Short-Term Inflation Forecast Combination Analysis for Uzbekistan

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Abstract

In this paper, we produce the short-term inflation forecast for Uzbekistan, using univariate and multivariate econometric models. In particular, we use Auto Regressive Integrated Moving Average (ARIMA) model, Bayesian Vector Auto regression Model (BVAR) and Vector Error Correction model (VECM) to project CPI inflation and its decomposed subcomponents. The results of the forecast combination analysis are in line with the outcomes of the other research done in this field. The relative performance of combined forecasts based on the RMSE weighting scheme are on average 33

Index terms— inflation, short-term forecasting, forecast combination, ARIMA, BVAR, and VECM.

1 I. Introduction

he process of policy-making involves evaluating the potential direction of the economy, and making policy decisions to move that direction in a favorable trajectory. Forward-looking nature of these policy decisions entails the importance of the macroeconomic forecasting, which is in turn a critical component of the underlying decisions. Recurrent analysis of forecasting models assist policy makers in identifying the one that explains prevailing driving factors behind movement of the selected variable, thus making prudent monetary policy decisions. However, designing a unique empirical model to describe and forecast behavior of the economy is subject to many challenges that have a material effect on the forecast outcomes. These challenges may include the sample period and a number of observations chosen for the model, transformation methods applied for the data set, specification and estimation techniques, to name a few.

A common strategy is to make a choice of "outperforming" from available forecast alternatives. Nevertheless, the chosen model may eventually diverge from the actual values in which significance of the unknown explanatory components that drives the behavior of the economy or a selected variable extended. In addition, the choice of a single best model ignores all of the other alternatives, which in most cases, may be nearly as good as or possibly even overwhelm the model that was selected ultimately. If those other models have different implications, such as one forecast Author ?: e-mail: husmanaliyev@gmail.com contains a particular variable or information that others have not considered or the forecast is based on a different assumption of the relationship between variables in scrutiny, then one can probably disregard central location and uncertainty around the forecasts.

In contrast, one of the advantages of the combination of forecasts is that it allows for control over an extensive data set. Instead of adding all available variables into a single model, the combination method allows for diversifying the use of the available data. Consequently, the process reduces the risks of losing degrees of freedom and multicollinearity, which may arise because of adding up all available explanatory variables in a single model. Another distinguishing feature of the combination method is in its flexibility during the periods of structural breaks. In order to identify presence of breaks in the data set with a single model, it takes a prolonged time, efforts and enough observations to re-evaluate all potential correlations. In this case, the model would give inaccurate results until the structural breaks are identified. Nevertheless, the process of combination involves regular revision of weights assigned to each model, thereby allowing maximum transparency to occurring structural breaks. Since the method is based on the allocation of the weights to each model, forecast errors are diversified, in terms of averaging.

Since the Central Bank of Uzbekistan announced a gradual shift towards inflation targeting regime in 2017, the need for projections of macroeconomic variables, especially of inflation, start to play a vital role in formulation of the monetary policy stances. A short-run inflation forecast is largely based on the current statistics (now casting), information (primary data on inflation expectations) from regional branches and forecasts obtained from the vast number of statistical and econometric models. From latter perspective, the evaluation of the inflation forecasts obtained from different models and thus provision of a better characterization of uncertainty coming from various internal and external economic shocks is immense to make credible policy decisions. Hence, in this paper we discuss the development of the short-term CPI inflation forecast analysis in Uzbekistan.

The paper organized as follows. In Section II we discuss the theoretical background and methodological aspects of the forecasts combination method considering the research done in this field by central banks. In Section III and IV we address data description, empirical models to be used and methodology for forecast combination. Section V provides the outcomes of the forecast combination analysis for the selected time horizons. Section VI outlines the conclusions and recommendations for further research.

2 II. Literature Review

With respect to aforementioned advantages and the objectives of the targeting inflation in a constantly evolving environment, we outline theoretical motives and empirical outcomes of the forecast combination method, which will ultimately assist in easing policymaking processes.

3 a) Theoretical background of forecast combination

The method of forecast combination have at least existed since a seminal work of Bates and Granger (1969). They obtain two separate sets of forecasts based on the airline passenger data from which policymakers were supposed to decide. To enhance the accuracy of the forecasts, the authors show that the composite set of forecasts can yield comparatively lower mean-square error. To combine forecasts, they estimate past errors of the original forecasts, which then were used to formulate weights. Overall, the authors conclude that each set of fore cast may contain independent information and thus combination of them can yield improvements for the overall forecast performance.

In recent years, Timmerman is one of the notable contributors in the development of the theoretical and empirical aspects of forecast combination methods. Timmermann (2006) emphasizes three main reasons for why forecast combination method may be a superior than ex-ante individual forecasting model. His first argument was motivated by a simply portfolio diversification (hedging). In decisionmaking process, policy-makers often face challenges with identifying information sets underlying each of the individual forecasts. From this standpoint, he argues to combine the forecasts to make full use of information contained in different fore cast models. Second rational in favor of this method is that structural breaks within datasets can be better explained with one model over another. For instance, one model may overwhelm the others by responding more operatively to structural shocks, while the latter may possess a particular parameter that is relatively slow in post structural shocks. Hence, the combination of forecasts may robustify these instabilities than forecast of an individual model. The last motivation for the usage of combination comes from models' subjectivity to various misspecification biases. He claims that combining forecasts may average down the biases and thus improve projection accuracy.

Using large cross-sectional macroeconomic variables, **??**iolfi and Timmermann (2006) provide forecasting performance of linear and non-linear time series models with several persistence measures. To improve the performance through forecast combination, they propose new four-stage conditional combination methods: (1) sorting the models into cluster based on their past performance, trimming; (2) pooling forecasts within each particular cluster, pooling; (3) estimating optimal weights for clusters, optimal weighting and (4) reducing to the equal weights, shrinkage estimation. The authors argue that these conditional combination methods outperform simply strategy of using previous best model or averaging across all forecasting models.

4 b) Empirical experience with implementation

Since it is immense to project inflation rate with accuracy under inflation targeting regime, most central banks have been implementing several forecast combination methods in their empirical studies.

Bjørn land, et al (**??**008), the specialists of Norges Bank, under the project of improving short-term forecasts initiated the development of the combinationbased forecast analysis (SAM-the System of Averaging Models) of gross domestic product and consumer price inflation excluding taxes and energy prices. The analysis incorporates the models such as various types of AR models, factor models, term structure models and more complex DSGE model. Forecasts of these models are then evaluated to derive weights for the combination purposes. The authors concluded that model combination is superior upon forecasts from individual models. However, even with consideration of optimal weights choice according to Kullback-Leibler divergence and empirical example in Hall and Mitchell (2007), they leave the question on the optimal choice of forecast densities open.

Akdogan, et al (2012) produce the forecast of inflation for Turkey, using various parametric and nonparametric econometric models. In particular, the authors employ univariate models, decomposition based approaches, time varying parameter model under Phillips curve scheme, dynamic factor and VAR and Bayesian VAR models. To combine forecasts of above models, they use linear combination scheme, which varies from constant weights to time varying weights approaches. In total, they consider seven alternative forecast combinations and ultimately focus on methods with lower forecast errors, namely Performance Based (PB) weights and Recent Best Forecaster

(RBF). It is notable that both these combination schemes are based on the squared forecast errors. Under the former scheme, weights are obtained recursively, while emphasizing more on recent performance through discount factor, which was proposed by Stock and Watson (2004). Nevertheless, under the combination scheme of RBF, all weights are assigned to model with the lowest squared forecast error in previous quarter, while remaining models are kept with zero weight. Despite the authors have not proposed further modifications, findings are in line with empirical studies. Particularly, they suggest that the method of forecast combination outperform a simple random walk or the relative performance of forecasts by 30 percent better for 2 quarters ahead.

Andreev (2016) in his short-term inflation analysis at the Bank of Russia also demonstrates the forecast combination methods. By disaggregating CPI into 18 subgroups and employing 6 econometric models (i.e. random walk, linear trend autoregressive model, unobserved components model, ordinary least square, VAR and BVAR models), the author uses optimal weighting approach for combination firstly proposed by Bates and Granger (1969). Since the selection of the weights is a stationary process with weights for particular model being static across all forecasting horizons, forecast may significant suffer from reflecting structural breaks or errors of a particular model if forecast horizon is prolonged.

Tuleuov (2017) proposes different methodology for encountering abovementioned problem of static weights in his short-run analysis of inflation at National Bank of Kazakhstan. Instead of estimating weights based on the pseudo-out-of-sample forecast for a month, the author suggests to obtain weights recursively.

5 III. Data Description

A key feature of our combination approach is the emphasis on disaggregation. The models methodologies used in the combination are not directly applied to the consumer price index (CPI), but to subgroups that make up the CPI. Forecasts are estimated for each subcomponent, which are then aggregated using respective CPI expenditure weights. Considering country-specific features of Uzbekistan, the CPI is divided into three main subgroups, namely food, administratively-regulated prices and non-food items and services (referred to core inflation). This is due to the fact that the majority of products within food subgroup demonstrate much higher volatility with standard deviation being two or threefold larger than the items of other subgroups. In addition, most of the food products, especially fruit and vegetables, have seasonal characteristics that require individual treatment in terms of smoothing procedures. Finally, most food products are assumed to contain heterogeneous information and thus the disaggregation makes it possible for exploiting more information within those subgroups. In the case of regulated prices, the forecast process employs the draft version of the potential increase in the prices that are provided a year before.

6 Short-Term Inflation Forecast Combination Analysis for Uzbekistan

To account for monetary and non-monetary factors of inflation, we incorporate exogenous variables (i.e. M0 effective, remittances from abroad, exchange rate of UZS/UZD and the FAO Index).

The frequency of the observations is monthly, beginning from January 2006. All endogenous and exogenous variables are taken in the logarithmic form. Moreover, to adjust for seasonality in time series, we use X-12 ARIMA algorithm.

7 IV. Methodology of Forecasts Combination a) Models i. Auto Regressive Integrated Moving Average (ARIMA) model

We can define an ARIMA (p, d, q) model as I(d) process whose d-th integer difference follows ARMA (p, q) stationary process. The polynomial form of the model can be shown as:??(??)(1 ? ??) ?? (?? ?? ? ?? ??) = ??(??)?? ?? 1.1

Where ??(??) is AR polynomial, F is a lag operator, (1-F) is the regular difference and ??(??) is MA polynomial. To render a projection, the model uses historical variations of a time series. The ARIMA projections are considered advanced form of trend extension.

8 ii. Bayesian Vector Auto regression Model (BVAR)

We use the BVAR model to deal with dimensionality problem by shrinking the parameters through imposition of priors. For this purpose, we employ the procedures developed by the Litterman (1986) and impose the Minnesota-style priors. Another advantage of this model is that it allows for accounting the substation and complementary effects of CPI sub components within the n group.?? ?? ?? = ?? ?? ?? ?? + ?? ?? ?? ?? + ?? ?? , ?? ? 1, 9 ????? 1.2

where ?? ?? ?? is the vector of endogenous variables, ?? ?? ?? is the matrix of lagged values of endogenous variables for the group of n and ?? ?? ?? is the vector of exogenous variables.

9 iii. Vector Error Correction Model (VECM)

To avoid spurious regression and account for cointegration between subgroups of inflation and explanatory variables, we employ the Vector Error Correction model (VECM), which can be specified as:??? ?? ?? = ??(??)??? ?? ?? + ?? ?? ?? ?? + ?? ?? 1.3

where X t is a vector of explanatory variables. ? indicates the first difference and ?(L) is the coefficients matrix (matrices) for lag operators L. ? is the cointegration vectors capturing the long-run relation amongst the variables in the model.

10 b) Forecasts combination methodology

The combination of forecasts takes the following form. Initial recursive estimation of inflation rate (Y) with the outlined models is a function of the vector of models' variables (X) and unknown parameters (µ).?? ??+???? ?? = ?? ?? ??? ??+???? ?? ; ?? ??+???? ?? ? + ?? ??+???? ?? , ??? 1, ?? ??? 1.1

Where i represents the model h=1, ?, s months, s is the number of period ahead for out-of-sample forecasts, andt is the beginning of the time period for testing accuracy of model i.

To test the accuracy (?) h time srecursively from 1 to s, we estimate the root mean squared errors (RMSEs) of the each model.?? ??,? = ????? ?? ?? ? ; ?? ?? ?,???? {?? + ?? ? ? + 1, ? , ?? 0 }; 1.2

where the accuracy of each model (?) is the function of forecasts of each model (?? ?) and actual values of dependent variable for the period of T (t 0 is the beginning of out-of-sample forecasts).

Estimated RMSEs (h times recursively) are then used to calculate appropriate weights for the period of T.?? ??,? = ?? ??,? ?1 ? ?? ??,? ?1 ?? ??=1 , ? ?? ??,? ?? ??=1 = 1; 1.3

where recursive weights (w) is the ratio of out-of-sample inverse of RMSE of a model i to the summation of all model i's out-of-sample inverse of RMSEs.

Since the maximum number of estimated weights (recursive) for each model i is equal to h, the forecasts combination of the all models based on these recursive weights can be shown in the form of sxs matrix.?? ? ?? = ?? ?? ? ?? 0 +?? ?? ?? ??=1 * ?? ??,?? ? ?? =1,?? ???? , 1.4

where ? ?? ? ?? 0 +?? ?? ?? ??=1 * ?? ??,?? is j th element of the column matrix Y.

11 V. Analysis of Empirical Results

According to the pseudo-out-sample empirical estimates in four various time horizons, applied forecast combination method significantly improves the quality of the final forecasts. Obtained outcomes shows that none of the particular model outperforms others in robustness (See Table 1 in Appendices). The model that has an absolute advantage in predicting inflation in a particular time-period completely fails to forecast the true value in another period. This is because of the fact that financial and macroeconomic datasets, particularly inflation, may incorporate an economic information, which cannot be explained with the certain number of predictors included in the best performing model. Under structural breaks and shocks, the point estimation of an economic variable with certain number of predictors that are robust in in-sample period does not guarantee to satisfy all the requirements of statistical tests and explain the drivers of the movement in the out-of-sample period.

In general, forecast performance of the VECM for CPI food subcomponents is not promising. The model demonstrates relative high forecast error in terms of RMSEs compared to other considered model. **??**tock and Watson (2005) assert that with the economic variable, that fluctuates less far from the unconditional mean, it is difficult to outperform over univariate models. In the case of Uzbekistan, the relatively stable and accurate performance of the univariate model ARIMA is surprising given it lacks the information coming from macroeconomic variables that is considerably important in emerging market economies. In addition, the food inflation does not represent such a stable dynamics even after adjusting for seasonality.

Nevertheless, the statistical tests of the selected models significantly improve when they are used for the projection of non-food and services. In particular, enhanced accuracy is clearly evident in the VECM. While one can observe a gradual decrease in the VECM accuracy for food inflation projection with growing time horizons, i.e. the average RMSE for four time-period accounts for 1.86, the performance of non-food and services subcomponent enhances notably to 0.43.The model outperform the other models in 13 out of 24 forecasting horizons. Despite the best performing individual model for each time horizons differs, the accuracy of the BVAR model is stable and close to superior in all sample periods considered. Overall, the empirical results shows that despite certain favorable gains under individual models, there is a scope for improvement with combination method. The forecast combination allows for reducing projection error and one-third of the cases outperforms over BVAR when RMSE weighting scheme is applied. Finally, we then aggregate the forecasts of the all CPI subcomponents by allocating respective weights to obtain a final CPI inflation forecast.

12 VI. Conclusion

Since we outline in the literature review, nowadays there are a body of empirical evidence suggesting that forecast combination methods produce better forecasts on average than the forecasts of an individual model. This empirical paper has added further evidence to those conclusions. By implementing recursive RMSE weighting scheme, we have demonstrated the advantages of averaging forecasts from various individual models while projecting short-run inflation for Uzbekistan.

Prior to the forecast combination methods, we have developed a number of new forecasting models, a simple random walk model, unobserved component model, vector autoregressive and Bayesian vector autoregressive models. After adjusting for statistical ; tests and accuracy, we are left with three models outlined above. We have further compared and discussed individual and combined forecasts. According to the estimates, forecast combination method has generated 33% better performance than individual models in selected time horizons.

For further research in this field, we would suggest to consider the other weighting schemes for combining forecasts, since this can also increase the accuracy of the combined forecasts. Since we use only backward-looking type forecast models in our analysis, it is recommended to include into combination forwardlooking type forecast models such as DSGE or models that incorporate expectations. [1]

1

Forecast horizon	Forecasts errors (RMSEs) of CPI subgroups			Forecast combination	Forecast horizon	Forecasts errors (RMSEs) of CPI subgrou		
	ARIMA BVAR VECM					ARIMA BVAR VECM		
		Food prices					Market prices	
	January 2015-June 2015					January 2015-June 2015		
1	0.42	0.43	0.42	0.25	1	0.51	0.83	0.04
2	0.38	0.38	1.33	0.26	2	0.58	0.90	0.04
3	0.40	0.36	2.03	0.24	3	0.60	1.00	0.19
4	0.40	0.41	2.33	0.32	4	0.65	1.04	0.29
5	0.50	0.40	2.61	0.38	5	0.63	1.10	0.36
6	0.52	0.36	2.95	0.44	6	0.64	1.14	0.43
	July 2015-December 2015					July 2015-December 2015		
1	0.59	0.43	1.65	0.50	1	0.55	0.80	0.49
2	0.52	0.42	2.07	0.50	2	0.68	0.73	0.49
3	0.55	0.41	2.22	0.48	3	0.70	0.68	0.53
4	0.56	0.41	2.44	0.43	4	0.74	0.55	0.56
5	0.54	0.40	2.64	0.38	5	0.71	0.57	0.59
6	0.56	0.45	1.73	0.45	6	0.56	0.62	0.68
	January 2016-June 2016					January 2016-June 2016		
1	0.77	0.61	0.63	0.67	1	0.53	0.25	0.08
2	0.65	0.61	1.47	0.68	2	0.57	0.25	0.20
3	0.70	0.59	1.79	0.70	3	0.54	0.30	0.25
4	0.81	0.66	1.92	0.87	4	0.57	0.43	0.26
5	0.82	0.62	2.28	0.88	5	0.45	0.66	0.31
6	0.80	0.64	2.55	0.82	6	0.51	0.78	0.33
	July 2016-December 2016					July 2016-December 2016		
1	0.88	0.55	1.03	0.61	1	0.60	0.77	0.46
2	0.90	0.67	1.34	0.60	2	0.61	0.91	0.61
3	0.94	0.81	1.50	0.84	3	0.51	0.99	0.70
4	1.13	0.93	1.62	0.81	4	0.61	1.08	0.74
5	1.19	0.95	1.92	0.87	5	0.59	1.14	0.78
6	1.31	1.09	2.49	1.34	6	0.60	1.20	0.85

[Note: *the outperforming model forecast for each time horizon is bolded]

Figure 1: Table 1 :

[1] January 2015-June 2015 January 2016-June 2016 July 2015-December 2015 July 2016-December 2016 Graph 1: The pseudo-out-of-sample forecasts of CPI subcomponents (food) for selected time horizons

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