Forecasting GDP Growth with Financial Market Data in a Small Open Economy: Revisiting Stylized Facts during the Financial Crisis

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ABSTRACT

This paper examines the ability of financial variables to predict future economic growth above and beyond the history dependence of economic activity in a small open economy in the euro area. We also aim to clarify potential differences in forecasting economic activity during steady growth periods and economic turbulence.

Our results from Finland suggest that the proper choice of forecasting variables is related to general economic conditions. During steady economic growth, the preferable choice of a financial indicator is the short-term interest rate combined with past growth. However, during economic turbulence, the traditional term spread and stock returns play a more dominant role in forecasting GDP growth. This phenomenon may be exacerbated if the central bank implements a zero interest rate policy.

KEYWORDS: Term Spread, Short rate, Stock Market, Forecasting, Macroeconomy

JEL CLASSIFICATION: E44, E47

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1. INTRODUCTION

What GDP growth will occur in your country during the next quarter or the next year? Because economic growth is known to be positively serially correlated, during steady economic conditions, the persistence of growth provides a natural starting point for predicting future economic growth. However, economic turmoil poses additional challenges to forecasting. Economists would certainly like to have more predictors of economic growth than the persistence of growth. Financial market data are forward-looking aggregators of information that are easy to interpret and are observed in real time without measurement errors. Therefore, since the beginning of the 1980s, the potential for utilizing financial market information to forecast future economic activity has been explored. Certain financial variables, such as interest rates, term spreads and stock returns, are examples of readily available and precise indicators; however, can these variables provide consistently accurate forecasts of future economic activity during both steady growth and more turbulent conditions?

Since the late 1980s, many studies have documented the usefulness of the yield curve or even the simple term spread for predicting economic activity (e.g., Harvey, 1988; Laurent, 1989; Estrella & Hardouvelis, 1991; Stock & Watson, 2003; Estrella, 2005). It has become a standard procedure in the U.S. to use the term spread between the ten-year Treasury note and the three-month Treasury bill to predict recessions and future economic activity (e.g., Estrella & Mishkin, 1996; Haubrich & Dombrosky, 1996). The inversion of the term spread has been demonstrated to be a reliable “advance warning” of a subsequent recession; however, its ability to forecast GDP growth rates is less clear. Many studies have found that since 1985, the term spread has been a less accurate predictor of U.S. output growth (e.g., Stock & Watson, 2003; Chinn & Kucko, 2010). This phenomenon may reflect either the increased stability of output growth (the Great Moderation) and other macroeconomic variables since the mid-1980s or changes in the responsiveness of monetary policy to output growth and inflation (Wheelock & Wohar, 2009). If the central bank concentrates exclusively on controlling inflation, then the term spread will most likely be a less accurate predictor of GDP growth. Thus, given that the European Central Bank (ECB) focuses on the control of inflation, the term spread may not necessarily merit its status as the best single predictor of economic growth in the euro area. However, despite evidence that parameter instability may weaken the performance of the term spread in predicting growth, the spread has nonetheless reached the status of the single best indicator of economic activity and a "near-perfect tool" for forecasting (e.g., Estrella, 2005). Notwithstanding the predominance of the term spread, Ang, Piazzesi and Wei (2006) found that the short rate had more predictive power than any term spread for forecasting GDP growth in the U.S. during 1952–2001. It has not been determined whether this result is specific to the U.S., or whether this result holds true for other countries.

Stock prices are forward looking and thus represent another obvious financial indicator of future economic activity. Economists and investors have a well-known rule of thumb that stock market prices predict economic growth approximately half a year in advance. However, compared with the predictive content of the term spread, less empirical evidence exists regarding the ability of stock prices to predict economic performance (e.g., Stock & Watson, 2003). Chionis, Gogas & Pragidis (2010) found that augmenting the yield curve with a stock index significantly improved the ability to predict GDP fluctuations in the euro area. Nyberg's (2010) results supported this conclusion with respect to predicting recessions in Germany and in the U.S. Junttila & Korhonen (2011) discovered that both stock market dividend yields and short-term interest rates were relevant information variables for forecasting future economic activity in the U.K., the euro area and Japan, particularly during turbulent times. Furthermore, Henry, Olekans & Thong (2004) emphasized that stock returns predict economic growth when the economy is contracting but that the predictive power of stock returns in non-recession periods is less clear. These types of findings may explain Samuelson's (1966) famous notice: "The stock market has predicted nine out of the last five recessions." In any event, economic turbulence tends to strengthen the link between the stock market and economic activity.

The case of Finland is interesting in many ways. The vast majority of the previous literature has examined larger, particularly G7, countries; however, the predictive content of financial variables is less known in smaller European countries. As a member of the Economic and Monetary Union (EMU), the Finnish economy is subject to the monetary policy of the ECB, which strongly targets inflation. It has been argued that the predictive content of the term spread for economic growth might weaken if inflation control is the main concern of the central bank.

Moreover, the monetary policy of the ECB is conducted on the basis of the entire euro area; therefore, the interest rates of the euro area may be far from optimal for smaller euro countries that face asymmetric shocks. Indeed, evidence suggests that output shocks have been more country-specific in Finland than in other EU countries (e.g., Haaparanta & Peisa, 1997; Kinnunen, 1998), and the question of asymmetric shocks was among the main concerns when Finland considered EMU membership in the late 1990s. Thus, there are good reasons to assess the predictive content of the term spread and the short-term interest rate in small member countries in the euro area.

After Finland emerged from an economic depression at the beginning of the 1990s, it experienced an era of continuous and sound growth until the global financial crisis plunged the Finnish economy into a deep recession at the end of 2008 (Figure 1). A distinctive feature of this slump was its severity; during a single year, the Finnish GDP collapsed by an astonishing 10%, one of the largest collapses of economic activity among developed countries. Undoubtedly, the ups and downs of the Finnish economy pose a true challenge for forecasting economic activity.

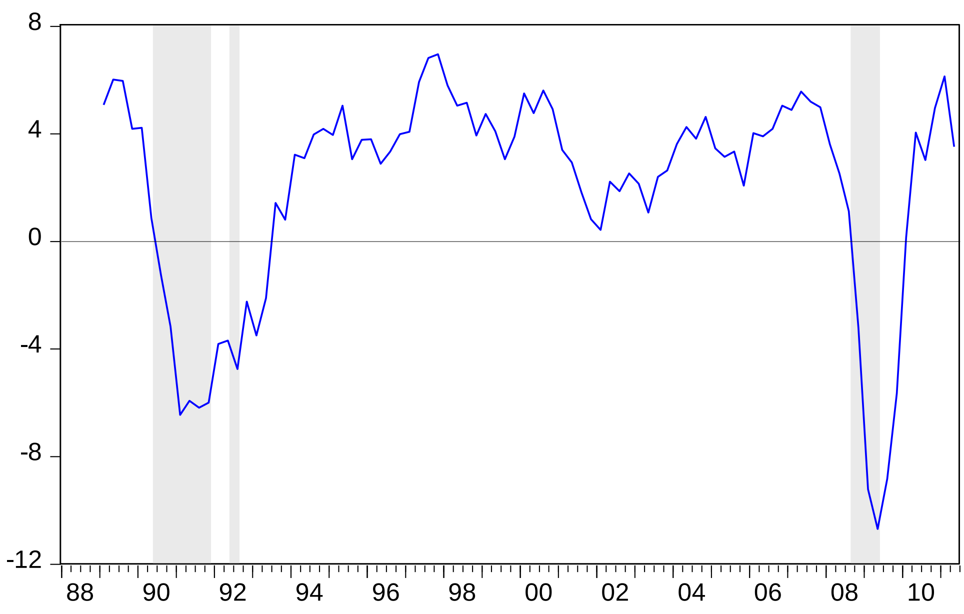

Figure 1. The annual GDP growth and recessions (shaded) in Finland from 1988:1 to 2011:2.

This paper contributes to the existing literature by explicitly addressing the predictive content of the classical term spread versus the short-term interest rate and stock returns in the context of a small open economy (SOE). Ang et al. (2006) found that compared with the term spread, short rates were a better predictor of economic activity in the U.S. Our aim is to test whether this result is also holds true outside the U.S. Furthermore, we seek to clarify potential differences in forecasting economic activity between eras of steady growth and economic turbulence, such as the recent financial crisis. Much of the previous literature has concentrated on the predictive content of a single financial indicator (e.g., Stock & Watson, 2003); however, we assess the predictive content of combinations of indicators. More broadly, this paper provides further information about the predictive ability of financial market indicators in smaller economies, a context that has rarely been examined in the previous literature.

The remainder of this paper is organized as follows. In section 2, we present the model setup and the data. Section 3 contains the empirical analysis of the study, and section 4 concludes the paper.

2. THE MODEL SETUP AND THE DATA

2.1. Forecasting models

In accordance with the previous literature, our financial market dataset consists of the following financial market variables: term spread, stock returns, and short rate. When constructing the empirical forecasting models, we apply the following modeling strategy. Because we are interested in the forecasting ability of financial market indicators above and beyond the history dependence of GDP growth, the information content of financial indicators is combined with past economic growth (equation 1). However, during exceptional and turbulent periods, past economic activity may lose its predictive content regarding future economic growth. Therefore, the forecasting performance of equation (1) is also compared to the predictive content of mere financial market information (equation 2). Finally, the forecasting ability of these models is compared to a simple autoregressive model, which serves as our benchmark (equation 3).

(1) $$(lny_{t+h} - lny_t) = \alpha^1 + \beta'^1 X_t + \sum_{i=1}^{m} \gamma_i^1 \Delta lny_{t-i+1} + u_{t+h}^1$$

(2) $$(lny_{t+h} - lny_t) = \alpha^2 + \beta'^2 X_t + u_{t+h}^2$$

(3) $$(lny_{t+h} - lny_t) = \alpha^3 + \sum_{i=1}^{m} \gamma_i^3 \Delta lny_{t-i+1} + u_{t+h}^3 \,,$$

where *y* is the level of real GDP, *X* is the vector of financial market indicators consisting of term spread (*TS*), stock returns (*R*) and short-term interest rate (*i*); i.e., *X* = (*TS, R, i*)', α is a constant term, β' and γ_i are parameter estimates and $u_{t+h,t}$ is the error term. The subscript *h* refers to the forecast horizon.

We focus on forecasts at the one-, two- and four-quarter horizons (*h* = 1, 2 and 4). Much of the previous literature has considered only a single financial market indicator as a forecasting variable; however, in our view, a single indicator may be too limited, and therefore we explore the forecasting ability of various combinations of financial indicators. However, we consider the term spread and the short rate as alternative forecasting variables and therefore do not include them in the same forecasting model. We assume conventionally that all the relevant predictive information of the financial market variables is included in the most recent observations of the financial indicators; therefore, lagged values of financial indicators are not included in the forecasting models. The forecast performance is evaluated by means of the root mean squared error (RMSE) criterion.

Regarding the specification of the history dependence of GDP growth, we assume that the relevant length of the history dependence is directly related to the forecasting horizon.[1] That is, when forecasting GDP growth one quarter ahead, the past quarterly growth is the most relevant measure of the history dependence. Hence, when forecasting GDP growth two quarters ahead,

[1] Alternatively, the number of AR terms could have been selected on the basis of information criteria. We conducted the analysis also by using the AIC criteria, which consistently suggested the AR(4) specification for the equations (1) and (3) irrespective of the forecasting horizon. Because the forecasting performance was worse, we preferred fixing the AR terms to the number of forecasting quarters. The results are available upon request.

Δlny_t and Δlny_{t-1} terms are included, and for the four-quarter forecasting horizon, $\Delta lny_t, \Delta lny_{t-1}, \Delta lny_{t-2}$ and Δlny_{t-3} terms are included.

We begin the forecasting analysis with only one financial indicator and move gradually into richer model specifications until all the relevant financial market forecasting variables are included in the forecasting model. This approach produces a total of eleven model specifications, including the autoregressive benchmark model.

2.2. Data

The data are quarterly and span the 1988:1–2011:2 time period. The economic activity is measured by the logarithmic changes of the Finnish real GDP index. Nominal quarterly stock market returns are calculated as logarithmic changes in the Finnish general stock market index (OMX Helsinki PI). The short rate is the 3-month market rate. The term spread is constructed by calculating the difference between the 10-year government bond yields and the 3-month interest rates. The details of the data and data transformations are given in Table 1.

The annual GDP growth in Finland is presented in Figure 1. The dependence of economic activity from past growth is evident. The financial market indicators are illustrated in Figure 2.

Table 1. The data.

$(lny_{t+h} - lny_t) \times 100$ $\Delta lny = (lny_t - lny_{t-1}) \times 100$	y = the Finnish gross domestic product index (volume, market prices). Source: OECD Economic Outlook database.
$R_t = (lnp_t - lnp_{t-1}) \times 100$	p = the Finnish general stock market index (OMX Helsinki PI). Source: OECD Main Economic Indicators database.
$TS_t = i10_t - i3_t$	$i10$ = the Finnish 10-year government bond yield. $i3$ = the Finnish 3-month interest rate (1988:1–1998:4 Helibor 3; 1999:1–2011:2 Euribor 3). Source: OECD Main Economic Indicators database.

The time series properties of the data were explored by means of the two most efficient unit root tests, the DF-GLS test by Elliot, Rothenberg & Stock (1996) and the Ng and Perron (2001) tests. The test results consistently suggested that all of the variables except for the short-term interest rate were stationary. The short rates were found to be non-stationary for the whole sample period; however, during the period of Finnish membership in the EMU (1999:1–), the test results suggested that the short rate was stationary.[2] The non-stationary nature of the short rate for the whole sample period is likely reflective of the exceptionally high interest rates in the late 1980s and the beginning of the 1990s, which were caused by inflationary pressures and the defense of the national currency during the ERM crisis. Because the forecasting analysis takes place during the EMU period, we estimated the forecasting models with short rates specified in levels.[3]

During the sample period, the Finnish economy has experienced two major recessions, which are indicated by the shaded areas in Figure 2. It is noteworthy that the negative term spread (an inverted yield curve) provided an early warning of both impeding recessions.

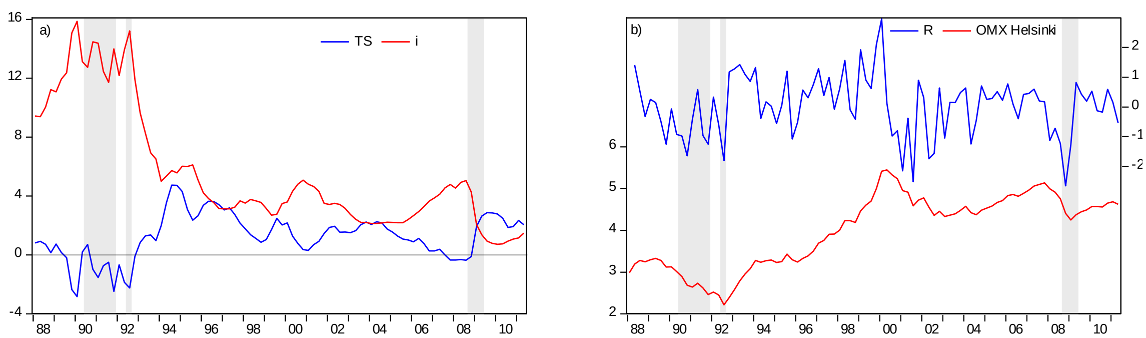

Figure 2. The financial variable values and recessions (shaded) for Finland.

Table 2 presents the descriptive statistics for the entire sample period (1988:1–2011:2) and the forecasting periods of the study (2004:1–2007:4 and 2008:1–2011:4). The former forecasting period is intended to represent a period of normal and steady economic growth, whereas the latter represents a time of economic turbulence, which was caused by the recent global financial crisis and its aftermath. The figures show that the relatively strong growth in GDP collapsed due

[2] The unit root test results are available upon request.
[3] We also estimated the models using the first differences of the short rate; in general, the level-based specifications demonstrated better forecasting performance.

to the financial crisis. One interesting observation is that despite the fact that the sample period includes the exceptionally deep economic depression in Finland at the beginning of the 1990s, the greatest annual drop in the Finnish GDP (-10.7%) occurred as a result of the financial crisis. Moreover, the volatility of economic activity increased substantially as a result of the financial crisis.

Large swings in performance are typical of the Finnish stock markets (see Figure 2). Stock prices collapsed by 60–70% on three separate occasions (1989–1991, 2000–2002 and 2008) during the sample period. However, stock market upswings (1993–1994, 1996–1999 and 2003–2007) were also exceptionally vigorous by international standards. Despite strong volatility, the compound annual stock return during the sample period was a relatively normal nominal rate of 6.3%.

Table 2. Descriptive statistics for the data.

		Δlny	$i3$	TS	R
Mean	1988:1 - 2011:2	0.50	5.26	1.23	1.53
	2004:1 - 2007:4	1.04	2.91	0.97	5.05
	2008:1 - 2011:4	-0.19	2.09	1.55	-3.63
Std. Dev.	1988:1 - 2011:2	1.28	4.08	1.55	13.65
	2004:1 - 2007:4	0.50	0.94	0.79	7.08
	2008:1 - 2011:4	2.13	1.72	1.29	13.08
Max	1988:1 - 2011:2	2.67	15.81	4.67	41.73
	2004:1 - 2007:4	1.89	4.72	2.19	11.94
	2008:1 - 2011:4	2.67	4.98	2.80	12.57
Min	1988:1 - 2011:2	-5.63	0.66	-2.89	-34.76
	2004:1 - 2007:4	-0.07	2.06	-0.41	-15.56
	2008:1 - 2011:4	-5.03	0.66	-0.42	-34.76

Notes: Δlny = quarterly GDP growth, *i3* = 3-month interest rate, *TS* = term spread, *R* = quarterly stock returns. For details of the data, see Table 1.

3. EMPIRICAL ANALYSIS

The forecasting analysis is conducted for two different time periods: the steady growth period from 2004:1 to 2007:4 and the financial crisis period from 2008:1 to 2011:2 (Figure 3). By separating the forecast periods in this way, it is possible to scrutinize the predictive content of financial market variables during different economic conditions. We estimate one-, two-, and four-quarter forecast models.

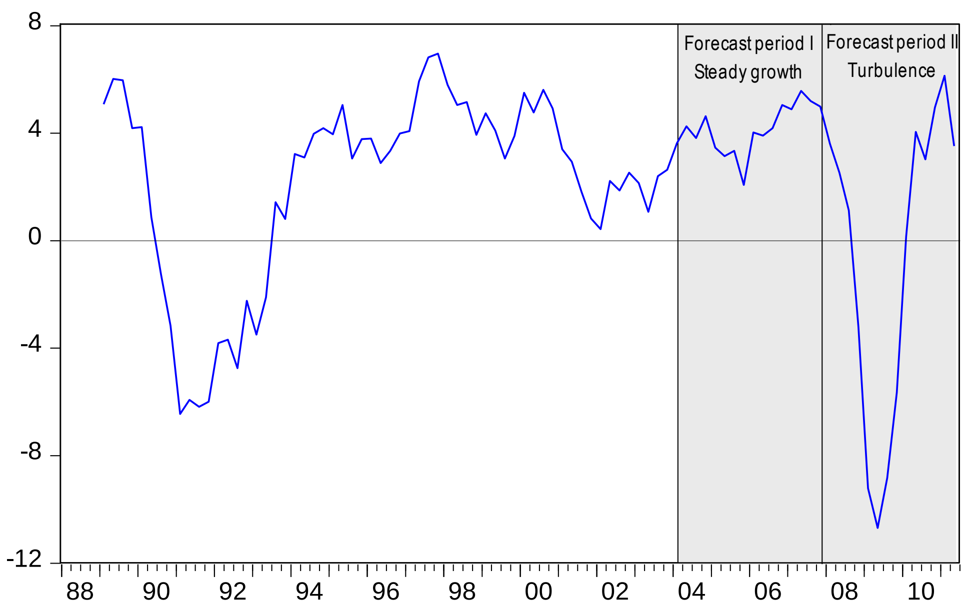

Figure 3. The annual GDP growth in Finland and the forecast periods.

To ensure that the forecasting procedure is as realistic and practical as possible, the forecasting analysis is conducted recursively. That is, for the first forecasting period (2004:1–2007:4), we first conduct regressions through 2003:4 and then use these estimates to compute forecasts for 2004:1, 2004:2 and 2004:4. The models are subsequently re-estimated through 2004:1, and the new forecasts for 2004:2, 2004:3 and 2005:1 are computed. This process is continued throughout the forecasting period. Thus, we consider only true out-of-sample forecasts. The recursive forecasting scheme has the intuitive advantage that all of the available information is utilized for the calculation of each forecast.

3.1. In-sample analysis

The initial parameter estimates are based on the sample of 1988:1–2003:4 for the first forecasting period and the sample of 1988:1–2007:4 for the second forecasting period. Because the estimation results were practically similar for both estimation periods, we present only the results for the first estimation period (Table 3). The estimation method was OLS with heteroscedasticity- and autocorrelation-robust Newey–West standard errors.

Table 3. In-sample regression results (1988:1–2003:4).

Dep. var. $(y_{t+1} - y_t) \rightarrow$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Expl. vars. ↓											
Const.	0.15	**0.48**	**1.54**	0.16	**1.39**	0.29	0.11	0.29	**1.17**	0.13	**1.14**
TS_t	**0.34**			**0.30**			**0.25**			**0.24**	
R_t		**0.03**		**0.02**	**0.02**			**0.02**		**0.01**	**0.01**
i_t			**-0.14**		**-0.13**				**-0.11**		**-0.11**
Δy_t						**0.47**	0.26	**0.39**	0.17	0.21	0.18
$\overline{R^2}$	0.27	0.11	0.29	0.30	0.33	0.21	0.31	0.24	0.33	0.32	**0.34**
Dep.var. $(y_{t+2} - y_t) \rightarrow$											
Expl. vars. ↓											
Const.	0.26	**0.95**	**3.20**	0.27	**2.88**	0.27	0.02	0.29	**1.80**	0.06	**1.69**
TS_t	**0.72**			**0.63**			**0.40**			**0.36**	
R_t		**0.06**		**0.03**	**0.03**			**0.03**		**0.03**	**0.03**
i_t			**-0.30**		**-0.27**				**-0.18**		**-0.17**
Δy_t						**0.68**	**0.41**	**0.50**	**0.39**	0.29	0.27
Δy_{t-1}						**0.78**	**0.62**	**0.80**	**0.57**	**0.66**	**0.61**
$\overline{R^2}$	0.42	0.18	0.45	0.48	0.52	0.52	0.61	0.57	0.63	0.64	**0.66**
Dep.var. $(y_{t+4} - y_t) \rightarrow$											
Expl. vars. ↓											
Const.	0.47	**1.77**	**6.55**	0.44	**5.87**	0.74	0.05	0.70	**5.51**	0.08	**5.18**
TS_t	**1.43**			**1.26**			**1.09**			**1.00**	
R_t		**0.11**		**0.07**	**0.07**			**0.07**		**0.06**	**0.05**
i_t			**-0.62**		**-0.56**				**-0.57**		**-0.53**
Δy_t						**1.52**	0.68	**0.96**	**0.56**	0.32	0.21
Δy_{t-1}						**1.36**	**0.87**	**1.29**	**0.70**	**0.85**	**0.70**
Δy_{t-2}						0.20	0.20	0.43	0.06	0.38	0.24
Δy_{t-3}						-0.84	-0.69	-0.69	**-0.73**	-0.59	**-0.63**
$\overline{R^2}$	0.49	0.22	0.54	0.57	0.62	0.43	0.62	0.50	0.70	0.66	**0.73**

Note: The bolded figures are statistically significant at the 10% level or better.

The in-sample estimation results indicated that in the models, the term spread and the stock returns were positively correlated and the short rate was negatively correlated with economic activity. This result is well in accordance with theoretical expectations. It is also noteworthy that all of the parameter estimates of the financial market indicator variables were consistently significant at the 10% level or better.

With respect to the in-sample explanatory power of the various model specifications, the following notable results were observed. First, the model specifications with history dependence yielded higher explanatory power than the model specifications without history dependence. This phenomenon occurred consistently irrespective of the forecast window. Second, the highest explanatory power was obtained by the model specification with stock returns, the short rate and the history dependence (AR terms) as explanatory variables. Third, the model specification that included stock returns as the only predictor had the lowest explanatory power. Clearly, one should avoid utilizing stock returns as the sole predictor of output growth, the short rate being a much better choice. Fourth, past growth alone was capable of explaining approximately 20% to 50% of the observed economic activity, and the parameter estimates confirm a fair amount of history dependence in economic activity.

3.2. Out-of-sample forecasting results

The forecasting results are presented in Table 4. The forecast accuracy is measured in terms of the root mean squared forecast errors (RMSE). The forecasting era was divided into two roughly equal time periods to examine the influence of the recent financial crisis on the forecasting performance. The first forecasting period (2004:1–2007:4) represents a steady growth period, whereas the second forecasting period (2008:1–2011:2) incorporates exceptional economic turbulence.

The first column of Table 4 displays the various forecasting model specifications of the study. The second and the fifth columns give the root mean square error (RMSE) of the forecasting model specification, which contains both financial market indicators and the past economic activity as forecasting variables (equation 1), while the third and the sixth column give the RMSE of the model specification with mere financial market indicators as forecasting variables (equation 2). The fourth and the seventh columns provide the Clark & McCracken (2001) MSE-*F* test statistics for the null hypothesis of equal forecast mean square errors between forecasting equations (2) and (1)[4]. The rejection of the null hypothesis suggests that the forecasting performance of equation (1) is significantly better than that of equation (2). That is, the model specification with both financial market information and history dependence (equation 1) is capable of yielding better forecasts than the model specification with mere financial market information (equation 2). Columns 2–4 provide the results for the forecasting period 2004:1–2007:4 while columns 5–7 provide the corresponding information for the forecasting period 2008:1–2011:2.

[4] Clark & McCracken (2001)'s MSE-F test deals with testing the null hypothesis of equal mean square error of the forecasts from a pair of nested models, in which the first model is a restricted version of the second. In the present case, model (2) is a restricted version of model (1). The test statistic is non-standard and tabulated in McCracken (2007).

Table 4. Out-of-sample forecasting results.

	Forecast period: 2004:1-2007:4			Forecast period: 2008:1-2011:2		
(1)	**(2) RMSE (eq.1)**	**(3) RMSE (eq.2)** Excl. AR terms	**(4) MSE-F**	**(5) RMSE (eq.1)**	**(6) RMSE (eq.2)**	**(7) MSE-F** Excl. AR terms
Dep.var. →	$(y_{t+1} - y_t)$	$(y_{t+1} - y_t)$		$(y_{t+1} - y_t)$	$(y_{t+1} - y_t)$	
Expl.vars. ↓						
$AR(1)$	0.648			1.923		
$AR(1), R_t$	0.662	0.682	0.981**	1.751	1.850	1.630**
$AR(1), TS_t$	0.679	0.736	2.763***	1.847	2.043	3.134***
$AR(1), i_t$	0.560	0.533	-1.501	2.057	2.290	3.354***
$AR(1), R_t, TS_t$	0.682	0.723	1.980**	1.730	1.834	1.726**
$AR(1), R_t, i_t$	0.572	0.556	-0.863	1.907	2.021	1.720**
Mean RMSE	0.634	0.646		1.869	2.021	
Dep.var. →	$(y_{t+2} - y_t)$	$(y_{t+2} - y_t)$		$(y_{t+2} - y_t)$	$(y_{t+2} - y_t)$	
Expl.vars. ↓						
$AR(2)$	0.691			4.092		
$AR(2), R_t$	0.755	1.097	17.756***	3.735	3.279	-3.209
$AR(2), TS_t$	0.815	1.204	18.973***	3.509	3.412	-0.760
$AR(2), i_t$	0.631	0.743	6.205***	3.950	4.042	0.656
$AR(2), R_t, TS_t$	0.828	1.168	15.844***	3.290	3.078	-1.748
$AR(2), R_t, i_t$	0.674	0.781	5.480***	3.645	3.564	-0.619
Mean RMSE	0.732	0.999		3.704	3.671	
Dep.var. →	$(y_{t+4} - y_t)$	$(y_{t+4} - y_t)$		$(y_{t+4} - y_t)$	$(y_{t+4} - y_t)$	
Expl.vars. ↓						
$AR(4)$	1.717			7.309		
$AR(4), R_t$	1.827	2.145	6.051***	6.577	5.189	-5.285
$AR(4), TS_t$	2.009	2.112	1.685*	5.262	4.999	-1.367
$AR(4), i_t$	1.166	1.310	4.226***	6.610	6.681	0.302
$AR(4), R_t, TS_t$	2.021	2.095	1.179	4.791	4.387	-2.260
$AR(4), R_t, i_t$	1.149	1.217	1.947*	5.967	5.782	-0.856
Mean RMSE	1.648	1.776		6.086	5.242	

Notes: MSE-F refers to the Clark & McCracken (2001) test statistics for the comparison of mean square errors (MSE) of forecasting equations (1) and (2). The null hypothesis is equality of the MSEs. If the null is rejected, the MSE of forecasting equation (1) is significantly lower than the MSE of equation (2). Significance levels: *** = 1%, ** = 5%, * = 10%.

Certain general outcomes are evident from the forecasting results. As expected, forecast errors increased consistently with the forecast horizon. The performance of the forecasts collapsed during the financial crisis, and the forecast errors were more than three times larger during the financial crisis than during the steady growth period. During normal economic conditions, the differences in RMSEs between the best and the worst model specifications were rather limited in a short forecast horizon; however, the differences become more notable as the forecast window is extended to longer horizons. Thus, the selection of a proper model specification is far from inconsequential. The results also suggested that during steady growth, past growth was clearly useful for forecasting purposes. The formal Clark & McCracken (2001) MSE-F test confirmed this to a large extent (column 4). However, during economic turbulence, the predictive power of the lagged GDP growth effectively vanished for longer forecast horizons. This finding was also supported unambiguously by the MSE-F test results.

What if one wishes to select a single financial market indicator for predicting GDP growth? Our results demonstrated that the short rate would be a better choice than the more traditional term spread or stock returns. It is also interesting to note that although stock returns or the term spread perform rather poorly as single predictors of GDP growth, the combination of these variables proves to be useful for forecasting purposes. Although the GDP growth appears to incorporate a degree of history dependence that is useful for forecasting purposes under normal economic circumstances, the usefulness of AR terms decreases considerably during economic turbulence in longer forecast horizons. The short rate was found to be the single most important financial market indicator for predicting economic activity during periods of steady growth; however, this finding did not hold true during more turbulent times. According to our results, stock returns and the term spread were the appropriate choices among financial market indicators for forecasting future growth during unsettled economic conditions.

3.3. The analysis of the forecasting results

The previous literature suggests that financial market variables are useful for predicting economic activity but that the predictive content is not robust with respect to different countries and time periods (Stock & Watson, 2003). Among different financial market variables, the term spread has gained the status of being the best single financial market indicator for future economic activity (e.g., Estrella, 2005; Wheelock & Wohar, 2009). The results by Kuosmanen and Vataja (2011) supported this conclusion in the Finnish context.

However, as emphasized by Stock & Watson (2003), the history dependence of economic activity has not been accounted for in many previous studies. Recent literature has suggested that the predictive content of the term spread has decreased since the mid-1980s; this decrease may be due to either the increased stability of economic activity (Wheelock & Wohar, 2009) or fundamental changes in the relationship between the term spread and economic activity across countries. These changes may have arisen as a result of a variety of factors, such as the birth of the European monetary union, the "great moderation", the global savings glut and the zero lower bound on nominal interest rates (Chinn & Kucko, 2010).

Although the term spread and stock returns represent the traditional financial market variables that are used to predict future economic activity, the results from the U.S. context by Ang et al. (2006) suggested that short rates have greater predictive power than the term spread for forecasting GDP growth. Our results suggested that this finding holds also true for Finland. The result is novel for a small open economy and lends support to the usefulness of short rates in predicting future economic activity during steady economic growth.

The importance of the short rate appears even more remarkable from the perspective of the euro area given that the monetary policy of the ECB targets the entire euro area and that Finland is only a tiny fraction of this region. Furthermore, even though the ECB concentrates exclusively on controlling inflation, short rates are found to play a crucial role in indicating future economic activity in Finland.

According to our results, the proper choice of indicator variables changes notably during exceptional growth periods. The forecasting ability of the short rate decreases during economic turbulence. Moreover, in unsettled conditions, the predictive content of past growth vanishes for longer forecast horizons. Instead, the traditional term spread and stock returns are found to be more appropriate indicator variables for future economic activity during turbulent times.

4. **CONCLUSIONS**

The purpose of this study was to reinvestigate and clarify the predictive content of readily available and easily observable financial market variables for forecasting future GDP growth during both normal and exceptional economic circumstances. Our results address Finland, a small open economy in the euro area that was heavily influenced by the financial crisis.

Our results confirmed the usefulness of financial market information for forecasting future economic activity. The proper selection of financial market indicator variables was found to be related to the general health of the economy. During steady growth periods, short term interest rates and the history dependence of past growth play a dominant role in forecasting economic activity. In contrast, during economic turbulence, the importance of the traditional term spread and stock returns notably increases. Our results also emphasize that stock returns as a sole financial predictor of GDP growth performs rather poorly. However, combining stock returns with other financial indicators improves the forecasting performance.

We also witnessed a dramatic increase in forecast errors during exceptional economic circumstances. This result indicates the severe difficulties that exceptional times pose for forecasting. Clearly, one should be very cautious in forecasting economic activity during periods of economic turbulence.

The results of this study suggest that the predictive power of the short rate and the term spread are related to the central bank's ability to conduct a conventional monetary policy. If the central bank is out of conventional monetary policy tools (at the bounds that are imposed by a zero interest rate policy), then the predictive content of the term spread and stock markets begin to play a more dominant role in forecasting economic activity. However, if the central bank is able to conduct a conventional monetary policy, then the short rate is the preferable growth indicator.

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