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Title: Predictive ability of financial variables in changing economic circumstances

Year: 2019

Version: final draft

Please cite the original version:

Kuosmanen, P., Rahko, J. & Vataja, J. (2019). Predictive ability of financial variables in changing economic circumstances. *North American Journal of Economics and Finance* 47(1), 37-47. https://doi.org/10.1016/j.najef.2018.11.012

Predictive Ability of Financial Variables in Changing Economic Circumstances

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ABSTRACT

We analyze three key financial variables, the term spread, real stock returns and the real short-term interest rate, and study which economic factors underlie changes in their predictive power for GDP growth in a large set of industrialized countries. Our results show that the enhanced predictive content of financial variables is connected to increased GDP and stock market volatility as well as turning points in business cycles. Periods with a zero lower bound of interest rates appear to reduce the predictive ability of stock markets. Moreover, we find qualified evidence that inflation persistence increases the predictive content of financial variables.

KEY WORDS: Term spread, Short-term interest rates, Stock market, Forecasting, Macroeconomy

JEL classification: E37, E44, E47

1. INTRODUCTION

The relationship between financial markets and the real economy is most intriguing and important in developed economies. This relation provides useful and readily available real time information about future economic activity for forecasting purposes. Accordingly, there exists a large body of evidence and established stylized facts about the predictive links between different financial variables and real economic activity across countries and time periods. However, many studies have also shown that the predictive ability of financial variables is far from consistent and stable over time (e.g., Stock & Watson, 2003; Estrella, 2005a, 2005b; Bordo & Haubrich, 2008; Kuosmanen, Nabulsi & Vataja, 2015). Moreover, Kuosmanen & Vataja (2018) observed that the changes in the predictive ability of financial variables tended to coincide in the G-7 countries. However, we lack systematic evidence regarding the economic circumstances under which financial variables tend to have more or less useful predictive content for GDP growth. The existing evidence has thus far focused on the U.S. economy and explained the changes in the predictive content of term spreads (Bordo & Haubrich, 2004; Benati & Goodhart, 2008; Ng & Wrigth, 2013; Hännikäinen, 2017). The aim of this paper is to broaden the analysis to cover the three most focal predictive financial variables, several economic conditions and a large set of countries. Thus, this paper contributes to the literature by offering the first systematic analysis of the circumstances underlying changes in the predictive power of several financial predictors.

In the first phase of our empirical analysis, we select the three most established and commonly used financial variables and use them to forecast GDP growth in a set of 20 industrialized countries. First, the term spread, the difference between long- and short-term interest rates, has gained widely accepted status as the single most important financial predictor of economic activity in Western economies (e.g., Estrella & Mishkin, 1996; Estrella, 2005b). However, the stability of term spread's predictive content has been frequently questioned since the mid-1980s (e.g., Haubrich & Dombrosky, 1996; Wheelock & Wohar, 2009). Second, stock prices are connected to the future cash flows of corporations, and they are thus forward looking by nature. Consequently, expected changes in future cash flows will be immediately reflected in stock prices and later in economic activity. Hence, stock returns are another obvious candidate for forecasting economic activity in developed economies (Stock & Watson 2003; Harvey 1989). Interestingly, Henry et al. (2004) show that stock markets better forecast economic activity when the economy is contracting. Finally, central banks try to steer economic activity by controlling interest rates. Hence, short-term interest rates are directly connected to the presumed future state of the economy. Benati and Goodhart (2008) call the nominal short-term interest rate "*the simplest possible measure of the monetary policy stance*." Ang et al. (2006) were among the first to observe the useful predictive content of short-term interest rates for GDP growth in the U.S. economy. Subsequently, the predictive role of the short-term interest rate has also been confirmed in other countries (Kuosmanen et al., 2015; Kuosmanen & Vataja, 2017). These three selected financial variables have been extensively used for forecasting economic activity because they are forward-looking aggregators of information that are easy to interpret and can be observed in real time with negligible measurement errors. Furthermore, they are widely available across countries.

In the second phase of the study, we identify several economic conditions and thereafter investigate whether they systematically influence the predictive association between financial markets and the real economy. The analyzed conditions are related to circumstances in the real economy (GDP volatility, business cycle turning points and recessions), financial market turbulence (stock market volatility) and monetary policy stance (inflation persistence and the zero lower bound (ZLB) of interest rates). We measure these conditions at the time point of forecasting. Thus, we attempt to identify the conditions under which the selected financial variables provide useful and trustworthy predictive content for a forecaster. To the best of our knowledge, this is the first paper to extensively study how different economic circumstances affect the time-varying predictive ability of three key financial variables in a large set of industrialized countries.

Our main findings suggest that it is possible to identify economic circumstances that are systematically associated with changes in the predictive content of financial variables across countries. Overall, financial markets contain more useful information about real economic activity during times of volatile GDP growth and increased uncertainty in the stock market. The turning points of economic activity and periods of recession also tend to enhance the predictive content of individual financial variables. Moreover, monetary policy conditions affect the predictive association between financial markets and the real economy via at least two channels: the ZLB clearly weakens the predictive content of stock market information, and in contrast, we find qualified evidence that inflation persistence positively affects the predictive ability of all three financial variables.

The study is organized as follows. Section 2 reviews the economic factors that are expected to be connected to the forecasting ability of key financial variables. Section 3 introduces the data and forecasting results of each of the countries. The results of the models explaining forecast performance are presented and analyzed in Section 4. Finally, Section 5 concludes.

2. ECONOMIC CIRCUMSTANCES AFFECTING FORECASTING PERFORMANCE

The varying predictive ability of financial variables suggests that their relationship to the real economy may be conditional on real economic, financial market and monetary policy conditions. Our first candidate to explain the changing predictive content of financial variables for GDP growth is GDP growth volatility. This is an intuitive starting point because, logically, the simple autoregressive (AR) forecasting model performs better when GDP growth is smooth and its volatility is low; alternatively, during high GDP volatility, financial variables may contain useful additional information over and above lagged GDP growth. The Great Moderation was the period from the 1980s until the financial crisis of 2008 that was characterized by a remarkable reduction in the volatility of many macroeconomic time series. This period coincided with the diminishing predictive content of two key financial variables – the term spread and stock returns – especially in the G-7 countries since the 1980s (e.g., Haubrich & Dombrosky, 1996; Dotsey, 1998; Binswanger, 2000; Estrella, Rodrigues & Schich, 2003; Stock & Watson, 2003; Binswanger, 2004; Giacomini & Rossi, 2006; D'Agostino, Giannone & Surico, 2006; Wheelock & Wohar, 2009; Kuosmanen & Vataja, 2017). These almost simultaneous losses of predictive content may be linked to the reduction in GDP growth volatility or may reflect the influence of some unknown factor. Consequently, Chinn and Kucko (2015) suggest that the predictive power of the term spread may have strengthened after the financial crisis because of increased macroeconomic volatility. The existing empirical evidence mainly analyzes the forecasting power of the term spread. While the evidence on other financial variables is scarce, the results on the term spread imply that GDP growth volatility may also affect the predictive power of stock markets and short-term interest rates. The financial crisis again increased the volatility in real economic activity, which provides an opportunity to test whether the predictive power of financial variables is restored and possibly associated with GDP growth volatility.

Changes in the forecasting ability of financial variables may also be linked to recessions or other phases of the business cycle. Prior evidence shows that uncertainty is higher when economic growth is low and that uncertainty increases strongly during recessions (Bloom, 2014). For example, Henry et al. (2004) find that stock returns are more useful for forecasting purposes during recessions. Moreover, credit spreads – the difference between corporate and government debt instruments – have been found to forecast economic activity better during recessionary periods (Faust, Gilchrist, Wright & Zakrajsek, 2013). In addition, evidence suggests that the term spread, stock returns and short-term interest rate have different informational content for GDP growth during normal growth periods than during recessions and economic turbulence in the Nordic countries (Kuosmanen et al., 2015). In contrast, Hännikäinen (2017) does not find any difference in the predictive content of the term spread during recessions or normal growth periods in the U.S. However, the existing literature does not identify an economic cause for the varying predictive content of financial variables over the business cycle (e.g., Wheelock & Wohar, 2009). Therefore, we systematically analyze whether recessions or business cycle turning points influence the forecasting ability of financial variables in a more comprehensive set of countries.

Moreover, financial markets are occasionally subject to increased uncertainty and severe shocks that are only vaguely connected to real economic activity (e.g., the stock market crash of 1987 or "flight-to-safety" of 1998, i.e., the unexpected swift transition by investors from stocks to U.S. government bonds). Especially during financial turbulence, the real economy and financial markets may be out of sync, and consequently, financial markets possibly send false signals about future real activity (Siegel 2014: 229–239). Samuelson (1966) expressed this famously as "*the stock market has predicted nine out of the last five recessions.*" Alternatively, increased volatility is likely to precede business cycle turning points, thus improving the predictive content of stock markets over and above the simple AR model. Hence, investors' fears and subsequent financial market volatility may lead to changes in the predictive ability of financial variables.

Well-based arguments indicate that variability in the predictive relation between financial variables and economic activity can also be associated with the monetary regime and the credibility of monetary policy. Bordo and Haubrich (2008) propose that the predictive ability of both the term spread and short-term interest rate is connected to the monetary regime in place. Moreover, Bordo and Haubrich (2004) suggest that the predictive content of the yield curve is specifically connected to inflation persistence. Under a monetary regime with low credibility, and thus high persistence of inflation, the term structure – or even the simple term spread – should provide credible signals for future economic activity. An inflation shock leads to persistently higher inflation, which will increase both short- and long-term interest rates by the same amount, leaving the yield curve intact. In this case, only real shocks will affect the slope of the yield curve, and consequently, the term spread will not provide noisy signals owing to temporary inflation shocks. In contrast, under a credible monetary policy regime, a temporary inflationary shock will leave long-term interest rates stable and raise only short-term rates, leading to a flattening of the yield curve. Such a shock sends the false signal that an economic slowdown is coming. Benati and Goodhart (2008) do not find a long-run systematic association between inflation persistence and the predictive ability of the term spread based on a sample from the U.S., the U.K., Canada, Australia and the Eurozone. In contrast, Hännikäinen (2017) finds that the predictive power of the term spread is positively linked to inflation persistence and negatively linked to inflation volatility in the U.S. Accordingly, we broaden the analysis by testing whether the predictive content of all three individual financial variables is connected to inflation persistence, i.e., to the underlying price stability.

Finally, current unconventional monetary policy and the ZLB of interest rates are exceptional in the history of developed countries. At the ZLB, short-term nominal interest rates are fixed to zero or close to zero. Hence, the short-term interest rates may cease to send signals connected to expected future economic activity. Moreover, the ZLB eventually restricts the possible values that the term spread may gain, and thus, the predictive content of the term spread may change (Hännikäinen, 2015). Because interest rates also affect asset prices in stock markets, the ZLB possibly changes the traditional predictive links between stock markets and the real economy. ZLB implies a lower discount rate of future dividends. Thus, under ZLB, stock prices reflect expected changes in firm profitability in the more distant future. Therefore, the power to predict near-future macroeconomic activity may be weakened. Moreover, under ZLB, stock prices may reflect the lack of other investment opportunities rather than changes in the firm's current profitability. Hence, it is a well-motivated goal to clarify the role of the ZLB in this context.

3. GDP FORECASTING

3.1. Forecasting models

When specifying forecasting models, we pursue the following modeling strategy. First, forecasting performance may be improved by using several financial predictors in forecasting models (e.g., Kuosmanen & Vataja, 2017; 2018). Therefore, we start by specifying a model that includes all three financial predictors. This estimation presents conditions depicting a general relation between financial markets and the real economy. Second, because our aim is to obtain more specified information about the underlying economic circumstances that influence the predictive ability of each financial variable, we estimate single financial predictor models one by one. We construct the forecasting models separately for each country because we do not want to a priori impose the restriction that financial variables should have similar predictive content for GDP growth in every country because, e.g., financial institutions differ across countries. These models provide a necessary basis for the subsequent panel analysis that explicitly aims to uncover which prevailing economic conditions are linked to the predictive content of each financial predictor. We compare these models to the AR benchmark following the widely established practice in the previous literature (e.g., Stock & Watson, 2003; Bordo & Haubrich, 2008; Chinn & Kucko, 2015; Hännikäinen, 2015).

We conventionally assume that all relevant information regarding future economic activity is included in the most recent observation of the financial time series. Consequently, only the contemporaneous values of the financial data are used in forecasting. Finally, as commonly established in the previous literature, lagged GDP growth values are included in the forecasting models. Hence, the models consider the marginal additional predictive content of the financial predictors over and above lagged GDP growth (Stock & Watson, 2003). Given the number of countries and forecasting models, we consider only the four-quarter forecast horizon, which has the highest relevance in practice. This strategy yields the following five forecasting models:

$$(1)\ \Delta^4 y_{j,t+4} = \alpha^1 + \sum_{k=1}^{n} \gamma^1_{jk} \Delta y_{j,t-k+1} + u^1_{j,t+4} \qquad \text{(benchmark)}$$

$$(2)\ \Delta^4 y_{j,t+4} = \alpha^2 + \beta^2_{j1} TS_{jt} + \beta^2_{j2} R_{jt} + \beta^2_{j3} i_{jt} + \sum_{k=1}^{n} \gamma^2_{jk} \Delta y_{j,t-k+1} + u^2_{j,t+4}$$

$$(3)\ \Delta^4 y_{j,t+4} = \alpha^3 + \beta^3_{j1} TS_{jt} + \sum_{k=1}^{n} \gamma^3_{jk} \Delta y_{j,t-k+1} + u^3_{jt+4}$$

$$(4)\ \Delta^4 y_{j,t+4} = \alpha^4 + \beta^4_{j2} R_{jt} + \sum_{k=1}^{n} \gamma^4_{jk} \Delta y_{j,t-k+1} + u^4_{j,t+4}$$

$$(5)\ \Delta^4 y_{j,t+4} = \alpha^5 + \beta^5_{j3} i_{jt} + \sum_{k=1}^{n} \gamma^5_{jk} \Delta y_{j,t-k+1} + u^5_{j,t+4}$$

where TS is the term spread, R is the quarterly real stock returns, i is the real short-term interest rate, Δy is the quarterly GDP growth, $\Delta^4 y$ is the GDP growth four quarters ahead, α is the constant term, and u is the error term. The superscripts refer to the model number, and the subscript k refers to the number of AR terms. The subscript t refers to the time period, and j refers to the country.

Note that stock returns and short-term interest rates are specified in real terms. Although it appears intuitive to use real economic predictors to forecast real growth, the previous literature has remained imprecise in this respect. However, Kuosmanen and Vataja (2017) showed that real financial variables yield better forecast results and are thus preferable to nominal variables when forecasting GDP growth in the G-7 countries. In addition, it is well grounded to specify short-term interest rates in real terms when the ZLB is binding because real interest rates may vary more than nominal rates close to the ZLB.

Out-of-sample forecasting analysis is conducted using rolling regressions with the estimation window of 40 quarterly observations (i.e., a 10-year estimation window). Rolling forecasts are preferred to recursive ones when parameter instability is expected. The global financial crisis substantially affected economic growth during the forecasting period (2000:1–2016:1). Hence, the concern for parameter instability is justified. Because the GDP data are not available at a monthly frequency, we have to use the quarterly data. An obvious drawback of using quarterly data is that the required estimation window is necessarily rather long in order to preserve enough observations for the estimation. Ideally, a shorter estimation window might be preferable; however, this is not possible in this case.

3.2. Construction of data

The data are obtained from the OECD database and comprise quarterly time series for twenty countries[1]. We obtain the data from a single source for data consistency except for

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[1] The data cover Australia (1980:1–2016:1), Austria (1990:1–2016:1), Belgium (1985:2–2016:1), Canada (1980:1 –2016:1), Denmark (1987:1–2016:1), Finland (1988:1–2016:1), France (1980:1–2016:1), Germany

data on the VIX, which are obtained from FRED Economic Data. Kuosmanen et al. (2015) and Kuosmanen and Vataja (2018) observed coinciding changes in predictive power in the Nordic and G-7 countries. Thus, our aim to analyze the underlying factors in a more comprehensive group of industrialized countries is well motivated. All the sample countries except South Africa belong to the group of advanced countries according to the IMF's classification, while South Africa belongs to the group of emerging market and developing economies (IMF World Economic Outlook, April 2016).

The variables for the forecasting models are formed as follows. GDP growth and stock returns series are constructed using log differences. The term spread is defined conventionally as the difference between the long-term (10-year bond) and short-term (3-month bill) interest rates. Real stock returns are calculated by deflating nominal stock prices by consumer price index, and the real short-term interest rate is calculated by subtracting the annual inflation rate from the nominal short-term interest rate. Details regarding the data and the variable construction are presented in Table 1.

(1980:1–2016:1), Ireland (1984:1–2016:1), Italy (1991:2–2016:1), Netherlands (1986:1–2016:1), New Zealand (1987:3–2016:1), Norway (1986:1–2016:1), Spain (1985:1–2016:1), Portugal (1993:3–2016:1), South Africa (1981:1–2015:4) Sweden (1987:1–2016:1), Switzerland (1980:1–2016:1), the U.K. (1980:1–2016:1) and the U.S. (1980:1–2016:1).

Table 1. Description of the data.

RAW DATA	DATA TRANSFORMATION	OECD SOURCE
Y = Real gross domestic product, expenditure approach, seasonally adjusted	$y = lnY$	Quarterly National Accounts
is = Short-term nominal interest rate; 3-month interbank rate		Key Short-Term Economic Indicators
il = Long-term interest rate; yield of 10-year government bond		Key Short-Term Economic Indicators
S = Share price index (2010 = 100); national broad share price index; dividends are not included	$s = lnS$	Monthly Monetary and Financial Statistics
P = Consumer price index, all items (2010 = 100)	$p = lnP$	Key Short-Term Economic Indicators
TRANSFORMED DATA	VARIABLE CONSTRUCTION	
Real annual GDP growth	$\Delta^4 y_{t+4} = (y_{t+4} - y_t) \times 100$	
Quarterly GDP growth	$\Delta y_t = (y_t - y_{t-1}) \times 100$	
TS = Term spread	$TS_t = il_t - is_t$	
R = Quarterly real stock returns	$R_t = [(s_t - p_t) - (s_{t-1} - p_{t-1})] \times 100$	
$\Delta^4 p$ = Annual inflation rate	$\Delta^4 p_t = (p_t - p_{t-4}) \times 100$	
i = Real short-term interest rate	$i_t = is_t - \Delta^4 p_t$	

3.3. Forecasting results

We estimate the five forecasting models separately for each of the 20 countries. The in-sample period ranges until 1999:1, and the out-of-sample period is from 2000:1 to 2016:1[2]. Following the previous literature, we evaluate forecasting performance on the basis of the root mean squared error (RMSE): the lower the RMSE, the better the forecasting performance. The number of the AR terms is determined based on the Schwartz information criterion. The maximum number of the AR terms is set to five. In most cases, the number of selected AR terms is one. The forecasting results are presented in Table 2.

[2] The length of the in-sample period is country specific and depends on data availability. See footnote 1.

Table 2. First-stage estimation. Out-of-sample forecasting results (RMSE) (2000:1–2016:1).

	(1) AR	(2) AR+TS+R+i	(3) AR+TS	(4) AR+R	(5) AR+i
Australia	0.944	1.020	0.924**	0.956	1.083
Austria	2.042	2.028*	1.896**	2.109	2.179
Belgium	1.675	1.650**	1.664	1.663	1.730
Canada	1.829	1.585***	1.767***	1.798**	1.893
Denmark	2.309	1.872***	1.899***	2.085***	2.414
Finland	2.150	1.563***	1.764***	2.015***	2.185
France	1.491	1.324***	1.312***	1.401**	1.621
Germany	2.556	2.278***	2.237***	2.329***	2.707
Ireland	4.247	4.477	4.777	3.911***	4.441
Italy	2.372	2.322*	2.488	2.316*	2.545
Netherlands	2.095	1.916***	1.951***	1.806***	2.328
New Zealand	1.850	1.988	1.851	1.727***	2.090
Norway	1.766	1.936	1.830	1.715**	1.873
Spain	1.782	1.708**	1.761	1.721**	1.899
Portugal	2.467	2.219***	2.340***	2.318***	2.546
South Africa	1.849	1.673***	1.986	1.709***	1.641***
Sweden	2.892	2.064***	2.315***	2.645***	2.838**
Switzerland	1.763	1.734*	1.638***	1.749	1.762
UK	2.136	1.858***	2.135	2.050***	2.120*
US	1.822	1.601***	1.752***	1.832	1.867

Notes: Significance levels for the Clark and McCracken (2001) test: *** = 1%, ** = 5%, * = 10%. The null hypothesis is that the RMSE of the corresponding model does not differ significantly from the RMSE of the benchmark AR model (Model 1).

The results provide strong support for the predictive ability of financial variables: in all the 20 countries, a financial model specification yields better forecasts than the AR benchmark (Model 1). In nine countries, the most richly parameterized financial model (Model 2) yields the lowest forecast errors. The model specification with the term spread or real stock returns (Model 3 or 4) generates the lowest RMSEs in five cases. The short-term interest rate specification (Model 5) yields the lowest forecast errors in only one special case, South Africa. Moreover, in 16 counties, the predictive ability of this financial model specification is even worse than that of the AR benchmark model. The term spread model, stock market model and model containing all three financial variables provide more accurate forecasts than the AR benchmark model in most of our sample countries.

Regarding the country-specific results, the forecast errors are distinctively larger in Ireland than in the other countries. Moreover, e.g., in Sweden, all financial variables appear to have predictive power, whereas in Australia, only the term spread is able to produce better forecasts than the AR model. Country-specific error spread graphs are available upon request.

4. FORECAST PERFORMANCE ANALYSIS

4.1. Variable formation

We analyze the forecast performance using country panel regressions. Panel regressions are used because we are searching for systematic variations in the predictive content of the financial predictors. In these estimations, we have two variants of the dependent variable. The first dependent variable is the error spread. Thus, we use a similar approach as, e.g., Ng and Wright (2013), Hännikäinen (2017), and Kuosmanen and Vataja (2018), to study the intertemporal behavior of the forecast errors. The error spread is defined for each financial variable forecasting model as follows:

$$(6) \qquad ERSPR^{i}_{j,t+4} = \sqrt{\left(\Delta^4 y_{j,t+4} - \Delta^4 \hat{y}^{1}_{j,t+4}\right)^2} - \sqrt{\left(\Delta^4 y_{j,t+4} - \Delta^4 \hat{y}^{i}_{j,t+4}\right)^2},$$

where $\Delta^4 y_{t+4}$ is the GDP growth, $\Delta^4 \hat{y}^{1}_{t+4}$ is the forecasted GDP growth from the AR model, and $\Delta^4 \hat{y}^{i}_{t+4}$ is the forecasted GDP growth from the financial variable model *i*. The more positive the error spread, the better the financial variable model forecast performed in comparison to the AR benchmark in that time period. We have four forecasting models (Models 2–5), and thus, we have four different error spreads for each country.

Our second dependent variable is a binary variable that takes the value of one when the model including financial variables outperforms the benchmark model, i.e., when the error spread is positive (Hännikäinen, 2017). The binary variable describes whether the financial variables contain more predictive power than the AR benchmark. In contrast, the error spreads also account for how much the financial variable model out- or underperforms the benchmark.

We study whether increased GDP growth volatility is linked to the forecasting performance of the financial variables, as suggested in the literature. Moreover, we include in the analysis financial market cycles and uncertainty in the stock market by using the stock market's expected volatility index (VIX). The volatility variables are defined as follows. GDP growth volatility is measured by the four-quarter moving standard deviation of quarterly GDP growth (Blanchard & Simon, 2001). Stock market volatility is measured using the forward-looking VIX index, which is calculated by the quarterly average of the implied 30-day volatility on S&P 500 index options.

Prior evidence implies that, e.g., credit spreads forecast economic activity better during recessions (Faust et al., 2013). Business cycle peaks are an opposite kind of economic situation, which may also change the predictive ability of financial variables. Therefore, we form the following dummy variables to analyze the role of different business cycle phases. The first dummy variable indicates recession periods and takes the value of one when GDP has been decreasing at least for two quarters in a row and zero otherwise. The second and third dummies indicate business cycle peaks and troughs and are formed using the OECD country-level output gap information. The original OECD data provide annual output gap estimates. These time series are transformed to quarterly estimates by using cubic spline interpolation. The dummy variable for business cycle peak takes the value of one when the quarterly output gap is at the country-specific top decile and zero otherwise. The dummy for business cycle trough takes the value of one when the output gap is at the bottom decile.

Moreover, we wish to measure inflation persistence. As conventional, inflation persistence is calculated as a sum of the AR coefficients from the estimated AR model for quarterly inflation (Andrews & Che, 1994; Benati, 2008). The AR models are estimated using a rolling estimation window of 40 quarters, and the number of AR terms is selected based on the Schwartz criterion.

Finally, currently conducted unconventional monetary policy with historically low or even negative interest rates may have affected the traditional predictive links between financial markets and the real economy. Therefore, we create a dummy variable to indicate situations when the interest rates are close to the ZLB. The dummy takes the value of one when the short-term interest rate is 0.25 or lower; higher interest rates give the dummy value of zero. The cut-off choice of 0.25 is not based on clear theoretical arguments. However, e.g., the FED's federal funds target range was set to 0-0.25 from 2008 until 2015. It is evident that at this limit, central banks' options to conduct further conventional monetary policy are practically non-existent and that the ZLB is binding.

4.2. Summary statistics

Our estimation sample includes 1198 observations from 20 countries and is an unbalanced panel because the OECD dataset does not cover early quarters for all countries. The OECD output gap data are not available for South Africa, and thus, the variables describing business cycle peaks and troughs exclude South Africa and contain fewer observations. Summary statistics are presented in Table 3.

Table 3. Summary statistics of forecast performance.

Variable	Mean	SD	Median
Error spread M2	0.014	1.193	-0.002
Error spread M3	-0.030	0.913	-0.007
Error spread M4	0.064	0.742	0.014
Error spread M5	-0.116	0.669	-0.034
M2 wins AR (D)	0.497	0.500	0.000
M3 wins AR (D)	0.481	0.500	0.000
M4 wins AR (D)	0.531	0.499	1.000
M5 wins AR (D)	0.439	0.496	0.000
GDP volatility	0.592	0.518	0.439
Inflation persistence	0.193	0.379	0.285
Inflation volatility	0.526	0.296	0.459
Quarterly VIX	20.673	8.392	19.169
Recession (D)	0.102	0.303	0.000
Business cycle peak (D)*	0.122	0.327	0.000
Business cycle through (D)*	0.094	0.293	0.000
ZLB (D)	0.101	0.301	0.000

Notes: 1198 obs, *1133 obs

4.3. Empirical methodology

In our forecast performance analysis, we first estimate the following equation:

(7) $$ERSPR^{i}_{j,t+4} = \alpha + \beta X_{j,t} + \upsilon_j + \tau_t + \varepsilon_{j,t+4},$$

where ERSPR denotes the error spread and $X_{j,t}$ is a vector of explanatory variables that includes GDP volatility, inflation persistence, the VIX, a ZLB dummy variable and a recession dummy or business cycle peak and trough dummies. The regressors are measured at the time period when the forecast is made. Furthermore, τ presents the time effects, and ν denotes the country fixed effect. The equation is estimated with fixed effect panel estimation. Country fixed effects control for, e.g., institutional or other time-invariant country-specific differences that cause the error spreads to differ across countries. We observe that the error spreads move in tandem in several countries, especially during the financial crisis. Thus, we use time fixed effects to check whether the changes in the explanatory power of the financial variables are associated with certain time periods in all countries (e.g., global financial conditions) and not necessarily with our variables describing economic conditions. We first estimate specifications without time fixed effects and then include them. Standard errors are clustered on countries to allow autocorrelated and heteroskedastic errors within countries.

Second, we consider a specification in which the dependent variable is a binary variable that takes the value one when the model including financial variables outperforms the benchmark model. Therefore, we estimate the following model:

$$\Pr\left(ERSPR^{i}_{j,t+4} > 0\right) = \Lambda\left(\beta X_{j,t} + \upsilon_j + \tau_t\right) + e_{j,t+4}, \tag{8}$$

where $\Lambda(.)$ is the logistic cumulative distribution. The equation is estimated with fixed effect logit estimation to account for country effects. The estimation approach is also called the conditional logit estimator because although it controls for the fixed effects, υ_i, they cannot be estimated as parameters. The explanatory variables, $X_{j,t}$, are the same as above. We also estimate a model in which time dummies are included.

4.4. Results

Tables 4–7 present the panel regression results explaining changes in the forecast error spreads and the binary variables. First, we have a model in which all three financial variables are included in the forecasting model (Table 4). This model describes a general relation between financial markets and the real economy. The results unambiguously indicate that the financial markets are more useful in forecasting real economic activity during turbulent GDP growth than during smooth growth circumstances. This finding is in line with prior studies indicating that the predictive relation between financial variables and real economic activity was weakened during the Great Moderation. Moreover, we find some evidence that times of recession and business cycle turning points further improve the predictive ability of financial markets. Interestingly, the results indicate that expected stock market volatility strengthens the predictive relationship between financial markets and the real economy; however, the logit estimations do not confirm this finding. These contradictory results may be due to the extreme values of error spreads that may, as outliers, affect the fixed effect panel regression, whereas they do not similarly affect the logit estimation, which considers only whether the error spread is positive or negative. Thus, columns 1-4 are more influenced by the turbulent times, whereas columns 5-8 give equal weight to more stable times.

Tables 5, 6 and 7 presents a more precise analysis explaining time variance in the predictive ability of each individual financial variable. Table 5 considers how different economic conditions influence the predictive content of the term spread. In general, the results indicate that the term spread contains more predictive power under volatile economic growth circumstances and under increased volatility of the stock markets. In addition, the results lend support to the stylized fact that the term spread is good at forecasting at business cycle peaks when the inverted yield curve precedes an economic slowdown (Estrella, 2005a). Moreover, during recession periods, the forecasting power of the term spread clearly increases. In sum, it is evident that the term spread has increased predictive power at business cycle peaks, during volatile GDP growth periods and under volatile stock market conditions. In contrast and somewhat surprisingly, we do not find evidence that the ZLB affects the predictive content of the term spread.

Table 6 considers the predictive link between stock markets and the real economy. Interestingly, increased values of the VIX index seem to improve the predictive ability of stock returns. This result indicates that increased stock market volatility precedes business cycle turning points or other changes in real economic activity that are linked to improvements in the predictive ability of stock markets. The regressions also demonstrate another clear outcome: the ZLB negatively affects the predictive ability of real stock returns for economic activity. This result is rather expected. Under unconventional monetary policy and close to the ZLB, stock prices reflect more the absence of alternative investment objects and less the short-term future changes in the profitability of listed companies. Another interesting outcome is that real stock returns systematically produce better forecasts during business cycle troughs than during peaks. This result is also in accordance with the findings of Henry et al. (2004). The asymmetric predictive ability of

Table 4. Second-stage estimation. Explanatory power of forecasting model 2 compared to AR benchmark.

	Error spread				Binary variable			
	1	2	3	4	5	6	7	8
GDP volatility	0.441**	0.536***	0.431**	0.493***	0.340**	0.570***	0.321**	0.539***
	(0.184)	(0.122)	(0.187)	(0.124)	(0.157)	(0.197)	(0.158)	(0.200)
Inflation persistence	0.113	0.056	0.071	0.032	0.071	0.148	-0.002	0.067
	(0.122)	(0.224)	(0.132)	(0.247)	(0.210)	(0.276)	(0.214)	(0.289)
VIX, quarterly average	0.019***	0.049***	0.019***	0.057***	0.010	-0.383	0.012	-0.493**
	(0.006)	(0.013)	(0.006)	(0.012)	(0.008)	(0.239)	(0.008)	(0.250)
Recession (D)	0.175	0.093			0.238	0.118		
	(0.162)	(0.233)			(0.215)	(0.278)		
Business cycle peak (D)			0.360**	-0.151			0.558***	-0.475
			(0.139)	(0.152)			(0.197)	(0.294)
Business cycle trough (D)			0.244*	0.309*			0.342	0.406
			(0.131)	(0.160)			(0.231)	(0.258)
ZLB(D)	0.002	-0.072	-0.030	-0.095	-0.232	-0.318	-0.263	-0.364
	(0.153)	(0.234)	(0.145)	(0.218)	(0.213)	(0.307)	(0.224)	(0.324)
Constant	-0.681***	-1.316**	-0.726***	-1.622***				
	(0.163)	(0.462)	(0.171)	(0.464)				
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1198	1198	1133	1133	1198	1198	1133	1133
R-squared/ Pseudo R-squared	0.057	0.220	0.066	0.230	0.010	0.106	0.016	0.114
Log likelihood					-758.779	-684.748	-711.894	-641.420

Notes: Forecasting model 2 specification: AR+TS+R+i

* p<0.10, ** p<0.05, *** p<0.01. Cluster robust standard errors are shown in parentheses.

Table 5. Second-stage estimation. Explanatory power of forecasting model 3 compared to AR benchmark.

	Error spread				Binary variable			
	1	2	3	4	5	6	7	8
GDP volatility	0.310***	0.318***	0.337***	0.301***	0.206	0.144	0.260	0.087
	(0.091)	(0.067)	(0.091)	(0.083)	(0.156)	(0.192)	(0.160)	(0.196)
Inflation persistence	0.172	-0.184	0.111	-0.145	0.507**	0.236	0.412*	0.483
	(0.106)	(0.228)	(0.096)	(0.264)	(0.215)	(0.283)	(0.219)	(0.297)
VIX, quarterly average	0.013**	0.028***	0.013**	0.028***	0.030***	0.179	0.025***	0.169
	(0.004)	(0.009)	(0.005)	(0.009)	(0.008)	(0.250)	(0.008)	(0.252)
Recession (D)	0.345**	0.262			0.662***	0.607**		
	(0.130)	(0.152)			(0.221)	(0.283)		
Business cycle peak (D)			0.547***	0.302***			1.498***	1.159***
			(0.075)	(0.077)			(0.228)	(0.305)
Business cycle trough (D)			0.150	0.285			0.379	0.638**
			(0.189)	(0.199)			(0.232)	(0.264)
ZLB(D)	0.050	0.144	0.072	0.075	-0.179	0.041	-0.146	-0.273
	(0.114)	(0.207)	(0.127)	(0.214)	(0.218)	(0.310)	(0.229)	(0.325)
Constant	-0.550***	-0.740**	-0.604***	-0.788**				
	(0.129)	(0.328)	(0.140)	(0.373)				
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1198	1198	1133	1133	1198	1198	1133	1133
R-squared/ Pseudo R-squared	0.068	0.227	0.092	0.233	0.032	0.133	0.059	0.144
Log likelihood					-741.680	-664.284	-681.781	-620.143

Notes: Forecasting model 3 specification: AR+TS

* p<0.10, ** p<0.05, *** p<0.01. Cluster robust standard errors are shown in parentheses.

Table 6. Second-stage estimation. Explanatory power of forecasting model 4 compared to AR benchmark.

	Error spread				Binary variable			
	1	2	3	4	5	6	7	8
GDP volatility	0.205**	0.103	0.182*	0.090	0.185	0.077	0.117	-0.034
	(0.086)	(0.067)	(0.087)	(0.072)	(0.156)	(0.193)	(0.157)	(0.197)
Inflation persistence	-0.030	0.088	-0.019	0.084	0.215	0.491*	0.320	0.576*
	(0.057)	(0.083)	(0.064)	(0.092)	(0.210)	(0.284)	(0.214)	(0.297)
VIX, quarterly average	0.010***	0.018***	0.012***	0.022***	0.029***	-0.085	0.029***	-0.203
	(0.003)	(0.006)	(0.003)	(0.007)	(0.008)	(0.241)	(0.008)	(0.253)
Recession (D)	0.103	-0.092			0.025	-0.221		
	(0.102)	(0.114)			(0.216)	(0.281)		
Business cycle peak (D)			-0.061	-0.200			-0.029	-0.450
			(0.050)	(0.125)			(0.194)	(0.285)
Business cycle trough (D)			0.156*	0.199***			0.693***	0.815***
			(0.088)	(0.059)			(0.237)	(0.267)
ZLB(D)	-0.203*	-0.222**	-0.256***	-0.284***	-0.589***	-0.585*	-0.808***	-0.906***
	(0.101)	(0.101)	(0.086)	(0.086)	(0.215)	(0.313)	(0.232)	(0.336)
Constant	-0.255***	-0.472	-0.268***	-0.637**				
	(0.077)	(0.286)	(0.083)	(0.293)				
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1198	1198	1133	1133	1198	1198	1133	1133
R-squared/ Pseudo R-squared	0.050	0.191	0.048	0.206	0.023	0.126	0.029	0.137
Log likelihood					-756.980	-676.964	-711.425	-632.555

Notes: Forecasting model 4 specification: AR+R

* p<0.10, ** p<0.05, *** p<0.01. Cluster robust standard errors are shown in parentheses.

Table 7. Second-stage estimation. Explanatory power of forecasting model 5 compared to AR benchmark.

	Error spread				Binary variable			
	1	2	3	4	5	6	7	8
GDP volatility	0.128	0.129*	0.125	0.106	0.300*	0.240	0.310**	0.250
	(0.084)	(0.063)	(0.089)	(0.073)	(0.153)	(0.185)	(0.156)	(0.189)
Inflation persistence	0.146	0.222	0.158	0.274*	0.168	0.638**	0.168	0.803***
	(0.092)	(0.143)	(0.096)	(0.143)	(0.212)	(0.280)	(0.217)	(0.295)
VIX, quarterly average	-0.007	-0.001	-0.008	0.001	-0.019**	-0.149	-0.021***	-0.246
	(0.005)	(0.007)	(0.005)	(0.007)	(0.008)	(0.234)	(0.008)	(0.241)
Recession (D)	0.057	0.092			0.369*	0.488*		
	(0.080)	(0.131)			(0.213)	(0.275)		
Business cycle peak (D)			0.148	0.016			0.555***	0.247
			(0.096)	(0.050)			(0.195)	(0.279)
Business cycle trough (D)			0.234**	0.233**			0.659***	0.703***
			(0.093)	(0.105)			(0.232)	(0.260)
ZLB(D)	0.052	-0.104	-0.002	-0.146*	-0.176	-0.499	-0.313	-0.697**
	(0.064)	(0.068)	(0.062)	(0.083)	(0.213)	(0.305)	(0.225)	(0.324)
Constant	-0.094	-0.004	-0.115	-0.124				
	(0.079)	(0.173)	(0.080)	(0.186)				
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1198	1198	1133	1133	1198	1198	1133	1133
R-squared/ Pseudo R-squared	0.013	0.122	0.027	0.147	0.007	0.086	0.017	0.096
Log likelihood					-755.141	-695.319	-705.747	-648.795

Notes: Forecasting model 5 specification: AR+i

* p<0.10, ** p<0.05, *** p<0.01. Cluster robust standard errors are shown in parentheses.

stock returns may reflect the fact that many noise traders have left the stock market at cycle troughs, and, consequently, there are relatively more professionals and informed traders acting in the markets. It is also interesting to contrast this result with the predictive ability of the term spread, which clearly improves at business cycle peaks. Thus, different financial predictors appear to send useful signals in different business cycle phases.

Table 7 presents the results for the forecasting ability of real short-term interest rates. The regressions indicate some noteworthy similarities with real stock returns: the real short rate offers more reliable predictions during business cycle troughs than during peaks, the ZLB has a negative effect on the predictive content of short-term interest rates, and GDP volatility plays a statistically significant role, at least in some of the regressions. These results offer further support for the conclusion that the unprecedentedly low nominal interest rates are confusing the predictive links between financial markets and real economies in industrialized countries. This is the case even though interest rates are defined in real terms and are not similarly bound by the ZLB. Moreover, the logit estimation indicates that the real short-term interest rate might have more predictive power during recessions and under conventional monetary policy.

The monetary policy conditions appear to have a noteworthy impact on the predictive links between financial variables and the real economy. The ZLB clearly has a negative effect on the predictive content of stock market and, evidently, interest rates. However, the influence of inflation persistence on the predictive content of individual financial variables is somewhat ambiguous. The error spread models do not show that inflation persistence has any significant impact on the predictive ability of the financial variables. In contrast, the logit estimations show statistically significant effects. In particular, two term spread models, two stock returns models, and two short-term interest rate models show that inflation persistence improves the predictive content of financial variables. Thus, financial variables contain more predictive power when inflation is stable. However, model 2, which combines all the financial variables, does not show a significant effect for inflation persistence. These results offer further support for and extend the findings of Bordo and Haubrich (2004), who connect inflation persistence and the predictive ability of the term spread. These results also show that Hännikäinen’s (2017) results that inflation persistence is a key variable affecting the predictive ability of the yield curve in the U.S. economy appears be generalizable to other countries and other financial variables. The differences that emerge between the error spread and binary variable models may stem from the fact that the error spreads strongly fluctuated during the financial crisis. These observations have a significant effect on the error spread analysis, but by definition, they do not have a similar impact on the binary variable analysis. In sum, the results from the logit estimations lend support to the notion that inflation persistence, i.e., predictable and stable inflation, enhances the predictive content of all financial variables.

5. CONCLUSIONS

This study contributes to the existing literature by providing the first systematic analysis of the links between economic circumstances and the predictive content of several financial variables. We identify economic conditions that are associated with the time-varying predictive relationship between financial markets and real economic activity in a comprehensive set of industrialized countries. The results unambiguously show that increased GDP growth volatility is connected to the improved predictive content of financial markets for GDP growth. This result corroborates prior evidence but in a larger context than before. Hence, we conclude that the reduced predictive content of financial markets prior to the financial crisis of 2008 was evidently linked to contemporaneous reduced GDP growth volatility. This outcome includes both good and bad news for economists forecasting GDP growth: the good news is that financial variables have useful predictive content during turbulent times when the need for better forecasts is most compelling, whereas the bad news is that forecast errors are also larger during turbulent times.

We also find that financial variables contain more useful information for forecasting purposes near business cycle turning points. Thus, not only is the improved predictive content of financial variables during business cycle turning points related to contemporaneously increased GDP volatility, but business cycle phases also have an independent effect on the predictive ability of financial variables. More specifically, confirming prior evidence, we find that the term spread has increased predictive content at the peaks of business cycles, whereas a new finding is that stock returns and the short-term interest rate have enhanced predictive content at the troughs. This distinct difference should be taken into account when forecasting economic activity. Moreover, an increase in expected stock market volatility evidently improves the predictive ability of financial variables, excluding the short-term interest rate. This novel finding implies that the VIX may reflect wider economic uncertainty beyond the stock markets. In sum, recessions, business cycle turning points and increased volatility in stock markets appear to be related to the enhanced predictive ability of financial variables. This is further good news for economists because it is very difficult to forecast real economic activity under high uncertainty and near the turning points of business cycles.

Factors connected to monetary policy also play a noteworthy role. We notice that the zero lower bound of interest rates strongly reduces the predictive ability of stock markets, which is a new yet logical outcome. The recent extremely low and even negative interest rates are historically rare events, although they have lately proven to be more frequent and long lived than previously believed (Mishkin, 2017). Thus, the zero-lower-bound problem may continue to confound the predictive power of financial markets in the future. Finally, our results also suggest that increased inflation persistence improves the predictive power of all the individual financial variables during stable conditions. These results are in line with Bordo and Haubrich (2004) and Hännikäinen (2017). However, our more comprehensive analysis of several financial variables and a larger set of countries suggests a weaker relationship than prior studies.

In sum, this study provides new guidelines to understand and anticipate forthcoming changes in the predictive content of key financial variables. It should be noted that our results do not necessarily indicate a causal relationship but rather provide insights into the circumstances coinciding with changes in the forecast performance. However, we have examined the economic circumstances at the time period when the forecast is made; thus, we have used information that is readily available for forecasters' use. We can state that the same financial forecasting model does not necessary fit for all conditions in the economy; rather, it is better to rely on different financial variables in different conditions. A logical next step in future research is to utilize this information to construct more accurate switching models. The focus of the present paper has been on domestic economic conditions; however, global economic or financial conditions may also lead to systematic changes in the predictive ability of financial variables, which merits further study.

Acknowledgements: We would like to thank Raoul Minetti, Heikki Lehkonen, Juha Junttila Maurice Peat and the participants at the 22nd International Conference of Macroeconomic Analysis and International Finance, Jyväskylä XXXV Summer Seminar for Finnish Economists, the Annual Meeting of the Finnish Economic Association 2017 and the 3rd Vietnam Symposium in Banking and Finance for their helpful comments.

REFERENCES

Andrews, D.W.K. & H-Y. Chen (1994). Approximately median-unbiased estimation of autoregressive models. *Journal of Business & Economic Statistics* 12:2, 187-204.

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

Benati, L. (2008). Investigating inflation persistence across monetary regimes. *Quarterly Journal of Economics* 123:3, 1005-1060.

Benati, L. & C. Goodhart (2008). Investigating time-variation in the marginal predictive power of the yield spread*, Journal of Economic Dynamics & Control* 32, 1236–1272.

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.

Blanchard, O. & J. Simon (2001). The long and large decline in US output volatility. *Brookings Papers on Economic Activity* 2001:1, 135–164.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives* 28:2, 153–176.

Bordo, M.D. & J.G. Haubrich (2004). The yield curve, recessions and the credibility of the monetary regime: long run evidence 1875–1997. *NBER Working Paper* 10431, April 2004.

Bordo, M.D. & J.G. Haubrich (2008). Forecasting with the yield curve; level, slope, and output 1875–1997. *Economic Letters* 99, 48–50.

Chen, S. & R. Ranciere (2016). Financial Information and Macroeconomic Forecasts. *International Monetary Fund Working Papers* No. 16/251.

Chinn, M.D. & K.J. Kucko (2015). The predictive power of the yield curve across countries and time. *International Finance* 18:2, 129–156.

Clark, T. E., and M.W. McCracken (2001). Tests of equal forecast accuracy and encompassing for nested models. *Journal of Econometrics*, 105, 85–110.

D'Agostino, A., D. Giannone & P. Surico (2006). (Un)predictability and macro-economic stability. *European Central Bank Working Paper* No. 605, April 2006.

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. (2005a). Why does the yield curve predict output and inflation? *Economic Journal* 115, 722–744.

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

Faust, J., S. Gilchrist, J.H. Wright & E. Zakrajšek (2013). Credit spreads as predictors of real-time economic activity: A Bayesian model-averaging approach. *Review of Economics and Statistics* 95, 1501–1519.

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.

Harvey, C. R. (1989). Forecasts of economic growth from the bond and stock markets. *Financial Analysts Journal*, 38-45.

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.

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. (2015) Zero lower bound, unconventional monetary policy and indicator properties of interest rate spreads. *Review of Financial Economics* 26, 47-54.

Hännikäinen, J. (2017). When does the yield curve contain predictive power? Evidence from a data-rich environment. *International Journal of Forecasting* 33, 1044-1064.

IMF World Economic Outlook, April 2016.

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

Kuosmanen, P. & J. Vataja (2017). The return of financial variables in forecasting GDP growth in the G-7. *Economic Change and Restructuring* 50:3, 259-277.

Kuosmanen, P. & J. Vataja (2018). Time-varying predictive content of financial variables in Forecasting GDP growth in the G-7 countries. Forthcoming in *Quarterly Review of Economics and Finance*.

Mishkin, F.S. (2017). Rethinking monetary policy after crisis. *Journal of International Money and Finance* 73, 252-274.

Ng, S., and J.H. Wright (2013). Facts and Challenges from the Great Recession for Forecasting and Macroeconomic Modeling. *Journal of Economic Literature*, 51, 1120–1154.

Samuelson, P. (1966). Science and stocks. *Newsweek* 19 (September), 92.

Siegel, J.J. (2014). *Stock for the Long Run*. McGraw-Hill. Fifth edition.

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

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), 419–44.