Box 2.5

Evaluation of Underlying Inflation Indicators

Consumer inflation is exposed to different types of shocks and can be volatile. In this framework, the headline figure may sometimes be misleading in terms of providing accurate information on the development of inflation. Policymakers are interested in the permanent part of inflation that is not affected by temporary shocks, seasonal effects and fluctuations, in other words, the *"underlying inflation".* This is related to the fact that in the medium term, the effects of temporary shocks and fluctuations disappear, and therefore, it is the "*permanent part of inflation*" that determines the medium-term course of headline inflation. Furthermore, by excluding items that are relatively beyond the scope of monetary policy, the underlying inflation can assist in focusing on items that monetary policy can affect. There is no single and precise way to measure the underlying inflation. For this reason, central banks use a variety of indicators based on different methods. This Box provides a brief overview of the indicators of underlying inflation monitored by the CBRT and their performance and summarizes the recent course for underlying inflation and the dispersion of price increases.

a. Alternative Indicators to Calculate Underlying Inflation

Underlying inflation can be calculated by different methods. In line with the literature, the indicators used at the CBRT can be categorized under three main groups: i) *permanent exclusion-based* methods, ii) *temporary exclusion-based* methods on the basis of the distribution of price changes and iii) *model-based* methods.

Permanent exclusion methods are based on the permanent exclusion of certain goods and services (such as food, energy) from the price index. This is the most commonly used method. The aim of this method is to exclude some goods and services that are subject to temporary supply shocks, such as unprocessed food, or that are relatively outside the monetary policy domain, such as energy. Thus, the aim is to extract the permanent part of the index, which exhibits low volatility and where the impact of monetary policy can be more pronounced. The main advantage of this method is that the excluded items are predetermined, so the scope does not change over time, and the index can easily be calculated and understood by the public. However, due to the exclusion of only certain items and the static nature of the indicator, this method may also exclude signals regarding the underlying inflation from time to time. The most commonly used indicators are the B index, which excludes unprocessed food, energy, alcohol-tobacco and gold from the CPI, and the C index, which excludes food, energy, alcohol-tobacco and gold from the CPI.

The second group of methods are statistical methods based on the distribution of monthly price changes of the items that make up the CPI. The approaches in this group are dynamic, and the goods and services excluded from the index may change from month to month. The most commonly used indicators in this group are the V_1, which is obtained by periodically excluding items with excessive volatility, SATRIM (seasonally adjusted trimmed monthly inflation) and median inflation indicators.[1] These indicators are calculated based on the seasonally adjusted monthly changes in the five-digit price indices in the CPI.[2] The V_1 indicator, which excludes volatile sub-items, is obtained by excluding goods and services that fall outside the one standard deviation range of the average of monthly price changes for each month from the index for that month. SATRIM is calculated by symmetrically trimming a certain percentage (currently 16% at each end) from the upper and lower ends of the distribution of monthly price changes in each month. Median inflation is the median value of monthly price changes.

The last group includes model-based methods. Although these methods are also dynamic, they aim to separate the permanent and transitory part of inflation through models with a large data set, thus revealing the general trend in prices.

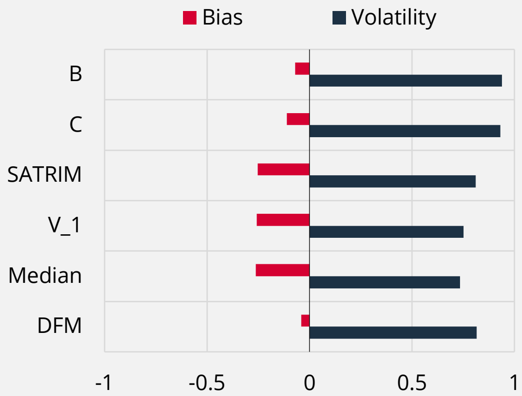
[1] For detailed information, see Atuk and Özmen (2009a) and Atuk and Özmen (2009b).
[2] As of 2024, there are 143 sub-items in the CPI at fiv3-digit level.

However, observations are subject to backward revision as model forecasts are updated with the release of new data. The CBRT uses a DFM indicator. Dynamic factor models are based on the view that the common dynamics of a large number of time series variables are driven by a relatively small number of unobservable factors, which in turn change dynamically over time. This method aims to reduce the number of variables by aggregating the high correlation among variables into one category (the first factor) and the remaining variation into another category (the second factor orthogonal to the first factor; third and higher factors can be reached in the same way) that explains most of the variation. In other words, this method is used as a dimension reduction technique. Thus, it is possible to capture common movements in inflation without excluding a particular sub-item. Similar to other alternative indicators, the DFM indicator uses seasonally adjusted monthly price changes at the five-digit level of the CPI, and it follows the DFM approach of Doz et al. (2011).

b. Performance Evaluation of Indicators

There are some properties that the underlying inflation indicators should fulfill. These properties are (i) being an unbiased predictor of headline inflation, (ii) being less volatile than headline inflation and (iii) being able to predict (out-of-sample) inflation. In this section, we examine the extent to which these indicators fulfill these properties.[3] An analysis of the bias and relative volatility of the indicators monitored by the CBRT reveals that the lowest bias is observed in the DFM, B and C indicators (Chart 1). The long-run average of other indicators is slightly lower than the headline inflation. In other words, these indicators are somewhat biased. As expected, indicators for underlying inflation are less volatile than headline inflation (Chart 1). The lowest volatility is in median inflation, followed by the V_1 indicator, which by definition excludes volatile items.

Chart 1: Bias and Volatility of Underlying Inflation Indicators*



Source: Authors' calculations.
* The bias is the average contemporaneous difference vis-à-vis headline inflation. Volatility is the standard deviation of each measure divided by the standard deviation of headline inflation. Sample period is 2005:02-2024:09.

Chart 2: Forecasting Performance of Underlying Inflation Indicators*

	12-Month RRMSFE (2006:04-2017:12)	12-Month RRMSFE (2006:04-2024:09)
B	0.83	0.87
C	0.80	0.85
SATRIM	0.76	0.85
V_1	0.75	0.77
Median	0.78	0.71
DFM	0.69	0.75

Source: Authors' calculations.
* 12-Month RRMSFE is calculated as the root mean squared forecast errors (RMSFE) of the seasonally adjusted last three-month annualized values of each indicator relative to 12-month-ahead annual headline inflation divided by the RMSFE of headline inflation.

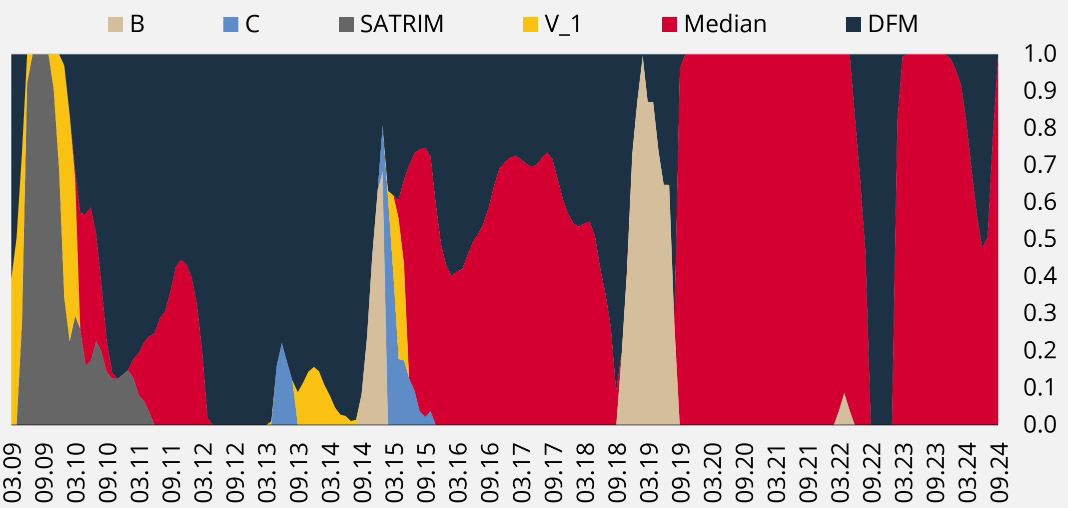
In order to evaluate the ability of indicators to signal the course of consumer inflation one year ahead, the predictive power of the last three-month (annualized) averages of the indicators for annual consumer inflation over the next 12 months was analyzed (Chart 2). This analysis was conducted for two different periods: (i) for the whole sample, and (ii) when consumer inflation was relatively mild. In the low-inflation period, the model-based indicator and distributional indicators (SATRIM, V_1 and median) perform better than B and C in predicting consumer inflation. Considering the whole sample, the indicator that excludes volatile items (V_1), the indicator based on the DFM and median inflation in particular stand out. Despite their low bias, indicators B and C have lower out-of-sample predictive

[3] The analysis is based on the approach in Bańbura et al. (2023).

power. In the analysis, median inflation stands out compared to the others in terms of both low volatility and high predictive power.[4]

In order to assess the change in the forecasting power of the indicators over time, the forecast combination that minimizes the RMSFE value one year later is analyzed. In this analysis, the optimal weights of the underlying inflation indicators that minimize the forecast error in a three-year sliding window were calculated (Chart 3). According to the findings, although the forecasting performance of indicators changes over time, the DFM indicator and median inflation tend to perform better. In particular, median inflation stands out among the underlying inflation indicators with its forecasting performance in recent years (Chart 3). The forecasting performance of other indicators, on the other hand, is cyclical. Another implication of the analysis is that indicators based on permanent exclusion such as B and C can exist in the optimal forecasting combination in a limited period, in other words, they perform poorly compared to other indicators in predicting 12-month-ahead consumer inflation throughout the sample.

Chart 3: Underlying Inflation Measures in an Optimal Forecast Combination
(Weight Assigned to Minimize the 12-Monh-Ahead RMSFE over A Three-Year Rolling)



Source: Authors' calculations.

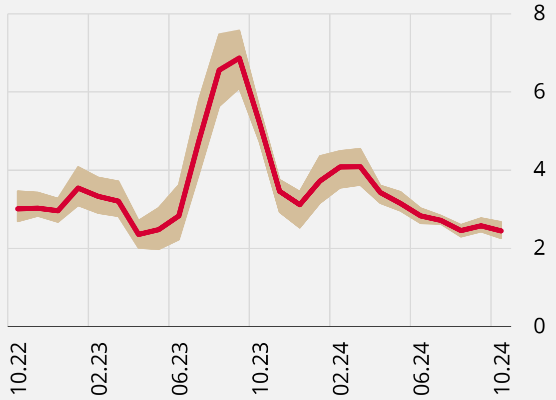
c. Observations on the Recent Course of Underlying Inflation and Pricing Behavior

The analyses point out that the performance of indicators varies according to different criteria (although the median inflation indicator stands out) and that it is important to monitor different indicators together to identify the persistent part of inflation. Accordingly, an analysis of the six indicators monitored by the CBRT as a whole reveals that the underlying inflation declined from 2.8% at the end of the previous quarter to 2.6% in the third quarter and to 2.3% in October (Chart 4).

In the third quarter, there was some divergence between exclusion-based indicators such as B and C and other indicators. In August, exclusion-based indicators signaled a flat course in the underlying inflation, while others signaled a slowdown. This divergence was driven by the periodic high price increases in groups with a pronounced tendency to time-dependent price determination, such as education and transportation services, which experienced the back-to-school effect. When there are periodic high price increases in a small number of items with relatively high weights, indicators such as B and C, which are based on permanent exclusion from the index, are more adversely affected, and indicators based on sub-item distribution may give a healthier picture of the underlying inflation during such periods.

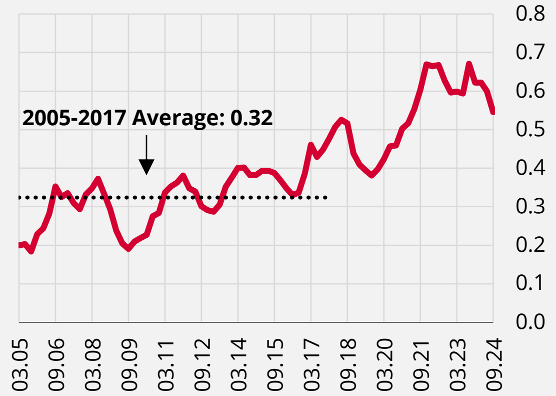
[4] In addition, Atuk and Özmen (2009a) also examined the performance of the underlying inflation indicators in tracking the inflation trend (based on 18-, 24- and 36-month central averages of CPI). Based on this approach, V_1, median and DFM indicators perform better. Among these indicators, the median inflation indicator has the best performance.

Chart 4: Underlying Inflation Indicators*
(Seasonally Adjusted, Monthly % Change, Three-Month Average)



Source: CBRT.
* Seasonally adjusted average of six different indicators: B, C, SATRIM, median inflation, DFM indicator and V_1 indicator. Shaded area shows the maximum and minimum range.

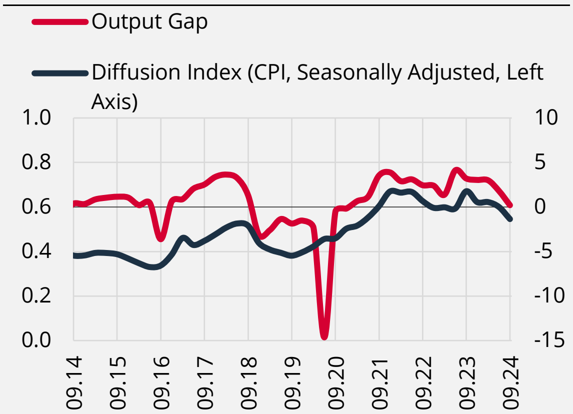
Chart 5: CPI Diffusion Index*
(Seasonally Adjusted, Quarterly Average)



Source: CBRT.
* Diffusion index is calculated as the ratio of the number of items with increasing prices minus the number of items with decreasing prices to total number of items within a given month and then adjusted for seasonal effects.

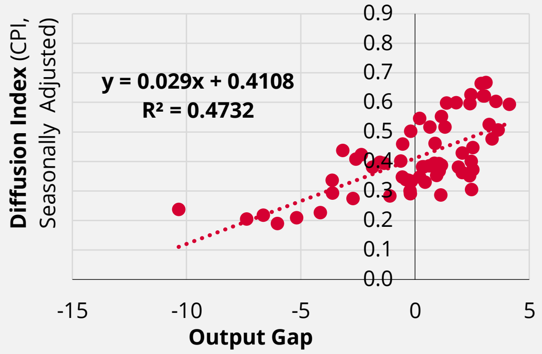
For the course of pricing behavior, the extent of price increases is as important as the size of price increases, and in this regard, besides the frequencies of price increases and decreases in micro data, diffusion indices are also used. The *diffusion index*, which is an indicator of how widespread price increases are, is calculated as the ratio of the difference between the number of items with rising prices and the number of items with falling prices to the total number of items. The seasonally adjusted diffusion index reached its highest value in the last quarter of 2021 and the following two quarters, and after reaching a similarly high level in the third quarter of 2023, when multiple shocks occurred simultaneously, it entered a steady downtrend with the monetary tightening (Chart 5). This was driven by the decline in the share of items with rising prices as well as the increase in the share of items with falling prices, which are subcomponents of the diffusion index. On the other hand, the current levels are significantly above past averages.

Chart 6: Demand Conditions and the Diffusion of Price Increases in CPI



Source: CBRT.

Chart 7: Scatter Plot of Output Gap and CPI Diffusion Index*



Source: CBRT.
* Sample Period: 2008Q2-2024Q3. 2020Q2 (Covid-19 period), 2021Q4 and 2023Q3 quarters, where supply-side effects are significant, are excluded from the sample.

Demand conditions affect not only the magnitude of the price increase but also its diffusion (Chart 6). In fact, there is a significant positive relationship between the output gap and the diffusion index (Chart 7). In cooling periods when the output gap takes negative values, the general diffusion of consumer price increases also decreases. In the current period, there is a slowdown in the diffusion index with the normalization in demand conditions (Chart 6). Analyses suggest that the diffusion of price increases will further weaken in the upcoming period as the output gap turns negative.

In sum, there is no precise way to define and measure underlying inflation. Therefore, different approaches may be used. The performance of indicators may vary according to different criteria and periods. By its nature, each indicator may respond differently to different economic conditions. Therefore, in order to make an accurate assessment of the medium-term course of inflation, it is important to monitor multiple indicators constructed by alternative methods together.

References

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