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The Role of Stock Markets vs. the Term Spread in Forecasting Macrovariables in Finland

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CONTENTS

ABSTRACT

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Money talks, but can it foresee economic future? A rule of thumb suggests that stock markets react a half a year before changes occur in macrovariables. On the other hand, it was discovered in the late 1980s that the steepness of the yield curve is a very useful tool for predicting macroeconomy. There exist a substantial body of stylized facts and empirical evidence about relations between yield curve, stock market and macroeconomy regarding the U.S. economy. However, the question whether this holds true for small open economies is less known. This paper focuses on forecasting content of stock markets versus the yield curve regarding GDP, private consumption, industrial production and inflation rate in Finland. In addition to stock market returns, market volatility is explicitly addressed in this study, the issue that has been largely overlooked in previous literature. Thus, both the return and risk aspects of the stock markets are covered. The sample period is 1987–2006.

The out-of-sample forecasting results suggest that the yield curve is a much better tool for predicting macroeconomy than the stock market variables. Only in the case of inflation the stock market variables appear to contain some additional information about the term spread and the best inflation forecasts are obtained by combining the information from the term spread and the stock market variables. The stock market volatility has not been found to contain any additional forecasting information about the stock returns. Overall, the empirical results confirm that the forecasting ability of the yield curve holds true also in small open economy like Finland.

KEY WORDS: term spread, stock market, macroeconomy

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1. INTRODUCTION

As stock returns are forward-looking and related to the future state of the economy, they also constitute potential predictors of output and inflation. The stock market is easy to observe, it is a good aggregator of information, and it reacts to news vigorously and with short delay. If investors have a strong enough belief that a recession is coming, the stock market will not wait and hesitate to send a signal and therefore the recession probably will not wait very long time either. On the other hand, "The stock market has predicted nine out of the last five recessions", as Samuelson (1966) famously expressed it, and stock prices are much too volatile to be justified only by subsequent changes in dividends as stated by Shiller (1981). Excessive stock market volatility may have important effects on economy and it may also have predictive power on economic activity and inflation. Still, the question remains: do stock market components, returns and volatility, include systematic and relevant information about the real economy and inflation?

There is a plenty of evidence that the yield curve is a quick, simple and reliable predictor of the future real activity and monetary policy. It has become a standard procedure to use ten-year Treasure note minus tree-month Treasure bill spread to predict U.S. recessions and the future economic activity (e.g. Estrella & Mishkin 1996; Haubrich & Dombrosky 1996). The yield curve has been found to be able to predict GDP, private consumption and industrial production growth and inflation, though some caution should be exercised in using the term structure as a guide for assessing inflationary pressures in the economy (Miskin 1988; Estrella 2004). Models that predict real activity are often found to be more stable than those predicting inflation (Estrella, Rodrigues & Schich 2003).

The purpose of this study is to analyze the ability of the stock market variables versus the yield curve to predict macroeconomy in Finland, the small open economy which has experienced a remarkable transition from highly regulated money and stock markets to liberalized market economy during the last 20 years. More specifically, we scrutinize the predictive potential of stock returns and their volatility and compare it with the predicting ability of the yield curve. The analysis is focused on the four central macroeconomic variables: GDP, private consumption, industrial production and inflation. The research period is 1987–2006. During this period the Finnish economy has experienced a number of structural changes and economic shocks. These include, among others, two vast bubbles (1989 and 2000) and subsequent crashes in the stock market, one of the absolutely worst recessions on the western hemisphere after the 1930s (1990-1993), a strong recovery and subsequent rapid economic growth, a remarkable slowdown of inflation, EMU membership (1998) and monetary transition to euro (2002). It can be concluded that during the research period the case of Finland as a small European open economy really tests the empirical regularities and stylized facts about stock markets and yield curves as the leading indicators of economy.

There is a substantial body of stylized facts and empirical evidence about relations between yield curve, stock market, real economy and inflation in the U.S. However, it is less known whether this applies to a small open economy such as Finland.

Besides focusing on forecasting ability of stock markets and the yield curve regarding the macroeconomy in small open economy, this study contributes to the existing literature by explicitly addressing stock market volatility as a potential predictor for macroeconomy. This issue has been overlooked in previous literature. Thus, both the return and risk aspects of the stock markets are covered in this study.

The rest of this paper is organized as follows. In Chapter 2 we review the previous evidence regarding empirical regularities and stylized facts between the yield curve and stock markets. Chapter 3 presents the data, while Chapter 4 contains the empirical analysis of this study. Finally, Chapter 5 concludes and discusses the main findings of this study.

2. STYLIZED FACTS AND EMPIRICAL REGULARITIES

2.1. Yield curve, real economy and inflation

It was in the late 1980s that the slope of the yield curve was really noticed as one of the best leading indicator of economy (see e.g. Estrella & Mishkin 1995; Estrella 2005). Monetary policy has a significant influence on the steepness of the yield curve: a rise in the short term rate tends to flatten the yield curve, and vice versa. The yield curve can also flatten if investors loose their faith in the future economic growth and start selling long term bonds, which drives long term rates down. In many cases instant graphical evidence shows that the yield curve tends to be flat or even negative at cyclical peaks. The inversion of the yield curve has turned out to be a precise predictor of the recession. On the other hand, the nearly flat yield curve, i.e. very low positive level of the ten-year minus three-month term spread, has been observed without a subsequent recession (Estrella 2005). However, the nearly flat yield curve has been found to be a sign of a slowdown in economic activity, or in the worst case, of an impending recession. On the other hand, the steep yield curve is usually followed by recovery and growing economy.

During the past twenty years research on forecasting economic activity and inflation has increased significantly. As the simple measure of the yield curve inversion has preceded every recession in the U.S. since 1960 except the recession in 1967, many authors have started to use the term structure to predict real output, real consumption growth and future recessions (e.g. Harvey 1988; Laurent 1988, 1989; Estrella & Hardouvelis 1991; Dueker 1997). Being very simple to use and providing a reasonable combination of accuracy and robustness, Estrella & Mishkin (1996) conclude that the yield curve (ten year Treasury rate minus three-month Treasury note) significantly outperforms the other financial and macroeconomic indicators in predicting recessions in the U.S. The yield curve has reached the status of being celebrated as the single best indicator of economy or as it was expressed in an article in *Fortune*: "A near-perfect tool for economic forecasting" or "an economist-obviation device" (Clark 1996).

The best forecast of future real activity is provided by the level of the term spread, not by the change in the spread, nor even by the source of the change in the spread. If a low or negative value of the spread is reached via an increase in the short-term rate or a decrease in the long-term rate, it is only the low level that matters (Estrella 2005). This stylized fact makes the yield curve a quick check to find out the state of the economy and it gives an instant indication of future changes in real activity.

Although we have a very good rule of thumb that recession is followed by the inversion of the yield curve, there are also some problems. First of all, inversions and recessions are not firmly connected by the economic theory. Even though there are predictive relationships between term spread and future real output, the precise parameters may change over time (Estrella 2005; Dotsey 1998; Haubrich & Dombrosky 1996). Since instability cannot be ruled out by theoretical arguments, it becomes an empirical issue (e.g. Estrella, Rodrigues & Schich 2003). Stock & Watson (2003) found the term spread to be the most reliable single asset price to predict output across countries, even though its good performance in some periods and countries was offset by poor performance in other periods and/or countries. Evidence from Germany and The United States has shown that models predicting real activity are more stable than those predicting inflation (Estrella, Rodrigues & Schirch 2003). Overall, it seems obvious that one should not expect a stable relationship between the term spread and the macroeconomy if economy is responding to both monetary and real shocks.

2.2. Stock market, real economy and inflation

Stock prices almost always fall prior to a recession and rally vigorously at signs of an impending recovery: if you can predict the business cycle, you can easily beat the buy-and-hold strategy (Siegel 2002). A commonly used rule of thumb is that stock market helps to predict future economy approximately half a year beforehand. The results of Estrella & Mishkin (1995) showed that stock prices are useful in macroeconomic predictions with 1–2 quarter horizons, and beyond 2 quarters the slope of the yield curve emerges as the clear choice, and it performs better by itself out of sample than in conjunction with other variables. There is also evidence that stock returns contain information that is useful for predicting growth when the economy is contracting, but in non-recession periods the evidence is less clear (Henry, Olekalns & Thong 2004). The evident problem is that the macroeconomy and the stock market are so often out of sync causing stock market to give misleading signals as Samuelson (1966) expressed it in his famous words. Therefore it is extremely challenging for investors to successfully forecast business cycles and turning points by using stock market data.

If stock prices are too volatile to be justified only by subsequent changes in dividends, then we can expect that volatility may also include information on the path of the economy's future growth. It is common knowledge that stock market volatility is related to the uncertainty of economic activity, and volatility moves counter cyclically, exhibiting high volatility during recessions and when stock prices are falling. In spite of the fact that there are large spikes in stock market volatility, it is striking that in the long run there is so little overall trend in volatility (Siegel 2002). The other stylized fact is that high or low stock market volatility tends to last several months, and even longer during major episodes in economy. Overall, one can conclude that stock market volatility is commonly assumed to be related to the general health of the real economy.

Schwert (1989) found evidence that stock market volatility helps to predict future macroeconomic volatility in the U.S. The volatility measures also helped to forecast GDP growth and greatly diminished the significance of stock index returns in forecasting GDP (Campbell, Lettau, Malkiel & Xu 2002). The results for the U.S. and Germany have shown that stock market volatility contributes significantly to the forecasting of future recessions (Annaert, De Ceuster & Valckx 2001). Guo (2002b) concluded that even though both stock market volatility and returns forecast output in the U.S., the information from stock returns is more important. There is also evidence that episodes of excess volatility may not have substantial real economic effects (Kupiec 1991). Stock and Watson (2003) showed that asset prices are more useful in predicting output growth than inflation. On the other hand, other information beyond the yield curve spread can be useful in forecasting inflation (Estrella 2004). Junttila & Kinnunen (2004) reported that the new economy stock returns have clear forecasting power for future inflation and changes in industrial production in the Finnish economy at short horizons. Junttila (2007) found it possible to forecast inflation in the U.S., Italy, France and Germany by using financial information.

3. DATA

3.1. Variables

The Finnish data set consists of the following financial market variables: stock returns (R), term spread (TS), stock market volatility (VOLA), change of stock market volatility (DVOLA), and the following macroeconomic variables: GDP growth (Y), private consumption growth (C), industrial production growth (IP), consumer price inflation (P).

Nominal stock market returns were constructed from daily logarithmic changes of the Finnish general stock market index (HEX, renamed to OMX in 2005) received from the ETLA database and from OMX. The stock market returns were defined as quarterly average of logarithmic daily returns.[1] In order to measure risk in stock markets, and thus in economy, stock market volatility variable was constructed as standard deviation of daily logarithmic stock returns over a quarterly interval. The term spread was constructed by calculating the difference between the 10-year government bonds and the 3-month interest rates. The quarterly interest rates were calculated from average daily observations. The daily interest rates were obtained from ETLA's databank and from the Bank of Finland. The consumer price index and the time series for the real GDP and private consumption were retrieved from the OECD Economic Outlook and the

[1] Note that defined this way, the variable does not represent the conventional definition of a quarterly stock return. However, multiplication of the daily average return by the number of market days in a quarter yields conventionally defined quarterly return. Thus, the time series behavior of the daily average stock returns is exactly same as the conventionally defined quarterly stock returns.

industrial production from the OECD Main Economic Indicators databases.[2] The macrovariables were transformed in logs and differenced, and the analysis was carried out by using annualized quarterly growth rates. The quarterly data cover the period 1987:1–2006:4 (80 observations).[3]

Table 1. Descriptive statistics of the data.

	C	P	IP	Y	DVOLA	TS	R	VOLA
Mean	2.26	2.28	3.89	2.49	0.00	1.20	0.17	1.51
Median	3.15	1.78	5.03	3.04	-0.03	1.21	0.40	1.15
Maximum	7.86	9.66	22.53	14.83	1.77	4.68	4.03	4.24
Minimum	-5.10	-1.66	-25.00	-8.29	-1.95	-2.85	-2.79	0.39
Std. Dev.	3.34	2.43	8.86	4.43	0.59	1.56	1.07	0.89
Skewness	-0.94	0.86	-0.52	-0.44	-0.13	-0.42	0.19	1.11
Kurtosis	2.97	3.40	3.71	3.45	5.40	3.72	4.37	3.44
Jarque-Bera (P-value)	11.59 (0.00)	10.38 (0.01)	5.16 (0.08)	3.26 (0.20)	19.16 (0.00)	4.00 (0.14)	6.62 (0.04)	16.88 (0.00)

Notes: C = quarterly private consumption growth (annualized), P = quarterly inflation rate (annualized), IP = quarterly industrial production (annualized), Y = quarterly GDP growth (annualized), DVOLA = change of standard deviation of stock returns, TS = term spread, R = stock returns, VOLA = standard deviation of stock returns. Jarque–Bera refers to the normality test, H_0: variable is distributed normally. The sample period is 1987:2–2006:4.

Descriptive statistics in Table 1 show that during the twenty years sample period the average annual GDP growth in Finland has been about 2.5 %. The growth of private consumption has been about 2.2 % while the growth has been highest in industrial production, almost 4 % annually. Moreover, industrial production has been clearly the most volatile of the macrovariables measured by standard deviation. The average inflation rate has been a little over 2 %. During the sample period the average difference between the long and short interest rates has been 1.2 % and the average stock returns have been about 10 % annually[4].

[2] Industrial production is seasonally adjusted due to a strong and distinct seasonal pattern in the raw data series. The seasonal adjustment was carried out using the U.S. Cencus Bureau's X12 seasonal program (for details, see Quantitative Micro Software 2004).
[3] Due to differencing the effective sample in the empirical analysis is 1987:2-2006:4 (79 observations).
[4] Note that the stock returns have been defined as quarterly average of daily returns. Thus annual average returns are 62×0.17%=10.5% (c.f. Table 1) assuming 62 market days during the quarter on average.

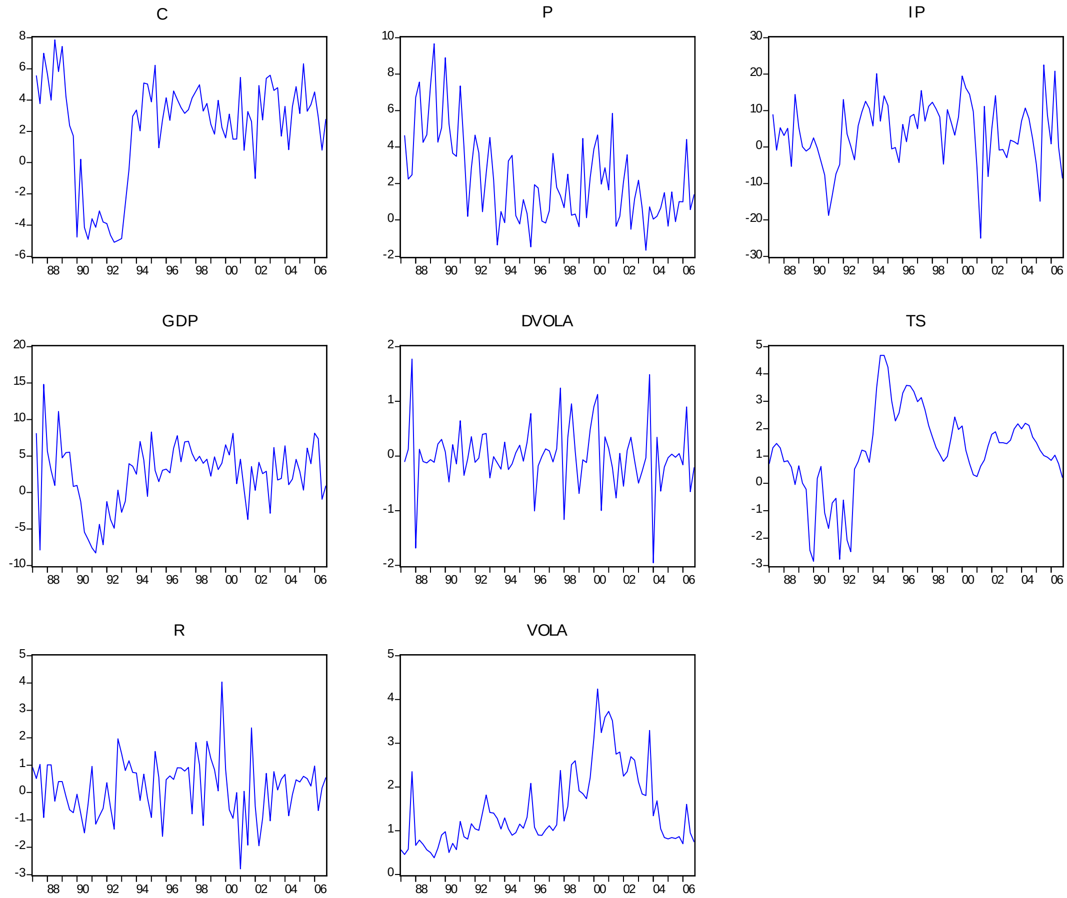

Figure 1. The time series of the data.

3.2. Research period

Figure 1 illustrates the time series of this study. The research period 1987–2006 covers many changes and transformations in the Finnish economy. In the beginning of the 1990s the Finnish economy was hit by one of the worst recessions in the western world after the 1930s: the real GDP and dropped amazing 13.5 % and the private consumption declined by 12.4 % during the three years period from 1990:2 to 1993:2. After the depression the Finnish economy has experienced a long lasting recovery. The recovery was accompanied by positive and steeping yield curve reaching its peak (about 4.70 %) at the end of 1994 after which the difference between the long and short rates has been decreasing steadily but has nonetheless stayed positive. The real GDP grew from 1993 to 2000 on average 4.7 % per year. During the 2000s the economic growth has slowed down a little, the average growth being nevertheless a good 3 % annually during 2000–2006.

The Finnish stock markets have fluctuated tremendously during the research period. We have seen 68% crash from 1989.2 to 1992.3 and 71% crash from 2000.1 to 2003.1, but also 2600 % boom from 1992.3 to 2000.1 in the general stock index. After the bursting of the IT-bubble in the beginning of the 2000s there was a clear drop in the stock markets for couple of years. During the sample period the stock market volatility seems to have had an upward trend until the beginning of the year 2000, after which volatility has decreased substantially.

4. EMPIRICAL RESULTS

4.1. Estimation models

While there is a large body of empirical evidence of the relationship between the yield curve and macroeconomy, standard theory of the relationship is lacking as Estrella (2005) points it out. Usually the relation between the yield curve and economic activity has been justified by the expectations theory of the term structure and the Fisher equation. Estrella (2005) shows theoretically that yield curve should have predictive ability for output and inflation in most cases and that the forecasting ability of yield curve is related to monetary policy reaction function. Furthermore, Estrella's theoretical results suggest that other information beyond the yield curve can be useful in forecasting output and inflation. Given this and the generally assumed forward-looking stock markets[5], it is interesting to compare the forecasting ability of yield curve with stock market variables.

[5] Theoretically the connection between stock market and macroeconomic future arises from the fact that revisions of equity valuation are related to expected changes of macroeconomic variables. For a more formal modeling of this, see e.g. Junttila (2007).

In this study we analyze the forecasting ability of term spread and stock market variables by estimating the following models and basing out–of–sample forecasts on them:

(1) $$X_{t+k} = \alpha + \beta_1 TS_t + u_{t+k}$$

(2) $$X_{t+k} = \alpha + \beta_2 R_t + \beta_3 VOLA_t + \beta_4 \Delta VOLA_t + u_{t+k}$$

(3) $$X_{t+k} = \alpha + \beta_1 TS_t + \beta_2 R_t + \beta_3 VOLA_t + \beta_4 \Delta VOLA_t + u_{t+k}$$

The vector *X* contains the Finnish GDP growth (Y), private consumption growth (C), industrial production growth (IP) and inflation rate (P), i.e. X = (Y, C, IP, P) and *u* is an error term of the regression. We consider three forecasting horizons: one quarter (*k*=1), half year (*k*=2) and one year (*k*=4) horizons. The in–sample estimation period is 1987:2–2001:4 and the out–of–sample forecasts are conducted for the five-year period 2002:1–2006:4.

The model set-up can be characterized as follows: model (1) takes in account only the information from the term spread while model (2) contains only the stock market variables. Finally model (3) combines both the information from the term spread and from the stock market variables. The modeling philosophy behind the equations (1-3) is based on the conventional assumption that the last observations of financial market data contain all the relevant information regarding macroeconomic future. Therefore no additional lags of the explanatory variables are introduced into the models.

Our analysis shares certain features with Junttila & Kinnunen (2004). Junttila & Kinnunen (2004) scrutinized an economic tracking portfolio (ETP) approach for forecasting macroeconomic variables in Finland and compared it with the forecasting ability of the dividend yield and the term spread. The macroeconomic variables were the same as in our study but their analysis period was shorter (1991–1999). The out–of–sample forecasting results of Junttila & Kinnunen (2004) showed that the model with industry portfolios outperformed the benchmark VAR model in all cases. Moreover, the pure ETP model outperformed also the model specification which included both the industry portfolios and the control variables of their analysis (dividend yield and term spread) in the case of GDP and industrial production growth and inflation. Only in the case of private consumption their combined model specification with the industry portfolios and the control variables performed better. Thus, Junttila & Kinnunen's results provided support for using industry based portfolios in forecasting the macroeconomy in Finland. However, from a practical point of view, e.g. due to reconstruction in industrial based stock indexes which has often taken place in Finland, it clearly would be advantageous if the relevant information from the stock market could be captured by means of the general stock market index. Although one of the main claims of Junttila & Kinnunen (2004) was that this is not the case, we aim to reconsider this issue by enriching the stock market information set with stock market volatility and changes in volatility. We assume that stock market volatility measures the degree of uncertainty of the macroeconomic future and the changes in stock market volatility capture the changes in uncertainty. Thus, our stock market variable setup captures both the growth (returns) and the risk (volatility) information regarding the macroeconomic future.

Existing empirical evidence regarding the stock market volatility and the future output appears to be rather mixed. Positive evidence has been reported by Campbell et al. (2002) for the U.S. and Annaert et al. (2001) for the U.S., Germany and Japan. Kupiec (1991) analyzed the relation between the average levels of volatility in financial markets and economic activity in OECD in the late 1980s and found no evidence on this. However, Finland was not included into Kupiec's study. To our knowledge, potential role of stock market volatility in macroeconomic forecasting has not been addressed previously for the Finnish economy.

4.2. Preliminary analysis of the data

As a preliminary assessment of the degree of correlation between the financial market and the macroeconomic, Table 2 presents pair-wise cross correlations between the financial market and macroeconomic variables for the whole sample period 1987:1–2006:4.

It can be seen that of the four financial market variables of the study, the term spread has generally the highest correlation with the macroeconomic variables, while the stock market volatility and especially its change have the lowest correlations.

Table 2. Cross correlations of the financial market and the macroeconomic variables.

	TS_{t-k}					R_{t-k}			
	k=0	k=1	k=2	k=4		k=0	k=1	k=2	k=4
Y_t	**0.47**	**0.47**	**0.52**	**0.49**		0.17	0.17	**0.40**	0.20
C_t	**0.56**	**0.61**	**0.63**	**0.63**		0.09	0.12	0.22	**0.23**
IP_t	**0.37**	**0.33**	**0.30**	0.19		0.04	**0.43**	**0.29**	**0.27**
P_t	**-0.43**	**-0.44**	**-0.40**	**-0.31**		-0.02	-0.05	-0.08	0.15
	$VOLA_{t-k}$					$dVOLA_{t-k}$			
	k=0	k=1	k=2	k=4		k=0	k=1	k=2	k=4
Y_t	0.13	0.09	-0.00	0.16		0.09	0.09	-0.02	0.12
C_t	0.05	0.10	0.11	**0.25**		-0.05	-0.01	-0.13	-0.01
IP_t	0.05	0.05	0.03	-0.05		0.01	0.02	0.09	-0.13
P_t	-0.19	-0.19	-0.20	**-0.25**		0.01	0.02	0.20	0.04

Notes: Bolded figures refer to the statistically significant correlation coefficients at the 5% significance level.

The signs of the correlation coefficients are as presumed for the term spread, the stock returns and the macroeconomic variables. A priori one would have expected negative correlation between the stock market volatility and the macroeconomy. Surprisingly the correlations are found to be positive (10/16) but insignificant in majority of the cases (14/16). The correlation between the stock market volatility and inflation is negative as expected but statistically significant only if the stock market volatility is lagged by four quarters. Finally, all the correlations between the change of stock market volatility and the macrovariables turn out to be statistically insignificant.

Generally, the correlations tend to increase with the lagged values of the financial market variables. This appears to be encouraging in terms of the forecasting potential of the financial market data. Most distinctively this happens with the stock market returns. Overall, this preliminary correlation analysis provides some support for the potential role of financial market variables in forecasting the macroeconomy. The correlation between the macroeconomic and financial market variables is strongest for the term spread, but significant correlation is detected with the stock returns as well. On the other hand, the correlations between the stock market volatility and especially its change and the macrovariables are less encouraging, the correlation is generally found to be rather low, insignificant and often unexpectedly signed.

4.3. Estimation and out-of-sample forecasting results

The empirical analysis consists of estimating the models (1–3) and conducting out-of-sample forecasts with the estimated models. We used 1987:2–2001:4 for estimation and 2002:1–2006:4 for forecasting period.

The in-sample estimation results:

The empirical forecasting models of this study are based on the conventional assumption that relevant information of the macroeconomic future should be reflected in the current values of the financial and stock market variables used in the study. Therefore any experiments with more general lag structures were not attempted. The Newey-West estimator was applied to correct the influence of potential serial correlation and heteroscedasticity on standard errors of the estimates (e.g. Stock & Watson (2003) and Junttila & Kinnunen (2004). Table 3 presents the in-sample estimation results.

Table 3a. In-sample estimation results.

	dY(t+1)	**dY(t+1)**	**dY(t+1)**	**dY(t+2)**	**dY(t+2)**	**dY(t+2)**	**dY(t+4)**	**dY(t+4)**	**dY(t+4)**
Constant	0.84 (0.38)	0.84 (0.68)	-0.16 (0.93)	0.53 (0.53)	1.32 (0.49)	0.30 (0.86)	0.61 (0.54)	0.31 (0.87)	-0.63 (0.69)
b1 TS(t)	**1.35 (0.00)**		**1.28 (0.00)**	**1.54 (0.00)**		**1.28 (0.00)**	**1.39 (0.00)**		**1.27 (0.00)**
b2 SR(t)		**1.13 (0.03)**	0.57 (0.17)		**2.03 (0.00)**	**1.44 (0.01)**		**1.41 (0.07)**	0.83 (0.19)
b3 SRVola(t)		0.78 (0.34)	0.80 (0.43)		0.42 (0.57)	0.23 (0.73)		0.98 (0.36)	0.73 (0.42)
b4 dSRVola(t)		0.90 (0.17)	**0.99 (0.06)**		0.42 (0.65)	0.47 (0.53)		1.45 (0.16)	**1.55 (0.09)**
Adj.R^2 / DW	0.23 / 1.71	0.09 / 1.27	0.30 / 1.65	0.32 / 1.50	0.18 / 1.00	0.45 / 1.25	0.32 / 1.18	0.13 / 0.92	0.39 / 1.20
	dC(t+1)	**dC(t+1)**	**dC(t+1)**	**dC(t+2)**	**dC(t+2)**	**dCt+2)**	**dC(t+4)**	**dC(t+4)**	**dC(t+4)**
Constant	0.45 (0.57)	0.87 (0.61)	-0.12 (0.94)	0.33 (0.62)	0.44 (0.78)	-0.55 (0.66)	0.19 (0.79)	-0.33 (0.83)	-1.22 (0.24)
b1 TS(t)	**1.28 (0.00)**		**1.26 (0.00)**	**1.32 (0.00)**		**1.25 (0.00)**	**1.30 (0.00)**		**1.19 (0.00)**
b2 SR(t)		0.68 (0.16)	0.12 (0.75)		**0.92 (0.05)**	0.35 (0.32)		**1.12 (0.04)**	0.58 (0.12)
b3 SRVola(t)		0.55 (0.39)	0.33 (0.55)		0.81 (0.16)	0.62 (0.18)		**1.20 (0.05)**	**0.97 (0.02)**
b4 dSRVola(t)		-0.05 (0.93)	0.04 (0.92)		-1.00 (0.18)	-0.95 (0.14)		-0.31 (0.65)	-0.22 (0.71)
Adj.R^2 / DW	0.38 / 0.76	0.00 / 0.46	0.37 / 0.77	0.41 / 0.87	0.07 / 0.52	0.43 / 0.89	0.42 / 0.88	0.13 / 0.72	0.47 / 1.12
	dIP(t+1)	**dIP(t+1)**	**dIP(t+1)**	**dIP(t+2)**	**dIP(t+2)**	**dIP(t+2)**	**dIP(t+4)**	**dIP(t+4)**	**dIP(t+4)**
Constant	1.85 (0.28)	1.05 (0.43)	-0.00 (0.99)	1.90 (0.25)	3.07 (0.33)	1.84 (0.52)	2.65 (0.23)	3.35 (0.35)	2.76 (0.45)
b1 TS(t)	**1.97 (0.01)**		**1.35 (0.05)**	**1.83 (0.01)**		**1.55 (0.02)**	1.19 (0.22)		0.79 (0.39)
b2 SR(t)		**4.31 (0.00)**	**3.71 (0.00)**		**2.63 (0.02)**	**1.92 (0.08)**		**2.84 (0.02)**	**2.48 (0.02)**
b3 SRVola(t)		1.38 (0.32)	1.15 (0.36)		0.14 (0.94)	-0.10 (0.95)		-0.04 (0.99)	-0.19 (0.93)
b4 dSRVola(t)		1.42 (0.28)	1.52 (0.23)		**3.02 (0.05)**	**3.08 (0.02)**		-1.73 (0.51)	-1.67 (0.53)
Adj.R^2 / DW	0.14 / 1.47	0.25 / 1.49	0.31 / 1.62	0.12 / 1.37	0.06 / 1.73	0.14 / 1.76	0.04 / 1.24	0.08 / 1.52	0.09 / 1.52

Notes: Estimation period 1987:1-2001:4. dY = GDP growth, dC = private consumption growth, dIP = industrial production growth, TS = term spread (interest rate spread), SR = Stock returns, SRVola = volatility of the stock returns. Standard errors are based on Newey-West corrected standard errors. Figures in parentheses are *p*-values.

Table 3b. In-sample estimation results.

	dP(t+1)	dP(t+1)	dP(t+1)	dP(t+2)	dP(t+2)	dP(t+2)	dP(t+4)	dP(t+4)	dP(t+4)
Constant	**3.42 (0.00)**	**3.64 (0.00)**	**4.13 (0.00)**	**3.30 (0.00)**	**3.99 (0.00)**	**4.39 (0.00)**	**3.18 (0.00)**	**3.71 (0.00)**	**4.07 (0.00)**
b1 TS(t)	**-0.65 (0.00)**		**-0.63 (0.00)**	**-0.56 (0.00)**		**-0.51 (0.01)**	**-0.44 (0.03)**		**-0.48 (0.02)**
b2 SR(t)		-0.29 (0.33)	-0.01 (0.97)		-0.32 (0.31)	-0.09 (0.77)		**0.35 (0.10)**	**0.56 (0.02)**
b3 SRVola(t)		-0.63 (0.17)	-0.52 (0.17)		**-0.89 (0.06)**	**-0.82 (0.05)**		-0.89 (0.11)	-0.80 (0.13)
b4 dSRVola(t)		0.27 (0.63)	0.22 (0.65)		**1.31 (0.00)**	**1.29 (0.00)**		0.46 (0.309	0.42 (0.34)
Adj.R^2 / DW	0.18 / 1.25	0.00 / 1.10	0.17 / 1.34	0.14 / 1.20	0.09 / 1.08	0.20 / 1.22	0.08 / 1.07	0.03 / 1.02	0.12 / 1.17

Notes: dP = inflation rate. Otherwise, see Table 3a.

Some general remarks appear noteworthy regarding the in-sample estimation results:

- The explanatory power of the GDP and the consumption growth equations are generally better than that of the industrial production and inflation equations.
- Of the three model specifications, the specification (3) containing both the term spread and the financial market variables tends to fit the data best.
- The consumption growth estimations suffer from a rather severe autocorrelation on the basis of the DW test statistics. As autocorrelation may be a symptom of misspecification, some important explanatory variable may be missing from the consumption equations.[6]
- Of the four explanatory variables, the term spread is statistically significant in 22 out of 24 cases being clearly the single most important variable in terms of the statistical significance.
- Statistically the stock returns are a more significant explanatory variable than the stock market volatility or the changes in volatility.
- The stock returns are consistently significant in the industrial production equations.
- The stock market volatility or its change appears to have only a little and non-systematic predicting ability.[7]
- The constant terms are consistently significant in inflation equations suggesting that inflation is affected by some systematic factor that the explanatory variables cannot capture.

[6] Though the DW test statistics are by no means "clean" for the other macrovariables, the problem appears not to be as severe as in the case of the consumption equations.

[7] It may also be noteworthy that the signs of the volatility variables are usually positive contrary to theoretically assumed negative relationship between the stock market volatility and the macroeconomy. Consumption equations provide an exception here (changes of the stock market volatility variable), but the estimates are insignificant.

Stability:

Predictive relationships may not remain stable over time and this may cause severe consequences for the forecasting performance of the econometric model. Because applied forecasting models rarely are very structural and are not derived from deep structural parameters, instability becomes an empirical issue which should be tested in practice as was stressed by Estrella et al. (2003). The predictive power of the yield curve may depend for example on the relative importance of real and nominal shocks and changes in a monetary policy reaction function (Estrella et al. 2003; Estrella 2005). In view of the turbulent sample period we consider the stability of the models first before turning into the forecasting results.

Although the estimation period for the is 1987:2–2001:4, we carried out the stability tests for the whole sample period up to 2006:4 to uncover a possible break due to the monetary transition to euro at the beginning of 2002. We employed two stability tests, the Andrews-Quandt structural break test (Andrews 1993; Andrews & Ploberger 1994) to test for a single unknown structural breakpoint within the sample, and the Chow test to test for a break in 2002:1 due to a change in the monetary policy reaction function as the European Central Bank took charge of the monetary policy. The stability test results are presented in Appendix 1. The results suggest that the stability concern is relevant mainly in the case of inflation relations. This is consistent with the results of Estrella et al. (2003) regarding the U.S. and Germany. The GDP and the industrial production growth relations were found to be stable, but some instability was detected in the private consumption growth associated to the recession in the beginning of the 1990s. Regarding the inflation models instability was detected both in the beginning of the 1990s and in the beginning of the 2002. It may be noteworthy that the inflation relations based on the mixed model including both the yield curve and the stock market variables were found to be stable.

Static out-of-sample forecasting results:

Static forecasts were calculated for the out-of-sample forecasting period 2002:1–2006:4. In static forecasts the actual values of the explanatory variables were used for the calculation of the forecasts. The forecasting performance was evaluated by means of the root mean squared error (RMSE) of the forecasts.

We used the random walk as a benchmark since beating random walk can be regarded as the minimum requirement for successful forecasts. The forecast horizons were taken into account when calculating the RMSEs. Accordingly the following random walk models were specified:

(4) $$X_{t+i} = X_t + u_{t+i}, \qquad i=1,2,4$$

When evaluating the forecasting performance, we will denote the models as follows: model (1) “the term spread model”, (2) “the stock variable model”, (3) “the mixed model”, and (4) “the random walk model”.

The out-of-sample forecasting results are presented in Table 4. The best forecast, i.e. the lowest RMSE, of each forecast horizon can be read from the rows while the total forecasting ability is evaluated by summing up each forecast horizons RMSEs (e.g. Junttila & Kinnunen 2004; Junttila 2007).

The results indicate that for the GDP growth the simple term spread model yields the lowest RMSEs outperforming the other forecasting models in all the forecasting horizons. It is also good to note that the mixed model specification (3) with both the stock market variables and the yield curve yields better forecasts than the pure stock market model (2). However, all the three model specifications are capable of beating random walk.

The strong performance of the term spread model shows up in forecasting the consumption growth yielding the lowest forecast errors on one and two-quarter forecast horizons. However, on the four-quarter forecast horizon the mixed model outperforms the simple term spread model suggesting that the stock market information becomes important on longer horizons. Note also that the mere stock market variable model (2) is not capable of beating the simple random walk model on one and two-quarter forecasting horizons while both the term spread and the mixed model outperform the random walk consistently in forecasting consumption growth. The relatively weak performance of the stock market variables model in forecasting private consumption growth appears rather surprising.

Table 4. Out-of-sample static forecasting results.

	(1) TERM SPREAD MODEL	(2) STOCK MARKET MODEL	(3) MIXED MODEL	(4) RANDOM WALK
dY				
t+1	**2.92**	3.34	3.17	4.22
t+2	**2.88**	3.19	2.90	4.12
t+4	**2.81**	3.57	3.24	4.32
Sum	**8.61**	10.1	9.31	12.66
dC				
t+1	**2.12**	2.64	2.21	2.51
t+2	**2.03**	2.58	2.12	2.23
t+4	2.03	2.53	**1.91**	3.25
Sum	**6.18**	7.75	6.24	7.99
dIP				
t+1	**8.95**	9.12	9.01	12.86
t+2	9.00	**8.57**	8.69	14.56
t+4	**8.93**	9.13	9.11	16.49
Sum	26.88	26.82	**26.81**	43.91
dP				
t+1	1.93	2.13	**1.88**	1.99
t+2	1.92	2.04	**1.82**	2.01
t+4	2.01	1.82	1.68	**1.42**
Sum	5.86	5.99	**5.38**	5.42

In the case of industrial production growth, the forecasting performance of the simple term spread models shows up positively yielding the lowest RMSE on one and four-quarter forecast horizons. However, on two-quarter forecast horizon, the mere stock variable model performs best. Overall, the RMSEs of the industrial production growth forecasts are much bigger than for those of the other macrovariables of the study[8] and the forecasting ability of the all three models is very similar. This is seen by the fact that the model specification (3) yields the best overall forecasting performance though no single RMSE on any forecast horizon is the best for the mixed model (3).

While the results concerning the GDP, the consumption and the industrial production growth provide rather strong support for the forecasting ability of the simple term spread model, this is not the case with inflation. On all forecasting horizons the mixed model specification (3), which contains both the term spread and the stock market variables, forecasts inflation better than the mere term spread model (1) or the mere stock variables model (2). Thus, stock market variables seem to contain relevant additional information beyond the term spread in forecasting inflation. What is rather surprising, however, is the finding that the simple random walk outperforms all the other models on four-quarter forecast horizon. Note also that on all forecast horizons the simple random walk model consistently yields better inflation forecasts than the mere stock variable model (2).

Recursive out-of-sample forecasting results:

Static forecasting results are based on the estimation results from the period 1987:2–2001:4. However, in practice the five years out-of-sample forecasting period may be too long. Therefore we also calculated recursive forecasts by first running the regression through 2001:4 and computing forecasts for 2002:1, 2002:2 and 2002:4. Then by

[8] This is consistent with Junttila's (2007) results from an international data set but inconsistent with Junttila & Kinnunen's (2004) results from the Finnish economy. Junttila (2007) studied financial market variables ability to forecast inflation and industrial production growth with the data set consisting of the U.S., Italy, Germany and France. Junttila & Kinnunen (2004) used an economic tracking portfolio approach for forecasting macroeconomy in Finland. The same macrovariables were analyzed than in our study. However, the sample period was shorter. (1991-1999).

estimating the models through 2002:1 and computing forecasts for 2002:2, 2002:3 and 2003:1, and so on.[9] The recursive forecasting results are presented in Table 5.

Table 5. Out-of-sample recursive forecasting results.

	(1) TERM SPREAD MODEL	(2) STOCK MARKET MODEL	(3) MIXED MODEL	(4) RANDOM WALK
Y				
t+1	**2.94**	3.30	3.15	4.22
t+2	**2.90**	3.14	2.92	4.12
t+4	**2.83**	3.45	3.2	4.32
Sum	**8.67**	9.89	9.27	12.66
C				
t+1	**2.07**	2.53	2.18	2.51
t+2	**1.97**	2.5	2.12	2.23
t+4	1.92	2.42	**1.87**	3.25
Sum	**5.96**	7.45	6.17	7.99
IP				
t+1	**8.98**	9.21	9.12	12.86
t+2	9.04	**8.67**	8.81	14.56
t+4	**8.99**	9.36	9.40	16.49
Sum	**27.01**	27.24	27.33	43.91
P				
t+1	1.80	2.01	**1.79**	1.99
t+2	1.78	2.04	**1.76**	2.01
t+4	1.85	1.81	1.68	**1.42**
Sum	5.43	5.86	**5.23**	5.42

A priori one would have expected that the recursive forecasting scheme had yielded better forecasts than the static ones. This happens in forecasting the consumption and industrial production growth, but not in the case of the GDP growth or inflation. However, the differences between the static and the recursive forecasts are rather small. As to the relative forecasting performance, the results remained very similar.

[9] An alternative would have been to use moving forecasting window as e.g. in Junttila & Kinnunen (2004) and Junttila (2007). Moving forecasting window has the advantage of increasing the number of forecasts, while the recursive forecasting may describe the practical forecasting situation more realistically.

4.3. Analysis of the results

The empirical evidence in this study has shown that there is a lot of wisdom in the stylized facts and the rules of thumb as far as the slope of the yield curve is concerned, and a small open economy like Finland makes no exception in that respect. The simple measure of the slope of the yield curve, the spread between 10-year and 3-moth interest rates, turned out to be a very useful predictor and a leading indicator of the real economy across the range of forecasting horizons examined. The importance of the stock market variables in predicting the real economy turned out to be much smaller than what was supposed a priori. Stock market volatility and returns contained some additional information about future inflation, but otherwise the stock market variables had a minor role in the out-of-sample predictions.

If recession is defined as a decline in GDP for two or more consecutive quarters, the Finnish economy has been in recession only once during the sample period from 1987 to 2006. The very deep recession, or we can say depression, in Finland lasted from 1990.2 to 1993.2 and was preceded by the steep inversion of the yield curve. Even though this was the only occasion during which the term spread turned negative in our sample, it suggests that the inversion of the yield curve anticipates serious economic consequences for small economy as well.

In this study we were able to verify many previous results in other studies. The slope of the yield curve, especially the term spread, turned out to be a very important tool in explaining and forecasting economy (Estrella 2005; Dotsey 1998; Dueker 1997; Estrella & Mishkin 1996; Haubrich & Dombrosky 1996; Estrella & Hardouvelis 1991). We found out that it is more difficult to predict inflation than the real variables. Consequently, some caution should be exercised in using the term spread as a guide for assessing inflationary pressures in the economy (Estrella 2004; Estrella, Rodrigues & Schirch 2003; Mishkin 1988). However, the results of Stock & Watson (2003) – asset prices being more useful in forecasting output growth than inflation – are opposite to what we have found out. We were able to verify the empirical regularity that models based on the term structure tend to explain 30 percent or more of the variation in real GDP (Estrella 2005). We also found out that the instability of the models can be a problem (Stock & Watson 2003) and models that predict real activity are more stable than those that predict inflation (Estrella, Rodrigues & Schirch 2003).

Consistent with Kupiec (1991) we did not find any strong evidence that increase in stock market volatility had serious negative effects on economic activity. On the other hand, our results are in contrast with those studies which emphasize stock market returns or volatility as good leading indicators of the real economy (Junttila 2007; Junttila & Kinnunen 2004; Guo 2002a; Guo 2002b; Annaert, De Ceuster & Valckx 2001; Campbell, Lettau, Malkiel & Xu 2002).

5. CONCLUSIONS

This paper has dealt with the usefulness of financial market variables in forecasting macroeconomy in small open economy. More specifically, we have compared the forecasting content of stock market variables with the term spread, which previously have been found to be very useful and robust predictors for macroeconomy in the US and the main industrial countries. As a novel feature we have explicitly addressed the role of stock market volatility, i.e. the risk aspects, as a potential predictor for the macroeconomy.

The results from the Finnish economy suggest that the forecasting content of the term spread is to be preferred over the stock market variables in forecasting macroeconomy. The simple term spread model yielded better out-of-sample forecasts for the GDP, the industrial production and the private consumption growth. Only in the case of inflation, augmenting the simple term spread model with the stock market variables yielded better forecasts than the simple term spread model. Regarding the stock market variables, the main predictive content was found to be included into the stock returns and augmenting the predictive variables set by stock market volatility turned out to be rather insignificant.

We also found out that the ability of financial market variables to forecast economic activity is better than their abilities to forecast inflation. Likewise, the inflation models were found to be unstable. As a whole, our results are to a large extent consistent with previous results from other main industrial countries. Thus our results provide evidence that the significant predictive content of term spread holds also true in small open economies. From a practical point of view, the results stress the importance of the simple term spread in the economist's toolbox. Although stock market information appears very natural and obvious in forecasting macroeconomic future, the results of this study suggest that much more attention should be paid to the simple term spread.

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Appendix 1. Stability test results for the whole sample period 1987:2-2006:4.

	i = 1 (a)	i = 1 (b)	i =1 (c)	(a) i = 2 (a)	(b) i = 2 (b)	(c) i = 2 (c)	(a) i = 4 (a)	(b) i = 4 (b)	(c) i = 4 (c)
dY(t+i)									
Max LR	5.12 (0.54)	4.67 (0.95)	2.02 (1.00)	3.58 (0.80)	6.76(0.76)	5.61 (0.97)	9.66 (0.11)	12.02 (0.21)	8.74 (0.69)
Break date									
Ave LR	0.96 (0.80)	1.76 (0.95)	0.74 (1.00)	1.05 (0.76)	3.11(0.62)	1.99 (0.98)	1.87 (0.42)	6.18 (0.12)	3.91 (0.66)
Chow	0.46 (0.63)	0.82 (0.52)	0.59 (0.71)	0.30 (0.74)	0.81(0.53)	0.44 (0.82)	0.14 (0.87)	1.19 (0.32)	0.74 (0.60)
dC(t+i)									
Max LR	**15.29 (0.01)**	11.92 (0.22)	9.51 (0.60)	9.86 (0.10)	10.31(0.35)	6.29 (0.93)	**13.43 (0.02)**	11.80 (0.23)	7.97 (0.78)
Break date	1990:3						1993:3		
Ave LR	3.94 (0.08)	4.01 (0.41)	3.34 (0.78)	3.98 (0.08)	3.79(0.46)	2.72 (0.90)	4.12 (0.07)	5.17 (0.22)	3.09 (0.83)
Chow	1.46 (0.24)	1.46 (0.23)	0.90 (0.49)	1.33 (0.27)	1.31(0.28)	0.82 (0.54)	2.11 (0.13)	1.31 (0.27)	0.79 (0.56)
dIP(t+i)									
Max LR	2.12 (0.98)	2.18 (1.00)	1.99 (1.00)	2.37 (0.96)	2.60(1.00)	1.41 (1.00)	6.65 (0.33)	5.87 (0.86)	3.97 (0.99)
Break date									
Ave LR	0.72 (0.91)	0.85 (1.00)	0.65 (1.00)	0.90 (0.83)	1.08(1.00)	0.65 (1.00)	1.12 (0.72)	3.54 (0.52)	1.94 (0.99)
Chow	0.28 (0.76)	0.47 (0.76)	0.31 (0.91)	0.51 (0.60)	0.17(0.95)	0.31 (0.91)	0.33 (0.72)	0.27 (0.90)	0.30 (0.91)
dP(t+i)									
Max LR	**22.41 (0.00)**	14.32 (0.10)	8.45 (0.72)	**23.83 (0.00)**	14.34(0.10)	9.71 (0.58)	**30.64 (0.00)**	**18.53 (0.02)**	11.72 (0.36)
Break date	1991:2			1991:3			1991:3	1993:2	
Ave LR	**7.13 (0.01)**	5.46 (0.18)	2.71 (0.90)	**7.69 (0.01)**	**7.90(0.04)**	5.09 (0.41)	**8.79 (0.00)**	7.25 (0.06)	4.51 (0.52)
Chow	**3.39 (0.04)**	1.92 (0.12)	1.27 (0.29)	**3.35 (0.04)**	1.85(0.13)	1.31 (0.27)	**3.34 (0.04)**	1.22 (0.31)	0.91 (0.48)

Notes: Max LR = the *Andrews-Quandt* maximum LR F-statistic.structural break test. *Break date* = the break date suggested by the Andrews-Quandt test. Ave LR = the *Andrews-Quandt* average LR F-statistic.structural break test. Chow = the Chow structural break test for the beginning of the EMU period (2002:1). The null hypothesis: no structural break. i = forecast horizon. The model specifications: (a) term spread model, (b) stock market model, (c) mixed model (both term spread and the stock market variables included). P-values in parentheses. P-values for the Andrews-Quandt tests are based on Hansen's (1997) approximations.