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by

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Brief Title: **Financial variables and real growth**

Abstract

This paper investigates the predictive ability of financial variables for real growth in the euro area through bivariate and multivariate non-parametric Granger causality tests. Apart from assessing the within-country forecasting ability of commonly-employed financial variables, such as the term spread, the stock market returns and the growth of real money supply, we also test for cross-country influences. Employing a monthly dataset for the period from January 1988 to May 2005, we find that financial variables are useful leading indicators for euro area growth at a joint level, albeit at different horizons, ranging from one to six quarters. In addition to non-parametrically testing for Granger causality, we consider testing the out of sample forecasting ability of the respective financial variables in a parametric framework for the period from 2001 onwards. Our results from this parametric framework corroborate our non-parametric findings, yielding the stock market returns and the term spread as the single more powerful predictor on a country and euro area basis, respectively.

JEL Classification: E52; C14;

Keywords: Granger causality; forecasting accuracy; money supply; output growth; term spread; stock returns;

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1 Introduction

A vast literature in finance and macroeconomics is devoted to the forecasting ability of financial variables for real economic activity. Empirical evidence is mixed and results are not robust with respect to model specification, sample choice and forecast horizon.[1] The financial variables often employed in empirical studies are the ones often identified as leading indicators of economic activity, such as stock returns, interest rates, interest rate spreads, and monetary aggregates.

Beckett (1961), Goldsmith (1969), Bosworth (1975), Hall (1978), Fama (1981), Geske and Roll (1983), as well as more recent studies by Barro (1990), Fama (1990), Schwert (1990), Lee (1992), Estrella and Mishkin (1998), Hassapis and Kalyvitis (2002), Hassapis (2003) and Panopoulou et al. (2005) are among the many studies that establish the forecasting ability of stock market returns for output growth. These studies find that stock returns are highly correlated with future real activity, for various data frequencies covering very long periods, and are robust to alternative definitions of the data series. Over the last years many researchers have revealed a positive association between the yield spread and future economic activity. It is also well established that the magnitude of the spread is related to the level of economic growth. With respect to monetary aggregates, these are often linked to the monetary stance and as a result to expectations for future growth and inflation. Among the plethora of studies that find that the term structure and/or monetary aggregates are associated with future economic activity, are the ones by Stock and Watson (1989), Harvey (1988, 1997), Estrella and Hardouvelis (1991), Plosser and Rouwenhorst (1994), as well as the more recent ones by Estrella and Mishkin (1997, 1998), Hassapis et al. (1999), Black et al. (2000), Galbraith and Tkacz (2000), and Hamilton and Kim (2002). However, Stock and Watson (2003) found a deterioration of the term spread as a predictor of US GDP growth since 1985. A similar conclusion is reached by Boulier and Stekler (2000), who discover a positive association of real economic activity and term spread along with a significant structural break in this relationship in the 1980s.

With the exception of a few, the aforementioned studies have concentrated and examined the predictive ability of financial variables for US future growth. Similar evidence for the euro area countries is quite scarse and more recent. Among the first to tackle this issue are Davis and Fagan (1997) who find that the yield curve improves the forecastability of output growth for the six out of the nine European countries examined, namely Germany, France, the UK, Belgium, Demark and the Netherlands. However, the only cases that significance is combined with stability and improved out-of-sample forecasting performance are Belgium, Denmark and the UK. Using a large data set consisting of 447 macroeconomic time series, Forni et al. (2003) evaluate the role of financial variables in forecasting output and inflation for the main euro area countries. Their results suggest that multivariate methods are to be preferred to univariate ones when forecasting both inflation and growth. Although the authors find that financial variables help forecasting inflation, the findings for output growth are not encouraging. Sensier et al. (2004) examine the roles of domestic and international variables in predicting business cycle regimes in four European countries, namely Germany, France, Italy and the UK. They find that real money growth and stock market prices are important for all countries except for Germany and Italy, albeit with differing signs and lag lengths. The yield curve, however, cannot beat the separate use of either long-term or short term rates, which are found to be significant with mostly a negative effect. On the contrary, Moneta (2005) finds that the yield spread is the single most powerful predictor of recessions in the euro area especially for forecasting horizons beyond one quarter. The same conclusion is reached by Duarte et al. (2005), who use aggregate data for the euro area over the period 1970-2004 and confirm the ability of the yield curve as a leading indicator for output growth and future recessions.

There are several theoretical channels through which financial market variables rationally signal (lead) changes in real activity. Following Fama (1990), Schwert (1990), Estrella and Mishkin (1998), Hamilton and Kim (2002), Hassapis and Kalyvitis (2002), Hassapis (2003) and others, we do not try to discriminate among these various hypotheses. Instead, we employ nonparametric techniques to investigate the correlation pattern between selected financial variables of the European Monetary Union (EMU) countries and their respective output growth. Against this background, this paper seeks to provide some evidence on the usefulness of financial variables in forecasting output growth in the EMU countries. To remedy potential caveats associated with the use of standard parametric techniques in the empirical investigation of the relationship between financial variables and output growth, we reinvestigate systematically this bivariate relationship by using the non-parametric methodology proposed by Cheung and Ng (1996).[2] These tests are based on the residual cross-correlation function of the series under scrutiny and are robust to distributional assumptions, which are likely to be important in the present case, where the variables at hand exhibit both autocorrelation and conditional volatility effects. To investigate the bivariate relationship between financial variables and industrial output growth in the context of these non-parametric methodologies we utilize monthly data from the euro area countries.

As a second step, following Lemmens et al. (2005) we extend our bivariate testing procedure to a multivariate one by pooling together the information from the whole panel of the euro area countries. This multivariate testing procedure was introduced by El Himdi and Roy (1997) and enables us to investigate the general predictive content of a candidate financial variable for economic growth for the entire panel. To the best of our knowledge, this multivariate testing methodology has been hardly employed in the literature. Specifically, El Himdi and Roy (1997), who proposed this methodology, applied this multivariate test to investigate the causal relations between money (M1 and M2) and income (Gross National Product) for Canada, as well as to study the causal directions between the Canadian and American economies. Lemmens et al. (2005) adapted the El Himdi and Roy (1997) test to jointly test the forecasting ability of multiple production expectation series for the members of the European Union. In this sense, they assessed whether part of the joint effect they found was due to cross-country influences and they determined the countries which have the most 'clout', i.e. are more useful in predicting other countries' growth along with those that are influenced more by the others, i.e. they display more 'receptivity'.

In addition, driven from the empirical literature that suggests that evidence in favor of Granger causality does not provide any assurance that a candidate variable can actually be a useful predictor (see Stock and Watson, 2003), we also test for the forecasting ability of financial variables in a parametric environment. Specifically, we consider out of sample tests of predictive accuracy of the candidate variables for euro area growth, both at a country and aggregate level. This parametric setup is based on a rather standard regression framework and the period of our analysis starts in 2001, the year the common currency was introduced in the euro area. The forecasting accuracy of various models and variables is evaluated through the mean squared forecast error (MSFE) and recently developed tests of equal predictive ability for nested models developed by McCracken (2004).

Summarizing our results, the term spread and stock market returns contain useful information for approximately half the euro area countries as suggested by the in-country Granger causality tests. At a joint euro area level, all the financial variables appear useful for predicting future growth at least for some horizon. Granger-causality running from the term spread to the euro area growth is detected at a five to six quarter horizon, while the respective horizon for stock market returns is confined to two quarters. The use of monetary aggregates for predicting growth is quite debatable as real money supply growth proves insignificant in a bivariate context, while significant at a joint level. Our results from testing the forecasting accuracy of the variables at hand are in line with the consensus that for some countries, some horizons, some variables contain useful information for future growth. However, consistent with our non-parametric tests, on an individual country basis, returns in the stock market appears to be the most accurate single predictor at all horizons. In this setting, more accurate forecasts can be constructed by combining the forecasts of the individual models rather than including them in the same model simultaneously. Turning to the euro area as a whole, we find that the safer way to conduct GDP foreacasts is to rely on euro area aggregate data and employ as predictive regressor the term spread for horizons up to 3 quarters, while for longer horizons the use of the term spread, money growth and stock market returns simultaneously in a model can improve forecasts. Moreover, employing combination forecast methods based on a GDP-weighting scheme can also provide quite accurate forecasts, superior to methods that combine forecasts based on the simple average.

The layout of this paper is as follows: Section 2 outlines the bivariate and multivariate Granger-causality testing procedures used for the empirical estimation of the relationship between growth and financial variables. The methodology for testing the out of sample predictability of financial variables for growth is also outlined in this section. Section 3 presents and comments on the empirical results for the euro area countries and euro area as a whole and section 4 summarizes the main findings of the paper.

2 Econometric Methodology

In this section, we briefly describe the non-parametric techniques utilized in the present study which aim at detecting any Granger causality running from financial variables to output growth. In subsections 2.1 and 2.2 we describe the bivariate and multivariate Granger-causality methodologies employed, respectively. We also complement our analysis with constructing forecasts and evaluating the forecasting accuracy of various models in a parametric setup. This parametric methodology is outlined in subsection 2.3.

2.1 Bivariate causality tests

Consider a bivariate stationary and ergodic stochastic process $Z_t = [y_t, x_t]^\top$, $t = 1, 2, \ldots$. In our case, y_t, represents output growth and x_t, a financial variable. Cheung and Ng (1996) proposed a test based on the sample cross-correlations function of the standardized residuals and involves two stages. In the first stage, univariate time-series models are estimated for both the series under scrutiny, such as the typical ARMA(p,q)-GARCH(1,1).

In our case the correct order of the ARMA(p,q) model for the mean of the series is determined by means of the Schwartz Information Criterion (SIC). In the second stage, we calculate the sample cross-correlations of the standardized residuals, typically defined as follows:

$$\begin{aligned}\widehat{u}_{yt} &= (y_t - \widehat{\mu}_{y,t})/\widehat{h}_{y,t} \\ \widehat{u}_{xt} &= (x_t - \widehat{\mu}_{x,t})/\widehat{h}_{x,t}\end{aligned}$$

where $\widehat{\mu}_{y,t}, \widehat{\mu}_{x,t}$ and $\widehat{h}_{y,t}, \widehat{h}_{x,t}$ are the estimated conditional means and variances of output growth and real stock returns, respectively.

The sample cross-correlation function of u_{yt} and u_{xt} ($\widehat{\tau}_{x,y}(k)$) is given by:

$$\widehat{\tau}_{x,y}(k) \equiv \frac{\widehat{C}_{x,y}(k)}{\sqrt{\widehat{C}_{x,x}(0)\widehat{C}_{y,y}(0)}} \tag{1}$$

where $\widehat{C}_{x,y}(k) = \begin{array}{ll} T^{-1}\sum_{t=k+1}^{T}[\widehat{u}_{yt}\widehat{u}_{xt-k}], & k \geqq 0 \\ T^{-1}\sum_{t=-k+1}^{T}[\widehat{u}_{yt+k}\widehat{u}_{xt}], & k < 0 \end{array}$ is the sample cross-covariance, $\widehat{C}_{x,x}(0)$, $\widehat{C}_{y,y}(0)$ are the sample variances of one of the financial variables and output growth, respectively, k is the lag length employed and T is the sample size. The test statistic, S, proposed by Cheung and Ng (1996) is given by the following formula:

$$S_{x \to y} = T \sum_{k=1}^{M} \widehat{\tau}_{x,y}^{2}(k) \tag{2}$$

where M is a bandwidth parameter which under the null hypothesis of no causality in mean from x_t to y_t follows asymptotically a X_M^2 distribution. Similarly, when testing for causality in mean running from y_t to x_t, $S_{y \to x} = T\sum_{k=-M}^{-1}\widehat{\tau}_{x,y}^{2}(k)$ is utilised. Finally, $S_{x \leftrightarrow y} = T\sum_{k=-M}^{M}\widehat{\tau}_{x,y}^{2}(k)$ can be used to test for bidirectional causality-in-mean. We should also note that in order to obtain correct inference, M should be large enough to include all potential nonzero cross-correlations.

2.2 Multivariate causality tests

Let Y_t and X_t be two multivariate time series with $Y_t \in R^{d1}$ and $X_t \in R^{d2}$. In our case, the dimension of these multivariate time-series is $d = d_1 = d_2 = 12$, the number of the EMU countries under scrutiny. El Himdi and Roy (1997), extended the bivariate methodology of Haugh (1976) to the multivariate case. They proposed a test statistic for the hypothesis of no Granger causality between multivariate series. Similar to the bivariate case, the multivariate time series are prefiltered separately through Vector Autoregressive GARCH (VAR-GARCH) models.[3] In this respect, the residual series U_{yt} and U_{xt}, obtained after filtering with a VAR model, are independent of the past of every single component of Y_t and X_t, respectively.[4] The estimated standardized residuals,

$$U_{yt} = \begin{pmatrix} u_{y1,t} \\ u_{y2,t} \\ \vdots \\ u_{yd_1,t} \end{pmatrix} \text{ and } U_{xt} = \begin{pmatrix} u_{x1,t} \\ u_{x2,t} \\ \vdots \\ u_{xd_2,t} \end{pmatrix}$$

are cross-correlated with cross-correlation function

$$\widehat{R}_{x,y}(k) = \begin{pmatrix} \widehat{\tau}_{x_1,y_1}(k) & \widehat{\tau}_{x_1,y_2}(k) & \cdots & \widehat{\tau}_{x_1,y_{d_1}}(k) \\ \vdots & & & \vdots \\ \widehat{\tau}_{x_{d_2},y_1}(k) & \cdots & \cdots & \widehat{\tau}_{x_{d_2},y_{d_1}}(k) \end{pmatrix} \in R^{d_2 \times d_1}$$

with $\widehat{\tau}_{x_i,y_i}(k)$ defined in (1). Similarly, we define the corresponding autocorrelations of X_t and Y_t, $\widehat{R}_{x,x}(k) \in R^{d_2 \times d_2}$ and $\widehat{R}_{y,y}(k) \in R^{d_1 \times d_1}$. The test statistic proposed by El Himdi and Roy (1997) is given by the following formula:

$$S_M = T \sum_{k=-M}^{M} \left[vec\left(\widehat{R}_{x,y}(k)\right)\right]^T A^{-1} \left[vec\left(\widehat{R}_{x,y}(k)\right)\right] \tag{3}$$

where A is the asymptotic covariance matrix of $\sqrt{T}\, vec\left(\widehat{R}_{x,y}(k)\right)$, that is $A = \widehat{R}_{x,x}(k) \otimes \widehat{R}_{y,y}(k)$. When testing for causality in the mean running from x_t to y_t, only positive values of the bandwidth parameter M should be employed. In this case, the above quadratic form is shown to follow a $X^2_{Md_1d_2}$ distribution. In the case that we are interested in revealing bidirectional causality between the series at hand, i.e. allowing for both positive and negative lags, the degrees of freedom are adjusted accordingly to $(2M+1)d_1d_2$.

Naturally, this multivariate test is more powerful as opposed to the bivariate one introduced in Section 2.1 due to mainly two reasons. First, all countries are pooled together in order to find evidence of Granger causality and second, Granger causality across countries is also allowed. Moreover, this testing procedure can be modified so as to reveal more information with respect to the interdependencies within the euro area. Specifically, if we are interested in testing whether the developments in financial variables of one country affect real economic activity in the remaining countries, i.e. to discover a country's "clout", we only include the financial variable x_i of country i and test whether it causes the variables y_j, with $j \neq i$. In such a case, $d_1 = 1$ and $d_2 = d - 1$,with d the number of countries participating in the panel. Similarly, we can test for the receptivity of a country, i.e. discover the countries that are more likely to be led by developments in the financial variables of the remaining ones in the euro area. In this case, we test whether real economic activity in country j is Granger-caused by the financial variables x_i of the remaining countries, with $i \neq j$. The test again follows a X^2 distribution with $M(d-1)$ degrees of freedom.

2.3 Construction of Out-of-Sample Forecasts and Evaluation

In this subsection, we briefly review the forecasting methodology, which is rather standard.[5] Specifically, we construct several models for each series to be forecasted and focus on forecast horizons (h) of 1, 3, 6 and 12 periods. Contrary to the text book approach of estimating a one-step ahead model and then iterating it forward to get the h-step predictions, we set the $h-$step ahead variable to be forecasted, y^h_{t+h}, equal to $\sum_{s=t+1}^{t+h} y_s$. In our case that the variable of interest is ouput growth, y^h_{t+h} represents the growth of output over the next h periods.[6] The models considered are all nested within the following class of Autoregressive Distributed Lag (ADL) models:

$$y^h_{t+h} = c + a(L)y_t + B(L)'Z_t + \varepsilon^h_{t+h} \tag{4}$$

where c is a constant, $a(L)$ is a scalar lag polynomial, $B(L)$ is a vector lag polynomial and Z_t is a vector of financial (predictor) variables. The choice/inclusion of Z_t differentiates the models. The number of lags for both y_t and Z_t is selected by the Schwartz Bayesian information criterion (SIC) setting the maximum lag length at 12 to avoid estimating any models with low degrees of freedom.

Not including financial variables in (4), i.e. setting $B(L)$ equal to zero, provides us with the simple autoregressive model (AR) which will be used as a benchmark when evaluating forecasts of the various models. The remaining models include either one of the elements of Z_t at a time or all of them simultaneously. Given that our interest lies on forecasts for euro area growth, the preceding methodology is applied to both the individual euro area countries and the euro area aggregate. The relevant aggregated series are constructed as the weighted average of the (transformed) country level data for all 12 countries. A fixed-weighting scheme is employed using each country's GDP share in the euro area aggregate in PPP exchange rates averaged over 2005.[7] Apart from forecasting the euro area aggregates directly using the respective aggregated series as independent variables, we also consider pooling country-specific forecasts in order to construct the euro area forecast. This is done in two ways: by employing the same fixed-weighting scheme using GDP weights and by simply averaging the country-specific forecasts, i.e. giving each country the same contribution in the euro area forecasts. If the country-specific models are time invariant, correctly specified, and parameters differ across countries, pooling country-specific forecasts would give more accurate forecasts than the ones based on aggregated series (see Lutkepohl, 1987). Another issue directly related to the forecasts from various models is that of pooling information from different models to construct a country-specific combination forecast. This issue is also considered by taking into account all the information contained in the various specifications not only on a country specific basis but on the euro area aggregate and pooled models, as well. Alternatively, one could apply the theory of optimal linear combination forecasts (see Bates and Granger, 1969 and Granger and Ramanathan, 1984) which suggests that combination forecasts are weighted averages of individual forecasts with weights obtained as regression coefficients of the true future value on the various forecasts. Given that optimal linear combination forecasts are often found to be inferior to simpler ones, such as means or medians, we construct the respective combination forecasts by simply averaging the forecasts of the individual models. (see, Stock and Watson, 2004).[8]

Evaluating the forecasting accuracy of the candidate models is of equal importance as constructing the forecasts. In this respect, we also undertake a simulated out-of-sample forecasting experiment. This experiment is fully recursive, i.e. lag selection, model estimation etc. is performed for each date of the out of sample forecast period. The forecasting performance of the various models is assessed by the simulated out-of-sample mean squared forecast error (MSFE) relative to the MSFE of the benchmark AR model. A value of this ratio lower than one suggests superiority of the respective model over a simple AR model and indicates that the candidate financial variable is a useful predictor for output growth. In order to establish the statistical significance of this ratio, one has to test the hypothesis that the population relative MSFE is equal to 1, against the alternative of a ratio less than one. Techniques for comparing the forecasting performance of two nested models, since the AR model is always nested within the remaining models considered were only recently developed. Specifically, McCracken (2004) proposes three tests for nested models. The first one is a modification of the popular Diebold and Mariano (1995) test originally designed for non-nested models. The second one is based on a method introduced by Granger and Newbold (1977) and used by Ashley et al. (1980) and is based on the $t-$statistic of the parameter γ of the following regression: $\epsilon_{1,t} - \epsilon_{2,t} = \gamma(\epsilon_{1,t} + \epsilon_{2,t}) + error\ term$. The third statistic that McCracken (2004) proposes for the comparison of the forecast accuracy of two nested models based on the MSFE criterion is as follows:

$$OOS - F = \frac{\sum_{t=1}^{P}[\epsilon_{1,t}^2 - \epsilon_{2,t}^2]}{P^{-1}\sum_{t=1}^{P}\epsilon_{2,t}^2} \tag{5}$$

where $\epsilon_{i,t}, i = 1, 2$ are the forecast errors of the restricted and the unrestricted model, respectively and P is the number of out of sample observations. The null hypothesis tested is that the unrestricted model MSFE is equal to the restricted model MSFE against the one-sided alternative that the unrestricted model MSFE is less than the restricted one. The limiting distributions of the aforementioned test-statistics are non-standard and numerical estimates of the asymptotic critical values for valid inference are provided by McCracken (2004). The power properties of the aforementioned tests depend on the number of restrictions and on the ratio of out of sample observations over the in sample ones. For our experiment, Monte Carlo evidence presented in McCracken (2004) shows that the OOS-F test is more powerful compared to the other two alternatives. In this respect, we test the significance of the forecast superiority of the unrestricted model over the restricted one on the basis of this test.

3 Empirical Evidence

In this section we apply the techniques outlined in the previous section to examine the empirical relationship between growth and financial variables in the euro area.[9] The financial variables considered are the term spread, real stock market returns and real money supply growth for the 12 euro area countries. Our data set is monthly and covers the period from January 1988 to May 2005.[10] As a measure of the growth rate of output we use the industrial production index (seasonally adjusted) from the OECD Economic Indicators (obtained by Datastream). Following Fama (1990) and other authors, stock market returns were obtained by use of Datastream-calculated composite indices and were appropriately adjusted for the inflation rate of the countries under consideration. The term spread is calculated as the difference between a long-term bond yield, mainly a 10-year one, and a short-term interest rate, mainly a three-month Treasury Bill obtained from the IMF, International Financial Statistics (Source: EcoWin).[11] As regards the monetary aggregates, we employed the M3 money supply, CPI deflated (Source: Datastream).

3.1 Bivariate predictive content

We begin the empirical analysis with the within-country forecasting ability of the term spread, assessed via the bivariate Granger causality tests analyzed in Section 2.1 with the bandwidth set at 15 months (5 quarters).[12] The relevant $p-$values for testing the hypothesis of interest, i.e. no causality from the term spread to future growth are reported on the main diagonal of Table 1. Our findings confirm the mixed evidence found in the literature concerning the within-country predictive ability of the term spread. Specifically, Granger causality is detected in 5 of the 12 euro area countries, namely Austria, Belgium, France, Germany and the Netherlands. Evidence is particularly strong in the cases of Belgium, Germany and the Netherlands as the corresponding $p-$values are lower than 1%. Our results reinforce the findings of Davis and Fagan (1997), who using parametric methods and a similar dataset found that the term spread improves forecasts of output growth in Belgium, Germany, France and the Netherlands.

[INSERT TABLE 1 HERE]

Next, we extend the bivariate causality tests to allow for dependence between the term spread in one country and real activity in the remaining countries. The respective $p-$values are reported in the off-diagonal elements of Table 1. More in detail, the (i, j) element corresponds to the $p-$value for the test that the term spread in country j Granger causes output growth in country i. Approximately one third of the 132 off-diagonal elements appear significant, suggesting the existence of substantial cross-country influences. Interestingly, developments in the term spread of Austria, Germany and France appear to have predictive ability over more than half of the euro area members' growth. The finding with respect to Germany and France is quite expected as these countries represent the driver forces behind the unification of Europe and are the more important euro area countries in terms of GDP. Especially for Germany, the German dominance hypothesis is quite established in the literature. Among others, Artis and Zhang (1998) and Barassi et al. (2005) find evidence of the leading role of German interest rates. Similarly, Moneta (2005) finds that among Germany, France and Italy, the German term spread seems to have the strongest predictive power for euro area growth as a whole. The clout of Austria, however, seems to be puzzling. One possible explanation is that it actually reflects its proximity and its close economic, political and cultural link to Germany. Given that the bivariate testing methodology does not filter cross-country correlations beforehand, it seems possible that increased correlations between financial variables and growth of the countries may emerge as strong causality patterns. Our multivariate procedures (see section 3.2) take this effect into account.

Our results with respect to market returns are reported in Table 2. Starting with the diagonal elements, we find significant links existing between stock market returns and real growth for half of the euro area countries. Specifically, we cannot reject the null of no Granger causality for Belgium, Finland, France, Germany, Italy and Spain. Given that the majority of these countries are the more developed in the euro area, our findings suggest that stock market returns act as a leading indicator in such countries. As pointed out by Mauro (2003), the association between stock market returns and growth is stronger in countries with high market capitalization such as the UK and the US.

[INSERT TABLE 2 HERE]

Turning to the cross-country influences, significant evidence of cross-country influences between returns and growth is found similarly to the case of the term spread. Among the countries with the highest predictive ability over others are Finland, France, Germany, Portugal and Spain. As already mentioned, these outcomes should be interpreted cautiously as our series are not prefiltered. Especially, in the case of market returns, this problem may be more acute, given the significant high correlation between returns.

Finally, we examine the predictive ability of real money growth for output. The respective figures are tabulated in Table 3.

[INSERT TABLE 3 HERE]

Interestingly, the evidence seems to be weaker compared to the other two variables. Our within-country tests suggest that only in Austria, Finland, Ireland and Spain, Granger causality from money to growth cannot be rejected. Our findings are in line with Stock and Watson (2003) that find the real M3 growth does not improve forecasts for growth 4 quarters ahead for France and Germany. Furthermore, cross-country linkages as far as monetary aggregate developments are concerned seem to be weak. Austria, Belgium and France are the countries that seem to affect more than four other member countries.

As aforementioned, the bivariate causality results should be interpreted with cautiousness due to the multiple testing problem, as well, which might lead to our estimates being biased downwards (see Bauer et al., 1988 and Lemmens et al., 2005). The problems associated with the bivariate testing environment can easily be addressed when extending our testing procedures to a multivariate framework. These results are discussed in the next subsection.

3.2 Multivariate predictive content

Turning to the joint testing of Granger causality, our results paint a different picture. Table 4 reports the test statistics and the corresponding $p-$values from the El Himdi and Roy (1997) test for causality between growth and financial variables at a joint euro area level and for a variety of bandwidths ranging from 3 to 18 months (one to six quarters). Allowing for various bandwidths when detecting causality enables us to gain some insight on the lag with which developments in financial variables affect economic activity. As a result informal guidance for the lag structure of parametric models is provided.

[INSERT TABLE 4 HERE]

Starting with the term spread, our results suggest that it can be a useful indicator for future euro area growth particularly at horizons beyond one year. The respective $p-$values marginally indicate significance at a 6 months' horizon, while significance at the 5% level is obtained for the five- and six-quarter horizon. This finding is not at all surprising, since the predictive power of the term spread is typically found to be maximized at longer horizons, usually over one year. For example, Duarte et al. (2005), employing quarterly aggregate euro area data, find that the highest explanatory power of the term spread when a linear model is employed, is found between three and six quarters ahead, similar to findings for the US (see Estrella and Mihskin, 1998). Stock market developments for the euro area as a whole seem to provide limited information on future growth, since evidence of Granger causality from returns to growth is limited and confined to a two-quarter horizon. This is quite expected, though, given that the majority of the euro area countries did not have a developed stock market until recently. The horizon at which we detect the strongest association between stock market and output growth is consistent with US findings (Fama, 1990 and Schwert, 1990 among others) and some limited evidence for the euro area (see Sensier et al. 2004). Specifically, these studies find that the link between growth and stock returns is maximized at a forecast interval of two to four quarters. Finally, monetary aggregates consistently lead euro area economic activity for horizons from one to five quarters. This result is in contrast with our bivariate analysis that indicated weak links between growth in money supply and output growth. The increased power of the multivariate tests due to the pooling of observations from the 12 countries as well as the prefiltering of the series may have led to clearer detection of the causality pattern. This finding complements the analysis of Sensier et al. (2004) who find that real money growth is important in predicting business cycle regimes in Europe.

Table 5 provides a more in-depth analysis with respect to cross-country dependence. Specifically, the Table reports the relevant p-values for assessing both the leading role ('clout') of each of the euro area countries' financial variables as well as their 'receptivity' to developments in the rest of the member countries.

[INSERT TABLE 5 HERE]

Developments in the term spread of Austria, Belgium, France, Germany and the Netherlands appear to be significant for the euro area countries, which on the whole appear quite receptive. The countries that appear to be non-responsive to developments in other countries' term spread are Ireland, Luxembourg and Portugal. Turning to stock returns, Austria, Germany and Italy appear to have significant 'clout'. On the other hand, nine out of the twelve euro area countries are receptive. Interestingly, Luxembourg and Portugal are included in the non-receptive countries along with Spain. As far as monetary aggregates are concerned, this subset of results conveys a similar message to the one of the multivariate test, i.e. increased interdependence. More in detail, the major countries, with the exception of Spain show the most clout and in terms of receptivity, only Ireland and Portugal appear secluded.

Next, we test whether our results on Granger causality provide a guidance to revealing a potential reliable indicator for future growth by estimating parametric models containing as explanatory variables the financial variables discussed above, constructing forecasts and evaluating them.

3.3 Model Forecasts and Evaluation

Our simulated out of sample forecasting experiment is conducted using a fully recursive methodology. The out of sample forecast period is 2001:4 to 2005:5 (50 observations) covering the more recent period of the monetary union and generating a ratio of out of sample (P) over in sample observations (R) equal to approximately 0.3 ($P/R = 0.3$). For the period 2001:4 onwards, we reestimate all the candidate models by adding one observation at a time and selecting the respective lag lengths for the employed independent variables on the basis of the SIC criterion.[13] The $h-$step ahead forecasts are generated for the periods of 1, 3, 6 and 12 months and the related MSFEs are calculated.

To conserve space and increase the readability of the paper, our parametric forecasting analysis is restricted to the within-country and aggregate euro area forecasting ability of financial variables. Including cross-country influences in this parametric setup would increase voluminously the number of models and would obscure our main findings.

The models estimated and employed in the forecasting experiment are the following:

Model (1): The benchmark AR model, i.e. Z_t is excluded from (4).

Models (2)-(4): An AR specification is combined with lags of the term spread, the stock market returns and the real money supply growth, respectively. In other words, one element of Z_t is included at each specification.

Model (5): An AR specification is combined with lags of all the financial variables, namely, the term spread, stock market returns and real money supply growth. As a result, all the elements of Z_t are included simultaneously.

The aforementioned models were estimated for the 12 euro area countries and the aggregate euro area. Aggregate euro area data were constructed by employing a fixed GDP-weighting scheme taking as weights each country's share in the euro area 2005 GDP in PPP terms. Our results for the 1-month forecast horizon are reported in the upper panel of Table 6. Specifically, the second row reports the MSFE of the benchmark AR model for the 1-period growth in decimal values, while rows 4 to 7 tabulate the ratio of the MSFE of models (2) to (5) relative to the AR benchmark. A value lower than 1 suggests that the additional financial variable(s) provide useful information for future GDP growth. We also consider the issue of combination of forecasts in two dimensions, both across variables and across countries. In detail, the last row of the upper panel of Table 6 reports the MSFE ratio of a model that averages the forecasts of models (2) to (4) and the last two columns report the respective figures for euro area pooled forecasts based on both the same weighting scheme employed to aggregate the data and on the simple average of forecasts.

[INSERT TABLE 6 HERE]

The information content on the upper part of Table 6 may be summarized as follows:

(i) On a country/variable basis, at least one financial variable is helpful in predicting next month's growth (ratio relative to the benchmark AR model less than 1) with the exception of Belgium and Portugal. The more informative of the financial variables appears to be the stock market returns that provides additional information in 9 out of 12 euro area countries and yields the lower MSFE ratios on average. Including all the financial variables in one model generally improves the forecasting ability of all the variables simultaneously, as indicated by the lower values of the relative MSFEs ratios, with the exception of Greece, Italy, Portugal and Spain.

(ii) Quite interestingly, combining the forecasts from the individual models on a country by country basis results in further gains in terms of forecastability, since the only countries for which we do not improve upon the benchmark AR specification are Greece and Spain. Considering the issue of whether we should include all financial variables in one model or forecast with individual models and then pool the forecasts, our results suggest that marginal gains can be attained by pooled forecasts. Specifically, in 7 of the 12 euro area countries, combining forecasts from individual models results in lower MSFE ratios compared to forecasts from a model including all the financial variables.

(iii) Turning to the euro area aggregate (column 14), financial variables provide additional information on growth either employed as single predictors or combined in the same model.[14] Moreover, the absolute euro area benchmark MSFE turns out to be the lowest when compared to the individual countries, suggesting that forecasting accuracy improves when employing models for the euro area as a whole. The lowest relative ratio (0.673) is attained when all the financial variables are included in one model simultaneously as opposed to pooling the forecasts from individual models, which however is quite successful as well since it yields a relative ratio of 0.758.

(iv) The same picture emerges when the forecasts of the euro area growth are generated by either taking the mean of the countries' forecasts (column 16) or a GDP-weighted average forecast (column 15). More in detail, the returns in the stock market turn out to be the most valuable single predictor producing forecasts that are more accurate than even the ones generated by combination methods.

(v) When comparing the three methods for generating forecasts for the euro area, the most powerful method seems to be the one that generates forecasts based on aggregate data followed by a GDP-weight combination method. Employing the simple average does not fare well contrary to the finding of Stock and Watson (2004) of superiority of simple combination forecasts, such as the mean, over more sophisticated adaptive combination methods. However, the authors do not compare various linear schemes with the simple average. Our result is expected since the countries that weigh heavily in the euro area (by relative GDP share) like Germany, France, Italy and Spain are the ones that yield more accurate forecasts.

The bottom panel of Table 6 reports the OOS-F statistic calculated from (5) that tests for the statistical significance of the ratio of forecasts, i.e. it tests the null hypothesis that the unrestricted model MSFE is equal to the restricted model MSFE against the alternative (upper tail) that the unrestricted MSFE is less than the restricted one. When the forecast horizon is $h = 1$, the test has a pivotal but non-standard distribution. McCracken (2004) tabulates critical values which depend on the ratio of in sample and out of sample observations and the number of parameter restrictions. Unfortunately, the fully recursive scheme cannot be applied in generating these statistics as the restricted and unrestricted models may change with every observation added and more importantly, the models are not always nested. In this respect, we restrict our experiment as follows. We generate the forecasts based on the SIC lag structure selected for the in sample set of observations, i.e. for the period up to March 2001. To ensure that the restricted model is nested in the unrestricted one, the lag structure of the AR benchmark is set identical to the respective one of the unrestricted model. This experiment is recursive in the sense that the models are reestimated with each observation added. The value of the OOS-F statistic is then compared to the corresponding tabulated values from McCracken (2004) taking into account the number of parameter restrictions and the ratio of out of sample over the in sample observations.[15] An issue arises with respect to the selection of appropriate values for testing the significance of the forecasting accuracy of the combined forecasts. To be on the safe side, we employ the same values with the most relevant richer specification. For example, when testing the significance of the ratio of the Austrian pooled model, we use the critical values associated with the model with all the financial variables included. For the most part, our results with respect to the statistical significance of the relative MSFEs do not contradict the outcomes based on the simple ratio as in only 10 out of 75 cases does a discrepancy appear between the ratio outcome and the outcome based on its significance.

Moving to higher forecast horizons, corresponding to 3-, 6- and 12-months ahead, the upper panels of Tables 7-9 report the MSFEs of the benchmark specification along with the relative MSFEs of the specifications considered. The information content in these tables may be summarised as follows:

(i) At a 3-month horizon, the more powerful predictor is the stock market return as it improves the forecast accuracy in 11 out of 12 countries, followed by the money supply growth and the term spread. This ranking of the financial variables as single predictors remains unaffected as the forecast horizon increases to 6 months and 1-year.

(ii) Combining all the financial variables in one model leads to a deterioration of the forecast accuracy as the improvement of forecasts over the benchmark specification is evident for 3, 5 and 7 countries only for the respective horizons.

(iii) On the other hand, pooling the forecasts of the three models works quite well as the improvement in forecast accuracy is evident for all the countries at hand for the longer horizon and for 11 out of 12 for the other two horizons.

(iv) Turning to the euro area aggregate, we have to note that at the 3-month and 6-month horizons, all financial variables prove to be useful for forecasting real growth, with the term spread providing the most accurate forecasts as suggested by the lower relative MSFE. At the 1-year horizon, only the term spread helps predicting growth. Including all the variables in one model fares well in all cases but the 3-month horizon, while pooling the forecasts of individual models beats the forecasts of the full model for all but the 1-year horizon.

(v) Evaluating the euro area forecasts generated by the three methods (euro area aggregate, mean combination forecasts and GDP-weighted foreacsts), our results suggest that at the 3- and 6- month horizon, the euro area aggregate model with the spread included as a single indicator is the most accurate model while at the 12-month horizon, the inclusion of all the financial variables in one model yields the best forecasts. Moreover, the superiority of the GDP-weighted combination foreacsts over the simple average combination foreacasts is confirmed for the longer horizons as well.

[INSERT TABLES 7-9 HERE]

As previously, the bottom panel of Tables 7-9 tabulate the OOS-F statistic for the significance of the ratios of MSFEs. The interpertation of the tables is similar to the one of Table 6. However, the statistical significance should be taken into account with cautiousness as the null distribution of the MSFEs for horizons greater than one are non-standard and non-pivotal. As a result the available tabulated values are not valid and as such they can only provide us with a rough guidance on the significance of the ratios. Based on these values, ratios that turned out to be misleading amounted for 19%, 11% and 15% of the outcomes.

4 Conclusions

The bulk of empirical studies have employed parametric models in order to study the role of financial variables in forecasting growth. Given that inference within parametric models is affected when some of the underlying assumptions are violated for the dataset at hand, non parametric methods can prove valuable in this respect. Furthermore, with the exception of a few, parametric studies have concentrated mainly on the US. The creation of the euro area monetary union brings to the fore the assessment of the forecasting ability of financial variables for the euro area member countries. No systematic examination, either parametric or non-parametric of these relationships has been conducted so far for the 12 member states.

In an attempt to fill this void, this paper takes a new approach to testing whether financial variables are useful in forecasting euro area output growth by utilizing both bivariate and multivariate non-parametric Granger causality tests. Our bivariate analysis revealed the within-country information content of financial variables along with the cross-country linkages. However, there is no a priori reason to disregard the information content in one country for the remaining members as well as for the whole panel. In this vein, our multivariate tests aimed at revealing the predictive content of financial variables at a joint euro area level and to uncover the member states that are more useful in predicting growth in other member countries along with the ones that are more receptive to other countries' financial developments. Following the empirical literature that suggests that results from in sample Granger-causality methods do not always reveal financial variables useful for forecasting, we extend our set of results to cover this aspect as well.

In general, our results are consistent with existing studies for the euro area and to some extent the US and may be summarized as follows:

(i) Within-country bivariate causality tests suggest that both the term spread and stock market returns contain useful information for approximately half the euro area countries, while evidence with respect to real money growth is weaker.

(ii) Our multivariate tests suggest that the information content of the term spread at a joint euro area level is maximized at a five to six quarter horizon, while the respective horizon for stock market returns is confined to two quarters. Contrary to our bivariate findings, monetary developments carry information for a variety of horizons ranging from one to five quarters.

(iii) In terms of 'clout', the German dominance hypothesis is confirmed as financial developments in Germany along with Austria appear to have significant impact on the remaining members. As far as 'receptivity' is concerned, the majority of the countries appear open, with Ireland, Luxembourg and Portugal being the least responsive.

(iv) Our results from the within-country forecasting ability of financial variables corroborate in part the non-parametric causality tests as they reveal that the returns in the stock market is the most accurate single predictor at all horizons. However, more accurate forecasts can be constructed by combining the forecasts of the individual models rather than including them in the same model simultaneously.

(v) From a policy perspective, the safer way to conduct GDP foreacasts for the euro area is to rely on euro area aggregate data and the term spread for horizons up to 3 quarters, while for longer horizons the use of the term spread, money growth and stock market returns simultaneously in a model fares better. Alternatively, combination forecast methods based on a GDP-weighting scheme can provide quite accurate forecasts.

The non-parametric Granger-causality methodology employed here can be employed to investigate any economic interdepedencies for a panel of countries and complement parametric studies that leave empirical questions open. Another promising route for further research stemming from our parametric study as well is modifying this multivariate testing framework to allow for a weighting scheme. In this way, countries may enter the panel with different weights, for example GDP weights and results will be more representative and informative for policymakers especially in the case of a monetary union.

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Notes

[1]See Stock and Watson (2003) for a review of the empirical literature.

[2]The methodology put forward by Cheung and Ng (1996) extends the one proposed by Haugh (1976) to test for both causality in mean and variance. In the present text, we adopt the two-stage procedure of Cheung and Ng (1996), which filters out second-order effects prior to testing for causality in mean.

[3]The order of each VAR is determined by the SIC criterion.

[4]Please note that these series differ from the ones employed in the bivariate tests. Specifically, the ones obtained with respect to the within country VARs may still carry information for the other countries.

[5]See, inter alia, Stock and Watson (2003) and Marcellino et al. (2003).

[6]The $h-$step ahead projection approach has mainly two advantages over the traditional one. First, in the case of a VAR model for example, additional equations need not be estimated in order to simultaneously forecast the remaining variables of the model at hand. Second, the potential impact of specification error in the one-step ahead model is reduced since the same horizon is used for both estimation and forecasting.

[7]Source: Statistics Pocket Book, April 2006, European Central Bank.

[8]Stock and Watson (2004) find that simple combination forecasts outperform sophisticated adaptive combination methods and state that such a result constitutes the 'forecast combination puzzle'.

[9]All the reported results were obtained by programs written in E-views 4.1 and are available from the author upon request.

[10]To ensure homogemeity of our results, especially for our multivariate procedures, we employed the longest dataset possible for which data were available for the 12 euro area countries.

[11]Moneta (2005) finds that the most informative term spread for future growth in the euro area is the one between the 10-year bond and the 3-month interbank rate when comparing over ten alternative specifications.

[12]The bandwidth is set approximately equal to $\sqrt{T}, T$ is our sample size.

[13]Results based on the Akaike or Hannan-Quinn criterion are qualitatively similar and available on request.

[14]The predictive content of money supply appears marginal as denoted by the ratio of just 0.999.

[15]An asterisk denotes rejection of the null hypothesis of equal forecasting ability at the 5% significance level. Given that McCracken(2004) does not tabulate critical values for P/R equal to 0.3, we base our inference on interpolated critical values of P/R equal to 0.2 and 0.4.

Table 1. Bivariate cross-country analysis for testing whether term spread in country j (jth column) Granger causes output growth in country i (ith row)

Country	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Luxembourg*	*Netherlands*	*Portugal*	*Spain*
Austria	**0.095**	0.107	0.381	0.154	0.223	0.212	0.937	**0.084**	0.103	0.490	0.715	**0.075**
Belgium	**0.049**	**0.008**	0.434	**0.004**	**0.049**	0.157	0.544	**0.015**	**0.060**	0.548	0.726	**0.077**
Finland	0.305	0.604	0.456	0.130	**0.062**	**0.004**	0.164	0.413	**0.024**	**0.008**	**0.029**	0.445
France	0.227	0.959	0.564	**0.072**	0.198	**0.059**	0.866	0.370	0.177	0.205	0.991	0.694
Germany	**0.001**	**0.044**	0.171	**0.024**	**0.003**	0.186	0.149	**0.088**	0.294	0.105	**0.064**	0.138
Greece	**0.031**	**0.010**	0.564	**0.080**	0.457	0.550	0.715	0.740	0.192	0.464	0.699	0.718
Ireland	0.200	0.427	0.853	**0.038**	0.409	0.212	0.521	0.372	0.211	0.107	0.790	0.312
Italy	**0.063**	0.110	0.770	**0.053**	**0.077**	0.193	0.609	0.250	0.032	**0.055**	0.351	0.102
Luxembourg	0.908	0.897	0.431	0.895	0.283	0.402	0.161	0.522	0.721	0.793	0.529	0.294
Netherlands	**0.006**	**0.007**	0.155	0.224	**0.034**	0.509	**0.035**	**0.054**	0.214	**0.006**	0.615	**0.005**
Portugal	**0.084**	0.585	0.548	0.535	**0.090**	0.484	0.415	0.692	0.315	0.514	0.435	0.574
Spain	**0.021**	0.264	0.573	**0.010**	**0.011**	**0.011**	0.372	0.117	0.351	0.048	0.610	0.399

Notes: p-values. The bandwidth is 15 months. Bold indicates significance at the 10% level.

Table 2. Bivariate cross-country analysis for testing whether stock market in country i (ith row) Granger causes output growth in country j (jth column)

Country	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Luxembourg*	*Netherlands*	*Portugal*	*Spain*
Austria	0.240	0.404	**0.027**	**0.050**	**0.031**	0.290	0.617	**0.008**	0.449	**0.082**	**0.008**	**0.085**
Belgium	0.170	**0.088**	**0.002**	0.443	**0.072**	0.172	0.319	0.586	0.747	0.268	0.248	0.299
Finland	0.284	0.488	**0.001**	**0.071**	**0.084**	0.359	0.019	0.325	0.694	**0.058**	**0.026**	**0.019**
France	0.174	**0.012**	0.110	**0.002**	**0.000**	0.179	**0.007**	**0.001**	**0.100**	**0.000**	**0.000**	**0.002**
Germany	**0.089**	0.513	0.133	**0.021**	**0.005**	0.101	0.423	0.145	0.179	0.142	0.371	0.250
Greece	0.895	0.335	**0.011**	0.712	0.840	0.658	0.742	0.189	0.737	0.671	0.500	0.143
Ireland	0.482	0.576	**0.006**	0.388	0.214	0.546	0.420	0.193	0.215	**0.046**	0.414	0.121
Italy	0.348	0.273	**0.005**	0.144	0.234	0.337	0.257	**0.010**	0.348	**0.082**	0.238	**0.011**
Luxembourg	0.490	0.867	0.604	0.728	0.857	0.725	0.824	0.680	0.603	0.900	0.818	0.979
Netherlands	0.539	0.624	**0.027**	0.165	0.125	0.153	0.400	0.315	0.143	0.221	0.600	0.729
Portugal	**0.045**	0.159	0.581	0.165	**0.098**	0.670	0.464	0.213	0.413	0.843	0.451	0.748
Spain	0.968	0.313	**0.016**	0.165	0.196	0.429	**0.098**	0.171	0.501	0.299	**0.044**	**0.097**

Notes: p-values. The bandwidth is 15 months. Bold indicates significance at the 10% level.

Table 3. Bivariate cross-country analysis for testing whether money supply in country i (ith row) Granger causes output growth in country j (jth column)

Country	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Luxembourg*	*Netherlands*	*Portugal*	*Spain*
Austria	**0.032**	**0.099**	0.184	**0.021**	0.896	0.355	**0.029**	0.157	**0.068**	0.269	0.487	0.342
Belgium	**0.003**	0.189	0.177	**0.000**	0.270	0.359	0.249	0.245	0.672	0.226	0.801	0.856
Finland	**0.056**	**0.081**	**0.020**	0.765	0.417	0.553	0.297	0.369	0.197	0.251	**0.005**	0.253
France	**0.084**	0.199	0.328	0.732	0.378	0.253	0.197	0.237	0.395	0.158	0.420	**0.027**
Germany	0.102	0.013	0.608	0.680	0.244	0.272	0.140	0.831	**0.034**	0.335	**0.057**	**0.002**
Greece	0.451	0.519	0.309	0.391	**0.002**	0.782	0.252	0.880	0.220	0.233	0.413	0.260
Ireland	0.971	0.781	0.921	0.393	0.594	0.349	**0.041**	0.869	0.830	0.596	0.221	0.949
Italy	0.530	0.296	0.230	0.209	0.370	0.517	0.196	0.977	0.663	0.317	0.759	0.308
Luxembourg	0.176	**0.039**	0.744	**0.070**	0.550	0.956	0.185	0.629	0.482	0.026	0.110	0.556
Netherlands	0.111	**0.018**	**0.066**	**0.016**	**0.023**	0.339	0.526	0.321	**0.070**	0.210	0.224	0.110
Portugal	0.217	0.921	0.355	**0.081**	0.550	0.606	0.486	0.821	0.867	**0.084**	0.977	0.822
Spain	0.142	**0.001**	**0.069**	0.216	**0.053**	0.573	0.133	0.766	**0.000**	0.485	0.128	**0.051**

Notes: p-values. The bandwidth is 15 months. Bold indicates significance at the 10% level.

Table 4. Multivariate cross-country analysis for testing whether financial variables cause output growth

Variable/lag	*Term spread*		*Stock market*		*Money supply*	
	stat	*p-value*	*stat*	*p-value*	*stat*	*p-value*
3	456.79	0.198	436.41	0.432	499.69	**0.013**
6	918.74	**0.096**	918.34	**0.097**	921.71	**0.085**
9	1337.01	0.209	1347.64	0.155	1363.41	**0.094**
12	1794.81	0.128	1758.66	0.298	1810.77	**0.081**
15	2290.47	**0.025**	2134.38	0.648	2268.57	**0.051**
18	2737.71	**0.023**	2566.56	0.635	2673.08	0.131

Note: Bold indicates significance at the 10% level.

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Table 5. Clout/Receptivity

Country/variable	*Term spread*		*Stock market*		*Money supply*	
	Clout	*Recepti vity*	*Clout*	*Recepti vity*	*Clout*	*Recepti vity*
Austria	**0.000**	**0.002**	**0.019**	**0.000**	**0.005**	**0.004**
Belgium	**0.003**	**0.000**	0.221	**0.000**	**0.000**	**0.001**
Finland	0.203	**0.000**	0.250	**0.000**	**0.048**	**0.000**
France	**0.000**	**0.023**	0.148	**0.000**	**0.000**	**0.000**
Germany	**0.001**	**0.000**	**0.062**	**0.000**	**0.072**	**0.001**
Greece	0.353	**0.013**	0.179	**0.001**	0.677	**0.000**
Ireland	0.277	0.397	0.159	**0.000**	0.718	0.383
Italy	0.145	**0.000**	**0.014**	**0.001**	**0.002**	**0.013**
Luxembourg	0.347	0.377	0.487	0.320	0.144	**0.000**
Netherlands	**0.047**	**0.000**	0.449	**0.021**	**0.055**	**0.003**
Portugal	0.550	0.893	0.323	0.936	0.121	0.937
Spain	0.108	**0.059**	0.535	0.560	0.215	**0.079**

Notes: p-values. The bandwidth is 15 months. Bold indicates significance at the 10% level.

Table 6. Out of sample forecasts: 1-month forecast horizon

Out of sample MSFE	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Luxembourg*	*Netherlands*	*Portugal*	*Spain*	*Euro area*	*Pooled euro area (1)*	*Pooled euro area (2)*
(1) AR[(1)]	2.793	1.500	4.153	0.709	1.428	4.288	28.024	0.456	7.461	2.981	4.258	1.383	0.438	0.484	0.603
MSFE relative to AR															
(2) AR+spread	0.912	1.113	1.043	0.977	0.830	1.036	1.009	0.966	0.990	1.085	1.048	1.055	0.785	0.892	0.927
(3) AR+stock market	0.911	1.016	0.818	0.828	0.923	1.189	0.963	0.947	0.975	0.777	1.009	0.958	0.752	0.789	0.811
(4) AR+money supply	0.913	1.020	0.922	1.017	1.029	0.999	0.910	1.081	0.975	1.010	1.011	1.007	0.990	1.026	0.952
(5) AR+all	0.896	0.969	0.743	0.877	0.838	1.185	0.964	1.115	0.915	0.787	1.025	1.037	0.673	0.807	0.817
(6) Pooled of (2)-(4)	0.884	0.961	0.840	0.917	0.880	1.036	0.943	0.968	0.974	0.891	1.005	0.991	0.758	0.866	0.872

OOS-F test statistic	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Luxembourg*	*Netherlands*	*Portugal*	*Spain*	*Euro area*	*Pooled euro area (1)*	*Pooled euro area (2)*
(2) AR+spread	4.832*	-5.071	-2.062	1.203*	10.246*	-1.753	-0.425	1.746	0.507	-3.896	-2.306	-2.606	13.715*	6.078*	3.918*
(3) AR+stock market	4.888*	-0.810	11.132*	10.355*	4.173*	-7.934	1.942*	2.772*	1.296*	14.365*	-0.438	2.205*	16.489*	13.408*	11.689*
(4) AR+money supply	4.771*	-0.991	4.214*	-0.854	-1.395	0.049	4.927*	-3.725	1.270*	-0.471	-0.524	-0.370	0.521	-1.244	2.496*
(5) AR+all	5.792*	1.626	17.288*	7.026*	9.647*	-7.814	1.892	-5.138	4.654*	13.504*	-1.232	-1.770	24.280*	11.993*	11.227*
(6) Pooled of (2)-(4)	6.537*	2.033	9.534*	4.510*	6.811*	-1.754	3.011*	1.641	1.312	6.146*	-0.245	0.457	15.978*	7.756*	7.314*

Notes: *(1) MSFE calculated for real growth in decimal values.*
(2) Pooled euro area (1) refers to combination of forecasts using a fixed-weighting GDP scheme based on GDP shares calculated in 2005 PPP exchange rates.
(3) Pooled euro area (2) refers to combination of forecasts using the simple average of individual forecasts.
(4) An asterisk denotes significance at the 5% level based on McCracken (2004) critical values.

Table 7. Out of sample forecasts: 3-month forecast horizon

Out of sample MSFE	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Luxembourg*	*Netherlands*	*Portugal*	*Spain*	*Euro area*	*Pooled euro area (1)*	*Pooled euro area (2)*
(1) AR	3.258	2.103	3.903	0.749	1.227	4.622	30.159	0.595	7.606	3.304	4.011	1.610	0.459	0.482	0.816
(2) AR+spread	0.902	0.960	1.057	0.995	0.888	1.041	1.014	1.012	0.992	0.971	1.078	0.948	0.743	0.907	0.993
(3) AR+stock market	0.950	0.925	0.858	0.777	0.937	1.231	0.940	0.968	0.750	0.835	1.052	0.867	0.925	0.821	0.738
(4) AR+money supply	0.914	0.972	0.937	1.049	0.987	0.901	0.936	1.003	0.996	0.986	1.026	0.950	0.991	0.967	0.957
(5) AR+all	0.903	0.858	1.004	1.093	1.143	1.159	0.961	1.117	1.127	1.024	1.126	1.065	1.028	1.068	0.958
(6) Pooled of (2)-(4)	0.887	0.917	0.819	0.896	0.847	0.974	0.953	0.980	0.851	0.873	1.023	0.886	0.810	0.844	0.853

OOS-F test statistic	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Luxembourg*	*Netherlands*	*Portugal*	*Spain*	*Euro area*	*Pooled euro area (1)*	*Pooled euro area (2)*
(2) AR+spread	5.424*	2.059	-2.693	0.244	6.275*	-1.966	-0.696	-0.600	0.399	1.498	-3.626	2.717*	17.335*	5.148*	0.339
(3) AR+stock market	2.631*	4.058*	8.253*	14.374*	3.376*	-9.389	3.170*	1.637	16.640*	9.858*	-2.466	7.649*	4.044*	10.876*	17.783*
(4) AR+money supply	4.709*	1.430*	3.351*	-2.339	0.670	5.518*	3.442*	-0.164	0.205	0.685	-1.252	2.607*	0.475	1.683	2.274
(5) AR+all	5.346*	8.241*	-0.213	-4.236	-6.246	-6.865	2.006	-5.253	-5.632	-1.179	-5.596	-3.063	-1.363	-3.163	2.213*
(6) Pooled of (2)-(4)	6.362*	4.524*	11.028*	5.810*	9.019*	1.349	2.462*	1.003	8.727*	7.280*	-1.136	6.410*	11.716*	9.256*	8.622*

Notes: See Table 6.

Table 8. Out of sample forecasts: 6-month forecast horizon

Out of sample MSFE	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Luxembourg*	*Netherlands*	*Portugal*	*Spain*	*Euro area*	*Pooled euro area (1)*	*Pooled euro area (2)*
(1) AR	4.723	3.091	5.039	0.970	1.536	5.404	37.164	0.798	9.395	3.978	5.162	2.161	0.625	0.661	1.447
(2) AR+spread	0.956	0.940	1.055	1.050	0.830	1.016	1.005	1.044	0.930	0.935	1.113	0.994	0.826	0.957	1.056
(3) AR+stock market	0.935	0.982	0.895	0.845	0.817	1.282	0.890	1.019	0.831	0.890	0.967	0.877	0.879	0.801	0.737
(4) AR+money supply	0.931	0.996	0.823	1.082	0.952	0.887	0.867	1.092	0.970	1.002	0.950	0.911	0.988	0.980	0.935
(5) AR+all	0.899	0.844	1.107	1.178	1.030	1.369	0.857	1.131	1.138	0.831	1.294	0.940	0.940	0.887	0.974
(6) Pooled of (2)-(4)	0.914	0.923	0.802	0.946	0.818	0.955	0.890	1.037	0.857	0.892	0.956	0.884	0.876	0.879	0.880

OOS-F test statistic	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Luxembourg*	*Netherlands*	*Portugal*	*Spain*	*Euro area*	*Pooled euro area (1)*	*Pooled euro area (2)*
(2) AR+spread	2.322	3.214*	-2.586	-2.382	10.261*	-0.764	-0.264	-2.124	3.760*	3.470*	-5.071	0.305	10.541*	2.268	-2.670
(3) AR+stock market	3.448*	0.905	5.886*	9.150*	11.190*	-10.993	6.150*	-0.932	10.151*	6.208*	1.694	6.987*	6.861*	12.390*	17.880*
(4) AR+money supply	3.698*	0.222	10.784*	-3.785	2.548*	6.387*	7.680*	-4.207	1.572	-0.099	2.630*	4.896*	0.605	1.037*	3.451*
(5) AR+all	5.597*	9.208*	-4.849	-7.557	-1.455	-13.489	8.324*	-5.796	-6.063	10.184*	-11.359	3.212*	3.195*	6.341*	1.346
(6) Pooled of (2)-(4)	4.692*	4.144*	12.311*	2.852*	11.152*	2.365*	6.174*	-1.771	8.366*	6.036*	2.294	6.573*	7.092*	6.867*	6.833*

Notes: See Table 6.

Table 9. Out of sample forecasts: 12-month forecast horizon

Out of sample MSFE	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Luxembourg*	*Netherlands*	*Portugal*	*Spain*	*Euro area*	*Pooled euro area (1)*	*Pooled euro area (2)*
(1) AR	6.272	4.405	9.719	1.313	2.489	6.662	50.056	1.140	15.602	5.458	7.688	2.896	1.000	1.090	2.791
(2) AR+spread	0.876	1.001	0.949	1.042	0.824	1.114	0.980	0.977	0.894	0.906	1.073	1.019	0.951	0.929	1.041
(3) AR+stock market	0.958	0.927	0.881	0.895	0.993	1.336	0.807	0.895	0.843	0.817	0.933	0.981	1.004	0.910	0.884
(4) AR+money supply	0.865	1.010	0.886	1.025	1.006	0.925	0.892	0.952	0.855	0.970	0.914	0.999	1.011	0.975	0.955
(5) AR+all	1.149	0.993	0.839	0.974	0.792	1.479	1.162	0.864	0.792	1.011	0.991	1.111	0.866	0.812	0.947
(6) Pooled of (2)-(4)	0.870	0.922	0.841	0.936	0.925	0.965	0.875	0.916	0.817	0.865	0.922	0.995	0.930	0.926	0.949

OOS-F test statistic	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Luxembourg*	*Netherlands*	*Portugal*	*Spain*	*Euro area*	*Pooled euro area (1)*	*Pooled euro area (2)*
(2) AR+spread	7.100*	-0.053	2.685*	-2.034	10.667*	-5.133	1.012	1.202	5.920*	5.177*	-3.381	-0.942	2.581*	3.799*	-1.969
(3) AR+stock market	2.206	3.923*	6.741*	5.842*	0.346	-12.577	11.925*	5.840*	9.318*	11.177*	3.607*	0.960*	-0.187	4.923*	6.546*
(4) AR+money supply	7.801*	-0.506	6.440*	-1.216	-0.299	4.064*	6.068*	2.494*	8.486*	1.559	4.723*	0.056	-0.545	1.304	2.357
(5) AR+all	-6.492	0.348	9.622*	1.310*	13.116*	-16.201	-6.969	7.894*	13.131*	-0.559	0.459	-5.000	7.749*	11.554*	2.775*
(6) Pooled of (2)-(4)	7.467*	4.207*	9.467*	3.416*	4.059*	1.833	7.129*	4.556*	11.184*	7.795*	4.223*	0.243	3.790*	4.007*	2.689*

Notes: See Table 6.

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