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Do Inflation Expectations Matter for Inflation Forecastability: Evidence from Pakistan

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We empirically investigate if the incorporation of inflation expectations helps improve the forecasting performance of a suite of univariate inflation models. Since inflation forecasts are instrumental to the conduct of an effective monetary policy, any possible improvement in the inflation forecastability may tend to enhance the effectiveness of monetary policy—by providing forward guidance both to the monetary authority and the market to effectively anchor inflation expectations. Our results are robust across specifications of our baseline models, sample sizes and forecast horizons. The introduction of inflation expectations, whether contemporaneously or with a 6-months lead improves the predictive ability—both in-sample and out-of-sample for 6 and 12-month horizons. Deterioration however is observed for a 3-month horizon, which point towards the weak representation of the expectations data for a 3-month horizon.

JEL Classification: E31, E37
Keywords: Inflation-expectations, Forecast-performance, Pakistan.

1. INTRODUCTION

In this paper we empirically examine if incorporation of the measure of inflation expectations improves forecasting performance of the suite of our baseline univariate inflation models, which are consistent with the univariate models of Kapetanios, *et al.* (2007) and Ogunc, *et al.* (2013). This investigation is important because the central banks across the globe are increasingly providing forward guidance to the public in order to enhance the effectiveness of monetary policy—as it helps efficiently anchor inflation expectations. Since the central monetary authority of the country, the State Bank of Pakistan (SBP) envisions implementation of the flexible inflation targeting as a high level goal in its strategic plan for 2016–2020, it is crucial to forecast inflation as accurately as possible. Under such a framework, accurate inflation forecasts greatly help the policy makers to formulate and conduct monetary policy effectively by successfully anchoring inflation expectations. Inflation expectations play a vital role in the forecasting models and the central banks are constantly making efforts to incorporate future expectations into a range of models to make it compatible with the theory—as the theory assumes

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rationality on part of the public. Often ample resources are advocated to supplement the forecast performance by collecting real time data on market expectations. Usually demand side surveys are conducted to collect and compile the economic expectations of various stakeholders and the resultant series are used in time series estimations for forecasting. Since the SBP and Institute of Business Administration (IBA) has recently started collecting information on market expectations through a nation-wide consumer confidence (CCS) survey from January 2012, the use of its overall inflation expectations index (IEI) may possibly improve the forecast performance of our proposed benchmark univariate inflation models.

It is pertinent to mention that although there is a huge empirical literature on Pakistan's monetary policy largely focused on exploring the determinants of inflation in Pakistan, little or no attention could be diverted to improve the inflation forecastability especially in terms of the potential role of inflation expectations.[1] To the best of our knowledge, no study in the context of Pakistan—theoretical or empirical has attempted to investigate into the role of inflation expectations either towards improvement or deterioration of inflation forecasts. For example, empirically Bokil and Schimmelpfennig (2005) attempted to give their own models that may possibly be used for forecasting inflation. They conducted their forecasting exercise based on three major models (i) the leading indicator model (LIM), (ii) ARIMA and (iii) a VAR model, and compared the results of all the three models to be able to conclude in favour of the use of one particular model for the central forecast. Bokhari and Feridun (2006) aimed at modelling various indicators of inflation such as SPI, WPI, CPI and GDP deflator through various specifications of ARIMA and VAR models for inflation forecasting. Haider and Hanif (2009) attempted to forecast inflation by using artificial neural networks (ANN) and compared its forecast performance with conventional univariate time series models. Riaz (2012) evaluated forecast efficiency of food price inflation and consumer price index by using rationality criterion of forecasts—while recently Hanif and Malik (2015) evaluated the forecast performance of different multivariate models against univariate models across low, moderate and high inflation regimes.

Unlike the work cited above, in the current paper, we specifically try to explore if the inclusion of inflation expectations into the set of our univariate inflation models improve their in-sample and out-of-sample predictive ability for three different shot-term horizons. For this purpose we first introduce a set of univariate baseline inflation models and try to determine the improvement (or deterioration) in the forecasting performance of these models in two steps. In the first step, we estimate these univariate models and observe their in-sample and out-of-sample forecasting performance over three short-term scenarios of 3, 6 and 12 months through the Root Mean Square Error (RMSE).[2] The

[1]See for example, Serfraz and Anwar (2009); Haider and Khan (2007); Khan and Gill (2007); Chaudhary and Ahmad (1996) and Ahmad and Ram (1991) among others.

[2]Forecast-assessment tests can broadly be categorised as the tests of forecast accuracy and the tests of forecast rationality namely weak, sufficient, strong and strict rationality. In the former case normally the distance between the forecasts and the outturns is taken into account while in the latter case the assessment is made on the basis whether the forecast errors are zero [Kapetanios, *et al.* (2007)]. We focus on the former where a number of formulas can be used such as sum of forecast errors, the sum of absolute errors, the sum of squared errors, Theil's U-statistic and the RMSE. We use the most widely used RMSE criterion for the purpose of forecasts-evaluation.

RMSEs obtained in the first step are then used as benchmarks for comparison with the corresponding RMSEs obtained after the introduction of the inflation expectations indicator into our models—both contemporaneously and with a six months lead. To be precise, if $RMSE_{IEI} < RMSE_{BASE,}$ we consider it an improvement in the forecast ability of the models.

Our results are robust across model specifications, sample sizes and horizons and show that the inflation expectations as measured by the survey expectations indicator deteriorates the predictive ability of the baseline univariate inflation models for a 3-month horizon—while significantly improve it for 6 and 12-month horizons. We further observe that by and large the incorporation of expectations contemporaneously yield better results than its incorporation with a 6-month lead.

The remainder of the paper is organised as follows. Section 2 specifies the baseline univariate inflation models. Section 3 highlights the data and conducts a preliminary analysis of the relationship between inflation and inflation expectations. Section 4 discusses the results and conducts the robustness checks while Section 5 draws the conclusion.

2. METHODOLOGY–SPECIFICATION OF THE UNIVARIATE BASELINE INFLATION MODELS

For the purpose of assessment of forecast performance, consistent with Kapetanios, *et al.* (2007) we specify a range of univariate baseline inflation models with increasing degree of complexity. For example, we start from a simple unconditional mean inflation model and end up with ARIMA model. These models are given as under.

2.1. Unconditional Mean Model (UM)

To start with, the unconditional mean inflation model is expressed as:

$$\pi_t = \alpha + \varepsilon_t.$$

The final model, after incorporation of dummies for seasonal factors (see Ahmad and Ashfaq, 2015 for evidence of seasonality in Pakistan) is given as:

$$\pi_t = \alpha + \sum_{i=1}^{12} \gamma_i SD_i + \varepsilon_t, \qquad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (1)$$

where π_t is the log change in consumer price index (CPI) and SD represents the monthly seasonal dummies. It is the same for the next two models.

2.2. Random Walk with Drift (RWD) Model

The RWD is given by the expressions as:

$$\pi_t = \alpha + \pi_{t-1} + \varepsilon_t.$$

While accounting for the seasonal factors, the final model takes the following form:

$$\pi_t = \alpha + \pi_{t-1} + \sum_{i=1}^{12} \gamma_i SD_i + \varepsilon_t. \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (2)$$

2.3. Random Walk with Drift and Trend (RWDT) Model

Here we introduce the trend component to the RWD model such that

$$\pi_t = \alpha + \pi_{t-1} + \tau t + \varepsilon_t,$$

where t denotes the time trend. After adjusting for seasonality, the final model is expressed as:

$$\pi_t = \alpha + \pi_{t-1} + \tau\, t + \sum_{i=1}^{12} \gamma_i SD_i + \varepsilon_t. \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (3)$$

2.4. Autoregressive (AR) Model

This model represents the time series generated by passing the white noise through a recursive linear filter. The output of such filter at time t is a weighted sum of 'p' previous values of the filter output. The integer parameter p is called the order of the AR-model. The AR-model of a random process y_t at time t is defined by the following expression:

$$y_t = \sum_{i=1}^{p} a_i \cdot y_{t-i} + \varepsilon_t \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (4)$$

where $a_1, a_2, \ldots, a_m$ are the coefficients of the recursive filter and ε_t represent white noise errors.

2.5. Moving Average (MA) Model

Contrary to the AR model, this model is generated by passing the white noise through a non-recursive linear filter. A moving average model of a random process y_t at time t is defined as:

$$y_t = \sum_{i=0}^{q} b_i \cdot x_{t-i} + \varepsilon_t \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (5)$$

where $b_1, b_2, \ldots, b_n$ are the coefficients of the non-recursive filter; q is order of the MA model, x_t are the elements of the (input) and ε_t are the white noise errors.

2.6. Integrated Autoregressive Moving Average (ARIMA) Model

This model represents the time series that is generated by passing white noise through a recursive as well as a non-recursive linear filter, consecutively. In other words, the ARIMA model is a combination of an autoregressive (AR) model and a moving average (MA) model. The order of the ARIMA model at time t is described by two integers (p, q), that are the orders of the AR and MA parts, respectively. The general expression for an ARMA-process y_t is the following:

$$y_t = \sum_{i=1}^{p} a_i \cdot y_{t-i} + \sum_{i=0}^{q} b_i \cdot x_{t-i} + \varepsilon_t \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (6)$$

where 'p' is the order of the AR-part of the ARMA model; $a_1, a_2, \ldots, a_p$ are the coefficients of the AR-part of the model (recursive linear filter); q is the order of the MA-part of the ARMA model; $b_1, b_2, \ldots, b_q$ are the coefficients of the MA-part of the model (of the non-recursive linear filter); x_t are the elements of the (input) white noise and ε_t is white noise error term.

3. DATA AND THE RELATIONSHIP BETWEEN INFLATION EXPECTATIONS AND OBSERVED INFLATION

The main sources of our data are the Pakistan Bureau of Statistics (PBS), SBP and IBA. Monthly CPI data is obtained from the PBS for the period covering July, 2002 to July, 2015 depending on the availability of a consistent data series. We use the 6-months ahead IEI data from the CSS carried out jointly by the SBP and IBA. This survey covers 1800 households from all over Pakistan contacted through fixed line telephones. After every alternate month the households are asked as to how they expect the prices in general will be over the next six months.[3] These qualitative responses are then quantified and used to construct prices expectations index, which is available from January, 2012 onwards at the SBP website. We use this index as the measure of six months ahead inflation expectations. Unlike other Asian countries such as China, India, Bangladesh and Korea where data on inflation expectations is collected every month (see Kim and Lee, 2012), the IEI is available only for alternate month. Therefore in order to have a consistent monthly data series, we filled the alternate monthly gaps through interpolation—by averaging the two adjacent data points before and after the missing value. A bird eye view of the key features of the data can be had from Table 1.

Table 1

Descriptive Stats of the Data

	CPI-Index	Inflation Expectations Index
Mean	184.8	92.2
Median	188.7	93.3
Maximum	201.6	100.0
Minimum	162.6	80.9
Std. Dev.	12.3	5.2
Observations	43.0	43.0

As far as the stationarity properties of the data are concerned, it is important to mention that both the inflation and IEI series are expressed in log form and their first difference is stationary (Table 1a).

Table 1a

Stationarity Properties of the Variables

	ADF		PP	
Variables	Level	First Difference	Level	First Difference
π	[0.81]	[0.00]***	[0.87]	[0.00]***
IEI	[1.00]	[0.00]***	[0.88]	[0.00]***

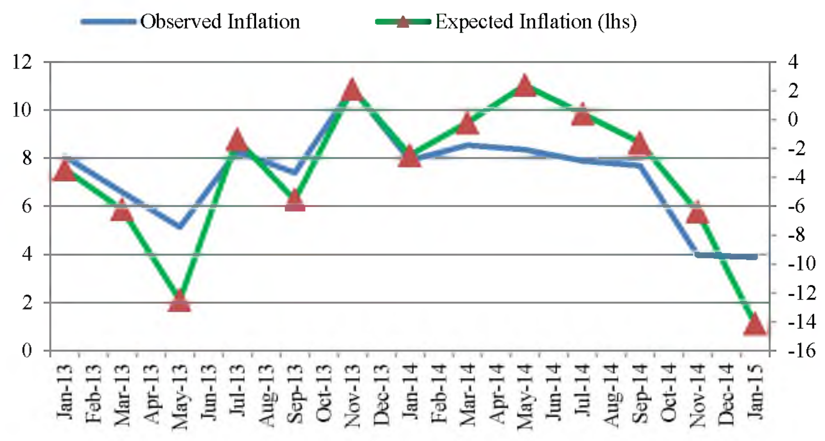
This table reports the P-values of the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. ***, ** and * indicate that the series are stationary at the 1 percent, 5 percent and 10 percent level of significance, respectively.

[3]The exact question is "How do you expect that prices in general will develop over the next six months from now? (a) go down significantly, (b) go down marginally, (c) no change, (d) go up marginally, (e) go up significantly and (f) do not know.

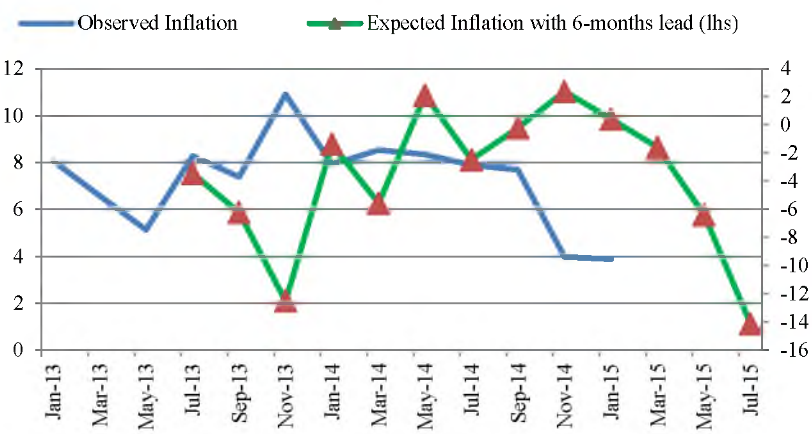
An important issue to highlight here is that the pertinent question in the survey contemplates the six months ahead expected inflation, however, the changes in the IEI seems to co-move with contemporaneous inflation (Figure 1, Panel A).[4] The relationship between the observed inflation and the expected inflation with a six month lead may not be corroborated to make a perfect sense because they instead seem to reflect a theoretically inconsistent inverse relationship (Figure 1, Panel B).

Fig. 1. Observed and Expected Inflation

Panel A: Contempopraneous Relationship



Panel B: Relationship with a 6-Months Lead

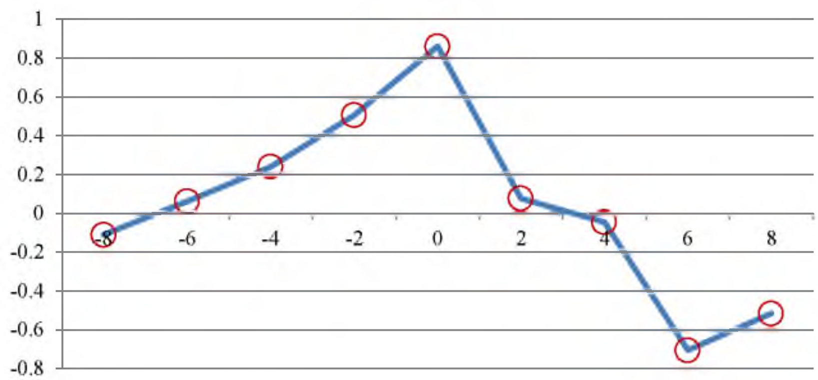


These relationships may also be confirmed by the comparison of correlations between observed and expected inflation both contemporaneously and with different leads and lags (Figure 2). For example, the contemporaneous correlation (at zero lag) is

[4]This is consistent with the findings of Kim and Lee (2012) for other Asian countries such as India, Bangladesh, Sri Lanka and so forth.

both positive and highest with a correlation coefficient of 0.86. The correlation coefficient with a 6 months lead of the expected inflation nonetheless is –0.76. This indicates that inflation expectations are more adaptive rather than forward looking.

Fig. 2. Cross-correlation between Expected Inflation and Lag (-) / Lead (+) of Actual Inflation



4. RESULTS AND ROBUSTNESS CHECK

4.1. Results

In order to assess if the inclusion of inflation expectations improve the forecast performance of our specified univariate baseline inflation models ranging from Equation 1 through Equation 6, we first estimated their RMSEs both in-sample and out-of-sample for different horizons 3, 6, and 12 months.[5] The coefficient estimates of the baseline models are produced in Table 2 whereas the results for the corresponding models after incorporation of the expectations variable are given in Table 3 and 4. If $RMSE_{IEI}$ < $RMSE_{BASE,}$ the IEI adds to the forecastability of the models and vice versa.

In line with lead-lag analysis, inflation expectations with six months lead turns out to be insignificant. Less educated households with little knowledge about the structure of economy and large informal sector may be possible reasons for such behaviour. As a result, households mainly formulate their expectations about inflation based on current and past inflation.[6] It is important to note that the baseline models (both before and after incorporation of the IEI) pass the key diagnostic tests for serial correlation, homoscedasticity and normality (Table 5). In the second step, after incorporation of the IEI indicator to our baseline models, we estimated the respective RMSEs for comparison with the RMSEs of the baseline models in order to observe any possible improvement (deterioration) across horizons and models. The results on the RMSEs are presented and discussed in the subsequent sub-sections.

[5] It is important to mention that before estimation the important steps of identification, estimation and diagnostics were conducted. These results however are not reported to save space and may be obtained from any of the authors upon request.

[6] To this effect, we used inflation expectations without lead, which turned out to be significant in all the models (Table 3).

Table 2

Baseline Models' Results

Dependent Variable is $_t$																					
Models	C	PD	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	Trend	SAR(3)	SAR(6)	SAR(12)	SMA(3)	SMA(4)	SMA(6)	SMA(12)
UM	-0.003	0.019	0.013	0.002	0.009	0.015	0.008	0.005	0.018	0.009	0.008	0.006	0.001								
	[0.20]	[0.00]	[0.00]	[0.362]	[0.002]	[0.00]	[0.00]	[0.06]	[0.00]	[0.00]	[0.01]	[0.37]	[0.76]								
RWD	0.086	0.011	0.016	0.003	0.014	0.021	0.010	0.011	0.018	0.017	0.011	0.016	0.009								
	[0.00]	[0.02]	[0.00]	[0.38]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]								
RWDT	0.078	0.011	0.016	0.003	0.014	0.021	0.010	0.011	0.018	0.017	0.011	0.016	0.009	0.00							
	[0.48]	[0.03]	[0.00]	[0.38]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.93]							
AR	0.005	0.014													0.220		0.206				
	[0.02]	[0.05]													[0.10]		[0.15]				
MA	0.007	0.015																0.312			0.267
	[0.00]	[0.12]																[0.01]			[0.06]
ARIMA	0.006	0.014														0.549	0.404		0.150	-0.672	
	[0.11]	[0.01]														[0.01]	[0.01]		[0.25]	[0.01]	

Where t is the log change in consumer price index (CPI), S1 to S11 represent monthly seasonal dummies, PD is the dummy of 2008 oil price shock and values in parenthesis are p-values. The character S before AR and MA, for example, SAR represent seasonally adjusted.

Table 3

Models' Results Using Inflation Expectations (contemporaneous)

Dependent Variable is $_{t}$

Models	C	^{e}	PD	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	Trend	SAR(3)	SAR(6)	SAR(12)	SMA(6)	SMA(12)
UM	-0.255	0.056	0.015	0.011	-0.002	0.009	0.017	0.009	0.007	0.015	0.008	0.003	0.009	0.002						
	[0.00]	[0.00]	[0.00]	[0.02]	[0.70]	[0.05]	[0.00]	[0.05]	[0.09]	[0.00]	[0.08]	[0.58]	[0.06]	[0.61]						
RWD	-0.141	0.035	0.013	0.016	0.004	0.015	0.022	0.011	0.012	0.018	0.017	0.011	0.015	0.009						
	[0.30]	[0.09]	[0.01]	[0.00]	[0.28]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]						
RWDT	-0.130	0.080	0.011	0.015	0.003	0.014	0.021	0.011	0.011	0.017	0.017	0.010	0.015	0.009	0.001					
	[0.32]	[0.01]	[0.02]	[0.00]	[0.39]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.01]	[0.05]					
AR	-0.267	0.061	0.015													0.147		0.376		
	[0.02]	[0.01]	[0.00]													[0.32]		[0.02]		
MA	-0.184	0.042	0.012																	0.864
	[0.01]	[0.01]	[0.01]																	[0.00]
ARIMA	-0.325	0.074	0.0151															0.77	-0.05	-0.883
	[0.00]	[0.00]	[0.00]															[0.00]	[0.34]	[0.00]

Where $_{t}$ is the log change in consumer price index (CPI), ^{e} is the log of inflation expectation index for survey data, S1 to S11 represents monthly seasonal dummies, PD is the dummy of 2008 oil price shock and values in parenthesis are p-values. The character S before AR and MA, for example, SAR represent seasonally adjusted.

Table 4

Models' Results Using Inflation Expectations (six months lead)

Dependent Variable is t																				
Models	C	e+6	PD	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	Trend	SAR(3)	SAR(6)	SAR(12)	SMA(6)	SMA(12)
UM	-0.103	0.014	0.022	0.011	-0.002	0.008	0.016	0.007	0.007	0.015	0.009	0.005	0.011	0.004						
	[0.30]	[0.02]	[0.31]	[0.04]	[0.77]	[0.12]	[0.00]	[0.17]	[0.18]	[0.00]	[0.10]	[0.42]	[0.06]	[0.48]						
RWD	0.204	-0.020	0.010	0.016	0.003	0.015	0.021	0.010	0.011	0.018	0.018	0.012	0.016	0.009						
	[0.16]	[0.41]	[0.04]	[0.00]	[0.36]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]						
RWDT	0.192	-0.039	0.011	0.017	0.004	0.016	0.022	0.011	0.012	0.018	0.018	0.012	0.016	0.009	0.000					
	[0.19]	[0.23]	[0.03]	[0.00]	[0.27]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.38]					
AR	0.056	-0.011	0.014													0.236		0.347		
	[0.67]	[0.70]	[0.00]													[0.11]		[0.04]		
MA	0.035	-0.007	0.011																	0.865
	[0.72]	[0.76]	[0.00]																	[0.00]
ARIMA	0.166	-0.039	0.015															0.787	-0.047	-0.905
	[0.23]	[0.21]	[0.01]															[0.00]	[0.36]	[0.00]

Where t is the log change in consumer price index (CPI), e 6 is the log of inflation expectation index with 6-months lead for survey data, S1 to S11 represent monthly seasonal dummies, PD is the dummy of 2008 oil price shock and values in parenthesis are p-values. The character S before AR and MA, for example, SAR represent seasonally adjusted.

Table 5

Diagnostics Tests of the Models (P-Values)

	UM	RWD	RWDT	AR	MA	ARIMA
Benchmark Models						
Serial Correlation	[0.45]	[0.18]	[0.30]	[0.96]	[0.1]	[0.54]
Heteroskedasticity	[0.40]	[0.93]	[0.97]	[0.55]	[0.53]	[0.11]
Normality	[0.35]	[0.81]	[0.59]	[0.38]	[0.56]	[0.68]
Models with Survey Expectations						
Serial Correlation	[0.46]	[0.12]	[0.1]	[0.96]	[0.29]	[0.27]
Heteroskedasticity	[0.40]	[0.74]	[0.72]	[0.67]	[0.92]	[0.10]
Normality	[0.36]	[0.65]	[0.54]	[0.38]	[0.32]	[0.46]

The tests for serial correlation, heteroscedasticity and normality are Breusch-Godfrey Serial Correlation LM Test, White Test and Jarque Berra, respectively.

4.1.1. *In-sample Forecast Performance (Short-sample)*

As a starting point, we estimate all the univariate benchmark models using a short-sample period starting from January, 2012 to July, 2015 as the survey data for expectations is available only for the mentioned period. After estimating the benchmark inflation models, in order to observe the in-sample forecast performance we estimated their RMSEs (both using 6-month lead and no-lead of IEI) for the three different horizons. These RMSEs are then used as benchmarks for comparison with the respective RMSEs after inclusion of the expectations indicator IEI to the models. The results are presented in Table 6.

Table 6

In Sample Forecast

	UM	RWD	RWDT	AR	MA	ARIMA
Root Mean Squared Error (3-months ahead forecast)						
Benchmark	0.69	0.08	0.49	0.77	0.79	0.47
Survey Expectations (6-months lead)	0.67	0.47	0.73	0.78	0.76	0.50
Survey Expectations (Contemporaneous)	1.67	1.40	0.71	1.97	1.98	1.62
Root Mean Squared Error (6-months ahead forecast)						
Benchmark	3.91	2.67	2.17	3.95	3.96	3.66
Survey Expectations (6-months lead)	3.79	2.27	2.03	3.87	3.85	3.56
Survey Expectations (Contemporaneous)	3.27	2.97	1.41	3.67	3.70	3.39
Root Mean Squared Error (12-months ahead forecast)						
Benchmark	6.15	3.60	3.07	6.70	6.69	6.34
Survey Expectations	5.86	2.90	2.75	6.50	6.49	6.08
Survey Expectations (Contemporaneous)	3.50	3.15	1.30	4.41	4.53	4.34

Note: The estimation period is from January 2012 to July 2015.

Since a lower value of the RMSEs reflects an improvement in the forecast performance of the model whereas a larger value indicates deterioration—after the introduction of the expectations, the forecasting performance of our baseline models significantly and consistently enhances for the 6 and 12-month horizons whether inflation expectations are incorporated contemporaneously or with a 6-month lead [(Table 6, Col (a)-Col (f)]. The results for a 3-month horizon largely show deterioration for most of the models. This deterioration is likely because the IEI fundamentally contemplates the extent of the expected price-movements for the next six months.

4.1.2. *Out-of-sample Forecast Performance (Short-sample)*

In order to check for the possible improvement in the out-of-sample forecast predictive ability of our baseline inflation models due to the introduction of the IEI, we first drop the respective observations for 3, 6 and 12 months, and estimate the RMSEs accordingly for the baseline models. We then introduce the IEI into the baseline models with a 6-month lead and repeat the process to obtain the corresponding RMSEs.[7] The results are presented in Table 7 indicating a slight improvement in most of the models for the 6 months horizon. However majority of the models for the 3 months and 12 months horizon do not witness any improvement. This might be due to the short sample size of the data.

Table 7

Out of Sample Forecast

	UM	RWD	RWDT	AR	MA	ARIMA
Root Mean Squared Error (3-months ahead forecast)						
Benchmark	0.67	1.39	0.81	0.70	0.70	0.86
Survey Expectations	0.90	1.27	1.83	1.79	1.35	2.23
Root Mean Squared Error (6-months ahead forecast)						
Benchmark	2.47	1.54	3.31	1.98	1.99	2.83
Survey Expectations	2.59	1.97	6.42	1.86	1.81	2.38
Root Mean Squared Error (12-months ahead forecast)						
Benchmark	8.67	10.50	9.40	8.46	8.15	7.96
Survey Expectations	10.56	9.38	9.27	9.69	9.07	8.78

Note: The estimation period is from January 2012 to July 2014.

4.2. Robustness Check

Since the span of our data set of expectations variable is not long enough, we fixed the values of our IEI indicator at 100 from July, 2002 until December, 2011 as we don't have survey data for this period. Nonetheless, we contemplate that this exercise would allow us to take into account more information than that of our previous estimation period and would serve as a robustness check on the results we obtained earlier.

[7]The RMSEs in order to assess the out-of-sample forecast using IEI contemporaneously may not be obtained due to limited data.

4.2.1. *In-sample Forecast Performance (Extended Sample)*

The results of our baseline models estimated with extended data sets from the July, 2002 to July, 2015 are presented in Table 8–9. The findings here also indicate that incorporation of the survey measure of expectations significantly improves the forecast performance almost across all the models for a 6 and 12-month horizon as compared to the 3-month horizon. The improvement observed using IEI contemporaneously is significantly higher than is observed for using IEI with a 6-month lead.

4.2.2. *Out-of-Sample Forecast Performance (6-months Lag, Extended Sample)*

Like the significant improvement in the in-sample forecast predictability, the introduction of the IEI into the extended sample considerably improves even the out-of-sample forecast capability of the univariate models. For example the RMSEs have declined for most of the models for almost all the three horizons (Table 9).

Table 8

In Sample Forecast

	UM	*RWD*	*RWDT*	*AR*	*MA*	*ARIMA*
Root Mean Squared Error (3-months ahead forecast)						
Benchmark	1.95	2.30	2.44	1.67	1.43	1.74
Survey Expectations (6-months lead)	1.60	1.85	1.92	1.40	1.00	1.38
Survey Expectations (contemporaneous)	2.13	2.59	2.80	2.17	1.89	2.25
Root Mean Squared Error (6-months ahead forecast)						
Benchmark	5.26	5.05	5.31	5.93	4.91	5.20
Survey Expectations (6-months lead)	4.38	3.97	4.00	4.58	4.30	4.74
Survey Expectations (contemporaneous)	3.71	3.41	3.49	3.41	3.34	3.60
Root Mean Squared Error (12-months ahead forecast)						
Benchmark	9.47	8.65	9.16	10.30	8.41	9.30
Survey Expectations (6-months lead)	7.23	6.37	6.51	7.42	7.20	7.85
Survey Expectations (contemporaneous)	5.11	3.72	3.60	3.95	4.14	4.23

Note: The estimation period is from July 2002 to July 2015.

Table 9

Out of Sample Forecast

	UM	*RWD*	*RWDT*	*AR*	*MA*	*ARIMA*
Root Mean Squared Error (3-months ahead forecast)						
Benchmark	2.00	3.03	3.65	1.86	1.69	2.35
Survey Expectations	2.97	2.84	3.27	2.00	1.71	2.00
Root Mean Squared Error (6-months ahead forecast)						
Benchmark	5.42	6.47	7.53	6.31	5.30	6.51
Survey Expectations	7.29	6.05	6.70	5.89	5.73	6.09
Root Mean Squared Error (12-months ahead forecast)						
Benchmark	9.32	10.70	12.40	11.06	9.02	12.06
Survey Expectations	13.07	10.42	11.46	10.27	10.27	10.83

Note: The estimation period is from July 2002 to July 2014.

4.2.3. Impulse Response Analysis

As another robustness-check we conducted impulse response analysis using a simple bivariate VAR model both for short and extended data. The results from this analysis also confirm that a shock to the expectations does not translate well to the observed inflation for the short-sample but significantly translates when the sample is extended (Figure 3, Panel A–B).

Fig. 3. Panel A: Accumulated Response of Actual Inflation to One S.D Shock to Inflation Expectations (Short-sample)

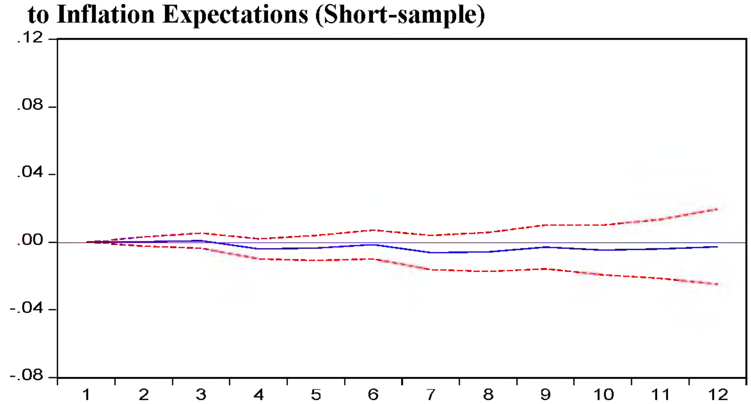
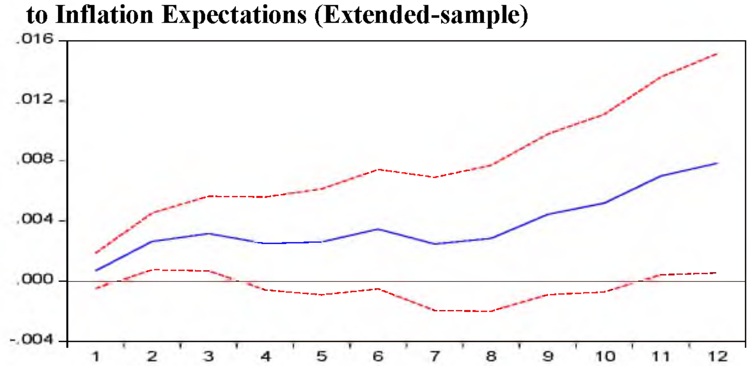


Fig. 3. Panel B: Accumulated Response of Actual Inflation to One S.D Shock to Inflation Expectations (Extended-sample)



5. CONCLUSION

In this paper we attempted to empirically explore if the introduction of inflation expectations indicator adds to the forecasting performance of our baseline inflation models. For the purpose we used a survey-based measure, which largely represents the households' expectations about the inflation over a six month horizon. Since the survey data is limited as the process of its collection has been started lately, we also extended the data set backward to account for more information that otherwise might be useful, and may also serve as robustness check.

Using 6 univariate baseline models for three different short-term forecast horizons of 3, 6 and 12 months, we found mixed results. On one hand, the introduction of expectations indicator to our baseline models significantly improve their in-sample and out-of-sample predictive ability for 6 and 12-month horizons and may therefore be advisable for the SBP to take into account the public's expectations for forecasting purposes. On the other hand, the predictive ability for a 3-month horizon is deteriorated.

A plausible reason for this could be the fact that the relevant survey questions enquire only about 6-months ahead expected inflation. This reduces the usefulness of IEI in terms of forecasting inflation for a 3-month time.

A word of caution nonetheless should also be followed that these results are robust only in the context of univariate inflation bias models. Whether the IEI equally improves forecasting performance for 6 and 12-months horizons in case of multivariate baseline models is an area yet to be explored.

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