for M2 as our indicator of money growth. It is sometimes argued that M3, the monetary aggregate most prominently featured in the ECB's monetary analysis, may be particularly well-suited to explain inflationary developments in the euro area (for example, Fischer *et al*. 2006). As a consequence, we would expect the M3-based bivariate BVAR to do as well as—if not better than—the M2-based BVAR compared to the univariate BAR model without money growth in explaining inflation. Figure 6 and Tables A5 and A6 in Appendix 2 report our results.

Figure 6. Difference in RMSE at different forecasting horizon between univariate and bivariate model



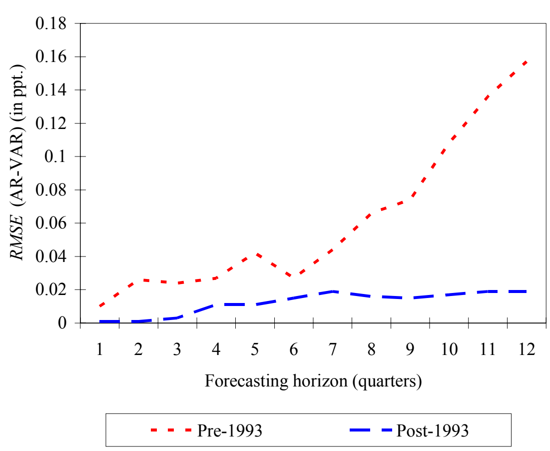
(M3-based)

Figure 6 indeed suggests that the M3-based BVAR model works well. It consistently outperforms the univariate model at margins that, in particular in the pre-1988 subsample, exceed the ones of the M2-based model. The difference in *RMSE* between the bivariate M2- and the bivariate M3-based model is about 0.2 on average across the full forecasting horizon during the earlier subsample and about 0.02 during the later subsample. All in all, it would seem that M2 and M3 are fairly close substitutes when it comes to predicting inflation out-of-sample in a simple bivariate framework like the one employed here.[25]

From a policy perspective, the results concerning the late subsample are clearly the most interesting—and the question arises how robust our findings are with regard to alternative **sample definitions**. For instance, an alternative (and also quite natural) starting point for the late-sample analysis could be early 1993, after the first ERM crisis. There is a natural concern about parameter instability or structural breaks, and making the later subsample shorter is one way of addressing this issue. An added advantage of choosing this breakpoint is that, arguably, the countries forming the euro area after 1999 started to act more homogenously along several dimensions as the road to European Monetary and Economic Union (EMU) opened gradually.

Figure 7 and Tables A7 and A8 in Appendix 2 report the results for the early and late subsamples around the new breakpoint 1993Q2. We use the model established in Section 4.1, that is, operate with informative steady-state priors (see Table 1) and employ M2 as a monetary aggregate. The results are very similar to our earlier findings: the bivariate BVAR including money growth is clearly the superior forecasting model with lower *RMSE* at all forecasting horizons.[26]

Figure 7. Difference in RMSE at different forecasting horizon between univariate and bivariate model (breakpoint 1993Q2).



[25] This is not necessarily true in more extensive models; see the note in Section 4.2.

[26] In another experiment (not reported), we kept the original sample split of 1988 but limited the forecasting period to observations after the year 2001—the period where, according to many, money-based models fail to explain euro area inflation. This seems not to be the case here. We find that the money-based BAR and BAVR models continue to produce lower RMSEs than the models excluding money (at horizons six and higher for the bivariate and at horizons shorter than five for the fourvariate model introduced in the following section).

Trivariate and fourvariate models

The discussion so far suggests that money has predictive power for inflation in the euro area, but the underlying models are fairly simple. Comparing a univariate inflation-only BAR model with a bivariate BVAR may bias the impact of money upward, for instance, because monetary developments could be reflecting other developments in the economy. In the fully separable money-in-utility framework, preferred by much of modern macroeconomic theory, household real balances demand will be driven by interest rates and output developments. This invites the question, whether money growth will contribute to out-of-sample inflation forecasts once these forces have been taken into account.

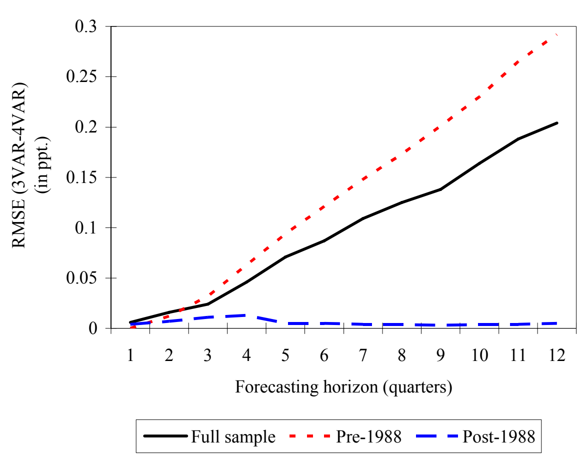
To answer this question, we again use the model described in equation (2)—that is, $\mathbf{G}(L)(\mathbf{x}_t - \boldsymbol{\mu}) = \boldsymbol{\eta}_t$—but $\mathbf{x}_t$ is an nx1 vector defined as $\mathbf{x}_t = (\Delta p_t \quad \Delta m_t \quad \Delta y_t \quad i_t)'$ in the fourvariate case and as $\mathbf{x}_t = (\Delta p_t \quad \Delta y_t \quad i_t)'$ in the trivariate case. Priors for the steady state values for all variables are given in Table 2. The steady-state priors for inflation and money growth (M2) were discussed in Section 4.1.1, where a potential real GDP growth of 2.5 percent also was assumed. Following convention, the steady-state value of the nominal interest rate of four percent is computed by combining the ECB's inflation target of two percent with an assumption of a real interest rate of approximately two percent. The breakpoint dividing the subsamples is again 1988Q2.

Table 2. 95 percent prior probability intervals for parameters determining the annual steady-state growth rates and steady-state interest rate.

	Δp_t	Δm_t	Δy_t	i_t
95 percent prior probability interval	(1.0, 3.0)	(3.5, 5.5)	(2.0, 3.0)	(3.0, 5.0)

Figure 8 and Tables A9 and A10 in Appendix 2 present our results in the now familiar format. The interpretation of the results is analogue to the previous section: If moving from the trivariate to the fourvariate model shows a positive marginal contribution of money growth to inflation forecasting accuracy (that is, if the *RMSE* in the fourvariate model are lower), we would conclude that money growth Granger-causes inflation.

Figure 8. Difference in RMSE at different forecasting horizon between trivariate and fourvariate model.



The findings support Granger causality of money growth for inflation even in a richer BVAR framework. The out-of-sample *RMSE* of the fourvariate models are strictly lower in the full sample as well as in both subsamples, and across all forecasting horizons.[27] In addition, the DM test statistics indicate that the improvement in forecasting performance may be statistically large as well.

That said, the contribution of money to the forecasting performance of the trivariate BVAR including inflation, real GDP growth, and interest rates in the post-1988 period is small. Figure 8 makes it clear that that the absolute improvement from using the fourvariate model is substantially larger in the pre-1988 subsample, in particular at longer horizons.[28] This seems to support the New Keynesian notion that, in a low inflation environment, money growth is, to a large degree, reflecting interest rates and current changes in real GDP (see, for instance, Woodford 2007b). Still, coming at little or no computational cost, adding money growth to the trivariate BVAR model will decrease the *RMSE* and improve the inflation forecast.

V. Horserace

As argued earlier, an advantage of causality tests based on out-of-sample forecasting performance is its considerable appeal to practitioners of monetary policy—which begs the question which model would be most useful for forecasting inflation. To that end, we compute the *RMSE* for the pre- and post-1988 subsamples for all four model discussed: univariate (inflation) BAR, bivariate (inflation, money growth), trivariate (inflation, output growth, interest rate), and fourvariate (inflation, output growth, interest rate, money growth) BVAR.

Figure 9 shows the level of the *RMSE*s of the four models for our two subsamples. Detailed results are in Appendix 2 (see Tables A9, A10, and A11).[29] Among other things, Figure 9 illustrates that the moderation of inflation rates since the 1980s has improved the forecasting performance of all models of inflation considerably, with the maximum *RMSE* falling from around four percent during the pre-1988 period to below one percent during the post-1988 period. As to the relative performance of the inflation models, as discussed in Section 4, the money-based models dominate the non-monetary models in the pre-1988 subsample as well as (even at a smaller margin) in the post-1988 subsample.

Perhaps the most important result stemming from the exercise is that the choice between the bivariate and fourvariate money-based BVAR models is a matter of the

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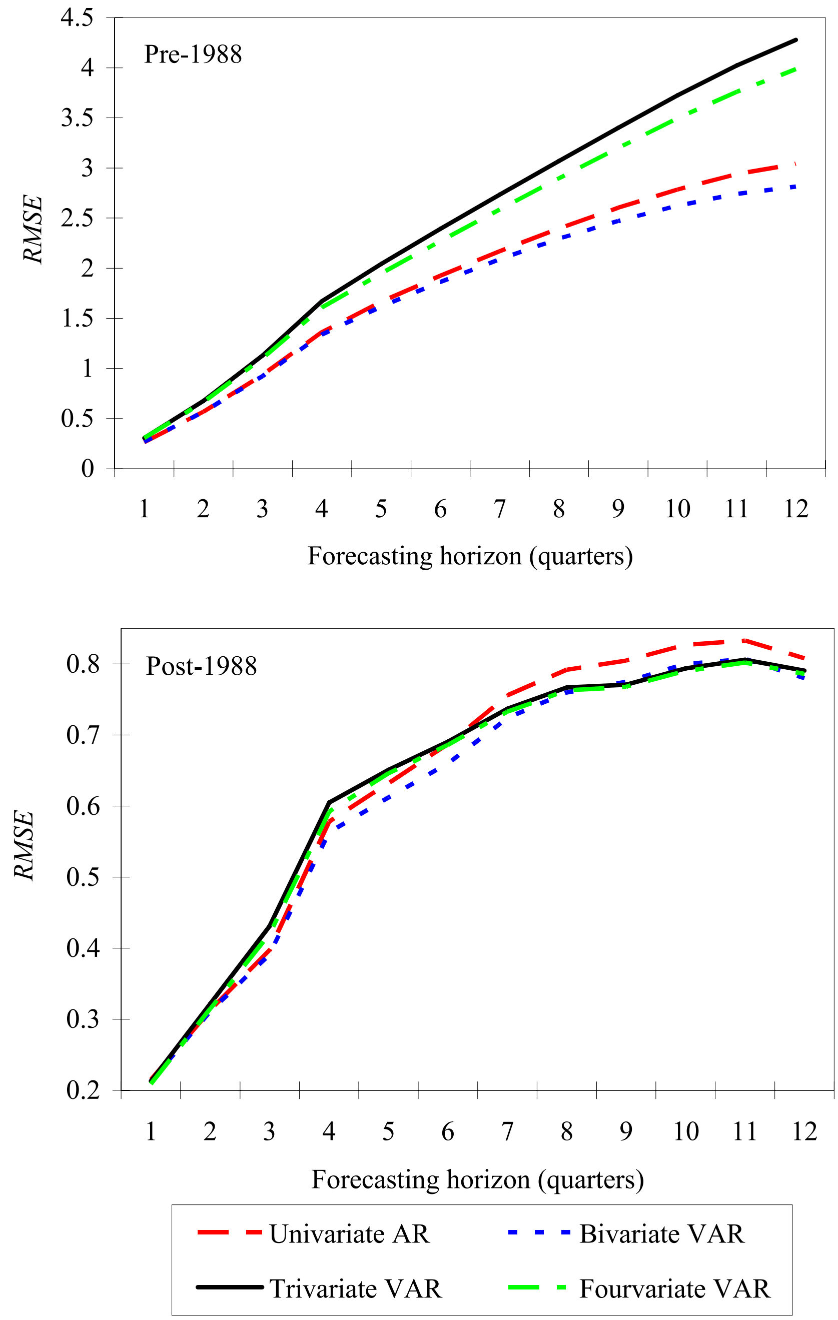
[27] Interestingly, this does not strictly hold for M3. We find that the trivariate model produces *RMSE*s at least as low as a fourvariate M3-based model. This is in contrast with the results in the bivariate case, where the M3-based model performed well compared to the univariate model as well as to the bivariate M2-based model. A possible explanation is that the portfolio shifts distorting M3 (see Fischer *et al*. 2006 and ECB 2007) feature more prominently in the fourvariate BVAR once the influence of real GDP growth and interest rates is taken into account. Indeed, using the ECB's M3 measure corrected for portfolio adjustments, the fourvariate model outperforms the trivariate model at least at short horizons in the later subsample. (Additional data from Reynard (2007); results available on request.)

[28] Given the generally much higher *RMSE* levels for all models during the pre-1988 period (see Appendix), the visual inspection of Figure 8 can be slightly deceiving. Indeed, the post-1988 contribution of money in percent of the trivariate *RMSE* for the first four quarters is of the same order of magnitude as pre-1988. However, there is a substantial relative decline at longer horizons.

[29] In order to compare the uni- and bivariate model against the tri- and fourvariate, we must use the exact same samples. Accordingly, Table A11 in Appendix 2 provides the *RMSE*s for the uni- and bivariate cases that are directly comparable to those in Table A9.

forecasting horizon and the sample under consideration. Clearly, the bivariate outperforms the fourvariate BVAR during the pre-1988 subsample as well as in the full sample (not shown). For the second subsample, however, the fourvariate model produces more precise forecasts and lower *RMSE*s at the very short (one quarter) and the very long end (9 to 11 quarters). In the intermediate range, the simpler bivariate model maximizes forecasting accuracy.

Figure 9. RMSE for all models for the pre- and post-1988 subsamples.



VI Conclusions

There is surprisingly strong evidence that money growth helps forecasting inflation out-of-sample in the euro area. Looking at forecasting horizons of up to 12 quarters ahead during the period 1970-2006, we find that bivariate mean-adjusted BVAR models including inflation and money growth consistently deliver better inflation forecasts than univariate models of inflation. Similarly, a fourvariate model, which includes inflation, money growth, real GDP growth, and three month interest rate, tends to predict inflation better than trivariate models excluding money growth. The results are robust to sensitivity experiments such as allowing for diffuse priors for the constant term and subsamples with alternative breakpoints. The relative forecasting performance of the bivariate or the fourvariate money-based models is a question of the sample period and forecasting horizon.

While any structural interpretation of time series evidence needs to be handled with care, the result that money Granger-causes inflation, seems to be running across the gist of the current workhorse of modern monetary economics, the New Keynesian model.[30] In this class of models, money is often introduced as an afterthought and is endogenous with regard to key variables such as the interest rate set by the central bank and the resulting (given shocks) changes in real GDP and inflation. Therefore, one way to read our results would be that there may be room to consider more general versions of the New Keynesian model that allow for a somewhat more prominent role for money. This could include, but is certainly not restricted to, introducing financial frictions (that is, allowing a causal role for money) or adjustment costs into money demand (that is, making money forward-looking).

That said, there is also reason not to overemphasize the role of money in forecasting inflation. The quantitative improvements in forecasting accuracy from including money growth are rarely dramatic. In addition, our results indicate that the predictive power of money growth has substantially decreased in more recent sample periods (post-1988 or post-1993) compared to the 1970s and 1980s. Arguably, it is the more recent periods that are most relevant for monetary policy and the ECB. This cautions against money-based inflation models anchored in very long samples.

[30] One well-known complication in the interpretation of non-structural results is the possibility that the link between one economic variable and another could be introduced by policy rules rather than economic structure. However, to what extent the ECB's interest rate policy does indeed reflect monetary developments independent of inflation and real growth, seems open to debate.

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Appendix 1

Consider the a simple bivariate BVAR given by

$$\mathbf{G}(L)(\mathbf{x}_t - \boldsymbol{\mu}) = \boldsymbol{\eta}_t, \tag{A1}$$

where $\mathbf{G}(L)$ and $\boldsymbol{\eta}_t$ are defined as in equation (2) and $\mathbf{x}_t = (\Delta p_t \quad \Delta m_t)'$. Then non-causality of money for inflation would imply that the lag polynomial $\mathbf{G}(L)$ is lower triangular, that is,

$$\mathbf{G}(L) = \begin{pmatrix} g_{\Delta p \Delta p}(L) & 0 \\ g_{\Delta m \Delta p}(L) & g_{\Delta m \Delta m}(L) \end{pmatrix}. \tag{A2}$$

To see the implication for impulse responses, write the BVAR in its vector moving average form as

$$\mathbf{x}_t = \boldsymbol{\mu} + \boldsymbol{\Psi}(L)\boldsymbol{\eta}_t, \tag{A3}$$

where $\boldsymbol{\Psi}(L) = [\mathbf{G}(L)]^{-1}$. The lower triangular form of $\mathbf{G}(L)$ implies that $\boldsymbol{\Psi}(L)$ also is lower triangular. This can be seen by noting that

$$\begin{pmatrix} g_{\Delta p \Delta p}(L) & 0 \\ g_{\Delta m \Delta p}(L) & g_{\Delta m \Delta m}(L) \end{pmatrix} \begin{pmatrix} \psi_{11}(L) & \psi_{12}(L) \\ \psi_{21}(L) & \psi_{22}(L) \end{pmatrix} = I, \tag{A4}$$

implying that $g_{\Delta p \Delta p}(L)\psi_{12}(L) = 0$ and, accordingly, that $\psi_{12}(L) = 0$.

Appendix 2

Table A1. Root mean square error of four-quarter ended CPI inflation forecasts (Fig. 2).

	1970Q3-1975Q2/2006Q3		1970Q3-1975Q2/1988Q2		1988Q3-1993Q2/2006Q3	
Forecasting horizon in quarters	Bivariate BVAR	Univariate BAR	Bivariate BVAR	Univariate BAR	Bivariate BVAR	Univariate BAR
1	0.252	0.259	0.297	0.304	0.203	0.205
2	0.463	0.475	0.598	0.616	0.304	0.307
3	0.704	0.714	0.980	0.996	0.391	0.403
4	1.028	1.043	1.442	1.460	0.563	0.583
5	1.207	1.229	1.735	1.754	0.611	0.637
6	1.374	1.396	1.998	2.020	0.665	0.698
7	1.516	1.554	2.201	2.234	0.734	0.768
8	1.625	1.680	2.351	2.409	0.779	0.815
9	1.726	1.789	2.485	2.572	0.823	0.857
10	1.796	1.889	2.578	2.702	0.862	0.899
11	1.877	1.991	2.677	2.841	0.896	0.931
12	1.957	2.091	2.798	2.988	0.922	0.957

Table A2. Diebold and Mariano test for the Euro area; bivariate versus univariate model.

Forecasting horizon in quarters	1970Q3-1975Q2/2006Q3	1970Q3-1975Q2/1988Q2	1988Q3-1993Q2/2006Q3
1	1.077	0.657	0.554
2	0.839	0.677	0.867
3	0.447	0.342	1.848**
4	0.438	0.274	1.817**
5	0.506	0.237	1.811**
6	0.484	0.248	1.767**
7	0.753	0.368	1.666**
8	0.989	0.678	1.549*
9	1.083	1.004	1.412*
10	1.567*	1.388*	1.403*
11	1.704**	1.622*	1.303*
12	1.759**	1.658**	1.311*

Notes: As discussed in the main text, the DM test is not directly applicable in this case and only indicative of the statistical relevance of the difference in *RMSE* based on the previous table. A "**" indicates significance at the 5 percent level, and a "*" indicates significance at the 10 percent level using the standard-normal approximation.

Table A3. Root mean square error of fourquarter ended CPI inflation forecasts (diffuse priors, Fig 5).

	1970Q31975Q2/2006Q3		1970Q31975Q2/1988Q2		1988Q31993Q2/2006Q3	
Forecasting horizon in quarters	Bivariate BVAR	Univariate BAR	Bivariate BVAR	Univariate BAR	Bivariate BVVAR	Univariate BAR
1	0.271	0.291	0.331	0.355	0.225	0.228
2	0.529	0.580	0.703	0.767	0.374	0.379
3	0.833	0.921	1.163	1.276	0.528	0.538
4	1.227	1.361	1.714	1.871	0.757	0.773
5	1.478	1.637	2.079	2.251	0.834	0.849
6	1.697	1.867	2.380	2.557	0.905	0.921
7	1.894	2.080	2.629	2.804	0.980	0.995
8	2.064	2.255	2.838	3.004	1.032	1.045
9	2.221	2.411	3.020	3.179	1.080	1.090
10	2.366	2.561	3.175	3.324	1.122	1.133
11	2.501	2.694	3.317	3.447	1.156	1.166
12	2.615	2.813	3.431	3.552	1.186	1.196

Table A4. Diebold and Mariano test for the Euro area; bivariate versus univariate model (diffuse priors).

Forecasting horizon in quarters	1970Q31975Q2/2006Q3	1970Q31975Q2/1988Q2	1988Q31993Q2/2006Q3
1	3.299**	2.723**	1.027
2	3.783**	2.990**	1.265
3	2.927**	2.293**	1.908**
4	2.668**	1.918**	1.950**
5	2.535**	1.733**	1.734**
6	2.476**	1.630*	1.674**
7	2.522**	1.563*	1.543*
8	2.479**	1.516*	1.414*
9	2.447**	1.509*	1.341*
10	2.461**	1.494*	1.445*
11	2.378**	1.430*	1.399*
12	2.332**	1.424*	1.409*

Notes: As discussed in the main text, the DM test is not directly applicable in this case and only indicative of the statistical relevance of the difference in *RMSE* based on the previous table. A “**” indicates significance at the 5 percent level, and a “*” indicates significance at the 10 percent level using the standard-normal approximation.

Table A5. Root mean square error of fourquarter ended CPI inflation forecasts (M3based, Fig. 6).

	1970Q31975Q2/2006Q3		1970Q31975Q2/1988Q2		1988Q31993Q2/2006Q3	
Forecasting horizon in quarters	Bivariate BVAR	Univariate BAR	Bivariate BVAR	Univariate BAR	Bivariate BVAR	Univariate BAR
1	0.257	0.259	0.297	0.304	0.202	0.205
2	0.463	0.475	0.585	0.616	0.296	0.307
3	0.684	0.714	0.928	0.996	0.381	0.403
4	0.981	1.043	1.332	1.460	0.548	0.583
5	1.123	1.229	1.563	1.754	0.591	0.637
6	1.253	1.396	1.768	2.020	0.647	0.698
7	1.377	1.554	1.936	2.234	0.711	0.768
8	1.466	1.680	2.065	2.409	0.753	0.815
9	1.554	1.789	2.191	2.572	0.792	0.857
10	1.621	1.889	2.269	2.702	0.828	0.899
11	1.684	1.991	2.345	2.841	0.852	0.931
12	1.752	2.091	2.442	2.988	0.871	0.957

Table A6. Diebold and Mariano test for the Euro area; bivariate versus univariate model (M3based).

Forecasting horizon in quarters	1970Q31975Q2/2006Q3	1970Q31975Q2/1988Q2	1988Q31993Q2/2006Q3
1	0.348	0.404	1.424*
2	0.596	0.744	2.356**
3	0.716	0.855	1.979**
4	0.782	0.910	1.871**
5	0.860	0.938	1.897**
6	0.950	1.003	1.806**
7	1.059	1.071	1.748**
8	1.204	1.223	1.688**
9	1.323*	1.363*	1.580*
10	1.474*	1.517*	1.500*
11	1.570*	1.604*	1.424*
12	1.597*	1.616*	1.360*

Notes: As discussed in the main text, the DM test is not directly applicable in this case and only indicative of the statistical relevance of the difference in *RMSE* based on the previous table. A “**” indicates significance at the 5 percent level, and a “*” indicates significance at the 10 percent level using the standard-normal approximation.

Table A7. Root mean square error of fourquarter ended CPI inflation forecasts (breakpoint 1993Q2, Fig. 7).

	1970Q31975Q2/1993Q2		1993Q31998Q2/2006Q3	
Forecasting horizon in quarters	Bivariate BVAR	Univariate BAR	Bivariate BVAR	Univariate BAR
1	0.277	0.287	0.210	0.211
2	0.538	0.564	0.272	0.273
3	0.859	0.883	0.301	0.304
4	1.260	1.287	0.387	0.398
5	1.498	1.540	0.364	0.375
6	1.722	1.749	0.355	0.370
7	1.894	1.938	0.368	0.387
8	2.021	2.087	0.375	0.391
9	2.147	2.221	0.384	0.399
10	2.225	2.333	0.382	0.399
11	2.313	2.449	0.369	0.388
12	2.416	2.573	0.365	0.384

Table A8. Diebold and Mariano test for the Euro area; bivariate versus univariate model.

Forecasting horizon in quarters	1970Q31975Q2/1993Q2	1993Q31998Q2/2006Q3
1	1.026	0.381
2	1.122	0.539
3	0.616	1.185
4	0.491	1.997**
5	0.642	1.708**
6	0.369	1.886**
7	0.577	1.899**
8	0.887	1.711**
9	0.959	1.534*
10	1.438*	1.609*
11	1.659**	1.586*
12	1.671**	1.531*

Notes: As discussed in the main text, the DM test is not directly applicable in this case and only indicative of the statistical relevance of the difference in *RMSE* based on the previous table. A "**" indicates significance at the 5 percent level, and a "*" indicates significance at the 10 percent level using the standard-normal approximation.

Table A9. Root mean square error of fourquarter ended CPI inflation forecasts (Fig. 8).

	1970Q31977Q2/2006Q3		1970Q31977Q2/1988Q2		1988Q31995Q2/2006Q3	
Forecasting horizon in quarters	Fourvariate BVAR	Trivariate BVAR	Fourvariate BVAR	Trivariate BVAR	Fourvariate BVAR	Trivariate BVAR
1	0.248	0.254	0.308	0.308	0.209	0.213
2	0.476	0.492	0.665	0.677	0.315	0.322
3	0.738	0.762	1.101	1.133	0.420	0.431
4	1.073	1.119	1.609	1.672	0.592	0.605
5	1.275	1.346	1.949	2.043	0.646	0.651
6	1.471	1.558	2.272	2.393	0.686	0.691
7	1.679	1.788	2.587	2.735	0.733	0.737
8	1.879	2.004	2.896	3.069	0.763	0.767
9	2.083	2.221	3.199	3.400	0.768	0.771
10	2.276	2.440	3.495	3.725	0.790	0.794
11	2.453	2.641	3.759	4.024	0.802	0.806
12	2.605	2.809	3.986	4.278	0.786	0.791

Table A10. Diebold and Mariano test for the Euro area; fourvariate versus trivariate VAR.

Forecasting horizon in quarters	1970Q31977Q2/2006Q3	1970Q31977Q2/1988Q2	1988Q31995Q2/2006Q3
1	0.922	0.038	1.511*
2	1.152	0.499	2.165**
3	0.955	0.737	2.899**
4	1.168	0.932	2.620**
5	1.272	1.020	1.183
6	1.231	1.030	0.946
7	1.275	1.044	0.771
8	1.285*	1.067	0.669
9	1.244	1.144	0.427
10	1.310*	1.198	0.496
11	1.327*	1.233	0.598
12	1.293*	1.237	0.717

Notes: As discussed in the main text, the DM test is not directly applicable in this case and only indicative of the statistical relevance of the difference in *RMSE* based on the previous table. A "**" indicates significance at the 5 percent level, and a "*" indicates significance at the 10 percent level using the standard-normal approximation.

Table A11. Root mean square error of fourquarter ended CPI inflation forecasts in a sample matching Table A9.

	1970Q31977Q2/2006Q3		1970Q31977Q2/1988Q2		1988Q31995Q2/2006Q3	
Forecasting horizon in quarters	Bivariate BVAR	Univariate BAR	Bivariate BVAR	Univariate BAR	Bivariate BVAR	Univariate BAR
1	0.236	0.239	0.269	0.264	0.213	0.215
2	0.437	0.441	0.567	0.568	0.311	0.313
3	0.654	0.654	0.924	0.937	0.391	0.397
4	0.941	0.948	1.336	1.362	0.563	0.578
5	1.099	1.124	1.618	1.665	0.612	0.632
6	1.247	1.278	1.863	1.925	0.660	0.687
7	1.395	1.452	2.089	2.169	0.724	0.756
8	1.527	1.605	2.292	2.396	0.760	0.792
9	1.649	1.740	2.472	2.603	0.775	0.805
10	1.755	1.871	2.625	2.783	0.800	0.827
11	1.841	1.975	2.741	2.936	0.807	0.833
12	1.887	2.039	2.816	3.041	0.780	0.808