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Forecasting the GDP Growth in Pakistan: The Role of Consumer Confidence

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Abstract: This paper investigates whether consumer confidence improves the prediction of GDP growth over what are popularly construed as fundamental economic variables. We use monthly data concerning Consumer Confidence Index (CCI) and its sub-indices to forecast GDP growth for Pakistan. Employing a set of univariate and multivariate models and comparing their forecasting performance against the Naïve mean model, we find that adding the consumer sentiments with fundamental economic variables improves the forecast of GDP growth. Vector autoregressive model with current economic conditions index and economic fundamentals, we find, performs the best. The results have potential policy implications in terms of tackling unemployment and inflation, for economic growth stimulation.

Keywords: Consumer Confidence Index; Forecasting; GDP growth; AR; ARMA; VAR.

JEL Classification: C32; C53; D12; E17

Forecasting the GDP Growth in Pakistan: The Role of Consumer Confidence

1. Introduction

Consumer confidence is widely used to predict economic developments by policymakers, financial institutions, government departments, and commercial enterprises. Some economists believe that business cycle fluctuations, such as the global recession of 1990-91 and the 2007-2008 Global Financial Crisis, were driven by crises of confidence (see, for instance, Dees, 2017; Matsusaka and Sbordone, 1995; Vuchelen, 2004).

As measures of alternative economic indicators, consumer confidence indices are regularly published by governments on a monthly or bi-monthly basis. These indices are based on the responses from surveys of randomly selected sample of consumers to specific questions regarding current and expected economic conditions (Ludvigson, 2004).

The observed correlation between measures of consumer confidence and economic activity across a wide range of countries has spurred researchers investigate the predictive power of consumer confidence indices to forecast future economic activity. Theoretically, there are two contrasting views in the literature on the role of consumer confidence in macroeconomics, as summarized by Barsky & Sims (2012): One is the "information" school of thought, which suggests that confidence indexes might contain information about future income which could affect consumption (Beaudry and Portier, 2006; Jaimovish and Rebelo, 2009). Household spending is a major driver of economic activity and growth in most economies, because of the high marginal propensities to consume in most economies. Hence, consumer confidence affects economic activity through consumption. The other school is that of what John Maynard Keynes referred to as "animal spirits", which contends that consumer confidence index does not contain economic information per se, rather it represents consumers' willingness to pay driven by emotional, non-economic factors such as political tensions (see Angeletos and La'o, 2013; Fuhrer, 1993).

The empirical literature that examines the link between consumer confidence and economic activity looks at whether the consumer confidence index (CCI) contains information beyond economic fundamentals. The predictive power of consumer confidence indices to forecast fluctuations in the business cycle, such as recessions and recoveries, has been examined in a number of studies (Ahmed and Cassou, 2016; Batchelor and Dua, 1998; Claveria, Pons and Ramos, 2007; Dees and Brinca, 2013; Islam and Mumtaz, 2016; and Ludvigson, 2004).

The evidence regarding the statistical significance of consumer confidence indices in predicting economic activity, however, is mixed. Some researchers document that inclusion of consumer confidence improves the predictive power of models that include traditional macroeconomic variables such as interest rates, stock prices, inflation, and unemployment. Benhabib and Spiegel (2017), Easaw, Garratt and Heravi (2005), Kwan and Cotsomitis (2006) and Wilcox (2007), for instance, find that the effects of consumer confidence on consumption are weak to modest. Moller, Norholm and Rangvid (2014) found that economic indicators are important in predicting expected returns in European countries, but found that consumer confidence did not play a significant role. Claveria, Pons and Ramos (2007) found that although consumer confidence provides useful information for improving economic forecasts, the improvements were significant in only a limited number of cases. Dees (2017) found that the consumer confidence index is a good predictor in those circumstances where household survey indicators observe large changes.

Given the mixed empirical evidence on role of consumer confidence in predicting economic activity in different economies, it is important to investigate how effectively consumer confidence indices are able to predict the economic activity in a developing country such as Pakistan. To the best of our knowledge, ours is the first study to employ "consumer confidence" and its sub-indices in forecasting economic activity (GDP growth) for Pakistan. We aim to forecast GDP growth in Pakistan using the consumer confidence index (CCI) and its sub-indices. The sub-indices are: the current economic conditions index (CEC) and the expected economic conditions index (EEC). A number of econometric models have also been implemented for estimation purposes, and their forecasting performance is reported using the root mean squared error (RMSE).

The paper is organized as follows: Section 2 provides motivation for undertaking the present study; in section 3 we discuss the data. Section 4 presents the various econometric models employed and our results are explained in section 5. Section 6 offers conclusions.

2. Consumer confidence indices and GDP growth in Pakistan

It is important to note that data on the GDP of Pakistan is only available on an annual basis. Keeping this in mind, we use the Quantum Index of Large-Scale Manufacturing (LSM) as a proxy for GDP, in line with a number of studies that utilize monthly data to forecast GDP, inflation and other key macroeconomic variables for Pakistan. LSM is the only high frequency output measure officially published by the Pakistan Bureau of Statistics for Pakistan; hence it is regularly used as a measure for forecasting and nowcasting economic output or GDP growth in Pakistan. Hussain, Hyder and Rehman (2018), for instance, utilize LSM growth to proxy for GDP growth, undertaking a nowcasting exercise. Other studies have used LSM or LSM growth as a proxy for output or GDP growth in forecasting exercises, including Syed and Lee (2020), Hussain and Mahmood (2017), and Hanif and Jahanzeb (2015)].

Figure 1: GDP Growth and Change in CCI

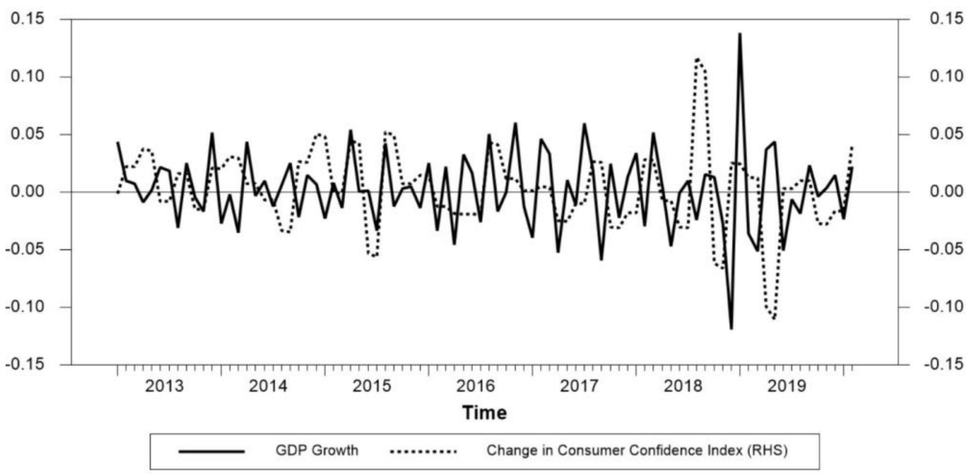
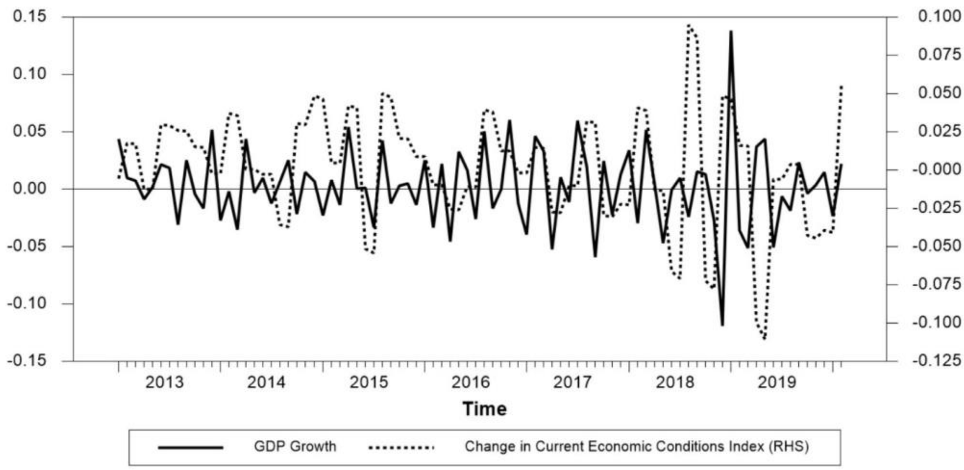
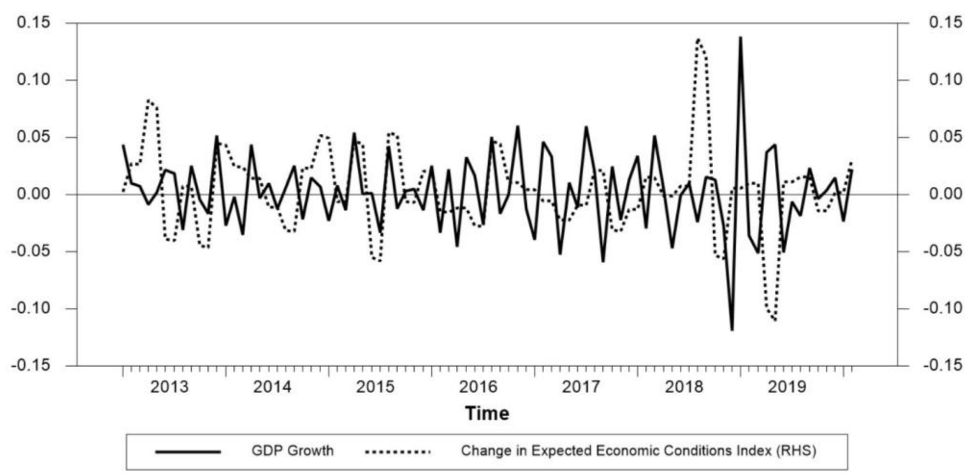


Figure 2: GDP Growth and Change in CEC



As researchers, we are interested in first understanding the relationship between changes in economic conditions and the consumer confidence index and its sub-indices. To examine this, we plot the changes in consumer confidence indices along with GDP growth in Figures 1-3. In all three figures, we observe that the changes in consumer confidence indices are highly correlated with GDP growth, as they closely follow each other.

Figure 3: GDP Growth and Change in EEC



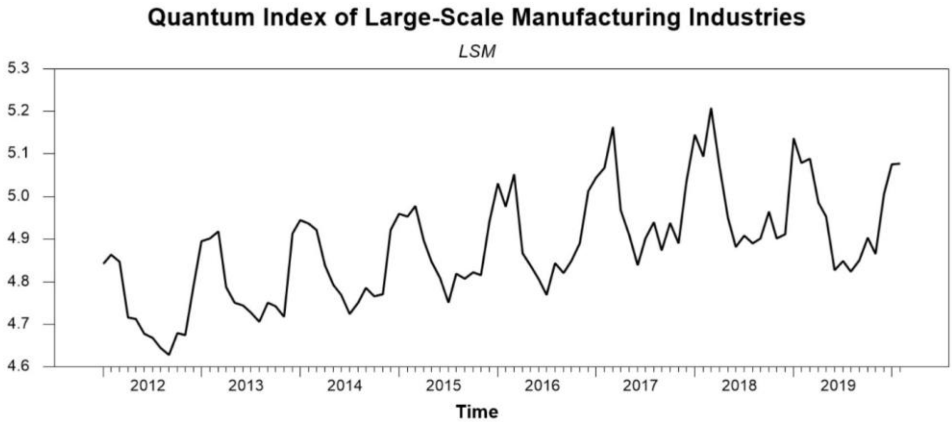
One important thing to focus on when testing to see if the CCI and its subindices act as leading indicators of economic growth are the turning points of GDP growth and the CCI. Another important observation is that GDP growth has remained in negative territory i.e. below zero on the graph in early 2018 while the CCI and its subindices remained positive (though they both were negative in the later months of 2018), A possible explanation as to why this may be the case could be the change in governing political parties in Pakistan, as a result of the 2018 general election that brought the Pakistan Tehreek-e-Insaf into power. But thse differences may imply that the CCI contains some information in addition to more commonly used macroeconomic indicators. This further strengthens our stance of testing the hypothesis that the inclusion of CCI (or its subindices) improve the predictive power of the models to predict GDP growth.

3. Data Description:

The variables used in this study are: real output, consumer confidence index, current economic conditions index, expected economic conditions, stock market general index of prices (S), consumer price index (CPI) and interest rates (R). The variables S, CPI and R comprise economic fundamentals set in our analysis. The data on CCI, CEC, EEC, S, CPI and R has been sourced from the State Bank of Pakistan (SBP). For a more detailed understanding of the consumer confidence indices, see Mirza (2020). LSM has taken from the website of the Pakistan Bureau of Statistics (PBS), and LSM is used as a proxy for GDP.

Aside from interest rates, all other variables are in log form. The sample period for analysis spans from January 2012 – February 2020. The period in question was selected for two reasons: first, the earliest recorded observations concerning Pakistani CCIs became available in January 2012. Second, the first detected case of COVID-19 in Pakistan was February 25th, 2020 – which also marked the start of an abnormal economic period in Pakistan (reflected elsewhere globally at the time). Data pertaining to CCI, CEC, and EEC in Pakistan are only available bi-monthly. As a consequence, therefore, we completed alternate monthly gaps via interpolation – averaging the two adjacent data points both before and after the missing value – in order to have a consistent monthly series of these variables in question.

Figure 4: Graph of Quantum Index of Large-Scale Manufacturing Industries (LSM)



Source: Pakistan Bureau of Statistics

Upon analysing the graph of LSM (Figure 4), we discovered it to exhibit seasonality. We then tested the series further for seasonality by running an Ordinary Least Squares (OLS) regression, containing constant and 11 dummies for January to November for the LSM series. A joint significance test on coefficients of these dummies was performed. The regression can be written as:

$$y_t = \alpha + \sum_{k=1}^{11} \gamma_k D_{kt} + \varepsilon_t \qquad (1)$$

Where y_t is the LSM at time t, α and γ_k are the constant and coefficients on "kth" seasonal dummy respectively, D_{kt} is the value of "kth" seasonal dummy, ε_t is error term for the current period, $\sum_{k=1}^{11} \gamma_k D_{kt}$ are seasonal components. With an F-statistic of 7.51 and a p-value of 0.000, the null hypothesis of no seasonality was rejected at the 5 percent level of significance. Therefore, LSM is seasonally adjusted, using the U.S. Bureau of Census X-11 procedure in statistical analysis software (SAS). The econometric models used to forecast GDP growth in order to carry out this analysis are laid out in the following section. Details of each variable used in this study are provided in Table 1.

Table 1: Details of the variables

Name	Transformations[a]	Short name[b]	Source
Quantum index of large-scale manufacturing industries	3	LSM	Pakistan Bureau of Statistics
SBP General Index of Share Prices/KSE All Index	3	S	State Bank of Pakistan
Consumer Price Index	3	CPI	State Bank of Pakistan
Consumer confidence index	3	CCI	State Bank of Pakistan
Current economic conditions index	3	CEC	State Bank of Pakistan
Expected economic conditions index	3	EEC	State Bank of Pakistan
Weighted average overnight repo rate	2	R	State Bank of Pakistan

[a] Transformations: 1: No transformation, 2: First difference and 3: First Difference of the log.
[b] Short-name refer to the short acronyms used to for the variables in the text and tables.

4. Econometric Models

To forecast Pakistani GDP growth we use eight models and compare their forecasting performance against the Naïve mean model. As a result, the benchmark model for our study is the naïve mean model. The details of each of these models is as follows:

4.1. Mean Model

The mean model is the simple unconditional average of the GDP growth series itself. It can be represented as:

$$Y_t = \mu + \varepsilon_t \tag{2}$$

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

4.2. Random Walk Model (RW)

The first competing model is the random walk model and is expressed as:

$$Y_t = Y_{t-1} + \varepsilon_t \tag{3}$$

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

4.3. Random Walk with Drift Model (RWD)

The next competing model is the random walk with drift model and is expressed as:

$$Y_t = \mu + Y_{t-1} + \varepsilon_t \tag{4}$$

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

4.4. Autoregressive Model (AR)

Some variables in time series data may have a relationship with its previous values, therefore the next model that we applied is the AR model. The AR model characterizes a time series produced by passing the white noise via a recursive linear filter. The lag length for the AR model is chosen by Bayesian Information Criteria (BIC) criteria. The model is given by:

$$Y_t = \mu + \sum_{i=1}^{p} \rho Y_{t-i} + \varepsilon_t \tag{5}$$

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

4.5. Autoregressive Integrated Moving-Average (ARIMA) model

ARIMA models consider both the AR and moving average (MA) components to model a time series. The ARIMA model involves the integrated factor and it is a generalization of an ARMA model. The ARIMA model has also established to be a superior forecasting model compared to the AR model as it considers both AR and MA components.

ARIMA (p,q) can be presented as:

$$Y_t = c + \Phi_1 Y_t - 1 + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \cdots + \theta_q \mu_{t-q} + \mu_t \tag{6}$$

with E(μ_t) = 0; E(μ_t) = σ^2; E(μ_t, μ_s) = 0, $t \neq s$,where φ_t and θ_t are the coefficients, p and q are the orders of AR and MA polynomials, respectively. "μ_t" is the pattern of irregular shocks and are supposed to be identically and independently distributed with mean zero, constant variance, and uncorrelated with each other over time. The lag length for the AR and MA terms in these models is chosen using the BIC.

When external regressors are added to an ARIMA model, the model becomes ARIMAX. As our variable of interest, GDP growth is already stationary, we estimate an ARMA model. Furthermore, we augment the model with other fundamental economic variables, as well as these fundamental economic variables coupled with one of the consumer confidences indexes.

It is important to note that we are interested in predicting the growth of GDP, i.e. output, using consumers' changing perception of the economy; therefore we have to account for changes in the economic environment. As a result our variables are in first differences. The change in the stock market general index of prices signifies the change in wealth of households. We compute inflation as the change in the CPI. We take the first difference in levels of interest rates and this shows the rise or fall in borrowing costs for households, which is a major determinant of their consumption and investment decisions.

To test for the stability of the univariate models (AR, ARMA and ARMA with exogenous regressors), we apply the Ljung-Box (1978) test with the null hypothesis of no autocorrelation, to examine the serial correlation among the residuals from each of the these models. Analysis of the Q-statistic would indicate that the estimated equations of these models produce white noise residuals.

4.6. Vector autoregressive model (VAR)

The VAR model permits feedback among the dependent and independent regressors using their own past values and were pioneered by Sims (1980). Generally, for this model, it is assumed that all the variables in the model are endogenous. The model can be written as:

$$Y_t = \delta_i + \sum_{i=1}^{n} \theta_{i,t} Y_{t-i} + \varepsilon_{i,t} \tag{7}$$

Where, Y_t is a vector of endogenous variables at time t, θ are the parameters and ε are the uncorrelated white noise disturbance terms.

Given that we have a very small sample and the VAR model tends to run into the degrees of freedom problem as more variables or lags are added to the model, we utilized the BIC for lag length selection. We run the VAR model in first differences. For a VAR model to be stable, the residuals from each VAR equation are required to be white noise. To test for serial correlation among the residuals from each VAR equation, we conducted a series of Ljung-Box tests with the null hypothesis of no autocorrelation. The Q-statistics show that the residuals from each VAR equation in all the models are white noise.

5. Forecasting Evaluation:

For forecast evaluation, we examine $h = 1, 2, \ldots, 12$ steps-ahead forecasts and use a training window of 5 years, which is 60 observations. Each model we described in the previous section is estimated within this window, from which $h = 1, 2, \ldots, 12$ steps-ahead forecasts are generated. The training window that starts from 2013-M2 is then moved forward one month until we reach the end of the sample, similar to Panagiotelis, Athanasopoulos, Hyndman, Jiang, and Vahid (2019), and Syed and Lee (2020). For each step, model parameters are re-estimated, and forecasts are generated. By following the process, we get $38 - h$ out-of-sample forecasts for each forecast horizon h, which are then used to compare the forecasting performance of different models. For the forecasting performance measurement, we use the root mean squared error (RMSE). The RMSE is one of the most commonly used scale-dependent accuracy measures.

6. Results:

As a first step, we tested all variables for stationarity using a series of augmented Dickey-Fuller (ADF) tests (Dickey and Fuller, 1981). Thus, we start discussion of our results by reporting the results of the ADF tests in Table 2.

With exception of S, according to both variants of the ADF test, the variables CCI, CEC, EEC, CPI, R and LSM are found to be non-stationary in log-levels/levels at a 5 percent level of significance. The variable S is found to be stationary with the ADF test containing drift, but not with the ADF test containing both drift and the trend. Therefore, it can be treated as stationary in log-levels according to the drift test.

Table 2: Results of Augmented Dickey Fuller Tests

Variable	Log-Levels/ levels	No of Augmenting Lags (Log-Levels/Levels)	First Difference	No of Augmenting Lags (First Difference)	Critical Value*
Panel A: Augmented Dickey Fuller Test with drift					
CCI	-2.56	4	**-3.47**	4	-2.90
CEC	-1.88	5	**-3.37**	4	-2.90
EEC	-2.64	4	**-3.73**	4	-2.90
CPI	0.76	4	**-3.93**	2	-2.90
S	**-3.16**	1	**-5.07**	1	-2.90
R	0.17	2	**-4.80**	1	-2.90
LSM	-1.94	2	**-12.52**	1	-2.90
Panel B: Augmented Dickey Fuller Test with drift and trend					
Variable	**Log-Levels/ levels**	**No of Augmenting Lags (Log-Levels/Levels)**	**First Difference**	**No of Augmenting Lags (First Difference)**	**Critical Value***
CCI	-1.57	5	**-4.25**	5	-3.45
CEC	-0.02	5	**-4.42**	4	-3.45
EEC	-3.31	5	**-5.60**	3	-3.45
CPI	-1.64	3	**-4.54**	3	-3.45
S	-2.01	1	**-5.52**	1	-3.45
R	0.33	1	**-5.30**	1	-3.45
LSM	-1.68	2	**-12.61**	1	-3.45

Notes: CCI: Consumer Confidence Index, CEC: Current Economic Conditions, EEC: Expected Economic Conditions, S: KSE general index of all shares price index, R: Weighted average overnight repurchase rate, LSM: Quantum Index of Large-Scale Manufacturing Industries.
* denotes critical value reported in the table at 5% level of significance and are taken from Table A in the supplementary material of Enders (2015) at www.time-series.net; The values in bold shows that the variable is stationary in log-levels/levels or first differences

Our purpose in this study as mentioned earlier, however, is to forecast the GDP growth which is proxied by the change in LSM. Therefore, the *changes* in the economic environment matters than the economic conditions at a given point in time. Therefore, our analysis contains the first difference of the log of S than the S in log-levels. Finally, all the variables are found to be stationary in first differences.

To assess how well GDP growth may be predicted by consumer confidence, we used a total of nine different models and forecasted GDP growth over a horizon of twelve months. The first four models are univariate models and the next four models are multivariate models. Each multivariate model is estimated, first with fundamental economic variables only and then by adding a measure of consumer confidence. We used CCI, CEC and EEC as a measure of consumer confidence, with results reported in Tables 3, 4 and 5, respectively. Each entry in the tables contain RMSE relative to the naïve benchmark (mean model) as a measure of forecast performance.

Table 3: Forecast accuracy for h = 1 to 12. Each entry shows RMSE relative to the naïve benchmark when CCI is used as a measure of confidence. Entry containing value below '1' shows that the competing approach performed better than the naive mean model. Bold entries indicate the lowest RMSE compared to the mean and all competing approaches across each row.

Horizon	AR	RW	RWD	ARMA	ARMAX1	ARMAX2	VAR1	VAR2
h = 1	0.7739	0.9223	0.9383	0.8746	0.7586	0.7651	0.8743	**0.7185**
h = 2	0.7410	0.8903	0.9103	0.8511	0.7232	0.7296	0.8530	**0.7220**
h = 3	0.7564	0.9117	0.9229	0.8540	**0.7472**	0.7685	0.8637	0.7823
h = 4	0.7394	0.8998	0.9122	0.8534	**0.7374**	0.7464	0.8483	0.7718
h = 5	**0.7284**	0.8862	0.9019	0.8914	0.8112	0.8272	0.8213	0.7593
h = 6	0.7688	0.9078	0.9208	0.9117	0.7749	0.7828	0.8166	**0.7678**
h = 7	0.7652	0.9009	0.9105	0.8865	0.7692	0.7733	0.8186	**0.7633**
h = 8	**0.7546**	0.8953	0.9090	0.8870	0.7834	0.7778	0.8276	0.7683
h = 9	**0.7625**	0.8979	0.9131	0.9327	0.8229	0.8213	0.8325	0.7683
h = 10	**0.7666**	0.8949	0.9072	0.9257	0.7873	0.7943	0.8290	0.7737
h = 11	**0.5768**	0.8133	0.7982	0.7092	0.5925	0.5993	0.6285	0.7107
h = 12	**0.7114**	0.9854	1.0184	1.1362	0.8577	0.8612	0.7813	1.0081

Notes: The competing models are: AR: Autoregressive Model; RW: Random Walk Model; RWD: Random Walk with Drift Model; ARMA = Autoregressive Moving Average Model; ARMAX1: Autoregressive Moving Average Model with Economic Fundamentals only; ARMAX2: Autoregressive Moving Average Model with Economic Fundamentals and Consumer Confidence Index; VAR1: Vector Autoregressive Model with Economic Fundamentals only and VAR2: Vector Autoregressive Model with Economic Fundamentals and Consumer Confidence Index.

The results reported in Table 3 show that AR Model outperforms all other models on the longer horizon (h = 5 and 8 onwards). Broadly speaking, VAR2 performs best at shorter horizons. Moreover, the VAR2 model which includes CCI and economic fundamentals shows a remarkable improvement at every horizon over the VAR1 model where only fundamental economic variables are included. This implies that the CCI does contain additional information over economic variables, thereby improving the prediction of the GDP growth.

Table 4 reports the RMSE relative to the naïve benchmark model where current economic conditions (CEC, a subindex of CCI) is used as measure of consumer confidence. Considering the VAR model as the best model for forecasting, it is clearly observed that predictive power of the model VAR4, where we add a measure of confidence along with fundamental economic variables substantially improves prediction at each horizon over the VAR3 model which includes economic variables only.

However, with few lags, the AR model and ARMAX3 which includes fundamental economic variables as exogenous variables perform best based on RMSE.

Table 4: Forecast accuracy for h = 1 to 12. Each entry shows RMSE relative to the naïve benchmark when CEC is used as a measure of confidence. Entry containing value below 1 show that the competing approach performed better than the naive mean model. Bold entries indicate the lowest RMSE compared to the mean and all competing approaches across each row. The last column shows the name of the model that performed the best at each horizon.

Horizon	AR	RW	RWD	ARMA	ARMAX3	ARMAX4	VAR3	VAR4
h = 1	0.7739	0.9223	0.9383	0.8746	0.7586	0.7687	0.8743	**0.6892**
h = 2	0.7410	0.8903	0.9103	0.8511	0.7232	0.7300	0.8530	**0.7024**
h = 3	0.7564	0.9117	0.9229	0.8540	**0.7472**	0.7677	0.8637	0.7845
h = 4	0.7394	0.8998	0.9122	0.8534	**0.7374**	0.7713	0.8483	0.7761
h = 5	**0.7284**	0.8862	0.9019	0.8914	0.8112	0.8240	0.8213	0.7512
h = 6	0.7688	0.9078	0.9208	0.9117	0.7749	0.7877	0.8166	**0.7533**
h = 7	0.7652	0.9009	0.9105	0.8865	0.7692	0.7726	0.8186	**0.7516**
h = 8	0.7546	0.8953	0.9090	0.8870	0.7834	0.7882	0.8276	**0.7452**
h = 9	0.7625	0.8979	0.9131	0.9327	0.8229	0.8195	0.8325	**0.7522**
h = 10	0.7666	0.8949	0.9072	0.9257	0.7873	0.7842	0.8290	**0.7546**
h = 11	**0.5768**	0.8133	0.7982	0.7092	0.5925	0.5842	0.6285	0.6827
h = 12	**0.7114**	0.9854	1.0184	1.1362	0.8577	0.8305	0.7813	1.0178

Notes: The competing models are: AR: Autoregressive Model; RW: Random Walk Model; RWD: Random Walk with Drift Model; ARMA = Autoregressive Moving Average Model; ARMAX3: Autoregressive Moving Average Model with Economic Fundamentals only; ARMAX4: Autoregressive Moving Average Model with Economic Fundamentals and Current Economic Conditions Index; VAR3: Vector Autoregressive Model with Economic Fundamentals only and VAR4: Vector Autoregressive Model with Economic Fundamentals and Current Economic Conditions Index.

In Table 5, results are produced for each model wherein a subindex of CCI, EEC, is used as a measure of consumer confidence. These results show that AR model is the best model to predict the GDP growth at all horizons except at horizon 2 and 4 where the ARMAX6 model with exogenous variables (fundamental economic variables and expected economic conditions) performs best.

Table 5: Forecast accuracy for h = 1 to 12. Each entry shows RMSE relative to the naïve benchmark when EEC is used as a measure of confidence. Entry containing value below 1 show that the competing approach performed better than the naive mean model. Bold entries indicate the lowest RMSE compared to the mean and all competing approaches across each row. The last column shows the name of the model that performed the best at each horizon.

Horizon	AR	RW	RWD	ARMA	ARMAX5	ARMAX6	VAR5	VAR6
h = 1	**0.7739**	0.9223	0.9383	0.8746	**0.7687**	0.7860	0.8743	1.0628
h = 2	0.7410	0.8903	0.9103	0.8511	0.7300	**0.7158**	0.8530	1.0071
h = 3	**0.7564**	0.9117	0.9229	0.8540	0.7677	0.7849	0.8637	1.2740
h = 4	0.7394	0.8998	0.9122	0.8534	0.7713	**0.7372**	0.8483	1.2702
h = 5	**0.7284**	0.8862	0.9019	0.8914	0.8240	0.8889	0.8213	1.3525
h = 6	**0.7688**	0.9078	0.9208	0.9117	0.7877	0.9571	0.8166	1.4107
h = 7	**0.7652**	0.9009	0.9105	0.8865	0.7726	1.0103	0.8186	1.4933
h = 8	**0.7546**	0.8953	0.9090	0.8870	0.7882	1.0037	0.8276	1.4922
h = 9	**0.7625**	0.8979	0.9131	0.9327	0.8195	1.3048	0.8325	1.4752
h = 10	**0.7666**	0.8949	0.9072	0.9257	0.7842	1.4802	0.8290	1.4730
h = 11	**0.5768**	0.8133	0.7982	0.7092	0.5842	1.9826	0.6285	1.6904
h = 12	**0.7114**	0.9854	1.0184	1.1362	0.8305	3.4303	0.7813	2.6396

Notes: The competing models are: AR: Autoregressive Model; RW: Random Walk Model; RWD: Random Walk with Drift Model; ARMA = Autoregressive Moving Average Model; ARMAX5: Autoregressive Moving Average Model with Economic Fundamentals only; ARMAX6: Autoregressive Moving Average Model with Economic Fundamentals and Expected Economic Conditions Index; VAR5: Vector Autoregressive Model with Economic Fundamentals only and VAR6: Vector Autoregressive Model with Economic Fundamentals and Expected Economic Conditions Index.

Surprisingly, the predictive power of multivariate models does not improve with the inclusion of the EEC. This could imply that consumers and investors are not forward-looking and may not take into account rational expectations when taking decisions.

Similarly, Pot, Dewulf, Biesbroek, Vlist and Termeer (2018) explain how investors are not necessarily and ostensibly “forward-looking”, as forward-looking decision-making requires administrators to use scenarios, visions, and flexible solutions in order to build support, avoid political risks, and encourage compliance with formal rules. To create awareness about future information and potential alternate paths, scenario developers need to involve administrators at an early stage of decision making, which may not be the case in Pakistan. In Pakistan’s case, therefore, liquidity constraints and unfavorable scenarios do not let consumers and investors to be forward-looking respectively.

Broadly speaking, the results appear to indicate that consumers are not forward-looking, and that their consumption behaviors are driven by current state of the economic conditions. The predictive power of the model improves when CEC is used as an additional predictor with fundamental economic variables.

These results are not surprising as the literature provides evidence that consumers and investors are not necessarily forward-looking (see, for instance Startz, 2011; Pot, Dewulf, Biesbroek, Vlist and Termeer, 2018). Startz (2011) argues that consumers consider only current economic conditions and are not forward-looking, not because of myopia, rather because of liquidity constraints.

The results imply that consumer confidence, which determines consumer spending, is useful not only in predicting the growth of the economy but it can also be used as a predictor of the effectiveness of monetary policy. Knowing the role of consumer confidence, the monetary policy committee of the State Bank of Pakistan (MPC) factors CCI and its sub-indices into consideration while making its decision (State Bank of Pakistan, 2019).

Our results are consistent with Benhabib and Spiegel (2017), Dees and Brinca (2013), Easaw, Garratt and Heravi (2005), Kwan and Cotsomitis (2006) and Howrey (2001) among others who document that consumer sentiments improve the predictability of GDP growth.

7. Conclusion:

Evidence in the literature on the ability of the consumer confidence index and its variants to forecast economic activity is mixed. With this in mind, we contribute to the literature on CCIs by testing the predictive ability of CCI and its sub-indices for GDP growth using a variety of econometric models for Pakistan. We use LSM as a measure of GDP growth and other variables such as the stock market general index of prices, consumer price index, and interest rates as measures of economic fundamentals. Consumer confidence index and its sub-indices, i.e., current economic conditions and expected economic conditions, are used as measures of consumer confidence.

We found that the performance of the multivariate model, VAR (measured as RMSE) improves when consumer confidence index is added to fundamental economic variables. We then test the predictive power of the model by using sub-indices of the model to examine which component of the consumer confidence index is more important in predicting GDP growth. It is observed that current economic condition index improves the performance of the VAR model when added into the model with economic fundamentals.

Consumer confidence is particularly important in the manufacturing of durable goods as their revenues are highly correlated with consumer spending. But even though this is the case in theory, when the expected economic conditions index is added into the model along with fundamental economic variables, the performance of the model does not show improvement. The results would appear to infer that Pakistani consumers are not forward-looking and their spending behavior only consider current economic conditions (Startz, 2011; Pot, Dewulf, Biesbroek, Vlist and Termeer, 2018).

This implies that as consumer sentiments and expectations are not fully reflected in fundamental economic variables, better forecasts of GDP growth may be obtained by using the indices of consumer confidence along with fundamental economic variables. This may be due to random behavior of the consumers and other political factors which affect the confidence of consumers and their spending. Hence, in Pakistan, the current economic conditions index is an important predictor of economic growth. It is currently being used by central banks to take monetary policy measures and can also be used to measure the effectiveness of monetary policy.

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