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Are sectoral stock prices useful for predicting euro area GDP?

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Abstract

This paper evaluates how well sectoral stock prices forecast future economic activity compared to traditional predictors such as the term spread, dividend yield, exchange rates and money growth. The study is applied to euro area financial asset prices and real economic growth, covering the period 1973 to 2006. The paper finds that the term spread is the best predictor of future growth in the period leading up to the introduction of Monetary Union. After 1999, however, sectoral stock prices in general provide more accurate forecasts than traditional asset price measures across all forecast horizons.

JEL Classification: C52, C53

Keywords: Forecasting Models, Asset Prices

1 Introduction

Both financial market participants and policymakers, such as central banks, closely follow financial market developments. However, the motivation for their interest in the financial markets differs in the sense that investors monitor asset price movements to optimize the risk-return profile on their investments, whereas central banks use financial market prices to infer information about market expectations of economic growth and inflation.

The purpose of this paper is to evaluate if financial asset prices and, in particular, sectoral stock prices can help to predict real economic growth. Earlier studies that have examined the predictive content of stock prices have employed broad-based indices. However, there are reasons to believe that some sectors making up the stock indices are more closely linked to the business cycle than others. The intuition for this is given by Browne and Doran (2005), "the return from industry groups whose profits are likely to be pro-cyclical relative to the share price of the industry group whose profits are likely to be a-cyclical should be a good forecast of the cycle itself".

This paper fills a gap in the existing literature by conducting a "horse race" study where the predictive content of sectoral stock prices is compared to the predictive content of other financial market candidates proposed in earlier studies. The study is applied to euro area financial market prices and real economic growth over the sample 1973 to 2006. Among the myriad of stock sectoral breakdowns that are available, this study uses the so-called economic sectors (as defined by Datastream). This choice of sectoral breakdown is motivated by the fact that many policymakers and market analysts use this decomposition when analysing and reporting on stock price developments.

The evaluation of the predictive power between the financial assets is based on the relative improvements in the Mean Square Forecast Errors (MSFE) compared to the MSFE of a simple optimal autoregressive (AR) model, in an out-of-sample forecasting exercise. To test if the inclusion of the financial assets significantly improves the MSFE or not, a test of equal predictive accuracy proposed by Clark and McCracken (2005) is implemented. Finally, to examine if the introduction of the Monetary Union has significantly impacted the predictive content of asset prices, the paper splits and evaluates the information content of the financial assets before and after the introduction of the monetary union in January

1999.

The three main findings of the paper can be summarized as follows. First, in line with previous findings within this strand of the literature, the term spread produces the lowest MSFE among the asset classes over the whole sample. Second, sectoral stock market prices do in several cases significantly improve the predictive power compared with the benchmark AR model, with the strongest improvements found for forecast horizons above one year. Third, the introduction of the euro seems to have brought about a substantial improvement in the predictive content of euro area financial assets. The relative improvements in the MSFE are particularly striking for euro area stock market sectors, where in several cases the MSFE is half the level of the pre-euro sample MSFE. One explanation for this interesting finding may be that the introduction of the single currency probably led to lower risk-premia embedded in euro area financial assets, making the prices of euro area financial assets to become relatively more informative as concerns future macroeconomic fundamentals.

The paper is organized as follows. Section 2 describes the related literature. Section 3 gives an overview of the database employed and outlines its main characteristics. Section 4 describes the forecasting model, and Section 5 presents the results of the forecast exercise. Section 6 concludes.

2 Background and related literature

This section briefly summarizes the interlinkages between asset prices and economic activity, and the main findings from this strand of the literature.

Stock market developments play an active role in future economic developments through various channels. A useful summary can be found in ECB (2002), which identifies four main channels. First, higher stock prices lower the cost of financing new investments. Second, the wealth effect channel states that a permanent increase in stock prices induces higher current and future consumption. Third, higher stock prices may also support future economic growth indirectly. In particular, higher stock prices tend to induce an improvement in consumer confidence sentiment, also for consumers not directly exposed to stock market fluctuations, thereby further supporting consumption and investment. Fourth, stock price fluctuations can also influence aggregate consumption and investments through the existence of market imperfections. For example, the amount agents can borrow is constrained on the basis of their future expected income streams. Thus, everything else held equal, an increase in the equity prices for the stocks held by the agents will increase their net wealth and also borrowing capacity, supporting investment and consumption.

The so-called dividend discount model is a useful tool to derive the leading indicator properties of stock prices, see Gordon (1959). The model states that the stock price of a firm at any time equals the discounted sum of current and expected future dividends. The firm's dividends are usually paid out as a constant fraction of its earnings. Consequently, since the earnings prospects of a firm are largely determined by the economic environment in which it is operating in, any changes in stock prices may therefore reflect revised market expectations concerning the future economic growth outlook.

It is also possible to derive theoretical linkages between interest rates across various maturities and future economic growth prospects. In economies where independent central banks either implicitly or explicitly aim at keeping prices low and stable, interest rates on shorter maturities contain information about output and inflation expectations over the medium term. Similarly, expectations of future economic activity also influence the yields on longer-term maturities. This can easily be seen from the well-known Fisher hypothesis, which states:

$$Y_t = Y_t^r + \pi_t^e + \vartheta$$

where Y_t denotes the t period nominal bond yield, Y_t^r is the t period expected real interest rate, and π_t^e the t period expected inflation rate. ϑ denotes the term premium. Higher expected real rates and/or increased inflation expectations would then be expected to put upward pressure on long-term bond yields. Examination of the term spread between long and short rates thus neatly reveals how the markets perceive the future macroeconomic outlook over medium and longer-term horizons. For instance, a tightening of the monetary policy, reflected by higher policy rates, usually dampen economic growth prospects over the medium term. As real rates are closely linked to growth prospects of the economy, long-term rates may decline as a result of the monetary policy tightening. These two movements then result in a narrowing of the level of the term spread. Thus, the a priori assumption is that future economic growth should be positively correlated with the level of the term spread.

This paper also includes the exchange rates and monetary aggregates as potential candidate predictors as they contains useful information concerning future economic growth. Regarding exchange rates, a depreciation of an economy's currency decreases the price of the domestic currency in terms of foreign currency. This in turn usually boosts exports and lowers imports which, everything else being equal, supports the growth rate of the economy. The relationship between money growth and output differs depending on the horizon. Aggregate demand relations state that higher money growth implies an initial increase in output growth. However, in the medium to long run, inflation equals adjusted nominal money growth, thus not affecting the economy's output (long-run neutrality).

Many papers, have tested the above relationship, for a wide variety of economies, see Stock and Watson (2003) for a thorough overview. The starting point of the literature, applied to US data, noted that short-term interest rates can be used as predictors of output and inflation, see Sims (1980) and Bernanke and Blinder (1992). Later studies have however suggested that the term spread is a better predictor than the level or changes in short-term rates. Turning to the euro area, various studies have found that the term spread can help to predict future economic growth, in particular Smets and Tsatsaronis (1997), using German data in a VAR framework, and recently Moneta (2003), applying a probit model.

Concerning stock prices and dividend yields and their ability to forecast economic growth, the evidence from a series of studies applied on the US is mixed, see Stock and Watson (2003) and Estrella and Mishkin (1998). One plausible explanation may be that non-fundamental factors over time can substantially influence stock prices, thereby blurring the economic link. Browne and Doran (2005) tested the forecast properties of various industry groups with the S&P 500. Results for the Industrial Production Index suggest that a number of the industrial groups produce better forecasts compared with benchmark AR forecasts. The few papers that have examined the link between stock prices and the real economy in the euro area mainly examined the wealth effect on consumption and the impact stock prices have on investments, see Paiella (2003) and Guiso, Paiella and Visco (2004) and Tease (1993). Notably, no studies have examined the predictive content of sectoral stock prices on economic activity. Given that some stock market sectors can be assumed to be more closely linked to the business cycle than others, it should be possible, by breaking up the indices into the economic sectors, to tighten the link between stock prices and economic activity.

In the following analysis the forecasting performance of the sectoral stock prices will be compared with those of other financial market indicators - term spread, exchange rate, dividend yield, real money growth and the aggregate stock prices indicator.

3 Data

The data used for this study span the period 1973 until 2006. The stock market data consist of Datastream's broad-based total market index and the ten economic sectors that make up the index. Dividend yield data are extracted from the same index. The exchange rate consist of DEM/USD over the 1973 - 1998 sample period and the EUR/USD from 1999 onwards. The short-term interest rate data we choose in this study consist of 3-month nominal German Treasury bills 1973 - 1998 and then the 3-month nominal Euribor. In the same vein, for the long-term bond market segment, ten-year nominal German government bonds are selected for the 1973 - 1998 period, and thereafter ten-year nominal government bond yields for the euro area. The term spread is calculated as the difference between the long and short-term interest rates.

Table 1: ***Relative weights of the economic sectors***

Sectors	**Weights in %**
Oil and gas	5.9
Basic materials	5.4
Industrials	12.3
Consumer goods	12.0
Healthcare	3.7
Consumer services	7.9
Telecommunications	5.3
Utilities	9.9
Technology	4.0
Financials	33.5

Note: The weights are based on market capitalization as of end-2006

Table 1 shows the relative importance of the ten economic sectors. The financial sector is by far the most important sector, making up a relative weight of around 30 percent. The industrials, consumer goods and utility sectors have around a ten percent weight in the index; by contrast; the oil and gas, basic materials, healthcare, consumer services, telecommunications and utilities have a relatively low weight in the index.

4 Forecasting model

To test whether asset prices can help predict future economic growth, a standard pseudo out-of-sample forecast exercise is performed. This exercise involves examining whether the forecast accuracy regarding euro area real GDP growth improves when asset prices are added to a benchmark autoregressive model. The purpose of choosing such a simple model as a benchmark is that it often outperforms more complex forecasting models. The transformed economic variable to be forecasted is:

$$Y_{t+h}^{h} = \frac{400}{h} log(\frac{GDP_{t+h}}{GDP_t})$$

where GDP_t represents real GDP in levels at time t (the factor of 400/h standardizes the units in level to annual percentage growth rates). To evaluate the forecasting power of the sectoral stock prices vis-à-vis the "standard" asset classes used in the literature, the following model is used:

$$Y_{t+h,u}^{h} = \alpha + \sum_{i=0}^{q_1} \beta_i Y_{t-i} + \sum_{j=0}^{q_2} \gamma_j X_{t-j} + u_{t+h}^{h} \qquad (1)$$

where X_t is the return on the various financial assets, h the forecasting horizon in quarters, u_{t+h}^{h} the error term and q_1 and q_2 represent lag lengths, the latter based on Akaike information criteria. The forecast horizon h is restricted to span between one and eight quarters. The exercise begins by estimating the out-of-sample MSFE for the restricted benchmark model:

$$Y_{t+h,r}^{h} = \alpha + \sum_{i=0}^{q_1} \beta_i Y_{t-i} + u_{t+h}^{h} \qquad (2)$$

The equation is estimated on a sub-sample called the estimation window (1973:Q1 to 1984:Q4) and for a given horizon h. The estimated coefficients are then used to forecast the GDP growth rate $h - steps$ outside the estimation window. After that, the estimation window is updated with one observation, the parameters are re-estimated based on the new sub-sample, and the $h - steps$ ahead forecast are again computed outside the new sample. The procedure is then iterated until the end of the sample (2006:Q1). The estimated forecasts of Y^h_{t+h}, labelled as $\widehat{Y}^h_{t+h,r}$ are stored and used to compute the $MSFE$ for forecast horizon h, defined for the restricted model as:

$$MSFE_{h,r} = \frac{1}{(T_2 - T_1)} \sum_{t=T_1+h}^{T_2} (Y^h_t - \widehat{Y}^h_{t,r})^2$$

where the subscript r refers to the restricted model. The $MSFE$ is a measure of the average forecast accuracy in the out-of-sample window T_{1+h} to T_2 (the first and last date of the evaluation period respectively). Table 2 below shows the results of the forecast exercise performed on the restricted model. The numbers in the table show the MSFE of the restricted model for various forecasting horizons h.

Table 2: ***MSFEs of the restricted benchmark specification***

	Horizon		
	1	***4***	***8***
MSFE	4.29 (7)	1.74 (5)	1.30 (8)

Notes: The number of lags is reported in brackets.

The models selected in Table 2 and the associated MSFEs will serve as a benchmark to assess the predictive power of the above-mentioned financial market indicators. The indicators are added one by one in *eq.*(2) (i.e. the benchmark specification) and the out-of-sample forecast simulation exercise is then repeated exactly in the same way as done for the benchmark model. The forecasts of the unrestricted equation *eq.*(1) are labelled $\widehat{Y}^h_{t+h,u}$. The assessment of the quality of the forecasts is determined by the $MSFE$ statistic for the unrestricted model defined as:

$$MSFE_{h,u} = \frac{1}{(T_2 - T_1)} \sum_{t=T_1+h}^{T_2} (Y^h_t - \widehat{Y}^h_{t,u})^2$$

where u refers to the unrestricted model.

To facilitate comparisons between the various asset classes, the results will be given in terms of the relative $MSFE$ statistics, defined as:

$$\frac{MSFE_{h,u}}{MSFE_{h,r}}$$

When the relative MSFE is less than one, the inclusion of the asset price improves the forecast precision of the benchmark model. For example, a value of 0.8 indicates that the candidate predictor improves the forecast performance of the benchmark model by 20%.

4.1 Test of equal predictive accuracy

The relative MSFE statistics used above to evaluate the forecasts provide a simple and timely measure of the predictive power of a candidate predictor. However, this statistic cannot be used to assess whether forecasts based on the financial market indicators are statistically different from those provided by the benchmark model. Generally this is addressed using the Diebold Mariano (1995) test. However when the models are nested, as is the case above, the Diebold and Mariano test is asymptotically invalid and cannot be applied. To overcome this problem, this paper employs the $MSFE-F$ statistic proposed by Clark and McCracken (2005), defined as:

$$MSFE-F = (P-h+1) \times \frac{\overline{d}}{MSFE_{u,h}}$$

where P is the number of observations used for the out-of-sample evaluation, h the forecast horizon and $\overline{d} = (P-h+1)^{-1}\sum_{t=R}^{T+h}\widehat{d}_{t+h}$ where $\widehat{d}_{t+h} = (Y_t^h - \widehat{Y}_{t,r}^h)^2 - (Y_t^h - \widehat{Y}_{t,u}^h)^2 = \widehat{u}_{t+h,r}^2 - \widehat{u}_{t+h,u}^2$ is a quadratic loss differential. McCracken (1999) shows that the $MSFE-F$ statistic has a non-standard but pivotal distribution for $h = 1$ and Clark and McCracken (2005) show that the statistic has a non-standard and non-pivotal distribution for $h > 1$, which lead them to recommend basing the inference on the following bootstrap procedure.

Let us assume that the forecasted variable Y_t (GDP growth in our case) and the candidate predictor X_t (asset price) are generated by the following data generating processes, in which the asset price variable is assumed to have no forecasting power for GDP growth:

$$Y_{t+1} = c_1 + \sum_{i=1}^{r_1}\delta_i Y_{t-i} + e_{1,t+1} \tag{3}$$

$$X_{t+1} = c_1 + \sum_{i=1}^{s_1} \phi_i X_{t-i} + \sum_{i=1}^{s_2} \varphi_i Y_{t-i} + e_{2,t+1} \tag{4}$$

The parameters of the two equations are estimated using the whole sample and the lag lengths are fixed based on the Akaike information criterion. The residuals from the two equations are stored and used to generate new series for the two processes. To initialize the procedure, the starting values of the two variables are set equal to zero.[1] Next, using the estimated parameters, a new pair of observations is generated by drawing the residuals in tandem, in order to keep the covariance structure unchanged. The procedure is iterated until observation 150+T. To minimize the impact of the starting values, the first 150 observations are dropped, leaving the total number of observations equal to the original size of the sample. This procedure is repeated 5000 times and, based on these pseudo-observations, new $MSFE - F$ statistics are generated. To evaluate whether the forecasts based on the financial market indicators can be considered as statistically different from the benchmark model, p-values are computed as the proportion of $MSFE - F$s above the empirical counterpart.

5 Results

This section shows the results of the forecasting exercise for the entire sample plus two sub-sample periods.

5.1 Full-sample analysis

Table 3 below summarizes the results of the forecasting exercise over the out-of-sample period 1985 to 2006. Three notable features can be inferred from the table. First, among the asset classes, the term spread in general generates the lowest relative MSFE. Over a two-year horizon, including the the term spread in the restricted model improves the predictive power by around 25%. Second, when the total stock market index is added as a candidate predictor to the benchmark specification, the MSFE worsens by some 10%. Third, stock market sectors in some cases lead to significant improvements in the MSFE. The oil and gas sector significantly improves the MSFE of around 6 and 9% at one and

[1]Results are robust to a different choice of the starting values.

four-quarter horizons. In addition, for the two-year horizon, the relative MSFEs for the basic materials, consumer goods, healthcare, consumer services, technology, financial and non-financial sectors significantly improve the performance of the benchmark by around 10%.

Table 3: ***Relative MSFEs of various asset prices***

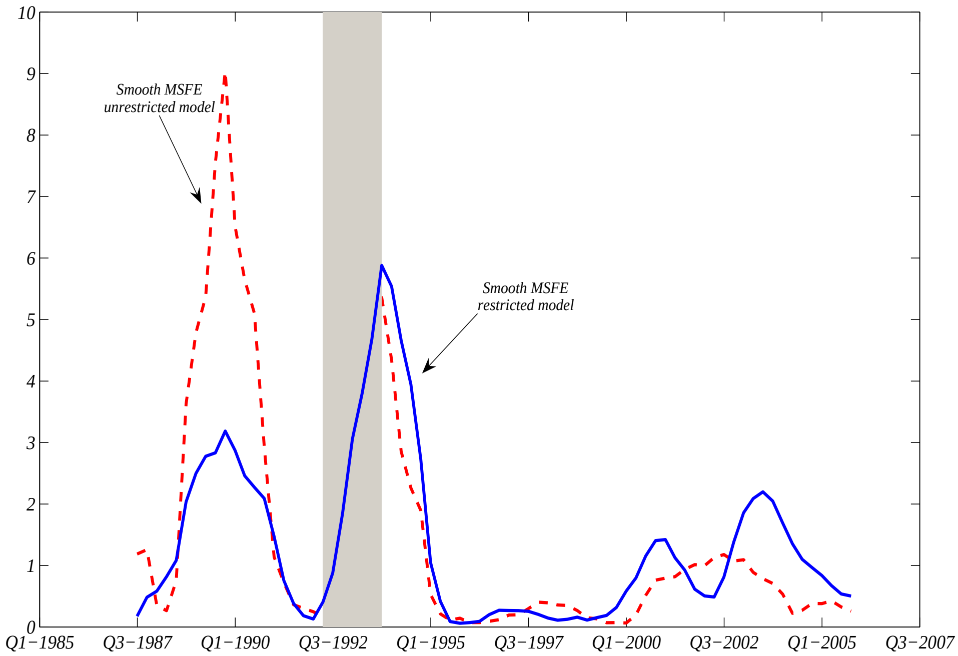
	Horizon		
Predictors	***1***	***4***	***8***
Oil and gas	0.94***	0.91***	0.98
Basic materials	1.05	1.27	0.93**
Industrials	1.07	1.32	1.00
Consumer goods	1.25	1.60	0.90**
Healthcare	1.06	1.07	0.91***
Consumer services	1.07	1.24	0.87**
Telecommunications	1.15	1.24	1.40
Utilities	1.28	1.37	1.01
Technology	1.26	0.96**	0.90**
Financials	1.16	1.46	0.94***
Non-financials	1.05	1.23	0.94*
Total market index	1.10	1.14	1.13
Term spread	1.01	1.00	0.74**
Exchange rate	1.10	1.45	1.10
Dividends	0.97**	1.00	1.17
m1	1.14	1.07	1.16
m1 real	1.26	1.29	1.59
AR	4.29	1.74	1.3

Note: Asterisks denote forecasts that are statistically more accurate than the benchmark at 1% (***), 5% (**) and 10% (*) significance level. Last row reports the absolute MSFEs for the AR specification.

5.2 Break point analysis

The results presented in Table 3 may not be completely representative if the predictive content of euro area financial assets has changed over the sample period. To gauge how stable our results are, a sub-sample exercise is conducted. There is no standard method how to determine the sub-sample periods. However, a natural starting point is to look at the forecast errors over time. Figure 1 therefore plots a filtered measure of the MSFE for both the restricted and the unrestricted model, which include the broad-based stock market index as a candidate predictor. The figure covers the two-year forecast horizon as this horison yielded the most significant improvement in the forecast accuracy over the entire sample period (see again Table 3).

Figure 1: *Mean square forecast errors for the restricted and unrestricted model (sample 1983:Q3 - 2005:Q3)*

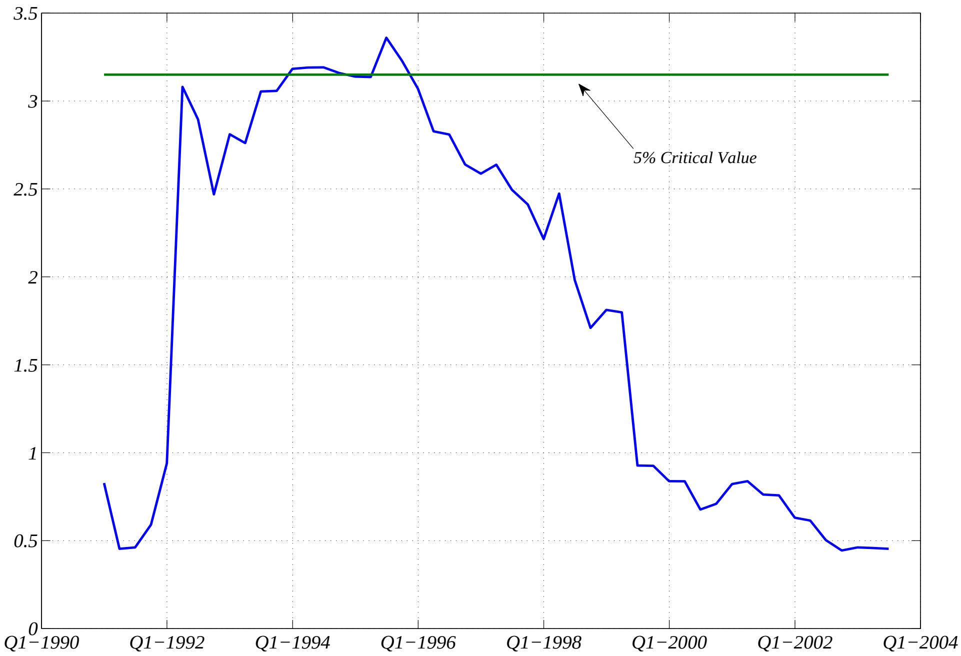


Note: Rolling one-year forecast error for the restricted and unrestricted model (including the euro area broad-based stock market index as candidate predictor). Forecast horizon is two years. The gray shaded area corresponds to the recession 1992:Q1 - 1993:Q3, as defined by the CEPR

Two interesting features can be noted from the figure. First, both models perform rather poorly during the latter part of the 1980s and early 1990, corresponding to the strong financial market turbulence in the late 1980s and the economic recession in the early 1990s respectively. Second, the smoothed MSFE estimates for the unrestricted model have, since the late 1990s, hovered at lower levels than the restricted AR model. This provides some tentative evidence that euro area financial assets in the latter part of the sample has become relatively more informative, compared to the autoregressive forecasting models.

A more elaborate approach is to perform some econometric test of a structural break in the series. We test the hypothesis of breaks in the coefficients of the stock prices variable by using the $F - sup$ statistics proposed by Quandt (1960); it is the sup of a sequence of traditional Chow χ^2 type tests performed to detect any possible break date over the sample.[2] The test is implemented on the two-year projection ($h = 8$) as outlined in *eq.*(1) and applied on the total market index. Figure 2 depicts the test statistics of the null hypothesis coefficients of total market index in *eq.*(1) are constant against the alternative of a break in at least one of these coefficients. As seen in the figure, the highest test statistics (and significant on the five percent level) is found in the latter part of 1995.

Figure 2: *Statistics for Breaks Detection in eq.(1)*



Note: Sequence of F statistics testing the null hypothesis of a break in the coefficients of the total market index in eq. 4.2. The sup of such sequence is reached in the third quarter of 1995; it exceeds the 5% critical value (tabulated by Andrews, 1993). The statistics are computed over the sample 1985-2006, with 15% trimming.

The preliminary results shown in Figure 1, suggest that the predictive power of asset prices changed in the late 1990s. One reason for the shift in predictive power may be linked to the introduction of the euro in 1999. There are well founded economical reasons of why this may be the case. First, the introduction of the common currency eliminated the foreign

[2] We use the distribution tabulated by Andrews (1993).

exchange risk for companies in the euro zone. Second, there is evidence that the integration of the euro area equity market has deepened after the introduction of Monetary Union, and that equity returns in the various euro area equity markets are increasingly determined by common news factors and less by country-specific factors, see Baele et al. (2004). Third, most analysts agree that introduction of a single currency also led to a stronger anchoring of long-term inflation expectations. Taken together, these three factors probably have brought about lower risk premiums demanded by investors to hold euro area financial assets. As a result, the prices of euro area financial assets may have become relatively more informative as concerns macroeconomic fundamentals in the latter part of the sample. Admittedly, the econometric results do not provide full support for basing the sub-sample analysis on the period before and after 1999. However, the strong economic arguments in favour of the 1999 breakpoint, coupled with the fact that the test statistics suggest a break in the series relatively close in time to 1999 altogether guides us to choose the sub-samples as pre-euro (1985 – 1998) and post-euro (1999 – 2006).

5.3 Sub-sample analysis

As explained above, the predictive content is recalculated over two sub-samples, one that spans the pre-euro (1985 - 1998) period, and one covering the period after the introduction of Monetary Union (1999 - 2006). Table 4 below reports the results.

The predictive power of the various asset classes differs greatly in the two sub-samples, with in general lower relative MSFEs observed in the latter period. For instance, over the two-year horizon, the consumer goods, healthcare and financial sectors improve the benchmark AR model by more than 50%. There strong and significant improvement in predictive power in the post-euro sample are probably linked to the fact that euro area asset prices, as mentioned above, are less influenced by risk premia in the latter sample period making market movements relatively more influenced by changes in the fundamentals.

The results also suggest that the broad index performs well in the latter sample, improving the forecasting power from the benchmark model by around 40%, whereas the improvements are less pronounced for the other asset price candidates (term spread, the exchange rate, dividends and money growth). To sum up, the very low relative MSFEs for some of the stock market sectors in this later period suggest that they should be closely monitored by policymakers as they can substantially improve standard benchmark forecasting models.

6 Conclusions

The literature on financial asset prices and the information they can convey concerning the economic outlook has become a popular field of applied research over the past decade. Many asset classes have been tested, and the bulk of the studies have concluded that the term spread, measured as the difference between yields on longer maturity bonds and money market interest rates, has outperformed other asset classes. The forecasting power of stock prices, usually in the form of broad-based indices, has been mixed. However, there are reasons to believe that some of the sectors making up the stock indices are more closely linked to the business cycle than others. Applied to the euro area, this paper therefore examines this issue in more detail by exploring the forecasting performance of the ten economic sectoral stock prices in addition to the standard asset prices previously suggested in this strand of the literature. The forecasting performance is evaluated in relation to an autoregressive model. To test if the inclusion of the financial assets significantly improves the forecasting power of the benchmark, a test of equal predictive accuracy proposed by Clark and McCracken (2005) is implemented. The sample spans between 1973 and 2006 and the forecast properties up to eight quarters ahead is analyzed. The forecast performance is evaluated in an out-of-sample exercise over the window 1985 to 2006.

In line with previous findings, the paper finds that the term spread on average tends to yield the lowest forecast errors. However, the predictive power is not constant over time. The introduction of the euro in 1999 seems to have resulted in a significant improvement in predictive power of future economic growth across most asset classes and sectoral stock prices in particular. This improved forecast power is probably linked to the fact that the Monetary Union eliminated foreign exchange risks and reduced investors' percieved inflation uncertainty. This in turn has probably led to lower risk-premia embedded in euro area financial assets, making the prices of euro area financial assets to become relatively more informative as concerns future macroeconomic fundamentals.

References

[1] Andrews, D (1993), "Tests for Parameter Instability and Structural Change with Unknown Change Point," Econometrica, 61, 821-856

[2] Baele. L., Ferrando. A., Hördahl. P., Krylova E. and Monnet C., ECB (2004), "Measuring Financial Integration in the Euro Area" ECB Occasional Paper No. 14

[3] Bernanke. B. and Blinder A. S. (1992), "The Federal Funds Rate and the Channels of Monetary Transmissions", American Economic Review 82:4

[4] Brown. F., Doran. D. (2005), "Do equity index industry groups improve forecasts of inflation and production? A US analysis ", Applied Economics, 37, pp 1801-1812

[5] Clark. T, and McCracken. M. W. (2005), "Evaluating Direct Multi- Step Forecasts", Econometric Reviews 24, pp 369-404

[6] Diebold, F. X., and R. S. Mariano, (1995), "Comparing Predictive Accuracy", Journal of Business and Economic Statistics, 13, pp 253-265

[7] ECB (2002), "The Stock Market and Monetary Policy", article published in the February issue of the Monthly Bulletin

[8] Estrella A., and Mishkin F. S., (1998), "Predicting U.S. Recessions: Financial Variables as Leading Indicators", Review of Economics and Statistics 80

[9] Gordon, M. J. (1959), "Dividends, Earnings, and Stock Prices ", Review of Economics and Statistics, Vol. 41, No 2, Part 1, pp 99-105.

[10] Guiso, L., Paiella M. and Visco I., (2004), "Do Capital Gains Affect Consumption? Estimates of Wealth Effects from Italian Households' Behaviour", mimeo

[11] McCracken, M.W., (1999), "Asymptotics for Out-of-Sample Tests of Causality", Working Paper 99-1, Louisiana State University

[12] Moneta, F., (2003), "Does the Yield Spread Predict Recessions in the Euro Area?", International Finance, Summer 2005 - Vol. 8 Issue 2

[13] Paiella, M. (2003), "Does Wealth Affect Consumption? Evidence for Italy", mimeo, Bank of Italy, Research Department

[14] Quandt, R. (1960), "Tests of the Hypothesis that a Linear Regression Obeys Two Separate Regimes", Journal of the American Statistical Association. 55, pp. 324–30

[15] Sims C. A. (1980), "A Comparison of Interwar and Postwar Cycles: Monetarism Reconsidered", American Economic Review 70, pp 250-257

[16] Smets F. and Tsatsaronis K., (1997), "Why Does the Yield Curve Predict Economic Activity? Dissecting the evidence for Germany and the United States" BIS Working Paper 49

[17] Stock, J. H. and Watson M. W.(2003), "Forecasting Output and Inflation: The Role of Asset Prices", Journal of Economic Literature, Vol. 41, Issue 3

[18] Tease, W. (1993), "The Stock Market and Investment", OECD, Economic Studies, No 20, 41-63

Table 4: ***Relative MSFEs of various asset prices - Sub-samples***

Pre-euro sample

	Horizon		
Predictors	***1***	***4***	***8***
Oil and gas	0.98*	0.92***	1.11
Basic materials	1.11	1.39	1.08
Industrials	1.12	1.45	1.13
Consumer goods	1.33	1.91	1.07
Healthcare	1.11	1.13	0.93**
Consumer services	1.11	1.35	0.97
Telecommunications	1.21	1.40	1.64
Utilities	1.28	1.37	1.01
Technology	1.27	0.99	0.93*
Financials	1.21	1.66	0.96*
Non-financials	1.11	1.37	1.11
Total market index	1.17	1.27	1.33
Term spread	1.01	0.99	0.69**
Exchange rate	1.09	1.58	1.09
Dividends	1.01	1.03	1.37
m1	1.12	1.17	1.22
m1 real	1.30	1.49	1.78
AR	5.79	2.01	1.49

Post-euro sample

	Horizon		
Predictors	***1***	***4***	***8***
Oil and gas	0.76***	0.83*	0.59**
Basic materials	0.66***	0.74**	0.52**
Industrials	0.76***	0.73**	0.72**
Consumer goods	0.76***	0.74**	0.46***
Healthcare	0.73***	0.78**	0.47***
Consumer services	0.94	0.63***	0.65**
Telecommunications	0.78***	0.72**	0.84*
Utilities	0.79***	0.84**	0.79**
Technology	0.72***	0.81***	0.76**
Financials	0.74***	0.65***	0.49***
Non-financials	0.68***	0.61***	0.56**
Total market index	0.68***	0.66***	0.61**
Term spread	1.10	1.09	0.77*
Exchange rate	1.15	1.06	1.12
Dividends	1.19	0.86*	0.58**
m1	0.89**	0.80**	1.04
m1 real	1.02	0.74**	0.84
AR	1.98	1.57	1.12

Note: Relative MSFEs of different predictors. Asterisks denote forecasts that are statistically more accurate than the Benchmark at 1% (***), 5% (**) and 10% (*) significance level. Last row reports the absolute MSFEs for the *AR* specification.