Forecasting Inflation: The Predictive Ability and Stability of Financial Variables

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Forecasting major macroeconomic variables has been a subject of key interest for many academicians and professionals over the past many years. This study examines the predictive ability of different financial and non-financial variables in forecasting inflation of Norway, Sweden and Finland. Using quarterly data from 1984 to 2013, the study finds that some variables provide better forecasting performance relative to the simple autoregressive benchmark model in out-of-sample forecasts. However, the performances of the predictors are not stable over time and across countries; and no individual variable produces forecast that is significantly different from the forecast generated by the benchmark model.

INTRODUCTION

Forecasting macroeconomic variables has been a subject of great interest over the past many years. Macroeconomists have dedicated much effort to the theoretical and empirical investigation about the role of different indicators in forecasting major macroeconomic variables. Thus, the demand for forecasts of inflation, a major macroeconomic variable, remains as strong as ever. According to Kanyama & Thobejane (2013), projection about macro-economic variables provides an idea of how the economy is likely to perform in the future; thus, obtaining a reliable forecasts of inflationis a matter of utter importance for policymakers who put forth monetary and fiscal policies, for investors who hedge the risks against their investments, for firms which set product prices as well as negotiate wage contracts with labor force, and for individuals who participate in the economy (Ang, Bekaert & Wei, 2007).

Research on forecasting major macroeconomic variables has rich contents in the literatures. Numerous studies have investigated the role of financial variables in predicting inflation (for example, Shamsuddin & Holmes (1996), Stock & Watson (2003), Marcellino, Stock & Watson (2003), Forni *et al.* (2003), Hendry & Clements (2004), Önder (2004), and Artis *et al.* (2005)). Marcellino *et al.* (2003) investigate the predictive ability of fifty variables including interest rates, money supply, stock price index, etc. and find that in most cases out-of-sample forecasts of inflation generated by univariate autoregressions perform better than the forecasts generated by multivariate models. This finding broadly contradicts Forni *et al.* (2003) and Stock & Watson (2003), who report better predictive ability of some financial variables. Conducting similar experiments, Banerjee *et al.* (2005) find consistent results with Stock & Watson (2003) and Havránek *et al.* (2010). Although there are some contradictory results in the literatures about the predictive ability of different financial variables, almost all studies unanimously find that in most of the cases those variables do not provide stable performance over time across countries.

Using different econometric models and data from the year 1984 to 2013, this paper investigates the role of financial variables in forecasting inflation from the year 2004 to 2013 in Norway, Sweden and Finland. This paper analyzes the predictive ability of different variables of these three Nordic countries due to the presence of some unexpected events in their economies during the sample period. After more than 50 years of financial stability, the stable macroeconomy of Nordic countries had suddenly been undermined in the early 1990s because of the financial liberalization, pegged exchange rates, high international capital mobility, and asymmetric shocks (Steigum, 2011). Specifically, the financial instabilities, which resulted from the systemic banking crisis in Norway, Sweden and Finland in 1991 to 1993, was triggered by the high real interest rate after the German unification in 1990 (Steigum, 2009). However, all three countries dealt with the crisis with major policy interventions by governments and parliaments that resulted in impressive economic growths after 1993 (Honkapohja, 2009). The long-term learning effects in the banking industries of Norway, Sweden and Finland have had substantial impact in the international financial crisis in late 2000s where the three countries managed to avoid significant bank losses that might have affected the economies even worse. During these two big crisis periods, policy interventions related to the asset prices and other financial variables played important roles in stabilizing the countrys' major macroeconomic variables including inflation. Adopting the approach of Stock & Watson (2003), this paper thus examines the ability of financial variables in forecasting inflation of these three Nordic countries.

The empirical results in this paper show that some variables perform better in predicting inflation in case of one quarter horizon for some countries in some periods. Among the indicators, long-term bond rate, stock price index and dividend yield forecast inflation relatively better than other variables and relative to the benchmark autoregressive model. However, no single variable produces forecast that is significantly different from the simple autoregression model. Moreover, the performances of the variables are not stable over time and across countries.

LITERATURE REVIEW

Inflation is one of the major macroeconomic variables that drive monetary and fiscal policy of a country. Thus, forecasting inflation has been the subject of interest in many studies over the past few years. A number of researchers investigate various forecasting methods and use many predictive variables in different countries to evaluate the relative performance of those methods as well as the forecasting ability of the predictive variables. Stock & Watson (2003) investigate the relative forecating performance of various methods of seven different countries including US, Canada, Japan, etc. Again, Marcellino *et al.* (2003), Artis *et al.* (2005) and Banerjee *et al.* (2005) conduct similar investigation for the Euro area, The UK and the acceding countries respectively. Since this paper focuses on the forecasting performance of several predictive variables in three European countries, a major portion of this section discusses about the past literatures based on Euro area followed by other related studies.

Marcellino, Stock & Watson (2003) investigate several time series models for forecasting inflation and real activity of 11 European countries using monthly data from 1982 to 1997. They consider approximately 50 variables for each country, typically including interest rates, monetary aggregates, exchange rates, industrial production, etc. In their investigation they find that in most of cases, out-of-sample forecasts generated by the univariate autoregressive models outperform the forecasts generated by the multivariate models. This findinding is inconsistent with Forni *et al.* (2003), who use large data set consisting of 447 monthly macroeconomic time series concerning the main countries of Euro area to simulate inflation forecast. The comparative success of univariate models in Marcellino *et al.* (2003) results from the fact that their sample covers a period of great economic change in Europe[1]; and hence, consequent instability of the multivariate relations among the variables makes forecasts from the univariate autoregressions more reliable.

Considering 46 Euro-area variables as indicators, Banerjee, Marcellino & Masten (2005) conduct a similar experiment to that of Marcellino *et al.* (2003) to investigate the efficacy of those variables in forecasting inflation. A major observation that emerges from their investigation is that, even though univariate leading indicator models outperform the autoregression models in case of inflation forecast, the best indicator is not persistent over time. This finding broadly contradicts Stock & Watson (2003) and Havránek *et al.* (2010). Hence, the predictive ability of a variable dose not guarantee the stability of that variable's predictive capability. However, they find that some labour market variables, prices, fiscal series and the GDP growth rate on average outperform autoregression in case of inflation forecasting.

Forni *et al.* (2003) use a large data set of 6 European countries to generate out-of-sample forecast of the Euro-area industrial production and the harmonized inflation index. Motivated by Stock & Watson (1999) and Forni *et al.* (2001b), they apply two multivariate models using 6 different blocks of data series among which block-1 contains a maximum of 118 financial variables. They evaluate the performance of the forecast by comparing the outcomes from multivariate models with those from the univariate autoregressive models. Their results show that multivariate models outperform univariate models for forecasting inflation at one, three, six and twelve month ahead, indicating a persistent predictive capability of the financial variables.

More recently, Havránek, Horváth & Matějů (2010) examine the interaction of financial variables and the macroeconomy within the block-restriction vector autoregression model and also evaluate the extent to which financial variables help forecasts of inflation. They use monthly data from 1991 to 2009 for both Czech Republic and Euro area. A salient feature of their paper is that they use a new set of financial variables such as bank liquidity, loan loss provisions, etc. along with others that have been used in past investigation. The motivation of the use of new set of variables come from the 2008-2009 economic and financial crisis in order to assess which financial variables matter particularly in turbulent periods in predicting major macroeconomic variables, precisely GDP growth rate and inflation. Consistent with the Stock & Watson (2003), they find a systematic effect on the macroeconomy that often improve the forecast of inflation, however, the predictive ability of the individual variables varies over time, in particular during the economic and financial crunch. Even though almost all the variables exhibit irregularities in forecasting performance, one exception is the stock market index that, according to their paper, seems to consistently improve the forecast of inflation.

A lot of similar researches have also been conducted based on different country level data besides Euro area or European countries, for example, Stock & Watson (2003), Abdymomunov (2013), Ang *et al.* (2007), Önder (2004), Shamsuddin & Holmes (1996), Feridun & Adebiyi (2005), etc. The findings of these investigations are mixed, that is there is no universally accepted optimal model for forecasting macroeconomic variables and no single predictive variable generate better forecast relative to others.

Stock & Watson (2003) investigate the predictive ability of various financial and non-financial variables in forecasting inflation examining 7 country data set. Collecting up to 26 series for each country from 1959 to 1999 with exceptions for certain series, they evaluate the forecasting performance by comparing the root mean square errors (RMSEs) of the predictive variables with those of univariate autoregressions. The results of their investigation show that some variables are useful predictors of inflation across countris over some time periods. However, there is no consistency of the performance of the variables; an individual variable that performs better in a particular country in a certain period does not guarantee that single variable will give similar performance in case of another country in another time period.

Using four different measures of consumer price index (CPI), Ang, Bekaert & Wei (2007) examine the performance of various models in forecasting US inflation[2]. In their analysis they report two different out-of-sample periods, labelling post-1985 and post-1995. Their results show the best time series model is mostly a simple ARMA(1,1) model, which comprises stochastic expected inflation following an AR(1) process and shocks to inflation. The result is robust to various measures of CPI and different time periods. Nevertheless, in some cases certain models that incorporate real activity information, term structure information or survey information, beat the ARMA(1,1) model even when ARMA(1,1) forecasts are considered as the benchmark in a forecast comparison regression.

Other studies based on emerging countries, for example Feridun & Adebiyi (2005), Bordoloi, Das & Jangili (2009), Velandia & Maya (2012), etc. show inconsistent findings regarding the best performing model for out-of-sample forecast and the predictive ability of various variables in forecasting inflation.

Nevertheless, these studies report considerable roles played by several financial and non-financial variables in forecasting major macroeconomic variables. Although there is no universally accepted optimal way to do so, forecasting is still conducted because of the importance of the inflation estimation for planning and policy making activities in an economy.

METHODOLOGY

In this study, all forecasting models are specified and estimated as a linear projection of an h-step-ahead variable, Y^h_{t+h}, where t is the base period, which at a minimum include its own lagged values, denoted by Y_t, and in some cases lagged values a series of interest, denoted by X_t. The types of the variable to be included and the lags of each variable depend on the forecasting models[3]. In general, the forecasting models all have the form,

$$Y^h_{t+h} = \mu + \alpha(\mathrm{L})Y_t + \beta(\mathrm{L})'X_t + u^h_{t+h} \quad (1)$$

where μ is a constant, α(L) is a scalar lag polynomial, β(L) is a vector lag polynomial, and u^h_{t+h} is the error term. The dependent variables are transformed to eliminate stochastic and deterministic trends and thus make the series stationary. Following Stock and Watson (2003) and Banerjee, Marcellino and Masten (2005), this study considers the first difference of the quarterly rate of inflation, at an annual rate. Thus, the dependent variable in case of first order integration or I(1) becomes, $Y^h_{t+h} = \sum_{t+1}^{t+h} \Delta Y_s$ so that $Y^h_{t+h} = Y_{t+h} - Y_t$. Similarly, in case of second order integration or I(2), the dependent variable becomes:

$$Y^h_{t+h} = \sum_{t+1}^{t+h} \Delta Y_s - h\Delta Y_t \text{ or } Y^h_{t+h} = Y_{t+h} - Y_t - h\Delta Y_t \quad (2)$$

This study analyses 1-step-ahead pseudo out-of-sample forecast for inflation for every country over two forecasting sample periods of five years each. The first sample period is from 2004:Q1 to 2008:Q4, where the estimation period for first quarter forecast i.e. 2004:Q1 is from 1984:Q1 to 2003:Q4. The second sample period is from 2009:Q1 to 2013:Q4, where the estimation period for first quarter forecast i.e. 2009:Q1 is from 1989:Q1 to 2008:Q4. The model estimation and selection is recursive that uses all available data as the forecasting exercise proceeds through time. All regressions in estimating the coefficients of the variables are conducted using Newey-West heteroscedasticity and autocorrelation consistent (HAC) approach to get more reliable t-statistics for the variables.

Description of Dependent Variables

In this study, the dependent variableY^h_{t+h} is constructed as, Y^1_{t+1}= 400ln (P_{t+1}/P_t), where P_t is the price level measured by the CPI at t quarter. Here, the factor of 400 standardizes the units to annual percentage rates.

Selection of Lag Lengths

The lag length of each model is selected based on the Akaike's Information Criterion (AIC) and Schwartz's Bayesian Criterion (SBC) for pseudo out-of-sample forecasts. In this case, the lag length is data dependent implying that different models take different lag lengths across countries and over time. The number of lags with which the regression outcome gives the minimum AIC and SBC value, is considered as the appropriate number of lags for that particular model[4]. In a certain case, if AIC and SBC generate minimum value for different lag lengths, a Likelihood Ratio (LR) test is conducted considering the model with smaller number of lags as restricted model and the model with higher number of lags as unrestricted model. The test statistic is compared with the corresponding Chi-square (χ^2) critical value. If the null hypothesis implying no difference is rejected, then the lags suggested by the AIC is considered as appropriate lag length. Otherwise, smaller lag length is considered. However, following Stock and Watson (2003), lag length is restricted to be between zero and four for univariate forecasts; for bivariate forecasts, it is restricted to be between zero and four lags for Y_t and between one and four lags forX_t. In case if AIC and SIC generate minimum value with lags more than four, the lags of the model that generate minimum AIC and SIC value within the four lags, are considered as appropriate lag length.

Forecasting Models

Various forecasting models mainly differ in the choice of X_t in equation (1). This study uses the following forecasting models in the analysis.

Autoregressive (AR) Process

An autoregressive model is one where the current value of a variable depends upon only the values that the variable took in previous periods plus an error term (Brooks, 2002, p. 239). Essentially, it is a univariate time series model. In general, an AR process of order $p$can be expressed as:

$$Y_{t+h}^{h} = \mu + \sum_{i=0}^{p} \emptyset_i \, Y_{t-i} + u_{t+h}^{h} \tag{3}$$

where $u_t$is a white noise disturbance term. Essentially, equation (3) is similar to the equation (1) except that there is no X_t variable. The study considers this the benchmark model for inflation forecast and reports the sample performance of other forecasting models relative to the univariate AR model.

Autoregressive Moving Average (ARMA) Process

ARMA process is a combination of univariate autoregressive process and univariate moving average process. Hence, it is essentially another type of univariate time series model. Unlike simple AR process, ARMA process is one where the current value of a variable depends on both the own values in the previous periods and the previous values of the white noise error terms of that variable. In general, the ARMA model of order (p, q) can be expressed as:

$$Y_{t+h}^{h} = \mu + \sum_{i=0}^{p} \emptyset_i \, Y_{t-i} + \sum_{i=0}^{q} \theta_i \, u_{t-i} \tag{4}$$

where the error term has zero mean, i.e. E(u_t) = 0, constant variance, i.e. E(u_t^2) = σ^2; also the error terms are uncorrelated with one another, i.e. E$(u_t u_s)$ = 0, t≠s here. Since the study uses the first differenced series of quarterly inflation at an annual rate, ARMA (p, q) process can also be defined as autoregressive integrated moving average (ARIMA) process of order (p, d, q)**.** In this case, d takes the value of one in inflation model.

ARIMA- Autoregressive Conditional Heteroscedasticity (ARCH)/ Generalized ARCH (GARCH) Process

The ARIMA model assumes that error term has constant variance. This assumption in the model can be relaxed following Engle (1982) and its extension by Bollerslev (1986) on modelling the conditional variance of the error term (Dua, Raje & Sahoo, 2003). Although serial correlations in the error terms are more common in financial series, the study performs the ARIMA- GARCH test in this paper on inflation rate to compare the forecasting performance relative to the simple AR model.

The basic ARCH model considers that the conditional variance of the current period shock is a linear function of the squares of the past shocks. An ARCH (1) model takes the form,

$$Y_t = \mathrm{E}\,[Y_t | \Omega_{t-1}] + u_t \tag{5}$$

$$u_t = v_t \sqrt{g_t} \tag{6}$$

$$g_t = \alpha_0 + \alpha_1 u_{t-1}^2 \tag{7}$$

where g_t is conditional variance, v_t is a white noise process and is independent of u_{t-1}; u_t has zero mean and is uncorrelated. The conditions α_0> 0, $\alpha_1 \geq 0$ and $0 \leq \alpha_1 \leq 1$ must be satisfied for g_t to be non-negative (Dua, Raje & Sahoo, 2003).However, the order of ARCH, q, needs to be quite large to capture the dynamic patterns in conditional volatility sufficiently. Since adding a large number of lags can be cumbersome because of the stationarity and non-stationarity constraints, including the lags of g_t can mitigate this drawback. This results in the GARCH model and can be captured the large order dynamic effect by simple first order of this model, i.e. GARCH (1,1). GARCH (1,1) has the structure,

$$g_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 g_{t-z} \tag{8}$$

For g_t to be non-negative in equation (8), the conditions α_0> 0, $\alpha_1 > 0$, and $\beta_1 \geq 0$ need to be satisfied.

Vector Autoregressive (VAR) Process

Unlike univariate models, VAR model does not require specification of the projected values of the exogenous variables. It allows the value a variable to depend on more than just its own lags. Thus, univariate AR model can be viewed as a restricted case of VAR model (Brooks, 2002). Sims (1980) expresses an unrestricted VAR as following,

$$Y_t = \mathrm{C} + \mathrm{A}\ (\mathrm{L}) Y_t + u_t \tag{9}$$

where Y is an (n× 1) vector of variables being forecasted, A (L) is an (n×n) polynomial matrix in the back-shift operator L with lag length p, C is an (n× 1) vector of constant terms, and u is an (n× 1) vector of white noise error terms. In this study, the ability of various financial and non-financial variables to forecast inflation rate is investigated by applying the bivariate VAR model for each individual series. In general, a bivariate VAR where there are two variables with k lags can be expressed as,

$$Y_{1t} = \beta_{10} + \beta_{11} Y_{1t-1} + \ldots + \beta_{1k} Y_{1t-k} + \alpha_{11} Y_{2t-1} + \ldots + \alpha_{1k} Y_{2t-k} + u_{1t} \tag{10}$$

$$Y_{2t} = \beta_{20} + \beta_{21} Y_{2t-1} + \ldots + \beta_{2k} Y_{2t-k} + \alpha_{21} Y_{1t-1} + \ldots + \alpha_{2k} Y_{1t-k} + u_{2t} \tag{11}$$

where u_{it} is a white noise disturbance term with E(u_{it}) = 0, (i = 1,2) and E($u_{1t}u_{2t}$) = 0.

Forecast Comparison

According to the Dua, Raje & Sahoo (2003), the best forecasting model is one that produces the most accurate forecasts where the predicted level is close to the actual realized values. To compare the forecast accuracy, the study employs three different forecast evaluation criteria. Initially, it computes the forecast accuracy by using those criteria for the AR benchmark and then compares the performance of other models relative to the benchmark model. Thus, a particular model is said to be better for forecasting when the relative performance is less than one compared to the AR benchmark.

Root Mean Squared Error (RMSE)

The RMSE at time t from the model $\mu$for variable j at horizon $t+h$ can be expressed as follows,

$$RMSE_h^{j,\mu} = \sqrt{\frac{1}{T-h} \sum_{t=1}^{T} (e_{t,t+h}^{j,\mu})^2} \tag{12}$$

$$e_{t,t+h}^{j,\mu} = Y_{t+h}^{j} - \hat{Y}_{t,t+h}^{j,\mu} \tag{13}$$

where e is the forecast error, Y is the actual value and $\hat{Y}$ is the forecasted value from the model μ for variable j at horizon $t+h$. In equation (12), T denotes the total sample size for which forecasts are available.

Mean Absolute Error (MAE)

One shortcoming of RMSE is that the error measures can be driven by one or two times when the model fits very badly. Therefore, in the presence of outliers in the data, this evaluation criterion cannot capture the forecast error accurately over time. An alternative approach for forecast comparison is computing MAE which is less influenced by the outliers compared to the RMSE. Hence, this method results in relatively more accurate outcomes. MAE has the structure,

$$MAE_h^{j,\mu} = \frac{1}{T-h}\sum_{t=1}^{T}\left|e_{t,t+h}^{j,\mu}\right| \tag{14}$$

where e is the forecast error from the model $\mu$for variable j at horizon $t+h$ and T is the total number of sample in the observation.

Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) gives the forecast error in percentage term; thus, makes it more comparable across various models. MAPE is given by,

$$MAPE_h^{j,\mu} = \frac{100}{T-h}\sum_{t=1}^{T}\left|\frac{e_{t,t+h}^{j,\mu}}{Y_{t+h}^{j}}\right| \tag{15}$$

where e is the forecast error from the model $\mu$for variable j at horizon $t+h$ and T is the total number of sample in the observation. The dependence of other methods such as RMSE or MAE on the scaling of the variables becomes inconvenience when the criteria are used for comparing predictive accuracy across different variables or different time ranges. Unlike other methods, MAPE gives scale independent outcome.

The study first calculates the forecast errors using all the above described methods for all the models employed, and then it computes the value of the forecast errors for different models such as ARMA or VAR relative to the benchmark AR model, for instance in case of ARMA model,

$$Relative\ RMSE_h^{j,ARMA} = \frac{\sqrt{\frac{1}{T-h}\sum_{t=1}^{T}(e_{t,t+h}^{j,ARMA})2}}{\sqrt{\frac{1}{T-h}\sum_{t=1}^{T}(e_{t,t+h}^{j,AR})2}} \tag{16}$$

$$Relative\ MAE_h^{j,ARMA} = \frac{\frac{1}{T-h}\sum_{t=1}^{T}\left|e_{t,t+h}^{j,ARMA}\right|}{\frac{1}{T-h}\sum_{t=1}^{T}\left|e_{t,t+h}^{j,AR}\right|} \tag{17}$$

$$Relative\ MAPE_h^{j,ARMA} = \frac{\frac{100}{T-h}\sum_{t=1}^{T}\left|\frac{e_{t,t+h}^{j,ARMA}}{Y_{t+h}^{j}}\right|}{\frac{100}{T-h}\sum_{t=1}^{T}\left|\frac{e_{t,t+h}^{j,AR}}{Y_{t+h}^{j}}\right|} \tag{18}$$

Forecast Accuracy

To ascertain if the differences in the forecast accuracy obtained between the models are statistically significant, the study performs Diebold & Mariano (1995) equal predictive accuracy test. It provides methods for testing whether the mean loss function values derived from the two alternative models, say

M_1 and M_2, are different with high degree of statistical significance. The test is applicable for to data with non-Gaussian, non-zero mean, serially correlated, and contemporaneously error terms (Eidestedt & Ekberg, 2012). The null hypothesis of Diabold-Mariano (DM) test is that the two models have equal forecast accuracy, in other words, the two sets of loss functions, say e^{j,M_1} and e^{j,M_2}, of forecasts derived from the competing models under investigation have equal mean. The DM test is defined according to,

$$DM_{j,h}^{M_1,M_2} = \frac{\frac{1}{T-h}\sum_{t=1}^{T} diff_{t,j,,h}^{M_1,M_2}}{\hat{\sigma}\left(diff_{t,j,,h}^{M_1,M_2}\right)} \sim aN\ (0,1) \tag{19}$$

$$diff_{t,j,,h}^{M_1,M_2}=L(e_{t,t+h}^{j,M_1}) - L(e_{t,t+h}^{j,M_2}) \tag{20}$$

Because of the extensive use in the literatures, the study applies the squared loss function in the DM test. Hence, equation (20) is modified as,

$$diff_{t,j,,h}^{M_1,M_2} = (e_{t,t+h}^{j,M_1})^2 - (e_{t,t+h}^{j,M_2})^2 \tag{21}$$

DESCRIPTION OF THE DATA

The study uses quarterly data of up to 26 series for each country (Norway, Sweden and Finland) from 1984:1 to 2013:4. However, some data are unavailable for certain series or are available only for shorter period. This study collects all the data from Global Financial Data and from Datastream. Few series are transformed to obtain new series for example overnight interest rate is transformed to real overnight interest rate by subtracting inflation rate from the overnight interest rate. Thus, this study gets in total up to 32 series for each country. The data are subject to the following transformations.

First, some series exhibit large outliers for example money market overnight rate, price-earnings ratio, etc. These outliers are placed by the median values of the series.

Second, some series that show seasonal variations, for example CPI, are transformed into seasonally adjusted series. Seasonal variations are determined by plotting the data for the total time span and also by regressing the variables on the lags of those variables. The seasonal adjustments are carried out by using "The X-12-ARIMA Seasonal Adjustment Program" of United States Census Bureau. The study collects seasonally adjusted series of few other variables that might show seasonal variations, such as industrial production, capacity utilization rate, employment etc. directly from the data source.

Third, data of few series like exchange rate, stock price, industrial production, money, etc. are transformed by taking logarithms in order to get more accurate outcomes while using linear regression models.

Fourth, variables that are highly persistent over time or show time trend are differenced until the stationarity of those variables is obtained. In this case, some series are differenced twice while most of the variables become stationary after taking the first difference. Additionally, few series, for instance real GDP, employment etc., are computed as gaps estimated using the Hodrick and Prescott filtering method.

Following Stock & Watson (2003), this study considers both level and first difference of few variables, such as interest rates since the authors report the ambiguity about more accurate versions between level and first difference of such variables. In total, the study gets a maximum 57 predictors for each country to forecast the inflation. Nevertheless, the variables used to forecast per country in both sample periods are subject to the availability of the data for the specific country; and are also subject to the availability of the data for a reasonable estimation period prior to the forecasting period. Descriptions of the series are reported in table 1 in the appendix.

TEST FOR STATIONARITY

All data are subject to unit root test in order to detect stationarity of every series. First, the Augmented Dicky-Fuller (ADF) unit root test is performed on the level data. If the test confirms the stationarity of the series then no further actions are taken. However, if the test finds the presence of unit root in a series then the first difference of that series is taken and the test is performed again. The test is continued until the series becomes stationary. The series is considered stationary if the null hypothesis implying presence of unit root in the series is rejected at 1 percent significant level. Few series have been subject to logarithmic transformation before the ADF test.

ADF test finds that most of the series becomes stationary after taking the first difference. However, housing price index, employment and M1 or currency and coins in circulations becomes stationary only after taking the second difference. Following Stock & Watson (2003), the study carries investigation with both level and 1st difference of majority of the series. Additionally, it considers 2nd difference for some series and measure the relative performance along with the level and 1st difference of these series.

RESULTS FOR OUT-OF-SAMPLE FORECASTS

This section discusses the predictive ability of different models and variables in forecasting inflation. The results for 1-step i.e. 1-quarter ahead forecasts relative to the AR benchmark model for all three countries are reported in table 2 in the appendix. The first row provides the root mean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) of the pseudo out-of-sample benchmark model. The second and third rows report the forecasting errors of univariate ARMA(p,q) model and GARCH(1,1) model relative to the AR model respectively. The subsequent rows show relative forecasting errors of individual predictors. Additionally, the tables exhibit the forecasting errors in two sample periods to check the stability of the forecasting performance of the predictors as in Stock & Watson (2003).

1-Quarter Ahead Forecasts

The study finds that some variables have relatively better forecasting ability for some countries in one or the other sample periods. For instance, the relative RMSE of long-term bond rate is 0.83, indicating a 17 percent improvement relative to the benchmark model in the second sample period for Norway. In case of Sweden, inflation forecast based on term spread has relative RMSEs of 0.93 and 0.94 for first and second sample periods respectively. Again, both nominal stock price index and wages and salary index produce relative RMSE of 0.94 in case of Finland in the first period. In some cases, first difference or second difference of some variables performs better when generating forecasts. For example, the first difference of real overnight interest rate produces a relative RMSE of 0.94 while the same variable in level produces a relative RMSE of 0.97 in case of Norway in first period. This observation is consistent across all three countries in both sample periods for most of the variables. Other error measures i.e. relative MAEs and relative MAPEs produce better outcome than relative RMSEs for most of asset price variables. However, other categories of variables, such as variables within activity or money category, show the opposite outcomes in most of the cases where relative measures of MAE and MAPE become worse-off than those of RMSE's.

Although some variables have better predictive ability relative to the AR model, the successes of the predictability are not stable over time across countries. For example, nominal stock price index performs better in case of Norway for both the sample periods; however, it becomes substantially worse in case of Sweden and Finland, except for the first period of Finland where it performs even better than Norway. Some variables perform better in one period but not in another such as M0 monetary base in case of Norway or employment in case of Finland. The observed instabilities of the variables in forecasting inflation is consistent with Banerjee *et al.* (2005) and Stock & Watson (2003). However, long-term bond rate and dividend yield produce comparatively better and stable forecasts over time across countries, although they do not perform substantially better than other predictor variables. Stock & Watson (2003) provide a possible explanation for the apparent forecasting performance instability which, according to them, results becasuse of the statistical artifact associated with the extimation error of the sampling distribution of the relative RMSEs.

Statistical Significance

The study finds that both univariate ARMA(p,q) model and GARCH(1,1) models produce very small values in DM test statistics for 1-step ahead forecast of inflation, indicating that the forecasts generated by these models are not significantly different from those generated by the AR model. DM statistics that are generated by the bivariate models with individual predictors show similar result. Real long-term bond rate in Norway produces the maximum DM test absolute value of 0.78 among all the variables across three countries in case of inflation forecasts. Although this variable performs better than other predictors in case of Norway, the performance does not persist in case of other two countries. No individual variable or univariate forecasting model produces forecast of inflation that is statistically different from AR benchmark model. The findings suggest that forecasts generated by different models and various predictors are neither superior nor inferior from the forecasts generated by the AR benchmark model.

SUMMARY OF OUT-OF-SAMPLE FORECASTS

Table 1 below exhibits the summary of pseudo out-of-sample forecasts for inflation forecasts. The first and second columns show the proportion of the relative RMSEs less than 1.00 for each country in 1-step ahead forecast. Third column represents the fraction of relative RMSEs less than 1.00 in both first and second sample periods whereas fourth column is the simple multiplication of first and second column. Finally, last column shows the number of series available in each sample. Analysis of table reveals that maximum 56-percent series of Finland have superior forecasting ability relative to AR benchmark model in the first period in case of 1-step forecasts of inflation. However, in the second period, Norway has maximum 53-percent series that perform better than AR benchmark in case of 1-step ahead forecast of inflation. The forecasting successes are not stable over time as maximum only 20-percent series of Norway has RMSEs less than 1.00 in both sample periods.

TABLE 1
SUMMARY OF PSEUDO OUT-OF-SAMPLE FORECAST ERRORS COMPARISON RELATIVE RMSES

Country	Inflation				
	1^{st}	2^{nd}	1^{st} and 2^{nd}	1^{st} X 2^{nd}	N
Norway	0.32	0.53	0.20	0.17	56*
Sweden	0.39	0.18	0.09	0.07	44
Finland	0.56	0.29	0.15	0.16	34

*There are 51 series for Norway in the 2^{nd} period.

The study finds that inflation forecast performances of various predictors are also not stable over time. The forecasting success of individual predictors in certain sample periods is not unusual since the predictors are chosen based on the past literatures. Moreover, the forecasting performances of variables are not significantly different from the AR benchmark model.

CONCLUSION

This paper contributes to the existing literature on the role of financial variables in forecasting inflation. In addition, separating the forecasting sample into pre- and post-crisis period, the paper studies the forecasting ability and performance stability of the variables before and after the financial turmoil that took place in late 2000s. The study of the literatures and the findings of my investigation draw several main conclusions.

Some variables perform better in forecasting inflation relative to the simple autoregressive process. For example, long-term bond rate has been a better predictor in Norway and Sweden in case of one quarter ahead inflation forecast. Other variables such as real Treasury bill rate, nominal stock price index, dividend yield, etc. show similar performances to that of long-term bond rate in case of inflation forecast. These findings are consistent with Banerjee *et al.* (2005), Forni *et al.* (2003) and Stock & Watson (2003), however, the findings contradict with Marcellino *et al.* (2003), who find univariate autoregressive process more useful for forecasting purpose. Although the investigation finds that some variables possess better forecasting abilities, no single predictor produces forecasts that are statistically significantly different from the forecasts generated by simple autoregressive process.

The performances of the individual variables and univariate forecasting models are neither universal nor stable over time across countries. For example, nominal stock price index and dividend yield produce better performance in Norway and in Finland but not in Sweden in case of one quarter ahead inflation forecast. Again, medium-term bond rate, industrial production index, employment, etc. produce better forecast in the pre-crisis period in Finland but not post crisis period in Finland whereas GDP deflator and commodity price index generate opposite outcome. Similar findings are also evident in case of Norway and Sweden. Moreover, the results show no distinctive pattern in forecasting abilities of predictors before and after the crisis, indicating that the recession of 2008 does not have any significance in macroeconomic variable forecasts.

The discussions point out few questions that remain tasks for future research. This study investigates only linear models for forecasting purpose. It is matter of interest whether the non-linear model produces better forecasts relative to the linear model and if they do then whether they are statistically different from each other. Again, it is also a topic to investigate why certain series in Sweden and Finland show parameter in-constancy during the 1990's and 2001's depression respectively but 2008's depression that affected the global economy.

ENDNOTES

1. Major economic changes result from the creation of European Union in November 1, 1993 and also from banking crisis and associated deep recession in the early 1990s as well as from boom in the later part of 1990s (Jacobson, Lindé and Roszbach, 2005).
2. Four measures of CPI are: 1. CPI for all urban consumers, all items, 2. CPI for all urban consumers, all items less shelter, 3. CPI for all urban consumers, all items less food and energy, and 4. Personal consumption expenditure deflator.
3. For example, in case of simple Autoregressive (AR) model, only lagged value of the dependent variable is included, whereas in Bivariate VAR model, lagged values of dependent variable and lagged values of another variable of interest are included.
4. Exceptions are the cases of ARMA and ARIMA- ARCH/GARCH model in which the appropriate lag lengths are selected applying the Box-Jenkins approach. Essentially, the lag lengths are selected by examining the correlogram of the series.

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APPENDIX

TABLE 1
SERIES DESCRIPTION

Series Label	Description	Available for Country
Asset Prices		
rovnght	Interest rate: money market overnight	Norway, Sweden
rtbill	Interest rate: short-term gov't. bills	Norway, Sweden
rbnds	Interest rate: short-term gov't. bonds	Norway, Sweden
rnotem/ rbndm	Interest rate: medium-term gov't. notes/bonds	Norway, Sweden, Finland
rbndl	Interest rate: long-term gov't. bonds	Norway, Sweden, Finland
rrovnght	Real overnight rate: rovnght-CPI inflation	Norway, Sweden
rrtbill	Real short-term bill rate: rtbill-CPI inflation	Norway, Sweden
rrbnds	Real short-term bond rate: rbnds-CPI inflation	Norway, Sweden
rrnotem/ rrbndm	Real medium-term notes/bond rate: rnotem/ rbndm-CPI inflation	Norway, Sweden, Finland
rrbndl	Real long-term bond rate: rbndl-CPI inflation	Norway, Sweden, Finland
rspread	Term spread: rbndl-rovnght	Norway, Sweden
exrate	Nominal exchange rate	Norway, Sweden, Finland
rexrate	Real exchange rate	Norway, Sweden, Finland
stockp	All-share stock price index	Norway, Sweden, Finland
peratio	Price-earnings ratio	Norway, Sweden, Finland
divyld	Dividend yield	Norway, Sweden, Finland
house	Housing price index	Sweden
Activity		
rgdp	Real GDP	Norway, Sweden, Finland
ip	Industrial production index (Manufacturing)	Norway, Finland
capu	Capacity utilization rate	Norway
emp	Employment	Norway, Finland
unemp	Unemployment rate	Norway, Sweden, Finland
Wages, Goods and Commodity Prices		
pgdp	GDP deflator	Norway, Finland
cpi	Consumer price index	Norway, Sweden, Finland
ppi	Producer price index	Norway, Sweden, Finland
earn	Wages and Salary	Finland
commod	Commodity price index (Manufacturing, mining and quarrying)	Norway, Sweden, Finland
oil	Oil price (Export price- Gasoline, Diesel oils and light distillates)	Norway
roil	Real oil prices (Based on real consumption)	Norway
Money		
m0	M0 or monetary base	Norway
m1	M1 or currency and coins in circulation	Norway, Finland
m2	M2 or broad money supply	Norway, Sweden
m3	M3	Norway, Sweden

Notes: 1. Short-term gov't bills are 3-month treasury bills for both Noway and Sweden. 2. Short-term gov't. bonds rate for Norway and Sweden are 2–year gov't. bonds and 1-year gov't. bonds respectively. 3. Medium-term gov't. notes/bonds rate for Norway, Sweden and Finland are 5-year gov't. notes, 5-year gov't notes and 5-year gov't bonds respectively. 4. Long-term gov't bonds are 10 year gov't bonds for all three countries.

TABLE 2
CPI INFLATION

Indicator	Tanas-formation	Norway						Sweden						Finland					
		2004-08			2009-13			2004-08			2009-13			2004-08			2009-13		
		RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
Univariate Forecasts																			
AR(4)		1.28	1.02	299.70	0.91	0.72	121.70	0.75	0.51	194.62	0.76	0.61	217.17	0.69	0.50	157.52	0.70	0.52	180.31
Relative Measures to Univariate AR(4)																			
ARMA(p,q)*		1.01	0.98	0.98	1.01	1.02	1.05	1.08	1.27	4.96	0.81	0.77	0.68	1.04	1.07	1.25	0.91	0.90	0.82
GARCH(1,1)		1.03	1.05	0.98	1.02	1.03	1.00	1.01	1.04	0.95	1.00	1.03	1.24	1.01	0.98	0.967	1.01	1.01	1.00
Bivariate Forecasts																			
rovnght	level	0.99	1.03	0.97				0.99	0.98	1.10	1.03	1.01	1.13						
rtbill	level	1.00	1.02	0.94	1.06	1.07	1.16	0.98	0.98	0.83	1.12	1.16	1.70						
rbnds	level	1.02	1.05	1.10	1.06	1.10	1.23	1.05	1.06	0.78	1.01	1.00	1.59						
rbndm/ rnotem	level	1.02	1.04	1.27	1.02	1.01	1.02	0.96	0.90	1.07	0.94	0.97	1.31	0.95	0.99	1.26	1.04	1.03	1.10
rbndl	level	0.99	0.95	1.14	0.83	0.81	0.72	0.96	0.90	0.96	0.96	0.98	1.30	0.94	1.00	1.19	1.01	1.01	0.97
rovnght	Δ	0.99	0.99	0.97				1.00	1.00	1.07	1.01	0.98	0.94						
rtbill	Δ	1.00	1.00	0.99	0.93	0.92	0.84	0.98	0.98	1.01	1.11	1.14	1.60						
rbnds	Δ	1.02	1.01	1.10	0.82	0.88	0.94	1.06	1.05	0.97	1.00	0.98	1.54						
rbndm/ rnotem	Δ	1.00	0.97	1.12	0.81	0.82	0.78	1.02	0.98	1.44	0.93	0.98	1.13	0.96	0.99	1.19	1.02	1.02	1.04
rbndl	Δ	0.98	0.95	1.16	0.82	0.84	0.77	0.99	0.96	1.67	0.95	0.98	1.25	0.96	0.98	1.13	1.00	1.01	0.93
rrovnght	level	0.97	0.95	0.90				1.06	1.14	2.51	1.07	1.06	1.04						
rrtbill	level	0.96	0.94	0.89	0.97	1.02	1.09	1.02	1.05	2.26	1.09	1.10	1.08						
rrbnds	level	1.00	1.03	1.20	0.94	1.05	1.14	0.98	0.95	0.82	1.01	0.89	0.78						
rrbndm/ rrnotem	level	1.04	1.10	1.45	0.91	1.00	0.95	1.10	1.28	3.08	0.97	0.97	1.47	0.98	0.98	1.04	1.08	1.09	1.18
rrbndl	level	0.97	0.94	1.14	0.86	0.89	0.92	1.08	1.28	2.77	0.96	0.95	1.44	1.01	1.03	1.18	1.02	1.07	1.14
rrovnght	Δ	0.94	0.90	0.89				0.99	0.97	1.54	1.06	1.09	1.37						
rrtbill	Δ	0.93	0.90	0.93	0.89	0.94	0.99	0.96	0.91	1.20	1.11	1.12	1.12						
rrbnds	Δ	0.96	0.97	1.09	0.90	1.02	1.12	1.08	1.10	3.42	1.07	0.96	0.71						
rrbndm/ rrnotem	Δ	0.99	1.04	1.29	0.91	1.00	1.00	0.97	0.98	1.43	1.03	1.02	1.06	0.94	0.99	1.02	1.17	1.12	1.32
rrbndl	Δ	0.97	1.00	1.25	0.91	0.96	0.91	0.96	0.99	1.67	1.04	1.00	1.12	1.00	1.04	1.20	1.02	1.07	1.15
rspread	level	1.00	0.97	1.00				0.93	0.94	1.07	0.94	0.86	0.96						
exrate	Δln	1.02	1.02	1.00	1.00	1.06	1.22	1.17	1.23	2.17	1.21	1.07	1.58	1.01	1.00	1.12	0.99	0.94	0.93
rexrate	Δln	1.01	1.01	1.00	1.03	1.10	1.18	1.14	1.17	1.87	1.25	1.09	1.72	1.00	1.01	1.13	0.98	0.93	0.93
stockp	Δln	0.97	0.95	0.80	0.98	1.05	1.14	1.05	0.97	0.83	1.06	1.09	1.55	0.94	0.94	0.76	1.03	1.08	1.37
peratio	level	1.01	1.00	1.04	0.92	0.93	0.97	0.99	0.99	0.79	1.04	1.09	1.18	1.01	1.06	1.22	0.99	1.00	1.01
divyld	Δ	0.94	0.91	0.66	1.33	1.17	1.33	1.14	1.22	2.39	1.12	1.04	0.80	0.95	0.95	0.73	0.79	0.82	1.17
house	ln							1.04	1.00	1.36	1.05	1.07	1.64						

Indicator	Tanas-formation	Norway						Sweden						Finland					
		2004-08			2009-13			2004-08			2009-13			2004-08			2009-13		
		RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
Bivariate Forecasts (Contd.)																			
house	Δln							0.99	1.07	1.67	1.06	0.97	0.88						
house	Δ^2ln							1.02	1.10	1.51	1.09	1.03	1.00						
rgdp	Δln	1.14	1.13	0.76	1.17	1.22	1.38	1.22	1.22	1.19	1.17	1.18	2.24	1.02	1.02	1.10	1.02	1.01	0.95
rgdp	gap	1.07	1.05	1.03	1.13	1.18	1.38	1.08	1.14	1.54	1.11	1.09	1.10	1.03	1.06	1.17	1.10	1.12	1.13
ip	Δln	1.05	1.04	1.16	0.84	0.86	1.01							0.96	0.92	0.80	0.99	1.03	1.08
ip	gap	1.07	1.10	0.99	1.15	1.05	1.09							0.97	1.00	1.08	1.19	1.32	1.50
capu	level	1.03	1.02	0.99	1.01	1.02	1.13												
emp	Δln	1.00	1.01	1.10	1.03	1.00	1.02							0.98	1.01	1.04	1.07	1.06	1.19
emp	gap	1.05	1.09	0.95	1.06	1.03	1.07							0.98	0.95	0.84	1.05	1.05	1.11
unemp	level	1.02	1.03	1.05	1.03	1.05	1.06	0.99	0.92	0.89	1.05	1.08	1.73	1.04	1.02	0.97	1.03	1.05	0.96
unemp	Δln	1.04	1.04	1.04	1.01	1.05	1.17	0.97	0.91	0.93	1.09	1.13	1.91	1.04	1.02	0.91	1.02	1.03	0.90
unemp	gap	1.03	1.04	0.95	1.03	1.02	1.03	0.99	1.05	1.87	1.05	1.07	1.30	0.99	0.98	0.90	1.03	1.03	1.06
pgdp	Δln	1.02	1.00	1.03	0.89	0.89	0.86							0.99	0.97	0.98	0.94	0.91	0.73
pgdp	Δ^2ln	0.99	0.98	1.00	0.87	0.86	0.69							0.99	0.96	0.98	0.98	0.99	0.81
ppi	Δln	1.15	1.15	1.50	1.01	1.03	0.95	1.21	1.34	2.05	1.06	1.11	0.89	0.98	1.08	1.30	1.01	0.99	0.91
ppi	Δ^2ln	1.16	1.19	1.96	1.13	1.18	1.34	1.24	1.30	1.63	1.03	1.08	1.49	0.99	1.08	1.30	0.99	0.95	0.94
earn	Δln													0.94	0.96	0.94	1.04	0.99	1.00
earn	Δ^2ln													0.96	0.95	0.83	1.06	1.03	1.02
oil	Δln	1.02	1.05	1.20	1.04	1.06	1.03												
oil	Δ^2ln	1.05	1.04	1.38	0.98	1.03	1.15												
roil	ln	1.02	1.03	1.04	0.90	0.88	0.76												
roil	Δln	1.03	1.04	1.15	0.87	0.93	0.96												
commod	Δln	1.11	1.13	1.34	1.06	1.05	0.93	1.05	0.99	1.52	1.13	1.08	1.00	1.00	1.06	1.12	1.00	0.96	0.95
commod	Δ^2ln	1.03	1.03	1.19	0.98	1.03	0.95	1.03	1.14	2.25	1.09	1.00	0.82	1.03	1.06	1.18	0.99	0.96	1.13
m0	Δln	0.93	0.90	0.74	1.12	1.15	1.13												
m0	Δ^2ln	0.94	0.93	0.79	1.10	1.14	1.25												
m1	Δln	0.99	0.94	0.86	0.94	0.95	1.05							1.00	0.99	1.18	1.02	1.01	0.98
m1	Δ^2ln	1.01	0.96	0.88	0.95	0.92	0.91							1.01	0.98	1.07	1.05	1.02	1.00
m2	Δln	1.03	0.95	0.69	0.96	0.99	1.19	1.05	1.01	1.45	1.02	1.04	1.43						
m2	Δ^2ln	1.05	0.97	0.72	0.99	0.94	1.03	1.08	1.04	1.72	1.05	1.09	1.47						
m3	Δln	1.01	1.00	1.44	0.75	0.83	0.93	1.29	1.28	3.54	1.20	1.14	1.51						
m3	Δ^2ln	1.05	1.05	1.18	1.21	0.99	1.00	1.30	1.31	3.37	1.12	1.00	1.09						

*Note: ARMA(p,q) lag length: Norway- inflation (4,2), Sweden- inflation(3,4), Finland- inflation(3,3)

TABLE 3
DIEBOLD-MARIANO TEST STATISTICS
(COMPARED TO UNIVARIATE AUTOREGRESSION)

Series	Transformation	Norway 2004-08	Norway 2009-13	Sweden 2004-08	Sweden 2009-13	Finland 2004-08	Finland 2009-13
Univariate Forecasts							
ARMA(p,q)		-0.02	-0.02	-0.22	0.49	-0.26	0.20
GARCH(1,1)		-0.20	-0.19	-0.04	-0.02	-0.05	-0.07
Bivariate Forecasts							
rovnght	level	0.06		0.09	-0.13		
rtbill	level	0.01	-0.33	0.07	-0.43		
rbnds	level	-0.09	-0.27	-0.11	-0.09		
rbndm/ rnotem	level	-0.11	-0.08	0.18	0.18	0.25	-0.22
rbndl	level	0.01	0.44	0.19	0.13	0.32	-0.10
rovnght	Δ	0.03		-0.09	-0.09		
rtbill	Δ	-0.01	0.21	0.09	-0.51		
rbnds	Δ	-0.04	0.32	-0.13	-0.07		
rbndm/ rnotem	Δ	0.00	0.37	-0.04	0.16	0.27	-0.18
rbndl	Δ	0.03	0.39	0.05	0.13	0.31	0.01
rrovnght	level	0.23		-0.35	-0.22		
rrtbill	level	0.15	0.11	-0.10	-0.24		
rrbnds	level	0.00	0.13	0.09	-0.20		
rrbndm/ rrnotem	level	-0.15	0.24	-0.26	0.04	0.14	-0.43
rrbndl	level	-0.62	-0.78	-0.19	0.06	-0.04	-0.11
rrovnght	Δ	0.30		0.06	-0.18		
rrtbill	Δ	0.21	0.24	0.28	-0.43		
rrbnds	Δ	0.13	0.19	-0.24	-0.30		
rrbndm/ rrnotem	Δ	0.05	0.25	0.22	-0.10	0.38	-0.36
rrbndl	Δ	0.11	0.30	0.23	-0.11	-0.03	-0.11
rspread	level	-0.13		0.31	0.22		
exrate	Δln	-0.13	0.00	-0.37	-0.36	-0.09	0.09
rexrate	Δln	-0.09	-0.06	-0.37	-0.34	-0.02	0.14
stockp	Δln	0.08	0.05	-0.13	-0.18	0.24	-0.06
peratio	level	-0.02	0.27	0.05	-0.17	-0.10	0.06
divyld	Δ	0.25	-0.30	-0.39	-0.14	0.26	0.33
house	ln			-0.13	-0.27		
house	Δln			0.08	-0.21		
house	Δ^2ln			-0.20	-0.26		
rgdp	Δln	-0.52	-0.44	-0.31	-0.45	-0.11	-0.18
rgdp	gap	-0.17	-0.51	-0.64	-0.48	-0.12	-0.62
ip	Δln	-0.10	0.29			0.44	0.02
ip	gap	-0.20	-0.27			0.12	-0.26
capu	level	-0.20	-0.02				
emp	Δln	-0.01	-0.22			0.12	-0.29
emp	gap	-0.24	-0.32			0.22	-0.54

Series	Transformation	Norway		Sweden		Finland	
		2004-08	2009-13	2004-08	2009-13	2004-08	2009-13
Univariate Forecasts							
ARMA(p,q)		-0.02	-0.02	-0.22	0.49	-0.26	0.20
GARCH(1,1)		-0.20	-0.19	-0.04	-0.02	-0.05	-0.07
Bivariate Forecasts							
unemp	level	-0.26	-0.52	0.05	-0.15	-0.35	-0.20
unemp	Δln	-0.28	-0.06	0.14	-0.27	-0.28	-0.29
unemp	gap	-0.15	-0.39	0.05	-0.48	0.16	-0.59
pgdp	Δln	-0.05	0.36			0.13	0.40
pgdp	Δ^2ln	0.04	0.30			0.06	0.10
cpi	Δln						
cpi	Δ^2ln						
ppi	Δln	-0.46	-0.03	-0.39	-0.17	0.13	-0.04
ppi	Δ^2ln	-0.37	-0.22	-0.29	-0.11	0.03	0.04
earn	Δln					0.22	-0.10
earn	Δ^2ln					0.13	-0.23
oil	Δln	-0.11	-0.12				
oil	Δ^2ln	-0.19	0.03				
roil	ln	-0.06	0.36				
roil	Δln	-0.06	0.34				
commod	Δln	-0.47	-0.17	-0.20	-0.39	0.00	-0.03
commod	Δ^2ln	-0.07	0.06	-0.08	-0.26	-0.12	0.07
m0	Δln	0.24	-0.39				
m0	Δ^2ln	0.35	-0.30				
m1	Δln	0.03	0.18			-0.04	-0.15
m1	Δ^2ln	-0.03	0.21			-0.09	-0.36
m2	Δln	-0.09	0.07	-0.16	-0.10		
m2	Δ^2ln	-0.18	0.03	-0.19	-0.27		
m3	Δln	-0.02	0.32	-0.38	-0.48		
m3	Δ^2ln	-0.12	-0.12	-0.40	-0.39		