THE RETURN OF FINANCIAL VARIABLES IN FORECASTING GDP GROWTH IN THE G-7

ABSTRACT

The financial crisis and the subsequent sovereign debt crisis together had a profound impact on the current economic environment. This study reexamines established stylized facts and previous evidence regarding the predictive association between financial variables and real economic activity in light of changed economic circumstances. This paper focuses on the predictive ability of the term spread, the short-term interest rate and stock returns for real GDP growth in the G-7 countries. We compare the predictive content of nominal financial variables with that of real financial variables and consider the proper number of financial predictors and time variation of the forecasting performance. The forecasting results unambiguously indicate that financial variables have regained their predictive power since the financial crisis. Moreover, this study finds that real financial variables are superior to nominal variables and that using several financial indicators in forecasting GDP growth is preferable.

1. INTRODUCTION

Only in the late 1980s did the term spread (the difference between long-term and short-term interest rates) begin to gain its status as the single most important predictor of economic activity in Western economies. However, the term spread's prevalence as the unambiguous leading indicator was short-lived because not long after it commenced, numerous studies emerged claiming that the term spread's forecasting power for the real economy had diminished since the mid-1980s (e.g., Haubrich & Dombrosky, 1996; Dotsey, 1998; Estrella, Rodrigues & Schich, 2003; Stock & Watson, 2003; Giacomini & Rossi, 2006; Wheelock & Wohar, 2009; Chinn & Kucko, 2015). The reasons for the deterioration of the term spread's predictive power have by and large remained a mystery. Eventually, the forecasting ability of the term spread proved to be unstable across countries and time periods; its good predictive ability in certain countries or time periods did not guarantee its good forecasting performance in the future (Stock & Watson, 2003). Moreover, Ang, Piazzesi and Wei (2006) found that the nominal short-term interest rate has more predictive power than any term spread in the U.S. Oddly enough, the diminishing forecasting ability of the term spread for real economic activity coincided with the weakening of the predictive content of stock returns in the U.S. and other G-7 countries since the 1980s (Binswanger, 2000; 2004). This near-simultaneous weakening of the predictive ability of the term spread and stock returns for economic activity may be accidental or may be attributable to more fundamental reasons.

The optimal number of financial predictors has largely remained an open question. The previous literature focuses primarily on the predictive ability of a single financial variable rather than studying the importance of additional financial predictors (e.g., Harvey, 1989, 1991; Kozicki, 1997; Domian & Louton, 1997; Dotsey, 1998; Binswanger, 2004; Bordo & Haubrich, 2008; Tsouma, 2009). Stock and Watson (2003) found that no clear systematic patterns of improvement in forecasting performance existed when additional candidate asset indicators were added to bivariate models in a dataset for the G-7 countries. However, multivariate forecasting models were found to be superior to bivariate models in forecasting GDP growth in the Nordic countries (Kuosmanen, Nabulsi & Vataja, 2015).

It initially seems obvious and logical that nominal financial predictors should be converted into real variables when forecasting real economic activity. However, nominal financial variables are reliably available at all times without errors related to the definition of the prevailing inflation rate. Although several studies use nominal stock returns to predict economic activity (e.g., Henry, Olekalns & Thong, 2004; Kuosmanen & Vataja, 2011), most studies utilize real stock returns (e.g., Tsouma, 2009; Mauro, 2003; Binswanger, 2000; 2004; Choi, Hauser & Kopecky, 1999). Stock and Watson (2003) used both nominal and real stock returns in their comprehensive forecasting analysis, but they did not take a clear position on which set of variables was preferable. Junttila and Kinnunen (2004) noted that because information about future inflation is contained in nominal returns, deflating nominal stock returns is not beneficial; rather, using stock returns calculated as the excess of the risk-free interest rate is preferable.

With respect to the use of the term spread, Estrella (2005) emphasized that only the level of the term spread matters in forecasting economic activity, not the change in the spread or even the source of the change in the spread. That is, it does not make any difference whether the change in the term spread originates from the change in the short-term rate or the change in the long-term rate. Notably, the inflation rate does not affect the magnitude of the term spread; rather, subtracting inflation from both ends of the yield curve leaves the term spread unchanged. Hence, in practice, the “nominal term spread” and the “real term spread” are identical to each other. However, this is not the case when the short end of the yield curve, i.e., short-term interest rates, is used to forecast economic activity. Again, whether the nominal or real short-term interest rate should be used in this case is unclear; although Stock and Watson (2003) used both rates, many other studies used only the nominal short-term interest rates (e.g., Ang, Piazzesi & Wei, 2006; Kuosmanen & Vataja, 2014; Kuosmanen et al., 2015). In summary, the preferable choice between nominal and real financial variables in forecasting real economic activity has been overlooked in prior research.

One of the main findings in the seminal study by Stock and Watson (2003) was that asset prices lack robustness in forecasting economic activity over time. However, the vast majority of the previous literature reports only a single measure of forecast errors, primarily the root mean squared error (RMSE). Given that a single forecast error measure reveals little about the variation of forecasting performance over time, we analyze the behavior of RMSEs over the entire forecast period in this study.

The recent financial crisis was a remarkable economic watershed. In particular, the "Great Moderation" gave way to the current turbulent and uncertain economic conditions, and the "New Normal" replaced tight inflation targeting in the monetary policies of Western economies. Given these changed economic circumstances, many of the established stylized facts and previous research results regarding the predictive association between financial variables and economic activity should be reexamined. In this context, Hännikäinen (in press) discovered that the term spread has re-gained its predictive ability for industrial production in the U.S. economy since the financial crisis. Moreover, Chinn and Kucko (2015) concluded that the relationship between the term spread and economic growth may have strengthened in some European countries with the increasing volatility of macroeconomic data over the past few years.

We focus on three issues that have not been sufficiently addressed and that have remained ambiguous in the previous literature: the optimal number of financial predictors to forecast economic activity, the selection between nominal and real financial indicators, and the time variation of forecasting performance over time, especially before and after the unsettled economic conditions. This study considers the predictive ability of the three main financial indicators – the term spread, the short-term interest rate and stock returns – for real GDP growth in the G-7 countries, i.e., Canada, France, Germany, Italy, Japan, the United Kingdom and the United States.

The results of this study suggest that the financial crisis has ushered in a new era of forecasting economic activity, at least with respect to the major industrialized countries. The key financial variables are re-gaining status and momentum in forecasting real activity after the Great Moderation. This study also emphasizes the use of real financial variables to forecast economic activity. Moreover, there seems to be a systematic pattern of improvement in economic forecasts when several financial indicators are included in a forecasting model. Our results also lend support to previous results indicating that financial indicators are largely unable to forecast the economic activity that occurred during the Great Moderation but that their predictive power is restored when analyzing the economic activity that occurred after the financial crisis.

The paper is organized as follows. Section 2 contains our modeling strategy and introduces the data. The results of the out-of-sample forecasts are presented and analyzed in Section 3. Finally, Section 4 concludes.

2. MODELING STRATEGY AND DATA

2.1. Forecasting models

We focus on a forecast horizon of four quarters, as it is most often needed in practice and has been found to be the most suitable period for financial data (Koziski, 1997; Wheelock & Wohar, 2009). The linear autoregressive (AR) model (Model 1) constitutes a natural and often-used benchmark against which more versatile competing models are compared.

(1) $lny_{t+4} - lny_t = \alpha^1 + \sum_{i=1}^{h} \beta_i^1 \, \Delta lny_{t-i+1} + u_{t+4}^1$

where y is real gross domestic product (GDP), α is a constant term, β_i represents the parameter estimates and u_{t+4} is the error term. The superscript refers to the model number.

In line with Stock and Watson (2003), we continue modeling GDP growth by specifying the bivariate model comprising the term spread (TS) and the AR part of economic growth (Model 2). This model is a simple framework that relates future GDP growth to the current value of the term spread. We conventionally assume that the latest observation of a financial indicator includes all relevant information about future economic growth, i.e., the models do not include lagged values of financial indicators. In addition, this model specification includes the marginal predictive content of the term spread for GDP growth above and beyond that for past GDP growth.

$$(2) \quad lny_{t+4} - lny_t = \alpha^2 + \sum_{i=1}^{h} \beta_i^2 \, \Delta lny_{t-i+1} + \gamma\beta_{h+1}^2 TS_t + u_{t+4}^2$$

As Stock and Watson (2003) noted, forecasts based on a single financial indicator are often unstable. Hence, we augment equation (2) with stock returns (*R*), which are another well-established leading indicator of economic activity.

$$(3) \quad lny_{t+4} - lny_t = \alpha^3 + \sum_{i=1}^{h} \beta_i^3 \, \Delta lny_{t-i+1} + \beta_{h+1}^3 TS_t + \beta_{h+2}^3 R_t + u_{t+4}^3$$

Next, based on the findings of Ang, Piazzesi and Wei (2006), equation (3) is further augmented with the short-term interest rate (*i*). Accordingly, the marginal predictive content of the short-term interest rate above and beyond the term spread and stock returns is captured in Model 4.

$$(4) \quad lny_{t+4} - lny_t = \alpha^4 + \sum_{i=1}^{h} \gamma_i^4 \, \Delta lny_{t-i+1} + \beta_{h+1}^4 TS_t + \beta_{h+2}^4 R_t + \beta_{h+3}^4 i_t + u_{t+4}^4$$

Finally, a similar modeling strategy is conducted using real financial variables (real stock returns and the real short-term interest rate) instead of nominal indicators (Models 5–6).

$$(5) \quad lny_{t+4} - lny_t = \alpha^5 + \sum_{i=1}^{h} \gamma\beta_i^5 \, \Delta lny_{t-i+1} + \beta_{h+1}^5 TS_t + \beta_{h+2}^5 R_t(real) + u_{t+4}^5$$

$$(6) \quad lny_{t+4} - lny_t = \alpha^6 + \sum_{i=1}^{h} \beta_i^6 \, \Delta lny_{t-i+1} + \beta_{h+1}^6 TS_t + \beta_{h+2}^6 R_t(real) + \beta_{h+3}^6 i_t(real) + u_{t+4}^6$$

The number of AR terms (*h*) is determined based on the Schwartz information criterion. Due to the serial correlation of the overlapping GDP data and the potential non-constancy of the error term, the estimation method is OLS with heteroscedasticity- and autocorrelation-robust Newey–West standard errors.

2.2. Introduction of data

The dataset for the G-7 countries comprises quarterly data over a 33-year period from 1980Q1 to 2014Q1, with the following exceptions: Italy’s time series begins in 1991Q2, Japan’s time series begins in 1989Q1, and the U.S.’s time series ends in 2013Q2 due to missing short-term interest rate data. Note also that Germany’s time series describes West Germany until 1990Q4, after which point the data are for reunified Germany. The data are taken from the OECD databases (for details regarding the data and data transformations, see Table 1).

GDP growth rates are calculated as logarithmic changes in real GDP indices, and nominal stock returns are calculated as logarithmic changes in the general stock market indices. The nominal short-term interest rate is a three-month interest rate, and the term spread is conventionally defined as the difference between the ten-year government bond yield and the three-month interest rate.

We found some ambiguity in the time series data for short-term interest rates, namely, the data appear to be non-stationary for the entire sample period. However, as stressed by Cochrane (1991: 207–208), short-term interest rates are already expressed in rate form and are thus stationary by definition. Moreover, Kuosmanen et al. (2015) experimented with the level and difference specifications of short-term interest rates when forecasting economic activity in the Nordic countries and found that the level specifications yielded the smallest forecast errors. On these grounds, short-term interest rates are specified in level form. The real short-term interest rate is calculated by subtracting inflation (defined by the consumer price index) from nominal interest rates. Similarly, real stock returns are calculated by subtracting inflation from nominal stock returns.

Table 1. Data description.

Raw data	Data transformation	Details and source of the data
y = Real GDP	$\Delta^4 lny = (lny_{t+4} - lny_t) \times 100$ Annual GDP growth $\Delta lny = (lny_t - lny_{t-1}) \times 100$ Quarterly GDP growth	Millions of national currency units. Seasonally adjusted. Source: OECD Quarterly National Accounts.
i3 = Nominal short-term interest rate *i3(real)* = Real short-term interest rate *Inf* = Annual inflation rate *CPI* = Consumer price index	 *i3(real) = i3 – inf* $Inf = ln(CPI_t) - ln(CPI_{t-4})$	Three-month interbank offer rate or three-month treasury bill, certificate of deposit or comparable instruments rate. Per cent per annum. Source: OECD Main Economic Indicators.
i10 = Nominal long-term interest rate *i10(real)* = Real long-term interest rate	 *i10(real)= i10 – Inf*	Ten-year government bond rate. Percent per annum. Source: OECD Main Economic Indicators.
TS = Term spread	$TS_t = i10_t - i3_t$	
P = Share price index *Inf(q)* = Quarterly inflation rate	 $Inf(q) = ln(CPI_t) - ln(CPI_{t-1})$	National all-share or broad share price index. Average of monthly figures, which are averages of daily quotations. Source: OECD Main Economic Indicators.
R = Nominal stock returns *R(real)* = Real stock returns	$R_t = (lnP_t - lnP_{t-1}) \times 100$ Quarterly nominal stock returns $R_t(real) = \ln(P_t) - ln(P_{t-1})$ $-(ln(CPI_t) - ln(CPI_{t-1})) \times 100$ Quarterly real stock returns	

The descriptive statistics for the data (Table 2) show that annual (average) real economic growth during the sample period was strongest in the U.S. (2.72%), followed by Canada (2.40%) and the U.K. (2.34%) and weakest in Italy (0.66%) and Japan (1.30%). Consequently, the stock markets in Japan (-0.59%) and Italy (0.76%) demonstrated the most modest performance among G-7 countries in terms of nominal returns. Similarly, average nominal stock returns were highest in the U.S. (1.87%) and the U.K. (1.80%), which is in line with their brisk economic activity. Real stock returns differed slightly from nominal returns to the extent that average real returns were highest in Germany (1.11%) followed by the U.S. (1.10%). The weak economic performances of Japan and Italy are also reflected in their low real short-term interest rates (1.00% and 2.03%, respectively). Furthermore, the widest average term spread is detected for Italy (1.65%), and the narrowest is found for the U.K. (0.25%).

Table 2. Descriptive statistics for the data.

Canada	$\Delta^4 lny$	*TS*	*R*	*R* (*real*)	*i*	*i* (*real*)
Mean	2.40	0.91	1.36	0.61	6.16	3.06
Max	6.34	3.33	18.95	17.50	20.74	9.15
Min	-4.00	-4.29	-37.24	-35.82	0.38	-2.17
Std. Dev.	2.21	1.56	7.60	7.60	4.34	2.67
Obs (1980Q1–2014Q1)	133	133	133	133	133	133
France						
Mean	1.74	1.08	1.78	1.06	5.94	2.93
Max	4.69	2.90	21.79	21.63	17.44	9.70
Min	-3.99	-4.14	-32.54	-33.00	0.20	-1.58
Std. Dev.	1.49	1.22	8.97	8.93	4.20	2.50
Obs (1980Q1–2014Q1)	133	133	133	133	133	133
Germany						
Mean	1.69	1.02	1.63	1.11	4.53	2.40
Max	6.65	3.16	23.03	22.41	13.16	7.50
Min	-7.09	-2.83	-31.47	-30.90	0.20	-1.80
Std. Dev.	2.12	1.26	8.87	8.82	2.83	1.93
Obs (1980Q1–2014Q1)	133	133	133	133	133	133
Italy						
Mean	0.66	1.65	0.76	0.09	4.81	2.03
Max	4.05	5.33	25.29	24.64	16.43	11.53
Min	-7.15	-2.62	-30.39	-29.98	0.20	-2.79
Std. Dev.	2.13	1.53	9.78	9.78	3.86	2.82
Obs (1991Q2–2014Q1)	92	92	92	92	92	92
Japan						
Mean	1,30	1,05	-0,59	-0,70	1,45	1,00
Max	7,42	2,71	22,80	22,87	8,31	5,43
Min	-9,66	-1,66	-35,41	-34,70	0,03	-1,57
Std. Dev.	2,56	0,84	9,15	9,13	2,28	1,47
Obs (1988Q1–2014Q1)	101	101	101	101	101	101
U.K.						
Mean	2.34	0.25	1.80	0.96	6.96	3.50
Max	6.52	3.46	15.47	14.32	15.61	9.91
Min	-7.03	-4.57	-24.62	-25.73	0.49	-3.68
Std. Dev.	2.31	1.63	6.30	6.25	4.12	3.03
Obs (1980Q1–2014Q1)	133	133	133	133	133	133
U.S.						
Mean	2.72	1.31	1.87	1.10	5.29	2.12
Max	8.20	3.51	18.66	18.44	17.52	7.66
Min	-4.18	-3.00	-36.29	-33.37	0.20	-3.44
Std. Dev.	2.08	1.38	6.69	6.61	3.65	2.55
Obs (1980Q1–2013Q2)	130	130	130	130	130	130

Notes: $\Delta^4 lny$ = annual real GDP growth, *TS* = term spread, *R* = stock returns, *R* (real) = real stock returns, *i* = nominal short-term (3-month) interest rate, and *i* (real) = real short-term (3-month) interest rate.

The forecasting period runs from 2002Q1 to 2014Q1. The preceding observations (1980Q1–2001Q4) are used to obtain initial parameter estimates (in-sample analysis) for the forecasting analysis (out-of-sample analysis). The in-sample period differs from the out-of-sample period in many respects (Figure 1). First, the financial crisis of 2008 divides the out-of-sample period into two distinct time frames (Table 3): a period of relatively steady growth (2002Q1–2007Q4) and a turbulent period (2008Q1–2014Q1). In addition, the integration of the world economy and financial markets can be detected in the increased correlation between countries' real economies and between the various financial markets. The average correlation of real GDP growth rates among G-7 countries is only 0.25 during the in-sample period but increases to 0.80 during the out-of-sample period. The same phenomenon is also observed in the financial market data; for example, the average correlation between nominal stock returns is 0.54 during the in-sample period but increases to 0.86 during the out-of-sample period.[1] The observed integration of financial markets also occurs in interest rate markets.

[1] All correlations are available upon request.

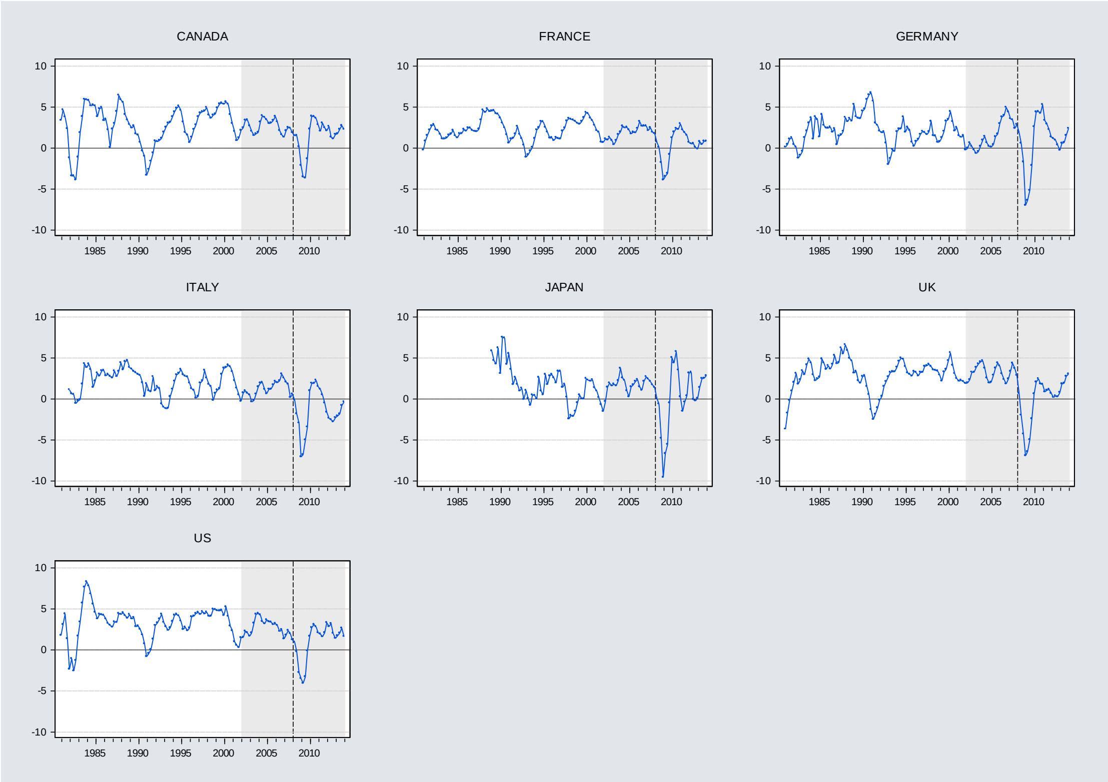

Figure 1. Annual GDP growth in the G-7 countries. The forecasting period is shaded.

Table 3. GDP growth and volatility during the forecasting periods.

	Canada	Canada	France	France	Germany	Germany	Italy	Italy
For.period	A	B	A	B	A	B	A	B
Mean	2.575	1.357	1.804	0.329	1.386	0.752	1.146	-1.442
Std.dev.	0.784	2.053	0.757	1.811	1.728	3.186	0.923	2.535
	Japan	**Japan**	**U.K.**	**U.K.**	**U.S.**	**U.S.**		
For.period	A	B	A	B	A	B		
Mean	1.565	0.164	3.089	-0.093	2.657	0.985		
Std.dev.	1.061	3.689	0.939	2.866	0.932	2.188		

Notes: Forecasting periods: A = 2002Q1 – 2007Q4, B = 2008Q1 – 2014Q1.

3. FORECASTING ANALYSIS

3.1. Forecasting results of GDP growth

The forecasting analysis of this study is conducted recursively outside the estimation period: when a new observation is received, the model is re-estimated, which in turn produces a new four-quarter GDP growth forecast. Hence, this pseudo out-of-sample analysis by Stock and Watson (2003) resembles the actual forecasting situation in the sense that it utilizes all information available up to the period in which the actual forecast is calculated. The forecasting performance is conventionally evaluated based on the RMSEs. The lower the model's RMSE is, the better the forecasting performance is. In addition to ranking the RMSEs, assessing the statistical significance between the RMSEs is of interest. The statistical significance of the RMSEs of the financial models (Models 2–6) is compared with that of the univariate AR model (Model 1). The difference between the RMSEs is formally tested by the Clark and West (2007) test, which is suitable when the forecasting models are nested, as it the case here (Models 2–6 nest Model 1).

The RMSEs of the nested models are equal in infinite samples if the data are generated by the more parsimonious model (Model 1), which constitutes the null hypothesis of the test. In finite samples, however, a less parsimonious model (Models 2–6) introduces noise to the forecasts because unnecessary parameters are estimated under the null hypothesis. Under the alternative, the RMSE of a larger model is lower than that of Model 1, and the null is rejected in favor of the larger model. Hence, the Clark and West test is one-sided. Clark and West (2007: 294) derived how to adjust the RMSE of the larger model to account for noise. Because the adjusted RMSE is less than the unadjusted RMSE, $RMSE_{adjusted}$ (Models 2–6) is possibly less than RMSE (Model 1), although $RMSE_{unadjusted}$ (Models 2–6) is initially greater than RMSE (Model 1). In Table 4, relevant examples can be observed in the cases of Canada (Model 2) and the U.S. (Models 3 and 5).

Table 4 Out-of-sample forecasting results.

Forecasting period: 2002Q1–2014Q1

Model specification	Canada RMSE	France RMSE	Germany RMSE	Italy RMSE	Japan RMSE	U.K. RMSE	U.S. RMSE
(1) AR	1.776	1.626	2.654	2.632	3.183	2.540	2.003
(2) AR+TS	1.781**	1.568	2.503**	2.563	3.140*	2.588	1.987*
(3) AR+TS+R	1.666**	1.517*	2.393**	2.364*	3.038**	2.546	2.063*
(4) AR+TS+R+i	1.649**	1.556*	2.396**	2.460	2.947**	2.550	1.997**
(5) AR+TS+R(real)	1.659**	1.516*	2.393**	2.357*	3.029**	2.544	2.048*
(6) AR+TS+R(real)+i(real)	1.593***	1.373**	2.318**	2.392*	2.560**	2.338***	1.748**

Notes: The asterisks refer to the significance of the Clark and West (2007) test for the comparison of the RMSEs of forecasting equations (1) and (2–6). The null hypothesis is the equality of the RMSEs. The rejection of the null means that the RMSE of the corresponding model specification is significantly lower than the RMSE of the benchmark AR model in Equation (1). Significance levels: *** = 1%, ** = 5%, * = 10%.

The forecasting results yield a number of interesting outcomes. First, augmenting the AR benchmark with the term spread (Model 2) improves the forecasting performance in six out of the seven cases, excluding that in the U.K. The improvement is statistically significant in four out of the seven cases (Canada, Germany, Japan, and the U.S.). Second, including nominal stock returns together with the term spread (Model 3) yields smaller RMSEs in all countries except for the U.S. Moreover, when the forecasting indicator set is further expanded by the nominal short-term interest rate (Model 4), the forecasting performance is still improved for Canada and Japan. Hence, including financial indicators in addition to the term spread is generally favorable in forecasting economic activity. Third, interestingly, when financial predictors are defined in real terms (Models 5–6), forecasting performance is unambiguously improved relative to nominal financial indicators (Models 2–4). In six of the G-7 countries, the best forecasting results are obtained by using the term spread, real stock returns and real short-term rates as the financial predictors. The exception is Italy, where the optimal set consists of the term spread and real stock returns. In most countries, the financial indicators improve the forecasting performance compared with the AR benchmark.

3.2. Time variation of forecast errors

Economic growth in the G-7 countries during the entire forecasting period is distinctly twofold (Figure 1) and may be divided into two sub-periods of approximately equal length: the pre-financial crisis period (2002Q1–2007Q4) and the financial crisis and the subsequent sovereign debt crisis period (2008Q1–2014Q1). During the crisis era, GDP growth collapsed and became markedly more volatile in all G-7 countries (Table 3). Taking into account the global nature of the financial crisis and prior research (e.g., Kuosmanen & Vataja, 2011, 2014; Kuosmanen et al., 2015; Chinn & Kucko; 2015), scrutinizing the behavior of forecast errors over time seems a worthwhile endeavor.

Figure 2 depicts the time variation of the best models' RMSEs for the entire forecasting period and the RMSEs of the AR benchmark (cf. Table 4). For all G-7 countries, excluding Italy, the best forecasting model specification includes the term spread, real stock returns and the real short-term interest rate (Model 6); for Italy, the best model includes the term spread and real stock returns (Model 5).

The time variation of the RMSEs clearly illustrates that the financial crisis is a significant watershed event for the forecasting ability of financial variables. Since the beginning of the financial crisis, the best models have systematically outperformed the AR benchmark in all G-7 counties, excluding Italy. In the case of Italy, the best model (Model 5) systematically outperforms the benchmark during the entire forecasting period, although the winning margin noticeably increases during the financial crisis era. As illustrated in Figure 2, during the first half of the forecasting period, i.e., during the pre-financial crisis era, the financial variables are primarily redundant in forecasting economic activity in France, Japan, and the U.K. and even more so in the U.S. and Canada.

Figure 2. Time variation of the RMSEs (2002Q1–2014Q1). The best financial indicator models (red line) in comparison with the AR benchmark (blue line).

The previous literature has shown that financial indicators began to lose their predictive ability for real activity in the mid-1980s. However, our results suggest that, since the global financial crisis, this loss of predictive power may no longer hold. Next, we scrutinize this outcome more formally by dividing the forecasting analysis into the two sub-periods during the entire forecasting era: the pre-financial crisis period (2002Q1–2007Q4) and the post-financial crisis period (2008Q1–2014Q1). The results of the analysis are presented in Table 5.

Table 5. Out-of-sample forecasts for the sub-periods.

(a) Forecasting period: 2002Q1–2007Q4.

Model specification	Canada RMSE	France RMSE	Germany RMSE	Italy RMSE	Japan RMSE	U.K. RMSE	U.S. RMSE
(1) AR	0.927	0.826	1.744	1.182	1.309	1.094	1.087
(2) AR+TS	1.292	0.847	1.841	1.183	1.255**	1.035*	1.275
(3) AR+TS+R	1.200	0.781	1.759	1.055*	1.340	1.139	1.344
(4) AR+TS+R+i	1.309	0.907	1.817	1.418	1.406	1.199	1.367
(5) AR+TS+R(real)	1.187	0.778**	1.758	1.059*	1.342	1.159	1.365
(6) AR+TS+R(real)+i(real)	1.342	0.811	1.790	1.369	1.411	1.155	1.295

(b) Forecasting period: 2008Q1–2014Q1.

Model specification	Canada RMSE	France RMSE	Germany RMSE	Italy RMSE	Japan RMSE	U.K. RMSE	U.S. RMSE
(1) AR	2.315	2.127	3.300	3.497	4.267	3.390	2.593
(2) AR+TS	2.148**	2.032*	3.003***	3.396	4.220	3.478	2.486*
(3) AR+TS+R	2.015**	1.982*	2.873**	3.145*	4.046**	3.385	2.571*
(4) AR+TS+R+i	1.919**	1.989*	2.843**	3.152*	3.889***	3.371	2.454**
(5) AR+TS+R(real)	2.010**	1.981*	2.873**	3.133*	4.031**	3.375	2.536*
(6) AR+TS+R(real)+i(real)	1.802***	1.751**	2.731**	3.069*	3.307***	3.071***	2.092**

Notes: see Table 4.

Panel (a) in Table 5 presents the RMSEs for the pre-financial crisis forecasting period. In line with Figure 2, the marginal predictive content of the financial indicators is considerably reduced compared with the results for the entire forecasting period in Table 4. The results demonstrate that the financial indicators do not contain predictive power for the GDP growth in Canada, Germany, and the U.S. However, this result is not fully robust for all G-7 countries: augmenting the forecasting model by the term spread yields the lowest forecast errors in Japan and the U.K.; in Italy, the best model also includes nominal stock returns, whereas the best model in France includes real stock returns.

Panel (b) shows that the forecasting performance has changed markedly since the financial crisis period. As expected, the forecast errors increase because of the increased volatility in economic activity: the RMSEs are approximately two to three times greater than they are during the pre-crisis period. However, the predictive content of the financial indicators (Models 2–6) has noticeably increased since the beginning of the financial crisis. Most importantly, the model specification with the term spread, real stock returns and the real short rate (Model 6) consistently yields the lowest RMSEs for all G-7 countries, and the forecast errors differ significantly from the AR benchmark in all cases. The improvements in forecasting performance are statistically significant and substantial compared with the simple AR benchmark: Canada 22%, France 18%, Germany 17%, Japan 22%, and the U.S. 19%. However, in the cases of Italy and the U.K., the improvements are somewhat smaller: Italy 12%, and the U.K. 9%. Given that the lack of robustness of financial variables' abilities to forecast GDP growth has been the distinctive feature in the previous literature, this consistent evidence for Model 6 is a remarkable and novel outcome.

4. CONCLUSIONS

The empirical analysis of this study yields three main outcomes. First, real financial predictors are preferable to nominal financial predictors in forecasting GDP growth in all the G-7 countries. Hence, nominal financial variables do not appear to contain useful additional information about future inflation that aids in forecasting real economic growth in developed economies. If short-term nominal interest rates are close at the zero lower bound (ZLB), the real short-term interest rate is a more useful predictor because the real interest rate may easily become negative. In addition, the term spread may also be a useful indicator at ZLB because whether the change in the term spread originates from the short-term rate or the long-term rate makes no difference (Estrella, 2005).

Our second main outcome suggests that all the key financial predictors – the term spread, the real short-term interest rate and real stock returns – should be used to forecast GDP growth in the G-7 countries after the financial crisis. This finding conflicts with the conclusions of Stock and Watson (2003), who argued that no clear systematic improvements are achieved when supplementary asset indicators are added to bivariate forecasting models.

Third, our results indicate that the reported weakening of the predictive ability of financial variables since the mid-1980s may have been a lengthy but temporary phenomenon. Several previous studies have suggested that a reduction in the predictive ability of the term spread is associated with changes in monetary policy (e.g., Estrella, Rodrigues & Schich, 2003; Estrella, 2004; Giacomini & Rossi, 2006; Hännikäinen, in press). This study covers five different central banks with different emphases on monetary policy; however, the results remain consistent. This outcome suggests, in line with Chinn and Kucko (2015), that the loss of the predictive content of financial variables since the mid-1980s may have been linked to a reduction in the volatility of numerous macroeconomic variables during the Great Moderation. The recent financial and sovereign debt crises have made a difference in that respect. Consequently, financial variables forecast economic activity better in the current turbulent economic conditions than they have in settings characterized by moderation. This finding is valuable because the need for sound forecasts is most pronounced under unstable economic circumstances. We conclude that, given the current economic circumstances, the main financial indicators demonstrate a promising resurgence in forecasting GDP growth in the G-7 countries. Whether this outcome holds as the crisis is mitigated remains to be seen.

REFERENCES

Ang, A., M. M. Piazzesi & M. Wei (2006). What does the Yield Curve tell us about GDP growth? *Journal of Econometrics* 131, 359–403.

Binswanger, M. (2000). Stock market booms and real economic activity: Is this time different? *International Review of Economics and Finance* 9, 387–415.

Binswanger, M. (2004).Stock returns and real activity in the G-7 countries: did the relationship change during the 1980s? *Quarterly Review of Economics and Finance* 44, 237–252.

Bordo, M.D. & J.G. Haubrich (2008). The yield curve as a predictor of growth: long run evidence, 1875–1997. *Review of Economics and Statistics* 90(1), 182–185.

Chinn, M.D. & K.J. Kucko (2015). The predictive power of the yield curve across countries and time. *International Finance* 18:2, 1–28.

Choi, J.J., S. Hauser & K.J. Kopecky (1999). Does the stock market predict real activity? Time series evidence from the G-7 countries. *Journal of Banking & Finance* 23, 1771–1792.

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138, 291–311.

Cohrane, J. (1991). What macroeconomists should know about unit roots: comment, in O. Blanchard & S. Fisher (eds.) *NBER Macroeconomics Annual, Vol.* 6. University of Chicago Press, 201–210.

Domian, D.L. & D.A. Louton (1997). A threshold autoregressive analysis of stock returns and real economic activity. *International Review of Economics and Finance* 6(2), 167–179.

Dotsey, M. (1998). The predictive content of the interest rate term spread for future economic growth. *Federal Reserve Bank of Richmond Economic Quarterly* 84(3), 31–51.

Estrella, A., A.P. Rodrigues & S. Schich (2003). How Stable Is the Predictive Power of the Yield Curve? Evidence from Germany and the United States. *Review of Economics and Statistics* 85(3), 629–644.

Estrella, A. (2004). Why does the yield curve predict output and inflation? *Economic Journal* 115 (July), 722–744.

Estrella, A. (2005). *The Yield Curve as a Leading Indicator: Frequently Asked Questions.* Available online at: http://www.ny.frb.org/research/ capital_markets/ ycfaq.pdf.

Giacomini, R. & B. Rossi (2006). How stable is the forecasting performance of the yield curve for output growth. *Oxford Bulletin of Economics and Statistic* 68, 783–795.

Haubrich, J.G. & A.M. Dombrosky (1996). Predicting real growth using the yield curve. *Federal Reserve Bank of Cleveland, Economic Review* 32(1), 26–35.

Harvey, C.R. (1989). Forecasts of economic growth from the bond and stock markets. *Financial Analyst Journal* (September/October), 38–45.

Harvey, C.R. (1991). The term structure and world economic growth. *Journal of Fixed Income* 1(1), 7–19.

Henry, Ó.T., N. Olekalns & J. Thong (2004). Do stock market returns predict changes to output? Evidence from a nonlinear panel data model. *Empirical Economics* 29, 527–540.

Hännikäinen, J. (In press). Zero lower bound, unconventional monetary policy and indicator properties of interest rate spreads. *Review of Financial Economics*.

Junttila, J. & H. Kinnunen (2004). The performance of economic tracking portfolios in an IT-intensive stock market. *Quarterly Review of Economics and Finance* 44, 601–623.

Kozicki, S. (1997). Predicting real growth and inflation with the yield spread. *Federal Reserve Bank Kansas City Economic Review* 82, 39–57.

Kuosmanen, P. & J. Vataja (2011). The role of stock markets vs. the term spread in forecasting macrovariables in Finland. *Quarterly Review of Economics and Finance* 51, 124–132.

Kuosmanen, P. & J. Vataja (2014). Forecasting GDP growth with financial market data in Finland: Revisiting stylized facts in a small open economy during the financial crisis. *Review of Financial Economics* 23(2), 90–97.

Kuosmanen, P., N. Nabulsi & J. Vataja (2015). Financial variables and economic activity in the Nordic countries. *International Review of Economics and Finance* 37, 368–379.

Mauro, P. (2003). Stock returns and output growth in emerging and advanced economies. *Journal of Development Economics* 41, 129–153.

Stock, J.H. & M.W. Watson (2003). Forecasting output and inflation: the role of asset prices. *Journal of Economic Literature* 41 (September), 788–829.

Tsouma, E. (2009). Stock returns and economic activity in mature and emerging markets. *Quarterly Review of Economics and Finance* 49, 668–685.

Wheelock, D.C. & M.E. Wohar (2009). Can the term spread predict output growth and recessions? A survey of the literature. *Federal Reserve Bank of St. Louis Review* 91 (September/October), 419–440.