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Does Consumer Confidence explain Demand in an Emerging Market Economy?

Ateeb Akhter Shah Syed
Assistant Professor,
Department of Economics,
Institute of Business Administration, Karachi, Pakistan.
ORCID ID: 0000-0003-3872-9609
Email: syed.ateeb@wmich.edu
(Corresponding Author)

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Abstract: *The purpose of this paper is to determine whether the information content in the consumer confidence index explains demand in Pakistan, beyond economic fundamentals. We use a wide range of models, starting from ordinary least squares to linear regression models that incorporate common factors driven by principal components, as well as advanced machine learning techniques, including penalized regression methods and neural networks. We apply both fixed and expanding window rolling forecasts to test this phenomenon and present our results using three forecast accuracy measures. Overall, our findings demonstrate that, for each technique considered, the model that includes the consumer confidence information set outperforms the model based solely on economic fundamentals. This indicates that the information content of consumer confidence enhances the explanation of demand-side indicators in Pakistan. This paper directly informs policymakers in developing countries generally, and in Pakistan specifically, that the consumer confidence index offers insights into the expectations of economic agents and should be integrated into analyses for improved policy decisions.*

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1. Introduction

Consumer confidence is one of the most widely followed alternative economic indicators by people working as academicians, analysts, and policy makers around the world. Consumer confidence provides information about perception that economic agents have about the current and future state of an economy. At the macro level, this information is usually reported in terms of an overall index, commonly known as the consumer confidence index (CCI) or Consumer Sentiment Index (CSI). This broad index may sometimes be composed of sub-indices containing information about the current and expected economic conditions of an economy. Economic literature describes these indicators as consumer's processing of objective information about the state of the economy and presenting it in a subjective form De Boef and Kellstedt (2004).

It is also well-known that macroeconomic policies such as the fiscal and monetary policy effects some of the key macroeconomic outcomes such as consumption and investment in the short run. Hence, given the fact that CCI provides important information regarding the beliefs of the economic agents regarding the current and future unfolding of economic outcomes, it is considered to be a helpful input to the fiscal and monetary authorities for an informed decision making (Elmassah, Bacheer and Hassanein, 2022). Although, it is a latent concept and quite hard to measure accurately; however, there have been attempts to operationally define this feature, with the University of Michigan's Survey of Consumers being the first. The importance of these indicators is evident in the fact that the US Department of Commerce uses the index of consumer expectations as one of the leading indicators in the formulation of the "Composite Index of Leading Indicators, " which can predict recessions in the United States economy (Curtin, 2007).

Economic theory posits that the primary channel through which the CCI impacts the economic outlook is the purchase of durable goods by consumers, such as homes, automobiles, and refrigerators. This is because consumers may, at their discretion, delay the purchase of such goods if the economic conditions are not favorable (Garner, 1991). Furthermore, there are two contrasting views in the literature regarding the role of consumer confidence in macroeconomics (Barsky & Sims, 2012). To put this assertion to the test, a fairly large number of studies have estimated the consumption function (with spending as a dependent variable) to determine the predictive power of the CCI using both bi-variate and multivariate analyses (including other fundamental economic variables as regressors in addition to the CCI). These forecasting papers served two distinct purposes: some of these studies concentrated on the incremental explanatory power or improved forecasting, whereas others solely focused on the performance of models when the CCI is added to regressions containing the fundamental economic variables.

The first strand of literature that finds CCI to provide valuable information for predicting consumer spending is extensive [see Mishkin et Al. (1978), Carroll, Fuhrer, and Wilcox (1994), Ludvigson (2004), Croushore (2005), Dee and Brinca (2013), Ahmed and Cassou (2016), among others], while the other strand of literature, which finds weak or no predictive power of CCI in forecasting consumer spending, is relatively scant [for example, see Easaw, Garratt, and Heravi (2005), Kwan and Cotsomitis (2006), Wilcox (2007), Al-Eyd, Barrell, and Davis (2009), and Moller, Norholm, and Ranvir (2014), Benhabib and Spiegel (2017)].

Given the mixed evidence regarding CCI as a reliable predictor of consumer spending, we aim to forecast the demand-side indicators in Pakistan. Our interest in these indicators arises from the fact that the monetary policy committee of the State Bank of Pakistan (SBP), the central bank, responds to inflation driven by the demand side. In the monetary policy statements that outline their decisions, growth in these indicators, as well as the CCI, is discussed.[1] It is evident that policymakers not only care about the state of economic growth- such as demand pressures and supply shocks- but also about the evolution of confidence among economic agents.

This paper contributes to the existing literature on forecasting demand-side indicators and spending in the following ways. First, to the best of our knowledge, it is the first paper to forecast the demand-side indicators for Pakistan[2] using CCI. Second, prior to our work, the most commonly used methodology for forecasting spending was the consumption function utilizing ordinary least squares (OLS). However, in

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[1] For an example, read the statement: https://www.sbp.org.pk/m_policy/2022/MPS-May-2022-Eng.pdf

[2] Readers who are interested in knowing if the consumer confidence plays a role in forecasting the supply side/output for Pakistan's economy are referred to Syed, Fatima and Naseer (2022)

this study, we employ models that utilize factors generated through principal component analysis (PCA) as regressors, in addition to the latest machine learning models.

2. Data Description

In line with economic theory, our focus is to forecast the sale of durables using the CCI in Pakistan. The only durable variable for which data is available on a monthly basis is the "Total of Auto Sales (TAS). " This variable is further divided into six categories: Sale of Cars and Jeeps (SCJ), Sales of Motorcycles (SMC), Sales of Trucks (STK), Sales of Buses (SBU), Sales of Light Commercial Vehicles (SLCV), and Sales of Tractors (STR). Moreover, during the Coronavirus (COVID-19) pandemic, SCJ and SBU sales dropped to zero in April 2020; hence, calculating YOY growth for the month of April 2021 is not possible (zero in the denominator). One solution to the problem might have been to apply an average YOY growth from historical data to April 2020; however, some may argue that growth does not always follow the average of historical data. Therefore, we do not forecast these two subcategories of the TAS.[3]

Although according to economic theory, CCI does not impact the economic outlook in the short run, several papers have forecasted consumer non-durables to investigate whether the CCI can explain their demand. Therefore, as a robustness check, we forecast three non-durable demand indicators: Petroleum, Oil, and Lubricant Sales (POLS), Domestic Cement Sales (DCS), and Fertilizer Off-take/Sales (FERTS).[4] The explanatory variables used in this paper include 13 time-series variables that are considered to impact sales of automobiles or demand in general. Details of the variables, their sources, and the transformations are provided in Table 1.

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[3] Some may also point out that the STK, SLCV and the STR are type of vehicles that are used by businesses and not the consumers; hence, testing how well they are forecasted by adding CCI along with the economic fundamentals on the right-hand side of the model may not be appropriate. However, most studies in the existing literature uses an overall automobile sales data for such kind of analysis and does not explicitly account for such details in forecasting. Therefore, we do not make this a barrier to our analysis and use all available sub-categories of automobile sales data. Furthermore, given that this study is about CCI, and the closest of the categories that may be used by consumer is the tractors, we conserve space, and report result for STR only; however, results of other categories can be made available upon a reasonable request.

[4] The results for the non-durable goods also show that addition of CCI to the information set improves forecast accuracy. we report the results of POLS only and not the other two variables. However, results for the other indicators are available from the author upon a reasonable request.

Table 1: Details of the variables

Serial No.	Variable Name (x_t):	Availability (Year: Month)	Source	T
1	Consumer Confidence Index	2012:1 to 2022:9	SBP	4
2	Karachi Stock Exchange 100 Index	2012:1 to 2022:9	SBP	4
3	Money Supply (Broad Money – M2)	2012:1 to 2022:9	SBP	4
4	National CPI (2015-16=100)	2012:1 to 2022:9	PBS	2
5	KIBOR offer Rate (6-months)	2012:1 to 2022:9	SBP	2
6	KIBOR offer Rate (1-Year)	2012:1 to 2022:9	SBP	2
7	Weighted Average Lending Rate	2012:1 to 2022:9	SBP	2
8	Real Effective Exchange Rate (2010=100)	2012:1 to 2022:9	Haver Analytics	4
9	Pakistani Rupee to US Dollar Nominal Exchange Rate	2012:1 to 2022:9	SBP	4
10	Year-on-year (YOY) Growth of Sales of Motorcycles	2012:1 to 2022:9	SBP	1
11	YOY Growth of Sales of Trucks	2012:1 to 2022:9	SBP	1
12	YOY Growth of Sales of LCVS (Pick Ups)	2012:1 to 2022:9	SBP	1
13	YOY Growth of Sales of Tractors	2012:1 to 2022:9	SBP	1
14	YOY Growth of Petroleum, Oil and Lubricants Sales	2013:7 to 2022:9	SBP	1
15	YOY Growth of Domestic Cement Sales	2012:1 to 2022:9	SBP	1
16	YOY Growth of Fertilizer Offtake/Sales	2012:1 to 2022:9	SBP	1
14	YOY Growth of Quantum Index of Large-Scale Manufacturing Industries (2015-16=100) (SA) – commonly known as the LSM	2012:1 to 2022:9	PBS	2
15	Avg Crude Oil Price (Brent/WTI/Dubai Fateh)	2012:1 to 2022:9	Haver Analytics	4
16	Workers' Remittances	2012:1 to 2022:9	SBP	4
17	Imports	2012:1 to 2022:9	SBP	4

Notes: 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. KIBOR = Karachi interbank offered rate

Table 1 presents three key pieces of information. First, it outlines the transformations applied to each variable; specifically, in accordance with recent literature on forecasting, the variables are transformed to be stationary and standardized to have a mean of zero and a standard deviation of one [for some recent examples, see Panagiotelis, Athanasopoulos, Hyndman, Jiang, and Vahid (2019) and Syed and Lee (2021), among others]. Second, it lists the sources of the data. Third, it specifies the sample period over which each variable is available.

SMC, STK, SLCV, and STR are available from 2012:1. For these variables, the sample is monthly, starting from 2013:1 to 2022:9. The first observation for DCS and FERTS is available in 2013:1; therefore, the sample period for these variables ranges from 2014:1 to 2022:9. Finally, for POLS, the first observation is available in 2013:7; hence, the sample for this variable extends from 2014:7 to 2022:9. The sample in each case starts with a lag of 12 months because each of these variables is used in a YOY growth basis.

We start our analysis by estimating the Ordinary Least Squares (OLS) model. Selecting relevant variables for the OLS is a crucial step in our analysis. Most studies on this subject have utilized the consumption function estimated using OLS to assess the forecasting strength that the Consumer Confidence Index (CCI) adds to a model; thus, we initiate our analysis with variables that affect consumption. It is widely recognized that the macroeconomic determinants of consumption include income, interest rates, and wealth; therefore, we employ the labor share of income (LSM) as a proxy for income in our models. Consumption may also be partially supported by workers' remittances (WR), which serve as a significant income source for many households in Pakistan. Accordingly, we incorporate WR in our models as well.

Consumption also depends on the prevailing interest rate in the economy, so we utilized not just one but several interest rates that are directly related to consumer borrowing in Pakistan. These include the Karachi Interbank Offer Rate for 6-month tenor (K6M) and 1-year tenor (K1Y), as well as the weighted average lending rate (WALR). Finally, to account for wealth, we use the KSE-100 index as a measure of wealth.

As Pakistan is a small open economy, part of its consumption consists of imported items. Therefore, we include imports in our model. Furthermore, it is influenced by fluctuations in the exchange rate. To account for the changes in the exchange rate, we use the Pakistani Rupee to US Dollar (USDPKR) and the Real Effective Exchange Rate (REER). Finally, international oil prices significantly impact the economy of Pakistan due to high oil imports; therefore, we also incorporate the average of West Texas Intermediate, Brent, and Dubai Fateh oil prices in our models. These endogenous and exogenous variables, which are directly related to Pakistan’s economy, are referred to as economic fundamentals in our paper. Hence, in our forecasting exercise, we will refer to this data as data1, and we will call it data2 when we augment this dataset with the CCI.

3. Forecasting Methods

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

$$y_{t+h} = \boldsymbol{x}'_t \widehat{\boldsymbol{\theta}}_l, \quad h = 1,2,\ldots,12 \tag{3.1}$$

where $\hat{y}_{t+h}$ is a h-step-ahead forecast of the target variable and $\widehat{\boldsymbol{\theta}} = \left(\hat{\theta}_{1,l}, \hat{\theta}_{2,l}, \ \ldots \ , \hat{\theta}_{K,l}\right)$, is the estimated coefficient on the lth variable.

For each variable of interest, when data1 is used to forecast the selected demand indicator, we refer to it as model-1. Conversely, we refer to the model as model-2 when data2 is used to forecast the variable of interest. In this way, model-1 serves as the benchmark, while model-2 serves as the competing model for each technique and demand indicator forecasted in our paper.[5] The explanation of our models closely follows the pattern established in Syed and Lee (2021). The details of the models used in our study are as follows:

3.1 Ordinary Least Squares (Consumption Function)

We use the OLS model as our first technique for forecasting the selected demand indicators. We regress each variable of interest on data1 and data2. Consequently, this technique, along with all others that follow, will have two models: model-1 and model-2, estimated using data1 and data2, respectively. The OLS model is defined as follows:

$$Y_t = \mu + \sum_{i=1}^{p} \theta_i \boldsymbol{X_t} + \varepsilon_t \tag{3.2}$$

Where Y_t is a dependent variable and $\boldsymbol{X_t}$ is a vector of independent variables at time t, μ is the constant parameter and ε_t is a stationary, white noise process.

[5] Two aspects of our work needs to be understood at this point: first, this paper is not about testing the forecast performance of models against a set benchmark model in forecasting demand indicators instead this paper takes each competing model and feeds it with two distinct information sets to forecast the variable of interest; second, the sample period over which the variables are available is too short; therefore, adding lags to models such as the commonly used Autoregressive model of order p [(AR(p)), where, p , even if selected on the basis of Bayesian information criteria (BIC) Schwarz (1978)] may lead to degrees of freedom problem. Hence, in our case, the estimation sample is too short to add p lags of each regressor in the OLS, FM, and ML models for comparison, so we do not add lags of the variables in any of the techniques used in our paper. This may be considered as an exercise in the future when a longer time-series of CCI becomes available.

3.2 OLS with Factors

Over time, forecasting variables of interest using a few factors that represent information extracted from a large set of predictors has become popular. In our paper, we employ Principal Component Analysis (PCA) to extract factors using data1 and data2. The first factor model we estimated contains the first principal component (FM1) extracted from data1 and data2. Generally, the first principal component explains the majority of the variation in the data and is, therefore, quite helpful in forecasting the target variable. However, sometimes adding more information through factors in a model improves the forecast; thus, we also estimate the model with the first five (FM5) and the first seven (FM7) principal components. The regression we run is as follows:

$$Y_t = \mu + \sum_{i=1}^{12} \theta_i \boldsymbol{F_t} + \varepsilon_t \tag{3.3}$$

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

3.3. Ridge Regression

Hoerl and Kennard (1970) coined the concept of Ridge regression, a linear regression model designed to minimize the sum of squared residuals while incorporating an additional l_2-norm penalty term. The overemphasized coefficients are penalized, meaning their effect on the target variable is diminished. Ridge regression shrinks the coefficients, but not all the way to zero. Nevertheless, the coefficients approach zero as the value of lambda increases. Ridge regression is represented by:

$$\mathrm{argmin}_{\beta} \sum_{i}(y_i - \beta' x_i)^2 + \lambda \sum_{k=1}^{K} \beta_k^2 \tag{3.4}$$

The value of lambda is crucial to the determination of the weight assigned to the penalty for coefficients. We use 10-fold cross-validation to find the optimal shrinkage parameter λ.

3.4. Least Absolute Shrinkage and Selection Operator

The concept of LASSO, introduced by Tibshirani (1996), is a regularization model that applies a penalty to the coefficients of linear models using the following formula:

$$\mathrm{argmin}_{\beta} \sum_i (y_i - \beta' x_i)^2 + \lambda \sum_{k=1}^{K} |\beta| \quad (3.5)$$

LASSO not only reduces the coefficients of the variables but can also push them all the way to zero. Therefore, the variables with a coefficient of zero are excluded from the model, consequently lowering the degree of overfitting within it.

It is important to note that LASSO drops variables it deems unimportant for a given dataset based on the value of lambda. Therefore, it is likely that CCI may have been dropped during some iterations as well. To avoid this issue, we coded the algorithm so that when we use data2, which contains CCI, the algorithm cannot drop this variable. Hence, our paper's purpose, which is to determine the improvement in forecasts of demand indicators, is achieved in this manner. We use 10-fold cross-validation to find the optimal shrinkage parameter λ.

3.5. Elastic Net

Elastic Net, introduced by Zou and Hastie (2005), uses a combination of both Ridge and LASSO characteristics. It reduces the impact of different variables while preserving some features. The Elastic Net, is mathematically expressed as:

$$\mathrm{argmin}_{\beta} \sum_i (y_i - \beta' x_i)^2 + \lambda_1 \sum_{k=1}^{K} |\beta| + \lambda_2 \sum_{k=1}^{K} \beta_k^2 \quad (3.6)$$

Similar to LASSO, there was a possibility that the EN would exclude CCI in some or all forecast iterations. Therefore, we once again programmed the EN algorithm to ensure it would not exclude CCI in any of the iterative forecasts of the demand indicators when data2 is provided to it. We use 10-fold cross-validation to find the optimal shrinkage parameters λ_1 and λ_2.

3.6. Neural Networks

Neural networks, due to their significantly improved forecasting ability, have been used to forecast and nowcast inflation and other macroeconomic variables for many countries, including Pakistan [see Haider and Hanif (2009) and Hanif et al. (2018)]. In this paper, we employ two techniques based on the concept of neural networks: the Multilayer Perceptron (MLP) and the Long Short-Term Memory (LSTM). For details on MLP and LSTM, see Hochreiter and Schmidhuber (1997) and Dennis, Rogers, and Kabrisky (1990), respectively.

3.7. Random Forest

Ensemble methods, such as random forests, have previously made significant contributions to economics because of their ability to produce accurate forecasts of economic data. Therefore, we apply random forests as an ensemble forecasting method.

It was introduced by Breiman (2001) and is based on bootstrap aggregation (bagging) of randomly created regression trees, aiming to reduce the variance of regression trees. These trees are recognized as a non-parametric model, which approximates an unknown nonlinear function with local forecasts through recursive partitioning of the response variable space (Breiman, 1996). Next, we explain the forecasting schemes and the evaluation criteria used in our paper.

4. Forecasting Schemes and Evaluation Criteria

We utilize both the fixed window rolling (FWR) and the expanding rolling window (EWR) for forecasting the demand variables. For the variables SMC, STK, SLCV, and STR, we have a total of 129 observations. Consequently, in line with the convention in the forecasting literature, we divide these into a training and test sample of 70% and 30% of the observations, respectively. This means that 86 observations are allocated for training the models, while the remaining observations are used for testing. For FWR, we maintain a fixed training window size of 86 observations and move it one step ahead each time estimation is performed. We then forecast the variables iteratively, 12 steps ahead at each interval, until the 117th observation. The last estimation cycle concludes in September 2021, and the final test set consists of data from October 2021 to September 2022.

Under the EWR, we again maintain the initial training window size of 86 observations; however, instead of shifting the window for re-estimation, we expand the training window by 1 observation and re-estimate the models. At each estimation, 12-step ahead forecasts are produced using the next 12 test set values. We maintain the same length of training window for the non-durable demand indicators DCS and FERTS, as we have 105 usable observations for these variables. However, for the POLS, only 99 observations are available; therefore, for this variable, we set a training data percentage of 70%, comprising 69 observations, and use the remaining data as the testing dataset. Similar to the other variables, both the FWR and EWR forecasting methodologies are applied to forecast POLS.

By following the forecasting process detailed above, we obtain out-of-sample forecasts for each forecast horizon 'h,' which are used to compare the forecasting performance of different models. Recent literature on forecasting employs various layouts to report results. For instance, Li and Chen (2014), Panagiotelis, Athanasopoulos, Hyndman, Jiang, and Vahid (2019), and Syed and Lee (2021) present relative accuracy measures, while Mederios, Vasconcelos, Alvaro, and Eduardo (2021) report the maximum, minimum, and average accuracy measures across horizons.

We integrate these two methods of reporting results and present our findings as follows: first, for each horizon of interest, we report the relative root mean squared error (RMSE), relative mean absolute error (MAE), and mean absolute deviation (MAD); second, we report the average of these measures across all horizons for each model.

5. Research results

This analysis includes multiple demand indicators for both durables and non-durables, each forecasted using various forecasting techniques. Thus, we present selected variables and discuss the results by focusing on one indicator at a time.[6]

5.1. Year-on-Year Growth in Sales of Motorcycles

5.1.1 Fixed Window Rolling Forecasts

Table 2 presents the forecasts of SMC when the FWR mechanism is employed. We find that the mere consumption function approach, with all variables used as regressors in the OLS, does not improve the forecast except for horizons 4 and 8, and only in terms of the RMSE measure. Although this result improves when considering the evaluation criteria produced by Ridge, LASSO, EN, and LSTM, the maximum addition of horizons that improves their performance with CCI is 6. On the other hand, neural networks demonstrate that adding CCI as a predictor to the dataset enhances forecasting performance across 7 forecast horizons.

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[6] Due to the nature of the results, that is, we estimated 10 models and generated h = 1 to 12 forecast accuracy measures using three techniques (RMSE, MAE and MAD); the tables are quite big and could not fit into the body of the paper. Hence, they are placed at the end of the paper right before the references.

Table 2: Forecast accuracy (RMSE, MAE and MAD)

		Horizons												Average Performance Across Horizons
Models	**Criteria**	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**	**h = 9**	**h = 10**	**h = 11**	**h = 12**	
OLS	RMSE	1.158	1.320	1.171	**0.928**	1.053	1.358	1.200	**0.930**	1.286	1.178	1.145	1.272	1.166
	MAE	1.790	1.711	1.451	1.638	1.774	2.092	1.858	1.669	1.874	1.801	1.925	2.257	1.820
	MAD	20.760	18.032	16.956	18.421	11.638	26.464	21.525	29.005	27.623	32.952	31.970	43.554	24.908
Ridge	RMSE	**0.998**	**1.000**	1.000	1.001	1.001	1.000	1.000	1.001	**0.999**	**0.999**	**0.999**	**0.999**	**1.000**
	MAE	1.003	1.006	1.008	1.010	1.012	1.006	1.008	1.012	1.005	**0.998**	**0.995**	**0.994**	1.005
	MAD	1.007	1.041	**0.894**	1.192	1.155	1.052	**0.992**	1.057	1.184	1.050	1.048	1.131	1.067
LASSO	RMSE	1.011	1.037	1.033	1.056	1.072	1.060	1.043	1.009	**0.957**	**0.963**	**0.976**	1.003	1.018
	MAE	1.063	1.059	1.061	1.161	1.173	1.140	1.094	1.014	**0.933**	**0.909**	**0.962**	**0.967**	1.045
	MAD	**0.859**	1.140	1.154	1.484	1.347	1.092	1.100	1.417	1.586	1.191	**0.995**	1.305	1.222
EN	RMSE	1.004	1.004	1.023	1.049	1.059	1.053	1.025	**0.995**	**0.973**	**0.998**	1.000	**0.994**	1.015
	MAE	1.014	**0.973**	1.029	1.079	1.088	1.042	1.015	**0.961**	**0.905**	**0.942**	**0.946**	**0.942**	**0.995**
	MAD	1.180	1.002	**0.982**	1.143	1.154	1.081	1.105	1.083	1.549	1.082	1.049	1.242	1.138
RF	RMSE	1.000	**1.000**	**1.000**	**0.999**	**1.000**	1.000	**1.000**	**1.000**	**1.000**	1.000	**1.000**	1.000	**1.000**
	MAE	1.002	1.003	**0.999**	1.000	1.000	1.001	**0.999**	**0.999**	**1.000**	1.001	**0.999**	1.000	1.000
	MAD	1.004	**0.993**	**0.956**	1.129	1.004	**0.973**	**0.864**	1.029	**0.889**	**0.870**	**0.972**	1.023	**0.975**
MLP	RMSE	**0.989**	1.008	1.010	1.009	1.009	**0.999**	1.006	**0.996**	**0.987**	**0.987**	**0.988**	**0.991**	**0.998**
	MAE	**0.994**	1.032	1.043	1.028	1.050	**0.990**	1.061	**0.942**	**0.907**	**0.934**	**0.917**	**0.922**	**0.985**
	MAD	1.198	1.304	1.211	**0.983**	1.627	1.115	1.367	**0.631**	**0.906**	1.199	1.028	**0.867**	1.120
LSTM	RMSE	1.007	1.008	1.002	1.002	**0.992**	1.004	**0.990**	**0.993**	**0.987**	**0.994**	**0.994**	**0.994**	**0.997**
	MAE	1.013	1.024	1.018	1.024	**0.975**	1.013	**0.988**	**0.961**	**0.952**	**0.985**	**0.980**	**0.980**	**0.993**
	MAD	1.184	1.069	1.202	1.068	**0.752**	**0.934**	1.180	**0.996**	**0.951**	1.033	1.330	**0.755**	1.038
FM1	RMSE	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
	MAE	**0.997**	**0.997**	**0.997**	**0.998**	**0.998**	**0.997**	**0.995**	**0.997**	**0.995**	**0.995**	**0.994**	**0.996**	**0.996**
	MAD	1.011	1.017	1.085	1.090	1.060	1.006	**0.991**	**0.991**	**0.992**	1.060	**0.990**	1.027	1.027
FM5	RMSE	1.082	1.003	1.003	1.001	1.001	**0.996**	**0.996**	**0.975**	**0.973**	**0.968**	**0.970**	**0.975**	**0.995**
	MAE	1.058	**0.953**	**0.943**	**0.920**	**0.929**	**0.894**	**0.895**	**0.797**	**0.803**	**0.778**	**0.805**	**0.845**	**0.885**
	MAD	1.050	1.228	1.291	1.287	1.323	1.333	1.382	1.334	1.496	1.307	1.255	1.376	1.305
FM7	RMSE	**0.964**	1.002	**0.998**	**0.995**	**0.993**	**0.994**	**0.994**	**0.994**	**0.995**	**1.000**	1.001	1.000	**0.994**
	MAE	1.034	1.048	1.013	**0.983**	**0.967**	**0.951**	**0.975**	**0.975**	**0.970**	**0.998**	1.016	1.021	**0.996**
	MAD	**0.936**	1.070	1.391	1.468	1.258	1.021	1.247	1.041	**0.983**	**0.991**	**0.920**	1.043	1.114

Note: for h = 1 to 12, when we use the Fixed window rolling forecasting scheme for forecast generation. The forecasted variable is the year-on-year growth of motorcycle sales. For each model, the row containing value of RMSE, MAE and MAD below 1 show that the model-2 (containing CCI) performed better than model-1 (without CCI) at the horizon of interest. These are represented by the bold entries. The last column (extreme right) contains the average forecasting performance of the model containing CCI against model-1.
Source: Author's calculations.

Amazing is to note the results of the factor models, especially the one that contains only the first factor as regressor. When RMSE is used as the criteria for evaluation, model-2 performs equally well against model-1 that does not contain the CCI. Further, MAE shows that the model-2 outperforms model-1 at each forecasting horizon. Though not as strong as the model with 1 factor but similar kind of forecasting performance holds when we add the first five or seven factors as regressors to this model.

Finally, we note that the overall forecasting performance across horizons is generally better for model-2 compared to model-1 for the MLP, LSTM, and factor models. These results clearly indicate that the addition of CCI, on top of economic fundamentals, enhances the forecasting accuracy of motorcycle sales growth in Pakistan.

5.1.2 Expanding Window Rolling Forecasts

Next, we apply the EWR scheme to data1 and data2 for each technique. This rolling method enables models to incorporate additional information at each step as the sample is extended one observation at a time. Results for these models are presented in Table 3. We find that with this scheme, model-2 in OLS outperforms model-1 at more than two horizons across different evaluation criteria, indicating that the addition of information over time by expanding the window at each iteration helps improve the forecasts.

Table 3: Forecast accuracy (RMSE, MAE and MAD)

		Horizons												Average Performance Across Horizons
Models	**Criteria**	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**	**h = 9**	**h = 10**	**h = 11**	**h = 12**	
OLS	RMSE	**0.997**	**0.999**	**1.000**	1.000	1.001	1.000	1.001	1.001	**0.999**	**0.999**	**0.999**	**0.998**	**0.999**
	MAE	**0.999**	1.000	1.003	1.005	1.012	1.005	1.012	1.013	1.006	1.002	**0.997**	**0.991**	1.004
	MAD	1.084	1.062	1.078	1.028	1.012	1.030	1.026	1.172	**0.940**	1.094	**0.996**	**0.806**	1.027
Ridge	RMSE	**0.998**	**0.999**	1.000	1.001	1.001	1.000	1.000	1.001	**0.999**	**0.999**	**0.999**	**0.999**	**1.000**
	MAE	1.003	1.004	1.006	1.007	1.010	1.006	1.007	1.011	1.003	**0.997**	**0.994**	**0.992**	1.003
	MAD	1.083	1.044	1.141	1.129	1.049	1.048	1.071	1.079	1.080	**0.981**	**0.965**	1.076	1.062
LASSO	RMSE	1.030	1.026	1.025	1.030	1.053	1.066	1.051	**0.993**	**0.979**	**0.998**	1.003	1.014	1.022
	MAE	1.075	1.039	**0.997**	1.085	1.115	1.128	1.069	**0.988**	**0.925**	**0.963**	**0.980**	1.001	1.031
	MAD	1.178	1.038	**0.923**	**0.854**	1.117	1.099	1.192	1.336	1.801	1.271	**0.995**	1.185	1.166
EN	RMSE	1.001	**0.999**	1.003	**0.994**	**1.000**	1.010	1.027	**0.998**	**0.976**	**0.982**	**0.984**	**0.982**	**0.996**
	MAE	**0.999**	**0.958**	**0.994**	1.010	**0.999**	**0.991**	1.005	**0.952**	**0.895**	**0.934**	**0.946**	**0.946**	**0.969**
	MAD	1.139	1.073	1.120	1.033	1.038	**0.926**	1.089	1.221	1.293	1.226	1.324	1.351	1.153
RF	RMSE	**1.000**	**1.000**	**1.000**	**1.000**	1.000	**1.000**	**1.000**	**1.000**	1.000	**1.000**	**1.000**	**1.000**	**1.000**
	MAE	1.004	1.003	1.002	1.001	1.001	1.001	1.001	1.001	1.000	**0.999**	1.000	1.000	1.001
	MAD	1.002	1.060	**0.905**	**0.856**	**0.975**	**0.885**	**0.959**	**0.880**	**0.869**	**0.897**	1.030	1.076	**0.950**
MLP	RMSE	**0.987**	1.008	1.013	1.013	1.014	1.010	1.018	1.017	1.014	1.012	1.010	1.013	1.011
	MAE	**0.996**	1.013	1.047	1.039	1.060	1.027	1.102	1.070	1.031	1.036	1.003	1.036	1.038
	MAD	1.386	1.527	1.570	1.676	1.352	1.599	1.692	1.474	1.289	1.507	1.301	1.012	1.449
LSTM	RMSE	1.003	1.014	1.004	1.004	1.004	1.004	**0.998**	**1.000**	**0.996**	**0.992**	**0.996**	**0.996**	1.001
	MAE	1.008	1.041	1.021	1.011	1.015	1.009	**0.991**	1.008	**0.974**	**0.940**	**0.959**	**0.997**	**0.998**
	MAD	**0.620**	1.689	**0.987**	1.098	1.016	**0.735**	**0.879**	**0.971**	1.469	1.016	1.335	**0.944**	1.063
FM1	RMSE	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
	MAE	**0.997**	**0.997**	**0.997**	**0.998**	**0.999**	**0.998**	**0.996**	**0.998**	**0.996**	**0.996**	**0.995**	**0.996**	**0.997**
	MAD	1.008	1.016	1.053	1.070	1.062	1.004	**0.991**	**0.992**	**0.991**	1.059	**0.983**	1.019	1.021
FM5	RMSE	1.068	1.003	1.003	1.002	1.001	**0.998**	**0.998**	**0.985**	**0.983**	**0.981**	**0.982**	**0.985**	**0.999**
	MAE	1.064	**0.974**	**0.959**	**0.938**	**0.944**	**0.911**	**0.904**	**0.824**	**0.825**	**0.809**	**0.840**	**0.879**	**0.906**
	MAD	1.150	1.402	1.561	1.590	1.403	1.334	1.324	1.321	1.464	1.379	1.368	1.376	1.389
FM7	RMSE	**0.966**	1.002	**0.999**	**0.995**	**0.995**	**0.995**	**0.996**	**0.998**	**0.998**	1.001	1.002	1.002	**0.996**
	MAE	1.034	1.048	1.013	**0.988**	**0.972**	**0.965**	**0.982**	**0.989**	**0.985**	1.008	1.015	1.021	1.002
	MAD	**0.929**	1.053	**0.893**	1.032	1.023	1.021	1.093	1.097	**0.910**	**0.927**	**0.919**	1.045	**0.995**

Note: for h = 1 to 12, when we use the Expanding window rolling forecasting scheme for forecast generation. The forecasted variable is the year-on-year growth of motorcycle sales. For each model, the row containing value of RMSE, MAE and MAD below 1 show that the model-2 (containing CCI) performed better than model-1 (without CCI) at the horizon of interest. These are represented by the bold entries. The last column (extreme right) contains the average forecasting performance of the model containing CCI against model-1.
Source: Author's calculations.

The penalizing regression EN with CCI can outperform model-1 at 8 and 10 forecast horizons when evaluated using the criteria of RMSE and MAE, respectively. Similar to the outcomes observed in the factor models within the FWR scheme, FM1, FM5, and FM7 also demonstrate that CCI enhances the models compared to model-1. Lastly, we find that EN, RF, and factor models, on average, outperform models without CCI at most forecast horizons.

5.2. Year-on-Year Growth in Sales of Tractors

5.2.1 Fixed Window Rolling Forecasts

The second demand indicator available from the sub-categories of automobile sales is the STR. Farmers who use these tractors are the end users; therefore, we believe that an enhanced level of consumer confidence should lead to higher demand for this type of vehicle. This, in turn, adds value to the forecasting performance of model-2 compared to model-1 for each technique considered.

Table 4 presents the forecast accuracy results for STR when forecasts are generated using the FWR technique. It is encouraging to see that the consumption function approach indicates model-1 is significantly outperformed by model-2 across all forecast horizons under the OLS. Among the penalized regression methods, we find that model-2 in Ridge outperforms model-1 at 8 forecast horizons when RMSE is utilized as a measure of forecast accuracy. In the neural network approaches, the MLP technique demonstrates that model-2 surpasses model-1 for the criteria RMSE and MAE at all forecast horizons.

Table 4: Forecast accuracy (RMSE, MAE and MAD)

		Horizons												Average Performance Across Horizons
Models	**Criteria**	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**	**h = 9**	**h = 10**	**h = 11**	**h = 12**	
OLS	RMSE	**0.898**	**0.775**	**0.745**	**0.734**	**0.563**	**0.790**	0.795	**0.827**	**0.747**	**0.672**	**0.813**	**0.882**	**0.770**
	MAE	**0.808**	**0.728**	**0.672**	**0.644**	**0.549**	**0.695**	0.768	**0.757**	**0.701**	**0.582**	**0.746**	**0.821**	**0.706**
	MAD	**0.554**	**0.764**	**0.650**	**0.568**	**0.574**	**0.615**	0.555	**0.551**	**0.710**	**0.497**	**0.811**	**0.727**	**0.631**
Ridge	RMSE	1.034	1.013	**0.998**	**0.984**	**0.972**	**0.974**	0.974	**0.976**	**0.977**	**0.963**	**0.977**	**0.984**	**0.985**
	MAE	1.019	**0.988**	1.003	**0.993**	1.011	1.005	1.005	1.016	1.007	**0.992**	1.011	1.018	1.006
	MAD	**0.980**	**0.908**	**0.995**	**0.908**	1.056	1.213	1.156	**0.937**	**0.950**	1.059	1.111	1.056	1.027
LASSO	RMSE	1.168	1.166	1.247	1.208	1.232	1.223	1.211	1.130	1.061	**0.924**	**0.948**	**0.898**	1.118
	MAE	1.131	1.106	1.142	1.128	1.128	1.113	1.135	1.084	1.016	**0.941**	**0.964**	**0.940**	1.069
	MAD	1.073	1.084	**0.863**	1.159	1.173	**0.878**	**0.908**	**0.954**	1.191	1.216	1.379	1.336	1.101
EN	RMSE	1.153	1.086	1.177	1.235	1.197	1.202	1.136	1.112	1.059	1.034	1.074	1.029	1.124
	MAE	1.030	**0.989**	1.086	1.094	1.073	1.070	1.077	1.011	**0.953**	**0.956**	1.005	**0.986**	1.027
	MAD	1.097	1.050	**0.993**	1.372	1.135	1.232	1.138	1.115	1.130	1.265	1.449	1.317	1.191
RF	RMSE	1.032	1.073	1.049	1.028	1.000	1.034	1.030	1.016	**0.979**	1.007	1.012	1.015	1.023
	MAE	1.002	1.036	1.051	1.031	1.011	1.035	1.033	**0.978**	**0.992**	1.005	1.040	1.034	1.021
	MAD	**0.987**	**0.995**	**0.879**	1.117	**0.922**	1.039	1.058	**0.924**	1.137	**0.836**	1.077	**1.000**	**0.998**
MLP	RMSE	**0.885**	**0.816**	**0.862**	**0.818**	**0.878**	**0.913**	**0.805**	**0.889**	**0.880**	**0.917**	**0.905**	**0.898**	**0.872**
	MAE	**0.897**	**0.858**	**0.973**	**0.858**	**0.943**	**0.988**	**0.902**	**0.967**	**0.970**	**0.983**	**0.947**	**0.983**	**0.939**
	MAD	**0.944**	**0.792**	**0.915**	**0.843**	1.061	1.104	1.035	1.013	1.132	1.059	**0.890**	1.017	**0.984**
LSTM	RMSE	1.771	1.001	**0.814**	**0.983**	1.199	1.751	**0.711**	1.390	1.435	1.377	1.415	1.213	1.255
	MAE	1.287	**0.891**	**0.788**	**0.961**	1.101	1.210	**0.796**	1.158	1.147	1.062	1.133	1.019	1.046
	MAD	**0.822**	1.041	**0.855**	**0.924**	1.251	1.458	**0.875**	**0.877**	1.048	**0.851**	1.334	**0.684**	1.002
FM1	RMSE	1.004	1.005	1.005	1.002	1.004	1.004	1.004	1.005	1.003	1.003	1.005	1.006	1.004
	MAE	1.000	1.007	1.007	1.002	1.009	1.009	1.010	1.012	1.011	1.010	1.011	1.014	1.008
	MAD	1.059	1.040	1.077	1.036	1.000	**0.979**	1.041	**0.981**	1.068	1.014	1.046	1.081	1.035
FM5	RMSE	**0.898**	**0.916**	**0.824**	**0.797**	**0.735**	**0.716**	0.697	**0.716**	**0.722**	**0.710**	**0.738**	**0.735**	**0.767**
	MAE	**0.882**	**0.916**	**0.827**	**0.789**	**0.751**	**0.696**	0.727	**0.741**	**0.728**	**0.708**	**0.724**	**0.740**	**0.769**
	MAD	**0.873**	**0.902**	**0.666**	**0.646**	**0.887**	**0.853**	1.044	**0.840**	**0.618**	**0.588**	**0.779**	**0.574**	**0.772**
FM7	RMSE	**0.994**	**0.989**	**0.961**	**0.959**	**0.954**	**0.957**	**0.965**	**0.967**	**0.975**	**0.962**	**0.980**	**0.985**	**0.971**
	MAE	1.038	1.027	**0.984**	**0.999**	**0.983**	**0.982**	**0.978**	**0.988**	1.004	**0.997**	1.007	1.026	1.001
	MAD	1.317	1.156	**0.997**	1.048	**0.990**	1.277	1.009	1.057	1.062	**0.877**	1.056	**0.914**	1.063

Note: for h = 1 to 12, when we use the Fixed window rolling forecasting scheme for forecast generation. The forecasted variable is the year-on-year growth of tractor sales. For each model, the row containing value of RMSE, MAE and MAD below 1 show that the model-2 (containing CCI) performed better than model-1 (without CCI) at the horizon of interest. These are represented by the bold entries. The last column (extreme right) contains the average forecasting performance of the model containing CCI against model-1.
Source: Author's calculations.

As far as the factor model is concerned, we find that this indicator is not forecasted as well by model-2 compared to model-1 when the first factor is used. However, when we incorporate more factors, the FM5 model-2 outperforms model-1 at all horizons, regardless of the evaluation criteria employed. This suggests that adding more factors can enhance forecast accuracy by bringing additional information into the models. Finally, OLS, MLP, and FM5 complement each other, resulting in an average of less than 1 for all the metrics of forecast accuracy. This indicates that data2, when used for forecasting the growth of tractors, provides valuable information compared to data1, which only includes economic fundamentals.

5.2.2 Expanding Window Rolling Forecasts

Table 5 presents the forecast accuracy results of model-2 compared to model-1 for each technique using the EWR method. The results indicate that MLP's performance remains unchanged, while RMSE and MAE demonstrate improvements in the STK forecasts for model-2 over model-1. Similar to the findings from the FWR scheme, the accuracy metrics show that FM5's model-2 continues to outperform model-1 at all forecast horizons.

Table 5: Forecast accuracy (RMSE, MAE and MAD)

		Horizons												**Average Performance Across**
Models	**Criteria**	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**	**h = 9**	**h = 10**	**h = 11**	**h = 12**	**Horizons**
OLS	RMSE	1.026	1.002	1.005	**0.994**	**0.988**	**0.990**	**0.982**	**0.997**	**0.996**	**0.985**	**0.997**	1.000	**0.997**
	MAE	1.023	1.001	1.012	1.003	1.009	1.009	1.001	1.008	1.001	**0.992**	1.009	1.009	1.006
	MAD	**0.994**	1.114	1.147	1.061	1.050	1.073	1.075	1.137	1.184	1.052	1.115	1.082	1.090
Ridge	RMSE	1.021	**0.997**	1.001	**0.989**	**0.984**	**0.990**	**0.984**	**0.991**	**0.982**	**0.965**	**0.976**	**0.982**	**0.988**
	MAE	1.018	**0.993**	1.008	**0.999**	1.003	1.006	**0.998**	1.009	1.000	**0.985**	**0.997**	1.004	1.002
	MAD	1.047	1.033	1.087	1.108	1.131	1.151	1.236	1.243	1.250	1.312	1.330	1.198	1.177
LASSO	RMSE	1.365	1.265	1.118	1.167	1.185	1.279	1.278	1.099	1.003	**0.983**	**0.994**	**0.947**	1.140
	MAE	1.178	1.087	1.047	1.056	1.076	1.163	1.168	1.064	1.017	**0.993**	1.028	**0.997**	1.073
	MAD	**0.923**	**0.823**	1.036	**0.955**	**0.956**	1.132	1.110	1.151	1.376	1.174	1.173	1.358	1.097
EN	RMSE	1.123	1.091	1.120	1.193	1.244	1.226	1.182	1.126	1.016	**0.991**	1.014	1.015	1.112
	MAE	1.021	**0.994**	1.049	1.097	1.110	1.121	1.123	1.058	**0.965**	**0.975**	1.010	1.021	1.045
	MAD	**0.847**	**0.809**	1.049	1.039	1.035	1.068	1.059	1.016	1.058	1.407	1.446	1.298	1.094
RF	RMSE	1.065	1.050	1.026	1.033	1.027	1.027	1.029	1.035	1.031	1.011	1.015	1.009	1.030
	MAE	1.061	1.030	1.004	1.002	**0.986**	**0.998**	1.003	**0.985**	**0.989**	1.003	**0.983**	**0.985**	1.002
	MAD	**0.959**	1.077	**0.931**	1.004	1.195	**0.820**	**0.996**	1.015	**0.920**	**0.936**	**0.956**	1.020	**0.986**
MLP	RMSE	**0.833**	**0.825**	**0.798**	**0.781**	**0.823**	**0.861**	**0.851**	**0.885**	**0.881**	**0.870**	**0.868**	**0.871**	**0.846**
	MAE	**0.908**	**0.939**	**0.880**	**0.864**	**0.903**	**0.929**	**0.980**	1.009	1.012	**0.984**	**0.964**	**0.999**	**0.948**
	MAD	1.009	1.139	1.023	**0.972**	1.031	1.058	1.066	1.441	1.426	1.240	1.136	1.067	1.134
LSTM	RMSE	**0.876**	1.165	**0.952**	1.108	**0.993**	**0.866**	1.622	1.159	1.423	2.114	1.077	1.288	1.220
	MAE	**0.990**	1.006	**0.821**	1.094	**0.883**	**0.820**	1.190	1.095	1.016	1.335	**0.880**	**0.982**	1.009
	MAD	1.446	**0.967**	**0.806**	1.267	**0.952**	1.018	1.073	1.279	**0.879**	**0.914**	**0.889**	1.069	1.047
FM1	RMSE	1.003	1.004	1.004	1.002	1.003	1.003	1.003	1.004	1.002	1.002	1.002	1.003	1.003
	MAE	**0.999**	1.000	1.003	**1.000**	1.004	1.007	1.008	1.009	1.009	1.006	1.004	1.007	1.005
	MAD	1.024	1.102	1.017	1.112	1.101	1.095	**0.984**	**0.965**	1.029	1.066	**0.998**	1.063	1.046
FM5	RMSE	**0.795**	**0.752**	**0.748**	**0.718**	**0.697**	**0.681**	**0.671**	**0.676**	**0.676**	**0.668**	**0.687**	**0.680**	**0.704**
	MAE	**0.737**	**0.692**	**0.697**	**0.664**	**0.661**	**0.636**	**0.642**	**0.657**	**0.648**	**0.637**	**0.649**	**0.655**	**0.665**
	MAD	**0.574**	**0.555**	**0.599**	**0.695**	**0.656**	**0.702**	**0.601**	**0.694**	**0.585**	**0.565**	**0.614**	**0.670**	**0.626**
FM7	RMSE	**0.982**	**0.972**	**0.970**	**0.963**	**0.956**	**0.961**	**0.962**	**0.961**	**0.956**	**0.953**	**0.976**	**0.984**	**0.966**
	MAE	**0.978**	**0.990**	**0.992**	**0.986**	**0.987**	**0.996**	**0.997**	**0.990**	**0.980**	**0.976**	**0.998**	1.004	**0.989**
	MAD	**0.995**	**0.985**	**0.899**	**0.994**	1.134	1.100	1.227	1.132	1.200	1.127	1.207	1.234	1.103

Note: for h = 1 to 12, when we use the Expanding window rolling forecasting scheme for forecast generation. The forecasted variable is the year-on-year growth of tractor sales. For each model, the row containing value of RMSE, MAE and MAD below 1 show that the model-2 (containing CCI) performed better than model-1 (without CCI) at the horizon of interest. These are represented by the bold entries. The last column (extreme right) contains the average forecasting performance of the model containing CCI against model-1.
Source: Author's calculations.

OLS, on the other hand, is found to have quite weak results when the expanding window scheme is used for forecasting STK. It only outperforms model-1 at eight forecast horizons when RMSE is used as the criterion for evaluation. Nonetheless, results continue to indicate that the addition of CCI through data2 as an explanatory variable improves forecasts of STK.

On average, model-2 has outperformed model-1 across each forecasting technique in 10 instances, which is close to the 12 instances recorded with the FWR scheme. Therefore, we conclude that adding CCI to the information set of economic fundamentals enhances the forecasts for the growth of the demand indicator STK.

Although economic theory suggests that the CCI is connected to durable goods and may therefore help explain the demand for such goods, several studies in the literature have forecasted non-durable goods with and without CCI as an explanatory variable [see Carroll, Fuhrer, and Wilcox (1994), Ludvigson (2004), Lahiri, Monokroussos, and Zhao (2016), among others]. Therefore, since data on a few non-durable goods is available in Pakistan, we forecast these demand indicators using data1 and data2 with each competing technique.

5.3. Year-on-Year Growth of POL Sales

5.3.1 Fixed Window Rolling Forecasts

The first non-durable demand indicator we forecast using data1 and data2 for the competing models is the POLS. Table 6 presents the results of the forecast accuracy measures when employing a FWR forecast scheme. The OLS model indicates that when RMSE is used as the forecast accuracy criterion, model-2 outperforms model-1 at six forecast horizons. This performance is notably strong, with the average RMSE remaining below 1, thereby highlighting the importance of CCI for this demand indicator.

Table 6: Forecast accuracy (RMSE, MAE and MAD)

		Horizons												Average Performance Across
Models	**Criteria**	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**	**h = 9**	**h = 10**	**h = 11**	**h = 12**	**Horizons**
OLS	RMSE	1.002	1.001	1.001	1.001	**0.999**	**0.996**	**0.988**	**0.983**	**0.988**	**0.998**	1.006	1.002	**0.997**
	MAE	**0.997**	1.001	**0.994**	**0.992**	**0.992**	**0.984**	**0.974**	**0.976**	**0.990**	1.000	1.008	1.002	**0.992**
	MAD	1.201	1.078	1.006	1.196	1.129	**0.929**	1.033	1.091	**0.952**	**0.964**	1.336	**0.965**	1.073
Ridge	RMSE	1.003	1.003	1.006	1.006	1.003	1.003	**0.992**	**0.990**	**0.993**	1.001	1.007	1.004	1.001
	MAE	**0.998**	1.001	1.006	1.000	**0.994**	**0.987**	**0.979**	**0.983**	**0.998**	1.020	1.020	1.015	**1.000**
	MAD	1.409	1.137	**0.862**	**0.949**	1.117	1.145	1.297	1.005	**0.716**	**0.772**	**0.895**	1.558	1.072
LASSO	RMSE	1.021	1.091	**0.996**	1.005	1.071	1.034	1.004	1.062	1.084	**0.933**	1.046	1.008	1.030
	MAE	1.013	1.086	1.003	1.048	1.108	1.028	1.031	1.039	1.042	**0.958**	1.084	**0.907**	1.029
	MAD	1.082	**0.995**	**0.908**	1.024	**0.859**	1.077	**0.703**	1.029	1.175	**0.992**	1.092	**0.910**	**0.987**
EN	RMSE	1.037	1.046	1.073	1.014	1.040	1.069	1.018	1.008	**0.924**	**0.788**	**0.956**	**0.945**	**0.993**
	MAE	1.016	1.056	1.065	1.008	1.044	1.053	1.010	**0.953**	**0.964**	**0.822**	**0.920**	**0.886**	**0.983**
	MAD	1.193	**0.896**	1.133	1.127	1.477	1.328	**0.623**	1.095	**0.973**	**0.756**	1.168	**0.650**	1.035
RF	RMSE	**0.988**	**0.993**	**0.999**	**0.982**	**0.987**	1.011	**0.990**	**0.975**	**0.979**	**0.993**	**0.990**	**0.995**	**0.990**
	MAE	**0.982**	**0.994**	**0.992**	**0.970**	**0.973**	1.015	**0.980**	**0.969**	**0.972**	**0.994**	**0.989**	1.007	**0.986**
	MAD	1.020	**0.961**	1.109	1.017	1.047	1.035	1.062	1.394	1.237	1.050	**0.789**	1.336	1.088
MLP	RMSE	**0.935**	**0.850**	**0.867**	**0.885**	**0.868**	**0.844**	**0.885**	**0.874**	**0.834**	**0.765**	**0.719**	**0.717**	**0.837**
	MAE	**0.936**	**0.829**	**0.859**	**0.872**	**0.870**	**0.846**	**0.888**	**0.841**	**0.853**	**0.792**	**0.753**	**0.767**	**0.842**
	MAD	**0.369**	1.871	**0.863**	1.606	1.703	1.489	**0.975**	**0.856**	**0.781**	**0.850**	**0.455**	**0.324**	1.012
LSTM	RMSE	**0.841**	**0.918**	**0.959**	1.022	1.000	1.070	1.174	1.166	1.285	1.173	1.158	1.132	1.075
	MAE	**0.897**	**0.931**	**0.934**	**0.995**	**0.983**	1.015	1.159	1.108	1.278	1.227	1.199	1.127	1.071
	MAD	**0.893**	1.136	**0.810**	**0.987**	**0.635**	**0.811**	**0.978**	**0.972**	1.304	**0.740**	1.611	1.820	1.058
FM1	RMSE	1.003	1.004	1.004	1.003	1.002	1.000	**0.997**	**0.996**	**0.997**	**0.995**	**0.994**	**0.994**	**0.999**
	MAE	**0.999**	1.001	1.001	1.000	**0.999**	**0.997**	**0.995**	**0.995**	**1.000**	**0.998**	**0.998**	**0.998**	**0.999**
	MAD	1.003	1.057	1.025	**0.978**	**0.999**	1.020	1.016	**0.924**	**0.926**	**0.996**	1.028	**0.952**	**0.994**
FM5	RMSE	1.014	1.035	1.054	1.038	1.022	**0.967**	**0.976**	**0.989**	1.006	1.002	1.028	1.012	1.012
	MAE	**0.968**	1.005	1.019	1.007	**0.991**	**0.945**	**0.964**	**0.991**	1.025	1.059	1.095	1.089	1.013
	MAD	1.069	1.468	2.084	1.721	1.063	**0.630**	1.347	**0.896**	**0.881**	**0.622**	**0.855**	**0.820**	1.121
FM7	RMSE	**0.998**	1.017	1.012	1.020	1.011	1.019	1.003	1.008	1.023	1.030	1.030	1.025	1.016
	MAE	**0.985**	1.021	1.024	1.031	1.015	1.013	1.001	1.008	1.048	1.070	1.072	1.071	1.030
	MAD	**0.917**	1.181	1.424	1.209	1.213	**0.692**	1.235	**0.819**	**0.812**	**0.724**	**1.000**	1.258	1.040

Note: for h = 1 to 12, when we use the Fixed window rolling forecasting scheme for forecast generation. The forecasted variable is the year-on-year growth of POL sales. For each model, the row containing value of RMSE, MAE and MAD below 1 show that the model-2 (containing CCI) performed better than model-1 (without CCI) at the horizon of interest. These are represented by the bold entries. The last column (extreme right) contains the average forecasting performance of the model containing CCI against model-1.
Source: Author's calculations.

This result is further supported by the MAE results of the OLS, which indicate that at eight forecast horizons, model-2 can outperform model-1. Similar results hold when the model is either EN or RF; on average, both the RMSE and MAE demonstrate that the addition of CCI to the information set improves the forecasting performance of these models. The RF also shows that model-2 consistently outperforms model-1 across horizons for both RMSE and MAE, thereby highlighting the importance of CCI for this demand indicator.

Of the neural network techniques, MLP demonstrates that the addition of CCI to the dataset substantially improves the forecasts, as evidenced by the RMSE, MAE, and their average across the horizons. In the factor model category, the single factor in the case of POLS performs exceptionally well; we find that model-2 comprehensively outperforms model-1 at most horizons across each forecast accuracy measure. The average performance across horizons indicates that incorporating CCI into the FM1 model helps to forecast POLS more effectively. OLS, EN, RF, and MLP also show that on average, model-2 better explains this demand indicator than model-1; therefore, the alternative economic indicator, the CCI, is important.

5.3.2 Expanding Window Rolling Forecasts

The results for EWR are presented in Table 7. When we use the EWR scheme and generate forecasts using data1 and data2 for each forecasting method, the results demonstrate a significant improvement. In the OLS approach, model-2 outperforms model-1 at 8 forecast horizons and at 10 forecast horizons when RMSE and MAE are used as measures of forecast accuracy, respectively. There is a significant enhancement in the forecasts produced by the MLP, as it shows that model-2 outperforms model-1 at all forecast horizons according to both the RMSE and MAE. Moreover, it can also deliver better forecasts on average when MAD is calculated.

Table 7: Forecast accuracy (RMSE, MAE and MAD)

		Horizons												**Average Performance Across Horizons**
Models	**Criteria**	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**	**h = 9**	**h = 10**	**h = 11**	**h = 12**	
OLS	RMSE	1.001	**0.999**	**1.000**	1.001	**0.999**	**0.994**	**0.985**	**0.979**	**0.984**	**0.995**	1.004	1.001	**0.995**
	MAE	**0.995**	**0.998**	**0.991**	**0.989**	**0.992**	**0.980**	**0.971**	**0.971**	**0.986**	**0.998**	1.008	1.003	**0.990**
	MAD	1.761	1.022	**0.898**	1.148	1.024	**0.940**	1.155	**0.973**	**0.946**	**0.872**	1.168	1.181	1.091
Ridge	RMSE	1.002	1.001	1.004	1.004	1.002	**1.000**	**0.990**	**0.988**	**0.992**	**0.999**	1.005	1.003	**0.999**
	MAE	**0.996**	**0.999**	1.004	**0.999**	**0.993**	**0.985**	**0.978**	**0.981**	**0.996**	1.016	1.020	1.014	**0.998**
	MAD	1.293	1.047	**0.901**	**0.984**	1.058	1.218	**0.886**	**0.960**	**0.551**	**0.538**	**0.698**	**0.897**	**0.919**
LASSO	RMSE	**0.995**	**0.975**	1.013	1.037	1.022	1.072	1.007	**0.972**	1.001	**0.917**	1.034	1.022	1.006
	MAE	**0.971**	**0.976**	1.010	1.029	1.054	1.021	**0.955**	**0.945**	**0.984**	**0.909**	**0.997**	**0.962**	**0.984**
	MAD	**0.923**	**0.978**	1.162	**0.942**	1.009	**0.921**	1.021	1.156	1.232	1.730	2.364	**0.860**	1.191
EN	RMSE	1.041	1.062	1.056	1.042	1.018	1.065	**0.983**	1.006	1.019	**0.885**	**0.967**	**0.950**	1.008
	MAE	1.022	1.079	1.070	1.037	1.007	1.067	**0.993**	**0.951**	**0.998**	**0.905**	**0.945**	**0.915**	**0.999**
	MAD	**0.980**	1.009	1.192	1.485	1.354	1.427	**0.611**	1.101	1.071	**0.868**	1.235	**0.833**	1.097
RF	RMSE	**0.987**	**0.994**	**0.996**	**0.987**	**1.000**	**0.997**	**0.995**	1.004	**0.994**	**0.995**	**0.993**	1.002	**0.995**
	MAE	**0.971**	**0.979**	**0.986**	**0.988**	**0.999**	1.006	**0.992**	1.001	**0.994**	**0.998**	**0.998**	1.020	**0.994**
	MAD	1.101	1.000	1.112	**0.865**	1.125	**0.942**	1.210	**0.970**	1.083	1.278	1.499	1.432	1.135
MLP	RMSE	**0.872**	**0.853**	**0.844**	**0.857**	**0.847**	**0.846**	**0.785**	**0.758**	**0.772**	**0.727**	**0.728**	**0.740**	**0.803**
	MAE	**0.874**	**0.835**	**0.837**	**0.813**	**0.841**	**0.831**	**0.813**	**0.779**	**0.799**	**0.746**	**0.761**	**0.803**	**0.811**
	MAD	**0.322**	1.356	1.012	**0.700**	1.258	1.763	1.423	1.094	**0.580**	**0.775**	**0.626**	**0.564**	**0.956**
LSTM	RMSE	**0.848**	**0.889**	**0.873**	**0.905**	**0.917**	1.091	1.044	1.079	1.085	1.184	1.206	1.332	1.038
	MAE	**0.869**	**0.869**	**0.858**	**0.885**	**0.879**	1.060	1.065	1.097	1.088	1.187	1.235	1.257	1.029
	MAD	1.156	**0.739**	**0.625**	1.062	1.228	1.083	**0.906**	**0.726**	1.175	1.137	2.769	2.935	1.295
FM1	RMSE	1.003	1.003	1.004	1.003	1.001	**0.998**	**0.995**	**0.994**	**0.995**	**0.993**	**0.992**	**0.993**	**0.998**
	MAE	**0.999**	1.001	1.000	**0.999**	**0.998**	**0.995**	**0.993**	**0.993**	**0.998**	**0.996**	**0.996**	**0.997**	**0.997**
	MAD	1.006	1.056	1.046	**0.977**	**0.996**	**0.987**	1.010	**0.918**	**0.922**	**0.965**	1.032	**0.955**	**0.989**
FM5	RMSE	1.010	1.035	1.046	1.037	1.018	**0.962**	**0.967**	**0.985**	**0.994**	**0.989**	1.018	1.001	1.005
	MAE	**0.965**	1.004	1.009	1.001	**0.984**	**0.942**	**0.957**	**0.990**	1.006	1.032	1.073	1.061	1.002
	MAD	1.132	1.737	2.206	1.657	**0.937**	**0.601**	1.192	**0.912**	**0.827**	**0.626**	**0.895**	**0.847**	1.131
FM7	RMSE	**0.997**	1.011	1.010	1.015	1.009	1.013	**0.999**	1.003	1.020	1.029	1.030	1.023	1.013
	MAE	**0.985**	1.015	1.022	1.025	1.014	1.009	**0.998**	1.004	1.042	1.068	1.074	1.073	1.027
	MAD	1.161	1.091	1.434	1.021	1.014	**0.773**	1.343	**0.833**	**0.907**	**0.709**	**0.958**	1.208	1.038

Note: for h = 1 to 12, when we use the Expanding window rolling forecasting scheme for forecast generation The forecasted variable is the year-on-year growth of POL sales. For each model, the row containing value of RMSE, MAE and MAD below 1 show that the model-2 (containing CCI) performed better than model-1 (without CCI) at the horizon of interest. These are represented by the bold entries. The last column (extreme right) contains the average forecasting performance of the model containing CCI against model-1.
Source: Author's calculations.

Factor-based model-1 continues to outperform model-1 in the majority of the forecast horizons when compared in terms of RMSE, MAE, or MAD. It also produces better forecasts on average across all horizons. These results, particularly from the OLS and MLP, demonstrate that the addition of CCI to the information set at each iteration has helped these models to forecast the POLS more accurately.

Some may wonder about the robustness of these findings; therefore, we note that the purpose of this paper is to determine whether the CCI can better explain the demand indicators when included with the fundamental variables, typically analyzed using the consumption function approach in the literature. Hence, consider the following: for a given target variable, if the FWR approach is utilized, and if the OLS can demonstrate that model-2 outperforms model-1 while LASSO yields a similar result, then it follows that LASSO supports the robustness of our findings. In other words, CCI adds value to the forecast of the target variable under both techniques. Therefore, each table above provides evidence that, despite varying the technique used to test our hypothesis, many techniques across different forecasting accuracy measures indicate that the addition of CCI to data1 enhances the explanation of the demand indicator under investigation. Finally, our results are robust across durable versus non-durable goods, as the forecast accuracy improves for both durable and non-durable variables when CCI is included with the economic fundamentals.

6. Conclusion

In this paper, we endeavored to demonstrate that the consumer confidence index contains important information about household consumption decisions in Pakistan at the macro level. For this purpose, we followed the literature and began with the most basic consumption function approach, estimated using OLS. The literature provides a set of specific variables employed in various econometric techniques that may serve as fundamental drivers of demand indicators, primarily informed by economic theory. Most studies have shown that adding consumer confidence to these fundamental drivers improves the forecasts of demand indicators and consumption. Therefore, we also constructed a dataset containing multiple indicators that may impact consumption and demand, augmenting these indicators with consumer confidence to examine whether an improvement is observed in the forecasts of demand variables beyond these standard macroeconomic indicators.

Further, we contribute to the current literature by employing multiple machine learning algorithms, which removes the bias a researcher might have in selecting explanatory variables for forecasting demand indicators. These statistical techniques select variables based on their importance in the data rather than the judgment of a researcher. Therefore, they provide a suitable approach for constructing a set of models that remain insulated from this bias.

Upon conducting the forecasting exercise, we have demonstrated that the consumption function estimated using OLS not only produces improved forecasts for the demand indicators when consumer confidence is included in the dataset, but many of the other techniques show similar findings, thus providing an automatic robustness check for our analysis.

Finally, although the CCI has been referenced in several statements by the monetary policy committee to assess economic conditions, highlighting its importance, no formal research study has been conducted to demonstrate that this indicator aids in explaining the demand indicators in Pakistan. We aimed to illustrate that this indicator is significant in elucidating the demand indicators in Pakistan, and the results support this claim.

Data Availability Statement: Data for this research can be obtained from the corresponding author upon a reasonable request.

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