Narrow money and the business cycle: Theoretical aspects and euro area evidence

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Abstract:
This paper analyses the information content of M1 for euro area real GDP since the beginning of the 1980s. After a literature review on the empirical results in individual euro area countries we review some theoretical arguments why real narrow money growth might be an important determinant of cyclical developments in real GDP beyond effects already captured by short-term interest rates. In the empirical part we first present some preliminary evidence on the M1-GDP connection against the background of the situation in the US, based on an approach developed by Hamilton and Kim 2002. This test suggests that compared with the U.S., in the euro area, M1 has better and more robust forecasting properties than the term spread. These properties are also maintained when looking at a broader set of non-monetary indicator variables. Narrow money therefore seems crucial for cyclical developments. We also evaluate the relative out-of-sample forecasting performance of different classes of VAR models comprising real M1, GDP and further potential leading indicator variables against a univariate benchmark model. As a result, once the information from narrow money is taken into account, what matters more for the forecast performance, is the model class rather than the selection of additional indicators. While within the class of VARs in levels, Bayesian VARs are the best performing models, they are not capable of outperforming the benchmark. Specifically, only VARs in first differences are able to outperform the benchmark model.

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List of variables and symbols

ß	discount factor
c	real private consumption expenditures
clr	composite lending rate
divr	real divisia aggregate
$\Delta_{1(4)}$	logarithmic first (fourth) difference
e	US-$/€ exchange rate
eeffn	nominal effective exchange rate of the €
eeffr	real effective exchange rate of the €
E	expectations operator
ε	elasticity
HICP	Harmonised Index of Consumer Prices
i	interest rate
is	short-term interest rate
il	long-term interest rate
i_m	own rate of interest of money
i_{ger}	interest rate in Germany
i_{real}	real interest rate
m	real money balances
m1r	real M1 calculated with the GDP deflator
oilp	oil prices (in $)
oilp€	oil prices (in €)
pgdp	GDP deflator
stock	world stock prices
σ	inverse of the intertemporal elasticity of substitution
u	per-period utility
y	real income, real GDP
$S\,(\,.\,)$	standard deviation of the prior distribution for lag l of variable j in equation i of a BVAR.
s_i, s_j	standard deviation of variable i,j in a VAR
g	overall tightness of prior in a BVAR
$g(l)$	tightness of prior on lag l relative to lag 1 in a BVAR
$f\,(i,\,j)$	tightness of prior on variable j in equation i relative to variable i.

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"The stock of money displays a consistent cyclical behavior
which is closely related to the cyclical behavior
of the economy at large."

(M. Friedman, 1963)

Non-technical summary

This study reviews the role of narrow money - predominantly real M1 - in terms of leading cyclical conditions in the euro area over the sample period 1981Q1 - 2001Q4. It also looks at how important real narrow money growth has been in relation to information already captured by short-term interest rates. Evidence is obtained on the basis of single-equation test regressions, as well as a more rigorous comparison of the out-of-sample forecast-performance of different VAR-specifications (VARs in levels, first-difference VARs, VECMs and BVARs) with a univariate benchmark model (where GDP is forecast only on the basis of past information in GDP itself). These VARs comprise real M1 growth, GDP growth and further potential leading indicator variables for real GDP. As alternative leading indicator variables, various measures of yield spreads, interest rates, and exchange rates as well as the oil price were considered.

As regards the main results, the information content of different interest rate measures (long-term/short-term, real and nominal) for future changes in GDP seems rather mixed, while the predictive content of M1 remains important and tends to be largely unaltered in terms of coefficient size and forecasting horizon (if different interest rate measures are used). Furthermore, in contrast to results obtained from studies for the U.S., in the euro area, M1 has better and more robust forecasting properties than the term spread (especially, when measured on the basis of historical euro-area interest rates). These properties of M1 are also maintained when comparing with a broader set of variables, like the real and nominal effective exchange rate and the oil price. (Interestingly, the coefficients of the exchange rate variables indicate that appreciations rather than depreciations have tended to be correlated with cyclical expansions at horizons of around 1 1/2 to 2 years and that real depreciations have signalled future cyclical contractions.) In all cases, narrow money seems crucial for cyclical developments. Especially, VARs in differences always outperform the benchmark irrespective of the forecast horizon considered. Estimates of forecast models based on other variables, ignoring the information content of money, may therefore be subject to a so-called "omitted-variable bias".

The paper also reviews a number of theoretical arguments why money may affect cyclical conditions beyond the information already captured by interest rates. In this context it reconsiders conditions for the existence of a real balance effect in the context of money-in-the-utility-function approaches originating from Sidrauski 1967. Furthermore it reviews the arguments recently re-stated by Meltzer 2001 and Nelson 2002 who focus on how money serves as a summary statistic reflecting what is going on in the transmission process in terms of the adjustment of a whole range of relative asset prices.

1. Introduction

Does money matter for real economic developments? And if yes, what are the theoretical justifications and what is the concrete transmission mechanism behind the connection? These questions are among the most hotly debated in monetary economics. The present paper tries to shed some light on these issues for the euro area. Especially, it concentrates on the forecast performance of M1 for real GDP. In doing this, we try to assess the role of M1 in the transmission of monetary policy effects beyond the information contained in short-term interest rates.

What is the effect of narrow money on output after taking into account several other variables, especially the monetary policy stance via a short-term interest rate and the term spread? There are plenty of empirical papers dealing with this question for the US (see e.g. Hamilton and Kim 2002, Amato and Swanson 2001, Vilasuso 2000, Swanson 1998, Estrella and Mishkin 1997, Feldstein and Stock 1997, Friedman and Kuttner 1992). The general conclusion is that M1 is not very useful in predicting future GDP growth in the U.S.[1]

Compared with these studies, evidence on this with respect to euro area countries is scarce. For **Germany**, Kirchgässner and Savioz 2001 show that for four-quarter ahead forecasts of real GDP growth real M1 clearly outperforms forecasts based on interest rate spreads. This positive indicator role for M1 is also apparent in Sauer and Scheide 1995, who present evidence that there is a causal relationship from M1 to real economic activity measured by real domestic spending. Moreover, Fritsche and Kouzine 2002, find that M1 is one of the best leading indicator for business cycle turning points, measured by the index of industrial production, within a Markov switching model.[2] On the other hand, in the paper by Estrella and Mishkin 1997, the one-quarter growth of M1 is not significant in an equation forecasting the annualised growth rate of GDP four to eight quarters ahead. In Plosser and Rouwenhorst 1994, past and future monetary growth only helps to predict future growth in industrial production for relatively long forecasting

[1] Exceptions are Swanson 1998, Vilasuso 2000 and Nelson 2002a. The first works with a special model selection procedure while the second uses detrended M1 growth that incorporates trend breaks. Nelson's paper is discussed in detail in section 2. Moreover, Leeper and Zha 2001, using a VAR analysis, conclude that the exclusion of money from this class of models is not empirically innocuous as the interpretation of the historical policy behaviour changes substantially once money is reintroduced. This result is confirmed by Favara and Giordani 2002, who examine the role played by shocks to the LM equation in shaping the dynamic behaviour of output, inflation and interest rates. A distinctive feature of their VAR analysis is that both the variables included in the system and the identifying restrictions used to isolate shocks to the LM equation are suggested by the class of models that assign a marginal role to monetary aggregates. They also find that all the variables they considered are not block-exogenous with respect to money.

[2] This is not true, however, when they use a probit model.

horizons (five years). Furthermore, they show that the term spread is a significant predictor of future M1 growth. And finally, Seitz 1998, who looks at the best leading indicators for the growth of GDP from the 1960s until the 1990s, shows that monetary aggregates do not play a significant role within a wide range of variables.

For **France**, Sauer and Scheide 1994, reveal a causal relationship between real M1 and real domestic spending within a cointegration framework whereas in Estrella and Mishkin 1997, monetary aggregates are not helpful in predicting GDP irrespective of the chosen forecasting horizon. For **Italy**, Sauer and Scheide 1994, interpret evidence of a common trend in M1 and real economic activity as a special case of a causal role between the two variables. Furthermore, the interest rate spread does not contain any additional information on future output developments. Comparing the information content of the term spread and M1 for real GDP in Italy, Estrella and Mishkin 1997, reveal a slight puzzle in that the spread only becomes significant once M1 is added to the relation, although the monetary aggregate itself is mostly insignificant and has the wrong sign. Altissimo et al. 2002, use two approaches to analyse the relation between surprises in GDP and innovations in monetary variables. The first requires filtering the new information contained in monetary variables by mapping surprises into estimates of the structural disturbances impinging on the variables of interest and then starting a new forecasting round of the model; the second looks directly at the correlations among surprises. The monetary variables taken into account are M2 and the currency component of M1. Within the first approach neither M2 nor currency contribute to reducing the forecast uncertainty on GDP. In contrast, the second approach reveals that there is information in the two monetary aggregates for forecasting real GDP.

Finally, Canova and de Nicoló 2002, assess the importance of different monetary disturbances as sources of cyclical movements for the G-7 from 1973 to 1995. For that purpose they use a VAR model with industrial production as a proxy for real activity, real M1, the term spread and inflation. The major result of their paper is that the combined contribution of these monetary disturbances for real economic fluctuations is large in Germany and Italy. In Germany, there is a single monetary shock which explains the major part of output variability. In contrast, in France, monetary disturbances do hardly contribute to output fluctuations. These conclusions are qualitatively insensitive to the sample period considered and to the inclusion of further variables, especially stock returns and short- and long-term nominal interest rates. The peculiarity with Canova and de Nicoló's approach is that monetary disturbances are an amalgam of many different factors, not just M1.

Overall, the results concerning the information content of M1 for real activity in general and real GDP in particular in euro area countries is not conclusive. Furthermore, up to now, there were only a few euro area countries under investigation.[3]

This study differs from the aforementioned ones in several respects. First, the role of narrow money for output has so far not been studied for the whole euro area. There are several papers dealing with the situation in individual euro area countries (see the discussion above) but the results may differ for the euro area as a whole. Second, we distinguish between different forecasting horizons ranging from one quarter to two years. Usually, only one such horizon is evaluated.[4] Third, in assessing the role of M1 for output we perform an ex-post and an ex-ante analysis. And fourth, we compare different optimal VARs in their forecasting ability because the time series properties of the data and the results from preliminary model analysis are ambiguous.

The paper is structured as follows. The next section presents an overview of theoretical arguments why money might be useful for the assessment of real GDP abstracting from the effects of monetary policy. The third section contains the empirical analysis. In this part, we first present some preliminary evidence that M1 might be useful for forecasting GDP by drawing on a recent study by Hamilton and Kim 2002. In a second step, we derive our univariate benchmark model against which we judge several models on their ability to track the performance of GDP out of sample. These models are VARs in levels, VECMs, VARs in first differences and Bayesian VARs building on the Minnesota Prior. The last chapter summarises and draws some tentative conclusions.

2. Why does money help forecast GDP – some theoretical arguments

2.1 The real balance effect and the IS curve

The consensus view in the economics' profession has become very much dominated by the money-less new-keynesian paradigm which generally assumes that the monetary policy stance is best captured by short-term interest rates (mostly the overnight rate) and not by monetary quantities. This is apparent in the specification of monetary policy rules which in nearly all cases

[3] There are also papers which try to construct composite leading business cycle indicators in which different measures of money enter, see e.g. Berk and Bikker 1995, for an analysis for, inter alia, several EU countries.

[4] Exceptions are Swanson 1998, for the US and Estrella and Mishkin 1997, as well as Plosser and Rouwenhorst 1994, in multi-country studies. Bagshaw 1985, compares the predictive performance of M1 relative to a univariate model of GNP and finds no significant differences. Furthermore, he stresses that the merits of M1 in helping to forecast output depends more on the forecasting period considered than on the forecast steps or the frequency over which M1 is measured (monthly versus quarterly).

are specified in terms of a money market interest rate.[5] Therefore, the implementation of monetary policy is usually based on the control of such an interest rate. Taken together, this necessarily raises the theoretical question about why money in general and M1 in particular might be useful in explaining and predicting business fluctuations over and above the influence of interest rates. In what follows, we present some of these arguments emphasised in the literature. All the models have in common that they concentrate on a transactions oriented non-interest bearing monetary aggregate as is the case for most of euro area M1. Svensson 2001, p. 290, calls this a separate money channel in aggregate demand determination or in the "IS relation", respectively.

Probably the first theoretical considerations about this relation originate from Pigou 1943 and Patinkin 1965. What has famously become known as the Pigou- or the real-balance effect, describes wealth effects created by a change in the stock of real money. Patinkin 1965, p. 20, defines the real balance effect as "an increase in the quantity of money, other things being held constant, [that] influences the demand for a commodity just like any other increase in wealth". There has been a long debate as to whether money should be treated as a part of wealth or not. Gurley and Shaw 1960, tried to clarify this discussion by introducing the distinction between outside and inside money.[6] Outside money is a part ofgovernment debt (including the central bank), while it is an asset of the private sector. An example is currency in circulation. Inside money is a debt of private agents as well as an asset held by them. This is true, for example, for overnight deposits. Ignoring distributional effects and the efficiency increasing effects of money compared to a barter economy, the above mentioned wealth effects would only apply to outside money.[7] This would imply that we should not pay attention to monetary aggregates per se, but to its composition into inside and outside money. In 2001, currency was only about 15 % of euro area M1 and only 2 % of total financial assets of the non-financial sector. Therefore, it would seem a bit surprising if increases in the real value of outside money alone could be of importance in terms of increasing expenditures. If, however, both types of money were endogenously linked to events in the real economy, (anticipated) changes in the whole money stock might once again be related to real output.

[5] In the volume by Taylor 1999, all the papers presented use such a formulation.

[6] Whether these wealth effects are only a transitory phenomenon or are also relevant in the long run is crucially dependent on the assumptions of money being the only financial asset or not and on the time horizon for individual decisions considered. If bonds co-exist with money and agents have an infinite horizon the wealth effects may even be existent in the long run, see Handa 2000, p. 492.

[7] Furthermore, one has to recognise that households fail to take the impact into account that a future creation of excess money may have on the economy.

In all actually existing economies, we observe that positive quantities of transactions balances are held by private parties despite the fact that they yield a lower return than other very short-term riskless assets. This indicates that there must be advantages to holding money not allowed for in our discussion above. The advantage stems from facilitating transactions or lowering transactions costs.[8] Examples which incorporate this idea are money-in-the-utility-function models (see e.g. Woodford 2003, ch. 2), shopping time models (see e.g. Bakhshi et al. 2002) or cash-in-advance models with population growth (Ireland 2002b).[9] Within the first class of models originating from Sidrauski 1967, the household maximises the expected value of the discounted sum of per-period contributions to utility u of the form

(1) $$E_0\left[\sum_{t=0}^{\infty} ß^t u(c_t, m_t)\right],$$

where $0 < ß < 1$ is the discount factor, E is the expectation operator and the per-period utility u depends positively on consumption c and real balances $m = M/P$. These arguments may be supplemented by preference shocks or variations in the transactions technology (Woodford 2003, ch. 2; Ireland 2002a). The period utility function $u(\,.\,)$ satisfies the usual assumptions $u_c > 0$, $u_m > 0$, $u_{cc} < 0$, $u_{mm} < 0$. The household chooses $\{c_t,\ m_t\}$ so as to maximise (1) subject to its intertemporal budget constraint eventually incorporating a borrowing limit. (Woodford, 2003, ch. 2). The intertemporal budget constraint states that the present value of the household's planned consumption over the entire indefinite future, plus the costs arising from its planned money holdings, must not exceed its initial financial wealth plus the present value of its expected after-tax income from sources other than financial assets. The way money affects the consumption path crucially depends on the assumption made about u_{cm}.

If $u(\,.\,)$ is additively separable between its arguments c and m in such a framework, an assumption often made for analytical or pedagogical reasons (see e.g. Obstfeld and Rogoff 1996, ch. 8.3), the marginal utility of consumption would be independent of real balances, just as in the case of a cashless economy. This implies that aggregate demand and the expectational IS curve would be unaffected by real money balances. There would be no real balance effect despite the

[8] For King 2002, even the proof of a significant role for money for real developments has to be based on the two observations that money reduces transactions costs and that transactions costs are important in determining asset prices. The frictions which money helps to overcome in financial markets have to be related to its role in providing liquidity services.

[9] Croushore 1993, shows that the first two models are functionally equivalent. Holman 1998, postulates that money-in-the utility-function models allow for transactions as well as precautionary and store-of-value motives for holding money. McCallum 2000, presents a reduced form shorthand of all these analyses by introducing a transactions cost function, which reflects the transaction-facilitating properties of money, in the per-period budget constraint.

fact that money enters the utility function. One alternative way of justifying the neglect of real balance effects on the marginal utility of consumption is Woodford's 2003, ch. 2.3.4, case of a "cashless limiting economy". In this model the marginal utility of additional real balances becomes quite large as household real balances fall to zero, so that it is possible in equilibrium to have a non-trivial interest-rate differential between monetary and non-monetary assets. Yet, at the same time, the transactions that money is used for are sufficiently unimportant so that variations in the level of real balances have only a negligible effect on the marginal utility of consumption. The idea is that in such an economy money is used for transactions of only a very few kinds, though it is essential for those. Imagine a situation in which the process of financial innovation has processed far enough so as to make transactions balances of sufficiently small importance in carrying out transactions. As a result, positive real balances are demanded even in the case of a substantial interest-rate differential (and hence, a substantial opportunity cost of holding money); but equilibrium real balances are very small relative to national income. Consider an economy in which a fraction a of goods may only be purchased with cash and make the parameter a arbitrarily small. This means that whereas the elasticity of u_m with respect to real expenditures (e_e) is positive[10]

(2) $$e_e = \frac{c \cdot u_{mc}}{u_m} > 0,$$

the elasticity of u_c with respect to real balances (e_m)

(3) $$e_m = \frac{m \cdot u_{cm}}{u_c},$$

which is essential for a real balance effect to be operative, is infinitesimally small. Note that

(3') $$e_m = l_m \cdot e_e \text{, where } l_m = \frac{mu_m}{cu_c} = \frac{i - i_m}{1+i} \cdot \frac{m}{c}$$

is the flow rate of effective expenditures by households on liquidity services expressed as a proportion of total expenditures. In equilibrium, this flow rate has to be equal to the opportunity costs ($i - i_m$) of holding these real balances; where i is the return on a non-monetary asset and i_m is the own rate of return of money. In a cashless limiting economy, l_m and consequently e_m are infinitesimally small. Woodford 1998, shows that if monetary policy may be characterised by an

[10] **Assuming** separability would imply that the elasticity e_e is negligible.

interest rate rule which specifies the short-term nominal interest rate as a function of the price level, there is no further need to consider the role of money in such an economy.

In the cashless-limit environment as well as in the consumption-money-separability environment money is redundant as real money balances are demand determined given the endogenously determined interest rates and output. The usual LM equation in such a framework serves the sole purpose of determining the quantity of money the central bank needs to supply to clear the money market.[11] The cashless-limiting-economy assumption, however, seems questionable as e.g. currency certainly provides valuable services to consumers. These may stem from its anonymity or from the fact that exchanges conducted with money can be done “without knowledge of individual histories” (Wallace 2000). And, as McCallum 2000, 2001, 2002, strongly argues, there is also no further compelling theoretical basis for the assumption of separability of u (see also Woodford, 2003, ch. 2.3.4). Separability is not very plausible as the marginal utility of consumption should depend on the level of real balances if real balances supply a non-pecuniary yield owing to their usefulness in conducting transactions and/or their anonymity in the case of cash. Thus, a direct money effect would arise if real balances enter the representative agent’s utility function,which in turn is not additively separable in consumption and real balances, but has a positive cross-derivative, i.e. $u_{cm} > 0$.[12] McCallum 2000, suggests to use the formula

(4) $$u(c_t, m_t) = c_t a_1 (c_t / m_t)^{a_2}$$

with $a_1 > 0$, $a_2 > 0$. This would result in an IS function depending on the real rate of interest, expected future output, government expenditures as well as real balances. Specifically, the usual IS relation additionally includes the following term

(5) $$\frac{c_t}{y_t} \cdot \frac{f}{f+s}\left(\log m_t - E_t \log m_{t+1}\right),$$

[11] Favara and Giordani 2002, show empirically for the US that even if household utility is additively separable, neglecting the role of money (measured by a broad monetary aggregate) induces serious economic implications (see footnote 1).

[12] The empirical analysis for the US in Koenig 1990, strongly suggests $u_{cm} > 0$. Once he took the effects of real balances, measured by M1, into account, there was little evidence that other variables like anticipated or lagged changes in income, stock prices, government purchases or any other variable that might influence u_c or serve as a measure of liquidity, have a direct impact on consumption or its timing. In Koenig’s study the effect of real balances on consumption is quite strong: a 10 percent increase in real M1 results in a three percent increase in spending on non-durables and services. This kind of non-separability has already been considered by Sidrauski 1967. Ireland 2002b, however, derives a real balance effect in an infinite-horizon optimising model which does not require non-separability in utility.

with $f = a_1(1+a_2)a_2(c/m)a_2$ and where s is the inverse of the intertemporal elasticity of substitution in consumption. Thus, an expression including real money balances appears in the expectational IS function based on optimising behaviour. Therefore, the goods market equilibrium is dependent on real balances.

2.2 Money as a proxy for a whole range of relative prices of assets

Friedman and Schwartz 1963, Meltzer 2001, and Nelson 2002a, b, evaluate the important role of money for real activity and prices from a more general perspective. In particular, they argue that monetary variables cannot legitimately be ignored because the transmission process involves the adjustment of all relative prices of assets. This means that money proxies the effects of many other asset prices on aggregate demand. If changes in money lead to changes in private sector portfolios and changes in yields of financial and real assets this in turn also influences real spending decisions. The usefulness of this channel and the portfolio balance effect that arises depends on the assets being imperfect substitutes. A special advantage of this kind of model is that it tries to identify separate effects of real money on aggregate demand which are not captured by a short-term real interest rate. Let us look further at this strand of argumentation(Nelson 2002a, section 3).

What are the theoretical rationalisations for a direct money term in aggregate demand functions? Meltzer 2001, Friedman and Schwartz 1982, and Brunner and Meltzer 1993, state that money demand is not only dependent on one interest rate but a function of many different asset yields and wealth including human and non-human wealth. Therefore, money plays a special role for real developments in that it proxies the effects of these different yields and wealth effects which are relevant for economic activity.[13] In Meltzer's view, the gap between desired and actual real balances is a measure of the relative price adjustment necessary to restore the new full equilibrium. And, as he argues, a measure of the real money stock serves as a good summary statistic of the various changes in yields and wealth. The relevant yields include the whole term structure of interest rates, the yield on shares, the exchange rate, yields on housing etc.

A model which tries to fully capture the role of money therefore has to incorporate multiple assets which are imperfect substitutes for each other. If the yields influencing money demand and the yields influencing aggregate demand are correlated, real balances will be a good indicator of real developments in that they summarise all the relevant aspects.

Nelson 2002a, derives this effect within an intertemporal general equilibrium model with Calvo price setting. He concentrates on only two yields, a long-term and a short-term interest rate, where aggregate demand is dependent on the real long-term interest rate. In his model money becomes important in explaining output once portfolio adjustment costs are present.[14] In Nelson 2002a, p. 697, this cost function *C (.)* reads as

$$C(m_t, m_{t-1}) = ß_1 \left\{ \exp\left[ß_1 \left(\frac{m_t}{m_{t-1}} \right) - 1 \right] + \exp\left[-ß_2 \left(\frac{m_t}{m_{t-1}} \right) - 1 \right] - 2 \right\}, \tag{6}$$

where $ß_1$, $ß_2 > 0$. This cost function has the feature that costs which are quite small nevertheless have important effects on aggregate dynamics. The adjustment costs render money demand forward-looking.

In this model, all variables beside real balances are invariant to the inclusion of portfolio adjustment costs. As in optimising IS-LM models in which money does not appear in the monetary policy rule, the money stock is not a state variable, so the paths of all other variables may be obtained without reference to money. Nelson, however, shows, using simulations, that including portfolio adjustment costs leads to real money demand being dependent on the long-term expectation of short rates. Consequently, the growth rate of real balances has a stronger correlation with the nominal long-term interest rate than with the nominal short rate. Furthermore, in the no-portfolio adjustment costs cases, the growth rate of real balances was negatively correlated with both the short and the long real rate. Including these costs makes the correlation with the long-term real rate more negative, but the correlation with the real short rate turns positive. All in all, portfolio adjustment costs transform real money balances into a much better indicator of long-term interest rates, both nominal and real, than of short-term rates. In trying to explain output developments money growth is supplying auxiliary information independent from that in the short rate. These results provide a rationalisation for the significance of money growth terms in output regressions.

In the present model, conditioning on the real long rate would be sufficient to remove the incremental information contained in money growth about economic activity. But it is conceivable that in more general cases, where many yields enter both aggregate demand and

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[13] The results of Coenen et al. 2001 within a New-Keynesian passive-money-type approach can be interpreted in the light of this argument. In their model money is a helpful summary statistic for uncertain real output as money demand depends on output.

[14] In Nelson 2002b, this is the case in an environment where current private sector shocks are not observable to the monetary authority. In such a world, looking at money is information-efficient and aids inflation stabilisation if current period nominal money growth can be observed.

money demand functions, the information in money about output would be beyond that contained in securities-market interest rates, both short-term and long-term.

The special role of money may still be more important when nominal interest rates are close to zero. Meltzer 2001, argues that a monetary expansion can stimulate the economy even in this case as nominal securities are not the only substitute for money. If, at some point, households and firms become satiated with money balances at the current level of income, any attempt to increase the money supply leads them to adjust their portfolios in order to limit their holdings of money. These portfolio changes lead to changes in relative yields on financial and real assets and hence on real spending. The essential question then is whether there exists such a satiation point (King 2002).[15]

3. Empirical analysis

The following three subsections constitute the main empirical part of the paper. First, we present some single-equation evidence in the spirit of Hamilton and Kim 2002 that money may be useful in forecasting real GDP growth in the euro area. This part also enables us to compare evidence from the euro area and the US. The next section develops a univariate benchmark model against which we assess the forecast performance of a battery of VARs.

3.1 Some preliminary evidence

Hamilton and Kim 2002, establish the importance of the yield spread for forecasting real output growth in the United States for the period 1953:Q2 to 1998:Q2. They use the following equation:

(7) $$\Delta y_t^h = a_0 + a_1 (il - is)_t + a_2 x_t + e_t ,$$

where $\Delta y_t^h = \frac{400}{h}\left(\ln Y_{t+h} - \ln Y_t\right)$ is the annualised real GDP growth over the next h quarters and x_t is a vector of alternative explanatory variables (e.g. M1) besides the term spread (il - is). Their general conclusion is that the term spread is especially useful in predicting real GDP growth up to two years ahead.

In what follows we estimate one specific test regression for the euro area. It reads as

(8) $$\Delta y_t^h = a_0 + a_1 (il - is)_t + a_2 \Delta_4 m1r_t + a_3 \Delta_4 x_t + e_t ,$$

[15] The dependence of the IS relation on M may also be rationalised within the credit channel framework as credit is the main balance sheet counterpart to M (Bernanke and Blinder 1988). However, at times when money and credit exhibit disparate movements, it seems worthwhile to treat both separately.

where $m1r$ is seasonally adjusted real M1 ($h = 1,...,8$). Our GDP measure (y) refers to seasonally adjusted GDP. Historical data for the euro area before 1999 are constructed on the basis of national series converted into euros.[16] As regards the spread, we do not only assess the performance of the long-term (the yield on 10-years government bonds) minus the short-term rate (the 3-month money market rate) (il-is), but also the difference between a composite lending rate and the money market rate (clr-is), the difference between the capital market rate and the own rate of M1 (il-i_{m1}) (see Calza et al. 2001), the difference between the money market rate and the own rate of M1 (is-i_{m1}) as well as the difference between the German yield on bonds and the German money market rate (il_ger-is_ger).[17] For the calculation of *is* before 1999 we use M3 weights; this series is linked to Euribor from 1999 onwards. For the calculation of *il* we use M3 weights for the whole sample. Nominal interest rates have been divided by 400. *Ex-post* real interest rates are calculated on the basis of

Figure 1: Real M1 and GDP: Log Levels

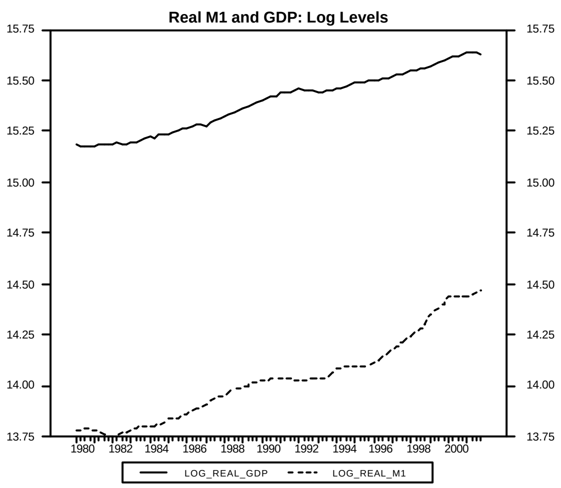
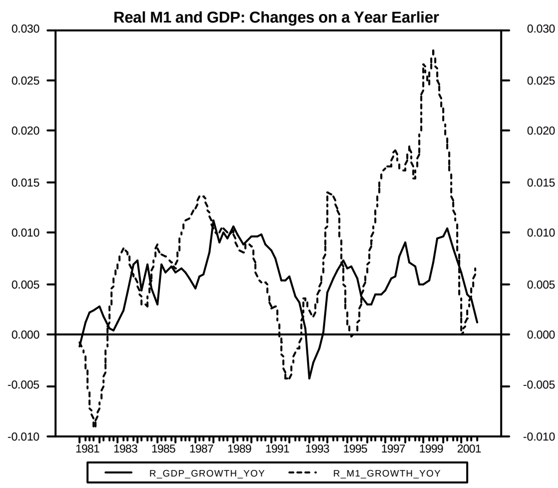


Figure 2: Real M1 and GDP: Changes on a Year Earlier



[16] National GDP data have been converted into euro using the irrevocable fixed exchange rates of 31 December 1998 for the period 1980 Q1-1998 Q4; from 1991 Q1 onwards the official Eurostat series is used. They are adjusted for German unification. The quarterly growth rates calculated from the euro-area-11 GDP series have been used to extend the euro-area-12 GDP observations from 2000:Q4 back to 1980:Q1. (Greek data have been converted on the basis of the irrevocable fixed exchange rate determined on 19 June 2000 for Greece).

[17] The inclusion of the German spread may be rationalised by the fact that within the former (asymmetric) European Exchange Rate Mechanism (ERM) the Bundesbank pursued an independent monetary policy aimed at price stability while the other ERM countries tried to maintain a stable exchange rate vis-à-vis the Deutsche Mark (De Grauwe, 2000, ch. 5, Wellink/Knot, 1996). If Uncovered Interest Parity holds, it seems natural to consider the German spread.

nominal interest rates and changes in the GDP deflator (*pgdp*) (or the HICP) on a year earlier (divided by 4). In one case, M1 is substituted by a Divisia aggregate (*divr*) calculated as suggested by Stracca 2001. Finally, x_t are additional variables like stock prices (*stock*) (a world wide stock price index highly correlated with the Euro Stoxx which could not be used as it only exists since the end of the 80s), oil prices in US-Dollars (*oilp*) and in euros (*oilp€*), the bilateral US-$/€ exchange rate (*e*) as well as the multilateral effective nominal (*eeffn*) and real (*eeffr*) exchange rates of the €. All data, except interest rates, are in logarithms. Our sample runs from 1980:Q1 to 2001:Q4.

Figure 1 and Figure 2 exhibit the data for euro-area real M1 and real GDP over the sample period. It is apparent that there is a pronounced increase in real M1 in 1999:Q1 - the time, when the single currency was launched.

Table 1 shows the coefficient estimates and the (Newey-West-corrected) t-ratios of the different models. For model 1 the estimated coefficients of the euro area term spread are not significant at the 5 percent test level. This is in contrast to the results of Hamilton and Kim 2002 for the US. Adding the growth rates of real M1 to the equation does not alter the results for the spread (model 2). However, the estimated coefficients of M1 are significant at the 1 percent test level. The adjusted R^2 is considerably higher than that of the first equation. On the other hand, the German interest rate spread (model 3) helps to forecast changes in output over time horizons h = 6 to 8, whereas the difference between the money market rate and the own rate of M1 (model 4) [between composite lending rate and the money market rate (model 6)] does so for the horizon h = 2, 3 [h = 1]. The spread between the capital market rate and the own rate of M1 (model 5) is more important for h = 1 to 4. It is worth noting that the coefficient of the money market rate (model 7) are significant for h = 1 to 5, whereas the real money market rate calculated with the GDP deflator (model 12) or the HICP (model 13) do not help to forecast output developments. The results change if the capital market rate is considered. This rate (model 8) and the real capital market rate (models 10 and 11) affect the growth rate of output significantly. All these approaches have one feature in common: in all cases the growth rate of M1 remains significant. This is also true if the regression equations only include M1 (model 9). This evidence does not change if the equations additionally contain other variables like the annual change of the world stock prices (model 14), of oil prices (models 15 and 16), of the US-$/€ exchange rate (model 17), of the nominal or real effective exchange rates (model 18 and 19). These other variables do not help to forecast output in the short term (h = 1 to 4). In the longer run (h = 4 to 8) some variables have significant coefficients, especially, the nominal effective exchange rate and the oil prices in euro. Interestingly, the coefficients of the exchange rate variables indicate that an appreciation rather than a depreciation would stimulate cyclical expansions, so that a terms-of-trade deterioration would indicate cyclical contractions. It is also worth noting that the results for the change of the real Divisia aggregate (model 20) point in the same direction as the M1 change.

Table 1: Results of predicting real GDP using different models (Hamilton Kim approach)

Model	Variables	Forecast horizon							
		1	2	3	4	5	6	7	8
1	il-is	.462 (1.638)	.471 (1.783)	.451 (1.813)	.402 (1.693)	.362 (1.636)	.323 (1.614)	.293 (1.625)	.273 (1.658)
	adj. R^2	.050	.093	.115	.108	.097	.087	.083	.082
2	il-is	.118 (.425)	.098 (.414)	.077 (.374)	.050 (.270)	.043 (.260)	.052 (.358)	.058 (.443)	.064 (.534)
	$\Delta_4$log(m1r)	.260 (4.401)	.280 (5.454)	.279 (5.663)	.263 (5.085)	.239 (4.406)	.205 (3.632)	.178 (3.120)	.157 (2.750)
	adj. R^2	.165	.320	.418	.427	.391	.331	.293	.266
3	il_ger-is_ger	.205 (1.100)	.195 (1.207)	.185 (1.259)	.194 (1.431)	.212 (1.691)	.239 (2.002)	.252 (2.254)	.257 (2.436)
	$\Delta_4$log(m1r)	.227 (3.987)	.246 (4.933)	.245 (5.024)	.221 (4.278)	.192 (3.510)	.152 (2.665)	.122 (2.117)	.100 (1.769)
	adj. R^2	.178	.340	.442	.462	.438	.399	.381	.370
4	is-i_{m1}	.193 (1.731)	.193 (2.151)	.185 (2.207)	.151 (1.813)	.116 (1.292)	.048 (.530)	-.012 (.146)	-.043 (.559)
	$\Delta_4$log(m1r)	.392 (5.229)	.409 (6.354)	.400 (5.916)	.360 (4.841)	.316 (3.806)	.244 (2.673)	.180 (1.973)	.141 (1.547)
	adj. R^2	.183	.350	.453	.454	.407	.332	.290	.265
5	il-i_{m1}	.296 (2.770)	.283 (3.292)	.261 (2.920)	.208 (2.074)	.165 (1.449)	.097 (.752)	.028 (.243)	-.007 (.063)
	$\Delta_4$log(m1r)	.403 (5.569)	.414 (6.126)	.401 (5.535)	.360 (4.446)	.319 (3.554)	.258 (2.549)	.200 (1.977)	.165 (1.668)
	adj. R^2	.202	.376	.479	.471	.419	.339	.291	.262
6	clr-is	-.573 (2.140)	-.445 (1.813)	-.389 (1.658)	-.336 (1.457)	-.275 (1.221)	-.190 (.883)	-.134 (.663)	-.102 (.518)
	$\Delta_4$log(m1r)	.354 (5.983)	.354 (6.506)	.343 (6.056)	.315 (5.091)	.283 (4.301)	.240 (3.495)	.205 (3.003)	.181 (2.672)
	adj. R^2	.200	.354	.452	.458	.414	.342	.279	.267
7	is	.168 (2.319)	.182 (3.345)	.188 (3.560)	.170 (2.945)	.151 (2.254)	.112 (1.519)	.066 (1.043)	.035 (.623)
	$\Delta_4$log(m1r)	.410 (5.807)	.437 (7.445)	.438 (6.990)	.405 (5.647)	.368 (4.511)	.307 (3.361)	.242 (2.734)	.196 (2.256)
	adj. R^2	.192	.373	.416	.492	.443	.358	.301	.266
8	il	.218 (3.083)	.226 (4.090)	.227 (3.926)	.200 (3.048)	.179 (2.356)	.144 (1.620)	.097 (1.245)	.066 (.982)
	$\Delta_4$log(m1r)	.413	.435	.431	.396	.361	.310	.252	.211

		(5.880)	(6.951)	(6.521)	(5.320)	(4.368)	(3.293)	(2.714)	(2.339)
	adj. R^2	.207	.396	.514	.510	.458	.372	.311	.273
9	$\Delta_4$log(m1r)	.280 (5.038)	.297 (5.575)	.292 (5.510)	.271 (4.876)	.246 (4.25)	.214 (3.544)	.187 (3.072)	.168 (2.771)
	adj. R^2	.172	.325	.422	.433	.397	.337	.299	.272
10	$il_{real(PGDP)}$	.475 (3.320)	.449 (4.273)	.424 (4.069)	.328 (2.615)	.262 (1.754)	.136 (.817)	.035 (.230)	-.003 (.021)
	$\Delta_4$log(m1r)	.369 (5.914)	.378 (6.669)	.360 (6.116)	.317 (4.671)	.281 (3.634)	.226 (2.591)	.179 (2.038)	.157 (1.836)
	adj. R^2	.216	.390	.474	.436	.375	.281	.229	.157
11	$il_{real(HICP)}$	.441 (3.327)	.436 (3.987)	.437 (4.160)	.408 (3.395)	.421 (2.925)	.417 (2.342)	.377 (1.992)	.346 (1.845)
	$\Delta_4$log(m1r)	.363 (6.431)	.376 (7.474)	.361 (6.902)	.330 (5.451)	.310 (4.561)	.282 (3.657)	.246 (3.163)	.223 (3.036)
	adj. R^2	.215	.398	.500	.492	.458	.391	.332	.273
12	$is_{real(PGDP)}$	.245 (1.031)	.240 (1.231)	.228 (1.286)	.186 (1.233)	.151 (1.152)	.059 (.490)	-.009 (.075)	-.037 (.320)
	$\Delta_4$log(m1r)	.370 (5.560)	.381 (7.083)	.363 (6.558)	.321 (5.175)	.284 (4.079)	.220 (2.863)	.170 (2.190)	.145 (1.879)
	adj. R^2	.179	.339	.419	.403	.354	.273	.228	.211
13	$is_{real(HICP)}$	.211 (1.038)	.217 (1.217)	.223 (1.367)	.219 (1.453)	.221 (1.521)	.195 (1.394)	.153 (1.159)	.125 (.983)
	$\Delta_4$log(m1r)	.359 (5.814)	.374 (7.502)	.361 (7.484)	.331 (6.107)	.308 (5.038)	.268 (3.992)	.225 (3.341)	.200 (2.972)
	adj. R^2	.178	.340	.430	.430	.395	.321	.265	.236
14	$\Delta_4$log(stock)	.00432 (.468)	.00014 (.016)	.00037 (.048)	.0018 (.266)	.0039 (.581)	.0070 (.992)	.0092 (1.249)	.0108 (1.415)
	$\Delta_4$log(m1r)	.267 (4.505)	.296 (4.943)	.291 (4.715)	.266 (4.105)	.236 (3.562)	.195 (2.967)	.163 (2.506)	.139 (2.170)
	adj. R^2	.164	.317	.415	.426	.393	.342	.316	.302
15	$\Delta_4$log(oilp)	.00530 (.596)	.00331 (.478)	.00004 (.007)	-.0035 (.641)	-.0053 (.925)	-.0072 (1.313)	-.0095 (1.919)	-.0103 (2.242)
	$\Delta_4$log(m1r)	.270 (4.601)	.290 (5.169)	.292 (5.428)	.278 (5.217)	.256 (4.889)	.227 (4.414)	.205 (4.133)	.186 (3.846)
	adj. R^2	.167	.320	.415	.431	.404	.360	.354	.346
16	$\Delta_4$log(oilp€)	.00313 (.478)	.00184 (.343)	-.0019 (.177)	-.0047 (1.041)	-.0067 (1.526)	-.0085 (2.034)	-.0101 (2.635)	-.0105 (3.032)
	$\Delta_4$log(m1r)	.275 (4.847)	.294 (5.425)	.294 (5.660)	.278 (5.395)	.256 (5.000)	.227 (4.452)	.202 (2.635)	.182 (3.783)
	adj. R^2	.165	.318	.416	.440	.422	.389	.387	.380
17	$\Delta_4$log(e)	.0049 (.385)	.0038 (.294)	.0086 (.722)	.0139 (1.239)	.0183 (1.706)	.0209 (2.051)	.0199 (1.952)	.0183 (1.733)
	$\Delta_4$log(m1r)	.278 (4.897)	.295 (5.360)	.289 (5.336)	.266 (4.824)	.239 (4.255)	.206 (3.574)	.179 (3.077)	.160 (2.734)
	adj. R^2	.163	.318	.421	.445	.428	.386	.349	.319
18	$\Delta_4$log(eeffn)	-.0047 (.204)	.00064 (.030)	.0130 (.693)	.0261 (1.530)	.0364 (2.266)	.0332 (2.781)	.0427 (2.767)	.0381 (2.380)
	$\Delta_4$log(m1r)	.280 (5.003)	.297 (5.554)	.292 (5.648)	.271 (5.238)	.246 (4.723)	.214 (4.039)	.186 (3.509)	.166 (3.098)
	adj. R^2	.163	.317	.420	.451	.446	.419	.391	.353
19	$\Delta_4$log(eeffr)	-.0154 (.652)	-.0087 (.400)	.0057 (.287)	.0215 (1.174)	.0341 (1.941)	.0428 (2.493)	.0433 (2.570)	.0393 (2.330)
	$\Delta_4$log(m)	.279 (5.038)	.296 (5.550)	.292 (5.624)	.272 (5.242)	.248 (4.768)	.216 (4.108)	.189 (3.579)	.168 (3.161)
	adj. R^2	.166	.318	.416	.441	.434	.409	.385	.350

20	il-is	.219 (.835)	.200 (.894)	.177 (.918)	.148 (.858)	.134 (.870)	.132 (.972)	.132 (1.054)	.134 (1.144)
	$\Delta_4$log(divr)	.478 (4.761)	.531 (6.108)	.534 (6.276)	.495 (5.494)	.447 (4.645)	.380 (3.729)	.321 (3.100)	.275 (2.669)
	adj. R^2	.183	.372	.494	.496	.449	.373	.318	.276

Notes: In parentheses are the Newey and West (1987) heteroskedasticity and autocorrelation consistent t-values. Column k is based on estimation for 1981:Q1to 2001:Q4-k, except for the regressions involving real interest rates, which start in 1982:Q1. The estimates of the intercept term are not shown.

In sum, this exercise gives preliminary evidence of the importance of M1 for future output developments in the euro area. However, the forecast performance is not assessed relative to a benchmark model and there is no forecast evaluation. Moreover, the analysis is only carried out within a single equation approach. These issues are addressed in the following sections.

3.2 The benchmark model

To assess the forecast performance of different models a benchmark is necessary. In finding this model, a univariate autoregressive specification of quarterly real GDP growth is considered for the period 1982:Q1 to 2001:Q4. Starting with a lag length of eight, insignificant coefficients are successively set to zero. This exercise results in the following equation:

(9)
$$\Delta_1 y_t = \underset{(3.31)}{0.0033} + \underset{(1.78)}{0.198}\Delta_1 y_{t-1} + \underset{(1.77)}{0.198}\Delta_1 y_{t-3},$$

Adj. R^2: .060, DW: 2.047, S.E: .0049, L.B.(16): 14.642 (.551), J.B.: .671 (.715), LMAR(1-4): .489 (.744), ARCH(1): 3.878 (.053), RESET(2): .801 (.453), Chow(12): .657 (.903).

where L.B. (16) is the Ljung Box test of autocorrelation for the first 16 lags, J.B. is the Jarque-Bera test for normality of residuals, LMAR(1-4) is the Lagrange Multiplier test of autocorrelation for the first four lags, ARCH is the autoregressive conditional heteroskedasticity test, where one lag is considered, RESET(2) is the a test of functional form where two terms are taken into account and Chow (12) is the forecast test for the last 12 quarters (1999:Q1 to 2001:4). It is apparent that the diagnostic statistics are not significant at the 5 % test level. However the Adj. R^2 is unacceptably small. Therefore, a specification in annual growth rates is considered. Once more, insignificant coefficient are set to zero. The preferred model is:

(10)
$$\Delta_4 y_t = \underset{(2.78)}{0.0036} + \underset{(16.22)}{1.051}\Delta_4 y_{t-1} - \underset{(3.58)}{0.534}\Delta_4 y_{t-4} + \underset{2.70}{0.325}\Delta_4 y_{t-5},$$

Adj. R^2: .805, DW: 1.982, S.E: .0055, L.B.(16): 8.832 (.940), J.B.: 4.870 (.088), LMAR(1-4): .115 (.977), ARCH(1): 2.005 (.161), RESET(2): 2.560 (.084), Chow(12): .662 (.781).

The diagnostic statistics are not significant at the 5 % test level and thus give no hint to any misspecification of the equation. . In comparison to the former equation, the Adj. R^2 is considerably higher. Therefore equation (10) is our benchmark model. The intercept in (10) -

together with the autoregressive coefficients - is consistent with a trend real GDP growth of 2 – 2.5 % over the period under consideration.

3.3 Different VARs

3.3.1 VAR and VEC models

In order to interpret responses to shocks as short-term dynamics around a stationary (steady) state, the VAR considered has to be stationary, possibly around a deterministic trend. Given the small sample size of our data set, ambiguous results of stationarity and cointegration rank tests and what economic theory tells us about relevant variables, we estimate VEC models as well as VARs in differences and levels.

In what follows, we try different VARs to assess the predictive content of M1. We start with unrestricted VARs since these are good approximations to the data generating process of any time series as long as enough lags are included (Canova 1995)

(11) $$X_t = \Gamma + A_1 X_{t-1} + ... + A_o X_{t-o}$$

where X_t is the vector of endogenous variables, G the matrix of deterministic terms, especially the intercept term and a linear deterministic trend, A_1 to A_o are the symmetric coefficient matrices and o the selected lag order of the VAR. If the variables are not stationary but cointegrated, the VAR is reparameterised as a vector error correction (VEC) model. The rank of the long run matrix is equal to the number of independent cointegrating relationships. If the variables are not cointegrated, the VEC becomes a VAR in first differences. The selection of the lag order o is based on the information criteria of Akaike (AIC) and Schwarz (SC) (see Lütkepohl 1993). Ng and Perron 2001, analyse the AIC and SC and show that it is necessary to hold the effective sample size fixed across models to be compared. In the present study, a maximum lag order of 7 is considered and the test period is 1982:Q1 to 2001:Q4. Corresponding to the benchmark model, the values of the criteria are additionally determined for VARs with lags 1 and 4 as well as 1 and 5. We select the VAR specification where a criterion obtains its minimum. For the chosen specification the freedom of autocorrelation is tested by a Lagrange-Multiplier test for autocorrelation of 1 to 8. Moreover, the cointegration hypothesis is checked using Johansen’s trace test (Johansen, 1995, 2000; Johansen/Juselius, 1990) on the assumption that the intercept term is unrestricted.

3.3.2 A Bayesian VAR

From a Bayesian perspective VARs have been tailored too much towards fitting historical data, based on the belief that all possible parameter values are equally likely, eventually leading to an overfitting problem risking to capture accidental features of the data rather than relevant structural relationships. Structural econometric models, on the other hand, probably tend to over- or underestimate the modeler's belief about the "hard-shape" exclusion restrictions imposed on most economic variables and equations, guided by economic theory, amounting to certainty in the belief that the coefficients are zero (see, e.g. Todd 1984). While, in principle, BVARs comprise as many coefficients as unrestricted VARs, the influence of the data on them is reduced by a statistical procedure to revise prior beliefs in light of the empirical evidence. In this sense, BVARs combine personal beliefs about the economy with objective, reproducable statistical procedures which permit the data to overwrite this suggestion if the evidence about a coefficient is strong.

As the construction of a complete normal prior on a VAR is intractable due to the number of coefficients, the Minnesota prior (Doan, Litterman and Sims 1984) uses a general prior involving only a few hyperparameters. As the number of coefficients in a BVAR grows rapidly with the number of lags and variables included, the Minnesota prior provides a system which makes deliberations about individual coefficients unnecessary. The best guess of model coefficients is based on the random walk hypothesis which capitalises on the simple statistical observation that most macroeconomic time series behave in a random manner, such that the best forecast of a future value is just its current value. This implies that the coefficient on the first (own) lag is one while all the others are set to zero - though not with unlimited confidence: The prior variance gets narrower, the longer the lag length, thus tightening the prior. The prior has thus the following characteristics.

- The priors on deterministic components are flat. Hence, the limiting form of each equation of the BVAR is a random walk with drift.
- Priors on lags of endogenous variables are independent normal.
- Means of prior distributions of all coefficients are zero with the exception of the first lag of the dependent variable in each equation which has a prior mean of one. Thus, longer lags have smaller variances around zero than shorter lags. Thereby, cross-lag variances have the same relative sizes as the coefficients of own lags.

To construct this prior the following information is needed to restrict $S(i,j,l)$, the standard deviation of the prior distribution for lag *l* of variable *j* in equation *i*, in the following form:[18]

(12) $$S(i,j,l)=\frac{[gg(l)f(i,j)]s_i}{s_j};\ f(i,i)=g(l)=1.0.$$

The scaling by the standard errors of variable i and j (s_i and s_j) is used to correct for different magnitudes in the data. The term $[gg(l)f(i,j)]$ reflects the tightness of the prior in terms of

- $g\ldots$ the overall tightness.[19]
- $g(l)\ldots$ the tightness of lag l relative to lag 1.
- $f(i,j)\ldots$ the tightness on variable j in equation i relative to variable *i*.

An overall tightness of $g=0.2$ would be considered as relatively loose. For the importance of the variables relative to each other, $f(i,j)=0.5$ is standard and can be symmetrically used for all $f(i,j)$-weights (i.e. for all $i\neq j$). For different choices of $f(i,j)$, in combination with the overall tightness either an unrestricted univariate model would be obtained (i.e $g=2$, $f(i,j)=0.001$), an unrestricted VAR (i.e. $g=2$, $f(i,j)=1.0$), a univariate Bayesian model (i.e. $g=0.1$, $f(i,j)=0.001$), or a multivariate Bayesian VAR (i.e. $g=0.1$, $f(i,j)=0.5$ - using a symmetric prior).

3.4 Results from the VAR models

The results of the lag order selection procedures within unrestricted VARs in levels are provided in Table 2. Using AIC, the lags 1 and 4 or 1 and 5 are selected (column 2). Nevertheless, the LM-test indicates that the null hypothesis of no autocorrelation is often rejected at the 5 percent test level for the fifth autocorrelation (column 3). The SC in most cases chooses a lag order of 1 (column 4). For this specification, the null hypothesis of no autocorrelation is rejected in more cases (column 5). The cointegrating properties are tested for the specifications selected by AIC (column 2 with the test results in column 6) and SC (test results in column 8). If both criterion select the same lag order the specification is given in Table 2. In some cases, the null hypothesis of no cointegration is rejected for the AIC specification. As the test gives no evidence for a cointegrating rank of two, this implies that no stationary process is considered. The LM-test of

[18] The scaling by the standard errors s_i and s_j is used to correct for different magnitudes in the data.

[19] Because of the restrictions on the *f* and *g* functions, g is the standard deviation of the first own lag.

no autocorrelation presents evidence that the specification of one cointegration rank reduces the probability to reject the null of no cointegration (column 7 compared to colmumn 3). For the SC specification the null hypothesis of no cointegration is mostly rejected (column 8). This specification implies autocorrelation in the estimated residuals (column 9). Therefore, the preferred VEC models are selected by the AIC.[20]

As the results of these lag order selection tests are not unambiguous, we decided to estimate VARS in levels, VARs in differences and VECMs. This procedure should be interpreted as a kind of robustness check of the forecasting results. As we are interested in the forecasting performance of M1 for real activity, we always keep *m1r* and *y* in the models considered.

In the context of BVARs, the lag-selection is not as crucial as in unrestricted VARs which build on "hard-shape" exclusion restrictions cutting off the lag length at a certain point. Therefore, the prior builds on an initial lag length which is rather generous (in our case 5 lags with quarterly data). This approach has been maintained for all BVARs presented in this study. The prior is usually tightened with the lag length by choosing a certain decay. The results presented here are obtained on the basis of a harmonic decay with coefficient 2, which gives some improvement over models without lag decays.

The BVARs have been set up in terms of levels, including a drift term. Using symmetric priors the BVARs are capable of outperforming the respective VARs in levels.[21] However, the forecasting performance could be further improved by choosing an asymmetric prior. Trivariate systems like $\left[m1r_t,(il-is)_t,y_t\right]'$, with $f(i,j)$ chosen in the following manner

$$\begin{bmatrix} 1 & 0.01 & 1 \\ 0.01 & 1 & 0.5 \\ 0.01 & 0.01 & 1 \end{bmatrix}$$

were found to perform better than other choices. This reflects the belief that real M1 and the yield spread are more important in affecting GDP than the other way around, and that real M1 is relatively more important in determining GDP than the yield spread. Conversely the remaining relative weights have been set close to zero. In cases, where systems with four variables are considered the corresponding (4×4) weighting matrix of priors has been constructed in the same manner.

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[20] Mills 1999, p. 36, shows that although theoretically the SC has advantages over the AIC, it would seem that the latter selects the preferred model on more general grounds.

Table 2: Lag order estimates of VAR in levels, cointegration tests and LM-autocorrelation tests

Variables	AIC lag order	LM-test	SC lag order	LM-test	Cointegration rank AIC	LM-test r=1	Cointegration rank SC	LM-test $r\geq 1$
y, m1r, il-is	1, 5	3	1	1,2	0	1,2	0	1,2,3,4,5
y,m1r,il	2	-	1	1,5	1	-	1	1
y,m1r,is	1,5	5	1	1,2,5	1	-	1	1,2
y,m1r,il_ger-is_ger	1,5	5	1,5	5	0	-	o=1, 1	1,2,3,4,5
y,m1r,il_ger	1,4	5	1	1,5	1	5	1	1,2,3
y,m1r,is_ger	1,4	5	1	1,2,3,5	0	-	1	1,2,3,5
y,m1r,clr-is	1,5	-	1	2	0	2	1	1,2,5
y,m1r,is-i_{m1}	1,5	5	1	1,2	0	-	1	1,2
y,m1r,il-i_{m1}	2	-	1	1,5	1	-	1	1,5
y,m1r,$il_{real(PGDP)}$	1,4	-	1	1,4,5	0	1	1	1,2,4,5
y,m1r,$il_{real(HICP)}$	1,4	5	1	1,2,5	0	2,3	1	1,2,3,4,5
y,m1r,$is_{real(PGDP)}$	1,5	5	1	5	0	5	1	1,3,5
y,m1r,$is_{real(HICP)}$	1,4	1	1	2,3,5	0	1,3	0	1,3
y,divr, il-is	1, 5	1	1	1	1	-	1	1,2,3
y,divr,il	2	2	1	1,5	1	2	1	1
y,divr,is	1,5	5	1	1,2,5	1	-	1	1,2,5
y, m1r,il-is,stock	1, 5	1,5	1	1,2,5	1	-	1	1,2,5
y,m1r,il,stock	2	5	1	1,5	0	5	2	1,5
y,m1r,is,stock	1	1,5	1	1,5	o=2; 0	-	2	1,5
y,m1r,il-is,oilp	1	1,5	1	1,5	o=2, 1	5	1	5
y,m1r,il,oilp	1	1,5	1	1,5	o=2, 1	2	2	1,5
y,m1r,is,oilp	1	1,2,5	1	1,2,5	o=2, 0	1,5	1	1,2,5
y,m1r,il-is,oilp€	1	1,5	1	1,5	o=2, 0	5	1	5
y,m1r,il,oilp€	1	1,5	1	1,5	o=2,1	-	1	1,5
y,m1r,is,oilp€	1	1,2,5	1	1,2,5	0	-	1	1,2
y,m1r,il-is,e	1,5	1,2,3	1	1,5	0	1,2	0	1,2
y,m1r,il,e	1	1,5	1	1,5	o=2,1	-	1	1
y,m1r,is,e	1,5	-	1	1,2	0	-	1	1,2
y,m1r,il-is,eeffn	1,5	1,2,3	1	1,5	1	2,3	1	1,2
y,m1r,il,eeffn	2	-	1	1,5	1	-	1	1
y,m1r,is,eeffn	1,5	-	1	2	1	2	1	1,2
y,m1r,il-is,eeffr	1,5	2,3	1	1,2,3	0	1,2,8	1	1,2,3
y,m1r,il,eeffr	1	1	1	1	o=2, 1	-	1	1
y,m1r,is,eeffr	1,5	-	1	1,2	0	-	1	1,2

Notes: AIC: Akaike information criterion, LM-test: Lagrange-Multiplier test of autocorrelation for lag order i, where i = 1,2,…,8. The cells of the respective column contain the lag orders o, where the null hypothesis of no autocorrelation at this lag is rejected at the 5 percent significance level. SC: Schwarz-criterion, Cointegration rank AIC: Cointegration rank test of Johansen, where the lag order of the corresponding unrestricted VAR is determined by the AIC. If the AIC (SC) lag order estimates are identical to the SC (AIC) lag order estimates, the lag order is augmented by one (is set to unity). Cointegration rank SC: Cointegration rank test of Johansen, where the lag order of the corresponding unrestricted VAR is determined by the SC. Test period is 1982:Q1 to 2001:Q4 and 1983:Q1 to 2001:Q4 for the test regressions involving real interest rates.

[21] To save space the results obtained using BVARs based on symmetric priors are not shown. They are available from the authors upon request.

The out-of-sample forecasts are computed with a recursive regression method.[22] A recursive estimation of the system yields a series of out-of-sample forecasts for the different forecasting horizons h=1,…,8. The starting coefficients are computed over the period 1980:Q1 to 1993:Q4. Using these coefficients, the first forecasts are determined. The forecast errors are the differences between the forecast of y and the historical values of y. In a next step, the sample is extended by one quarter and the system is re-estimated to calculate the forecasts again. This procedure is continued until the end of the sample.

The accuracy of forecasts can be judged by various statistics about the forecast errors. In this study the root mean square forecast errors (RMSFE) are used. To assess the relative predictive accuracy of two forecasting models, the Diebold Mariano test is selected, which has an asymptotic normal distribution (see Diebold and Mariano 1995).[23] The longest interval for all forecasts is from 1994:Q1 to 2001:Q4, hence the maximum length of the forecast period is 32. The values of the RMSFE for real output of the benchmark model are given in the first row of Tables 3 to 6, respectively. In general, they increase with the forecasting horizon. The results of the other approaches are all given relative to this benchmark (RMSFE of the alternative model divided by RMSFE of the benchmark model). Values greater than one indicate that the alternative model is worse than the benchmark model.

Table 3 shows the results of the different VARs in levels with a deterministic trend. It is apparent that all models are worse than the benchmark model. Very often the differences are even significant at the 5 or 1 percent level. Up to forecast horizon 3 the second-best model after the benchmark model is the one with the additional variable (*clr-is*), for the horizons 4 to 6 the model with *is* and *oilp* and for the two longest horizons 7 and 8 the model with the Divisia aggregate and *il*. It is worth noting that the differences are slightly smaller if VARs in levels without a deterministic trend are estimated (not shown, but available upon request). However, this alternative also does not dominate the benchmark in any case. The results of the VEC models are given in Table 4. Often the results are better than the results of the VARs in levels. Nevertheless, only for h=1 some variants of this model class outperform the benchmark. But the difference is in no case statistically significant at conventional significance levels. In most cases these models are worse than the benchmark. The models which perform best relative to the benchmark are those with the additional variables (i_l-i_{m1}) for h=1,2 and h=7,8 and i_s and *oilp* for h=3-6.

[22] A comparison of out-of-sample and in-sample tests of predictability may be found in Inoue and Kilian 2002.

[23] See the appendix for a description of the test.

Table 5 shows the results of the VAR models with variables in first difference, where a lag order of one is selected.[24] It is apparent that all models are better than the benchmark model for the whole range of forecast horizons. The reduction in the RMSFE is 20 to nearly 30 percent. The best model includes the variables *y*, *m1r* and (il-i_{m1}) for the horizon h = 1 to 6 (see the bold figures in Table 5). For h = 7 and 8, the best model is *y*, *m1r* and $il_{real(HICP)}$. Having in mind that the differences between the benchmark model and the alternative model are not significant if they are less than 10 percent this implies that the choice of the variables has only a small effect. It seems that it is more important to choose the "right" general class of VAR models.[25]

The results obtained on the basis of the BVAR models are shown in Table 6. It is evident that it was not possible to outperform the univariate benchmark model using a BVAR. This result is in line with recent findings in Canova (2002). Furthermore, except for one-step-ahead forecasts, BVARs are able to outperform the respective non-Bayesian VARs in levels over all horizons. The best performing model is the one containing the Divisia aggregate. Second to these models are BVARs containing real interest rate measures.

Table 3: Relative root mean square forecast errors for VARs in levels with a deterministic trend

Model/Variables	Spe-cifi-cation	Forecast horizon							
	o	1	2	3	4	5	6	7	8
Benchmark	1,4,5	.0040	.0062	.0082	.0097	.0112	.0126	.0124	.0124
y, m1r, il-is	1,5	1.301	1.650+	1.926+	2.265*	2.510*	2.771*	3.287*	3.663*
y,m1r,il	1,2	1.446*	1.817*	2.037*	2.279*	2.409*	2.553*	2.927*	3.221*
y,m1r,is	1,5	1.282	1.652#	1.967+	2.360+	2.669+	2.971*	3.549*	3.952*
y,m1r,il_ger-is_ger	1,5	1.256	1.607+	1.897+	2.263*	2.538*	2.843*	3.418*	3.799*
y,m1r,il_ger	1,4	1.212	1.483#	1.710+	1.999+	2.194*	2.397*	2.839*	3.195*
y,m1r,is_ger	1,4	1.156	1.430#	1.670+	1.960+	2.184*	2.420*	2.884*	3.215*
y,m1r,clr-is	1,5	1.126	1.391	1.617#	1.905+	2.114+	2.364*	2.852*	3.261*
y,m1r,is-i_{m1}	1,5	1.250	1.611#	1.920+	2.304+	2.602*	2.892*	3.447*	3.830*
y,m1r,il-i_{m1}	1,2	1.397*	1.737*	1.922*	2.119*	2.211*	2.319*	2.635*	2.904*
y,divr, il-is	1,5	1.268#	1.619*	1.919*	2.298*	2.577*	2.833*	3.289*	3.499*

[24] In most cases, where the AIC chooses a lag order of 1 and 4 or 1 and 5 for the level approach, a lag specification of 1 and 4 or 1 and 5 for the VARs in first differences does not yield better results than the presented ones.

[25] A single equation approach with D_4y, D_4y_{t-1}, D_4m1r and one or more of the variables taken into account in the Tables 3 to 6 would not be able to outperform the benchmark model with dynamic forecasts irrespective of the forecast horizon considered.

y,divr,il	1,2	1.283+	1.598*	1.761*	1.943*	2.025*	2.125+	2.370+	2.423+
y,divr,is	1,5	1.250	1.589+	1.865*	2.222*	2.497*	2.758+	3.232+	3.427+
y,m1r,il$_{real(PGDP)}$	1,4	1.293	1.605#	1.884+	2.270+	2.577*	2.890*	3.464*	3.848*
y,m1r,il$_{real(HICP}$)	1,4	1.288	1.545#	1.766+	2.092+	2.348*	2.628*	3.140*	3.474*
y,m1r,is$_{real(PGDP)}$	1,5	1.155	1.469	1.751#	2.128+	2.418+	2.727*	3.267*	3.655*
y,m1r,is$_{real(HICP)}$	1,4	1,339#	1.630+	1.850+	2.127*	2.305*	2.481*	2.871*	3.145+
y, m1r,il-is,stock	1,5	1.343	1.679+-	1.932+	2.232+	2.426+	2.621*	3.053*	3.322*
y,m1r,il,stock	1,2	1.398+	1.780*	2.035*	2.301*	2.447*	2.570*	2.910*	3.086*
y,m1r,is,stock	1,2	1.364#	1.744+	1.979*	2.201*	2.323*	2.439*	2.765*	2.966*
y,m1r,il-is,oilp	1	1.269	1.535+	1.730+	1.982*	2.162*	2.347*	2.753*	3.037*
y,m1r,il,oilp	1	1.408+	1.689+	1.855*	2.067*	2.194*	2.330*	2.686*	2.931*
y,m1r,is,oilp	1	1.356#	1.579+	1.697+	1.852+	1.955*	2.088*	2.432*	2.715*
y,m1r,il-is,oilp€	1	1.376#	1.616+	1.758*	1.934*	2.047*	2.174*	2.514*	2.753*
y,m1r,il,oilp€	1	1.448+	1.694*	1.826*	1.995*	2.092*	2.208*	2.536*	2.759*
y,m1r,is,oilp€	1	1.421+	1.646+	1.760*	1.907*	1.998*	2.118*	2.451*	2.704*
y,m1r,il-is,e	1,5	1.328	1.697	1.979#	2.305#	2.517+	2.746+	3.245*	3.612*
y,m1r,il,e	1,2	1.595+	2.004+	2.292+	2.617+	2.818+	3.012+	3.478*	3.832*
y,m1r,is,e	1,5	1.337	1.708	2.015	2.387#	2.655+	2.918+	3.478*	3.875*
y,m1r,il-is,eeffn	1,5	1.313	1.688	1.978#	2.299+	2.500+	2.726+	3.228*	3.607*
y,m1r,il,eeffn	1,2	1.578+	1.977+	2.274+	2.603+	2.798*	2.976*	3.404*	3.710*
y,m1r,is,eeffn	1,5	1.308	1.683	1.994	2.357#	2.609+	2.858+	3.405*	3.802*
y,m1r,il-is,eeffr	1,5	1.300	1.664#	1.946#	2.257+	2.447+	2.648+	3.109*	3.448*
y,m1r,il,eeffr	1,2	1.592+	2.010+	2.294+	2.595+	2.756+	2.897+	3.286*	3.559*
y,m1r,is,eeffr	1,5	1.260	1.611	1.906#	2.248#	2.487+	2.721+	3.232*	3.597*

Notes: The column "Specification" shows the lag order of the VAR. The row "Benchmark" contains the RMSFE of the benchmark model. The results of the other models are the respective RMSFE relative to the benchmark RMSFE. #,+,* denote significance at the 10, 5, 1 percent level, respectively. Normal distributed statistic using the critical values 1.64486; 1.95997; 2.55758.

Table 4: Relative root mean square forecast errors for VEC models

Model/Variables	Spe-cifi-cation	Forecast horizon							
	o|*r*	1	2	3	4	5	6	7	8
Benchmark	1,4,5	.0040	.0062	.0082	.0097	.0112	.0126	.0124	.0124
y, m1r, il-is	1,5|1	1.329#	1.581#	1.753+	1.930+	2.079+	2.230*	2.654*	2.757+
y,m1r,il	1|1	1.009	1.228	1.402	1.594#	1.689#	1.791+	2.002+	2.072+
y,m1r,is	1|1	1.104	1.339#	1.527+	1.730+	1.848*	1.972*	2.248*	2.407*
y,m1r,il_ger-is_ger	1,5|1	1.189	1.394	1.502-	1.645#	1.752+	1.871+	2.158*	2.330+

y,m1r,il_ger	1|1	0.936	1.114	1.256	1.399	1.462	1.535#	1.709+	1.793+
y,m1r,is_ger	1,4|1	1.287+	1.455+	1.629+	1.836+	2.004*	2.159*	2.471*	2.653*
y,m1r,clr-is	1|1	1.131	1.451+	1.670+	1.907+	2.032*	2.173*	2.486*	2.623*
y,m1r,is-i_{m1}	1|1	1.083	1.293#	1.460+	1.638*	1.736*	1.837*	2.071*	2.190*
y,m1r,il-i_{m1}	1|1	0.919	1.101	1.241	1.393	1.457	1.532#	1.687+	1.703+
y,divr, il-is	1,5|1	1.205	1.393	1.492	1.600	1.671	1.769	2.014#	1.933#
y,divr,il	1|1	1.035	1.234	1.347#	1.482+	1.535+	1.611+	1.787+	1.796#
y,divr,is	1|1	1.082	1.300#	1.416+	1.587+	1.709+	1.875+	2.214#	2.383#
y,m1r,$il_{real(HICP)}$	1|1	1.218	1.468#	1.672+	1.934+	2.112+	2.323+	2.740+	2.733+
y,m1r,$il_{real(PGDP)}$	1|1	1.063	1.169	1.251	1.386	1.426	1.492	1.675	1.760
y,m1r,$is_{real(HICP)}$	1|1	1.322	1.601	1.825#	2.100+	2.300+	2.534*	3.045*	3.468+
y,m1r,$is_{real(PGDP)}$	1,4|1	1.557+	1.862+	2.109*	2.417*	2.737*	3.079*	3.732*	4.203*
y, m1r,il-is,stock	1,5|1	1.174	1.385	1.564#	1.756#	1.890+	2.013+	2.303+	2.383+
y,m1r,il,stock	1|1	0.983	1.256	1.447	1.647#	1.736#	1.819+	2.016+	2.041+
y,m1r,is,stock	1|1	1.146	1.419+	1.623+	1.830*	1.951+	2.067+	2.348+	2.476+
y,m1r,il-is,oilp	1|1	1.139	1.297	1.423	1.579#	1.669#	1.760+	1.987+	2.103+
y,m1r,il,oilp	1|1	0.992	1.152	1.290	1.460	1.544	1.640-	1.836+	1.919+
y,m1r,is,oilp	1|1	0.954	1.093	1.203	1.327	1.401	1.497#	1.704+	1.810+
y,m1r,il-is,oilp€	1|1	1.259	1.514+	1.661*	1.833*	1.929*	2.039*	2.309*	2.355*
y,m1r,il,oilp€	1|1	0.952	1.122	1.255	1.414	1.490#	1.589+	1.780+	1.815+
y,m1r,is,oilp€	1|1	1.148	1.394#	1.551+	1.717*	1.808*	1.917*	2.177*	2.290*
y,m1r,il-is,e	1,5|1	1.385	1.720#	1.949#	2.196+	2.368+	2.588*	3.050*	3.301+
y,m1r,il,e	1,5|1	1.241	1.506#	1.727#	1.966+	2.135+	2.308+	2.685+	2.913*
y,m1r,is,e	1|1	1.296	1.658	1.921#	2.169#	2.321+	2.473+	2.855+	3.119+
y,m1r,il-is,eeffn	1,5|1	1.315	1.597	1.801#	1.992#	2.134+	2.278+	2.702*	2.805+
y,m1r,il,eeffn	1,5|1	1.212	1.447+	1.646+	1.865+	2.018+	2.184+	2.527*	2.685*
y,m1r,is,eeffn	1,5|1	1.309	1.589#	1.827#	2.065#	2.232+	2.412+	2.835+	3.156*
y,m1r,il-is,eeffr	1,5|1	1.361	1.658#	1.858#	2.047#	2.179+	2.310+	2.714*	2.834+
y,m1r,il,eeffr	1,5|1	1.236#	1.473+	1.670+	1.890+	2.039+	2.199*	2.539*	2.690*
y,m1r,is,eeffr	1,5|1	1.361#	1.656#	1.892#	2.128#	2.285+	2.459+	2.882+	3.206*

Notes: The specification includes the number of lag orders (p) and the selected cointegration rank (r). An unrestricted intercept is included in all models. In cases where a specification with lag order 4 or 5 is selected the alternative model with a lag order of 1 obtains higher root mean square forecast errors. #,+,* denote significance at the 10, 5, 1 percent level, respectively. Normal distributed statistic using the critical values 1.64486; 1.95997; 2.55758.

Table 5: Relative root mean square forecast errors for VARs in first differences

Model/Variables	Spe-cifi-cation	Forecast horizon							
	o	1	2	3	4	5	6	7	8
Benchmark	1,4,5	.0040	.0062	.0082	.0097	.0112	.0126	.0124	.0124
y, m1r, il-is	1	0.829#	0.837+	0.790*	0.781*	0.734*	0.750*	0.841+	0.844#
y,m1r,il	1	0.787+	0.796+	0.731*	0.751*	0.720*	0.743*	0.848+	0.836#
y,m1r,is	1	0.813#	0.826+	0.776*	0.778*	0.733*	0.752*	0.846+	0.841#
y,m1r,il_ger-is_ger	1	0.823#	0.829+	0.782*	0.776*	0.734*	0.753 *	0.848+	0.853
y,m1r,il_ger	1	0.779+	0.795+	0.737*	0.751*	0.718*	0.742*	0.846+	0.838#
y,m1r,is_ger	1	0.808+	0.821+	0.775*	0.775*	0.731*	0.751*	0.844+	0.843#
y,m1r,clr-is	1	0.815#	0.838#	0.783*	0.784*	0.729*	0.746*	0.833+	0.824#
y,m1r,is-i_{m1}	1	0.807+	0.821+	0.772*	0.777*	0.732*	0.751*	0.845+	0.839#
y,m1r,il-i_{m1}	1	**0.778+**	**0.780+**	**0.704***	**0.732***	**0.709***	**0.738***	0.852#	0.841#
y,divr, il-is	1	0.836#	0.843#	0.820+	0.837*	0.796*	0.798*	0.864+	0.876
y,divr,il	1	0.787+	0.791+	0.761*	0.807*	0.785*	0.796*	0.874+	0.885
y,divr,is	1	0.817+	0.823+	0.798*	0.826*	0.791*	0.798*	0.867+	0.878
y,m1r,$il_{real(PGDP)}$	1	0.815+	0.832+	0.806+	0.808+	0.761*	0.760*	**0.815***	**0.792***
y,m1,$il_{real(HICP)}$	1	0.831#	0.832+	0.795*	0.790*	0.743*	0.748*	0.810*	0.786+
y,m1,$is_{real(PGDP)}$	1	0.813+	0.823+	0.796*	0.804+	0.762*	0.766*	0.822+	0.803+
y,m1r,$is_{real(HICP)}$	1	0.831#	0.831+	0.791*	0.787*	0.743*	0.750*	0.813*	0.792+
y, m1r,il-is,stock	1	0.828#	0.854#	0.828+	0.818*	0.775*	0.780*	0.849+	0.809*
y,m1r,il,stock	1	0.778+	0.817+	0.779*	0.796*	0.772*	0.783*	0.865#	0.803*
y,m1r,is,stock	1	0.811+	0.849#	0.823+	0.820*	0.781*	0.789*	0.860+	0.808*
y,m1r,il-is,oilp	1	0.809+	0.821+	0.783*	0.786*	0.739*	0.750*	0.825+	0.804+
y,m1r,il,oilp	1	0.806+	0.805+	0.738*	0.760*	0.724*	0.742*	0.825+	0.792+
y,m1r,is,oilp	1	0.809+	0.817+	0.773*	0.782*	0.736*	0.750*	0.827+	0.800+
y,m1r,il-is,oilp€	1	0.844#	0.868	0.820+	0.806+	0.748*	0.753*	0.820+	0.796+
y,m1r,il,oilp€	1	0.849	0.852#	0.765*	0.775*	0.731*	0.746*	0.830+	0.789+
y,m1r,is,oilp€	1	0.852	0.870	0.814+	0.808+	0.749*	0.757*	0.827+	0.792+
y,m1r,il-is,e	1	0.889	0.903	0.871#	0.828#	0.754+	0.757+	0.838+	0.836#
y,m1r,il,e	1	0.841	0.841+	0.792*	0.785+	0.733+	0.748*	0.846-	0.830#
y,m1r,is,e	1	0.869	0.880	0.846+	0.819+	0.749+	0.758+	0.843+	0.835#
y,m1r,il-is,eeffn	1	0.875	0.911	0.888	0.851#	0.775+	0.766+	0.829+	0.805+
y,m1r,il,eeffn	1	0.833#	0.846+	0.798*	0.799+	0.750+	0.758*	0.839#	0.804+
y,m1r,is,eeffn	1	0.860	0.884#	0.852+	0.832+	0.765+	0.765*	0.834+	0.804+
y,m1r,il-is,eeffr	1	0.871	0.904	0.878-	0.845-	0.773+	0.766*	0.831+	0.806+

y,m1r,il,eeffr	1	0.831#	0.843+	0.790*	0.796+	0.750+	0.759*	0.842#	0.804+
y,m1r,is,eeffr	1	0.857	0.881#	0.845+	0.829+	0.764+	0.766*	0.837+	0.804+

Notes: The column "Specification" includes the lag order (o) of the VAR in first differences. #,+,* denote significance at the 10, 5, 1 percent level, respectively. Normal distributed statistic using the critical values 1.64486; 1.95997; 2.55758. The bold values gives the lowest RMSFE for this forecast horizon for all approaches.

Table 6: Root mean square forecast errors for Bayesian VAR in levels

Model Variables	Spe-cifi-cation	Forecast horizon							
	o	1	2	3	4	5	6	7	8
Benchmark	1,4,5	.0040	.0062	.0082	.0097	.0112	.0126	.0124	.0124
y, m1r, il-is	5	1.665#	1.541	1.537#	1.620+	1.660+	1.759*	2.093*	2.487+
y,m1r,il	5	1.636	1.490	1.460	1.520	1.545+	1.632+	1.939+	2.305+
y,m1r,is	5	1.531	1.409	1.405	1.485	1.531#	1.641+	1.977+	2.386+
y,m1r,il_ger-is_ger	5	1.532	1.422	1.434	1.523#	1.569+	1.678+	2.013+	2.418+
y,m1r,il_ger	5	1.636	1.490	1.460#	1.519	1.545+	1.632+	1.939+	2.305+
y,m1r,is_ger	5	1.531	1.409	1.405	1.485	1.531#	1.641+	1.977+	2.386+
y,m1r,clr-is	5	1.636	1.484	1.448	1.500	1.518#	1.596+	1.888+	2.235+
y,m1r,is-i_{m1}	5	1.586	1.455	1.442	1.517	1.557+	1.660+	1.989+	2.382+
y,m1r,il-i_{m1}	5	1.625	1.478	1.446	1.501	1.523+	1.605+	1.903*	2.258+
y,divr, il-is	5	1.228	1.095	1.122	1.216	1.290	1.418	1.731	2.089
y,divr,il	5	1.186	1.005	0.978	1.034	1.095	1.221	1.510	1.849
y,divr,is	5	1.203	1.055	1.066	1.157	1.238	1.380	1.707	2.086
y,m1r,$il_{real(PGDP)}$	5	1.531	1.388	1.376	1.443	1.473#	1.572#	1.884#	2.274#
y,m1r,$il_{real(HICP)}$	5	1.501	1.353	1.333	1.393	1.419	1.514#	1.814#	2.192#
y,m1r,$is_{real(PGDP)}$	5	1.594	1.440	1.411	1.469	1.490#	1.581#	1.884#	2.266#
y,m1r,$is_{real(HICP)}$	5	1.611	1.460	1.430	1.491	1.516#	1.610+	1.921+	2.306#
y,m1r,il-is,stock	5	1.565	1.440	1.429	1.496	1.519+	1.600+	1.898+	2.258+
y,m1r,il,stock	5	1.565	1.416	1.377	1.417	1.421	1.486+	1.751+	2.077+
y,m1r,is,stock	5	1.540	1.405	1.381	1.440	1.463#	1.547+	1.844+	2.204+
y,m1r,il-is,oilp	5	1.630	1.502	1.493	1.570+	1.606+	1.702*	2.028*	2.414+
y,m1r,il,oilp	5	1.610	1.460	1.424	1.476	1.496#	1.577+	1.872*	2.226+
y,m1r,is,oilp	5	1.586	1.454	1.438	1.511#	1.550+	1.652+	1.979+	2.370+
y,m1r,il-is,oilp€	5	1.641+	1.511	1.499	1.575+	1.610+	1.703*	2.023*	2.402+
y,m1r,il,oilp€	5	1.625	1.474	1.437	1.489	1.510+	1.591+	1.884*	2.233+
y,m1r,is,oilp€	5	1.602	1.469	1.452	1.526+	1.565+	1.665+	1.991*	2.378+

y,m1r,il-is,e	5	1.692	1.568	1.565	1.650#	1.688+	1.784+	2.115*	2.504+
y,m1r,il,e	5	1.668	1.524	1.494	1.554	1.576#	1.655+	1.953+	2.307+
y,m1r,is,e	5	1.629	1.503	1.493	1.574	1.614#	1.715+	2.045+	2.438+
y,m1r,il-is,eeffn	5	1.690#	1.569	1.568	1.656#	1.697+	1.795*	2.129*	2.549+
y,m1r,il,eeffn	5	1.667	1.527	1.500	1.565	1.591#	1.673+	1.976*	2.333+
y,m1r,is,eeffn	5	1.628	1.504	1.496	1.581	1.626#	1.729 +	2.063+	2.457+
y,m1r,il-is,eeffr	5	1.660#	1.536	1.532	1.615#	1.654+	1.750*	2.076*	2.456+
y,m1r,il,eeffr	5	1.634	1.491	1.461	1.521	1.546#	1.627+	1.923*	2.271+
y,m1r,is,eeffr	5	1.602	1.477	1.466	1.547	1.591+	1.692+	2.020*	2.406+

Notes: The column "Specification" shows the lag order selected. The first row gives the RMSFE of the benchmark model. #,+,* denote significance at the 10, 5, 1 percent level, respectively. Normal distributed statistic using the critical values 1.64486; 1.95997; 2.55758.

4. Summary and Conclusions

The purpose of this paper was to assess the forecast performance of narrow M1 for real activity, measured by the growth rate of real GDP, in the euro area. After a brief review of the empirical literature, we recall a number of theoretical arguments why money might be useful for real developments beyond the effects of monetary policy captured by a short-term interest rate.

It seems that models which neglect the information content of money may constitute over-simplifications or may be mis-specified. Building on a single equation methodology recently proposed by Hamilton and Kim 2002, it is found that M1 proves to be important even after taking account of other variables. In contrast to findings for the U.S., the evidence in the euro area seems to suggest that - over the sample period under investigation (i.e. 1981-2002) - M1 outperforms the yield curve in terms of its predictive content for cyclical movements in GDP. These properties are also maintained when looking at a broader set comprising non-monetary indicator variables. Narrow money therefore seems crucial for cyclical developments. Taking this result as a starting point for a more rigorous forecast comparison exercise, the study looks at the out-of-sample forecasting performance of different classes of VAR models compared with a univariate benchmark model 1 to 8 quarters out. As a result, only VARs in first differences are able to outperform the univariate benchmark model and yield significantly better forecasting results at all forecast horizons. This may be due to the facts that the evidence for the existence of cointegration relationships is not unambiguous and that most level variables seem to contain a unit root. Moreover, as Clements and Hendry 1998, ch. 6 and 7 show, vector autoregressions in first differences are better able to capture structural breaks during the forecast period than

VECMs or VARs in levels even if they are mis-specified. The best models for the shorter horizons (up to six quarters) is the one which - besides real M1 and real GDP growth – includes the spread between the yield on government bonds and the own rate of return of M1. For the two longest horizons (7-8 quarters), the best model additionally takes into account the real yield on government bonds where the price component is calculated via the GDP deflator.

The empirical results tend to support the view that money may play a role in the transmission mechanism beyond short-term interest rates. Considering the distinction between inside and outside money, the existence of a traditional real-balance effect seems plausible only in a limited sense. More recent research suggests that the importance of money may crucially depend on the way money holdings affect the marginal utility of household consumption. Other recent approaches built on the conviction that the real money stock serves as a summary statistics of a whole range of relative yields on financial and human and non-human wealth. Based on this, the real money stock can be included in a forward-looking IS-curve as a separate variable. The present study adds to the current debate by assessing the issue from an empirical perspective.

According to our results, the information in narrow money should not be neglected as far as real developments are of interest. Theoretically, this should be due to the transactions function of money which is best captured by narrow money. Therefore, one interesting field of future research should be to elaborate in more detail on the theoretical justifications on the indicator properties of M1 for real activity. Empirically, one could analyse which of the components of M1, i.e. currency and overnight deposits, are responsible for the results. Moreover, it may also be interesting to examine the model performance at forecast horizons longer than 2 years or use other metrics as the root mean squared error, e.g. the direction of change or the general forecast-error second moment matrix (Clements and Hendry 1998, ch. 3.6). And finally, as the primary goal of the monetary policy of the ECB is to maintain price stability, it is of overriding importance to assess how changes in demand conditions indicated by movements in M1 affect price developments.[26] These considerations should be taken up in further research.

[26] Leading indicator properties of M1 for prices have also been analysed in Nicoletti Altimari (2001).

Appendix: The Diebold Mariano Test

The accuracy of forecasts can be assessed by various statistics about the forecast errors. In this study, the root mean square forecast errors are selected. To check the relative predictive accurarcy of two forecasting models, different test statatistics are suggested and analysed by Diebold and Mariano (1995). Their preferred test statistic is

$$\hat{d}_F = F^{-1/2} \frac{\sum_{t=T+1}^{S-h} (\hat{e}^2_{0,t+h} - \hat{e}^2_{1,t+h})}{\hat{s}_F}$$

where T denotes the length of the estimation period, F is the length of the forecast period, hence S=T+F, $h \geq 1$ is the forecast horizon, $\hat{e}^2_{0,t+h}$ and $\hat{e}^2_{1,t+h}$ are the squared forecast errors of the benchmark model and the alternative model, respectively, using consistent estimators, and

$$\hat{s}_F = \frac{1}{F} \sum_{t=T+1}^{S-h} (\hat{e}^2_{0,t+h} - \hat{e}^2_{1,t+h})^2 + \frac{2}{F} \sum_{j=1}^{l_F} w_j \sum_{t=T+1+j}^{S-h} (\hat{e}^2_{0,t+h} - \hat{e}^2_{1,t+h})(\hat{e}^2_{0,t+h+j} - \hat{e}^2_{1,t+h+j}),$$

where $w_j = 1 - \frac{j}{l_F + 1}$, $l_F = o(F^{1/4})$. The parameter ω_j is the Bartlett weight and l_F is the truncation parameter depending on the converging rate of F. For F = 32 we choose l_F =2. The test statistic is denoted the Diebold Mariano (dm) test. The null of equal predictive ability is

$$H_0 : E(e^2_{0,t+h} - e^2_{1,t+h}) = 0$$

while the alternative is

$$H_1 : E(e^2_{0,t+h} - e^2_{1,t+h}) \neq 0$$

Under the null hypothesis, this statistic has an asymptotic standard normal distribution. Harvey, Leybourne and Newbold (1997, 1998) analyse the test statistic using an extensive Monte Carlo design, and find that the test has good size and fairly good power properties.

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