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Inflation Forecasting for Pakistan in a Data-rich Environment

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This paper uses machine learning methods to forecast the year-on-year CPI inflation of Pakistan and compare their forecasting performance against the comprehensive traditional forecasting suite contained in Hanif and Malik (2015). It also augments the comprehensive forecasting suite with the dynamic factor model which is able to handle a large amount of information and put all of these models in competition against the latest machine learning models. A set of 117 predictors covering a period of July 1995 to June 2020 is used for this purpose. We set the naïve mean model as the benchmark and compare its forecasting performance against 14 traditional and 5 sophisticated machine learning models. We forecast the year-on-year CPI inflation over a 24 months horizon. Forecasting performance is measured using the RMSE. Our results show that the machine learning approaches perform better than the traditional econometric models at 18 forecast horizons.

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1. INTRODUCTION

The recent availability of high-frequency data has allowed researchers to forecast key macroeconomic variables in a data-rich environment. At the same time, use of the machine learning (ML) algorithms to forecast these key variables has risen. For example, central banks all around are using sophisticated ML algorithms to forecast key variables such as inflation, gross domestic product (GDP) growth, interest rates, etc. Pratap & Sengupta (2019).

Inflation forecasting has remained at the heart of macroeconomic forecasting literature since 1990 when a number of central banks adopted the inflation targeting regime. Under this system, inflation forecasts become an explicit intermediate target Svensson (1997). Therefore, accurate and timely forecasts of inflation become an

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important element for central banks around the world. Resultantly, for the purpose of forecasting inflation, academics, researchers, and staff at the central banks have used univariate to multivariate econometric models. Among these models, the dynamic factor model (DFM) which can accommodate a large amount of information in the shape of a few factors has gained popularity overtime. The main reason for this fame emerged due to the fact that the factor models could bypass the usual problem of the "curse of dimensionality", faced by the existing vector autoregressive (VAR) and other econometric methods at the time Bernanke, et al. (2005).

The popularity of this method was initiated with the work of Stock & Watson (2002), where the authors forecasted the Federal Reserve Board's index of industrial production using a large set of variables representing different sectors of the US economy. However, Boivin & Ng (2006) pointed towards the addition of relevant factors with the idea that this may result in an increase in the forecasting power of the models and provide improved forecasts. Following their paper, the literature moved toward the selection of explanatory variables through different statistical methods. For example, Stock & Watson (2012) minimised the weights on less relevant principal components using shrinkage methods from the recently developed machine learning literature.

Ever since, there has been a vast number of studies that used this technique to forecast key macroeconomic variables such as inflation, industrial production, key interest rates, etcetera. While the use of DFM was on the rise, machine learning gradually started to make its way into the economic literature, Hanif, et al. (2018). For a discussion on the use of machine learning and a large amount of information in the field of economics, see Mullainathan & Spiess (2017).

Expansion in this strand of literature continued and many authors came up with forecasts of inflation and other key macroeconomic variables with a combination of the DFM and ML models. For example, Li & Chen (2014) used the least absolute shrinkage and selection operator (LASSO) based approaches and LASSO combined with DFM to forecast several key macroeconomic variables using a dataset containing 107 macroeconomic indicators of the US economy. Upon comparison of predictive accuracy with the DFM model as the benchmark, the authors found that the LASSO-based approaches outperformed the DFM at all forecast horizons for all the variables forecasted.

With regards to Pakistan, Syed & Lee (2021) used several ML methods to forecast inflation, GDP growth, and policy interest rate and compared their forecast performance with conventional models including the DFM. Papers written prior to their work have either used the conventional econometric models to forecast inflation or the artificial neural network and compared its forecasting performance against the conventional econometric methods (see Hanif, et al. 2018; Haider & Hanif, 2009). However, none of the papers before their work employed the DFM model for forecasting the key macroeconomic variables for Pakistan.

More recently, there has been an interest to forecast inflation using a set of classical econometric models and compare their forecast accuracy against sophisticated ML techniques. For example, Medeiros, et al. (2021) used the FRED-MD database to forecast U.S. inflation using conventional techniques and several ML techniques. They found that the random forest (RF) outperformed the benchmark and other models at the majority of the forecast horizons. A similar kind of exercise has been undertaken for other countries as well, for example, Australia (see, Milunovich, 2020) and Brazil (see, Araujo & Gaglianone, 2020, among others). Although, there are studies present that compare the forecasting accuracy of ML methods against the classical econometric models for forecasting inflation. There is not a single paper that compares ML with a comprehensive forecasting suite from a well-renowned inflation forecasting paper for any country.

Therefore, our paper contributes to the existing literature on inflation forecasting in the following ways. First, to the best of our knowledge, there is not a single paper in the existing literature that compares forecasts from 16 econometric models including the DFM against 5 machine learning algorithms. Second, a forecast evaluation from a set of econometric models that can predict inflation well is not easily available for every country; therefore, our paper is unique in the sense that it provides such a suite in the shape of Hanif & Malik (2015) and uses a long time-series for comparing most of their models with the ML algorithms. Finally, such a paper has not been written for Pakistan in the past; hence, a focused contribution of our work is to enhance the existing literature on inflation forecasting in general and on Pakistan's economy in particular.

The rest of the paper is organised as follows. Section 2 provides details about the data used in our study. Section 3 contains the alternative forecasting methods we employ in this paper. Section 4 discusses the measures of forecasting accuracy we use, and Section 5 contains the main empirical results. Section 6 contains discussion and conclusion.

2. MATERIAL AND METHODS

2.1. Data Description

The dataset used in this paper contains 118 aggregate and dis-aggregated macroeconomic time series variables covering the real sector, fiscal sector, monetary and financial sector, and the external sector of the economy of Pakistan.[1] The frequency of the data is monthly, and the sample period is from July 1995 to June 2020. The data is taken from the Statistics and Data Warehouse Department, State bank of Pakistan (SBP) (the central bank).

There are no specific codes/acronyms assigned to the variables by SBP, therefore we assigned short names based on the complete names of the variables included. All the non-stationary variables have been transformed to make them stationary. Both the variables stationary in levels and in transformed shape have been standardised to have mean zero and standard deviation one (similar to Panagiotelis, et al. 2019) and Table A1 in the appendix contains the variables along with details of transformations.[2]

[1]As Pakistan is a small open economy and oil imports comprise a heavy portion of Pakistani imports; therefore, we also add world oil prices in our dataset under the external sector.

[2]It is important to note that Hanif & Malik (2015) did not transform their variables in such a manner; however, in our case as we are going to compare the results of their models with the DFM and ML models. Therefore, for consistency across the use of information, all the variables used in the models taken from their paper are also made stationary and standardised.

2.2. Forecasting Methods

In this paper, we use several classical econometric models taken from Hanif & Malik (2015) and compare their forecasting accuracy against the DFM and ML models. We follow Syed & Lee (2021) in explaining the general methodology for forecasting used in this paper. We initiate our analysis by using the simple mean model (naïve), the AR, the ARDL models, the structural VAR models followed by the DFM, and the sophisticated machine learning techniques such as the Ridge (Ridge), the LASSO, the elastic net (EN), artificial neural network (ANN) and the RF.

Let $x_t = \{x_{i,t}\}_{1 \le i \le K}$ be a vector of length K where each element represents the value of macroeconomic variable i at time t, after it has been transformed to stationary and standardised to have mean zero and standard deviation one. Now $(x_t \, , x_{t-1}, \; . \; . \; ., x_{t-L+1})'$ includes all the lagged information available at time t. We define y_t as the target variable which will also be an element of x_t. All learning methods we consider in this paper assume linear combination of the predictors and have the general form:

$$\hat{y}_{t+h} = x_t'\hat{\theta}_1 \; + \; x_{t-1}'\hat{\theta}_2 \; + \cdots + \; x_{t-L+1}'\hat{\theta}_L \; , \quad h = 1,2,\ldots,24 \qquad \ldots \; (3.1)$$

where $\hat{y}_{t+h}$ is a h-step-ahead forecast of the target variable and $\hat{\theta}_l = (\hat{\theta}_{1,l}, \hat{\theta}_{2,l}, \; \ldots \; , \hat{\theta}_{K,l})$ is the estimated coefficient on the l^{th} lag of the variables.

To select the lags for each model estimated in the paper, we use the Autoregressive (AR), $AR(p)$ model which is a natural competitor against the univariate techniques that use big data. Since the data is at a monthly frequency, we allow for a maximum of 10 lags and select p by minimising the Bayesian Information Criteria (BIC) Schwarz (1978). We found $p = 1$ for the standardised inflation series. To have a consistent comparison across models, we keep 1 lag of all the explanatory variables in all the machine learning models considered in this paper. For the autoregressive distributed lag (ARDL) models and the VAR models, we allow 10 lags, and the BIC picks the appropriate number of lags for each iteration that ensures the stability of these models. The models used in this paper are listed below.

2.2.1. *Unconditional Mean Model*

The mean model is the simple unconditional average of the standardised YOY inflation series itself. It can be represented as:

$$Y_t = \mu + \varepsilon_t \qquad \ldots \qquad \ldots \qquad \ldots \qquad \ldots \qquad \ldots \qquad \ldots \qquad \ldots \quad (1)$$

Where Y_t is a dependent variable at time t, μ is the constant parameter and ε_t is a stationary, white noise process.

2.2.2. *Autoregressive Model*

AR model is given by:

$$Y_t = \mu + \sum_{i=1}^{p} \theta_i Y_{t-i} + \varepsilon_t \quad \ldots \qquad \ldots \qquad \ldots \qquad \ldots \qquad \ldots \qquad \ldots \quad (2)$$

Where Y_t is a dependent variable at time *t,* μ is the constant parameter and ε_t is a stationary, white noise process.

2.2.3. *Moving-average Model*

Moving-average model is given by:

$$Y_t = \mu + \sum_{i=1}^{p} \theta_i \varepsilon_{t-i} \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (3)$$

Where Y_t is a dependent variable at time t, μ is the constant parameter and ε_t are the errors.

2.2.4. *Autoregressive Distributed Lag Models*

The ARDL model is given by:

$$Y_t = \mu + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=1}^{q} \theta_i \boldsymbol{X_{t-j}} + \varepsilon_t \quad \dots \quad \dots \quad \dots \quad \dots \quad (4)$$

Where Y_t is a dependent variable and X_t is a vector of independent variables at time t, μ is the constant parameter and ε_t is a stationary, white noise process. We estimated two variants of the ARDL model. ARDL1 contains inflation as a dependent variable while average lending rate, global oil price, money supply, and output gap as the independent variables. In ARDL2, we capture the impact of world inflation, nominal exchange rate, money supply, industrial production proxied by the quantum index of large-scale manufacturing, and output gap on CPI inflation. We allow ARDL models to choose the appropriate length for each simulation based on the BIC.

2.2.5. *Vector Autoregressive Models*

For multivariate models, we use the widely used Sim's (1980) VAR methodology with different variables and Choleski decomposition scheme to produce its structural variants. The VAR(p) is given by:

$$Y_t = \mu + \sum_{i=1}^{p} \theta_i Y_{t-i} + \varepsilon_t \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (5)$$

Where Y_t is a vector of endogenous variables at time t, $\theta_i's$ are the parameters and ε_t are the uncorrelated white noise disturbance terms. A maximum of 10 lags is allowed for the lags in the VAR models and BIC is used to select the lag at each iteration.[3] We estimated five variants of the VAR model. In each model below, the model variables are listed in terms of their ordering in the Choleski decomposition. Credit VAR (CVAR) contains a Discount rate, treasury bill rate of 3 months, weight average lending rate, private sector credit, and inflation.

Monetary VAR (MVAR) contains Discount rate, weighted average lending rate, reserve money, money supply, and inflation External VAR 1 (EVAR1) contains global oil price, US industrial production, remittances, real effective exchange rate, industrial

[3]A series of different checks have been conducted to ensure that the results are robust to all these checks. They are; competing naïve, RW and AR model with each other to select the benchmark and then compare its performance with all the advanced models used to forecast inflation in this paper, estimation of all models with 6 lags, change in the ordering of the variables, addition of world oil price (Brent, Dubai Fateh and average of the two). All these checks revealed that the results of our models qualitatively remained the same.

production (Pakistan), and inflation. External VAR 2 (EVAR2) contains World inflation, output gap, money supply, nominal exchange rate, and inflation. External VAR 3 (EVAR3) contains global oil prices, world food prices, output gap, money supply, weighted average lending rate, real effective exchange rate, and inflation

2.2.6. *Bayesian Vector Autoregressive Models*

It is well known that the Bayesian estimated VARs provide more accuracy depending on the reduced parametric estimation Canova (2007). The bayesian approach treats data as given and it estimates the parameters inferences conditional on the data. To tackle the issue of a high number of parameter estimations, Bayesian methodology uses the prior information which is given in form of density function. One such example is Minnesota priors which was originally proposed by Litterman (1986); Doan, et al. (1984), and been found to increase the forecasting performance of VAR models in forecasting different macroeconomic time series.

Therefore, we also used the benchmark Minnesota priors from Canova (2007), which are (0.2, 1, 0.5), representing the general tightness parameter, decay parameter, and other variable lags parameter respectively. We tried to keep the variables almost the same as in the structural VAR models for different sectors.

We estimated three variants of the Bayesian VAR model. Bayesian Monetary VAR (BMVAR) is a five-variable model and includes discount rate, weighted average lending rate, reserve money, money supply, and inflation. Bayesian Credit VAR (BCVAR) is comprised of six variables: discount rate, public sector borrowing, Treasury bill rate, weighted average lending rate, private sector credit, industrial production, and inflation. Bayesian External VAR (BEVAR) is a seven-variable model and includes global oil price, US industrial production, discount rate, real effective exchange rate, remittances, industrial production (Pak), and inflation.

2.2.7. *Dynamic Factor Model*

The DFM assumes that a small number of unobserved dynamic factors can explain the information set of the predictors (117 variables). We estimate these factors by principal component analysis (PCA), following Stock and Watson (2002) who use the expectation-maximisation (EM). Once the factors are estimated, CPI inflation is then forecasted as follows:

$$Y_t = \mu + \sum_{i=1}^{p} \theta_i f_{t-i} + \varepsilon_t \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (6)$$

Where Y_t is CPI inflation, f_t is the vector of unobserved factors and ε_t are the uncorrelated white noise disturbance terms. We estimate two variants of the DFM model. DFM5 contains the first five and DFM10 contains the first ten factors estimated from the complete information set respectively.

2.2.8. *Ridge Regression*

Introduced by Hoerl & Kennard (1970), Ridge regression is a well-known linear regression model which minimises the sum of squared residuals with an additional l_2-norm penalty term. Ridge adds this penalty to the overemphasised coefficients. The value of lambda plays a significant role in determining the weight assigned to the penalty for coefficients. Ridge does not shrink the coefficients to zero. However, the coefficients get closer and closer to zero as the value of lambda becomes larger. Ridge regression is given by:

$$argmin_{\beta} \sum_i (y_i - \beta' x_i)^2 + \lambda \sum_{k=1}^{K} \beta_k^2 \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (7)$$

We use 10-fold cross-validation to find the optimal shrinkage parameter λ.

2.2.9. *Least Absolute Shrinkage and Selection Operator*

The second shrinkage method we implement in our forecasting exercise is the LASSO that was introduced by Tibshirani (1996). LASSO, short for Least Absolute Shrinkage Selection Operator is a regularisation model that assigns penalty to the linear model coefficients using the formula:

$$argmin_{\beta} \sum_i (y_i - \beta' x_i)^2 + \lambda \sum_{k=1}^{K} |\beta| \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (8)$$

Hence, variables with zero coefficients are eliminated. This is known as shrinkage, where values are shrunk to a central point, for instance, mean. From the formula, we can infer that lasso adds a penalty equal to the Lamba multiplied by the absolute value of the coefficients' magnitude. This penalty shrinks many coefficients to zero, which are then eliminated. Consequently, the degree of overfitting is reduced within the model. We use 10-fold cross-validation to find the optimal shrinkage parameter λ.

2.2.10. *Elastic Net*

The third machine learning algorithm that we apply to our data is the Elastic Net. Elastic Net was proposed by Zou & Hastie (2005) and it is a combination of both Ridge and Lasso characteristics. It reduces the effect of different variables while preserving some of the features. The Elastic Net can be mathematically written as:

$$argmin_{\beta} \sum_i (y_i - \beta' x_i)^2 + \lambda_1 \sum_{k=1}^{K} |\beta| + \lambda_2 \sum_{k=1}^{K} \beta_k^2 \quad \ldots \quad \ldots \quad (9)$$

We use 10-fold cross-validation to find the optimal shrinkage parameters λ_1 and λ_2.

2.2.11. *Neural Network*

Neural Networks have extensively been used to forecast inflation in many countries including Pakistan (see, Haider & Hanif, 2009; Hanif, et al. 2018). In this paper, we employ Long Short-Term Memory (LSTM) which is a type of recurrent neural network (RNN) architecture. It was developed to model temporal sequences more accurately with their long-range dependencies than the traditional RNNs. LSTM forgets all irrelevant data and remembers past knowledge that has been passed through the network.

Hence, LSTM contains special units; "memory blocks", in the hidden recurrent layer. These memory blocks consist of "memory cells" with self-connections which store the network's temporal state. In addition to the temporal state, special multiplicative units called gates are also stored. A typical network consists of 4 different gates: input gate, output gate, cell state and forget gate. These gates filter out the useless data and only keep what is required. After identifying the data, it can pass information down the chain of sequences in order to make predictions.

2.2.12. *Random Forest*

The only ensemble method we use in our study is the random forecast. Introduced by Breiman (2001), the random forest model is based on bootstrap aggregation (bagging) of randomly created regression trees and strives to reduce the variance of regression trees. A regression tree is very well-known is a non-parametric model which is an approximation of an unknown nonlinear function with local forecasts that uses recursive partitioning of the response variable space Breiman (1996).

3. FORECASTING EVALUATION

For forecast evaluation, we examine h = 1, 2, . . . , 24 steps-ahead forecasts and use a training window of 22 years, which is 264 observations. Each model we described in the previous section is estimated within this window, from which h = 1, 2, . . . , 24 steps-ahead forecasts are generated. The training window is then moved forward one month at a time until we reach the end of the sample. For each step, model parameters are re-estimated, and forecasts are generated. By following this process, we get out-of-sample forecasts for each forecast horizon "h" and these are used to compare the forecasting performance of different models.

For the lag structure of ARDL and VAR models, each model is allowed to choose lags based on BIC for each simulation. Hence, each simulation utilised data points in a range of 254-264 depending on the lag structure picked by the models. Finally, as mentioned earlier, to be consistent across classical as well as machine learning models, we use 1 lag of each predictor in machine learning models. For the forecasting accuracy measurements, we consider the root mean squared error (RMSE). For fixed forecast horizon h, we can calculate RMSE with $\sqrt{mean(e_{t+h}^2)}$ where $e_{t+h} = \hat{y}_{t+h} - y_{t+h}$.

4. EMPIRICAL RESULTS AND CONCLUSION

In this section, we present the results of our analysis. Table 1 presents the forecast accuracy for h = 1 to 24 steps ahead forecast of competing forecast approaches for the year-on-year CPI inflation. Each entry in the table shows the RMSE of the forecasting method relative to the naïve benchmark model. The entries in bold show the RMSE equal to or lower than the naïve benchmark model attained by forecasting model across each row.

An analysis of Table 1 shows that the competing approaches are able to beat the naïve benchmark model at all forecast horizons, that is, we observe at least one entry is below the value of 1 in each row of the table. The main result of the study is that the LASSO beats all the other competing approaches and the naïve benchmark model at 17 forecast horizons (first 16 forecast horizons and at the 22nd horizon). Hence, it is the best model for forecasting year-on-year CPI inflation against the models applied and the sample period considered in our study.

A few other notable results are; first, the DFM model that has been used extensively in the past two decades as a forecasting tool for macroeconomic forecasting is comprehensively beaten by the LASSO, second, the elastic net beats the naïve benchmark at all 24 forecast horizons, followed by the LASSO and the random forest, these models outperform the naïve benchmark model at 23 forecast horizons. Table 1 also shows that the random forest model beats the naïve benchmark and all other models at a single forecast horizon whereas the classical econometric models beat all the competing models at 6 forecast horizons.

It is also common knowledge that the forecast performance of models usually deteriorates as we move to longer forecast horizons; we can observe with phenomenon in the RMSE figures produced by the competing models in Table 1. We note that with exception of three models, all the competing approaches perform quite worse than the benchmark.[4]

At a broader level, our results are in line with Li and Chen (2014) who found that the LASSO-based approaches outperform the commonly used DFM in forecasting a set of macroeconomic indicators including the CPI. Therefore, we conclude that for the sample period of our study, the machine learning approaches perform better than the DFM and all the other classical econometric methods in forecasting the year-on-year CPI inflation for the economy of Pakistan.

5. ROBUSTNESS CHECK

In this section, we report the results for one of the ways to confirm that our analysis is robust to the different sets of checks we applied in this paper. We first compared the forecasting performance of the naïve model, the RW, and the AR model against each other. We found that the RW model beats the mean model at 13 different forecast horizons whereas the AR model beats the naïve model at 12 different forecast horizons.

Once we found that both these models beat the naïve mean model at 13 and 12 forecast horizons respectively, we tested to see how these models perform against each other. We found that the RW model beats the AR model at 18 different forecast horizons. Therefore, we select the RW as the benchmark model in our robustness check analysis and compare its forecasting performance against the classical econometric as well as the machine learning models.

Table 2 contains the results of the models against the RW model. An analysis of Table 2 shows that the LASSO once again beats the RW benchmark model and all the other competing models at 16 forecast horizons. It outperforms all from 1-14th, 16th, and 22nd forecast horizons, respectively. The random forest model now beats the forecast approaches at 2 forecast horizons than only 1 in the results against the naïve benchmark. Finally, we see that the MVAR beats the competing approaches at 3 forecast horizons, which is about the same/similar to the case of the naïve model as a benchmark. The BEVAR continues to beat all others at the 23rd forecast horizon, whereas the last horizon is once again dominated by the benchmark model itself. None of the competing approaches beat the RW model at the 24th forecast horizon.

[4]This is not a computational error, the RMSE figures in the table has been checked multiple times before we conclude that they are computed correctly. If this was a computational error, only a single value or a few models should have produced large RMSE figures; showing supremacy of the naïve model over these approaches. However, we find that except for a few models, the RMSE values for all the models rise substantially at the last forecast horizon.

Table 1

Table 1

Forecast accuracy for h = 1–24. Each entry shows RMSE relative to the naïve benchmark. All models use full information set and does not contain lags of the dependent variable (Standardised year-on-year CPI inflation). Bold entries indicate the RMSE equal to or lower than the benchmark model achieved by the competing approaches for the variable of interest across each row

h	AR	MA	ARDL1	ARDL2	BCVAR	BEVAR	BMVAR	MVAR	CVAR	EVAR1	EVAR2	EVAR3	LASSO	RIDGE	EN	NN	RF	DFM5	DFM10
1	1.005	1.005	1.166	1.203	**0.990**	1.003	1.021	1.064	1.048	1.004	1.030	**0.987**	**0.707**	1.135	**0.806**	2.114	**0.746**	**0.946**	1.018
2	1.001	1.001	1.145	1.185	1.010	**0.991**	1.036	1.057	1.068	**0.984**	1.010	**0.995**	**0.711**	1.146	**0.804**	1.474	**0.737**	**0.952**	1.018
3	1.002	1.003	1.158	1.183	1.009	**0.992**	1.029	1.048	1.055	**0.985**	1.012	1.025	**0.709**	1.102	**0.809**	1.458	**0.753**	**0.950**	1.018
4	**0.995**	**0.996**	1.169	1.199	1.004	**0.982**	1.035	1.057	1.069	**0.998**	1.016	1.048	**0.719**	1.070	**0.816**	1.389	**0.742**	**0.967**	1.031
5	**1.000**	**1.000**	1.168	1.205	**0.988**	1.008	1.057	1.080	1.038	1.073	1.047	1.079	**0.745**	1.154	**0.849**	1.338	**0.772**	**0.976**	1.009
6	**1.000**	**1.000**	1.156	1.194	**0.985**	**0.986**	1.059	1.092	1.004	1.034	1.053	1.121	**0.754**	1.129	**0.852**	1.389	**0.772**	**0.973**	1.008
7	**0.995**	**0.996**	1.146	1.185	**0.985**	**0.954**	1.036	1.056	1.018	1.020	1.044	1.049	**0.755**	1.159	**0.845**	1.598	**0.811**	**0.974**	1.020
8	1.001	1.002	1.168	1.205	**0.989**	**0.961**	1.046	1.070	1.029	1.033	1.002	1.029	**0.770**	**0.992**	**0.810**	1.506	**0.780**	1.001	1.054
9	1.006	1.006	1.160	1.230	**0.993**	1.006	1.042	1.066	1.031	1.059	1.099	1.092	**0.756**	1.003	**0.810**	1.489	**0.775**	1.005	1.064
10	**0.997**	**0.998**	1.148	1.218	**0.996**	1.033	1.069	1.112	1.033	1.084	1.086	1.114	**0.769**	1.086	**0.826**	1.217	**0.831**	1.019	1.085
11	**0.999**	**0.999**	1.127	1.202	**0.976**	**0.985**	1.050	1.087	1.001	1.023	**0.951**	1.050	**0.733**	1.067	**0.810**	1.255	**0.762**	1.025	1.077
12	**1.000**	1.001	1.110	1.188	**0.967**	**0.996**	1.017	1.034	**0.985**	1.021	**0.949**	**0.998**	**0.734**	1.065	**0.809**	1.576	**0.793**	1.019	1.072
13	**0.983**	**0.986**	1.092	1.168	**0.927**	**0.941**	**0.960**	**0.993**	**0.958**	1.018	**0.890**	**0.966**	**0.734**	**0.955**	**0.818**	1.659	**0.764**	1.010	1.068
14	**0.989**	**0.992**	1.170	1.255	**0.943**	**0.972**	**0.921**	**0.913**	**0.969**	1.078	**0.914**	**0.927**	**0.783**	1.011	**0.844**	1.062	**0.796**	1.082	1.168
15	**1.000**	1.001	1.203	1.272	**0.967**	1.043	**0.953**	**0.943**	**0.990**	1.141	1.001	**0.863**	**0.830**	1.013	**0.864**	1.907	**0.826**	1.099	1.170
16	**0.986**	**0.984**	1.217	1.289	1.014	1.030	**0.957**	**0.941**	1.059	1.123	1.067	**0.895**	**0.793**	**0.933**	**0.877**	1.508	**0.805**	1.074	1.133
17	**0.959**	**0.960**	1.244	1.286	**0.826**	**0.833**	**0.686**	**0.577**	**0.850**	1.033	**0.929**	**0.838**	**0.655**	1.004	**0.738**	**0.865**	**0.656**	1.084	1.246
18	1.002	1.002	1.276	1.339	**0.886**	**0.836**	**0.724**	**0.634**	**0.915**	1.117	1.020	**0.927**	**0.715**	1.050	**0.739**	1.583	**0.698**	1.063	1.319
19	1.005	1.005	1.252	1.284	**0.778**	**0.925**	**0.668**	**0.621**	**0.784**	1.197	**0.823**	**0.975**	**0.678**	**0.960**	**0.669**	1.497	**0.716**	1.088	1.322
20	1.038	1.031	1.332	1.353	**0.731**	**0.990**	**0.677**	**0.624**	**0.720**	1.375	**0.990**	**0.976**	**0.700**	**0.937**	**0.682**	**0.734**	**0.727**	1.150	1.397
21	1.062	1.044	1.219	1.248	**0.773**	**0.989**	**0.834**	**0.813**	**0.829**	1.363	1.112	**0.882**	**0.757**	1.056	**0.781**	1.801	**0.706**	1.043	1.419
22	1.144	1.117	1.132	1.166	**0.878**	1.161	1.085	1.027	1.095	1.500	1.466	1.044	**0.552**	1.421	**0.645**	1.641	**0.751**	1.000	1.710
23	**0.767**	**0.711**	**0.365**	1.509	1.523	**0.198**	**0.661**	1.240	2.515	**0.739**	1.006	1.488	**0.985**	2.836	**0.587**	4.945	**0.836**	**0.759**	1.802
24	**0.223**	**0.560**	1.132	5.252	10.896	2.897	21.852	32.182	19.737	3.711	6.504	12.373	1.523	9.302	**0.983**	54.270	9.914	2.262	2.504

Models used: AR = autoregressive, MA = moving-average, ARDL = autoregressive distributed lag. BCVAR, BEVAR and BMVAR denotes Bayesian credit, external and monetary vector autoregressive models respectively. MVAR, CVAR and EVAR denotes monetary, credit and external vector autoregressive model respectively. LASSO, Ridge, EN, NN and RF denotes least absolute shrinkage operator, Ridge, elastic net, neural network and random forest model respectively. Finally, DFM5 and DFM10 denotes dynamic factor model with 5 and 10 factors respectively.

Table 2

Table 2

Forecast accuracy for h = 1–24. Each entry shows RMSE relative to the RW benchmark. All models use full information set and does not contain lags of the dependent variable (Standadardised CPI year-on-year inflation). Bold entries indicate the RMSE equal to or lower than the benchmark model achieved by the competing approaches for the variable of interest across each row

Horizon	MA	ARDL1	ARDL2	BCVAR	BEVAR	BMVAR	MVAR	CVAR	EVAR1	EVAR2	EVAR3	LASSO	RIDGE	EN	NN	RF	DFM5	DFM10
1	1.000	1.161	1.197	**0.986**	**0.998**	1.017	1.060	1.044	**0.999**	1.026	**0.983**	**0.704**	1.130	**0.802**	2.105	**0.743**	**0.942**	1.014
2	1.001	1.145	1.185	1.010	**0.991**	1.036	1.057	1.069	**0.984**	1.010	**0.995**	**0.711**	1.146	**0.804**	1.474	**0.737**	**0.952**	1.018
3	1.002	1.157	1.181	1.008	**0.991**	1.028	1.047	1.054	**0.984**	1.011	1.024	**0.708**	1.101	**0.808**	1.456	**0.752**	**0.948**	1.017
4	1.001	1.175	1.205	1.009	**0.988**	1.041	1.063	1.074	1.004	1.021	1.054	**0.723**	1.076	**0.821**	1.396	**0.746**	**0.972**	1.037
5	1.000	1.168	1.205	**0.988**	1.009	1.057	1.081	1.038	1.073	1.047	1.079	**0.745**	1.154	**0.849**	1.338	**0.772**	**0.976**	1.009
6	1.000	1.156	1.194	**0.985**	**0.986**	1.058	1.092	1.004	1.034	1.053	1.121	**0.754**	1.129	**0.852**	1.389	**0.772**	**0.973**	1.007
7	1.001	1.152	1.192	**0.991**	**0.959**	1.042	1.062	1.024	1.026	1.050	1.055	**0.760**	1.166	**0.850**	1.607	**0.816**	**0.979**	1.026
8	1.001	1.167	1.204	**0.988**	**0.960**	1.044	1.069	1.027	1.031	1.001	1.028	**0.770**	**0.991**	**0.809**	1.504	**0.779**	**0.999**	1.053
9	**1.000**	1.152	1.222	**0.986**	**1.000**	1.035	1.059	1.024	1.052	1.092	1.085	**0.751**	**0.996**	**0.805**	1.480	**0.770**	**0.999**	1.057
10	1.000	1.151	1.221	**0.999**	1.035	1.071	1.114	1.036	1.087	1.089	1.117	**0.771**	1.089	**0.829**	1.220	**0.833**	1.021	1.087
11	**1.000**	1.128	1.204	**0.977**	**0.986**	1.051	1.089	1.003	1.024	**0.952**	1.051	**0.734**	1.069	**0.811**	1.257	**0.763**	1.026	1.079
12	1.001	1.110	1.188	**0.967**	**0.996**	1.017	1.034	**0.985**	1.021	**0.949**	**0.998**	**0.734**	1.065	**0.809**	1.576	**0.793**	1.019	1.072
13	1.004	1.111	1.189	**0.943**	**0.958**	**0.977**	1.010	**0.975**	1.035	**0.906**	**0.983**	**0.747**	**0.972**	**0.833**	1.688	**0.777**	1.028	1.087
14	1.003	1.183	1.269	**0.954**	**0.983**	**0.932**	**0.923**	**0.979**	1.090	**0.925**	**0.937**	**0.791**	1.022	**0.854**	1.073	**0.805**	1.094	1.181
15	1.001	1.204	1.273	**0.967**	1.044	**0.953**	**0.943**	**0.990**	1.141	1.001	**0.863**	**0.830**	1.013	**0.864**	1.908	**0.826**	1.099	1.170
16	**0.999**	1.235	1.308	1.029	1.046	**0.972**	**0.955**	1.075	1.140	1.083	**0.908**	**0.805**	**0.947**	**0.890**	1.531	**0.818**	1.090	1.150
17	1.001	1.298	1.341	**0.861**	**0.869**	**0.715**	**0.602**	**0.886**	1.077	**0.968**	**0.873**	**0.683**	1.047	**0.769**	**0.902**	**0.685**	1.130	1.300
18	1.001	1.275	1.337	**0.884**	**0.834**	**0.723**	**0.634**	**0.914**	1.115	1.019	**0.926**	**0.714**	1.048	**0.738**	1.580	**0.697**	1.061	1.317
19	1.001	1.246	1.278	**0.774**	**0.921**	**0.665**	**0.618**	**0.781**	1.192	**0.820**	**0.971**	**0.675**	**0.956**	**0.667**	1.491	**0.713**	1.084	1.316
20	**0.994**	1.284	1.304	**0.705**	**0.954**	**0.652**	**0.601**	**0.694**	1.325	**0.955**	**0.941**	**0.675**	**0.903**	**0.657**	**0.708**	**0.701**	1.108	1.347
21	**0.985**	1.151	1.178	**0.730**	**0.933**	**0.788**	**0.768**	**0.783**	1.287	1.049	**0.833**	**0.714**	**0.997**	**0.738**	1.700	**0.666**	**0.984**	1.339
22	**0.991**	1.005	1.035	**0.780**	1.030	**0.963**	**0.912**	**0.972**	1.331	1.301	**0.927**	**0.490**	1.261	**0.573**	1.456	**0.667**	**0.887**	1.518
23	**0.918**	**0.471**	1.948	1.966	**0.256**	**0.854**	1.601	3.248	**0.955**	1.300	1.922	1.272	3.663	**0.759**	6.387	1.080	**0.981**	2.328
24	2.233	4.518	20.954	43.477	11.559	87.189	128.405	78.749	14.807	25.951	49.367	6.078	37.113	3.923	216.536	39.558	9.026	9.989

Models used: MA = moving-average, ARDL = autoregressive distributed lag. BCVAR, BEVAR and BMVAR denotes Bayesian credit, external and monetary vector autoregressive models respectively. MVAR, CVAR and EVAR denotes monetary, credit and external vector autoregressive model respectively. LASSO, Ridge, EN, NN and RF denotes least absolute shrinkage operator, Ridge, elastic net, neural network and random forest model respectively. Finally, DFM5 and DFM10 denotes dynamic factor model with 5 and 10 factors respectively.

These results support our main findings that the LASSO model is the best model for predicting the year-on-year CPI inflation in Pakistan. Furthermore, in line with the earlier results we find that the forecast performance of all the models deteriorates enormously at the last forecast horizon. Hence, re-affirming our position that the computations of the models have been computed, examined, and reported with extreme care.

Conflict of Interest: The authors certify that there is no conflict of interest.

APPENDIX A

Table A1

Transformation (T) denotes the transformation applied to achieve stationarity: 1 = no transformation; 2 = first difference; 3 = log; 4 = first difference of log; 5 = second difference of log. Seasonally Adjusted (SA) denotes seasonal adjustment of variables using the Bureau of Census X12 procedure using Eviews.

S. No.	T	Name of the Variables	Short Names
		Real Sector (Output)	
1	4	Production of Paints & Varnishes (l) (SA)	PNVL
2	4	Production of Hydrochloric Acid (SA)	HYCA
3	4	Production of Paints & Varnishes (s) (SA)	PNVS
4	4	Production of Soda Ash (SA)	SODAA
5	4	Production of Polishes & Creams (SA)	PNCR
6	4	Production of Chlorine Gas (SA)	CHGAS0
7	4	Production of Sulphuric Acid (SA)	SULA
8	4	Production of Cement (SA)	CMNT
9	4	Production of Glass Plates & Sheets (SA)	GPNSH
10	5	Production of Jeeps and Cars (NSA)	JNCR
11	4	Production of Tractors (SA)	TRACT
12	4	Production of L.C.V.s (NSA)	LCVS
13	4	Production of Scooters/Motor Cycles (SA)	STMC
14	4	Production of Buses (NSA)	BUS
15	4	Production of Trucks (NSA)	TRKS
16	4	Production of Coke (NSA)	COKE
17	4	Production of Pig Iron (NSA)	PIRON
18	4	Production of Billets (SA)	BLTS
19	4	Production of H.R sheets/strips (NSA)	HRSS
20	4	Production of Phosphatic Fertilisers (NSA)	PFERT
21	4	Production of Nitrogenous Fertilisers (Total) (SA)	NFERT
22	4	Production of Electric Transformers (SA)	ETRANS
23	4	Production of Refrigerators (SA)	REGRI
24	1	Production of Switch Gears (NSA)	SGEARS
25	4	Production of T.V. Sets (SA)	TVSET
26	4	Production of Electric Tubes (NSA)	ETUBES
27	4	Production of Electric Meters (SA)	EMETRS
28	4	Production of Air conditioners (SA)	ACS
29	4	Production of Electric Bulbs (SA)	EBULBS
30	4	Production of Electric Motors (SA)	EMTRS
31	4	Production of Upper Leather (SA)	ULEAT
32	4	Production of Sole Leather (SA)	SLEAT
33	4	Production of Cotton Yarn (SA)	CYARN
34	4	Production of Cotton Cloth (SA)	YCLOTH
35	4	Production of Woolen & Carpet Yarn (SA)	WCARY

36	4	Production of Jute Goods (Total) (SA)	JDS
37	4	Production of Knitting Wool (SA)	KWOOL
38	4	Production of Vegetable Ghee (SA)	VEGG
39	4	Production of Sugar (NSA)	SUG
40	1	Production of Cigarettes (SA)	CIG
41	4	Production of Cooking Oil (SA)	COIL
42	4	Production of Tea (SA)	Tea
43	4	Production of Tablets (SA)	TAB
44	4	Production of Liquid/Syrups (SA)	LIQS
45	4	Production of Injections (SA)	INJ
46	4	Production of Capsules (SA)	CAPs
47	4	Production of Galenical (Tincture/Spirits) (NSA)	GALS
48	4	Production of Ointments (SA)	ONTT
49	4	Production of Caustic Soda (SA)	CSODA
50	4	Production of Leather Footwear (SA)	LEATFW
51	4	Production of Paper & Board (SA)	PNB
52	4	Production of Safety Razor Blades (SA)	SRBLD
53	4	Production of Bicycles (SA)	BCYC
54	1	Production of Sewing Machines (SA)	SMACH
55	1	Production of Power Looms (NSA)	PLOOMS
56	4	Production of Diesel Engines (SA)	DENG
57	1	Production of Sugarcane Machines (NSA)	SCANEM
58	1	Production of Shuttles (SA)	SHUTS
59	4	Production of Wheat Thrashers (NSA)	WTRASH
60	4	Production of Chaff Cutters (SA)	CCUTS
61	4	Production of Cycle Tires (SA)	CYCT
62	4	Production of Motors Tires (SA)	MTYRE
63	4	Production of Motors Tubes (SA)	MTUB
64	4	Production of Cycle Tubes (SA)	CYCTUB
65	4	Quantum Index of Large-Scale Manufacturing Industries (SA)	SALAM
		External Sector	
66	4	Gold	GOLD
67	4	Foreign Exchange Reserves with SBP	FXSBP
68	4	Foreign Exchange Reserves with Scheduled Banks	FXSch
69	4	Workers’ Remittances	WREM
70	4	Exports (BOP)	EXP
71	4	Imports (BOP)	IMP
		Exchange Rates and Interest Rates	
72	4	Saudi Arabian Riyal	SAR
73	4	UAE Dirham	UAED
74	4	US Dollar	USD
75	4	Canadian Dollar	CAD
76	4	UK Pound Sterling	GBP
77	4	Euro	EURO
78	4	Japanese Yen	JPY
79	4	French Franc	FFRANC
80	4	Deutsche Mark	DMARK
81	4	Real Effective Exchange Rate (REER)	REER
82	4	Nominal Effective Exchange Rate (NEER)	NEER
83	2	Call Money Rate	CMR
84	2	Discount Rate	DR
		Fiscal Sector	
85	4	Accounts - National Savings Scheme (NSS)	ANSS
86	4	Certificates – NSS	CNSS
87	4	Prize Bonds – NSS	PBNSS
88	4	Permanent Debt	PD

89	4	Floating Debt	FD
90	4	Unfunded Debt	UFD
91	4	Foreign Currency Loans	FCL
		Monetary Sector (Money, Reserves and the Banking System)	
92	4	Currency in Circulation	CIC
93	4	Other Deposits with SBP	ODSBP
94	4	Bank Deposit with SBP	BDSBP
95	4	Currency in Tills of Scheduled Banks	CTSCH
96	4	Demand Deposit	DD
97	1	Time Deposits	TD
98	4	Resident Foreign Currency Deposits	RFCD
99	4	Government Sector Borrowing (net)	GSB
100	4	Budgetary Support	BSUP
101	4	Commodity Operations	COPS
102	5	Credit to the Private Sector	CPS
103	4	Credit to Public Sector Enterprises	CPSE
104	5	Net Domestic Assets - SBP	NDASBP
105	5	Net Domestic Assets - Scheduled Banks	NDASCH
106	4	Net Foreign Assets - SBP	NFASBP
107	4	Net Foreign Assets - Scheduled Banks	NFASCH
		Stock Market	
108	4	SBP General Index of Share Prices/KSE All Index	SBPGI
109	4	SBP Sensitive Index of Share Prices/KSE 100 Index	SBPSI
110	4	Market Capitalisation	MCAP
111	1	Turnover	TOV
		Prices	
112	4	Consumer Price Index - Food	CFOOD
113	5	Consumer Price Index - Non-Food	CNONF
114	4	Consumer Price Index - Core	CPIC
115	4	Consumer Price Index - General	CPIG
116	4	World Oil Price	OP
117	4	Wholesale Price Index	WPI
118	4	Consumer Price Index - Year-on-Year Inflation	INF

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