Predictive Ability of Financial Variables in Changing Economic Circumstances

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ABSTRACT

A large body of literature has established stylized facts about the predictive links between different financial variables and real economic activity across countries. Many studies have also shown that the predictive ability of financial variables is far from consistent and stable over time. However, under which economic circumstances financial variables tend to have more or less useful predictive content for GDP growth has remained surprisingly unexplored. In this study, we analyse three key financial variables, namely, term spread, real stock returns and real short-term interest rate, and study how their predictive power relates to varying economic circumstances in a large set of industrialized countries. Our analysis shows that the enhanced predictive content of financial variables is connected to increased GDP growth volatility and the turning points of business cycles. Monetary policy conditions also play a noteworthy role; in particular, 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). Nevertheless, it has remained surprisingly unexplored whether there are systematic changes in the predictive power and under which economic circumstances financial variables tend to have more or less useful predictive content for GDP growth. The existing evidence has thus far mostly focused on the U.S. economy and explained the changes in the predictive content of term spread (Bordo & Haubrich, 2004; Benati & Goodhart, 2008; Ng & Wrigth, 2013; Hännikäinen, 2016). In addition, Henry, Olekalns and Thong (2004) show that stock markets better forecast economic activity during recessions. The aim of the present paper is to broaden the analysis to cover the three most focal predictive financial variables, several economic conditions and a large set of countries. This broader and more systematic approach is the main contribution of the present paper.

In the first phase of our empirical analysis, we select three established and commonly used financial variables and use them to forecast GDP growth in a set of 20 industrialized countries. First, term spread, the difference between long- and short-term interest rates, has widely gained status as the single most important predictor of economic activity in Western economies (e.g., Estrella & Mishkin, 1996; Estrella, 2005b). 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). 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 & Goodhart (2008) call the nominal short-term interest rate "*the simplest possible measure of the monetary policy stance*." This view is supported by Ang, Wei and Piazzesi (2006), who are among the first to observe the useful predictive content of short-term interest rates for GDP growth in the U.S. economy. The selected three 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.

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 selected conditions are related to 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 them at the time point of forecasting. Thus, we attempt to identify under which conditions the selected financial variables provide useful and trustworthy predictive content. To the best of our knowledge, this is the first paper to systematically and 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 associated with the predictive content of the financial variables. Overall, financial markets contain more useful information for real economic activity during times of volatile GDP growth. The turning points of economic activity and periods of recession also tend to enhance the predictive content of individual financial variables. Moreover, monetary policy affects the predictive association between financial markets and the real economy at least via two channels: the ZLB clearly weakens the predictive content of stock market information, and in contrast, 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 forecast 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 the relationship may be conditional on real economic or financial market circumstances. 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 volatility is low; alternatively, during high GDP volatility, financial variables may contain useful additional information over and above lagged GDP growth. Consequently, Chinn and Kucko (2015) suggest that the predictive power of the term spread may have strengthened after the financial crisis of 2008 due to increased macroeconomic volatility. The Great Moderation was a period with a remarkable reduction in the volatility of many macroeconomic time series from the 1980s until the financial crisis. 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; Chinn & Kucko, 2015). 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. The existing empirical evidence mainly analyses the term spread. While the evidence on other financial variables is scarce, the results on 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 is possibly associated with GDP growth volatility (see, e.g., D'Agostino, Giannone & Surico, 2006; Wheelock & Wohar, 2009; Kuosmanen & Vataja, 2014).

Changes in the forecasting ability of financial variables may also be linked to recessions or other phases of the business cycle. For example, Henry, Olekalns and Thong (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 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, Nabulsi & Vataja, 2015). In contrast, Hännikäinen (2016) 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, why the predictive content of financial variables varies over the business cycle (e.g., Wheelock & Wohar, 2009). One possible reason is that the increase in predictive content is linked to increased economic volatility during recessions and business cycle turning points. 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, real economy and financial markets tend to be out of sync, and consequently, financial markets may 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.*" Moreover, prior evidence shows that uncertainty is higher when economic growth is low and that uncertainty increases strongly during recessions (Bloom, 2014).

Hence, we expect that financial market turbulence 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 is also associated with the monetary regime and 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 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 a false signal that an economic slowdown is coming. Interestingly, the predictive ability of the term spread indicates that the monetary regime is not credible, or stated differently, a fall in the predictive power of the term structure indicates improvements in the credibility of the monetary regime. 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 the sample from the U.S., the U.K., Canada, Australia and the Eurozone. In contrast, Hännikäinen (2016) find that the predictive power of the term spread is both positively linked to inflation persistence and negatively linked to inflation volatility in the U.S. Accordingly, we broaden the perspective by testing whether the predictive contents of all three individual financial variables are connected to inflation persistence, i.e., to the underlying price stability.

Finally, current unconventional monetary policy and the ZLB of interest rates are unprecedented 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 also implies a lower discount rate of future dividends. Thus, under ZLB stock prices reflect changes in firm profitability in more distant future. Therefore, the power for predicting near future macroeconomic activity may be weakened. Moreover, under ZLB stock prices may reflect the lack of other investment opportunities rather than changes in firm's current profitability. Hence, it is well motivated 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, as prior research (Chen & Ranciere, 2016; Kuosmanen, Nabulsi & Vataja, 2015) suggests, forecasting performance can be improved by using several financial predictors in forecasting models. Therefore, we start by specifying a model that includes all three financial predictors. This estimation presents conditions depicting a broader relation between financial markets and the real economy. Second, to obtain more specified information about 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 don't want to a priori restrict that financial variables should have similar predictive content for GDP growth in every country, because the 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 common practice in the previous literature.

We conventionally assume that all relevant information regarding the 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:

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

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

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

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

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

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, while 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 the 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, previous literature has remained imprecise in this respect. However, Kuosmanen and Vataja (2017) suggest that real financial variables are preferable to nominal variables when forecasting GDP growth in G-7 countries. Besides the logical argument, specifying short-term interest rates in real terms is also useful when the ZLB is binding, because real interest rates may vary more than nominal rates close to the ZLB.

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. Moreover, we strive to have a sufficiently comprehensive group of countries in the sample. All the countries except South Africa belong to the group of advanced countries according to 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

[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 (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).

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.

Table 1 here

3.3. Forecasting results

We estimate the five forecasting models separately for each of the 20 countries. 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.

Table 2 here

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 only in a 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. The county-specific forecast performances are further illustrated in the error spread graphs presented in Appendix 1.

4. FORECAST PERFORMANCE ANALYSIS

4.1. Variable formation

We analyze the forecast performance using country panel regressions. We conduct panel regressions, because we are searching for systematic variations in the predictive content of financial predictors. In these estimations, we have two variants of the dependent variable. The first dependent variable is the error spread. 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*. Subscript j refers to countries. 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. 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 economic or financial market volatility is linked to the forecasting performance of financial variables, as suggested in the literature (e.g., Chinn and Kucko, 2015). Therefore, our explanatory variables include GDP and stock market volatility. The volatility variables are defined as follows: GDP growth volatility is measured by the four-quarter moving standard deviation of quarterly GDP growth; stock market volatility is measured similarly, i.e., by the four-quarter moving standard deviation of quarterly stock returns (Blanchard & Simon, 2001).

Prior evidence suggests 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 hence, the variables describing business cycle peaks and troughs exclude South Africa and contain fewer observations. Summary statistics are presented in Table 3.

Table 3 here

4.3. Empirical methodology

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

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

where ERSPR denotes the error spread and $X_{j,t}$ is a vector of explanatory variables that includes GDP volatility, inflation persistence, stock market volatility, 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. The error spread graphs in Appendix 1 indicate 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 financial variables is associated with certain time periods in all countries 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:

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

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 conditional logit estimator, because while 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 regressions results explaining changes in the forecast error spreads. 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 line with prior studies indicating that the predictive relation between financial variables and the real economic activity was vague, or non-existent, during the Great Moderation (e.g., Stock & Watson, 2003). Moreover, we find some evidence that times of recession and business cycle turning points improve the predicting ability of financial markets. Finally, the results indicate that stock market volatility weakens 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 are weight in the fixed effect panel regression, whereas the logit estimation considers only whether the error spread is positive or negative. Thus, columns 1-4 give more weight to turbulent times, and columns 5-8 give equal weight to more stable times.

Table 4 here

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 on the predictive content of the term spread. In general, the results again indicate that the term spread contains more predictive power under volatile economic growth circumstances. This is well in line with the prior research. In addition, the results lend support to the stylized fact that the term spread is good at forecasting economic turning points, especially at business cycles peaks when the inverted yield curve precedes an economic slowdown (Estrella, 2005a). The evidence concerning the business cycle troughs is not quite as clear, however, our results point to an improvement in predictive content. 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 the turning points of economic activity and during volatile growth periods. In contrast, we do not find evidence that stock market volatility and the ZLB affect the predictive content of the term spread.

Tables 5, 6 & 7 here

Table 6 considers the predictive link between stock markets and the real economy. These regressions demonstrate one 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 changes in the profitability of listed companies. The other interesting outcome is that real stock returns produce better forecasts during business cycle troughs than peaks, which is also in accordance with the findings of Henry, Olekalns and Thong (2004). Surprisingly, we find mixed evidence regarding stock market volatility, and thus, we are not able to make final conclusions. However, it should be noted that our measure for stock market volatility is based on quarterly returns, and a more detailed measure might shed more light on this matter.

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 more reliably predicts during business cycle troughs than 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 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 financial variables. In contrast, the logit estimations show statistically significant effects. In particular, all the four logit models indicate that inflation persistence improves the predictive content of real stock returns. Furthermore, we obtained the same results for two term spread models and two short-term interest rate models. 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 lend overall support to Hännikäinen (2016), who find that inflation persistence is a key variable affecting to the predictive ability of the yield curve in the U.S. economy. 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 a systematic analysis of the links between economic circumstances and predictive content of financial variables. We identify several economic conditions that affect the time-varying predictive relationship between financial markets and real economic activity in a comprehensive set of industrialized countries. The results show that increased GDP growth volatility is connected to the improved predictive content of financial markets for GDP growth. Hence, we conclude that the reduced predictive content of financial markets during the Great Moderation era 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 forecasts errors are also larger during turbulent times.

We also find that financial variables, especially the term spread and short-term interest rates, contain useful information for forecasting purposes, notably near the business cycle turning points. Recessions and business cycle troughs and to some extent business cycle peaks 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 activity near turning points of business cycles. In contrast, extreme stock market volatility may weaken the predictive relation between financial markets and the real economy. Factors connected to monetary policy also play a noteworthy role. We notice that the zero lower bound of interest rates clearly reduces the predictive ability of stock markets. 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 individual financial variables during stable growth conditions.

In sum, this study provides new guidelines to understand and anticipate forthcoming changes in the predictive content of key financial variables. However, it should be noted that our results do not necessarily indicate a causal relationship but rather provide insights on the circumstances coinciding with changes in the forecast performance.

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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	$\Delta^4 y_{t+4} = (y_{t+4} - y_y) \times 100$	
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	$i_t = is_t - \Delta^4 p_t$	

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 (1981) 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).

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
Stock market volatility	6.655	4.519	5.349
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

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	0.587***	0.515***	0.592***	0.462***	0.389**	0.582***	0.365**	0.551***
	(0.168)	(0.121)	(0.175)	(0.126)	(0.159)	(0.197)	(0.161)	(0.200)
Stock market volatility	-0.039**	-0.056**	-0.030*	-0.063**	-0.008	0.037	0.002	0.027
	(0.017)	(0.024)	(0.015)	(0.025)	(0.015)	(0.026)	(0.015)	(0.027)
Inflation persistence	0.090	-0.003	0.041	-0.006	0.084	0.187	0.024	0.081
	(0.140)	(0.212)	(0.151)	(0.232)	(0.211)	(0.278)	(0.215)	(0.289)
Recession (D)	0.482***	0.105			0.345	0.109		
	(0.138)	(0.228)			(0.216)	(0.279)		
Business cycle peak (D)			0.427***	-0.142			0.611***	-0.480
			(0.145)	(0.154)			(0.194)	(0.294)
Business cycle trough (D)			0.217	0.389**			0.330	0.372
			(0.125)	(0.155)			(0.231)	(0.260)
ZLB(D)	-0.152	-0.041	-0.159	-0.084	-0.292	-0.338	-0.307	-0.368
	(0.142)	(0.228)	(0.134)	(0.206)	(0.212)	(0.307)	(0.223)	(0.324)
Constant	-0.122	-0.267	-0.212	-0.426				
	(0.126)	(0.282)	(0.136)	(0.281)				
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	0.059	0.220	0.060	0.246	0.009	0.108	0.015	0.114
Log likelihood					-759.510	-683.672	-713.100	-640.925

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	0.384***	0.302***	0.407***	0.276***	0.266*	0.144	0.292*	0.082
	(0.093)	(0.060)	(0.097)	(0.079)	(0.158)	(0.192)	(0.162)	(0.196)
Stock market volatility	-0.016	-0.045*	-0.006	-0.052**	0.013	0.001	0.026*	-0.016
	(0.015)	(0.022)	(0.014)	(0.022)	(0.015)	(0.026)	(0.015)	(0.027)
Inflation persistence	0.178	-0.232	0.123	-0.176	0.612***	0.236	0.515**	0.474
	(0.133)	(0.229)	(0.124)	(0.253)	(0.216)	(0.284)	(0.222)	(0.298)
Recession (D)	0.509***	0.272*			0.811***	0.607**		
	(0.093)	(0.144)			(0.222)	(0.283)		
Business cycle peak (D)			0.601***	0.309***			1.607***	1.157***
			(0.088)	(0.092)			(0.227)	(0.305)
Business cycle trough (D)			0.135	0.349*			0.357	0.660**
			(0.186)	(0.190)			(0.232)	(0.267)
ZLB(D)	-0.036	0.168	0.009	0.083	-0.298	0.041	-0.198	-0.273
	(0.103)	(0.206)	(0.120)	(0.205)	(0.216)	(0.310)	(0.228)	(0.325)
Constant	-0.233*	-0.095	-0.337**	-0.119				
	(0.130)	(0.222)	(0.130)	(0.243)				
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	0.061	0.242	0.080	0.252	0.023	0.133	0.055	0.145
Log likelihood					-748.678	-664.283	-684.810	-619.967

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	0.223**	0.095	0.209**	0.078	0.199	0.080	0.142	-0.038
	(0.082)	(0.064)	(0.083)	(0.069)	(0.158)	(0.193)	(0.159)	(0.198)
Stock market volatility	0.006	-0.020*	0.008	-0.025**	0.033**	0.009	0.034**	-0.009
	(0.006)	(0.011)	(0.006)	(0.011)	(0.015)	(0.026)	(0.015)	(0.027)
Inflation persistence	0.012	0.067	0.020	0.069	0.361*	0.501*	0.447**	0.569*
	(0.062)	(0.083)	(0.070)	(0.088)	(0.210)	(0.286)	(0.216)	(0.298)
Recession (D)	0.156	-0.087			0.092	-0.223		
	(0.112)	(0.116)			(0.216)	(0.281)		
Business cycle peak (D)			-0.007	-0.197			0.107	-0.450
			(0.052)	(0.131)			(0.190)	(0.285)
Business cycle trough (D)			0.146	0.230***			0.675***	0.828***
			(0.086)	(0.055)			(0.237)	(0.269)
ZLB(D)	-0.241**	-0.211*	-0.289***	-0.280***	-0.667***	-0.590*	-0.865***	-0.903***
	(0.098)	(0.103)	(0.085)	(0.084)	(0.214)	(0.313)	(0.231)	(0.336)
Constant	-0.103	-0.093	-0.102	-0.171				
	(0.077)	(0.194)	(0.077)	(0.183)				
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	0.039	0.196	0.035	0.212	0.018	0.127	0.023	0.137
Log likelihood					-761.196	-676.904	-715.632	-632.498

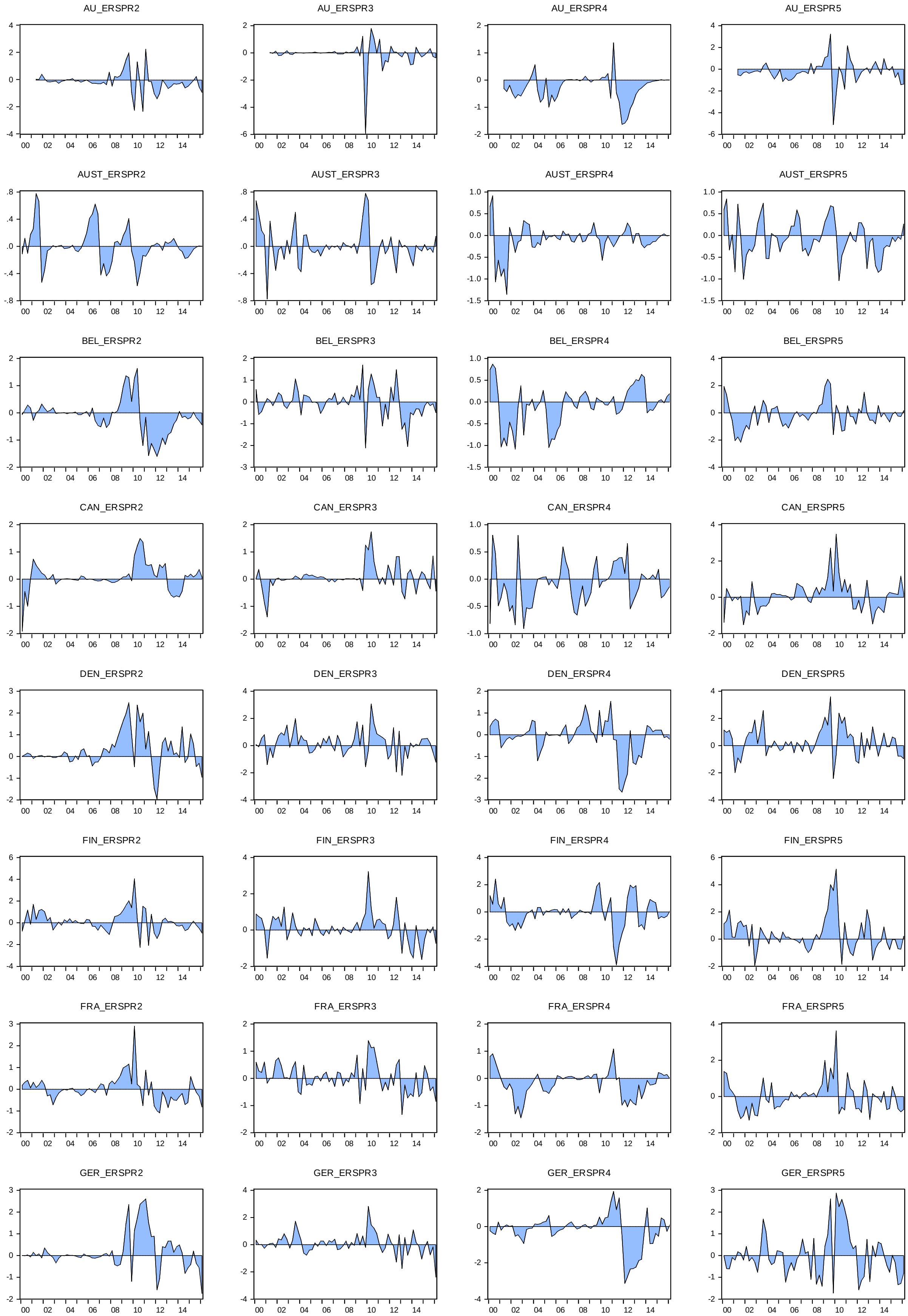
Notes. Forecasting model 4 specification: AR+R.
* p<0.10, ** p<0.05, *** p<0.01. Cluster robust standard errors are shown in parentheses.

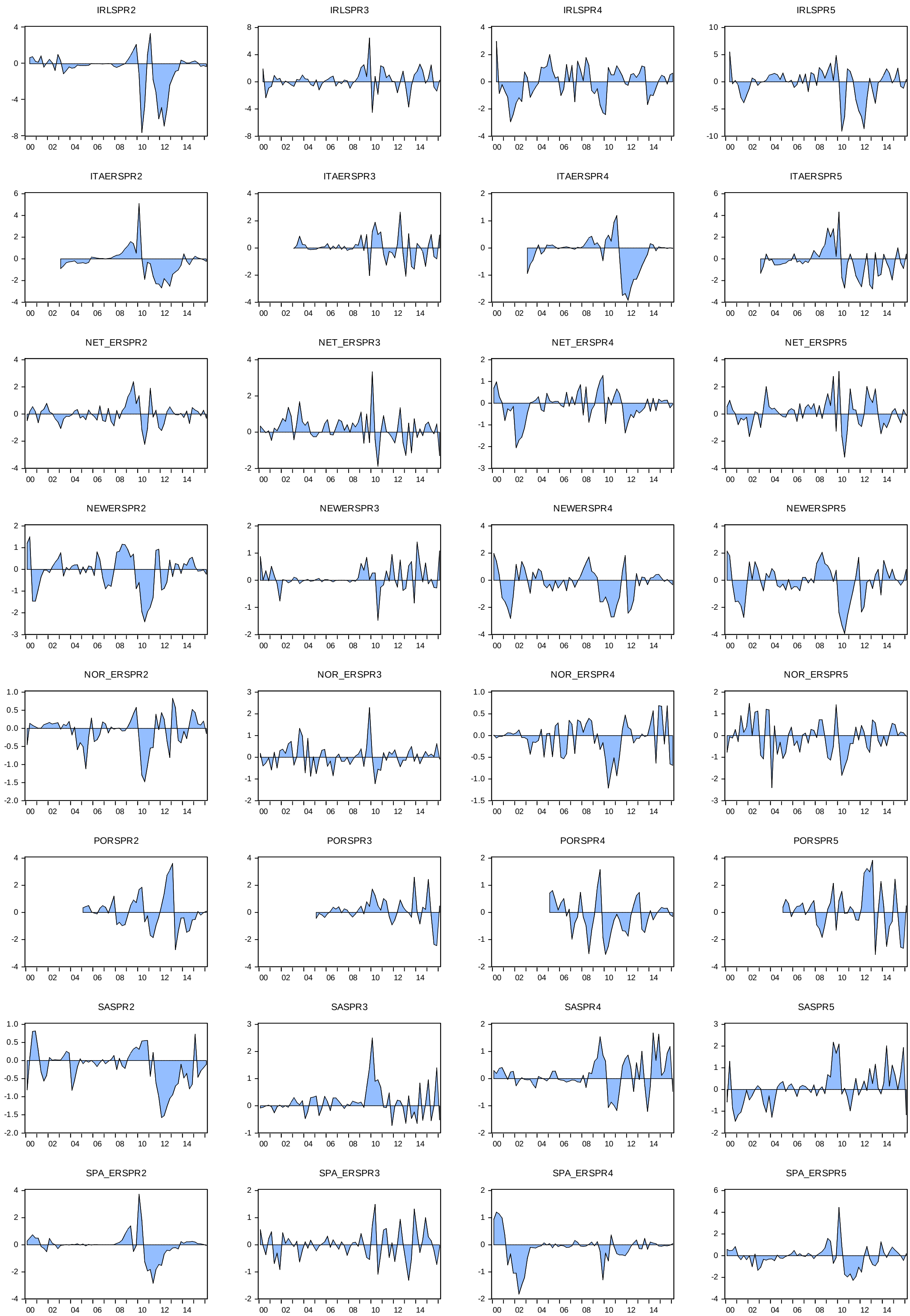
Table 7. Second stage estimation. Explanatory power of forecasting model 5 compared to AR benchmark

	Error spread				Binary variable			
	1	2	3	4	5	6	7	8
GDP volatility	0.125	0.130*	0.111	0.105	0.327**	0.245	0.300*	0.249
	(0.074)	(0.063)	(0.079)	(0.072)	(0.156)	(0.185)	(0.157)	(0.190)
Stock market volatility	-0.008	0.003	-0.006	-0.002	-0.038**	0.011	-0.029*	-0.001
	(0.008)	(0.009)	(0.008)	(0.011)	(0.015)	(0.026)	(0.015)	(0.027)
Inflation persistence	0.111	0.225	0.130	0.272*	0.037	0.651**	0.067	0.802***
	(0.092)	(0.150)	(0.096)	(0.149)	(0.213)	(0.282)	(0.218)	(0.295)
Recession (D)	0.039	0.091			0.381*	0.486*		
	(0.086)	(0.132)			(0.215)	(0.275)		
Business cycle peak (D)			0.111	0.017			0.447**	0.247
			(0.106)	(0.050)			(0.191)	(0.279)
Business cycle trough (D)			0.240**	0.236*			0.669***	0.704***
			(0.091)	(0.112)			(0.232)	(0.263)
ZLB (D)	0.070	-0.106	0.017	-0.146*	-0.152	-0.505*	-0.279	-0.697**
	(0.054)	(0.070)	(0.056)	(0.084)	(0.212)	(0.305)	(0.224)	(0.324)
Constant	-0.170**	-0.030	-0.216***	-0.105				
	(0.075)	(0.087)	(0.074)	(0.085)				
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	0.009	0.122	0.020	0.147	0.007	0.086	0.015	0.096
Log likelihood					-755.048	-695.226	-707.647	-648.794

Notes. Forecasting model 5 specification: AR+i.
* p<0.10, ** p<0.05, *** p<0.01. Cluster robust standard errors are shown in parentheses.

APPENDIX 1. Error spread graphs.

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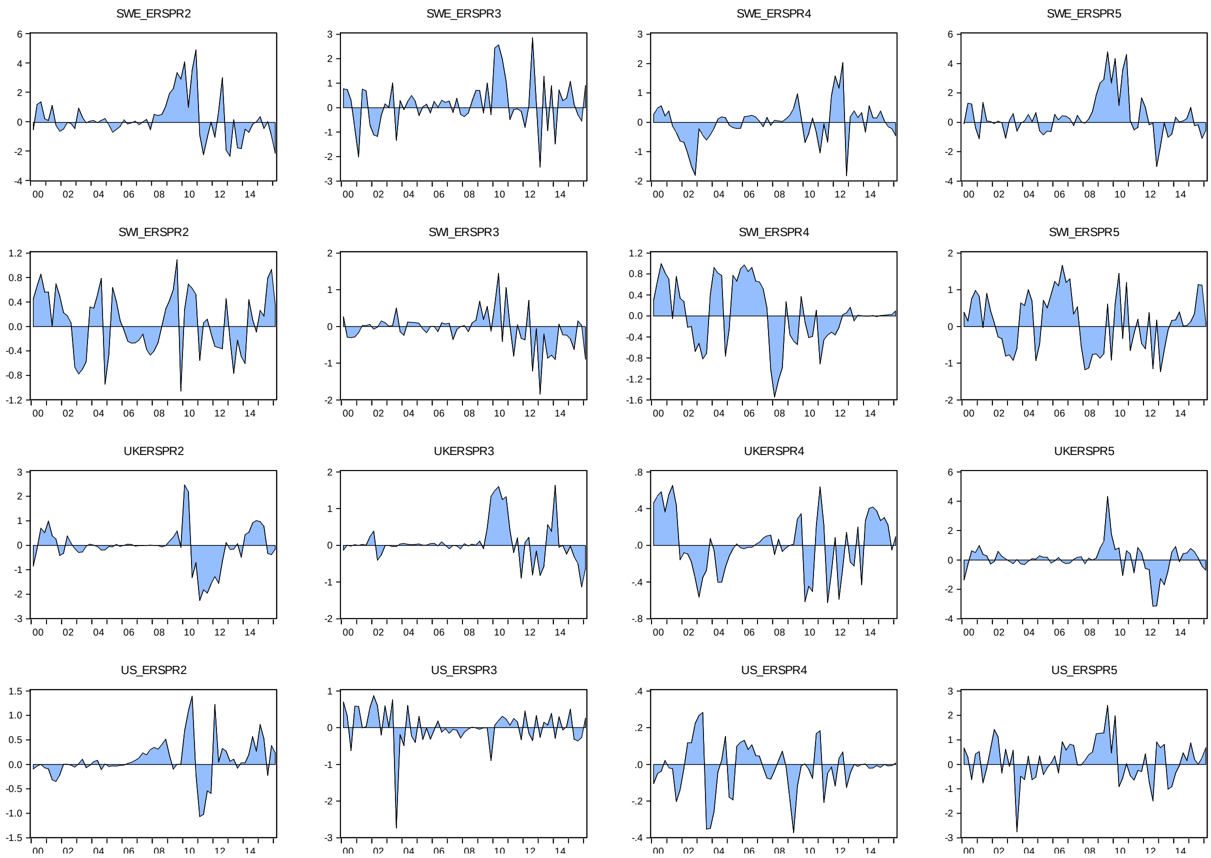
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APPENDIX 2. Correlation table.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Error spread M2	1.000														
2. Error spread M3	0.688*	1.000													
3. Error spread M4	0.505*	0.315*	1.000												
4. Error spread M5	0.338*	0.195*	0.046	1.000											
5. M2 wins AR (D)	0.650*	0.356*	0.332*	0.308*	1.000										
6. M3 wins AR (D)	0.358*	0.579*	0.240*	0.149*	0.327*	1.000									
7. M4 wins AR (D)	0.273*	0.160*	0.608*	0.021	0.258*	0.165*	1.000								
8. M5 wins AR (D)	0.221*	0.141*	0.031	0.636*	0.285*	0.155*	0.030	1.000							
9. GDP volatility	0.137*	0.083*	0.155*	0.061*	0.093*	0.062*	0.081*	0.082*	1.000						
10. Inflation persistence	0.034	0.006	0.039	0.043	0.020	0.024	0.058*	0.031	-0.035	1.000					
11. Inflation volatility	0.034	0.034	0.075*	0.010	0.032	0.040	0.043	-0.031	0.162*	-0.263*	1.000				
12. Stock market volatility	-0.044	0.011	0.104*	-0.042	0.021	0.065*	0.098*	-0.033	0.294*	-0.081*	0.352*	1.000			
13. Recession (D)	0.097*	0.149*	0.098*	-0.007	0.046	0.112*	0.046	0.036	0.141*	0.000	0.195*	0.332*	1.000		
14. Business cycle peak (D)	0.106*	0.194*	0.004	0.043	0.086*	0.222*	0.022	0.060*	0.005	0.132*	0.043	-0.034	0.003	1.000	
15. Business cycle through (D)	0.038	0.022	0.028	0.084*	0.025	0.001	0.039	0.064*	0.022	-0.127*	0.113*	0.001	-0.023	-0.120*	1.000
16. ZLB (D)	-0.043	-0.034	-0.118*	0.016	-0.045	-0.062*	-0.112*	-0.018	-0.086*	-0.130*	-0.025	-0.105*	-0.003	-0.129*	0.318*