



Easydata-MD: A Monthly Dataset for Macroeconomic Research on Pakistan

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Abstract: This paper introduces the monthly State Bank of Pakistan's EasyData, for conducting empirical macroeconomic analysis and forecasting for Pakistan's economy. For this purpose. We perform a forecasting exercise using the conventional econometric models and the most recent machine-learning algorithms. We find that the machine-learning models outperform the benchmark and regression models based on observed factors. Furthermore, the dataset has a higher ability to predict the external variables, a possible outcome of Pakistan's economy and its persistent balance of payment problem. The focus of policy has been to address this issue.

Keywords: EasyData; factors; forecasting; machine learning; machine-learning; Pakistan.

JEL Classification: C55, F47.

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1. Introduction

This study uses the EasyData (ED) database recently launched by the State Bank of Pakistan (SBP), the central bank of Pakistan, to forecast key macroeconomic indicators for Pakistan's economy. We use the most up-to-date machine-learning (ML) approaches (as of the publication of this article) as well as a factor-based regression model (FM), and compare their forecast performance against the benchmark Ordinary Least Squares (OLS) method. On balance, ML models compete very closely on most forecast horizons and beat the benchmark OLS model for each variable of interest.

Studies have indicated that using machine-learning to forecast key macroeconomic variables such as inflation, output or GDP growth, and key interest rates, has become a recent and recurring trend [see Eickmeier & Ng (2011), Li & Chen (2014), Panagiotelis, et al. (2019), Syed & Lee (2021), Mederios, et al. (2021), among others]. These techniques are generally capable of handling a large amount of data and outperform the commonly used univariate and multivariate econometric models (inclusive of the dynamic factor model, which can handle a large amount of data) (Mederios, et al. (2021)).

Another recent development that has helped macroeconomic forecasting and the use of what is popularly often referred to as "Big Data", along with machine-learning, is the availability of macroeconomic databases from different central banks worldwide. There are limitations to what these economic databases can offer, however: First, they do not provide data on all the variables that may best represent all the sectors/areas of an economy. Second, they do not provide the data in user-friendly Excel or comma-delimited file formats; Third, they do not provide online tools to transform series into year-on-year (YOY)/month-on-month (MOM), for preliminary analysis; Finally, there is neither an easy-to-understand document that comprehensively either defines each variable or a research paper demonstrating the use of the database in economic analysis. Until recently, the Federal Reserve Bank of St. Louis's online database, known as Federal Reserve Economic Data or FRED, was the sole exception to the aforementioned shortcomings.

Since its inception in 1991, FRED has become a very comprehensive resource, providing data on 818,000 US and international time series from 110 sources, as of the time of writing. McCracken & Ng (2016) compiled a macroeconomic database comprising a monthly time series from the FRED (FRED-MD). Since that time, their database has extensively been used for macroeconomic research on the economy of the United States of America (US).

The State Bank of Pakistan (SBP) - the central bank of Pakistan - made EasyData (the macroeconomic database that contains data on more than 8,000 macroeconomic variables for Pakistan's economy) public on June 1, 2022. It offers features similar to FRED; users can not only download data in comma-delimited files, but they can also examine graphs online as well as transform the variables into the desired units (YOY or MOM, or a simple percentage change).

Our study is motivated by McCracken & Ng (2016), and introduces a macroeconomic database for research containing monthly macroeconomic variables for Pakistan's economy. Before we introduce the database we have put together for research on the economy of Pakistan, it is paramount that we highlight our study's contribution to this strand of literature. First, to the best of our knowledge, our paper is the pioneering effort to assemble a publicly available dataset containing the key macroeconomic variables for research on Pakistan's economy. Second, Pakistan is the only developing country whose central bank offers a database with more than 8,000 macroeconomic variables. Third, this paper uses this database to forecast 13 key macroeconomic indicators using the latest machine-learning approaches and conventional econometric models. Fourth, our paper aligns with the current trend in the forecasting literature, where researchers assemble a macroeconomic research database. For example, see Bokun, et al. (2023). Finally, we add to the growing literature on putting econometric models against the latest machine-learning techniques for macroeconomic forecasting, using data from different countries of the world.

2. Material and Methods:

The State Bank of Pakistan (SBP) launched a publicly available macroeconomic database called "EasyData" in June, 2022. This database contains more than 8,000 time series. However, EasyData has yet to explicitly spell out a set of indicators that could represent different sectors of the economy that can be used in research. As a consequence, we strive

to undertake this task and build a macroeconomic database for research, keeping in view problems such as the change in the base year and changes in the items that underlie the formation of the activity index (which poses a real challenge and provides important context as to why our sample is relatively short).

Our database for macroeconomic research is comprised of 41 indicators, with the selection of such supported by the fact that most of these indicators are part of the “selected economic indicators” section of the SBP’s monthly statistical bulletin, save for the Quantum Index of Large-Scale Manufacturing Industries (QIM). We selected QIM as it is the only measure of output available monthly from the Pakistan Bureau of Statistics (PBS) in Pakistan and is part of the ED.

Some important observations must be noted before laying out the forecasting methods used in this paper: First, the data on prices in Pakistan is compiled by the PBS; therefore, maybe due to this reason, the central bank did not publish the spliced consumer price index (CPI) data on ED. Instead, it published the YOY and MOM inflation series based on the CPI indices, available only from 2016:07 in the ED. Second, we use the QIM as a measure of output/GDP or output/GDP growth as almost all studies that have used monthly datasets to forecast inflations, or any other macroeconomic variable in a multivariate setting for Pakistan, have used the same variable to proxy for output/GDP [see Syed & Lee (2021), Hussain, et al. (2018), Hussain & Mahmood (2017) and Hanif & Malik (2015)]. However, the base of this measure was revised from 2005-06 to 2015-16 by the PBS on January 19, 2022. Moreover, 11 more items were added to compute this index on the new base. Therefore, even though the data for this indicator is available on the old base, we could not splice the series to form a more extended time series as the two series (QIM on the new and old base) do not represent or comprise the same items.

Given the information above, our study sample starts from 2016:07 and ends at 2022:05.¹ Following the vast literature on forecasting using a large number of predictors in factor and machine learning models, all the variables are made stationary and standardized to have a mean of zero and a standard deviation of one. The details of the transformations applied to each variable for establishing stationarity are in the appendix. With stationary and standardized variables, our final sample for the forecasting

¹ ED was launched on June 1, 2022. Hence, as soon as it was launched, we started working on this paper; this is why our sample stopped in May 2022.

exercise that remains spans from 2016:09 to 2022:05 (69 observations or time periods).

Out of 41 variables, we forecast 13 macroeconomic indicators important to Pakistan, which is a small open economy.² They are: YOY-CPI Inflation (CI), YOY wholesale price index-based inflation (WI), QIM growth (QG), Worker's Remittances (WR), Real Effective Exchange Rate (REER), Nominal Pakistani Rupee to US Dollar Exchange Rate (E), Total Imports (IMP), Total Exports (EXP), Karachi Stock Exchange 100 Index of the last working day of the month (KSE), Weighted Average Overnight Repo Rate (R), Special Convertible Rupee Account Inflows (SCRA) as a proxy for Foreign Portfolio Investment (FPI), Foreign Direct Investment Inflows (FDI) and Broad Money Supply (M2).

In this study, we forecast 13 macroeconomic variables for Pakistan's economy using the latest machine-learning techniques. We compare their forecast evaluation with the benchmark OLS and commonly used big data econometric model, the FM. We initiate our analysis by using OLS, followed by the FM and sophisticated machine-learning techniques such as the Ridge (Ridge), the LASSO, the Elastic Net (EN), Random Forest (RF), Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), Ensemble 1 containing (ENS1), Ensemble 2 containing (ENS2) and Ensemble 3 containing (ENS3).

Let $x_t = \{x_{i,t}\}_{1 \leq i \leq K}$ 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 standardized to have mean zero and standard deviation one. Now $(x_t)'$ includes all the information available at time t . We define y_t as the target variable which will also be an element of x_t .

$$y_{t+h} = x_t' \hat{\theta}_l, h = 1, 2, \dots, 6 \quad (3.1)$$

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

² One of the significant components of Pakistan's imports is oil. Therefore, some may argue that our dataset should contain oil prices. However, our purpose here is to introduce this database and show that it allows for macroeconomic analysis and forecasting of Pakistan's economy. Hence, we do not add anything from outside the ED database.

The selection of relevant variables for the OLS model was an essential step in our analysis. To select the variables for the OLS model, we find the statistically significant correlations of the variable of interest with the remaining 40 variables in the dataset. Once the significant variables are identified, the variable of interest is regressed on the significantly correlated variables. Results from the OLS model are treated as a benchmark in our analysis.³

2.1 OLS model

We use the OLS model as our first and the benchmark model. We regress each variable of interest on variables that are significantly correlated with it.

The OLS model is given by:

$$Y_t = \mu + \sum_{i=1}^p \theta_i X_t + \varepsilon_t \quad (1)$$

Y_t is a dependent variable, 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. At the same time, p is the number of variables selected through correlation screening.

2.2 The Factor-based Regression Model (FM)

Forecasting variables of interest using a few factors that represent information extracted from a large number of predictors has gained attention over time. We use the Principal Component Analysis (PCA) to extract factors using the complete information set. To select factors, following McCracken & Ng (2016), we first tried the PC_p criteria developed by Bai & Ng (2002). However, the value was below 1, meaning this criterion did not select a single factor from this set of variables. We then looked at the number of statistically significant factors, which in this case was 12. Hence, we use the first 12 factors to forecast each variable of interest.

³ It is important to note that we did not select OLS as a benchmark than the commonly used Autoregressive model of order p [(AR(p)), p selected based on Bayesian information criteria (BIC) Schwarz (1978)], due to their preference. We do this because, in the literature, a similar number of lags of each variable are added to the competing forecasting techniques for a reasonable comparison across models. However, in our case, the estimation sample needs to be longer to add p lags of each regressor in the OLS, FM, and ML models for comparison against the benchmark. Therefore, we do not add lags of the variables in any of the techniques used in our paper.

The regression we run is as follows:

$$Y_t = \mu + \sum_{i=1}^{12} \theta_i F_t + \varepsilon_t \quad (2)$$

Y_t is a dependent variable, F_t is a vector of independent variables at time t , μ is the constant parameter, and ε_t is a stationary, white noise process.

2.3 Ridge Regression:

Hoerl & Kennard (1970) introduced ridge regression, a linear regression model that minimizes the sum of squared residuals with an additional l_2 -norm penalty term, and with the penalty according to the square of the estimated coefficients. The lambda value is crucial to determining the weight assigned to the penalty for coefficients. Ridge regression shrinks the coefficients, but not to zero. However, the coefficients get closer and closer to zero as the value of lambda becomes larger. Ridge regression is given by:

$$\operatorname{argmin}_{\beta} \sum_i (y_i - \beta' x_i)^2 + \lambda \sum_{k=1}^K \beta_k^2 \quad (3)$$

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

2.4 Least Absolute Shrinkage and Selection Operator:

The LASSO technique was introduced by Tibshirani (1996). LASSO, short for Least Absolute Shrinkage Selection Operator, is a regularization model that assigns a penalty to the linear model coefficients using the formula:

$$\operatorname{argmin}_{\beta} \sum_i (y_i - \beta' x_i)^2 + \lambda \sum_{k=1}^K |\beta_k| \quad (4)$$

LASSO, in addition to shrinking the coefficients on the variables, can also push them to zero. Hence, the variables with a coefficient of zero are eliminated. Consequently, the degree of overfitting is reduced within the model. We use 10-fold cross-validation to find the optimal shrinkage parameter λ .

2.5 Elastic Net

Elastic Net was proposed by Zou & Hastie (2005), 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 mathematically is represented as:

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

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

2.6 Neural Networks

It is common knowledge that Neural Networks have been used to forecast/nowcast inflation and other macroeconomic variables for many countries, including Pakistan [see Haider & Hanif (2009) and Hanif et al. (2018)]. In this paper, we use two models based on the concept of neural networks: the Multilayer Perceptron (MLP) and the Long Short-Term Memory (LSTM).⁴

2.7 Random Forest

The well-known ensemble method we apply to our data is the random forest. 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 a well-known non-parametric model, which is an approximation of an unknown nonlinear function with local forecasts that use recursive partitioning of the response variable space (Breiman, 1996).

2.8 Ensemble (nested) models

Thus far, we have only individually applied the conventional and ML models on the dataset. However, it is well-known that combining forecasts from multiple techniques can substantially improve forecast accuracy. In order to find out if that is indeed the case with our indicators of interest, we combined the model forecasts as follows: First, we combined forecasts from the LASSO and EN (ENS1); second, we combined the forecasts from RF, LASSO, and EN (ENS2) and finally a combined forecasts from RF, LASSO, EN, and MLP (ENS3).

⁴ For details on MLP and LSTM, see Hochreiter & Schmidhuber (1997) and Ruck, Rogers, & Kabrisky (1990), respectively.

3. Forecasting Schemes and Evaluation Criterion

We use the fixed rolling window (FRW) and the expanding rolling window (ERW) to forecast our 13 macroeconomic variables of interest. Under the FRW, we keep a fixed training window size of 46 observations and move it 1 step ahead each time estimation is performed. We then forecast the variables iteratively 6 steps ahead at each step until the end of the sample (69th observation). The last estimation cycle ends in November 2021, and the final test set comprises December 2021 to May 2022. Under the ERW, we once again keep the size of the initial training window of 46 observations; however, we do not move the window for re-estimation; instead, we keep expanding the training window by 1 observation and re-estimate the models. At each estimation, 6-step ahead forecasts are generated using the next 6 test set values.

Following the forecasting process detailed above, we get out-of-sample forecasts for each forecast horizon “*h*”, which are used to compare the forecasting performance of different models. For the forecasting accuracy measurements, we consider the root mean squared error (RMSE), the mean absolute error (MAE), and the median absolute deviation (MAD).

4. Results

The recent literature on forecasting uses different layouts to report results. For example, Li & Chen (2014), Panagiotelis, et al. (2019), and Syed & Lee (2021) report the relative accuracy measures. In contrast, Mederios, et al. (2021) report the maximum, minimum, and average accuracy measures across horizons. These studies also report tests of superior predictive ability (SPA), the model confidence set (MCS), and forecasts stability tests (FST).

In Table 1 through Table 13, we report the relative accuracy measures [root mean squared error (RMSE), mean absolute error (MAE), and median absolute deviation (MAD)] for each variable of interest along with the Hansen's SPA test results for each horizon. Before we discuss the interesting aspects that emerged from our forecasting exercise, we summarize the main findings. First, for most variables of interest, each relative accuracy measure shows that one of the competing techniques outperforms the benchmark at each forecast horizon when fixed window rolling forecasts are generated. Second, for the fixed window rolling forecasts, almost all the models perform poorly in forecasting the nominal Pakistani Rupee to US Dollar rate and the YOY CPI inflation.

Second, the overall results are quite promising when an expanding window forecast scheme is used to forecast the variables of interest. In most cases, one of the competing models outperforms the benchmark at each forecast horizon. Although the forecasting performance remains poor for the Pakistani Rupee to US Dollar rate, it is no longer the case for the YOY CPI inflation. All three accuracy measures for the YOY CPI inflation show that the competing models outperform the benchmark at each forecasting horizon. Finally, we find that the Hansen test of superior predictive ability shows that the ridge model's forecasts are superior to that of the benchmark for nearly all the variables. Although the forecasts generated by other models are not superior to the benchmark, we still find that most of these models outperform the benchmark model when relative accuracy measures are considered.

A few interesting findings need to be mentioned at the onset: First, many models beat the benchmark models for almost every external sector variable with statistical significance. This may be attributed to the fact that Pakistan has seldom attained a current account surplus, and most of the policies are directed towards mitigating a balance of payment crisis. Second, for CPI Inflation, although the forecasts are poor for some of the models considered, we still find that the ridge and EN perform quite well in the case of the expanding window rolling scheme. This result hints that adding more information to the model at each step helps the model forecast inflation for the sample period and the variables considered. Finally, except in a few instances, factor-based forecasts are comprehensively beaten by the ML techniques for all the variables and each forecast horizon.

5. Conclusion

This study attempted to forecast the key macroeconomic variables using a newly established database by Pakistan's central bank. As a result of the revision in the base year of some of the key variables of Pakistan's economy, the sample length was quite limited. Furthermore, due to the degrees of freedom problem, time-series models with lags could not be used. However, we framed our analysis in such a way that we used the OLS from the econometrics toolkit and a model based on factors extracted from the dataset.

We find that even the model with 12 factors that summarize the information content of this vast dataset cannot beat the ML models, thus showing the power of these new tools to the economic profession. On

balance, the ML models outperform the benchmark and factor-based models for most variables and most horizons of interest. We would have preferred to include lags in the estimations and keep autoregressive models in competition; however, the data limitation prevented us from doing so. We leave this as an agenda for ourselves and other fellow researchers in the future.

Declaration of competing interest:

The authors declare that they have no conflict of interest.

Table 1

	Panel A						Panel B						Panel C					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	<u>0.72</u>	0.72	0.78	0.86	0.86	0.88	<u>0.72</u>	<u>0.74</u>	<u>0.76</u>	0.84	<u>0.82</u>	0.85	<u>0.79</u>	1.21	1.04	0.97	1.06	0.89
LASSO	0.94	0.79	0.87	0.81	0.85	0.81	0.95	0.83	0.91	0.86	0.84	0.81	0.92	1.11	0.94	1.03	1.08	<u>0.83</u>
EN	0.93	0.79	0.82	0.79	0.82	0.78	0.94	0.82	0.86	0.83	0.78	0.82	1.07	1.17	<u>0.93</u>	1.04	<u>0.82</u>	1.46
RF	0.92	0.76	0.85	0.93	0.95	0.95	1.03	0.90	1.00	0.98	1.06	1.04	1.72	1.47	1.53	1.25	2.12	1.87
MLP	0.88	0.90	1.00	1.00	1.05	1.26	1.03	1.08	1.18	1.14	1.19	1.43	1.87	1.86	2.12	1.46	2.35	2.75
EN1	0.84	<u>0.70</u>	<u>0.74</u>	0.68	0.73	0.69	0.88	0.77	0.81	0.74	0.83	<u>0.78</u>	1.22	1.29	1.07	<u>0.90</u>	1.45	1.31
EN2	0.85	0.71	<u>0.74</u>	0.72	0.76	0.72	0.90	0.78	0.83	0.78	0.83	0.81	1.24	1.20	1.16	0.92	1.54	1.48
EN3	0.83	0.72	0.77	0.75	0.79	0.79	0.91	0.81	0.88	0.83	0.87	0.88	1.32	1.58	1.29	1.06	1.50	1.53
LSTM	0.82	0.74	0.79	<u>0.63</u>	<u>0.68</u>	<u>0.64</u>	0.93	0.84	0.94	<u>0.72</u>	0.85	<u>0.78</u>	1.58	1.32	1.69	1.12	1.68	1.62
FM12	1.20	0.92	0.93	1.17	1.13	1.47	1.10	0.97	0.98	1.15	1.11	1.34	1.12	1.75	1.16	0.94	1.67	1.65
	Panel D						Panel E						Panel F					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	<u>0.79</u>	<u>0.79</u>	0.80	0.83	0.82	0.84	0.79	0.84	0.82	0.84	0.82	0.84	0.80	1.22	0.96	0.89	0.88	0.79
LASSO	0.94	0.85	0.83	0.78	0.77	0.74	1.02	0.94	0.91	0.85	0.84	0.83	1.25	1.23	1.09	1.06	1.26	1.32
EN	0.94	0.85	0.82	0.78	0.70	0.76	0.99	0.94	0.91	0.87	0.78	0.83	0.98	1.18	1.10	1.23	1.14	1.30
RF	0.96	0.81	0.79	0.74	0.71	0.78	1.07	1.02	0.97	0.86	0.83	0.88	0.96	1.56	1.06	1.18	1.21	1.29
MLP	1.02	1.09	1.13	1.09	1.11	1.27	1.21	1.41	1.39	1.29	1.24	1.45	1.67	2.17	1.94	2.01	1.98	2.31
EN1	0.93	0.81	0.79	<u>0.71</u>	0.71	0.68	1.02	0.96	0.93	<u>0.81</u>	0.84	<u>0.79</u>	1.18	1.56	1.07	1.12	1.26	1.22
EN2	0.93	0.81	0.79	<u>0.71</u>	0.71	0.69	1.02	0.96	0.92	<u>0.81</u>	0.82	<u>0.79</u>	1.20	1.48	1.09	1.14	1.30	1.25
EN3	0.90	0.83	0.81	0.75	0.74	0.76	1.02	0.99	0.96	0.87	0.85	0.86	1.18	1.61	1.26	1.18	1.37	1.35
LSTM	0.97	0.86	<u>0.73</u>	0.76	0.68	0.65	1.10	1.06	0.89	0.93	<u>0.77</u>	0.81	1.16	1.81	1.19	1.36	1.07	1.17
FM12	1.35	1.07	0.96	1.09	0.97	1.36	1.20	1.14	1.02	1.10	0.96	1.19	<u>0.79</u>	1.36	0.88	0.92	<u>0.70</u>	0.92

Note: Forecast accuracy for $h = 1-6$. Each entry in Panel A, B, and C shows RMSE, MAE, and MAD, respectively, and these numbers are relative to the naïve benchmark when a fixed rolling window forecast scheme is used to forecast month-on-month QIM growth. Panel D, E, and F show RMSE, MAE, and MAD, respectively, and these numbers are relative to the naïve benchmark when an expanding rolling window forecast scheme is used. All models use a full information set of the independent variables except the OLS and the Ridge models. These two models use variables significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally or better than the benchmark across each column. Every underlined entry shows the minimum RMSE, MAE, or MAD attained by the competing model. Entries in grey indicate that the competing model's forecasts are superior to that of the benchmark at each horizon (across row).

Table 2

	Panel A						Panel B						Panel C					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.91	0.84	0.84	0.90	0.88	0.88	0.92	0.89	0.88	0.92	0.92	0.89	1.33	1.45	1.36	1.33	1.16	0.99
LASSO	1.03	0.94	1.21	1.18	1.18	1.21	1.05	1.02	1.24	1.25	1.26	1.27	1.59	1.55	1.94	1.64	1.19	0.78
EN	1.04	1.00	1.14	1.11	1.18	1.28	1.04	1.13	1.20	1.19	1.22	1.33	1.35	1.57	1.88	1.49	0.95	0.92
RF	0.99	0.87	0.89	0.83	0.79	0.86	0.94	0.91	0.87	0.77	0.76	0.78	1.16	1.23	1.06	0.72	0.65	0.75
MLP	0.99	1.10	1.10	1.28	1.31	1.52	0.98	1.09	1.11	1.30	1.30	1.55	1.05	1.00	1.18	1.67	1.40	1.22
EN1	0.87	0.68	0.76	0.67	0.67	0.65	0.84	0.70	0.74	0.64	0.64	0.58	1.15	1.02	0.85	0.80	0.76	0.52
EN2	0.87	0.67	0.77	0.68	0.69	0.69	0.84	0.68	0.75	0.63	0.67	0.64	1.09	0.91	0.84	0.76	0.70	0.59
EN3	0.85	0.70	0.81	0.75	0.75	0.78	0.85	0.74	0.81	0.76	0.75	0.77	1.12	1.01	1.23	0.93	1.03	0.75
LSTM	1.06	1.02	0.93	0.83	0.96	0.93	1.02	0.95	0.85	0.78	0.94	0.85	1.26	0.83	0.93	0.87	0.94	0.62
FM12	0.84	1.00	1.14	1.10	1.09	1.19	0.84	1.03	1.15	1.12	1.10	1.19	1.24	1.55	1.66	1.69	1.36	1.24
	Panel D						Panel E						Panel F					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.98	0.94	0.94	0.94	0.94	0.94	0.97	0.95	0.94	0.95	0.95	0.94	0.98	0.89	1.00	0.97	0.94	0.90
LASSO	1.05	1.35	1.54	1.53	1.35	1.31	1.03	1.31	1.47	1.54	1.34	1.27	0.87	1.04	1.28	1.55	1.20	1.31
EN	1.22	1.35	1.63	1.54	1.32	1.45	1.26	1.32	1.62	1.54	1.34	1.47	0.89	0.94	1.69	1.45	1.21	1.34
RF	<u>1.08</u>	0.97	1.04	1.01	0.92	0.96	0.96	0.91	0.93	0.89	0.82	0.85	0.73	0.55	0.69	0.51	0.66	0.78
MLP	1.18	1.44	1.39	1.50	1.45	1.82	1.18	1.37	1.31	1.49	1.46	1.82	0.83	0.92	1.09	1.23	1.15	1.14
EN1	0.96	0.88	0.85	0.81	0.73	0.75	0.83	0.77	0.75	0.73	0.65	0.68	0.76	0.43	0.61	0.50	0.62	0.55
EN2	0.95	0.87	0.86	0.82	0.76	0.79	0.82	0.74	0.78	0.75	0.70	0.74	0.73	0.43	0.56	0.58	0.62	0.59
EN3	0.93	0.91	0.93	0.91	0.85	0.90	0.81	0.83	0.90	0.91	0.83	0.86	0.61	0.65	0.74	0.88	0.79	0.73
LSTM	1.20	1.29	1.17	1.17	1.13	1.07	1.16	1.26	1.04	1.07	1.09	1.03	1.00	0.91	0.85	0.83	1.05	0.73
FM12	1.05	1.24	1.35	1.32	1.42	1.67	0.99	1.14	1.22	1.24	1.36	1.62	1.11	1.13	1.52	1.13	1.13	1.16

Note: Forecast accuracy for h = 1–6. Each entry in Panel A, B and C show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when fixed rolling window forecast scheme is used to forecast Karachi Stock Exchange 100 Index. Panel D, E and F show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when expanding rolling window forecast scheme is used. All models use full information set of the independent variables except the OLS and the Ridge models. These two models use variables that are significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally well or better than the benchmark model across each column. Every underlined entry shows the minimum RMSE, MAE or MAD attained by the competing model. Entries in grey indicates that the competing model's forecasts are superior to that of the benchmark at each horizon (across row).

Table 3

	Panel A						Panel B						Panel C					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	1.47	1.15	1.25	1.12	1.06	1.03	1.23	1.15	1.12	1.15	1.16	1.05	1.10	0.88	1.08	<u>0.90</u>	1.66	1.19
LASSO	0.99	0.97	0.98	1.00	1.02	0.98	<u>0.92</u>	<u>0.85</u>	<u>0.90</u>	0.94	0.97	0.94	1.03	<u>0.81</u>	0.91	0.91	1.08	1.02
EN	1.10	1.07	1.06	1.07	1.10	1.07	0.98	0.97	0.97	1.02	1.04	1.04	1.09	1.04	1.09	1.20	1.16	
RF	2.64	2.80	2.60	2.83	2.77	2.44	1.96	2.29	2.06	2.31	2.40	2.03	1.85	1.71	1.42	1.47	1.73	1.05
MLP	6.74	6.11	6.07	6.23	6.29	6.33	6.80	6.23	5.90	6.32	6.41	6.63	8.78	6.38	6.32	6.15	6.57	9.97
EN1	4.58	4.91	4.97	5.12	5.17	4.80	4.33	4.70	4.81	5.29	5.32	5.01	6.63	6.22	6.48	6.97	6.80	6.17
EN2	3.83	4.14	4.13	4.27	4.32	3.96	3.51	3.89	3.90	4.28	4.32	4.01	4.61	4.41	4.48	4.75	4.72	3.91
EN3	3.76	3.78	3.76	3.91	3.95	3.71	3.47	3.55	3.51	3.93	3.90	3.86	4.18	3.95	3.68	4.80	4.66	4.51
LSTM	6.88	6.81	7.62	6.96	7.05	6.61	7.73	7.76	8.74	8.17	8.81	8.11	11.99	11.29	10.54	12.90	12.83	11.07
FM12	2.39	2.54	2.34	2.66	3.08	2.93	2.61	2.77	2.59	3.05	3.27	3.15	3.49	3.70	2.97	3.79	3.90	3.11
	Panel D						Panel E						Panel F					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	1.05	1.06	1.03	1.04	1.01	0.99	1.02	1.08	1.02	0.99	1.05	1.01	1.17	1.26	1.23	1.00	0.93	1.01
LASSO	0.99	0.97	0.97	0.98	1.02	0.95	<u>0.91</u>	<u>0.89</u>	<u>0.89</u>	<u>0.95</u>	0.99	0.92	1.00	0.83	0.76	0.73	0.79	0.70
EN	1.04	1.04	1.02	1.05	1.06	1.00	0.99	0.99	0.96	1.03	1.08	1.00	1.21	1.09	1.10	1.11	1.45	1.03
RF	2.36	2.69	2.71	2.69	2.76	2.60	1.76	2.21	2.13	2.25	2.39	2.18	1.03	1.00	1.23	1.33	1.39	1.07
MLP	7.53	6.90	6.52	6.77	6.76	7.12	7.72	6.93	6.36	7.04	7.07	7.61	9.18	6.01	6.22	7.16	7.34	8.05
EN1	4.96	5.39	5.40	5.52	5.52	5.10	4.72	5.21	5.25	5.76	5.91	5.36	7.00	6.88	7.00	8.15	8.06	5.94
EN2	4.02	4.42	4.42	4.50	4.52	4.18	3.72	4.18	4.18	4.57	4.72	4.27	5.00	4.82	4.85	5.55	5.56	3.76
EN3	3.96	4.06	4.02	4.13	4.16	3.95	3.72	3.88	3.80	4.22	4.31	4.17	4.43	4.44	3.90	5.23	5.26	4.11
LSTM	7.15	7.48	7.44	8.22	8.12	7.37	8.10	8.46	8.60	10.36	10.23	9.06	13.81	11.71	13.19	12.95	14.75	9.46
FM12	2.81	2.87	2.56	2.86	2.95	2.69	3.04	3.18	2.88	3.30	3.44	3.03	4.51	4.21	3.47	4.00	4.18	3.87

Note: Forecast accuracy for $h = 1-6$. Each entry in Panel A, B and C show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when fixed rolling window forecast scheme is used to forecast Money Supply. Panel D, E and F show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when expanding rolling window forecast scheme is used. All models use full information set of the independent variables except the OLS and the Ridge models. These two models use variables that are significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally well or better than the benchmark model across each column. Every underlined entry shows the minimum RMSE, MAE or MAD attained by the competing model. Entries in grey indicates that the competing model's forecasts are superior to that of the benchmark at each horizon (across row).

Table 4

	Panel A							Panel B							Panel C						
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6		h = 1	h = 2	h = 3	h = 4	h = 5	h = 6		h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	
Ridge	0.85	0.93	0.93	0.93	0.97	0.96		0.87	0.93	0.93	0.93	0.95	0.95		0.75	0.86	0.86	1.04	1.06	0.99	
LASSO	0.81	1.11	1.05	1.03	1.28	1.12		0.85	1.10	0.98	0.94	1.06	1.01		0.73	0.98	1.00	0.85	0.76	0.71	
EN	0.81	1.11	1.05	1.03	1.28	1.12		0.85	1.10	0.98	0.94	1.06	1.01		0.73	0.98	1.00	0.85	0.76	0.71	
RF	0.62	0.96	0.95	0.90	1.10	0.97		0.73	0.98	0.95	0.85	0.91	0.86		0.87	1.12	0.93	0.94	0.83	0.67	
MLP	1.03	0.94	0.80	0.80	1.17	0.99		1.06	0.97	0.83	0.83	0.98	0.82		0.94	0.96	0.74	0.72	0.60	0.67	
EN1	0.80	1.10	1.04	1.03	1.28	1.12		0.84	1.09	0.97	0.94	1.06	1.01		0.72	0.99	1.01	0.86	0.75	0.70	
EN2	0.75	1.06	1.02	1.00	1.25	1.09		0.80	1.05	0.94	0.89	1.03	0.98		0.79	0.93	1.01	0.85	0.75	0.66	
EN3	0.73	0.98	0.92	0.90	1.19	1.03		0.79	0.99	0.87	0.85	0.99	0.91		0.69	0.85	0.78	0.70	0.84	0.77	
LSTM	0.75	1.02	1.06	1.02	1.22	1.13		0.81	0.98	1.04	0.88	1.05	1.03		0.79	0.84	0.95	0.65	0.78	0.69	
FM12	1.45	1.11	1.15	1.18	1.15	1.27		1.37	1.11	1.17	1.26	1.22	1.27		0.97	0.69	0.96	0.80	1.09	1.08	
	Panel D							Panel E							Panel F						
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6		h = 1	h = 2	h = 3	h = 4	h = 5	h = 6		h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	
Ridge	0.90	0.97	0.95	0.95	0.98	0.97		0.91	0.96	0.94	0.94	0.96	0.95		1.03	1.09	0.94	1.13	1.05	1.00	
LASSO	0.94	1.19	1.08	1.05	1.28	1.12		0.94	1.18	1.00	0.96	1.08	1.03		1.01	1.18	1.11	0.92	0.76	0.72	
EN	0.94	1.19	1.08	1.05	1.28	1.12		0.94	1.18	1.00	0.96	1.08	1.03		1.01	1.18	1.11	0.92	0.76	0.72	
RF	0.69	0.91	0.91	0.87	1.00	0.93		0.77	0.92	0.90	0.91	0.93	0.90		0.99	0.81	1.01	1.07	0.81	0.76	
MLP	1.17	1.01	0.81	0.86	1.19	0.99		1.13	1.04	0.80	0.87	1.04	0.88		1.30	1.21	0.70	0.86	0.73	0.69	
EN1	0.93	1.19	1.07	1.05	1.28	1.12		0.93	1.18	0.99	0.96	1.08	1.02		0.99	1.19	1.13	0.93	0.76	0.72	
EN2	0.86	1.12	1.03	1.00	1.23	1.08		0.86	1.10	0.94	0.92	1.05	1.00		1.13	1.09	1.19	0.95	0.75	0.69	
EN3	0.84	1.04	0.94	0.91	1.18	1.02		0.86	1.04	0.89	0.89	1.02	0.94		1.08	1.04	0.90	0.82	0.82	0.79	
LSTM	0.98	1.20	1.11	1.08	1.27	1.06		1.03	1.28	1.03	1.00	1.06	0.93		1.02	1.16	1.14	1.02	0.80	0.66	
FM12	1.60	1.16	1.17	1.18	1.14	1.26		1.46	1.21	1.21	1.26	1.22	1.28		1.48	1.11	1.21	0.95	1.06	1.15	

Forecast accuracy for h = 1–6. Each entry in Panel A, B and C show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when fixed rolling window forecast scheme is used to forecast Weighted Average Overnight Repurchase Rate. Panel D, E and F show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when expanding rolling window forecast scheme is used. All models use full information set of the independent variables except the OLS and the Ridge models. These two models use variables that are significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally well or better than the benchmark model across each column. Every underlined entry shows the minimum RMSE, MAE or MAD attained by the competing model. Entries in grey indicates that the competing model's forecasts are superior to that of the benchmark at each horizon (across row).

Table 5

	Panel A						Panel B						Panel C					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	1.04	1.03	1.03	1.02	1.01	0.98	1.12	1.08	1.09	1.09	1.06	0.97	0.62	0.78	0.87	0.83	0.76	0.83
LASSO	1.07	1.10	1.17	1.22	1.19	1.12	1.14	1.17	1.27	1.36	1.24	1.18	0.97	1.65	1.56	1.10	1.38	0.91
EN	1.08	1.15	1.18	1.17	1.10	1.10	1.15	1.24	1.30	1.29	1.15	1.13	0.96	1.11	1.49	1.22	1.26	1.15
RF	0.93	0.89	0.87	0.91	1.03	0.96	0.96	0.99	0.94	0.99	1.12	1.03	0.48	0.62	1.01	1.07	0.95	0.75
MLP	1.14	1.26	1.28	1.29	1.20	1.27	1.26	1.44	1.45	1.46	1.35	1.39	0.42	0.74	1.04	1.28	0.64	0.70
EN1	1.18	1.16	1.18	1.17	1.15	1.07	1.34	1.32	1.36	1.35	1.32	1.21	0.72	0.88	0.89	1.03	0.78	0.56
EN2	1.10	1.09	1.11	1.11	1.10	1.04	1.24	1.24	1.27	1.29	1.27	1.15	0.53	0.83	0.68	0.72	0.87	0.58
EN3	1.06	1.09	1.11	1.12	1.09	1.05	1.19	1.23	1.26	1.29	1.24	1.16	0.52	0.79	0.84	0.87	0.70	0.49
LSTM	1.39	1.30	1.35	1.28	1.22	1.19	1.57	1.49	1.54	1.42	1.36	1.28	0.53	0.74	1.07	1.64	0.97	0.87
FM12	0.95	0.95	0.96	0.97	0.95	0.98	1.01	1.03	1.05	1.07	1.05	1.05	0.54	0.73	0.86	0.98	0.99	0.55
	Panel D						Panel E						Panel F					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	1.03	1.01	1.02	1.01	1.03	1.02	1.04	1.03	1.04	1.02	1.04	1.03	0.89	0.74	1.08	1.36	0.94	0.87
LASSO	1.11	1.14	1.24	1.19	1.27	1.26	1.15	1.20	1.26	1.27	1.33	1.34	1.12	1.66	1.52	1.71	1.39	1.51
EN	1.10	1.13	1.23	1.18	1.23	1.25	1.13	1.19	1.25	1.25	1.26	1.31	1.16	1.67	1.57	1.70	1.14	1.26
RF	0.96	0.92	0.93	0.99	1.09	1.05	0.97	0.98	1.00	1.06	1.15	1.12	0.77	0.87	1.02	1.38	1.27	1.15
MLP	1.21	1.35	1.38	1.44	1.35	1.39	1.29	1.48	1.50	1.55	1.45	1.48	0.83	1.14	1.53	2.28	1.35	1.47
EN1	1.20	1.17	1.20	1.19	1.24	1.21	1.31	1.29	1.33	1.33	1.37	1.35	1.09	1.10	1.62	1.59	1.12	0.99
EN2	1.13	1.11	1.14	1.14	1.20	1.18	1.23	1.22	1.26	1.27	1.33	1.31	0.87	0.89	1.30	1.45	1.11	1.01
EN3	1.09	1.11	1.16	1.17	1.21	1.19	1.19	1.23	1.27	1.30	1.33	1.32	0.92	0.92	1.25	1.19	1.06	0.90
LSTM	1.42	1.36	1.42	1.38	1.33	1.28	1.55	1.52	1.57	1.51	1.47	1.37	0.67	0.59	0.83	1.66	1.08	1.02
FM12	1.04	1.07	1.08	1.08	1.04	1.08	1.07	1.12	1.13	1.14	1.07	1.13	0.88	1.06	1.38	1.52	1.29	0.95

Forecast accuracy for $h = 1-6$. Each entry in Panel A, B and C show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when fixed rolling window forecast scheme is used to forecast Workers' Remittances. Panel D, E and F show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when expanding rolling window forecast scheme is used. All models use full information set of the independent variables except the OLS and the Ridge models. These two models use variables that are significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally well or better than the benchmark model across each column. Every underlined entry shows the minimum RMSE, MAE or MAD attained by the competing model. Entries in grey indicates that the competing model's forecasts are superior to that of the benchmark at each horizon (across row).

Table 6

	Panel A						Panel B						Panel C					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.90	0.97	0.85	1.02	0.95	0.95	0.91	1.03	0.90	1.04	0.96	1.00	1.03	0.86	0.85	0.99	1.00	0.95
LASSO	0.87	0.96	0.88	0.98	1.01	0.96	0.86	0.99	0.88	0.97	1.01	1.00	0.82	0.98	0.90	0.92	0.86	0.99
EN	0.86	0.92	0.82	0.95	0.94	0.88	0.87	0.95	0.83	0.95	0.91	0.91	0.78	0.94	0.86	0.82	0.69	0.87
RF	0.99	1.13	1.06	1.13	1.12	1.04	0.94	1.11	1.05	1.09	1.05	1.03	1.08	0.91	0.94	1.10	1.11	1.40
MLP	1.34	1.46	1.33	1.43	1.25	1.43	1.26	1.46	1.30	1.34	1.31	1.54	1.19	1.07	0.87	0.97	0.85	1.14
EN1	1.51	1.65	1.52	1.65	1.54	1.48	1.48	1.63	1.50	1.60	1.50	1.49	1.64	1.70	1.57	1.91	1.70	1.94
EN2	1.32	1.44	1.32	1.44	1.33	1.28	1.30	1.44	1.30	1.39	1.30	1.30	1.37	1.48	1.47	1.74	1.41	1.47
EN3	1.12	1.25	1.15	1.23	1.09	1.05	1.07	1.20	1.08	1.14	1.05	1.03	1.14	1.15	1.17	1.21	1.12	1.17
LSTM	1.92	1.75	1.74	1.88	1.70	1.57	1.97	1.70	1.67	1.89	1.71	1.53	0.78	0.93	0.96	0.91	1.27	1.60
FM12	0.94	0.97	0.86	1.05	1.03	1.06	0.93	0.95	0.81	1.02	1.05	1.11	0.90	0.75	0.61	1.01	1.08	1.44
	Panel D						Panel E						Panel F					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.94	0.97	0.93	1.00	0.92	0.93	0.94	1.04	0.97	1.02	0.93	0.96	0.97	0.90	0.89	1.09	0.95	0.90
LASSO	0.85	0.92	0.92	0.99	1.03	0.93	0.85	0.96	0.92	1.03	1.03	0.98	0.74	0.96	0.96	0.92	0.62	0.87
EN	0.89	0.90	0.84	0.95	0.97	0.86	0.91	0.96	0.85	1.00	1.00	0.86	0.74	0.96	0.92	0.98	0.73	0.69
RF	1.00	1.08	1.07	1.15	1.14	1.01	1.00	1.13	1.12	1.18	1.16	1.05	1.07	1.07	1.07	1.34	1.19	1.39
MLP	1.42	1.51	1.41	1.47	1.28	1.51	1.37	1.51	1.39	1.44	1.35	1.57	1.32	1.08	0.83	1.28	1.24	1.50
EN1	1.54	1.64	1.58	1.66	1.59	1.46	1.52	1.66	1.57	1.66	1.60	1.49	1.71	1.75	1.63	1.99	1.72	2.05
EN2	1.33	1.42	1.37	1.44	1.38	1.26	1.34	1.45	1.36	1.44	1.39	1.30	1.38	1.57	1.52	1.83	1.47	1.65
EN3	1.13	1.22	1.19	1.23	1.13	1.02	1.11	1.21	1.14	1.19	1.12	1.02	1.13	1.13	1.22	1.36	1.16	1.09
LSTM	1.75	1.94	1.61	1.82	1.83	1.73	1.67	1.84	1.58	1.80	1.82	1.76	1.28	1.03	0.92	1.37	1.46	1.35
FM12	0.98	0.99	0.93	1.06	1.05	1.02	0.94	0.95	0.86	1.02	1.03	1.02	1.09	0.76	0.68	0.91	0.83	1.04

Forecast accuracy for h = 1–6. Each entry in Panel A, B and C show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when fixed rolling window forecast scheme is used to forecast Real Effective Exchange Rate. Panel D, E and F show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when expanding rolling window forecast scheme is used. All models use full information set of the independent variables except the OLS and the Ridge models. These two models use variables that are significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally well or better than the benchmark model across each column. Every underlined entry shows the minimum RMSE, MAE or MAD attained by the competing model. Entries in grey indicates that the competing model’s forecasts are superior to that of the benchmark at each horizon (across row).

Table 7

	Panel A						Panel B						Panel C					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	1.03	1.10	1.03	1.08	1.09	1.17	1.03	1.17	1.03	1.09	1.12	1.18	1.03	1.50	0.82	0.95	0.64	0.75
LASSO	1.10	1.06	0.99	0.96	0.97	1.42	1.16	1.11	1.03	1.07	1.06	1.49	1.26	1.29	0.87	1.00	0.98	1.71
EN	1.14	1.13	1.07	1.04	1.08	1.52	1.24	1.25	1.19	1.19	1.25	1.69	1.44	1.53	1.28	1.16	1.25	1.82
RF	1.66	1.56	1.40	1.26	1.30	1.66	1.80	1.62	1.48	1.30	1.30	1.74	1.61	1.58	0.99	0.58	0.82	1.07
MLP	1.78	1.70	1.68	1.74	1.90	2.52	1.87	1.75	1.75	1.87	2.12	2.81	1.38	1.24	0.94	1.25	1.23	2.02
EN1	1.83	1.77	1.74	1.67	1.68	2.18	2.05	2.03	2.02	1.95	1.99	2.51	3.02	2.86	2.42	2.25	2.45	2.61
EN2	1.60	1.56	1.51	1.44	1.45	1.90	1.82	1.78	1.73	1.67	1.71	2.16	2.41	2.35	2.10	1.87	1.66	2.00
EN3	1.46	1.43	1.39	1.35	1.37	1.82	1.66	1.62	1.56	1.56	1.58	2.01	2.07	1.89	1.86	1.76	1.40	2.31
LSTM	2.46	2.35	2.18	1.93	2.29	2.72	2.73	2.63	2.50	1.93	2.52	2.91	3.69	2.68	1.88	1.29	3.15	2.89
FM12	1.91	1.78	1.62	1.60	1.63	1.87	1.93	1.81	1.67	1.71	1.63	1.96	1.83	1.91	1.73	1.41	1.36	2.17
	Panel D						Panel E						Panel F					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	1.10	1.13	1.12	1.11	1.12	1.30	1.12	1.18	1.17	1.14	1.14	1.32	1.13	1.26	1.26	0.93	1.19	0.93
LASSO	1.17	1.14	1.08	1.09	1.16	1.68	1.34	1.27	1.19	1.24	1.37	1.75	1.42	1.46	1.26	1.15	1.91	1.92
EN	1.21	1.21	1.18	1.21	1.28	1.79	1.42	1.41	1.38	1.43	1.58	1.96	1.74	1.77	1.35	1.84	2.35	2.16
RF	1.73	1.63	1.51	1.46	1.51	1.84	1.91	1.73	1.57	1.43	1.49	1.83	2.00	1.59	1.38	0.93	1.04	1.04
MLP	1.77	1.71	1.79	1.85	2.02	2.71	1.85	1.76	1.86	2.06	2.35	2.95	0.70	1.08	1.10	1.45	1.69	2.41
EN1	1.84	1.82	1.88	1.84	1.87	2.38	2.12	2.13	2.21	2.16	2.30	2.71	2.87	2.82	2.58	2.91	3.70	2.89
EN2	1.62	1.60	1.64	1.60	1.62	2.10	1.90	1.88	1.91	1.89	2.00	2.38	2.31	2.40	2.25	2.42	2.60	2.30
EN3	1.49	1.47	1.49	1.50	1.52	2.03	1.74	1.71	1.74	1.77	1.86	2.25	2.08	2.11	1.99	2.19	2.18	2.68
LSTM	2.58	2.18	2.87	2.66	2.89	3.00	2.92	2.54	2.85	2.96	3.09	3.28	2.94	1.75	2.11	2.14	2.92	3.84
FM12	1.86	1.75	1.65	1.62	1.68	1.89	1.93	1.79	1.72	1.77	1.83	2.06	2.15	1.94	1.62	1.60	2.04	2.20

Forecast accuracy for $h = 1-6$. Each entry in Panel A, B and C show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when fixed rolling window forecast scheme is used to forecast Pakistani Rupee to US Dollar Nominal Exchange Rate. Panel D, E and F show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when expanding rolling window forecast scheme is used. All models use full information set of the independent variables except the OLS and the Ridge models. These two models use variables that are significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally well or better than the benchmark model across each column. Every underlined entry shows the minimum RMSE, MAE or MAD attained by the competing model. Entries in grey indicates that the competing model's forecasts are superior to that of the benchmark at each horizon (across row).

Table 8

	Panel A						Panel B						Panel C					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.91	0.87	0.82	0.76	0.87	0.81	0.90	0.84	0.81	0.77	0.83	0.80	0.77	0.79	0.91	1.09	0.96	0.91
LASSO	0.97	0.96	0.87	0.81	0.88	0.81	0.99	0.92	0.87	0.83	0.86	0.78	1.07	0.81	0.85	1.36	1.00	0.95
EN	0.97	0.95	0.87	0.81	0.88	0.81	0.99	0.92	0.87	0.83	0.86	0.78	1.09	0.81	0.87	1.35	1.00	0.95
RF	1.11	1.02	0.91	0.86	0.90	0.91	1.18	0.98	0.91	0.87	0.91	0.91	1.34	0.76	0.67	0.98	0.74	0.77
MLP	1.35	1.20	1.02	0.92	1.01	0.98	1.61	1.22	1.05	0.97	1.03	0.98	1.80	0.96	1.01	1.35	1.17	1.42
EN1	0.97	0.94	0.85	0.78	0.85	0.77	1.04	0.95	0.88	0.82	0.84	0.75	1.16	0.91	0.88	1.30	1.07	1.03
EN2	0.98	0.95	0.85	0.79	0.85	0.79	1.03	0.94	0.87	0.82	0.84	0.77	1.12	0.88	0.87	1.28	1.02	0.92
EN3	0.94	0.90	0.81	0.74	0.82	0.75	0.97	0.86	0.80	0.74	0.79	0.72	1.06	0.79	0.78	0.94	0.74	0.62
LSTM	1.01	1.00	1.05	0.82	0.93	0.86	1.09	1.00	1.04	0.86	0.91	0.80	1.23	0.96	1.12	1.12	1.07	0.91
FM12	1.00	0.94	0.88	0.82	0.98	0.92	1.08	0.88	0.82	0.80	0.92	0.85	1.03	0.54	0.48	0.81	0.97	1.09
	Panel D						Panel E						Panel F					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	1.02	0.93	0.88	0.84	0.85	0.85	1.08	0.97	0.88	0.84	0.83	0.84	1.52	1.02	0.81	0.81	0.91	0.91
LASSO	1.12	1.05	0.95	0.89	0.86	0.89	1.17	1.07	0.98	0.92	0.86	0.89	1.71	1.19	0.80	1.02	1.17	0.96
EN	1.11	1.04	0.94	0.89	0.86	0.88	1.16	1.06	0.97	0.91	0.86	0.88	1.70	1.20	0.80	1.04	1.15	0.99
RF	1.21	1.11	0.97	0.95	0.97	0.96	1.25	1.12	0.95	0.94	0.95	0.91	1.50	1.00	0.69	0.93	1.07	1.02
MLP	1.53	1.27	0.98	0.96	0.94	1.06	1.87	1.37	1.02	0.99	0.94	1.00	2.48	1.66	0.70	1.11	1.03	1.07
EN1	1.08	1.00	0.89	0.85	0.82	0.83	1.16	1.06	0.93	0.88	0.83	0.83	1.64	1.22	0.79	1.07	1.16	1.02
EN2	1.09	1.01	0.90	0.86	0.84	0.85	1.14	1.04	0.93	0.88	0.85	0.84	1.73	1.25	0.73	1.06	1.13	1.01
EN3	1.06	0.96	0.84	0.80	0.80	0.79	1.09	0.97	0.84	0.80	0.79	0.76	1.28	0.95	0.71	0.73	0.75	0.68
LSTM	1.20	1.14	1.02	0.99	1.06	0.99	1.22	1.17	1.03	1.03	1.05	0.97	1.89	1.15	0.96	1.08	1.15	0.85
FM12	1.19	1.03	0.92	0.90	0.93	0.97	1.21	0.99	0.87	0.87	0.91	0.93	1.53	0.94	0.65	0.87	0.97	0.97

Forecast accuracy for h = 1–6. Each entry in Panel A, B and C show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when fixed rolling window forecast scheme is used to forecast Foreign Direct Investment. Panel D, E and F show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when expanding rolling window forecast scheme is used. All models use full information set of the independent variables except the OLS and the Ridge models. These two models use variables that are significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally well or better than the benchmark model across each column. Every underlined entry shows the minimum RMSE, MAE or MAD attained by the competing model. Entries in grey indicates that the competing model’s forecasts are superior to that of the benchmark at each horizon (across row).

Table 9

	Panel A						Panel B						Panel C					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.96	0.93	0.89	0.90	0.91	0.70	0.99	0.97	0.92	0.93	0.92	0.75	1.11	1.14	1.08	1.08	1.05	0.80
LASSO	0.86	0.93	0.82	0.85	0.86	0.63	1.02	1.05	0.99	1.00	0.98	0.73	1.11	1.18	1.51	1.00	1.07	0.82
EN	0.86	0.92	0.82	0.85	0.85	0.61	1.01	1.04	0.98	0.99	0.97	0.70	1.11	1.19	1.47	1.00	1.09	0.74
RF	0.94	0.90	0.87	0.90	0.83	0.74	1.00	0.91	0.90	0.89	0.79	0.74	0.90	0.93	0.90	0.71	0.75	0.53
MLP	1.05	0.97	0.94	0.95	0.93	1.07	1.20	1.11	1.06	1.04	1.00	1.07	1.49	1.28	1.34	1.12	1.03	0.86
EN1	0.82	0.87	0.81	0.83	0.82	0.64	0.97	1.00	0.96	0.94	0.91	0.76	1.11	1.20	1.33	1.08	1.00	0.90
EN2	0.83	0.87	0.81	0.83	0.81	0.64	0.96	0.97	0.92	0.92	0.89	0.74	1.08	1.11	1.26	0.99	0.87	0.77
EN3	0.86	0.86	0.80	0.82	0.81	0.67	1.00	0.96	0.91	0.89	0.87	0.74	1.06	0.95	1.07	0.93	0.82	0.68
LSTM	0.89	0.92	0.88	0.92	0.85	0.69	0.98	0.95	0.93	0.96	0.88	0.74	1.00	0.90	0.62	0.89	0.97	0.85
FM12	1.24	1.00	1.03	1.09	1.07	0.81	1.18	1.05	1.15	1.22	1.16	0.90	1.31	1.46	1.51	1.28	1.35	1.08
	Panel D						Panel E						Panel F					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.97	0.96	0.92	0.92	0.93	0.75	0.99	0.99	0.95	0.95	0.94	0.78	1.31	1.33	1.19	1.07	0.98	0.76
LASSO	0.88	0.89	0.86	0.85	0.83	0.76	1.00	1.00	1.02	0.98	0.92	0.85	1.44	1.45	1.44	1.11	1.03	0.96
EN	0.88	0.90	0.86	0.85	0.84	0.76	0.99	1.00	1.01	0.98	0.93	0.85	1.41	1.44	1.44	1.11	1.03	0.96
RF	0.94	0.97	0.96	0.95	0.86	0.79	0.91	0.94	0.99	0.93	0.84	0.79	1.16	1.04	1.19	0.74	0.63	0.68
MLP	1.09	1.03	1.01	0.95	0.97	1.25	1.22	1.15	1.13	1.01	1.03	1.16	2.19	1.55	1.44	1.10	1.11	0.90
EN1	0.84	0.90	0.86	0.85	0.84	0.76	0.97	1.00	1.01	0.97	0.93	0.85	1.42	1.44	1.43	1.10	1.04	0.94
EN2	0.84	0.89	0.86	0.85	0.83	0.76	0.94	0.96	0.98	0.95	0.90	0.83	1.36	1.37	1.41	0.99	0.91	0.87
EN3	0.88	0.88	0.85	0.83	0.83	0.81	0.97	0.95	0.95	0.91	0.88	0.84	1.42	1.17	1.21	0.90	0.78	0.68
LSTM	1.03	1.04	0.95	0.87	0.87	0.84	1.11	1.10	1.05	0.92	0.86	0.88	2.06	1.49	1.44	1.18	0.86	1.05
FM12	1.27	1.03	1.03	1.02	1.06	0.86	1.22	1.07	1.07	1.04	1.06	0.89	1.61	1.79	1.49	1.00	0.99	0.65

Forecast accuracy for $h = 1-6$. Each entry in Panel A, B and C show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when fixed rolling window forecast scheme is used to forecast Foreign Portfolio Investment (through Special Convertible Rupee Account). Panel D, E and F show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when expanding rolling window forecast scheme is used. All models use full information set of the independent variables except the OLS and the Ridge models. These two models use variables that are significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally well or better than the benchmark model across each column. Every underlined entry shows the minimum RMSE, MAE or MAD attained by the competing model. Entries in grey indicates that the competing model's forecasts are superior to that of the benchmark at each horizon (across row).

Table 10

	Panel A						Panel B						Panel C					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.88	0.86	0.83	0.80	0.79	0.76	0.88	0.84	0.82	0.77	0.75	0.72	0.84	0.98	0.88	1.13	1.04	0.83
LASSO	0.82	0.71	0.72	0.70	0.64	0.62	0.73	0.67	0.73	0.72	0.65	0.58	0.99	1.03	0.94	1.27	1.11	0.91
EN	0.82	0.70	0.72	0.71	0.65	0.62	0.74	0.67	0.73	0.72	0.66	0.58	0.98	0.94	0.93	1.37	1.13	0.84
RF	0.87	0.72	0.78	0.74	0.66	0.62	0.89	0.73	0.81	0.79	0.70	0.62	1.13	0.93	1.04	1.31	1.10	0.91
MLP	1.12	0.92	0.86	0.99	0.93	0.99	1.04	0.86	0.80	0.90	0.82	0.86	1.03	1.13	0.76	1.39	1.06	1.09
EN1	0.88	0.77	0.77	0.75	0.71	0.65	0.86	0.73	0.76	0.73	0.70	0.59	0.92	1.10	0.97	1.21	1.01	0.82
EN2	0.86	0.74	0.76	0.74	0.69	0.64	0.84	0.72	0.75	0.73	0.69	0.59	0.88	0.94	0.94	1.24	1.02	0.79
EN3	0.87	0.74	0.75	0.75	0.70	0.66	0.86	0.73	0.75	0.74	0.69	0.61	0.94	0.85	0.91	1.11	0.97	0.78
LSTM	0.98	0.90	0.77	0.70	0.72	0.74	0.96	0.88	0.75	0.69	0.67	0.70	1.01	1.12	0.84	1.05	0.68	1.05
FM12	0.85	0.82	0.81	0.81	0.79	0.85	0.83	0.80	0.80	0.81	0.81	0.82	0.68	0.56	0.59	0.83	0.69	0.82
	Panel D						Panel E						Panel F					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	1.00	0.99	1.00	0.99	1.03	1.03	0.97	0.96	0.98	0.96	0.99	0.99	0.93	0.83	0.89	0.89	0.83	0.87
LASSO	1.09	1.10	1.09	1.09	1.10	1.10	1.06	1.04	1.06	1.05	1.05	1.03	0.98	0.82	0.84	0.91	0.79	0.93
EN	1.09	1.09	1.08	1.11	1.09	1.02	1.06	1.01	1.05	1.06	1.01	0.92	0.84	0.82	0.86	0.93	0.82	0.80
RF	1.07	1.07	1.08	1.11	1.08	1.10	1.09	1.07	1.09	1.10	1.07	1.09	0.87	0.79	0.82	1.00	0.90	1.09
MLP	1.40	1.34	1.26	1.50	1.44	1.67	1.35	1.25	1.17	1.29	1.21	1.42	1.11	1.03	0.79	1.11	0.80	0.89
EN1	1.14	1.18	1.16	1.16	1.16	1.13	1.13	1.09	1.11	1.08	1.08	1.00	1.05	0.99	0.91	1.06	0.94	0.96
EN2	1.10	1.13	1.11	1.13	1.12	1.09	1.10	1.05	1.08	1.06	1.05	0.99	1.00	0.95	0.92	0.95	0.84	0.88
EN3	1.12	1.12	1.09	1.15	1.13	1.13	1.11	1.06	1.06	1.08	1.05	1.02	0.90	0.83	0.83	0.88	0.73	0.74
LSTM	1.25	1.34	1.24	1.21	1.19	1.32	1.18	1.21	1.18	1.10	1.10	1.18	0.83	0.89	0.78	0.76	0.68	0.93
FM12	1.05	1.11	1.07	1.00	0.95	1.12	0.95	0.99	0.96	0.87	0.81	0.99	0.60	0.77	0.47	0.62	0.52	0.74

Forecast accuracy for h = 1–6. Each entry in Panel A, B and C show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when fixed rolling window forecast scheme is used to forecast Imports. Panel D, E and F show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when expanding rolling window forecast scheme is used. All models use full information set of the independent variables except the OLS and the Ridge models. These two models use variables that are significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally well or better than the benchmark model across each column. Every underlined entry shows the minimum RMSE, MAE or MAD attained by the competing model. Entries in grey indicates that the competing model’s forecasts are superior to that of the benchmark at each horizon (across row).

Table 11

	Panel A						Panel B						Panel C					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.88	0.86	0.83	0.80	0.79	0.76	0.88	0.84	0.82	0.77	0.75	0.72	0.84	0.98	0.88	1.13	1.04	0.83
LASSO	0.80	0.71	0.66	0.76	0.69	0.91	0.81	0.73	0.67	0.70	0.71	0.79	0.75	0.87	0.57	0.86	1.09	0.78
EN	0.80	0.73	0.66	0.76	0.69	0.93	0.81	0.74	0.69	0.72	0.69	0.82	0.70	0.90	0.62	0.80	1.12	0.88
RF	0.90	0.75	0.72	0.60	0.60	0.63	0.91	0.77	0.77	0.62	0.63	0.61	0.97	1.23	0.98	0.95	0.98	0.98
MLP	0.84	0.81	0.73	0.62	0.64	0.67	0.83	0.81	0.74	0.64	0.66	0.66	0.78	1.04	0.95	0.94	0.96	1.06
EN1	0.86	0.77	0.68	0.61	0.56	0.63	0.84	0.76	0.69	0.60	0.59	0.60	1.01	1.17	0.97	1.20	0.91	1.03
EN2	0.85	0.75	0.67	0.61	0.56	0.63	0.85	0.75	0.70	0.61	0.59	0.60	0.93	1.07	0.88	1.15	0.89	0.93
EN3	0.80	0.73	0.66	0.60	0.56	0.65	0.80	0.73	0.69	0.61	0.59	0.62	0.88	1.12	0.79	0.99	1.05	0.86
LSTM	0.77	0.82	0.77	0.67	0.60	0.67	0.74	0.79	0.74	0.62	0.57	0.57	0.71	1.17	0.73	0.70	0.68	0.59
FM12	0.85	0.82	0.81	0.81	0.79	0.85	0.83	0.80	0.80	0.81	0.81	0.82	0.68	0.56	0.59	0.83	0.69	0.82
	Panel D						Panel E						Panel F					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.93	0.90	0.89	0.85	0.84	0.79	0.92	0.87	0.86	0.81	0.80	0.75	0.89	0.92	0.99	1.04	1.09	1.02
LASSO	0.81	0.76	0.73	0.66	0.70	0.71	0.82	0.77	0.77	0.65	0.72	0.68	0.60	0.95	0.80	0.76	0.97	0.98
EN	0.81	0.78	0.77	0.71	0.72	0.75	0.81	0.78	0.79	0.70	0.74	0.72	0.79	0.87	0.92	0.78	0.88	1.01
RF	0.93	0.82	0.78	0.69	0.66	0.69	0.94	0.83	0.80	0.69	0.71	0.69	0.88	1.05	0.95	0.92	1.26	1.27
MLP	0.92	0.86	0.79	0.74	0.78	0.77	0.93	0.87	0.79	0.74	0.80	0.76	0.93	1.05	0.97	1.04	1.27	1.29
EN1	0.91	0.84	0.78	0.63	0.62	0.64	0.89	0.83	0.77	0.61	0.63	0.60	0.96	1.16	1.07	1.12	1.15	1.05
EN2	0.89	0.82	0.76	0.63	0.62	0.65	0.89	0.82	0.77	0.63	0.65	0.62	0.88	1.00	0.95	1.04	1.07	0.96
EN3	0.84	0.79	0.74	0.63	0.63	0.65	0.84	0.79	0.76	0.64	0.67	0.65	0.85	1.06	0.88	0.92	1.18	1.19
LSTM	0.87	0.87	0.77	0.74	0.71	0.74	0.81	0.85	0.72	0.66	0.64	0.63	0.81	0.94	0.76	0.69	0.78	0.76
FM12	0.86	0.82	0.82	0.81	0.81	0.85	0.87	0.81	0.79	0.79	0.83	0.81	0.63	0.64	0.67	0.84	0.77	1.12

Forecast accuracy for $h = 1-6$. Each entry in Panel A, B and C show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when fixed rolling window forecast scheme is used to forecast Exports. Panel D, E and F show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when expanding rolling window forecast scheme is used. All models use full information set of the independent variables except the OLS and the Ridge models. These two models use variables that are significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally well or better than the benchmark model across each column. Every underlined entry shows the minimum RMSE, MAE or MAD attained by the competing model. Entries in grey indicates that the competing model's forecasts are superior to that of the benchmark at each horizon (across row).

Table 12

	Panel A						Panel B						Panel C					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	1.13	1.15	1.17	1.12	1.13	1.14	1.14	1.17	1.18	1.15	1.13	1.16	0.98	0.96	0.84	1.00	1.03	1.03
LASSO	1.19	1.16	1.19	1.11	1.13	1.15	1.24	1.23	1.25	1.15	1.14	1.17	1.48	1.53	1.41	1.23	1.11	0.95
EN	1.11	1.12	1.14	1.08	1.11	1.13	1.17	1.19	1.19	1.13	1.14	1.18	1.51	1.40	1.16	1.23	1.13	1.30
RF	16.69	15.92	15.10	13.12	14.00	14.09	18.25	16.03	14.86	12.14	12.82	11.93	24.93	20.30	14.94	9.98	9.81	10.81
MLP	24.31	24.36	23.07	26.43	26.92	36.22	32.90	32.61	29.78	29.86	27.94	37.63	72.68	62.70	55.41	49.74	33.59	46.59
EN1	31.89	31.36	28.77	26.04	25.93	26.11	38.99	38.36	34.37	29.35	28.07	27.87	59.66	63.60	48.11	34.94	25.29	24.98
EN2	26.13	25.50	23.52	21.22	21.35	21.41	30.91	30.07	26.96	23.11	22.29	22.04	46.64	48.41	35.80	25.96	20.75	18.10
EN3	21.57	21.18	19.65	17.99	18.06	18.83	26.12	25.78	23.11	20.49	19.82	21.08	45.23	50.52	31.81	27.68	19.50	26.03
LSTM	32.34	29.35	25.28	22.18	21.48	23.02	41.54	38.12	32.60	27.09	24.58	26.92	78.01	82.24	65.56	50.64	35.50	26.10
FM12	14.69	13.64	13.05	14.47	14.10	14.82	16.56	16.13	15.74	16.71	15.51	17.32	23.04	29.73	27.56	25.76	17.39	23.46
	Panel D						Panel E						Panel F					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.90	0.89	0.87	0.88	0.87	0.87	0.89	0.88	0.87	0.88	0.89	0.87	0.93	0.92	1.07	1.09	1.10	0.95
LASSO	1.06	1.03	1.03	1.02	1.03	1.01	1.02	1.02	1.03	1.01	1.00	0.97	0.91	0.99	0.90	0.86	0.77	0.91
EN	1.00	0.99	0.99	0.99	0.99	0.98	0.96	0.95	0.96	0.97	0.96	0.94	0.77	0.83	0.80	0.86	0.88	0.86
RF	13.64	13.31	12.86	12.71	12.28	12.34	14.62	13.34	13.19	12.42	11.26	11.12	18.40	17.25	13.17	9.48	8.42	10.95
MLP	20.23	19.94	19.03	21.16	22.16	31.89	25.80	24.94	23.30	24.31	24.17	31.72	54.29	52.08	40.88	41.50	34.69	39.23
EN1	27.56	26.82	24.50	23.67	23.59	23.25	32.79	31.72	28.20	26.07	25.34	24.08	49.31	45.16	38.52	27.45	23.89	22.81
EN2	22.40	21.82	19.98	19.38	19.30	19.09	25.75	24.94	22.09	20.50	20.01	19.16	39.24	34.72	28.89	20.32	19.65	16.30
EN3	18.25	17.87	16.54	16.19	16.12	16.68	21.24	20.73	18.69	17.73	17.44	18.13	33.10	35.57	24.35	21.61	19.40	22.93
LSTM	26.60	25.78	20.99	21.60	21.07	21.07	33.11	32.80	26.80	26.16	24.75	23.96	64.01	53.78	46.24	41.00	36.49	39.88
FM12	12.59	11.75	11.20	12.65	12.52	13.07	14.10	13.47	12.88	14.31	13.92	15.02	18.47	17.66	18.13	18.09	18.25	21.04

Forecast accuracy for h = 1–6. Each entry in Panel A, B and C show RMSE, MAE and MAD respectively, and these numbers are relative to the naive benchmark when fixed rolling window forecast scheme is used to forecast year-on-year CPI Inflation. Panel D, E and F show RMSE, MAE and MAD respectively, and these numbers are relative to the naive benchmark when expanding rolling window forecast scheme is used. All models use full information set of the independent variables except the OLS and the Ridge models. These two models use variables that are significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally well or better than the benchmark model across each column. Every underlined entry shows the minimum RMSE, MAE or MAD attained by the competing model. Entries in grey indicates that the competing model's forecasts are superior to that of the benchmark at each horizon (across row).

Table 13

	Panel A						Panel B						Panel C					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.93	0.85	0.82	0.84	0.83	<u>0.75</u>	0.96	1.09	1.16	0.97	1.03	0.91	0.96	1.31	1.71	0.98	1.27	1.14
LASSO	1.02	0.91	0.88	0.89	0.89	0.82	1.10	1.22	1.28	1.04	1.14	1.00	0.98	1.18	1.08	1.01	1.49	1.22
EN	1.01	0.90	0.87	0.89	0.87	0.82	1.09	1.21	1.26	1.06	1.11	1.01	0.95	1.36	1.13	0.91	1.44	1.15
RF	1.11	1.00	0.95	0.96	0.91	0.82	1.20	1.35	1.44	1.20	1.22	1.05	1.23	1.31	1.07	0.75	0.84	1.01
MLP	1.00	0.85	0.82	0.86	0.92	1.01	1.13	1.12	1.21	1.00	1.21	1.20	0.85	1.25	1.49	0.98	1.07	1.31
EN1	1.03	0.94	0.91	0.92	0.94	0.84	1.07	1.21	1.30	1.05	1.18	1.03	0.73	1.16	1.50	0.96	1.31	1.02
EN2	1.02	0.94	0.90	0.91	0.92	0.82	1.09	1.22	1.31	1.07	1.18	1.02	0.60	1.08	1.29	0.89	1.29	1.00
EN3	0.99	0.89	0.85	0.86	0.87	0.80	1.05	1.17	1.23	1.01	1.11	1.00	0.65	0.69	0.93	0.61	0.98	0.84
LSTM	1.10	0.84	0.86	0.82	0.82	0.77	1.05	<u>1.00</u>	1.17	0.94	0.99	0.85	0.86	0.74	1.46	0.79	0.87	0.81
FM12	0.95	0.79	0.74	0.86	0.81	0.82	1.05	1.35	1.59	1.22	1.31	1.18	0.93	1.66	2.58	1.34	1.81	1.33
	Panel D						Panel E						Panel F					
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
Ridge	0.95	0.86	0.85	0.90	0.94	0.92	0.97	0.82	0.81	0.91	0.97	0.97	0.99	0.73	0.95	0.88	1.05	1.23
LASSO	0.96	0.89	0.87	0.93	0.98	0.98	1.03	0.87	0.86	0.93	1.02	1.07	1.09	0.58	0.61	0.96	1.27	1.53
EN	0.97	0.89	0.87	0.92	0.98	0.98	1.03	0.88	0.86	0.94	1.01	1.07	1.11	0.63	0.69	0.92	1.14	1.40
RF	0.99	0.86	0.87	0.93	1.00	1.01	1.06	0.86	0.90	0.98	1.07	1.13	0.97	0.56	0.52	0.68	1.01	1.18
MLP	0.98	0.83	0.81	0.86	0.97	1.19	1.08	0.81	0.82	0.87	1.02	1.24	0.91	0.64	0.83	0.86	0.90	1.53
EN1	0.99	0.90	0.90	0.94	1.03	0.99	1.01	0.86	0.89	0.94	1.05	1.08	0.85	0.61	0.82	0.91	1.14	1.22
EN2	0.97	0.89	0.89	0.93	1.01	0.99	1.01	0.86	0.89	0.94	1.04	1.08	0.76	0.54	0.72	0.90	1.12	1.18
EN3	0.94	0.84	0.84	0.88	0.96	0.96	0.98	0.82	0.83	0.88	0.98	1.06	0.73	0.36	0.50	0.61	0.87	1.09
LSTM	0.99	0.80	0.91	0.86	0.90	0.85	0.99	0.70	0.79	0.83	0.87	0.86	0.81	0.46	0.37	0.53	0.75	0.77
FM12	0.91	0.79	0.78	0.89	0.90	0.91	0.92	0.74	0.74	0.89	0.88	0.96	0.89	0.52	0.59	0.91	0.88	1.34

Forecast accuracy for $h = 1-6$. Each entry in Panel A, B and C show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when fixed rolling window forecast scheme is used to forecast year-on-year WPI Inflation. Panel D, E and F show RMSE, MAE and MAD respectively, and these numbers are relative to the naïve benchmark when expanding rolling window forecast scheme is used. All models use full information set of the independent variables except the OLS and the Ridge models. These two models use variables that are significantly correlated with the variable of interest. Bold entries indicate that the competing model performed equally well or better than the benchmark model across each column. Every underlined entry shows the minimum RMSE, MAE or MAD attained by the competing model. Entries in grey indicates that the competing model's forecasts are superior to that of the benchmark at each horizon (across row).

References

- Bokun, K. O., Jackson, L. E., Kliesen, K. L., & Owyang, M. T. (2023). FRED-SD: A real-time database for state-level data with forecasting applications. *International Journal of Forecasting*, 39(1), 279–297. <https://doi.org/10.1016/j.ijforecast.2021.11.008>
- Breiman, L. (1996). Bagging predictors. *Machine Learning*, 24(2), 123–140.
- Breiman, L. (2001). Random Forests. *Machine Learning*, 45, 5–32. https://doi.org/10.1007/978-3-030-62008-0_35
- Eickmeier, S., & Ng, T. (2011). Forecasting national activity using lots of international predictors: An application to New Zealand. *International Journal of Forecasting*, 27(2), 496–511. <https://doi.org/10.1016/j.ijforecast.2009.10.011>
- Haider, A., & Hanif, M. N. (2009). Inflation forecasting in Pakistan using artificial neural networks. *Pakistan Economic and Social Review*, 123–138.
- Hanif, M. N., & Malik, M. J. (2015). Evaluating Performance of Inflation Forecasting Models of Pakistan. *SBP Research Bulletin*, 11(1), 43–78.
- Hanif, M. N., Mughal, K. S., & Iqbal, J. (2018). *A Think ANN Model for Forecasting Inflation* (No. 99).
- Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8), 1735–1780.
- Hoerl, A. E., & Kennard, R. W. (1970). Ridge regression: applications to nonorthogonal problems. *Technometrics*, 12(1), 69–82.
- Hussain, F., Kalim, H., & Rehman, M. (2018). Nowcasting LSM Growth in Pakistan. *SBP Research Bulletin*, 14(1), 1–16.
- Hussain, F., & Mahmood, A. (2017). Predicting Output Growth and Inflation in Pakistan: The Role of Yield Spread. *SBP Research Bulletin*, 13(1), 53–75.
- Li, J., & Chen, W. (2014). Forecasting macroeconomic time series: LASSO-based approaches and their forecast combinations with dynamic factor models. *International Journal of Forecasting*, 30(4), 996–1015. <https://doi.org/10.1016/j.ijforecast.2014.03.016>
- McCracken, M. W., & Ng, S. (2016). FRED-MD: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, 34(4), 574–589.
- Medeiros, M. C., Vasconcelos, G. F. R., Veiga, Á., & Zilberman, E. (2021). Forecasting Inflation in a Data-Rich Environment: The Benefits of Machine Learning Methods. *Journal of Business and Economic Statistics*, 39(1), 98–119. <https://doi.org/10.1080/07350015.2019.1637745>
- Panagiotelis, A., Athanasopoulos, G., Hyndman, R. J., Jiang, B., & Vahid, F. (2019). Macroeconomic forecasting for Australia using a large number of

- predictors. *International Journal of Forecasting*, 35(2), 616–633. <https://doi.org/10.1016/j.ijforecast.2018.12.002>
- Ruck, D. W., Rogers, S. K., & Kabrisky, M. (1990). Feature Selection Using a Multilayer Perceptron. *Journal of Neural Network Computing*, 2(2), 40–48.
- Schwarz, G. (1978). Estimating the Dimension of a Model. *The Annals of Statistics*, 6(2), 461–464. <https://doi.org/10.1214/aos/1176344136>
- Syed, A. A. S., & Lee, K. H. (2021). Macroeconomic forecasting for Pakistan in a data-rich environment. *Applied Economics*, 53(9), 1077–1091.
- Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, 58(1), 267–288.
- Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 67(2), 301–320.

Appendix

Serial Number	Name of the Variable (x_t)	T
1	Imports of goods FOB	5
2	Exports of goods FOB	4
3	Exports of services	3
4	Imports of services	3
5	Workers' Remittances	3
6	Foreign Currency Deposits	5
7	Gold Reserves	4
8	FX Reserves with SBP	4
9	FX Reserves with Banks	4
10	Foreign Direct Investment Inflows	3
11	Foreign Direct Investment Outflows	3
12	Special Convertible Rupee Account Inflows	4
13	Special Convertible Rupee Account Outflows	3
14	Nominal Effective Exchange Rate	4
15	Real Effective Exchange Rate	4
16	Pakistani Rupee to US Dollar Nominal Exchange Rate	4
17	Overall Quantum Index of Large-Scale Manufacturing Industries	1
18	Total Automobile Sales	3
19	Total Auto Production	3
20	Domestic Cement Sales	3
21	Export Cement Sales	4
22	Total electricity Generation	3
23	Overall, POL Sales	3
24	Total Fertilizer Off-take	3
25	National CPI Inflation (YoY)	2
26	Urban CPI (YoY)	2
27	Rural CPI (YoY)	2
28	WPI (YoY)	2
29	SPI Inflation (YoY)	2
30	Karachi Stock Exchange 100 Index	4
31	Foreign Currency Deposits	2
32	Weighted Average rate of All banks on Outstanding Loans including 0 Markup incl. Interbank	6
33	Weighted Average rate of foreign banks on Outstanding Deposits including 0 Markup incl. Interbank	2
34	SBP Policy Rate	2
35	KIBOR 6 month offer rate	2
36	Weighted Average Overnight Repo Rate	6
37	Long Term Financing Facility for Over 5 years and up to 10 years End User's Rate	2
38	M1	4
39	M2	4
40	M3	4
41	Economic Policy Uncertainty	3

x_t denotes an observed variable in levels. Transformations (T) denotes the transformation implemented to achieve stationarity: 1 = no transformation, 2 = first difference, 3 = log, 4 =

first difference of the log, 5 = second difference of the log, 6 = double difference. Seasonally Adjusted (SA) denotes seasonal adjustment of variables using Bureau of Census X11 procedure in EViews.