Forecasting Inflation in Czech Republic Using VAR and BVAR

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Abstract: Forecasting of inflation has become crucial for both policy makers and private agents since many Central Banks implemented inflation targeting rules. Inflation forecasting is considered to be very complicated issue because univariate regression models and structural macroeconomic models are often outperformed by naive random walk model. This work aims for forecasting inflation in the Czech Republic by employing (Bayesian) Vector Autoregression - (B)VAR models with various predictors.

A set of almost 39 time series covering various economic indicators including forward looking variables extracted from surveys is considered. Various VAR and BVAR models are constructed for different combinations of used predictors. Forecasting performances of various models are compared by applying the the Theil statistics and several related statistics based on square errors, absolute errors and also square-root errors. One year forecasting horizon is considered due to its importance for central banks. VAR models proved to outperform Random Walk and AR models in forecasting performance, however, employing of BVAR models instead of VAR brings mixed results. The accuracy of forecasts based on absolute errors and especially square-root errors is more stable over time than employing the most common square errors. The most important individual predictors are 'Broad money' measure and 'Real exports' followed by several surveys time series that are found to be important inflation predictors.

Keywords: VAR; inflation forecasting; Czech republic, forecast accuracy,

JEL classification: C11, C32, C52, C53

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Introduction

Inflation forecasting is undoubtedly an important issue of economic research that is demanded by both policy makers and private agents. Its importance even grew due to inflation targeting rules that have been implemented by many central banks. However, inflation forecasting is generally considered to be very complicated issue. Several approaches for determination of inflation can be found among the huge amount of related literature.

The traditional and New Keynesian Phillips curve is heavily discussed trade-off relationship between inflation and unemployment or output gap. It is the most common econometric basis for prediction of inflation, however the usefulness of the Phillips curve has been questioned by several authors. Critiques follow two main directions. The first is that there exist economic variables (e.g. confidence indices) that allow for more accurate inflation forecasts [1], moreover parameters of models based on Phillips curve change over time. The second is that any forecast based on Phillips curve is worse than naive forecasts or simple univariate autoregression [2]. This stream of critique makes Phillips curve certainly inappropriate for efficient inflation forecasts.

Vector autoregression (VAR) models that are more related to this paper usually involve large datasets - large number of predictive variables. However, adding variables to VAR model leads to overparametrization. This effect even gains importance due to relatively short available reliable macroeconomic time series because of relatively short period of economic stability in post-socialistic countries like Czech Republic. This problem can be overcome by averaging the forecasts of different smaller models. This approach dates back to the work of Granger and Bates (1969) [3]. It is widely discussed that the best predictive performance is obtained by equal weight averaging of forecasts from many models. It is unlikely that the 'true' optimal weights of many different models are exactly equal, but the error, introduced by estimating these weights, may more than offset any benefits [4]. However, Bayesian model averaging (BMA) is successfully used in current literature. This method averages the models according to their posterior model probability [5]. The other option is imposing the restrictions on the parameters of VAR models employing the rules of Bayesian econometrics - so called Bayesian vector autoregression (BVAR).

Bayesian econometrics is the developing field of econometrics for the past two decades. Comprehensive and readable monograph on Bayesian Econometrics by Gary Koop [6] may serve as an overview of important concepts of Bayesian econometrics for readers that are not familiar with the concept. Methodology of this article, however, concerns basic Bayesian vector autoregression (BVAR). Bayesian VAR approach has been introduced by Litterman (1979), expanded by Doan, Litterman and Sims (1984) and somewhat summarized in Litterman (1985) with 'five years of experience' proving the forecasting ability of BVAR models [7]. BVAR approach proved to be a flexible and effective forecasting method [8].

BVAR model with general prior is atheoretical or statistical time-series model as well as VAR without any structural restriction to parameters. This advantage over macroeconomic structural models is already pointed in Litterman, 1985 [7]. Short quotation right from the second paragraph of this forty-pages article is more than illustrative: '(BVAR) does not require judgemental adjustment. *Thus it is a scientific method* which can be evaluated on its own, without reference to the forecaster running the model' (Litterman, 1985). However, complete specification requires, among others, to specify the model variables. Variables are often selected according to their economic plausibility (and thus dependent on the forecaster's judgement). Nevertheless, in this work, many possible predictors are involved and model variables are selected according to their pseudo out-of-sample forecast ability.

Under Bayesian framework, *a priori* information can be incorporated into models through priors. Priors impose general restrictions on parameters avoiding the problem of overfitting. Many different priors were defined and used, though the majority of works, along with this one, still keep in with originally proposed prior by Litterman: Minnesota prior. The estimation procedure in this article is based on Econometric Toolbox for Matlab by James P. LeSage [9]. The toolbox contains functions that provide estimation procedure and multi-step forecast of VAR model and BVAR model with Minnesota prior. We use these functions for programming functions that allow for pseudo-out-of sample predictions and automatic forecast performance evaluation.

This article is organized as follows. Firstly, brief literature review of inflation forecasting using BVAR and related techniques is provided. The estimation procedure is explained in a detail in the methodology section. Results section provides all the results including simple graphical output. Last two sections discuss the results, raise the issues of future work and conclude.

Literature review

Original research articles that deal with inflation forecasting can be considered as a patchwork consisting of several pieces. The first piece is the fundamental*econometric approach* used. Typical examples are: univariate model, bivariate model, structural macroeconomic model, VAR, factor model, Bayesian approach etc. The second piece of inflation forecasting patchwork is the data that are used, i.e. the choice of the possible *inflation predictors*. The proper choice is partly dependent on the econometric methodology used, but very often quite general datasets are employed. The third, and often underestimated piece is the *evaluation of predictive* accuracy. Simple comparison of mean square errors is the most often used, however, more sophisticated techniques are also utilized (e.g. Granger-Newbold or Diebold-Marianno tests). Absolute freedom in combining those three mentioned pieces of inflation forecasting makes the conclusions of different papers incomparable to each other.

Comprehensive articles

Seminal paper on US inflation forecasting at the 12-month horizon is by Stock and Watson [1]. Bivariate (i.e. single predictor) models are used along with factor models (i.e. reduction of many predictors into few factors). Simple model averaging is also employed. Measures of real economic activity are used as inflation predictors since Phillips curve examination is a prime interest. Predictive accuracy is determined from simple regression comparing produced forecast to simple autoregressive forecast. Phillips curve outperform forecasts based on other macroeconomic variables, however, forecasts based on aggregate activity predictors (factors) can improve the Phillips curve forecasts.

One of the comprehensive articles that deals with inflation forecasting and uses BVAR is by Fabio Canova [10]. This 'horse-race' article compares different econometric approaches for inflation forecasting in G7 countries. ARIMA models are used along with bivariate theory-based models and also VAR and BVAR models. Canova compares performance of pseudo-out-of-sample forecasts of various models for one quarter, one year and two years forecasting horizons. All the models are then estimated recursively and pseudo out-of-sample forecasts are compared to the real values via Theil-U statistics based on square errors (discussed in detail in Methodology section).[1] Main findings are that AR models are generally better than naive steady-state forecast. Theory-based models improve over univariate specification at long horizons only. BVAR and VAR models improves significantly over univariate models only for time varying coefficients specification.

Similarly comprehensive article is by Ang et al. [11]. Univariate models and small regression models with different specifications are used for comparison between predictive ability of different macroeconomic time-series. Surveys describing inflation expectations of different economic agents are also included in the data set. Predictive accuracy is estimated via simple regression models over the forecasts, similarly to Stock and Watson [1]. The most useful inflation predictors survey-based measures with the exception of consumer's surveys.

Advanced predictive accuracy determination

Most of the papers stick to the direct comparison of mean square errors (MSE) of the respective forecasts [12], [13]. Some of the already mentioned papers use small regression models [1], [11]. Other authors use slightly more advanced statistics that directly compare MSE of the given forecast to MSE of either random walk forecast [10] or to simple univariate model forecast [14]. Proper statistical comparisons

[1] Theil-U statistics has already been successfully used by Litterman as a Theil coefficient.

of predictive accuracy based on Diebold-Marianno test and Granger-Newbold test are utilized by Arratibel et al. [15] and Horváth et al. [16], respectively. Less rigorous but more practical approach for forecast accuracy evaluation is presented by Cecchetti et al. [17]. Many forecasts are produced using bivariate regression models employing many inflation predictors. Calculated forecasts are then not compared for whole period considered, but the forecasts are compared for each year separately. The main result is that even if the forecast seems to be powerful over whole period, it is often inferior over many sub-periods. In other words, the predictive power of inflation predictors is not stable over time. In extreme cases, the predictor that performs best over a decade may have not been the best predictor in any of the one-year sub-periods. Time stability of given forecast and inflation predictor(s) should, therefore, be always evaluated.

Bayesian approach

Bayesian econometric methods can be applied to the virtually any kind of econometric model. However, Bayesian vector autoregression is the most used approach.

Bikker (1998) [8] provides estimations of BVAR models for EU-7 and EU-14 countries and compares forecasts of these models to forecasts by OECD. Author used 15 time series concerning the most important economic indicators, but each model consists of eight variables only. BVAR forecasts compare well to OECD forecasts at both one year and two years forecasting horizons.

Authors Ballabriga and Castillo (2003) [18] provide BVAR model for forecasting aggregate EMU inflation. They conclude that forecasting yields favorable results with respect to forecasts of other analysts. Important influence to inflation comes from external sector - GDP growth in outer states and commodity prices.

Joiner (2002) and Bloor and Matheson (2009) [19] used BVAR to describe monetary policy effects in Australia and New Zealand respectively. However, the methodology which incorporates restrictions in both contemporaneous and lagged relationships in the model [20] to decompose particular effects in BVAR must be used.

Jochmann, Koop and Strachan (2010) [21] extend standard VAR model by stochastic search variable selection that allows for automatic selection of powerful inflation predictors via advanced setting of Bayesian priors. Moderate improvements of forecasting accuracy over standard VAR when using US macroeconomic dataset is reported. The methodology is further exploited in Koop and Korobilis (2011) [22]. Apart of dynamic predictors selection, the dynamic Bayesian model averaging is developed and utilized. Joint utilization of dynamic model selection and dynamic greatly improves forecast performance when compared to more traditional forecasting methods.

Recent paper by Baxa, Plašil and Vašíček (2012) [23] uses Bayesian model averaging for estimation of time-varying regression model with stochastic volatility. Marginal costs indicators like labour costs or output gap are utilized for estimation of New Keynesian Phillips Curve based model. However, inflation persistence and volatility of inflation shocks are investigated in favour of forecasting issues. Koop and Onorante (2012) [24] use regression and VAR methods to estimate Phillips curve. New Keynesian forward looking Phillips curve is supported and professional forecasts by ECB forecasters are successfully embedded in comparing real inflation anf inflation expectations.

Inflation forecasting in Czech Republic

The most related paper from Czech economic environment is Borys and Horváth (2007) [25]. Paper concerns the understanding the transmission mechanism of monetary policy to inflation and other real economic variables. Principle component analysis is employed onto large number of economic time series to overcome the problem of limited number of variables that can be included in VAR model. Factor augmented VAR (FAVAR) model is subsequently estimated. Provided discussion concerning the data is important for this work. Sample is restricted to the data from 1998 on, since inflation targeting has been adopted by Czech national bank by January 1998. While other studies often employ quarterly data, given the length of the sample authors decided to work at monthly frequency (and so it is in this work). Authors also discuss the drawback of VAR literature for its backward-looking dimension. On the other hand, inflation targeting monetary policy is typically forward looking. However, this fundamental drawback of VAR can be weaken by including forward looking variables.

Modelling of the inflation in the Czech republic has also been undertaken by Golinelli and Orsi (2001) [26] using multivariate cointegration empirical models. Other papers focus more on evaluation of inflation targeting in Czech republic (e.g. [27], [28], [29], [30], [31] etc.).

Data

Following Borys and Horváth [25] we use data from January 1998. This is the time of adoption of pure inflation targeting by Czech National Bank. Due to the reduced length of the sample we decided to use monthly data. When it is possible, we choose data in the form of percentage change on the same period of the previous year. Data were downloaded on the 22nd of February 2012 and have not been furthermore updated in any way.

The data were downloaded from database OECD Stats that is available for subscribers. Only data that covers whole period from January 1998 were used, altogether 39 time series. Description of all time series can be found at *http://stats.oecd.org/*, including methodology of collecting surveys data. In the following text we will use the names of the time series as they appear at OECD

Stats so they are easily traceable. As the inflation data we use 'Consumer prices: all items (change to the same period of the last year)' time series. This choice is quite common (e.g. [5]).

The time series - inflation predictors - can be divided into three groups: Real economy variables, Money related variables and Surveys [11].

Real economy time series

1	Exports in goods, s.a.
2	Imports in goods, s.a.
3	Share prices
4	Industrial production, s.a.
5	Retail trade (volume), s.a.
6	Harmonised unemployment rate, s.a.
7	Industrial production (ratio to trend)
8	Output gap
9	GDP - expenditure approach
10	Private final consumption expenditure
11	General government consumption expenditure
12	Gross fixed capital formation

The last five time series (GDP measures) are available only with quarterly frequency. Monthly data are computed by employing cubic spline interpolation.

Money related time series

1	Broad money, s.a.
2	Domestic producer prices - manufacturing
3	Overnight interbank rate
4	Exchange rates, USD monthly averages
5	3 month interbank rate

Surveys 21 time series capturing different surveys data collected by OECD were used. However, some time series are closely related and as a result mutually correlated. When pair of the series is highly correlated (correlation coefficient of whole series ¿ 0.9) then only one series was used (usually the most general one - e.g. 'Composite indicator' or 'EC indicator'). The amount of time series was reduced to 16. Surveys are regularly (once a month) collected by OECD in a form of short questionnaire. Professionals in the fields of manufacturing industry, construction industry and retail industry are asked about current and future activity in respective sectors, current state of finished goods, selling prices and employment. Composite indicators are then constructed.

16 used survey series can be described as follows:

1	Leading indicator, amplitude adjusted
2-7	Manufacturing (6 series) - Production (current, future),
	Finished Goods, Selling Prices, Employment, EC indicator
8-9	Construction (2 series) - Activity, Composite indicator
10-14	Retail (5 series) - Activity, Volume, Employment, Orders, Composite indicator
15-16	Consumer situation (2 series) - Inflation, EC indicator

Methodology

The aim of this study is to develop forecasts of inflation in Czech Republic with high forecast accuracy. Principal methods are vector autoregression (VAR) and Bayesian vector autoregression (BVAR) employing the most common Minnesotta prior. Pseudo out-of-sample forecasts are computed recursively and the forecasting accuracy is evaluated. Models with different inflation predictors are estimated and the best predictors are chosen.

Benchmark models and recursive forecasting Inspired by Canova [10], we compare VAR and BVAR forecasts to simple benchmark models, namel Randomw Walk (RW) forecast and univariate autoregressive model (AR). Steady state (naive, random walk) recursive forecast is easily performed only by shifting the vector of the data forward by required forecasting horizon (we will refer to forecast horizon -number of steps of forecast - as k). Simple AR(3) model - including three lagged values - has been estimated recursively.

When computing the forecast for the time $t+k$, the model uses only data upto time t. The model is therefore estimated on data up to time t. Then the k-steps ahead forecast is computed step-by-step using the chain rule of forecasting. We focus only on the one-year forecasting horizon. Then time t is moved one step forward (thus for estimation we use one data up to $t+1$). Model parameters are re-estimated and new k-steps ahead forecast is computed. The result of the procedure is then the vector of forecast. The re-estimating of the model can be regarded as learning of the model.

It is clear that pseudo out-of-sample forecast close to the beginning of time series is not reliable, since model estimation is based there only on a very short time series. Therefore we consider period form January 1998 to December 2003 only as learning period. The period from January 2004 to December 2011 is used as the test period, containing 96 data points.

Figure 1 shows the inflation data that we aim to forecast recursively. Note that the data time series consist of periods with different behaviour. In the first part - until middle of 2007 - the inflation oscillates within narrow band around 2%. From mid-2007 until end of 2008, there is a period of high inflation followed by period of low inflation in 2009. During 2010 and 2011 the inflation is relatively stabilized

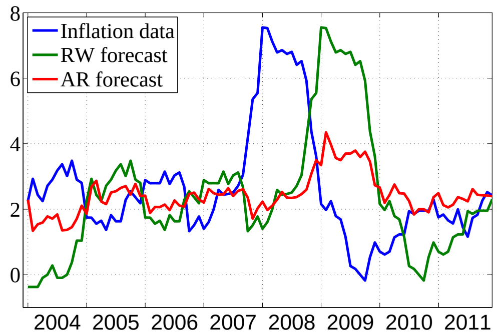

Figure 1: Inflation data and forecast by RW and AR

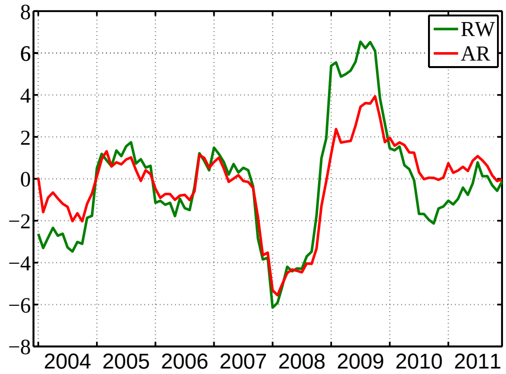

Figure 2: Forecast error

around 2%. Random walk forecast is also depicted in the Figure 1. It is obvious that this naive forecast is computed only by shifting the data by forecasting horizon (12 months) forward. Forecast using simple AR(3) model is included. Figure 2 shows the forecast errors of RW and AR forecasts. It is obvious that the periods of high inflation increase and subsequent sharp decrease are predicted with the lowest accuracy.

Vector autoregression - VAR

We consider reduced VAR model with standard specifications:

$$
\begin{aligned}
y_t^1 &= c_1 + \beta_{1,1}^1 y_{t-1}^1 + ... + \beta_{nlag,1}^1 y_{t-nlag}^1 + \beta_{nlag,2}^1 y_{t-1}^2 + ... + \beta_{nlag,n}^1 y_{t-nlag}^n + \varepsilon_t^1 \\
y_t^2 &= c_2 + \beta_{1,1}^2 y_{t-1}^1 + ... + \beta_{nlag,1}^2 y_{t-nlag}^1 + \beta_{nlag,2}^2 y_{t-1}^2 + ... + \beta_{nlag,n}^2 y_{t-nlag}^n + \varepsilon_t^2 \\
\ldots &= \ldots \\
y_t^n &= c_n + \beta_{1,1}^n y_{t-1}^1 + ... + \beta_{nlag,1}^n y_{t-nlag}^1 + \beta_{nlag,2}^n y_{t-1}^2 + ... + \beta_{nlag,n}^n y_{t-nlag}^n + \varepsilon_t^n
\end{aligned}
$$

n is number of variables included in the VAR and $nlag$ is the number of lags. The same can be shortly written as:

$$
y_t^i = c_i + \sum_{ijm} \beta_{m,j}^i y_{t-m}^j + \varepsilon_t^j,
$$

where $i = 1 \ldots n$; $j = 1 \ldots n$; $m = 1 \ldots nlag$. i thus labels the equation of VAR, j labels the variable of right hand side and m labels the lag. Note that constant term is always included.

VAR model is estimated using only data upto time t. Multi-step forecast for time $t + k$ is computed for all variables included in the model by chain rule. The t runs from the beginning of the data (actually $t_{min} = nlag$ - number of lags included in the VAR -, so that the right hand side values are all available) to the end of the data T (actually $t_{max} = T - k$ so that we can compare the last value of the forecast to the existing data). Model is re-estimated in each step. The vector of forecast for given forecasting horizon k is thus computed for all variables included in VAR. The pseudo-out-of might be then compared to the data and the forecast accuracy might be evaluated. Vector of forecasts can also be used in graphical representation.

Particular VAR model is fully specified by the set of the inflation predictors and by the number of lags included. Clearly, the more predictors we include and the more lags we consider, the more parameters have to be estimated. When the amount of parameters is too high, the model looses its plausibility nad forecast accuracy.

Common solution is to impose *ad hoc* restrictions to parameters acording to more or less plausible assumptions from economic theory. Some relationships are then suppressed (this effectively means setting some groups of parameters to zero) and thus number of parameters is reduced (so called 'parsimonious VAR approach'). Such models then go from being *overparametrized* to being *overidentified* [**?**].

Another option, preferred in this study, is to impose common structure on the coefficients using Bayesian methods.

Bayesian vector autoregression - BVAR

Bayesian vector autoregression prevents the problem of possible overparametrizing of the VAR model. Under Bayesian framework, *a priori* information can be incorporated into models through priors. Priors impose general restrictions on parameters avoiding the problem of overfitting (more details can bfound e.g. in Koop, 2003 [6]). Many different priors were defined and used, though the majority of works still keep in with originally proposed prior by Litterman: Minnesota prior.

BVAR model estimation procedure is similar to VAR case. More complicated usually Bayesian methods involve computationally demanding posterior simulations, however, when using simple Minnesota prior, the estimation of BVAR is done only via simple matrix multiplication, similarly to any regression exercise. The estimation of parameters in VAR is based only on data. In BVAR, the estimation mixes the information from the data and the information from the prior. This is the key feature of Bayesian estimation. Eliciting appropriate prior is fundamental issue.

The prior used in this paper is the basic Minnesota prior and it is well described by LeSage [9] in the Matlab toolbox documentation. Minnesota prior was originally proposed by Litterman, Doan and Sims (1984). The parameters of the VAR model are regarded as random variables and they are assumed to be in the form of the Normal distribution. Thus the prior for each parameter is defined by the mean and variance of the Normal distribution

Minnesota prior is based on the belief that random walk is a good proxy for the evolution of economic variables in time. This means that the mean of the prior for the parameter is equal to *one* for the first lag of the dependent variable in each equation. All other parameters (connected to all other variables and also to all higher lags of the dependent variable) are endowed with the prior with zero mean. Minnesota prior thus take the form [9]:

$$\beta^i_{1,i} \sim N\left(1, \sigma^2_{i1i}\right) \tag{1}$$

$$\beta^i_{m,j} \sim N\left(0, \sigma^2_{imj}\right) \tag{2}$$

where $\beta^i_{1,i}$ are parameters associated with the first lag of dependent variable in each equation and $\beta^i_{m,j}$ are all other parameters in the model (thus assumed that $i \neq j \vee m \neq 1$). Index i refers to the number of the equation and $i = 1 \ldots n$. This implies that each variable included in the model is assumed to be dependent mainly on its own first lag. Higher-order lags and lags of other model variables are thus regarded as less important.

The prior variances σ^2_{imj} specify uncertainty about the prior means. Since we are interested in model without judgemental adjustment we use general formula proposed by Litterman [7]. Using that, we generate prior variances by three parameters only.

$$\sigma_{imj} = \theta w(i,j) m^{-\phi} \left(\frac{\hat{\sigma}_{uj}}{\hat{\sigma}_{ui}}\right), \tag{3}$$

where θ is so-called overall tightness parameter; ϕ is decay parameter, w represents is element of so-called weight matrix and finally $\hat{\sigma}_{ui}$ is estimated standard error from a univariate autoregression involving variable i (i. e. for each variable, an univariate autoregression model with optimized number of lags is estimated in order to get standard error $\hat{\sigma}_{ui}$ of the residuals). The term $\left(\frac{\hat{\sigma}_{uj}}{\hat{\sigma}_{ui}}\right)$ is thus scaling factor that balances different magnitudes (variances) of model variables.

Prior parameter θ indicates the general weight of the priors vis-a-vis the data (the higher θ the lower weight of the prior). The term $m^{-\phi}$ causes that the prior tightens the parameters associated with higher lags to their zero means. Thus these parameters are becoming less important. The higher is the parameter ϕ the faster is this decay. So-called weight matrix allows for arbitrary tightening (or loosening) of prior of any parameter in the model - for example based on some structural relationships. However, in this work we only distinguish the priors imposed on dependent variable in each equation. We usually set tighter prior on the parameters associated with other variables than the dependent one. In other words, the priors on autoregressive terms are weaker. It must be noticed that no prior is imposed on constant term.

After setting the prior parameters, the BVAR model is recursively estimated as in the VAR case. The one-year ahead forecasts are computed and their performance is evaluated.

Forecast accuracy Forecast errors are calculated from pseudo out-of-sample forecasts vector and the vector of the data. Forecast is absolutely accurate when both vectors are equal. Figure 2 shows the evolution of forecast errors of AR and RW model over time. Different statistics might be used for summarizing the information from the vector of the errors.

The most common statistics for determining forecast accuracy is mean square error (MSE) defined as:

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(f_t - y_t)^2, \tag{4}$$

where f is vector of forecast; y is vector of data and T is the length of the time period that was used for comparing the forecast and the data. Mean square error is common statistics used for estimation of differences between two vectors (series). The lowest bound is obviously zero (absolutely exact forecast), there is no upper bound. The lower value the better forecast. Note that the all models are estimated employing minimizing the sum of square errors. This allows for calculation of parameters of regression via simple matrix multiplication. Comparison of the forecast and the data is therefore a natural choice that is in line with the process of model estimation.

Several authors also use 'Relative MSE'. MSE of the forecast is compared to the MSE of some benchmark model - either RW forecast or simple univariate model. Comparison ro RW model is sometimes referred to as The following statistics is referred to as Theil-U statistics [10], Theil statistics or Theil coefficient [7]. We may define Theil statistics according to [32] as:

$$Theil = \frac{\sqrt{\sum_{t=1}^{T-k}(f_{t+k} - y_{t+k})^2}}{\sqrt{\sum_{t=1}^{T-k}(y_t - y_{t+k})^2}} \tag{5}$$

Meaning of the symbols is the same as in the definition of MSE. The nominator describes square root of MSE, but in the denominator there is square root of errors of random walk (steady state) forecast. Theil statistics thus compares given forecast to potential random walk forecast. The lower is the value of the Theil statistics, the better is the forecast. '0' represents exact forecast. '1' describes forecast that is the same accurate as random walk forecast. Values lower than '1' signalize that forecast is better than steady state forecast, on the other hand, values higher than '1' signalize that the forecast is worse than the random walks forecast.

Essentially the same statistics is used by Hofmann, 2009 [33] in the form:

$$CRW_{square} = \frac{\sum_{t=1}^{T-k} (f_{t+k} - y_{t+k})^2}{\sum_{t=1}^{T-k} (y_t - y_{t+k})^2} \tag{6}$$

Abbreviation CRW_{square} stands for 'comparison to random walk, based on square errors'. It clearly holds that $CRW = Theil^2$.

Instead of MSE error some authors make use of mean absolute error (MAE):

$$MAE = \frac{1}{T} \sum_{t=1}^{T} |f_t - y_t| \tag{7}$$

Some studies pay only limited attention to the method of evaluation of forecast accuracy. However some results strongly depends on the method used. This is one of the reasons of inconclusiveness of current literature concerning inflation forecasting.

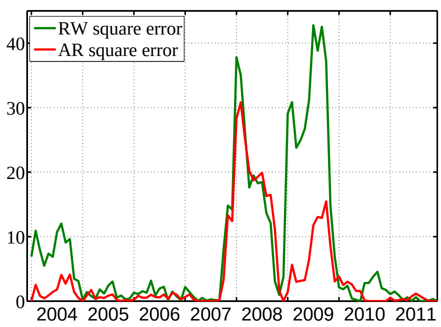

Figure 3: Squared errors of RW and AR models

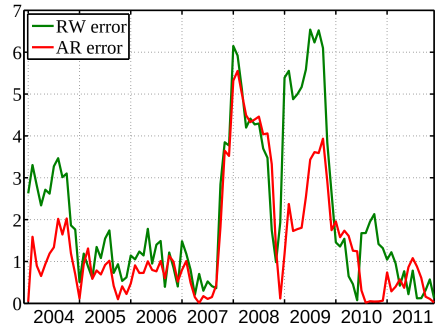

Figure 4: Absolute errors of RW and AR models

In this study, we want to systematize some simple methods of forecast comparison. Figure 3 shows the *square* errors of the benchmatk models. MSE statistics for each model is simply the sum of the errors divided by the number of data points. Note that MSE for the depicted series is given almost exclusively by the period between mid-2007 until the end 2009. The forecast accuracy of the model in other periods is irrelevant for MSE statistics. Figure 4 shows the *absolute* errors. The 'hard to forecast' period is not amplified as in the case of the square errors. Mean absolute error therefore takes into account also other periods with higher weight. When seeking for the forecast that is highly accurate over whole period, the MAE is more favourable.

Since linear evaluation of errors (absolute errors) seems to be more favourable than convex evaluating of errors (square errors), let us employ some concave evaluating of errors. Square-root of errors is a natural candidate.

We propose using mean square-root error in the form:

$$ME_{sqrt} = \frac{1}{T}\sum_{t=1}^{T}\sqrt{f_t - y_t} \tag{8}$$

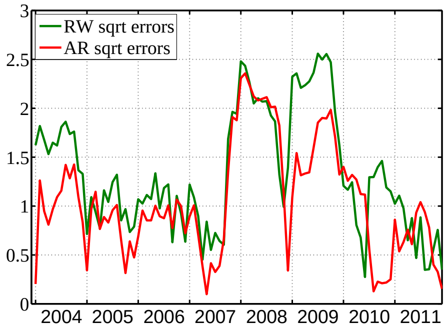

Figure 5: Square root error

Figure 5 shows the square-root errors of RW and AR forecast. The bigger errors are suppressed when compared to the absolute errors evaluation. Assuming that data time series includes both 'easy to forecast, low volatility - stable - periods' and 'hard to forecast, turmoil periods' than evaluation based on square-root errors will support models that perform well in both types of time periods. Conversely, the square errors are sensitive only to the highest forecast errors over whole sample, supporting models performing well only during 'high volatility - turmoil' periods disregarding the performance during other periods.

Overview of forecast accuracy statistics

Following preceding discussion, the forecast accuracy statistics can use either square errors, absolute errors and square-root errors. We can also use simple mean statistics, comparison to RW forecast and comparison to simple univariate model (e.g. AR model). Altogether 9 combinations.

Mean error - based on square errors, absolute errors and square-root errors

$$
\begin{aligned}
MSE &= \frac{1}{T}\sum_{t=1}^{T}(f_t - y_t)^2 && (9)\\
MAE &= \frac{1}{T}\sum_{t=1}^{T}|f_t - y_t| && (10)\\
ME_{sqrt} &= \sum_{t=1}^{T}\sqrt{f_t - y_t} && (11)\\
& && (12)
\end{aligned}
$$

Comparison to RW forecast - based on square errors, absolute errors and square-root errors

$$
\begin{aligned}
CRW_{square} &= \frac{\sum_{t=1}^{T-k}(f_{t+k} - y_{t+k})^2}{\sum_{t=1}^{T-k}(y_t - y_{t+k})^2} && (13)\\
CRW_{abs} &= \frac{\sum_{t=1}^{T-k}|f_{t+k} - y_{t+k}|}{\sum_{t=1}^{T-k}|y_t - y_{t+k}|} && (14)\\
CRW_{sqrt} &= \frac{\sum_{t=1}^{T-k}\sqrt{f_{t+k} - y_{t+k}}}{\sum_{t=1}^{T-k}\sqrt{y_t - y_{t+k}}} && (15)\\
& && (16)
\end{aligned}
$$

Comparison to AR forecast - based on square errors, absolute errors and square-root errors

$$
\begin{aligned}
CAR_{square} &= \frac{\sum_{t=1}^{T-k}(f_{t+k} - y_{t+k})^2}{\sum_{t=1}^{T-k}\left(f_{t+k}^{AR} - y_{t+k}\right)^2} && (17)\\
CAR_{abs} &= \frac{\sum_{t=1}^{T-k}|f_{t+k} - y_{t+k}|}{\sum_{t=1}^{T-k}|f_{t+k}^{AR} - y_{t+k}|} && (18)\\
CAR_{sqrt} &= \frac{\sum_{t=1}^{T-k}\sqrt{f_{t+k} - y_{t+k}}}{\sum_{t=1}^{T-k}\sqrt{f_{t+k}^{AR} - y_{t+k}}} && (19)\\
& && (20)
\end{aligned}
$$

Diebold-Marianno test

Diebold-Marianno test (DM test) is a statistical test that is used for comparing two different forecasts. It is decisive in whether which forecast is better and more importantly whether the forecast is significantly different (i.e. significantly better) then the other one. DM test is employed by Arratibel,2009 [15] and it is used in this study for its high versatility.

The test statistics S is defined as

$$S = \frac{\bar{d}}{\sqrt{L\hat{R}V_d/T}}, \tag{21}$$

where

$$\bar{d} = \sum_{t=1}^{T} d_t d_t = L(e_{1,t}) - L(e_{2,t}) \tag{22}$$

$$L\hat{R}V_d/T = \gamma_0 + 2\sum_{j=1}^{\infty} \gamma_j \tag{23}$$

We use following notation:

- $e_{1,t}$, $e_{2,t}$ - forecast errors of two different models
- $L(e_t)$ - loss function of forecast error
- $L\hat{R}V_d/T$ - long-run variance (takes into account serial correlation)
- $\gamma_j = cov(d_t, d_{t-j})$

Statistics S is then Normally distributed with zero mean and unity variance: $S \sim N(0, 1)$. Zero hypothesis is that both forecasts possess the same predictive accuracy - $H_0 : E(L(e_{1,t})) = E(L(e_{2,t}))$. Therefore, when $S < -1.96$ then the first forecast is significantly (5% confidence level) better than the second forecast and similarly when $S > 1.96$ then the second forecast is significantly better than the first one.

Note that for similar forecasts, the series d_t possesses low long run variance and the DM test can distinguish which forecast is better although mean errors of both forecasts are similar. On the other hand very different forecasts will not be distinguished by Diebold-Mariano test (due to high variance of d_t) even though the mean error of one of the forecast is much higher and the forecast is 'obviously' worse.

The versatility of the DM test is given by the freedom in the choice of loss function $L)e_t)$. Therefore we can base the loss function on square errors $L_{square}(e_t) = e_t^2$, absolute errors $L_{asbs}(e_t) = |e_t|$ and also square-root errors $L(e_t) = \sqrt{e_t}$. Utilizing Diebold-Marianno test is therefore in line with other statistics used.

The comparison of multiple forecasts using Diebold - Marianno test might be done pair-wise. Following methodology has been developed for this reason. First, the models are sorted according to the mean error (square, absolute or square-root -

must be in accordance with the loss function of the DM test we wish to use). Note that DM test cannot prefer model with higher mean error adjacent to the chosen loss function. Second, the first forecast is compared to all other forecasts. The forecasts that are found to be significantly worse are discarded. The second best (not yet discarded) forecast according to the mean error is elicited and this forecast is compared to all forecasts with higher mean error. Significantly worse forecasts are again discarded. This step is repeated until we test all (non-discarded) forecasts to each other. Note that without dynamic discarding of forecasts, the computation time is extremely increased. As a result, we get the set of forecasts in that there is no forecast significantly worse than any other.

Forecast accuracy in sub-periods

It was shown by Cecchetti, 2000 that stability of forecast accuracy is very low. More specifically, even when statistics computed for whole time period show that given forecast is much better than benchmark forecast, the forecast still might be inferior in some time sub-periods. As a result, even though given predictor performs comparably well over whole period, in each sub-period there might be some predictor performing significantly better in this particular sub-period. We slightly modified the methodology in Cecchetti, 2000 to use it within recursive forecasting. We simply divided the 96 time periods (months) sample to 8 sub-periods (i.e. 8 years). We compare separately the accuracy of the forecast in each sub-period. Particularly, we compute all above mentioned statistics for each sub-period independently (including those comparing forecasts to benchmark RW and AR forecasts and including Diebold-Marianno test with discarding methodology).

Overview of developed forecast accuracy criteria

Forecasts were compared according to several criteria that were separately based on square errors, absolute errors and square root errors. Criteria can be divided into statistics concerning whole period (8 years) and statistics describing year-by-year performance. Note that we often compared several hundreds of model between each other.

Whole period statistics are the following two:

- mean error (i.e. MSE or MAE or mean square-root error)
- Diebold-Marianno test (good model is not discarded by procedure explained above)

Six different criteria are employed for estimating year-by-year forecasting performance .

- Average placing of given model in each year among all models

All compared models are ordered according to their mean error in each year. The order numbers of given model in all years are then averaged.

- Proportion of years in that model is not significantly worse than any other model according to Diebold-Marianno test

Diebold-Marianno test discarding procedure is performed separately for each sub-period. The model in the given sub-period is either discarded (test value = 0) or promoted (test value = 1). Average value for all sub-periods (years) is then computed.

- Proportion of years in that model is better than RW forecast
- Proportion of years in that model is better than AR forecast

CRW and CAR statistics are computed for each model for each year. If $CRW < 1$ ($CAR < 1$) then the forecast is better than RW (AR) forecast (test value = 1). Average value for all sub-periods (years) is then computed.

- Median of CRW statistics computed for each year
- Median of CAR statistics computed for each year

Median of CRW and CAR statistics evaluated for each year is elicited. The mean of such statistics is extremely biased due to single outlying value (especially for square errors), therefore we use median value.

We have totally eight different criteria for forecast evaluation. We sorted the models according each criterion. A model that was the best one or the second best in at least two criteria was promoted into 'top' models. Furthermore, we wish to place more weight on whole period mean error statistics (note that ordering according to mean error is identical to ordering using CRW or CAR). Therefore, we consider top six models within this criterion (instead of only two top models for all other criteria).

Finding good predictors First, let us describe the methodology of model selection. Each VAR model is characterized by the number of the lags included and by the variables (predictors) that are included. The aim is to select inflation predictors and optimal number of lags to obtain models with highest forecasting accuracy according to developed criteria. Models of different sizes (different amount of inflation predictors) must be considered. The algorithm computes all possible combinations of inflation predictors (variables) for models involving one inflation predictor, two predictors, etc. The model for each combination of inflation predictors and also for each considered amount of lag is recursively estimated and the pseudo out-of-sample forecast is computed. Note that for substantially big initial set of possible predictors, the amount of possible combinations significantly grows. Moreover VAR model involving too many predictors and/or too many lags is over-parametrized. Maximum amount of variables involved and maximum lags are therefore limited. Forecast performances are then compared according to the described criteria and the best models and the most useful predictors are identified.

Matlab programming environment (version R2010b) was used for all computations including graphical output (except of some basic manipulations in MS Excel). Econometric toolbox for Matlab by James P. Le Sage [9] has extensively been used for estimating VAR and BVAR models.

Results and discussion

Inflation predictors identification - reduction of data set

According to Ang et al., 2007, 39 time series of potential inflation predictors were divided into three groups concerning money related variables, real economy variables and surveys. The most useful inflation predictors were selected according to the previously described criteria within each group and also using complete data set. Selected useful predictors are in **bold**.

1. Money related time series 3 predictors selected out of 5

1	**Broad money, s.a.**
2	Domestic producer prices - manufacturing
3	**Overnight interbank rate**
4	Exchange rates, USD monthly averages
5	**3 month interbank rate**

Selected three predictors comprise both interbank rate measures and also the only monetary base measure. Surprisingly, domestic producer prices are not involved in the best predictors.

2. Real economy time series 7 predictors selected out of 12

1	**Exports in goods, s.a.**
2	**Imports in goods, s.a.**
3	**Share prices**
4	**Industrial production, s.a.**
5	**Retail trade (volume), s.a**.
6	Harmonised unemployment rate, s.a.
7	Industrial production (ratio to trend)
8	Output gap
9	GDP - expenditure approach
10	**Private final consumption expenditure**
11	General government consumption expenditure
12	**Gross fixed capital formation**

The predictors that have not been promoted as useful predictors are actually more interesting. Neither unemployment nor GDP nor output gap have been found as useful inflation predictors. Therefore, in examined setting, the usefulness of Phillips Curve or and New Philips Curve has not been confirmed. Among GDP measures, only gross fixed capital formation time series has been found as a useful predictor.

3. Surveys time series 8 predictors selected out of 16

1	Leading indicator, amplitude adjusted
2	Manufacturing - Production (current),
3	**Manufacturing - Production (future)**,
4	**Manufacturing - Finished Goods**
5	**Manufacturing - Selling Prices**
6	Manufacturing - Employment
7	**Manufacturing - EC indicator**
8	Construction - Activity
9	**Construction - Composite indicator**
10	Retail - Activity
11	**Retail - Volume**
12	**Retail - Employment**
13	Retail - Orders
14	**Retail - Composite indicator**
15	Consumer situation - Inflation
16	Consumer situation - EC indicator

Surveys data proved to be very useful for inflation forecasting. Data from all three monitored sectors - Manufacturing, Construction and Retail proved to be useful in inflation forecasting. On the other hand, consumers' opinion on inflation has been found to be useless in estimated models.

4. All time series
Finally, similar elicitation procedure performed within each data block has been performed for all data. This computer-time consuming operation chose 13 useful predictors out of 33 time series in accordance with results within separate blocks. Following predictors are considered to be useful for inflation forecasting

1-8	**All previously selected survey series (8 series) !!**
9	**Export in goods, s.a.**
10	**Industrial production, s.a.**
11	**Gross fixed capital formation**
12	**Broad money, s.a.**
13	**3 month interbank rate**

Obvious and strong usefulness of survey data is one of the most important results of this study since this type of surveys is often omitted in literature dealing with inflation forecasting. Only three time-series of real economy data block (export, industrial production and fixed capital formation) and two series of money related data block (broad money, 3 month interbank rate) have been found as useful in the competition with surveys data. We believe that this surprising result is of significant importance.

Inflation predictors identification - the best models and the best predictors

Reduced set of predictors was used to determine the best models and select the best inflation predictors. Three groups inflation predictors datasets were created. The first group consists of both real economy variables and money related variables, jointly denoted as 'MR'. Second group consists of survey data only - 'S'. Finally, third group includes both data sets - all data.

The best models were selected according to the 'scoring algorithm' as described in detail in methodology section. Apart of three different data sets we used two principal methods (VAR and BVAR) and finally three types of errors are used (square, absolute and square root), altogether 18 combinations. 'Top' models for each combination are listed in Appendix A. Note that amount of models 'top' models differs for each combination since a model must be successful in at least two categories to be promoted to 'top' models and obviously successfulness distribution differs over combinations.

Altogether 172 'top' models were found and subjected to further analysis. The average amount of predictors in one model is 2.8 and the average lag included is 3.5. There is a trade-off relationship between amount of predictors and included lags. The amount of predictors used and lags involved of course depends on the number of all available predictors. For instance, when we consider all data (13 predictors), the average amount of predictors in one model is 5.2 and the lags involved 2.6 only.

The best predictors

In the Table , the usefulness of respective predictors is compared. The number in the last column describes the probability that the predictor is present in randomly chosen 'top' model. Complete data set ('all data') is taken into account.

The most useful predictor is seasonally adjusted measure of broad money. This is favourable result since it proves the effect of amount of money in the economics on the inflation rate, therefore it claims that monetary policy might be efficient in one year horizon.

The second most useful predictor are exports in goods. Exports proved to be much more important inflation predictor than any measure of economic activity (industrial production or GDP). Those two real economy predictors are followed by a block of three survey measures. Looking to Appendix A, it is clear that there is simply no 'top' model that would not include time series of at least on of this surveys. Surveys considering manufacturing, retail and construction proved to be very important predictors of inflation. It must be also noted that composite indicators provided by OECD are more useful predictors than individual surveys time series.

1	MB	Broad money, s.a.'	0.80
2	RE	Exports in goods, s.a.'	0.75
3	SMI	Manufacturing EC indicator	0.65
4	SRI	Retail Composite indicator	0.56
5	SCI	Construction Composite indicators	0.50
6	M3	3 month interbank rate'	0.39
7	SMP	Manufacturing Production Future	0.38
8	SRE	Retail Employment	0.34
9	SRV	Retail Volume	0.28
10	SMS	Manufacturing Selling Prices	0.25
11	SMG	Manufacturing Finished Goods	0.16
12	RG	Gross fixed capital formation	0.12
13	RP	Industrial production, s.a.'	0.06

Table 1: Reduced set of inflation predictors used for estimation of VAR and BVAR models - all data, sorted according to the usefulness of the predictor, probability that the 'top' model includes given predictor

All 'top' models are fully described in Appendix A. For the purpose of simple comparison, 'top 5 models' were considered and the performance statistics were simply averaged (mean of each statistics was computed). The performance of the best models can therefore be compared over datasets, estimation methodology (VAR vs. BVAR) and type of errors. The results are provided in Appendix B.

Figures 6 - 8 show the average monthly errors of VAR models in years 2004 - 2011.

Square, absolute and square-root errors are considered. The forecasts are based on simple averaging of top 5 models for each data set and error type. Forecasting errors are compared also to errors of RW and AR models. It is clear that when using the square errors, the performance in the 'hard-to-forecast period' is decisive for the overall forecast performance. On the other hand, in the case of square-root errors, the weights of different periods are more comparable.

It is clear from the Figs 6 - 8 that VAR forecasts are better than RW forecast in all years disregarding dataset or type of error used. On the other hand, VAR forecasts are not better than AR forecast in all years, though they are better in vast majority of mutual comparisons. The performance of forecasts using different datasets cannot be unambiguously compared.

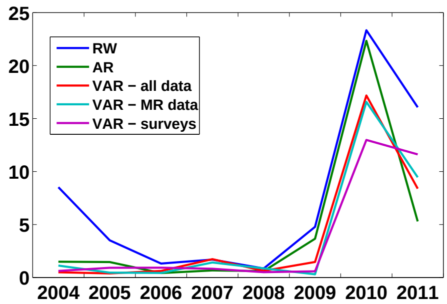

Figure 6: VAR - Square errors

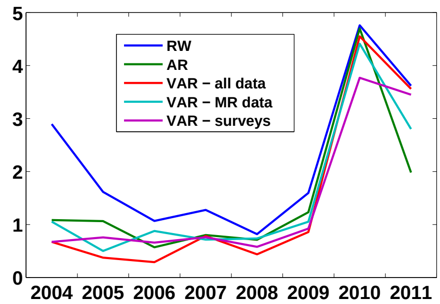

Figure 7: VAR - Absolute errors

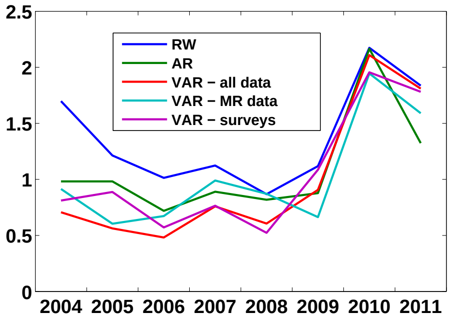

Figure 8: VAR - Square root errors

Once having all necessary results, natural questions arise:

- Is BVAR better then VAR?
- Is using square root errors better than absolute errors and square errors?

- Is using all data better than using surveys and money and real economy related variables?

To answer those questions rigorously, we used simple **t-test** based on two statistics describing models' forecasting performance:

- average amount of years when forecast is better then RW forecast
- average amount of years when forecast is better then AR forcast

Unfortunately, only these two statistics can be compared across all models disregarding type of error.
Zero hypothesis is that test statistics has the same mean for both compared cases. I.e.if hypothesis rejected then 'YES' is the answer to given question.

Following tables provide the results of the respective t-tests and the answers to the questions under consideration.
VAR vs. BVAR

Question	Result (RW)	p-val (RW)	Result (AR)	p-val (AR)
BVAR better than VAR	NO	0.6	NO	0.4

Square vs. absolute vs. square root errors

Question	Result (RW)	p-val (RW)	Result (AR)	p-val (AR)
ABS better than SQ	YES	$1x10^{-3}$	YES	$2x10^{-3}$
SQRT better than SQ	YES	$1x10^{-4}$	YES	$7x10^{-4}$
SQRT better than ABS	NO	0.2	YES	$1x10^{-3}$

All Data vs. money and real economy related variables (M,R) vs. survey data (S)
* 10 % confidence level only

Question	Result (RW)	p-val (RW)	Result (AR)	p-val (AR)
ALL data better than MR data	NO	0.4	YES	$4x10^{-3}$
ALL data better than surveys	NO	0.6	YES	$6x10^{-3}$
Surveys better than MR data	NO	0.2	YES*	0.07

It follows form the results that using Bayesian restrictions on model parameters does not improve the forecasting performance. This can be attributed to using too simple Minnesota prior. On the other hand, using absolute errors and square root errors lead to significantly better forecasting performance of models then when using by far the most standard square errors. Finally, using data set including surveys is favourable for forecasting performance, however, the statistical significance of this improvement is ambiguous.

Conclusion

Following conclusions can be drawn from presented inflation forecasting study:

- Large dataset of possible predictors was used to forecast inflation in Czech republic in one year forecasting horizon. Pseudo-out-of-sample methodology experiment was performed and high amount of VAR and BVAR models with different combinations of predictors were estimated.
- Three different datasets were used for the estimation. The first included time series describing real economy and money related variables. The second one included only soft-data time series based on OECD surveys. The third dataset combined the previous two sets.
- Evaluation of forecast performance was based based on common square errors, less common absolute errors and also using novel approach by employing square-root errors.
- It was shown that robust comparison of different forecasts is uneasy. In particular, forecast with good overall performance may not be powerful in many (or even vast majority of) sub-periods. Advanced 'scoring algorithm' was developed to maximize robustness of forecasts comparison.
- It was shown that there are periods when inflation can be forecast with quite high accuracy, whereas in some periods the error of forecast is substantially higher. Therefore, when using square errors, only short sub-periods in that inflation is 'hard-to-forecast' are decisive for overall performance of given forecast. Using absolute errors or even square-root errors was found to be better in this respect.
- The best VAR and BVAR models' forecasts outperform Random Walk forecasts in all sub-periods for all datasets and errors used. The best VAR and BVAR models' forecasts outperform AR forecasts in majority of sub-periods.
- The most important individual predictors are 'Broad money' measure and 'Real exports'. Following those two predictors, several surveys time series were found to be important inflation predictors.

- Employing Bayesian restrictions via Minnesota prior did not improve forecasting performance.

Appendix A

Complete description and performance of all 'top models'.

1	I	Inflation rate
2	RE	Exports in goods, s.a.'
3	MB	Broad money, s.a.'
4	RP	Industrial production, s.a.'
5	M3	3 month interbank rate'
6	SMP	Manufacturing Production Future
7	SMG	Manufacturing Finished Goods
8	SMS	Manufacturing Selling Prices
9	SCI	Construction Composite indicators
10	SRI	Retail Composite indicator
11	SRV	Retail Volume
12	SRE	Retail Employment
13	SMI	Manufacturing EC indicator
14	RG	Gross fixed capital formation

Table 2: Reduced set of inflation predictors used for estimation of VAR and BVAR models - all data

Legend:

- **ME** - mean error (based on squere errors or absolute errors or square root errors)
- **dm** - Diebold-Marianno test - either '1' (no other model is significantly better) or '0' (some other model found as significantly better)
- **av dm** - Diebold-Marianno computed for each year - average over years
- **CRW** - compare mean error to mean error of RW forecast
- **CAR** - compare mean error to mean error of AR forecast
- **years/RW** - proportion of years for that given forecast is better than RW forecast
- **years/AR** - proportion of years for that given forecast is better than AR forecast
- **best in-** amount of criteria for that given forecast was the best or the second best

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
2	MB,M3,SMP,SRI,SMI	2.826	1	0.125	0.361	0.711	0.875	0.625	3
3	MB,M3,SMS,SRI,SMI	2.848	1	0	0.364	0.716	0.875	0.375	3
1	RE,MB,SMS,SRI,SMI	2.845	1	0	0.363	0.716	0.500	0.250	2
1	RE,MB,SMP,SMS,SRI,SMI	2.857	1	0	0.365	0.719	0.500	0.250	2
1	RE,MB,SMP,SRI,SMI	2.871	1	0	0.367	0.722	0.500	0.125	2
1	RE,MB,M3,SMP,SRI,SMI	2.918	1	0	0.373	0.734	0.625	0.125	2
3	RE,SMG,SCI,SRI	3.648	0	0.250	0.466	0.918	0.875	0.625	2

Table 3: Top models using VAR and square errors

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
3	RE,MB,SMP,SCI,SRE	1.188	1	0.250	0.553	0.834	1.000	0.625	4
2	MB,M3,SMP,SRI,SMI	1.178	1	0	0.549	0.827	0.875	0.625	3
2	MB,M3,SMP,SMS,SRI,SMI	1.185	1	0	0.552	0.832	0.875	0.750	3
3	MB,SCI,SRV,SRE	1.202	1	0.125	0.559	0.843	1.000	0.625	3
3	RE,MB,RP,M3,SMP,SRV,SMI	1.192	1	0	0.555	0.837	0.875	0.375	2
3	RE,MB,M3,SCI,SRE,SMI	1.193	1	0.125	0.555	0.837	0.875	0.375	2
3	RE,MB,SCI,SRE,SMI	1.197	1	0.125	0.557	0.840	0.875	0.375	2
3	MB,M3,SMS,SRI,SMI	1.201	1	0	0.559	0.843	0.875	0.375	2
3	RE,MB,SMS,SCI,SRV,SRE	1.214	1	0.250	0.565	0.852	1.000	0.500	2
3	RE,SMG,SCI,SRI,SRV	1.246	1	0.125	0.580	0.874	1.000	0.625	2
3	MB,RP,M3,SMS,SRI,SMI	1.256	1	0	0.585	0.882	0.875	0.375	2

Table 4: Top models using VAR and abs errors

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
3	RE,MB,SMP,SCI,SRE	0.912	1	0.250	0.683	0.869	1.000	0.750	5
3	RE,MB,SCI,SRV,SRE	0.929	1	0.125	0.696	0.885	1.000	0.750	5
3	RE,MB,M3,SCI,SRE,SMI	0.919	1	0.125	0.689	0.876	0.875	0.500	3
3	RE,MB,SCI,SRE,SMI	0.920	1	0.125	0.689	0.877	0.875	0.500	3
3	RE,MB,M3,SMP,SCI,SRE	0.929	1	0.250	0.696	0.885	1.000	0.750	3
3	RE,MB,SCI,SRV,SRE,SMI	0.924	1	0.000	0.692	0.881	0.875	0.625	2
2	RE,SMG,SCI,SRE	0.952	1	0.125	0.713	0.908	0.750	0.625	2
3	RE,SMG,SCI,SRI,SRV	0.965	1	0.125	0.723	0.920	1.000	0.625	2

Table 5: Top models using VAR and square root errors

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
2	RE,MB,M3,SMP,SRI,SMI	2.773	1	0.000	0.354	0.697	0.875	0.625	3
3	MB,M3,SRI,SMI	2.817	1	0.000	0.360	0.709	0.750	0.375	3
3	MB,M3,SMS,SRI,SMI	2.846	1	0.000	0.364	0.716	0.750	0.375	3
3	RE,SMG,SCI,SRI,SRV	3.611	0	0.125	0.461	0.908	0.875	0.625	3
1	RE,MB,SMS,SRI,SMI	2.848	1	0.000	0.364	0.716	0.500	0.250	2
1	RE,MB,SMP,SMS,SRI,SMI	2.860	1	0.000	0.365	0.720	0.500	0.250	2
1	RE,MB,SRI,SMI	2.872	1	0.000	0.367	0.723	0.500	0.125	2

Table 6: Top models using BVAR and square errors

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
2	MB,M3,SMP,SRI,SMI	1.161	1	0.125	0.541	0.815	0.875	0.625	3
3	MB,M3,SRI,SMI	1.169	1	0.000	0.544	0.820	0.875	0.500	3
2	MB,M3,SMP,SMS,SRI,SMI	1.175	1	0.000	0.547	0.825	0.875	0.625	3
3	RE,SMG,SCI,SRI,SRV	1.228	1	0.250	0.572	0.862	1.000	0.625	3
3	SRE,SMI	1.177	1	0.000	0.548	0.826	0.875	0.500	2
3	RE,MB,RP,M3,SMP,SRV,SMI	1.180	1	0.000	0.549	0.828	0.875	0.500	2
2	RE,SRE	1.187	1	0.000	0.553	0.833	0.875	0.500	2
3	RE,MB,SMP,SCI,SRV,SMI	1.197	1	0.000	0.557	0.840	1.000	0.625	2
3	RE,MB,SMP,SCI,SRE	1.198	1	0.000	0.558	0.841	1.000	0.625	2
3	MB,M3,SMS,SRI,SMI	1.198	1	0.000	0.558	0.841	0.875	0.375	2
3	RE,SCI,SRI,SRV	1.239	0	0.250	0.577	0.869	1.000	0.625	2

Table 7: Top models using BVAR and abs errors

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
3	RE,MB,SCI,SRE	0.927	1	0.000	0.694	0.883	1.000	0.750	5
3	RE,MB,SMP,SCI,SRE	0.922	1	0.000	0.690	0.879	1.000	0.625	3
3	RE,MB,SMP,SCI,SRV,SMI	0.922	1	0.000	0.691	0.879	0.875	0.750	3
3	RE,MB,M3,SCI,SRE,SMI	0.921	1	0.125	0.690	0.878	0.875	0.500	2
3	RE,MB,SCI,SRE,SMI	0.921	1	0.125	0.690	0.878	0.875	0.625	2
3	RE,SMG,SCI,SRV	0.929	1	0.000	0.696	0.886	0.875	0.625	2
3	RE,SMG,SCI,SRI,SRV	0.953	1	0.125	0.714	0.908	1.000	0.625	2
3	RE,MB,RP,SMP,SMS,SRV,SMI	0.953	1	0.000	0.714	0.909	0.875	0.500	2
3	MB,M3,SRI,SMI	0.962	1	0.000	0.721	0.917	0.875	0.375	2

Table 8: Top models using BVAR and square root errors

1	I	Inflation rate
2	RE	Exports in goods, s.a.'
3	RI	Imports in goods, s.a.'
4	MB	Broad money, s.a.'
5	RP	Industrial production, s.a.'
6	RT	Retail trade (Volume), s.a.'
7	MO	Overnight interbank rate'
8	M3	3 month interbank rate'
9	RF	Private final consumption expenditure
10	RG	Gross fixed capital formation

Table 9: Reduced set of inflation predictors used for estimation of VAR and BVAR models - money related and real economy variables

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
4	RI,MO	2.867	1	0.125	0.366	0.721	0.875	0.375	3
2	RE,RT,MO,RF	2.872	1	0.000	0.367	0.722	0.625	0.250	2
2	RE,RI,RT,MO,RF	2.937	1	0.000	0.375	0.739	0.625	0.250	2
3	RI,MO	2.962	1	0.125	0.378	0.745	0.750	0.375	2
4	RI	2.981	1	0.125	0.381	0.750	0.625	0.250	2
3	RI	3.015	1	0.250	0.385	0.758	0.625	0.250	2
2	RI	3.067	1	0.250	0.392	0.772	0.625	0.250	2
6	RI,RT,MO,M3	3.636	0	0.000	0.464	0.915	0.875	0.500	2
3	RE,MB,M3,RG	3.786	1	0.125	0.484	0.952	0.750	0.375	2
3	RI,MO,RG	3.939	1	0.125	0.503	0.991	0.750	0.375	2
3	RE,MO,RG	4.041	1	0.125	0.516	1.017	0.875	0.250	2

Table 10: Top models using VAR and square errors, MR

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
4	RT,MO,M3	1.219	1	0.125	0.568	0.856	1.000	0.500	4
4	RI,MO	1.176	1	0.000	0.547	0.825	0.875	0.375	3
5	RI,RT,MO,RF	1.470	0	0.375	0.685	1.032	0.875	0.625	3
3	RI,MO,M3	1.204	1	0.000	0.561	0.845	0.875	0.250	2
3	RI,MO	1.208	1	0.125	0.562	0.848	0.875	0.375	2
5	RI,MO	1.216	1	0.125	0.566	0.853	0.875	0.375	2
4	RE,RP,RT,MO,M3	1.217	1	0.125	0.567	0.854	0.875	0.375	2
2	RI,MO,M3	1.233	1	0.000	0.574	0.865	0.875	0.375	2
5	RI,M3	1.252	1	0.000	0.583	0.878	1.000	0.500	2
5	RE,MO,M3	1.256	1	0.250	0.585	0.882	0.875	0.500	2

Table 11: Top models using VAR and absolute errors, MR

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
4	RI,MO	0.957	1	0.125	0.717	0.912	0.875	0.375	3
4	RE,RP	0.976	1	0.125	0.731	0.931	0.875	0.625	3
5	RI,MO	0.963	1	0.250	0.722	0.918	0.875	0.375	2
4	RE,RP,RT,MO,M3	0.964	1	0.250	0.722	0.919	0.875	0.500	2
3	RI,MO,M3	0.965	1	0.000	0.723	0.920	0.875	0.500	2
3	RI,MO	0.967	1	0.125	0.724	0.922	0.875	0.500	2
4	RE,MO	0.969	1	0.125	0.726	0.924	0.875	0.500	2
4	RE,RT,MO,M3	0.970	1	0.125	0.726	0.924	1.000	0.500	2
2	RE,MO,M3	0.981	1	0.000	0.735	0.935	0.750	0.500	2
5	RE,MO,M3	0.982	1	0.250	0.735	0.936	1.000	0.500	2
6	RE,RT,MO,M3	0.993	1	0.375	0.744	0.946	1.000	0.500	2
5	RI,MO,M3	1.004	1	0.250	0.752	0.957	0.875	0.625	2
4	RE,MB,RP,MO	1.014	1	0.250	0.760	0.967	0.875	0.750	2

Table 12: Top models using VAR and square root errors, MR

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
4	RI,MO	2.865	1	0.125	0.366	0.721	0.750	0.375	3
5	RI,MO,RF	3.801	0	0.375	0.486	0.956	0.875	0.500	3
2	RE,RT,MO,RF	2.873	1	0.000	0.367	0.723	0.625	0.250	2
2	RE,RI,RT,MO,RF	2.924	1	0.000	0.373	0.736	0.500	0.250	2
3	RI,MO	2.963	1	0.125	0.379	0.745	0.750	0.375	2
2	RI,RG	2.964	1	0.000	0.379	0.746	0.625	0.250	2
4	RE,RT,MO,M3	3.171	1	0.250	0.405	0.798	1.000	0.250	2
3	RI,MO,RG	3.717	1	0.125	0.475	0.935	0.625	0.375	2

Table 13: Top models using BVAR and square errors, MR

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
4	RI,MO	1.171	1	0.125	0.545	0.822	0.875	0.500	3
5	RI,MO	1.187	1	0.250	0.553	0.833	0.875	0.375	3
4	RE,RT,MO,M3	1.194	1	0.125	0.556	0.838	1.000	0.375	3
4	RE,MO,M3,RF	1.188	1	0.000	0.553	0.834	0.875	0.375	2
3	RI,MO,M3	1.194	1	0.000	0.556	0.838	0.875	0.250	2
4	RE,RP,RT,MO,M3	1.201	1	0.000	0.559	0.843	0.875	0.375	2
5	RE,MO,RF	1.203	1	0.125	0.560	0.845	1.000	0.500	2
5	RE,MO,M3,RF	1.204	1	0.125	0.560	0.845	0.875	0.500	2
2	RI,MO,M3	1.228	1	0.000	0.572	0.862	0.875	0.375	2
5	RE,MO,M3	1.228	1	0.125	0.572	0.862	0.875	0.500	2
6	RI,MO	1.231	1	0.250	0.573	0.864	0.875	0.250	2
5	RI,MO,RF	1.335	0	0.125	0.622	0.937	0.875	0.625	2

Table 14: Top models using BVAR and abs errors, MR

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
5	RE,MO,RF	0.938	1	0.250	0.703	0.894	1.000	0.750	5
5	RE,MO,M3,RF	0.956	1	0.125	0.716	0.911	1.000	0.500	4
4	RE,MO,M3,RF	0.946	1	0.000	0.709	0.902	0.875	0.500	3
4	RI,MO	0.953	1	0.250	0.714	0.909	0.875	0.375	3
5	RI,MO	0.950	1	0.000	0.712	0.906	0.875	0.375	2
5	RE,RI,MO	0.955	1	0.250	0.716	0.911	0.875	0.500	2
4	RE,MB,RP,MO,M3	0.970	1	0.250	0.727	0.925	0.875	0.750	2
4	RE,RP,MO,M3	0.980	1	0.125	0.734	0.934	0.875	0.625	2
5	RI,RP,RT,M3,RF	0.988	1	0.125	0.740	0.942	0.875	0.625	2

Table 15: Top models using BVAR and square root errors, MR

1	I	Inflation rate
2	SMP	Manufacturing Production Future
3	SMG	Manufacturing Finished Goods
4	SMS	Manufacturing Selling Prices
5	SCI	Construction Composite indicators
6	SRI	Retail Composite indicator
7	SRV	Retail Volume
8	SRE	Retail Employment
9	SMI	Manufacturing EC indicator

Table 16: Reduced set of inflation predictors used for estimation of VAR and BVAR models - all data

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
7	SRE,SMI	3.559	1	0.250	0.455	0.895	0.750	0.500	4
2	SRE,SMI	3.007	1	0.125	0.384	0.756	0.750	0.250	2
2	SMP,SRE,SMI	3.056	1	0.250	0.390	0.769	0.750	0.250	2
3	SRE,SMI	3.090	1	0.125	0.395	0.777	0.750	0.375	2
2	SMP,SMS,SRI,SMI	3.095	1	0.125	0.395	0.779	0.750	0.250	2
2	SMP,SRI,SRE,SMI	3.102	1	0.125	0.396	0.780	0.750	0.250	2
2	SRI,SRE,SMI	3.106	1	0.125	0.397	0.781	0.750	0.250	2
6	SMS	3.242	1	0.000	0.414	0.816	0.625	0.250	2

Table 17: Top models using VAR and square errors, S

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
3	SRE,SMI	1.186	1	0.000	0.552	0.832	0.875	0.500	5
7	SMS,SRE	1.291	1	0.125	0.601	0.906	0.750	0.500	3
7	SRE,SMI	1.303	1	0.250	0.607	0.914	0.875	0.500	3
3	SMP,SRE	1.218	1	0.125	0.567	0.855	0.875	0.250	2
3	SMS,SRE	1.221	1	0.000	0.568	0.857	0.875	0.375	2
3	SRI,SRE	1.230	1	0.125	0.573	0.863	0.875	0.375	2
6	SRE,SMI	1.234	1	0.125	0.574	0.866	0.875	0.375	2
3	SMG,SRE,SMI	1.235	1	0.125	0.575	0.867	0.875	0.375	2
6	SMS	1.255	1	0.000	0.584	0.880	0.625	0.375	2

Table 18: Top models using VAR and abs errors, S

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
3	SMS,SRE,SMI	0.961	1	0.000	0.720	0.916	0.875	0.500	3
6	SRE,SMI	0.968	1	0.125	0.725	0.923	1.000	0.500	3
7	SRE	0.977	1	0.125	0.732	0.931	1.000	0.500	3
3	SRE,SMI	0.952	1	0.000	0.713	0.907	0.875	0.500	2
3	SMP,SRE,SMI	0.963	1	0.125	0.721	0.918	0.875	0.500	2
3	SMG,SRE,SMI	0.978	1	0.125	0.732	0.932	0.875	0.375	2
3	SRI,SRE,SMI	0.980	1	0.000	0.734	0.934	0.875	0.625	2
5	SMP,SMS	0.980	1	0.000	0.734	0.935	0.750	0.500	2
7	SMS,SRE	1.005	1	0.250	0.753	0.958	1.000	0.500	2
3	SMP,SMG,SCI,SRI,8	1.010	1	0.250	0.756	0.963	0.750	0.500	2
2	SRI,SRV,SRE	1.059	0	0.125	0.793	1.010	0.750	0.500	2
2	SMG,SRI,SRV,SRE	1.062	0	0.125	0.796	1.012	0.750	0.500	2

Table 19: Top models using VAR and square root errors, S

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
2	SRE,SMI	3.005	1	0.125	0.384	0.756	0.750	0.375	3
3	SRE,SMI	3.061	1	0.125	0.391	0.770	0.750	0.375	3
7	SRE,SMI	3.420	0	0.125	0.437	0.860	0.750	0.500	3
2	SMP,SRE,SMI	3.053	1	0.125	0.390	0.768	0.750	0.250	2
2	SMP,SRI,SRE,SMI	3.093	1	0.125	0.395	0.778	0.750	0.250	2
2	SRI,SRE,SMI	3.098	1	0.125	0.396	0.779	0.750	0.250	2
3	SMP,SRE,SMI	3.105	1	0.125	0.397	0.781	0.625	0.250	2
2	SMP,SMG,SRI,SRV,SMI	3.107	1	0.250	0.397	0.782	0.625	0.250	2
4	SMS,SMI	3.196	1	0.000	0.408	0.804	0.625	0.375	2
6	SMS	3.242	1	0.000	0.414	0.816	0.625	0.250	2

Table 20: Top models using BVAR and square errors, S

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
3	SRE,SMI	1.177	1	0.125	0.548	0.826	0.875	0.500	4
3	SMP,SRE,SMI	1.204	1	0.125	0.560	0.845	0.875	0.375	2
3	SMS,SRE,SMI	1.211	1	0.000	0.564	0.850	0.875	0.375	2
6	SRE,SMI	1.213	1	0.000	0.565	0.852	0.875	0.375	2
3	SMG,SRE,SMI	1.226	1	0.125	0.571	0.861	0.875	0.375	2
6	SMS	1.244	1	0.000	0.579	0.873	0.625	0.375	2
7	SMS,SRE	1.268	1	0.250	0.591	0.890	0.875	0.375	2
7	SRE,SMI	1.272	0	0.125	0.592	0.893	0.875	0.500	2
7	SMP,SRE,SMI	1.276	1	0.250	0.594	0.896	0.750	0.375	2

Table 21: Top models using BVAR and absolute errors, S

nlag	predictors	ME	dm	av dm	CRW	CAR	years/RW	years/AR	best in
3	SRE,SMI	0.942	1	0.125	0.706	0.898	0.875	0.625	5
3	SMP,SRE,SMI	0.956	1	0.125	0.716	0.911	0.875	0.625	3
3	SMS,SRE,SMI	0.957	1	0.000	0.717	0.913	0.875	0.500	3
6	SRE,SMI	0.965	1	0.000	0.723	0.920	0.875	0.375	2
6	SMS,SRE,SMI	0.970	1	0.125	0.727	0.925	0.875	0.375	2
3	SMP,SMS,SRE,SMI	0.972	1	0.125	0.728	0.926	0.875	0.625	2
7	SMS,SRE,SMI	0.982	1	0.250	0.735	0.936	1.000	0.500	2
2	SMS,SRI,SRV,SRE	1.007	1	0.375	0.754	0.960	0.750	0.500	2

Table 22: Top models using BVAR and square root errors, S

Appendix B

Comparison of of averages of descriptive statistics of 'top 5 models' for different datasets, estimation methodology and type of errors. For legend, please consult Appendix A.

Model	MSE	av dm	CRW	CAR	years/RW	years/AR
VAR-sq-all	2.849	0.025	0.364	0.717	0.650	0.325
VAR-sq-MR	2.924	0.075	0.373	0.736	0.700	0.300
VAR-sq-S	3.162	0.175	0.404	0.795	0.750	0.325
BVAR-sq-all	2.879	0.025	0.381	0.749	0.750	0.450
BVAR-sq-MR	3.085	0.125	0.394	0.776	0.700	0.350
BVAR-sq-S	3.127	0.125	0.399	0.787	0.750	0.350

Table 23: Average of top 5 models - square errors

Model	MSE	av dm	CRW	CAR	years/RW	years/AR
VAR-abs-all	1.189	0.075	0.554	0.834	0.925	0.600
VAR-abs-MR	1.255	0.125	0.585	0.881	0.900	0.425
VAR-abs-S	1.244	0.100	0.579	0.873	0.850	0.425
BVAR-abs-all	1.182	0.075	0.550	0.830	0.900	0.575
BVAR-abs-MR	1.187	0.100	0.553	0.833	0.900	0.375
BVAR-abs-S	1.206	0.075	0.562	0.847	0.875	0.400

Table 24: Average of top 5 models - absolute errors

Model	MSE	av dm	CRW	CAR	years/RW	years/AR
VAR-sqrt-all	0.922	0.175	0.691	0.879	0.950	0.650
VAR-sqrt-MR	0.965	0.150	0.723	0.920	0.875	0.475
VAR-sqrt-S	0.964	0.075	0.722	0.919	0.925	0.500
BVAR-sqrt-all	0.922	0.05	0.691	0.879	0.925	0.650
BVAR-sqrt-MR	0.949	0.125	0.711	0.904	0.925	0.500
BVAR-sqrt-S	0.958	0.075	0.718	0.914	0.875	0.500

Table 25: Average of top 5 models - square root errors

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