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Predictive Abilities of Inflation Expectations and Implications on Monetary Policy in Korea*

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This paper examines the predictive abilities of various inflation expectation indicators for inflation in Korea. We conducted real-time out-of-sample forecasting experiments utilizing three inflation expectation indicators – the general public's expectation, professional forecasters' expectation, and break-even inflation (BEI). The results can be summarized as follows: (i) BEI is at least as useful as the other expectation indicators in forecasting inflation; (ii) regression-based models using industrial production, oil price, and exchange rate do not help out-of-sample inflation forecasting in general; (iii) the policy interest rate, in contrast, can significantly reduce the forecasting errors; and (iv) a one percent-point increase in the policy interest rate is estimated to suppress inflation for the subsequent 12 months by around one percent-point. These results suggest that monetary policy is effective for controlling inflation and a simple model using the policy interest rate and an inflation expectation indicator may be preferred for inflation forecasting.

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I. Introduction

Inflation is the key variable that steers monetary policy. Most central banks adjust policy interest rates to ensure that inflation does not drift away from the implicit or explicit target levels. In order to effectively achieve such a policy goal, it is crucial to come up with reasonable forecasts of future inflation because monetary policy

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transmission is associated with significant lags.

Against this backdrop, a vast amount of literature has examined inflation models, mainly based on the Phillips curve and its variants.[1] As for forecasting, however, structural models, despite their theoretical merits, do not consistently produce better performance than simple time-series models such as random walk.[2] This disturbing result may stem from unpredictable changes in economic structures and monetary policy behaviors, which can hardly be incorporated into a statistical model.

For this reason, more attention has been paid to various indicators of inflation expectations, measured through surveys or derived from relevant financial market variables.[3] Since statistical models exploit past relationships between variables, their forecasting performance turns out to be poor at significant inflection points of structural changes, whereas individuals are free to use judgments to discern if those relationships have changed.

Therefore, most central banks monitor inflation expectations surveyed for general public and/or professional forecasters. Some central banks also pay attention to inflation expectations implied by financial market variables, a leading example of which is Break-Even Inflation (BEI) --- the difference in yield rates between nominal and inflation-protected government bonds. As its predictive abilities for future inflation have been found useful in the United States and Euro area,[4] BEI has become an indicator for gauging inflation pressures closely watched by the central banks as well as financial market participants.[5]

BEI has been available in Korea, too, since the Inflation-Linked Korea Treasury Bond was introduced in March 2007. To our knowledge, however, there has been no research to scientifically investigate the usefulness of BEI for inflation forecasting,

[1] See Stock and Watson (1999) for extensive analyses in this vein, among many others. However, Stock and Watson (2009) admit that Phillips curve inflation forecasts perform better than naïve models only when unemployment rates substantially deviate from the normal rates.

[2] A pioneering work of Atkeson and Ohanian (2001) shows that the forecasts based on a random walk model (that is, one-year ahead inflation is best predicted by the previous year's inflation) produce smaller root mean squared errors than the forecasts based on Phillips curve relationships in the simulated out-of-sample forecasting experiments. Similarly, Duncan and MartÌnez-GarcÌaz (2019) show that a naïve random walk model outperforms most conventional models for 14 emerging countries data. Faust and Wright (2013) provides an article that encompasses various issues regarding inflation forecasting.

[3] From extensive out-of-sample inflation forecasting experiments for U.S. data, Ang et al. (2007) show that survey indicators outperform other forecasting methods such as time-series ARIMA models, regressions using real activity measures motivated from the Phillips curve, and term structure models that include linear, non-linear, and arbitrage-free specifications. Meyer and Pasaogullar (2010) and Gil-Alana et al. (2012) also find similar results from the out-of-sample forecasting performance comparisons of survey expectations with statistical models.

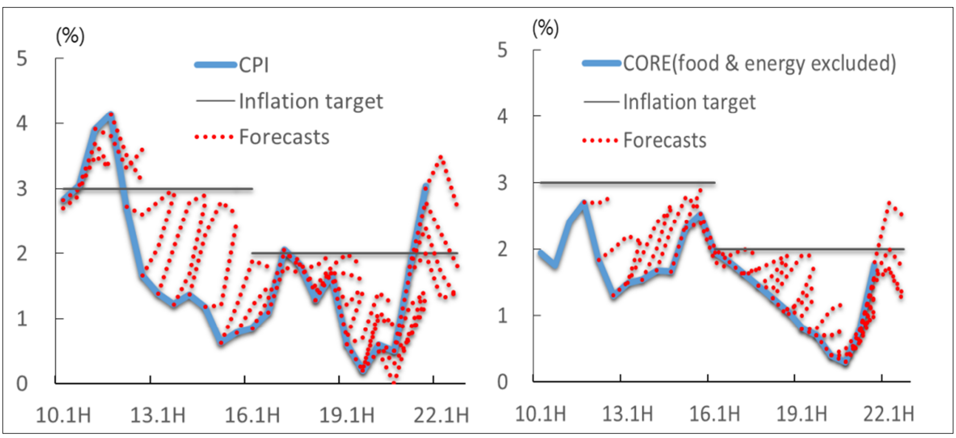
[4] See, for example, Church (2019) for the predictive power of BEI.

[5] For example, official statements of the FOMC meetings explicitly mentioned 'market-based measures of inflation compensation' throughout 2017.

perhaps because Korea's Inflation-Linked Bond market is young and shallow.[6] Nevertheless, to the extent that BEI contains the concentrated information of circumspect investors' forecasts, it seems worthwhile to test whether BEI can be utilized to improve inflation forecasting capacities.

Studies on inflation forecasting are particularly meaningful in Korea, given that the central bank of Korea, supposedly the most prudent inflation forecaster, has repeatedly over-predicted inflation for a long period of time. [Figure 1] shows that the Bank of Korea kept predicting inflation to climb up toward the target level of 3% during the 2012∼2015 period, but actual inflation continued to decline, finally ending up with a downward adjustment of the target to 2% in 2016. In contrast, BEI already began to decline from 2013 (presented in the next section), sending the signal that bond market participants expected inflation to subside. This episode of disparate predictions asks a natural question: Would Korea's monetary policy be more effectively conducted for inflation targeting, if BEI were taken into account more seriously?

[Figure 1] Actual Inflation and the Bank of Korea's Forecasts



Note: Updated and Reproduced from Cho (2020).

To answer this question, we conduct real-time out-of-sample forecasting experiments for various models utilizing three inflation expectation indicators --- BEI, professional forecasters' expectation, and the general public's expectation --- along with the previous year's actual inflation that can be regarded as a completely backward-looking inflation expectation hypothesis. The results can be summarized as follows: (i) BEI is at least as useful as other expectation indicators in forecasting

6 The volume of the Inflation-Linked Korea Treasury Bond has been fluctuating around 1 percent of total Treasury Bond volume (3 percent of the same 10-year maturity volume) in terms of both issue amount and transaction size. (Ministry of Economy and Finance, https://ktb.moef.go.kr/isuAmountNdBlce.do).

inflation; (ii) regression-based models using industrial production, oil price, and exchange rate do not help out-of-sample inflation forecasting in general; (iii) the policy interest rate set by the monetary authority, in contrast, can significantly reduce the forecasting errors by approximately 30 percent; and (iv) a one percent-point increase in the policy interest rate is estimated to suppress inflation for the subsequent 12 months by around one percent-point, which is far larger than the previous estimates based on macro-econometric model simulations or vector auto-regression models.[7] All in all, this paper's results suggest that monetary policy is effective for controlling inflation and a simple estimation using the policy interest rate in conjunction with an inflation expectation indicator may be preferred for inflation forecasting.

The paper is organized as follows. Section 2 explains the inflation expectation indicators used in this paper and their direct predictive abilities. Section 3 presents the simulated out-of-sample forecasting performance of regression-based models using industrial production, oil price, and exchange rate, focusing on Root Mean Squared Errors (RMSE). Section 4 provides the results for the models using the policy interest rate as a proxy variable for aggregate demand pressures in the expectation-augmented Phillips curve specification. Section 5 concludes with some remarks.

II. Naïve Forecasting Using Inflation Expectation Indicators

2.1. Data

The most widely cited inflation expectation indicator by Korean media is the general public's expectation (PUB, henceforth) that is surveyed by 2,200 households and released by the Bank of Korea. This indicator is similar in nature to the median expectation from the University of Michigan's Survey of Consumers in the United States. Another expectation indicator used in this paper is the median inflation prediction of 27 professional forecasters such as global investment banks (PRO, henceforth), which is compiled by Consensus Economics, a British company, and

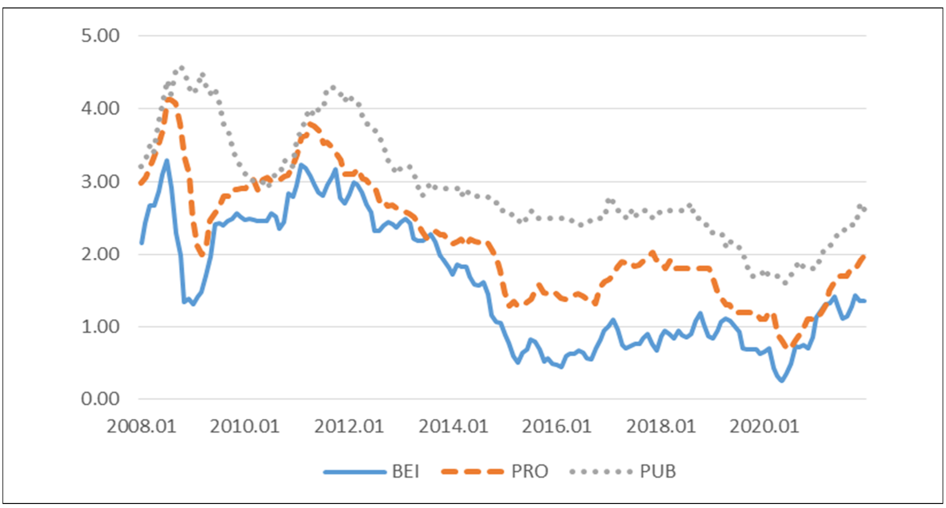
[7] For example, the macro-econometric model of the Bank of Korea (BOK20) composed of 37 behavioral equations generates only a 0.12% cumulative change in inflation for 3 years in response to a 1% change in the policy interest rate (see Park et al., 2021). Many other empirical papers that employ various forms of vector auto-regression models also report less than a 0.5% inflation response with respect to a 1% shock in the policy rate (see Kim (2009), among others). The only exception, to our knowledge, is Kim and Nahm (2020) who report approximately a 1% inflation response in 4 to 5 quarters after a 1% change in the policy interest rate from a factor-augmented vector auto-regression model.

reported in the Monetary Policy Report of the Bank of Korea. Both of these indicators are based on surveyees' expectations about one-year ahead inflation updated every month.

We also used a market-based inflation expectation indicator, BEI, compiled by the Yonhap Infomax. As BEI is derived from 10-year maturity bond prices, however, its implicit forecast horizon must be far longer than a year, the forecasting horizon we are concerned with in this paper. Notwithstanding the inherent handicap due to the horizon mismatch, we will let BEI compete on an equal footing with the other indicators for the one-year ahead forecasting experiments.

[Figure 2] shows that the three indicators have moved in roughly the same directions: they had declined since 2012 and began to recover after hitting the bottom in 2020. Yet, the three indicators clearly differ in their levels: PUB was always the highest, while BEI the lowest. There are also some differences in their variations and inflection timings: BEI declined the most drastically during the 2013∼2015 period, and began to recover slightly earlier than the other indicators in 2020.

[Figure 2] Inflation Expectation Indicators (%)



2.2. Naïve Forecasting

We first test whether these expectation indicators by themselves are useful predictors of inflation by simply looking at the difference between actual year-on-year inflation at month t, π_t, and expected inflation formed 12 months ago, π^e_{t-12}, which can be interpreted as a one-year ahead forecast error of the expectation indicator. As for π^e_{t-12}, we used BEI_{t-12}, PRO_{t-12}, and PUB_{t-12}, respectively. In addition, we used the realized year-on-year inflation at the month of prediction,

π_{t-12}, as another proxy for π^{e}_{t-12}, following the literature on inflation forecasting, which can be regarded as a complete backward-looking expectation hypothesis. This random-walk-like model essentially predicts that the next year's inflation will be the same as the previous year's inflation.

[Table 1] presents Root Mean Squared Errors (RMSE) and Mean Errors (ME) of BEI, PRO, and PUB, along with the random walk (R.W. hereafter) model as a benchmark *a la* Atkeson and Ohanian (2001), for 12 years from 2010 to 2021.[8] The table also reports the results for two half-sized sub-samples, before and after 2016, which happen to coincide with the periods before and after the downward adjustment of the inflation target from 3 percent to 2 percent. As for the inflation index, we explore both headline and core CPI inflation. Insofar as central banks are concerned about persistent inflation pressures, core CPI that excludes volatile food and energy prices may be a better measure to monitor than headline CPI, though the official inflation target is set for headline CPI.

[Table 1] Naïve Forecasting Performances (%)

		Headline Inflation				Core Inflation			
		BEI	PRO	PUB	R.W.	BEI	PRO	PUB	R.W.
Whole Sample	**RMSE**	**1.13**	**1.16**	**1.65**	**1.19**	**0.86**	**0.97**	**1.54**	**0.76**
(2010.01-2021.12)	ME	0.13	-0.44	-1.20	-0.02	0.00	-0.57	-1.33	-0.13
Before 2016	**RMSE**	**1.13**	**1.25**	**1.82**	**1.16**	**0.93**	**1.14**	**1.76**	**0.85**
(2010.10-2015.12)	ME	-0.27	-0.70	-1.38	-0.34	-0.41	-0.83	-1.51	-0.09
After 2016	**RMSE**	**1.14**	**1.06**	**1.46**	**1.23**	**0.79**	**0.75**	**1.30**	**0.65**
(2016.01-2021.12)	ME	0.53	-0.17	-1.03	0.29	0.41	-0.30	-1.15	-0.17

Some points are noteworthy in [Table 1]. First, the average forecast errors for headline inflation, greater than 1 percent in terms of RMSE, may look large compared to the realized inflation of 1 to 3 percent during the experiment period. However, research for the US and Euro data also reported that RMSEs of out-of-sample one-year ahead inflation forecasts are larger than 1 percent for most cases regardless of sample periods and applied models.[9] The relatively smaller RMSE for core inflation indicate that a substantial portion of the forecast errors for headline inflation stems from erratic movements of food and energy prices.

Second, forecasting performance in terms of RMSE are roughly comparable across the indicators except for PUB, a definitely inferior predictor. If there is any

[8] Although the data is available from March 2007, we decided to report the results for the data from 2010 for several reasons. First, the 2007∼2009 period was extremely turbulent due to the Global Financial Crisis. Second, the Inflation-Linked Korea Treasury Bond market was just born and not well established at that time. Third, it is more convenient to maintain consistency with the next section in which regression-based forecasting is discussed. In any case, the results including the 2007∼2009 period, which are available upon request, are very similar to those reported in [Table 1].

[9] See Meyer and Pasaogullar (2010), Cecchetti et al. (2000), and Grothe and Meyler (2015).

pattern to note, it may be that the expectation indicators such as BEI and PRO appear to out-perform the random walk model for headline inflation, whereas they under-perform for core inflation. Mechanically interpreting, this result indicates that core inflation was more persistent than expected by the financial market and professional forecasters. However, the expectation indicators are supposed to predict headline inflation, and thus more attention needs be paid to headline than core inflation. In this regard, the result that BEI and PRO can provide at least as good forecasts as the random walk model seems meaningful, given the literature's finding that even sophisticated models do not outperform a random walk model in inflation forecasting.[10]

Third, PUB produces by far the worst performance in terms of RMSE, mainly due to the huge over-prediction bias of more than 1 percent (namely, ME $<-1\%$) as evidently shown in [Figure 2]. This result is contrasting to the case for the United States, where the median expectation from the University of Michigan's Survey of Consumers performs relatively well.[11]

The biases of other expectation indicators are relatively mild: BEI tends to under-predict inflation, while PRO tends to over-predict. The over-prediction of PRO may not be too surprising in that Korea's inflation declined so rapidly as to be hardly expected even by professional forecasters. In this context, the under-prediction of BEI is rather surprising. A possible explanation is the low liquidity problem of the Inflation-Linked Korea Treasury Bond, which tends to increase its liquidity premium and thus lower BEI (or shrink the yield rate gap between the Inflation-Linked Bond and Nominal Treasury Bond).[12] Another possible explanation is the longer-than-a-year horizon of BEI. That is, the financial market might have anticipated that the declining trend of inflation is likely to persist for more than a year, producing lower BEI than the next year's inflation.

It is beyond the scope of this paper to rigorously assess how much of the BEI's bias is attributable to each factor, but the results from the two-year ahead forecasting experiments in [Table 2] are suggestive. The only difference of this table from [Table 1] is that we used the average annual inflation rate for the next two years (24 months), namely, $(\pi_t + \pi_{t+12})/2$ instead of π_t. Comparing [Table 2] with [Table 1], one can find that the BEI's bias is clearly reduced, while the biases of PRO and PUB are not. This result suggests that the financial market, unlike professional forecasters, anticipated low inflation would persist. Thanks to the reduced bias, BEI dominates PRO and PUB in terms of RMSE in every case for

[10] See Atkeson and Ohanian (2001), Stock and Watson (2009), Bauer and McCarthy (2015), and Duncan and MartÌnez-GarcÌaz (2019), among others.

[11] See Meyer and Pasaogullar (2010).

[12] See Carlstrom and Fuerst (2004) and Andreasen et al. (2017) for more detailed discussion about the liquidity premium for inflation protected bonds.

two-year ahead forecasting, though PRO and PUB are supposed to be used for one-year ahead forecasting.

[Table 2] Naïve Forecasting Performances (%): Two-Year Ahead

		Headline Inflation				Core Inflation			
		BEI	PRO	PUB	R.W.	BEI	PRO	PUB	R.W.
Whole Sample	**RMSE**	**0.74**	**1.00**	**1.59**	**0.68**	**0.99**	**1.11**	**1.63**	**1.02**
(2010.01-2021.12)	ME	-0.09	-0.71	-1.45	-0.40	-0.01	-0.64	-1.38	-0.43
Before 2016	**RMSE**	**0.90**	**1.33**	**1.93**	**0.75**	**1.15**	**1.26**	**1.69**	**1.25**
(2010.10-2015.12)	ME	-0.58	-1.16	-1.81	-0.62	-0.06	-0.64	-1.29	-0.83
After 2016	**RMSE**	**0.64**	**0.71**	**1.34**	**0.64**	**0.77**	**0.91**	**1.50**	**0.81**
(2016.01-2021.12)	ME	0.34	-0.40	-1.24	-0.37	0.23	-0.51	-1.35	-0.05

III. Regression-Based Forecasting

3.1. Out-of-Sample Forecasting Simulation Strategy

In addition to the naïve forecasting, we also experimented with the following simple model for one-year ahead inflation forecasting:

$$\pi_t = \alpha_{(t)} + \beta_{(t)} \pi^e_{t-12} + \gamma_{(t)} X_{t-12} + e_t , \tag{1}$$

where π_t is the year-on-year inflation rate at time t, π^e_{t-12} is the inflation expectation formed at time $t-12$, X_{t-12} is a set of control variables at time $t-12$ that are expected to help predict inflation, e_t is an in-sample forecast error, and $\alpha_{(t)}$, $\beta_{(t)}$, $\gamma_{(t)}$ are the coefficient estimates from the data available at time t. Then a one-year ahead out-of-sample forecast error, ε_{t+12}, is obtained by:

$$\varepsilon_{t+12} = \pi_{t+12} - \{\alpha_{(t)} + \beta_{(t)}\pi^e_t + \gamma_{(t)}X_t\} . \tag{2}$$

Note that the monthly year-on-year inflation data, π_t, actually measures the cumulative increases of consumer price index (CPI) over the previous 12 months. One-year ahead out-of-sample forecasting for π_{t+12} in real time, therefore, should employ the coefficient estimates from the regression utilizing only the information available up to time t. As an example, a one-year ahead forecast for $\pi_{December,2021}$ is obtained by using the observed values of $\pi^e_{December,2020}$ and $X_{December,2020}$ in conjunction with the coefficients estimated by the regression utilizing data up to $\pi_{December,2020}$, $\pi^e_{December,2019}$ and $X_{December,2019}$.

We conducted this regression-based forecasting exercise recursively. That is, we estimated a regression model using the first sample up to time t to obtain the forecast value for inflation at time $t+12$, and then re-estimated the same regression model with the data up to $t+1$ to obtain the forecast value for inflation at time $t+13$, and so on. A remaining issue is whether to accumulate the sample observations or to delete the first observations as the period updates, namely, cumulative vs. rolling regressions. In principle, cumulative regressions should perform better as the sample size increases if the regression relationship is stable. If the relationship is not stable, however, rolling regressions may perform better because relying on information from the distant past in this case can deteriorate, rather than improve, forecast precisions. We will report the results from both cumulative and rolling regression experiments.

An unavoidable limitation of regression-based exercises is that forecast values cannot be produced for the first part of the sample period because a reasonably large size of the sample needs to be secured to obtain reliable coefficient estimates. For this reason, we could not generate the results comparable to the first sample period in [Table 1], 'Before 2016,', and decided to present the results for the second sample period, 'After 2016,' for comparison convenience. Therefore, the first sample period for recursive regressions is from January 2010 to December 2015, and then cumulative regressions increase the sample size as a new observation is added, while rolling regressions keep the 6-year (72 observations) sample size by sequentially dropping the first observation of the previous sample.

3.2. Forecasting with Conventional Factors for Inflation

We considered 3 variables for X_t in Equation (1) that are most frequently used in the empirical literature on inflation: industrial production index (IPI), oil price index (OIL), and won/dollar exchange rate (FX). IPI is expected to represent demand-side pressures in the spirit of the Phillips curve argument, OIL is expected to capture the cost-side inflation pressures, and FX is expected to control for the effect of external shocks. All of the variables are converted into year-on-year growth rates for the regression analyses.

[Table 3] reports the detailed regression results for the whole sample period (January 2010~December 2020), and [Figure 3] shows all of the coefficient estimates from the 72 cumulative regressions for headline inflation (results for core inflation and results from rolling regressions are not reported to save space). A couple of points are notable, before looking at forecasting performance. First, the coefficient estimates of OIL and FX are small (statistically insignificant) and of 'wrong' signs in many cases. This result shows that the realized fluctuations of oil price and exchange rate are important to explain current inflation as repeatedly proven in the empirical inflation literature, but do not help predict future inflation for the next 12 months. The negative coefficient estimates for OIL, in particular, reflect the fact that the oil price itself exhibits a mean-reverting property: an extraordinary hike in OIL in the current month is likely to be related to a fall in OIL in the future. Second, IPI consistently yields stable and statistically significant coefficient estimates regardless of the included expectation indicator, though the magnitudes are substantially reduced for core inflation. This result appears to suggest that the realized aggregate demand pressures represented by industrial production slowly affect future inflation, revealing a possibility that IPI may help out-of-sample prediction.

[Table 3] Regression Results for the Sample from January 2010 to December 2020

	Headline Inflation				Core Inflation			
	BEI	PRO	PUB	Lagged	BEI	PRO	PUB	Lagged
constant	0.22	**-1.01**	**-1.18**	-0.11	**0.77**	0.05	-0.15	**0.57**
	(0.20)	(0.28)	(0.41)	(0.18)	(0.12)	(0.18)	(0.25)	(0.15)
π^e	**0.62**	**1.00**	**0.81**	**0.74**	**0.41**	**0.62**	**0.53**	**0.52**
	(0.10)	(0.12)	(0.13)	(0.08)	(0.06)	(0.08)	(0.08)	(0.08)
IPI	**0.15**	**0.15**	**0.16**	**0.14**	**0.04**	**0.04**	**0.04**	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
OIL	-0.01	**-0.02**	-0.01	**-0.04**	**-0.03**	**-0.04**	**-0.03**	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
FX	**0.03**	**0.02**	0.00	0.00	-0.01	-0.01	**-0.02**	**-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.37	0.48	0.37	0.49	0.30	0.39	0.30	0.31

Note: Numbers in parentheses are standard errors and bold letters denote the estimates significant at a 5% level.

[Figure 3] Coefficient Estimates from Cumulative Regressions: Headline Inflation

[Table 4] reports the RMSEs of the out-of-sample forecasts using these regression results, leaving out MEs to save space. The figures in the first row are copied from the 'After 2016' row in [Table 1] for comparison. For the regressions using the previous year's inflation, we labeled AR(1) instead of random walk because the relevant coefficient is now to be estimated. We also added parsimonious cases in which π^e only, or π^e and IPI only, are included in the regressions as OIL and FX may increase nuisances in forecasting.

Reading the table vertically, regression-based experiments do not significantly improve the forecasting performance in general, no matter whether a cumulative or rolling regression strategy is employed. An exception is the case of PUB, whose RMSEs are reduced by substantial margins compared with the case of naïve forecasting. This is simply because regressions allow intercept terms that correct the large upward biases of PUB. For the other expectation indicators, regression-based forecasting appears to marginally improve the performance for headline inflation in some cases, but deteriorate for core inflation in all cases. This result seems to indicate that the control variables do not help predict the underlying inflation pressures represented by core inflation, as opposed to short-term fluctuations of headline inflation due to temporary shocks such as oil-price hikes and exchange rate fluctuations.

[Table 4] RMSEs of Recursive Regression-Based Forecasts, 2016～2021

		Headline Inflation				Core Inflation			
Regression	Control Variables	BEI	PRO.	PUB	AR(1)	BEI	PRO.	PUB	AR(1)
Naïve		1.14	1.06	1.46	1.23	0.79	0.75	1.30	0.65
Cumulative		1.09	1.15	1.13	1.06	0.86	0.83	0.92	0.84
Cumulative	IPI	1.14	1.18	1.23	1.14	0.91	0.85	0.92	0.84
Cumulative	IPI, OIL, FX	1.19	1.30	1.31	1.17	0.89	0.77	0.96	0.82
Rolling		1.04	1.01	0.92	0.94	0.82	0.83	1.00	0.83
Rolling	IPI	1.02	1.01	1.00	1.01	0.89	0.89	1.05	0.85
Rolling	IPI, OIL, FX	1.06	1.09	1.18	1.05	0.84	0.81	1.10	0.86

All in all, the results in [Table 4] seem to suggest that naïve forecasts based on BEI or PRO do not greatly miss the target in comparison with other sophisticated forecasts employing regressions with additional information. That is, the variables like IPI that significantly reduce in-sample forecast errors do not help improve the performance when it comes to real-time out-of-sample forecasting. This conclusion may not be surprising, considering the related literature's finding that structural models do not out-perform simpler models such as random walk or survey-based forecasting.

IV. Expectation Augmented Phillips Curve and Monetary Policy

The regression specification of Equation (1) can be interpreted as a form of expectation-augmented Phillips curve in that future inflation depends on inflation expectation and other factors including demand pressures. Yet, there was a disaccord of the previous section's experiments with the theoretical Phillips curve: we did not set the coefficient of the expectation indicators, β, equal to 1. Recalling that the regression-based forecasting did not out-perform naïve forecasting, which can be interpreted as a special case of Equation (1) with the restrictions of $\alpha = 0$, $\beta = 1$, and $\gamma = 0$, we explored the case of $\beta = 1$ that follows the theoretical Phillips curve specification more faithfully.[13] We therefore repeated the previous section's exercises with the restriction of $\beta = 1$, but the RMSE results did not significantly change (not reported). In short, utilization of the information available in real time on IPI, OIL, and FX could hardly improve the one-year ahead inflation forecast over the naïve model.

This result may not be encouraging to the monetary authority that sets the policy interest rate to steer future inflation toward the target level, for which a solid forecasting capacity is necessary. Despite the failure to find an appropriate empirical forecasting model, however, it is generally believed that a change in monetary policy alters aggregate demand conditions, and hence future inflation, through various transmission channels such as borrowing costs, exchange rate, asset prices, and so forth. Thus we examined whether or not the interest rate policy indeed affects future inflation by directly looking at reduced-form regressions rather than structural models. For this, we used the policy interest rate of the Bank of Korea (RATE) in place of control variables, invoking the model in which monetary policy affects future aggregate demand conditions in the expectation-augmented Phillips curve through various implicit channels.

The regression results in [Table 5] shows that monetary policy does affect future inflation to a substantial extent: a one percent-point increase in RATE this month tends to reduce inflation by more than 0.5 percent-point over the next 12 month period, after controlling for inflation expectation. This estimate of the monetary policy effect on future inflation appears far larger than those reported in the previous literature, probably because our reduced-form specification is not disturbed by the noises of the intermediate proxy variables that are supposed to transmit the monetary policy effect in the structural-form specifications.

[13] The standard Expectation-Augmented Phillips Curve specification, $\pi_t = \pi_t^e + \gamma X_t + e_t$, sets the coefficient of the expected inflation to be 1 so that inflation becomes the same as the expected inflation when aggregate demand is zero. If not, inflation would drift even when aggregate demand continues to be zero.

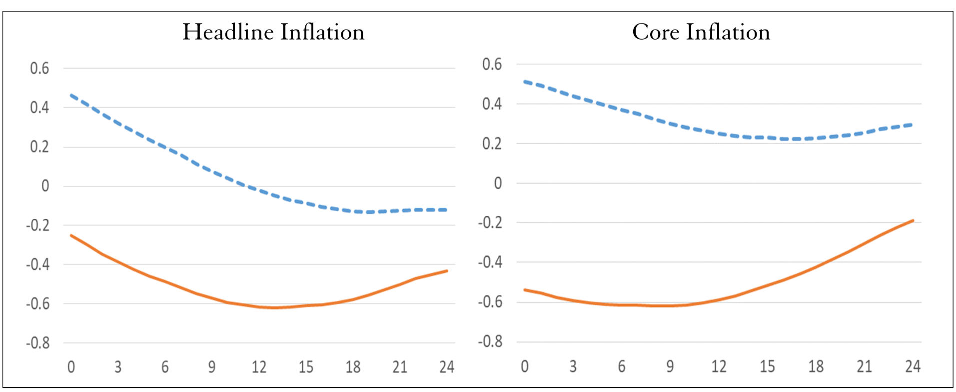
[Table 5] Regression Results for the Sample from January 2010 to December 2020

	Headline Inflation				Core Inflation			
	BEI	PRO	PUB	R.W.	BEI	PRO	PUB	R.W.
constant	**1.76**	**0.64**	-0.39	**1.17**	**1.64**	**0.52**	**-0.51**	**-0.36**
	(0.25)	(0.24)	(0.28)	(0.28)	(0.20)	(0.19)	(0.20)	(0.20)
π^e	1	1	1	1	1	1	1	1
RATE	**-0.87**	**-0.61**	**-0.48**	**-0.67**	**-0.83**	**-0.57**	**-0.44**	0.06
	(0.12)	(0.11)	(0.13)	(0.13)	(0.09)	(0.09)	(0.09)	(0.09)
constant	0.03	**-0.56**	**-1.33**	**-0.15**	-0.03	**-0.63**	**-1.40**	**-0.24**
	(0.05)	(0.05)	(0.07)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)
π^e	1	1	1	1	1	1	1	1
RGAP	**-1.69**	**-1.49**	**-1.32**	**-1.19**	**-0.92**	**-0.72**	**-0.55**	0.10
	(0.11)	(0.10)	(0.14)	(0.16)	(0.13)	(0.12)	(0.13)	(0.12)

Note: Numbers in parentheses are standard errors and bold letters denote the estimates significant at a 5% level.

The contrasting results of [Table 5] with those in the previous literature can also be explained by comparing unconditional correlations with conditional ones. [Figure 4] shows that the unconditional correlations between the policy interest rate at time t ($RATE_t$) and future inflation in s months (π_{t+s}) are either positive or close to zero for both headline and core inflation. Of course, the strong positive correlation for a small s must reflect the monetary policy *responses* to inflation rather than the policy *effects* on inflation: that is, the policy rate was raised when actual inflation in the recent months appeared to be high. Then the policy effect (the negative correlation) gradually kicks in, offsetting the initial positive correlation, as s increases. Yet, the near-zero correlation for a large s is likely to produce an impression that an adjustment of the policy interest rate in the current month may not significantly affect future inflation. The correlations turn into large negative values at all time horizons, however, once the future inflation is subtracted by an

[Figure 4] Correlations between $RATE_t$ and π_{t+s} (dotted) vs. $\pi_{t+s} - BEI_{t-12+s}$ (solid)

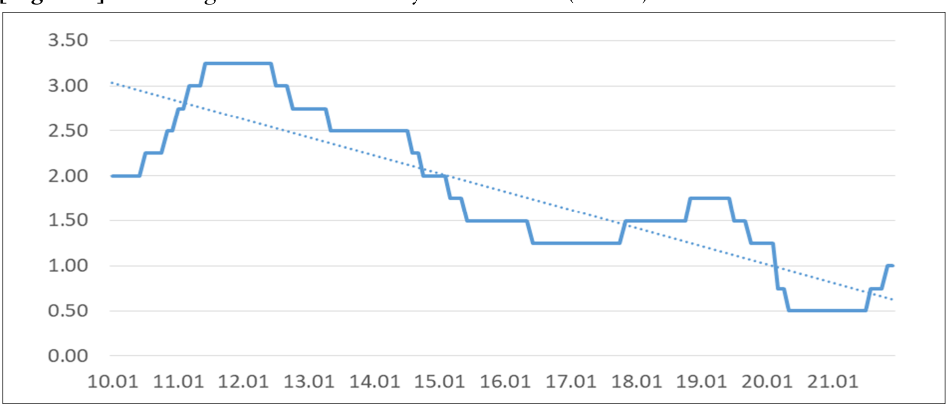


Note: Horizontal axis denotes the month, s, of the future unconditional or conditional inflation.

inflation expectation indicator such as BEI that was formed a year ago ($\pi_{t+s} - BEI_{t-12+s}$). That is, a change in the policy interest rate clearly appears to affect unanticipated inflation in the future. Additionally notable is that the largest negative correlation is observed at around 12 month lags, or a year, which coincides with the time horizon of this paper's interest as well as the common perception about the time lag of monetary policy.

[Table 5] also reports the regression results for a de-trended interest rate (RGAP) instead of RATE, considering the declining interest rate trend in Korea (see [Figure 5]) along with the rapidly declining potential growth rate as spelled out in Cho and Kwon (2018). That is, the same policy interest rate of 2 percent, for example, used to represent an extremely loose monetary policy stance in 2010, but became a tight stance in 2020, taking the declining neutral interest rate into account. While there are various techniques to estimate the changing neutral interest rate, we adopted the simplest methodology, linear time trend, for our experiments. The effect of monetary policy for one-year ahead inflation then appears to be more pronounced with RGAP than with RATE: a one percent-point increase in RGAP leads to more than a one percent-point decrease in headline inflation and slightly less than a one percent-point decrease in core inflation, after controlling for inflation expectation.

[Figure 5] Declining Trend of the Policy Interest Rate (RATE)



An additional finding from [Table 5] is that BEI, among the inflation expectation indicators, generates the sharpest negative correlation between the naïve forecast error ($\pi_{t+12} - \pi_t^e$) and the policy interest rate ($RATE_t$ or $RGAP_t$) for every case. Perhaps striking in this vein is that the random walk model does not generate any significant correlation for core inflation: that is, how much next year's core inflation changes from the previous year's ($\pi_{t+12} - \pi_t$), unlike the next year's deviation from the expected inflation ($\pi_{t+12} - \pi_t^e$), has nothing to do with current monetary policy.

Finally, in order to check whether these strong in-sample correlations can help improve real-time out-of-sample forecasting performance, we conducted the recursive regression-based exercises in the same manner as in the previous section.[14] The results reported in [Table 6] show that the consideration of policy interest rate fluctuations clearly reduces RMSEs compared to the corresponding naïve models for most cases. In particular, the model using BEI and RGAP, which appears to be the best performer, can improve the forecasting precision by approximately 30 percent (0.85 or 0.75 as opposed to 1.14 for headline inflation, and 0.48 or 0.56 as opposed to 0.79 for core inflation).

[Table 6] RMSEs of Recursive Cumulative Regression-Based Forecasts, 2016~2021: Coefficient of Expectation Indicator Preset to 1

		Headline Inflation				Core Inflation			
Regression	Control Variable	BEI	PRO.	PUB	R.W.	BEI	PRO.	PUB	R.W.
Naïve		1.14	1.06	1.46	1.23	0.79	0.75	1.30	0.65
Cumulative	RATE	1.05	1.21	1.27	1.37	0.88	0.89	0.79	0.77
Rolling	RATE	0.73	0.85	0.89	1.33	0.97	1.09	1.10	1.02
Cumulative	RGAP	0.85	1.00	1.12	1.16	0.48	0.48	0.46	0.72
Rolling	RGAP	0.75	0.86	0.92	1.15	0.56	0.62	0.61	0.80

[Figure 6] presents the coefficient estimates from the cumulative regressions for headline inflation (results for core inflation are almost the same except that the coefficient estimates for RGAP are smaller, though not reported here to save space), which also shows that the estimates are fairly stable throughout the sample period, especially for the case of BEI. It is interesting to note that the constant term is virtually zero for the BEI – RGAP model, implying that BEI is an unbiased predictor once the effect of RGAP is taken into account. In other words, the under-prediction tendency of BEI observed for the 'After 2016' period in [Table 1] is attributable to the policy interest rates that were set at lower-than-trend levels, or a negative average value of RGAP during the period. This interpretation seems to be compatible with the results in [Table 2] in that BEI represents the financial market's longer-term inflation expectations, while the short-term deviations of actual inflation from BEI can largely be explained by the policy interest rate fluctuations around the neutral rate.

[14] Despite theoretical discussions on the standard expectation-augmented Phillips Curve, a model without the restriction of $\beta = 1$ may empirically perform better, but our preliminary experiments were not really encouraging: RMSEs of the models without the restriction are slightly smaller for headline inflation, but far larger for core inflation.

[Figure 6] Coefficient Estimates from Cumulative Regressions: Headline Inflation Coefficient of Expectation Indicator Preset to 1

Taking the BEI—RGAP model with zero constant, one can then come up with a very simple one-year ahead inflation forecast --- BEI adjusted by RGAP with the corresponding coefficients, -1.6~-1.7 for headline inflation and -0.9~-1.0 for core inflation, respectively. Despite its simplicity, this forecasting model based on the expectation-augmented Phillips curve specification appears to out-perform all other models considered in this paper.

V. Concluding Remarks

This paper examines the predictive abilities of inflation expectation indicators in real-time out-of-sample forecasting simulations. The results show that BEI, combined with the policy interest rate in particular, is at least as useful as other expectation indicators, while regression-based models using industrial production, oil price, and exchange rate do not significantly help out-of-sample inflation forecasting in general.

Of course, the empirical studies conducted in this paper have many limitations, and thus the results need to be interpreted with caution. The most important among them is the limited sample period due to the relatively young Inflation-Linked Korea Treasury Bond market. The 12 year period for the whole sample, in particular the 6 year period for the forecasting experiments, may be too short to generalize the findings of the paper. No doubt further research is warranted as the relevant data accumulates. Also helpful would be comparable studies for other advanced countries in which longer time-series data are available. Such analyses may shed light on how much the paper's results can be generalized and how different Korea's monetary policy and inflation dynamics are from those in other countries.

Nevertheless, the results presented in this paper provide a ground for the monetary authority to closely monitor market-based inflation expectation indicators such as BEI, insofar as medium-term inflation is the main target for monetary policy. At the same time, the paper's results make the case that monetary policy can effectively control inflation by appropriately adjusting the policy interest rate. The Bank of Korea whose primary goal is to maintain inflation stability in the medium-tem, therefore, needs to adjust the policy rate to the inflation gap from the target in the short-run, while carefully managing inflation expectations not to deviate from the target level to a significant extent.

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우리나라 인플레이션 기대 지표들의 예측력과 통화정책에 대한 함의*

조 동 철** · 오 완 근***

초 록 이 논문은 인플레이션 기대 지표들(일반인과 전문가 기대 인플레이션, Break-Even Inflation(BEI)의 실제 인플레이션 예측력을 실시간 표본외 실험을 통해 살펴보았다. 그 주요 결과들은 다음과 같다: (i) 인플레이션 예측에 있어 BEI는 최소한 여타 인플레이션 기대 지표들만큼 유용하였다; (ii) 산업활동, 유가, 환율 등을 포함한 회귀분석모형은 표본외 예측에 별다른 도움을 주지 못하였다; (iii) 반면, 기준금리에 대한 고려는 예측오차를 상당 폭 줄이는 것으로 나타났다; (iv) 기준금리의 1%p 인상은 이후 12개월간 인플레이션을 1%p 가량 억제하는 것으로 추정되었다. 이와 같은 결과들은 통화정책이 인플레이션을 통제하는 데에 상당히 효과적임을 시사하고 있으며, 기준금리와 인플레이션 기대 지표로 구성된 간단한 모형이 인플레이션 예측을 위해 유용할 수 있음을 나타내고 있다.

핵심 주제어: 인플레이션, 예측, BEI, 통화정책

경제학문헌목록 주제분류: E31, E37, E52

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