ESTIMATION OF UNDERLYING INFLATION IN TURKEY: A DYNAMIC FACTOR MODEL APPROACH

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ABSTRACT

ESTIMATION OF UNDERLYING INFLATION IN TURKEY:
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A measure of underlying inflation is helpful for monetary policymakers, academics, economic analysts, and long-term investors. Traditional measures of underlying inflation ignore or down-weight the more volatile sub-components of the consumer price index (CPI), thereby omitting information helpful in assessing current and future inflation trends. This paper proposes a new indicator of underlying inflation. It is constructed using monthly inflation of 5-digit disaggregated price data from the CPI and is based on an econometric modeling technique called a dynamic factor model. Then, with this new measure, the performance of the commonly used measures of underlying inflation for the Turkish economy is analyzed. The results indicate that the new indicator provides a good measure of underlying inflation and is a valuable tool for policy analysis.

Keywords: Underlying Inflation, Dynamic Factor Model, Monetary Policy

ÖZ

TÜRKİYE İÇİN ENFLASYON ANA EĞİLİM TAHMİNİ:
DİNAMİK FAKTÖR MODELİ YAKLAŞIMI

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Enflasyonun ana eğiliminin ölçülmesi para politikası yapıcıları, akademisyenler, ekonomik analistler ve uzun vadeli yatırımcılar için faydalıdır. Geleneksel ana eğilim ölçümleri, tüketici fiyat endeksinin (TÜFE) daha oynak alt bileşenlerini dışlamakta veya bu kalemlerin ağırlıklarını azaltmaktadır, böylece mevcut ve gelecekteki enflasyon eğilimlerini değerlendirmede yararlı olan bilgileri göz ardı edebilmektedir. Bu çalışmada enflasyonun ana eğilimine ilişkin yeni bir gösterge oluşturulmuştur. Bu gösterge, TÜFE'den alınan 5 basamaklı ayrıştırılmış fiyat verilerinin aylık enflasyonu kullanılarak oluşturulmuştur ve dinamik faktör modeli adı verilen bir ekonometrik modelleme tekniğine dayanmaktadır. Daha sonra, bu yeni gösterge ile birlikte, Turkey ekonomisi için yaygın olarak kullanılan enflasyon ana eğilim göstergelerinin performansı analiz edilmiştir. Sonuçlar, yeni göstergenin enflasyonun ana eğilimini iyi bir şekilde ölçtüğünü ve politika analizi için faydalı bir araç olduğunu göstermektedir.
Anahtar Kelimeler: Enflasyon Ana Eğilimi, Dinamik Faktör Modeli, Para Politikası

To My Family

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LIST OF ABBREVIATIONS

COICOP: Classification of Individual Consumption According to Purpose

CPI: Consumer Price Index

DFM: Dynamic Factor Model

FRBNY: Federal Reserve Bank of New York

MCT: Multivariate Core Trend

MLE: Maximum Likelihood Estimation

PCA: Principal Component Analysis

PCE: Personal Consumption Expenditures

SATRIM: Seasonally Adjusted Trimmed Mean

TURKSTAT: Turkish Statistical Institute

UIG: Underlying Inflation Gauge

WM: Weighted Median

CHAPTER 1

INTRODUCTION

The Consumer Price Index (CPI) is the most widely used indicator of consumer price inflation in Turkey. Although the public's attention on inflation often focuses on headline inflation, the underlying inflation is essential for policy authorities, long-term investors, academics, etc. The reason is that headline inflation is susceptible to a variety of external shocks, making it too volatile to provide reliable information about the inflation process. Consequently, there have been several efforts to define various measures of inflation to extract accurate knowledge from the inflation process. This situation has led to the creation of different underlying inflation measures.

The underlying inflation indicators are beneficial in the context of inflation targeting. Central banks target a particular inflation rate for the future, usually the medium term, to promote price stability in this framework. The time frame sufficient for the policy decisions to take effect is the medium period. Forecasting future inflation trends is essential from this angle, and central banks can take proactive measures to meet their objectives. However, since headline inflation is subject to various temporary shocks and is inherently volatile, central banks need smooth inflation measures over time and provide information about future inflation. In particular, these measures should be free from noise and able to predict future inflation. Central banks can obtain more accurate information about the inflation process by using underlying inflation measures. Therefore, underlying inflation indicators are valuable for policymakers to guide operational policy within the inflation-targeting regime. To understand the underlying inflation concept, it is generally accepted that the persistent and transitory components of inflation form the inflation process, and the persistent part reflects the underlying inflation. Policymakers are interested in this part because they take a forward-looking approach. In other words, since, in the short term, policymakers cannot affect inflation and economic activity, they attempt to comprehend inflation trends and future inflation dynamics over a more extended period.

Cecchetti (1997) highlights that short-lived shocks, which should not influence policymakers' decisions, are crucial for central banks when measuring inflation. Additionally, Ehrmann et al. (2018) outline the basis for analyzing indicators of underlying inflation. They state that since the central banks encounter the obstacle of determining the signal on medium-run inflationary pressure in the inflation data from the noise caused by temporary or idiosyncratic parts, measures of underlying inflation should be routinely tracked. The transitory part of inflation is volatile and adds noise to price data, so it should be removed to have accurate information regarding the inflation process. Therefore, when policymakers monitor inflation developments, make decisions, and communicate with the public, they consider the persistent part of the inflation, not the transitory part.

Briefly, it is accepted that underlying or core inflation captures the persistent part of inflation for the policymaker's interested period and cuts out the features that should not affect the policymaker's decision-making process.

Theoretically, the literature outlines simple general requirements that an underlying inflation measure should fulfill. In particular, a useful underlying inflation indicator should have several desirable traits, including a similar mean to the target inflation rate, forecasting power for the target inflation series, tracking the underlying trend in the target inflation series, and convenient designability. According to Roger (1998), an underlying inflation indicator should possess specific characteristics, including timeliness, credibility, comprehensibility, and lack of significant bias toward a targeted measure. Furthermore, as Wynne (1999) suggested, An underlying inflation indicator should be capable of computation in real time, exhibit a forward-looking orientation, be robust, unbiased, and have a track record and a theoretical basis. Even though there is some certainty regarding the characteristics of a valuable underlying inflation measure, there is no single measure for it.

There are various methods to measure underlying inflation. One of the most common techniques is constructing measures by excluding items considered volatile from the CPI basket, which is called the permanent exclusion method. This method was first proposed by Robert J. Gordon in 1975 and is still frequently used as an underlying inflation measure. However, various alternative measures of underlying inflation have been introduced over time. These candidate series include weighted median measures (Bryan & Cecchetti, 1994), exponentially smoothed measures (Cogley, 2002), etc. In Turkey, mostly B, C, and D indicators are used as an underlying inflation measure based on a permanent exclusion approach. In addition to these indicators, the most commonly used measures in Turkey are the periodic exclusion of volatile items, the weighted median (WM), the seasonally adjusted trimmed mean (SATRIM), the median, and the indicator based on principal component analysis.

One of the weaknesses of traditional measures is not considering the time dimension of the subcomponents of inflation, which show different degrees of persistence over time. For example, energy prices are primarily influenced by exchange rates, while food prices are affected by seasonal factors, making them volatile groups in the CPI. Consequently, they are typically excluded from the consumer basket to have accurate information regarding the inflation process. However, examining the persistence of their price changes before excluding them from an indicator of underlying inflation is crucial. The application of modern techniques allows for integrating data pertaining to both the cross-sectional distribution of prices and the time-series properties of prices within a unified structure. Large data factor models have been frequently applied as statistical techniques to supplement current real activity and underlying inflation measures.

One of the econometric modeling techniques with various applications recently is a dynamic factor model. This technique permits the capture of persistent movements within data sets by extracting a limited number of variables that represent the typical fluctuations observed in the series. Compared to other measures of underlying inflation, the dynamic factor model utilizes information about price changes of sub-indices in the CPI from both the time-series and cross-sectional dimensions. Furthermore, studies have shown that a factor model can provide a valuable measure of inflation by offering statistical evidence in the literature. For instance, Bryan and Cecchetti (1994) show that a factor model can solve the problem related to transitory noise caused by non-monetary shocks. According to Bryan and Cecchetti (1993), a factor model can address both the measurement bias caused by measuring particular prices and the weighting bias resulting from the weighting procedure in CPI inflation. Therefore, reduced-bias inflation estimates can be computed from the CPI series using a factor model by extracting the data series' common component.

A new underlying inflation indicator for Turkey is proposed in this study. It is obtained using a dynamic factor model with disaggregated prices from Turkish CPI at a 5-digit level. This indicator is defined as the persistent part of the inflation, and it dates back to 2005. Then, together with this new measure, which is called DFM, the regularly used underlying inflation indicators for the Turkish economy are analyzed. A performance analysis of all the indicators is provided. To achieve this, a set of criteria is used for the measurements to evaluate their informativeness and utility for the analysis of inflation as a whole. The criteria are selected primarily to test their predictive power and to comprehend the information content of each underlying inflation measure. In the end, the performance of the DFM is discussed, and whether or not it is a good indicator.

The paper's findings indicate that no underlying inflation indicator is the best. Different indicators may be suitable depending on different periods. Therefore, it is crucial to monitor various indicators for different time horizons. In this respect, DFM tracks the inflation trend, displays a close relationship with headline inflation, and has predictive ability. Therefore, it is a valuable indicator of underlying inflation. This indicator is a suitable substitute for other measures of underlying inflation. The findings in this paper are significant for policymakers and other economic agents as they all depend on measures of underlying inflation to comprehend the underlying trend in target, current, and future inflation developments. One of the significant contributions of this work is the satisfaction of the recent need for a new underlying inflation measure. The question of what constitutes underlying inflation has gained significant importance, particularly during periods of high inflation.

While traditional measures of underlying inflation exist, alternative measures can offer a different perspective on tracking inflation dynamics. Furthermore, Turkey has no widely used model-based approach for measuring underlying inflation. Other central banks use dynamic factor-based approaches to monitor underlying or core inflation. Examples are common around the world. For instance, the New York Federal Reserve has two different-factor models as underlying inflation indicators. One of these models is the Underlying Inflation Gauge (UIG), based on a dynamic factor model that uses sub-indices of the CPI and a broad range of real, nominal, and financial variables. The Multivariate Core Trend (MCT) is the second measure to assess inflation's persistence in the seventeen main personal consumption expenditures (PCE) price index groups. It is based on a time-varying parameters dynamic factor model. For Turkey, Tekatlı (2010) introduced a new core inflation indicator based on a factor model. However, this indicator is calculated using 12 subcomponents of the CPI and is not monitored regularly. Therefore, the DFM fills the gap by adopting a similar technical perspective, the dynamic factor model with 5-digit level subcomponents of the CPI, to extract accurate information about the inflation process. It grabs the persistent inflation component by removing transitory changes from headline inflation, making it a good substitute for other measures of underlying inflation. As a result, it can be a valuable measure for policy-makers etc.

The structure of the paper is as follows: Chapter 2 summarizes the literature on constructing underlying inflation indicators for different countries. Chapter 3 outlines the underlying inflation framework and the concept and methodology of the most commonly used indicators for Turkey. Chapter 4 introduces the data and methods to estimate the indicator, specifically the dynamic factor modeling framework. Chapter 5 presents the results of the estimation and comparisons of the DFM with the most commonly used underlying inflation measures for Turkey. Additionally, the informativeness and usefulness of DFM are evaluated by applying specific criteria used in the literature. Finally, Chapter 6 briefly summarises the results obtained and concludes the thesis.

CHAPTER 2

LITERATURE REVIEW

There is a large body of literature on the construction and study of underlying inflation. As there is no clear methodology for determining underlying inflation, there is a variety of research related to constructing an underlying inflation indicator. This chapter outlines the most outstanding examples in the literature. At the end of the chapter, the approach for creating the underlying inflation indicator preferred in this paper is explained.

In the literature, it is argued that there is no exact way to compute underlying inflation. Therefore, there are various types of approaches to construct underlying inflation measures. Robert J. Gordon introduced the overall price increase without considering energy and food prices in 1975. This approach is called the permanent exclusion-based method and has been one of the most widely used methods since the 1970s. This method aims to obtain inflation by excluding volatile subclasses in the consumer price index basket. The most excluded groups are energy and food.

Furthermore, Bryan (1991) proposes using median price change as an alternative measure. This method is considered a simple and useful indicator. It provides a direct way to track short- and long-term inflation. In addition to these methods, limited influence estimators are also frequently used methods to measure underlying inflation in the literature. The main idea behind these estimators is to generate a core indicator unaffected by extreme price variations. Bryan and Cecchetti (1994) and Bryan, Cecchetti, and Wiggins (1997) suggest limited-influence estimators, such as the weighted median and trimmed means. The main idea behind these estimators is removing a certain percentage from the tails of the distribution of inflation and then calculating the weighted average of the remaining items' inflation. In other words, it is the method of removing items whose inflation rates fall in the tails of the cross-class/sub-class distribution.

A limited influence estimation approach is generally adopted in different studies as well. For instance, Bakhshi and Yates (1999) study the theoretical and empirical arguments for trimming inflation in the United Kingdom. The paper shows that the proposed indicator is a reasonable estimate of inflation because this estimate includes the most information about the future general price level. However, the authors also note that it is critical to define the optimal trim ratio, which is the number of tails that should be cut off, and it can be challenging to compute the optimal trim in practice. Furthermore, as a similar example, Dolmas (2005) from the Federal Reserve Bank of Dallas research department constructs the trimmed mean using the price index for Personal Consumption Expenditures[1] (PCE) to build a new underlying inflation measure. Dolmas and Koenig (2019) then compare trimmed mean PCE and overall inflation without energy and food groups. The findings suggest that the trimmed-mean approach does not dominate in forecasting headline inflation in real-time. Additionally, since this method eliminates the short-term fluctuations in headline inflation, trimmed mean inflation has a long-run relationship with headline inflation. Smith (2004) examines the performance of the weighted median for the US. The findings indicate that adjusting for bias enhances forecasting, and therefore, it is a successful forecaster and a good core inflation indicator.

For the Turkish price series, Berkmen (2002) constructed a trimmed mean (TRIM) by removing specific distribution tails. The study discovered that trimmed means offer statistically efficient inflation estimators. Nevertheless, this approach cannot discriminate between signal and noise when dealing seasonal items. For this reason, Atuk and Ozmen (2009a) introduce SATRIM, which is seasonally adjusted trimmed mean inflation for Turkey to overcome this drawback. They show that the new indicator outperforms the TRIM measure in tracking inflation trends in different periods. Moreover, Atuk and Ozmen (2009b) describe other commonly used

[1] PCE is a measure of the prices paid by individuals in the United States or on their behalf for goods and services. The PCE price data is obtained from the U.S. Bureau of Economic Analysis every month.

underlying inflation indicators based on different methods in Turkey, including weighted median, SATRIM, volatility-based indicators, etc., and they compare their performance.

In the literature, using wavelets is another method to construct underlying inflation measures. Baqaee (2010) developed an underlying inflation indicator for the case of New Zealand using this method. The most volatile parts of inflation are discarded thanks to this approach. The paper's results show that the proposed indicator significantly correlates with overall inflation and performs well compared to others in nowcasting medium-term inflation. Dowd et al. (2011) present wavelet approaches for estimating US core inflation. The authors argue that wavelets are well-suited for smoothing non-stationary time series. The suggested measures sometimes perform better when comparing the wavelet-based measures with traditional measures in terms of their ability to follow trend inflation and predict future inflation. For Turkey, Akkoyun et al. (2011) use a two-step approach that combines wavelet and bandpass filters to handle short-term fluctuations in inflation series that are complemented within one year. Specifically, wavelet filters are applied to the inflation series to exclude variations from 2 to 8 months in the first step. The remaining data series are then filtered in a second stage using the Christiano-Fitzgerald filter to eliminate oscillations between 8 and 12-month frequencies. The paper suggests that this approach provides smoother time series data than the seasonal adjustment approach. Additionally, when applied to a popular particular CPI aggregate, this method reasonably accurately indicates the underlying inflation.

Model-based approaches are another frequently preferred method in the literature while constructing an underlying inflation indicator. Factor models are usually used in the literature for several reasons. Reis and Watson (2010) decompose US inflation into pure inflation, the aggregate relative price index, and idiosyncratic relative prices using a dynamic factor model. The results suggest that pure inflation is smoother compared to other inflation measures. In addition to this paper, Cristadoro, Forni, Reichlin, and Veronese (2003) support the idea that changes in the relative prices of goods and services should not be included in core inflation; instead, core inflation should capture only the portion of the price change common to all products. Bryan and Cecchetti (1993) have a similar understanding of this content. They also provide solutions to the two problems regarding using the CPI to measure inflation using factor models. While the first problem is associated with the transitory noise owing to non-monetary shocks, the second problem relates to weighting bias from the expenditure-based weighting method in CPI inflation. This study suggests that a factor model, which objectively assesses the common component of individual price fluctuations, can solve these two issues. Furthermore, Eickmeier and Ziegler (2006) discuss existing applications of these models for inflation through a meta-analysis and evaluate the determinants of the forecasting power of large factor models compared to other models. The paper finds that factor models outperform small models.

One of the famous studies regarding an underlying inflation measure based on a factor model is the underlying inflation gauge (UIG), which belongs to the Federal Reserve Bank of New York (FRBNY). UIG was created by Amstad et al. (2014) to estimate the persistent part of inflation in the US dating back to 1995 using dynamic factor models. This paper presents two measures for the underlying inflation indicator. The first measure includes only the sub-indices of the CPI. The second measure comprises the CPI sub-indices and a wide range of nominal, real, and financial variables. When comparing the UIG with traditional core inflation measures in the US, three essential features of the UIG stand out. Firstly, the UIG can use information regarding price changes of sub-indices from both time-series and cross-sectional dimensions. Secondly, it can consider a wide range of extra series in addition to price variations of the sub-indices. Thirdly, it has demonstrated superior forecasting precision compared to traditional underlying inflation indicators, offering a more precise and timely signal of turning points in inflation over different periods. They state that this study adds to the body of knowledge already available regarding US inflation, complementing the traditional indicators of underlying inflation.

Like the UIG, factor models are frequently preferred to create underlying inflation indicators in other economies, especially for the euro area. Using data from a variety of time series on the disaggregated prices of industrial production, labor market indicators, and financial and monetary variables, Cristadoro et al. (2001) developed a core inflation indicator for the euro area. By generating the indicator that takes the common inflation component, measurement inaccuracy, differences in data collection methods, etc., are eliminated from the headline inflation. The paper demonstrates that this indicator performs well as a predictor of the euro area harmonized consumer price index at a one- and two-year period, which is considered an appropriate time horizon for the European Central Bank's monetary policy. Subsequently, another measure for the euro area was published by Cristadoro et al. (2005). They prefer a dynamic factor model that employs data from over 400 series, including prices and other real and nominal variables, from a huge monthly database. This method produces smooth data series by removing measurement errors and volatile parts from monthly inflation. The proposed measure has advantages over traditional inflation measures. It provides a timelier and more accurate signal of the inflationary process. It also has a strong ability to forecast inflation in the euro region over different periods. Therefore, it outperforms most of the alternative measures. Additionally, according to the authors, this situation confirms its ability to outline all the facts on inflationary pressures successfully.

Another example of the euro area is the analysis by Camba-Mendez and Kapetanios (2005) of dynamic factor measures of underlying inflation in forecasting inflation. This paper estimates core inflation using a factor model with a large dataset. Then, it compares this estimate with other measures of underlying inflation derived from traditional methods in terms of forecasting power. This paper finds that core inflation constructed by dynamic factor methods performs well in forecasting headline inflation over 12 to 18 months compared with traditional measures.

Altissimo et al. (2009) also use the same method to study the sustainability of overall inflation in the euro region. Using a dynamic factor model for more than 400 inflation sub-indices of the euro area inflation, the study breaks down the dynamics of inflation sub-indices into two components: one owing to a standard macroeconomic shock and the other owing to sector-specific idiosyncratic shocks. This paper specifically examines the role of cross-sectional aggregation in illustrating the dissimilarities between micro and macro inflation dynamics. To this end, it utilizes the diversity of CPI sub-indices in inflation dynamics within the euro area. Another example in the euro area is the Persistent and Common Component of Inflation (PCCI) indicator by Bańbura and Bobeica (2020). It is based on a dynamic factor model estimated on disaggregated HICP (Harmonized Index of Consumer Prices) inflation rates for 12 countries in the euro area. The authors specify that this indicator has several attractive features and successfully tracks more persistent inflationary developments.

Other prominent examples of factor models in constructing an underlying inflation indicator in different countries are as follows. For New Zealand, Giannone and Matheson (2007) introduce a measure of core inflation estimated using a dynamic factor model and disaggregated consumer price data. The paper indicates that this indicator provides relatively accurate estimates of core inflation. Additionally, the proposed underlying inflation indicator is timelier and can be calculated as soon as the CPI data are released. Khan et al. (2013) estimated a monthly factor model using the components of the consumer price index to create the indicator for Canada. Their findings show that industry-specific pricing variations that could distort the signal in other underlying inflation indicators have no effect on the recommended measure. Also, they add that it captures price movements that indicate fluctuations in aggregate demand in the Canadian economy. Therefore, they support the idea that this measure is a valuable complement to the existing indicators of underlying inflation that the Bank of Canada monitors. The Swiss National Bank (SNB) produces a daily evaluation of inflation in Switzerland using a gauge called dynamic factor inflation (DFI), as described by Amstad and Fischer (2009a and 2009b). Amstad et al. (2014) developed a measure for China using a dynamic factor model with a broad range of variables that could affect inflation. For a large emerging economy, this paper is the first to apply such a model for inflation. The authors also note that the proposed indicator outperforms traditional core measures over different samples.

For Turkey, Tekatlı (2010) proposes a core indicator using a factor model with the CPI inflation sub-indices. This indicator removes relative price variations from headline inflation monthly. The analysis uses twelve subcomponents[2] of CPI inflation. Then, the performance and usefulness of the constructed indicator, namely, Fcore, is examined by comparing it with the core measures of H and I[3]. The findings

[2] Twelve subcomponents of CPI inflation in this analysis are Food and Non-Alcoholic Beverages, Alcoholic Beverages-Tobacco, Clothing-Footwear, Housing, Water-Electricity-Gas and Other Fuels, Furnishings-Household Equipment-Routine Maintenance of the House, Health, Transport, Communications, Education, Recreation-Culture, Hotels, Cafes-Restaurants, Miscellaneous Goods-Services.

[3] The core measure H excludes unprocessed food, alcoholic beverages, energy, gold and tobacco products from the CPI and the indicator I excludes energy, food, alcoholic and non-alcoholic beverages, gold and tobacco products.

demonstrate that the created indicator is a valuable tool for policy research and a reliable indication of underlying inflation.

A recent underlying inflation indicator for the US economy is the Multivariate Core Trend (MCT) constructed by Almuzara and Sbordone (2022). This indicator is estimated using a dynamic factor model with time-varying parameters on monthly data for the seventeen significant Personal Consumption Expenditures (PCE) price index sectors. Their model follows the paper by Stock & Watson (2016), and the model decomposes inflation in each sector into common trends, sectoral trends, common transitory shocks, and sectoral transitory shocks. To calculate the trend in PCE inflation, the common and sectoral trends are added together and weighted by their respective expenditure shares. This paper introduces MCT as an indicator of inflation persistence in the main sectors of the PCE price index. In other words, this metric aids in assessing the degree and scope of inflation persistence. According to the authors, some unique characteristics of the MCT model are appropriate for inflation data, such as allowing for outliers and accounting for the noisiness in the data.

Other than factor models, different methodologies have also been adopted in the literature. A few of these examples are summarized as follows. For the euro area, Conflitti (2020) introduces two indicators as a substitute measure to the HICP, excluding energy and food. The first indicator is based on a Phillips curve model. This indicator distinguishes between disaggregated prices that are sensitive to the business cycle and those that are not. The second one is generated using a factor model to eliminate parts that are vulnerable to extreme price fluctuations, which are unlikely to be associated with the underlying inflation trend owing to their unique nature. The proposed indicators have similar properties compared to others, and none of the underlying inflation measures are superior or accurate. Therefore, the authors recommend that policymakers monitor a broad range of indicators to thoroughly evaluate the behavior of price dynamics over the medium term. For the Euro area, Bihan et al. (2023) have constructed a new measure based on a multivariate regime-switching approach that is jointly estimated on disaggregated sub-components of Euro area inflation. This measure provides real-time information on the asymmetric risks of inflationary pressures. The proposed indicator has three main advantages. Firstly, it can quickly detect sudden alterations in underlying inflation. Secondly, it helps to monitor changes in underlying inflation on time. Finally, it performs well based on various relevant criteria for monitoring inflation.

All in all, various studies in the literature on constructing an underlying inflation indicator exist. There is no single method for it. The factor models are generally preferred because they consider both the time series and cross-sectional dimension of the data series while producing a core inflation measure. It can also be seen that the examples of factor models for generating an underlying inflation measure are generally available for developed countries but not for developing countries. Turkey has no underlying inflation indicator based on the dynamic factor approach with disaggregated price indices. Therefore, this paper adopts the dynamic factor model approach to construct an underlying inflation indicator to obtain a promising policy tool.

CHAPTER 3

UNDERLYING INFLATION

This section first reviews the concept of underlying inflation. The concept and methodology of traditional and alternative measures of underlying inflation for Turkey are then explained. Finally, the descriptive and distributional statistics of the traditional and alternative measures are presented and interpreted. The discussion in this section motivates the definition of underlying inflation, the choice of methodology, and the data set used in this paper.

3.1. Defining Underlying Inflation

The concept of underlying inflation provides a fundamental additional basis for evaluating medium-term inflation dynamics. Therefore, it is a valuable benchmark for monetary policy. The literature identifies underlying inflation as a persistent component of inflation. In other words, it indicates the expected rate of price change under normal economic conditions, which means resource utilization does not affect inflation. Rudd (2020) defines underlying inflation as the expected inflation rate without supply shocks, idiosyncratic relative price changes, economic slack, or other disturbances. To illustrate the concept of underlying inflation in a theoretical framework, the following equation can be written for any realized headline inflation (π_t):

$$\pi_t = \pi_t^* + c_t$$

where π_t^* represent the underlying inflation rate and c_t shows the discrepancy between the headline and the underlying inflation rate. In Amstad et al. (2014) paper, underlying inflation is defined as:

$$E_t[\pi_{t+h}] = E_t[\pi_{t+h}^*] \text{ as h rises.}$$

where π_{t+h} presents headline inflation in the period $t + h$ and π^*_{t+h} indicates the underlying inflation rate in the period in period $t + h$. This equation implies that as the horizon extends to the future, the expected transitory component converges to zero, i.e. $E_t[c_{t+h}] \rightarrow 0$. Therefore, the paper states that one of the desirable features of an indicator of underlying inflation is that it should represent the portion of inflation that persists during times when policymakers are interested in it.

Overall, underlying inflation should be more stable by excluding the transitory component from inflation, and it should provide more accurate information about the inflation process than headline inflation.

3.2. Traditional and Alternative Underlying Inflation Measures in Turkey

Underlying inflation cannot be observed directly, and it is a theoretical notion that needs to be estimated. There are no precise indicators or methods for measuring underlying inflation in the literature, resulting in various indicators. However, all the measures attempt to capture the permanent component of inflation by removing the transitory parts to extract the correct information about the inflation process.

There are several underlying inflation measures in Turkey. The most commonly used measures based on permanent exclusion, the periodic exclusion of volatile items, the weighted median (WM), the seasonally adjusted trimmed mean (SATRIM), the median, and the indicator based on principal component analysis. These core indicators depend on different methodologies. The concepts and methods of these measures are explained in detail in the following section.

3.2.1. Permanent Exclusion

Excluding certain items from the CPI basket permanently is the most popular and frequently used method. Currently, the Turkish Statistical Institute (TURKSTAT) explains six core indicators based on the permanent exclusion method under the name of "Indicators for the CPIs having specified coverages (2003=100)". The detailed explanations of these measures are below.

A: Indicator A excludes seasonal products.

B: Indicator B excludes energy, unprocessed food, alcoholic beverages, tobacco, and gold.

C: Indicator C excludes energy, food, alcoholic beverages, non-alcoholic beverages, tobacco, and gold.

D: Indicator D excludes unprocessed food, alcoholic beverages, and tobacco.

E: Indicator E excludes alcoholic beverages and tobacco.

F: Indicator F excludes administered and directed prices.

There are two primary motivations for the permanent exclusion method. Firstly, supply shocks can affect some CPI basket items, and significant price fluctuations in these goods are more likely to reflect changes in relative prices than a general increase in prices. (Atuk and Ozmen, 2009b). In other words, since some items in the CPI basket are vulnerable to supply shocks, it is hard to evaluate the general outlook of inflation correctly. For instance, unprocessed food items are susceptible to supply shocks. To be more precise, prices of fresh fruit and vegetables in the unprocessed food group depend mainly on weather conditions. Thus, this situation causes volatility in headline inflation. Therefore, these items can be excluded. Secondly, policymakers cannot control the price changes of some items in the basket. For example, since energy prices, indirect taxes, and interest payments like mortgages are unstable and endogenous to monetary policy, they are usually removed from the basket (Silver, 2007). Thus, the central bank can focus on the items it can control.

The primary benefit of the permanent exclusion method is its ease of calculation and communication with the public. Additionally, this method does not require any assumptions or limitations, and there is no need for any revisions. Hence, it is easily understandable and acceptable by the public. However, this measure is ineffective in eliminating all the supply shocks and volatility in the inflation series because excluded items are fixed and not updated with data realization.

3.2.2. Period-by-Period Exclusion of Volatile Items

Identifying and eliminating all supply shocks and volatility in pricing data is also accomplished by a period-by-period exclusion procedure. This method may be more appropriate than the permanent exclusion method. It is more important to determine the primary source of volatility. Excluding the entire group may lead to ignorance of a significant signal of the general inflation trend. In other words, excluding the volatile items instead of the whole group from the basket may provide a more accurate view of the general inflation trend. A data-driven analysis should be conducted to identify whether an item is volatile or not.

With this technique, items that exhibit more volatility in price movements than the average will only be excluded. To elaborate, each month at the five-digit aggregation level, all indices' standard deviation and mean of the seasonally adjusted monthly price changes are calculated. Then, the monthly inflation of all indices is compared with the estimated standard deviation and the mean of the whole sample. In other words, items are identified as volatile depending on the threshold criteria, such as 1, 1.5, 2, or 2.5 standard deviations of the mean.

3.2.3. The Weighted Median (WM)

The weighted median is considered a different form of trimmed mean. Both distribution tails are removed for a given period so that only the 50^{th} percentile of the sorted seasonally adjusted price changes stands in the data.

3.2.4. The Seasonally Adjusted Trimmed Mean (SATRIM)

This approach mainly involves removing a certain percentage of the data symmetrically from both tails of the distribution of price changes. It takes a weighted average of the rest of the price changes. When the distributions of price changes are not normally distributed, trimmed means provide statistically more efficient inflation estimators than weighted sample means (Berkmen, 2002).

In order to clarify the computation, the seasonally adjusted monthly inflations for each series are first arranged by their respective CPI weights. The cumulative weights of the ordered series are used to calculate the trimming percentage. The distribution tails are then symmetrically trimmed according to the designated percentage, and the trimmed mean inflation for a specific period is computed by calculating the weighted average of the remaining series.

In addition, the aggregation level of the price series is crucial for calculation. As the data aggregation increases, a smaller trim percentage is required to obtain a more efficient measure (Atuk & Ozmen, 2009a). In this paper, SATRIM is based on the five-digit aggregation level calculation. For the five-digit aggregation level, the

Turkish price series's optimal trim ratio is 18 percent from each tail of the price change distribution for a given month[4].

3.2.5. The Median

The median represents the midpoint of the ordered data series. As a core inflation indicator, the median is calculated from seasonally adjusted monthly inflation in a five-digit aggregation level.

3.2.6. Principal Component Analysis (PCA)

One dimensionality reduction method frequently used to lower the dimensionality of big data sets is principal component analysis (PCA). With this technique, an extensive set of variables can be divided into smaller ones while retaining most of the original data. This approach creates new variables as linear combinations of the original variables. The combinations are done in a way that new variables are uncorrelated, and the first components contain the most information.

As a core inflation indicator, principal component analysis is calculated from the seasonally adjusted monthly inflation of eight selected indicators for the CPIs having specified coverages. These groups are clothing and footwear, durable goods (excluding gold), other core goods, rent, hotels-cafes-restaurants, transportation, telecommunication, and other services.

3.3. Descriptive and Distributional Statistics of the Traditional and Alternative Underlying Inflation Measures in Turkey

The presentation of the descriptive and distributional statistics of the traditional and alternative underlying measures of inflation is vital for understanding the fundamental properties of these measures. This section demonstrates mean, median, standard deviation, coefficient of variation, minimum and maximum value, kurtosis, and skewness statistics. These statistics are also presented for headline inflation. In addition, two different periods are considered. The first is the period between 2005 and 2023, and the second is between 2005 and August 2018. As the 2003 base year

[4] For details, see Atuk and Ozmen (2009).

price index was published in January 2005, 2005 was the starting point. Moreover, the reason for providing the second period is that there are different economic shocks, such as the exchange rate in the Turkish economy, especially after September 2018. Therefore, excluding the periods with economic shocks may provide more reasonable results in terms of interpreting the data. The monthly inflation series begins in February 2005 and ends in December 2023.

Table 1 demonstrates the descriptive and distributional statistics of the monthly inflation for the headline CPI and the underlying inflation measures for the two different sample periods. When considering the first period, it is seen that the means of monthly inflation of B, C, and D indices, as well as PC1, are similar to that of the headline inflation. The means of the monthly weighted median, SATRIM, the median, and volatility-based measures have lower means than the CPI. When median statistics are taken into account, it is observed that the volatility-based indicators, SATRIM, and the median have lower values than others. All core measures' standard deviations are lower than the headline inflation's. Since standard deviation is commonly used as a volatility measure, it can be stated that all the underlying inflation indicators are less volatile than the headline inflation. Among the underlying inflation indicators, the volatility-based indicators, SATRIM, and the median have lower standard deviations. Therefore, these measures are more stable than the other indicators.

The coefficient of variation shows the relative dispersion of data points in a data series around the mean. When considering the statistics of the coefficient of variation, it is evident that the C and D indices have higher values than headline inflation, while the B indicator has the lowest value. This situation creates inconsistency among the indicators based on the permanent exclusion method. When the kurtosis and skewness are considered, it can be observed that the values are very close to each other. Data sets with high kurtosis tend to have heavy tails or outliers. Indicator B exhibits the highest kurtosis value, followed by indicators of C, WM, V_1, and D indices, respectively[5]. Skewness is a measure of the lack of symmetry in a distribution. In other words, a distribution is symmetric when it appears the same to the left and right of the

[5] For New Zealand, Roger (1997) attempts to construct a robust indicator of core inflation which proves that "high kurtosis makes the sample mean a less efficient and less robust estimator of the population, or underlying, mean price change than is an order statistic such as the median".

center point. Higher values of skewness indicate less symmetry in the data. According to the table, the indicators based on the permanent exclusion method, WM, and V_1 have higher skewness values. Briefly, it can be inferred that the monthly inflation distributions for all measures are not typical, with high skewness and kurtosis statistics.

When considering the second period, the means of all underlying inflation measures are lower but close to the headline inflation. Additionally, as shown in the table, the means of the headline and underlying inflation indicators are lower than the period between 2005 and 2023. This situation confirms that the period after September 2018 can be considered inflationary. When considering the median statistics, it is seen that all underlying inflation measures have lower values than the CPI. Additionally, all core measures' standard deviations and coefficients of variation are lower than the CPI during this period. This outlook is more reasonable because underlying inflation is expected to be less volatile than headline inflation. The standard deviation values are lowest for WM and median indicators, followed by B, V_1, SATRIM, and PC1, respectively.

Similarly, the coefficient of variation value is lowest for B indices, followed by WM, median, PC1, V_1, and SATRIM, respectively. Upon examining the kurtosis and skewness statistics, it is evident that all values are lower than those observed between 2005 and 2023. During this period, B, C, WM, the median, and PC1 exhibit lower kurtosis and skewness values compared to other indicators. Additionally, it can be observed that volatility based on indicators and SATRIM exhibit higher values of kurtosis and skewness. Shortly, the distribution of monthly price changes for all indicators deviates significantly from a normal distribution.

Although underlying inflation measures are typically calculated from monthly data, annual inflation is essential for evaluation and comparison. However, it should be noted that annual inflation includes base effects, which can be particularly noticeable during inflationary periods. The annual inflation series began in January 2006 and ended in December 2023. Table 2 presents the descriptive and distributional statistics of the annual inflation rates of the underlying inflation measures and the headline CPI. Similar to the monthly data statistics, the means of the annual WM, SATRIM, and volatility-based measures are lower than those of the CPI, while others have similar means. The standard deviations of all core measures are lower than headline inflation, and WM has the lowest value, followed by median, SATRIM, and volatility-based indicators.

Table 1: Descriptive and Distributional Statistics of Monthly Inflation of the Underlying Inflation Measures

2005-2023	**Mean**	**Median**	**Stdev**	**CV**	**Min**	**Max**	**Kurtosis**	**Skewness**
CPI	1.25	0.88	1.76	1.40	-1.51	13.95	19.78	3.90
B	1.18	0.69	1.49	1.26	-1.46	14.30	27.70	4.19
C	1.13	0.66	1.62	1.43	-1.83	14.30	25.18	4.34
D	1.20	0.75	1.73	1.44	-1.57	14.23	23.00	4.28
WM	0.97	0.58	1.33	1.37	0.07	11.72	25.16	4.41
V_1	1.00	0.57	1.33	1.33	0.00	11.64	24.07	4.31
V_1.5	1.03	0.59	1.35	1.32	0.01	10.45	17.81	3.80
V_2	1.07	0.63	1.42	1.33	-0.05	10.98	18.87	3.93
V_2.5	1.09	0.65	1.46	1.33	-0.17	11.20	18.96	3.94
SATRIM	0.99	0.58	1.36	1.37	-0.20	11.40	21.81	4.14
Median	0.98	0.59	1.28	1.31	0.13	10.70	21.69	4.10
PC1	1.16	0.71	1.51	1.31	-0.38	11.02	17.67	3.84
2005-Aug.2018	**Mean**	**Median**	**Stdev**	**CV**	**Min**	**Max**	**Kurtosis**	**Skewness**
CPI	0.73	0.67	0.58	0.80	-0.88	2.91	1.59	0.67
B	0.64	0.63	0.26	0.41	0.01	1.67	2.46	1.03
C	0.62	0.56	0.36	0.58	-0.38	2.28	2.60	0.80
D	0.68	0.64	0.42	0.62	-0.41	3.23	7.54	1.53
WM	0.53	0.49	0.24	0.45	0.07	1.61	2.60	1.08
V_1	0.55	0.51	0.28	0.50	0.00	1.96	5.79	1.72
V_1.5	0.57	0.49	0.33	0.58	0.01	2.45	7.66	2.06
V_2	0.59	0.51	0.35	0.58	-0.02	2.66	7.90	2.02
V_2.5	0.61	0.52	0.36	0.59	-0.12	2.68	6.33	1.78
SATRIM	0.53	0.48	0.28	0.52	0.00	2.22	8.65	1.96
Median	0.52	0.47	0.24	0.47	0.13	1.64	2.67	1.30
PC1	0.64	0.60	0.31	0.48	-0.27	2.08	3.35	0.87

Table 2: Descriptive and Distributional Statistics of Annual Inflation of the Underlying Inflation Measures

2006-2023	**Mean**	**Median**	**Stdev**	**CV**	**Min**	**Max**	**Kurtosis**	**Skewness**
CPI	16.15	9.66	17.63	1.09	3.99	85.52	5.71	2.58
B	15.06	8.72	16.56	1.10	3.22	72.60	3.93	2.29
C	14.34	8.58	16.11	1.12	2.64	70.41	4.53	2.38
D	15.44	9.23	17.28	1.12	2.66	84.67	5.79	2.56
WM	12.18	7.09	13.63	1.12	3.28	65.20	4.90	2.46
V_1	12.57	7.54	13.79	1.10	3.05	63.73	4.49	2.37
V_1.5	12.98	7.73	14.51	1.12	2.97	65.93	4.48	2.38
V_2	13.51	8.04	14.90	1.10	3.12	69.35	4.78	2.42
V_2.5	13.90	8.15	15.17	1.09	3.20	70.27	4.71	2.40
SATRIM	12.45	7.15	14.21	1.14	2.94	65.80	4.81	2.44
Median	12.32	7.20	13.75	1.12	3.07	64.56	4.54	2.36
PC1	14.58	9.01	16.09	1.10	3.41	72.12	4.85	2.46
2006-Aug.2018	**Mean**	**Median**	**Stdev**	**CV**	**Min**	**Max**	**Kurtosis**	**Skewness**
CPI	8.73	8.57	2.14	0.24	3.99	17.85	2.25	0.76
B	7.77	8.09	2.47	0.32	3.22	16.59	1.65	0.55
C	7.35	7.38	2.54	0.35	2.64	17.03	1.16	0.66
D	8.12	7.83	2.60	0.32	2.66	18.12	1.44	0.68
WM	6.38	6.57	1.76	0.28	3.28	12.53	0.71	0.50
V_1	6.56	6.95	1.90	0.29	3.05	13.15	0.39	0.20
V_1.5	6.72	6.84	2.04	0.30	2.97	14.37	0.71	0.33
V_2	7.07	7.23	2.01	0.28	3.12	14.86	0.88	0.36
V_2.5	7.30	7.21	2.09	0.29	3.20	15.90	1.72	0.65
SATRIM	6.34	6.52	1.78	0.28	2.94	13.17	1.14	0.42
Median	6.22	6.00	2.05	0.33	3.07	13.01	0.27	0.64
PC1	7.74	7.89	2.14	0.28	3.41	14.96	0.43	0.07

When analyzing the statistics of the coefficient of variation, it is evident that the values are very close, with V_2.5 having the lowest value among the underlying inflation measures. Upon examining the kurtosis and skewness statistics, it is evident that the values of the underlying inflation indicators are very similar. Indicator B has the lowest kurtosis and skewness value. As a summary of the distribution statistics, the annual inflation distributions of all indicators are non-normal.

When considering the period between 2006 and August 2018, it is again seen that the means of all measures are lower than between 2006 and 2023. Furthermore, the outlook remains the same regarding means, with all underlying inflation measures having lower means than headline inflation. Nevertheless, the standard deviation outlook differs. WM, SATRIM, volatility-based measures, and median have lower standard deviations than the CPI. When examining the coefficient of variations, it is observed that WM has the lowest value, followed by SATRIM, V_2, and PC1, respectively. Additionally, looking at the kurtosis and skewness statistics, it is observed that all values are lower than those in the period between 2006 and 2023. The median indicator has the highest kurtosis value among the underlying inflation indicators, while V_2.5 exhibits the lowest value. PC1, on the other hand, has the lowest skewness value, while the indicator of D has the highest value. Shortly, the distribution of annual price changes of all the underlying inflation measures indicates a significant deviation from normal distribution.

CHAPTER 4

DATA & METHODOLOGY

In this part, the concept of data in generating a new underlying inflation indicator is presented with the descriptive and distributional statistics of data. Then, the methodology that is preferred in this paper is explained.

4.1. Data

Seasonally adjusted monthly inflations at the 5-digit aggregation level are used to construct the underlying inflation indicator. The ARIMA model applies seasonal adjustments to each index value before converting the data series to month-on-month changes. The seasonal adjustment method used in this analysis is the TRAMO/SEATS[6], a model-based seasonal adjustment method. At the 5-digit aggregation level, there are prices of 143 subgroups as of 2024. However, some subgroups are added to the basket yearly, while others are excluded. Therefore, the number of subgroups at the 5-digit level may change from one year to another. This analysis uses the most comprehensive dataset, including subgroups excluded from previous years. As a result, this work utilizes 153 subgroups[7].

When the distribution of 5-digit level subgroups is examined according to the classification of individual consumption according to purpose (COICOP), 36 of the subgroups are in the food and non-alcoholic beverages group, 5 of them are in the alcoholic beverages and tobacco group, 11 of them are in the clothing and footwear

[6]TRAMO/SEATS refers to "Time Series Regression with ARIMA noise, Missing Observations and Outliers" / "Signal Extraction in ARIMA Time Series".

[7] For the names of the subgroups, see Appendix B.

group, 9 of them are in the housing-water-electricity-gas and other fuels group[8]. There are 21 subgroups in the furnishings-household equipment-routine maintenance of the house group, 9 in the health group, 17 in the transport group, 3 in the communications group, 20 in the recreation and culture group, 5 in the education group, 4 in the hotels-cafes and restaurants group and finally, 13 in the miscellaneous goods and services group.

The monthly inflation series begins in February 2005 and ends in December 2023. This period is chosen because the 2003 base year price index was published in January 2005. Additionally, inflation data is available for previous years. Before the 2003 base year price index, there was a price index with a base year of 1994, which was used until 2004. However, this price index is different from the current one in terms of both coverage and methodology. The 1994 base year index was generated using a fixed relative weight scheme and has maintained coverage throughout its lifespan. Also, it uses arithmetic mean as the calculation methodology and covers the prices for 19 provinces and seven regions. In contrast, the 2003 base year index is a chain index that updates its coverage and weighting scheme annually. Moreover, it uses geometric mean as a calculation methodology and includes prices of 81 provinces and 26 regions. Therefore, this analysis uses the 2003 base year index because the current price series are constructed based on it, and the starting point is preferred to be 2005 as it was first published in January of that year.

4.1.1. Descriptive and Distributional Statistics of the Data

Table 3 presents descriptive and distributional statistics of 5-digit disaggregated monthly price changes for three different versions. Monthly inflation starts in February 2005 and ends in December 2023. The first column shows the statistics for the entire sample. The second shows the same statistics for the same period, excluding the natural gas item. The reason for this exclusion is that in May 2023, natural gas was supplied to households completely free of charge, and it was announced that the first 25 cubic meters of household natural gas consumption would be free for the next 11

[8] The Classification of Individual Consumption According to Purpose (COICOP) is an international reference classification of household expenditure. Its aim is to provide a framework of homogeneous categories of goods and services that represents a function or purpose of household consumption expenditure.

months. This situation has distorted the natural gas price series in the CPI basket. Therefore, excluding this item may provide more reasonable statistics. Finally, the third one offers statistics for 2005 and August 2018 because, after September 2018, there were economic shocks in the Turkish economy that led to inflationary periods.

When looking at the two columns of Table 3, it can be seen that the natural gas subgroup significantly changes the statistics. The statistics appear more reasonable when the natural gas is removed. Furthermore, the main observation from the table is that the average means, medians, and standard deviations, as well as the coefficient of variations of the monthly price changes between 2005 and 2023, are significantly higher than those between 2005 and August 2018. This situation supports the idea that the period after September 2018 can be considered inflationary. In addition, positive skewness indicates a longer tail on the right-hand side of the distribution. Thus, it appears that the distributions of monthly price changes of the subgroups of the CPI are not normal, as expected, i.e., leptokurtic and skewed to the right. In other words, the distribution of the monthly inflation demonstrates a significant deviation from normal distribution with high skewness and kurtosis statistics, especially in the period between 2005 and 2023.

Table 3: Descriptive and Distributional Statistics of 5-Digit Disaggregated Monthly Price Changes

	2005-2023	**2005-2023***	**2005-Aug.2018**
Mean	20.88	1.23	0.68
Median	0.73	0.73	0.62
Stdev	294.24	1.57	0.40
CV	14.09	1.28	0.58
Kurtosis	226.97	17.14	2.99
Skewness	15.06	3.71	1.25
Min	-0.11	-0.11	-0.11
Max	4434.35	12.05	2.54

*Natural gas is removed from the CPI.

Table 4: Descriptive and Distributional Statistics of 5-Digit Disaggregated Annual Price Changes

	2005-2023	**2005-2023***	**2005-Aug.2018**
Mean	16.10	16.11	8.26
Median	9.25	9.12	8.30
Stdev	18.00	18.02	2.27
CV	1.12	1.12	0.28
Kurtosis	4.76	4.66	1.84
Skewness	2.42	2.41	1.03
Min	4.89	4.92	4.89
Max	83.11	82.56	17.13

*Natural gas is removed from the CPI.

Before analyzing the statistics of annual inflation, it should be noted that it may include base effects, especially in periods of high inflation. When the statistics of annual inflation of the subgroups at the 5-digit disaggregated level are analyzed from Table 4, it can be seen that all the statistics of the whole sample are very similar to the sample, excluding the natural gas item from the CPI, which is a different outlook from the monthly inflation case. This situation is because the natural gas effect will affect the statistics in 2024, as annual inflation is considered. It can also be observed that in the period between 2005 and August 2018, the statistics of all measures are lower than those of the whole sample. Again, this situation can be explained by the high inflation rate after September 2018. Looking at the distribution statistics, all indicators' annual inflations show a significant deviation from the normal distribution.

4.2. Model and Methodology

Improved factor models for cross-sectional data were extended to time series by Geweke (1977) and Sargent and Sims (1977) to create dynamic factor models (DFMs). The idea behind DFMs is to capture the covariation in macro time series using several factors. In particular, DFMs suggest that a small number of latent factors represent the shared dynamics of a greater number of time series that have been observed. (Stock & Watson, 2016). Sargent and Sims (1977) and Geweke (1977) prefer using the frequency domain method to investigate a dynamic factor framework and estimate the significance of the factor. However, these approaches do not allow for direct factor estimation, so they could not be utilized for forecasting. Later, the literature has been developed to include the time domain method, which enables direct estimating of the factor. Initial dynamic factor models, also known as parametric models, were created for a limited number of variables, and the parameters are estimated by applying the Kalman filter and Gaussian maximum likelihood estimation (MLE). Under the model assumptions and parameters, this approach gives optimal estimates of factors. Later, a large set of variables are included in the dynamic factor model framework. Principal components and related techniques are usually used to estimate the factors. This approach is known as a nonparametric model. Finally, these two methods are combined. The parameters of the state-space model used in the first approach are estimated using the nonparametric factor estimates in the second approach, thus dealing with the associated dimensionality issue identified in the first approach (Stock & Watson, 2011).

As an empirical application, DFMs are typically used for large datasets containing various series, as statistical theory recommends. They are commonly used for obtaining nowcasts and short-term forecasts of economic activity and inflation (Stock & Watson, 2002; Gianonne et al., 2008). They are also widely used in macroeconomic monitoring, time series interpolation, and forecasting, where they are used to create coincident business cycle gauges. (Mariano & Murasawa, 2003). Dynamic factor models are frequently used in the literature for nowcasting and forecasting, particularly for the US economy and the Euro Area. Additionally, Dynamic factor models have numerous applications as an underlying inflation measure. The work most similar to this thesis is that of Amstad et al. (2014). They constructed an underlying inflation gauge (UIG) to monitor inflation in the US, which is derived from a broad dataset that includes price series and a wide range of nominal, real, and financial variables using a dynamic factor model approach.

In this thesis, the dynamic factor model is applied to construct an underlying inflation measure that shows the persistent part of the common inflation component. This method is chosen because it extracts a small number of variables that capture the typical fluctuations in the data series without excluding any specific data series, unlike most commonly used core inflation measures such as B, C, etc., which are based on the permeant exclusion method. One drawback of these measures based on the permanent exclusion method is that they do not regard the time dimension of the different, time-varying persistence of sub-components of inflation. For instance, although energy and food prices are highly volatile, it is crucial to assess the persistence of their changes before excluding them from a measure of underlying inflation. In this respect, combining data from the time-series characteristics of individual prices and the cross-sectional distribution of prices into a single framework is made possible by a dynamic factor model. In other words, a dynamic factor model uses information about subgroups' price changes from the time series and cross-sectional dimensions in constructing an underlying inflation indicator.

Generally, DFMs are typically formulated in state space form. For the estimation procedure, the Kalman filter with various solution algorithms are used. The most widely used algorithms in the literature are the Expectation Maximization (EM) algorithm (Doz et al., 2012) and the widespread mixed frequency generalization of Banbura & Modugno (2014). This paper follows the approach of Doz, Giannone, and Reichlin (2011). Their paper proves the consistency of estimating the factors in the two-step procedure in a dynamic factor model framework when the time series panel is large. In the first step, they estimate the model's parameters based on ordinary least squares (OLS) on principal components. In the second step, they estimate the factors via the Kalman smoother. The parametric approach adopted in their analysis improves the theory for the estimator analyzed in Giannone et al. (2004) and Giannone et al. (2008), as well as the many empirical works applying this structure for nowcasting. Briefly, the two-step estimation approach of Doz, Giannone, and Reichlin (2011) is chosen for this paper due to its extreme efficiency on larger datasets.

In the theoretical setting, dynamic factor models are efficiently estimated using the EM algorithm by permitting missing data on stationary data with time-invariant system matrices. The following classical assumptions should hold in this context:

1. Constant relationships and linearity (no structural breaks)

2. No direct relationship between the lagged factors and the series (*ceteris paribus* contemporaneous factors)

3. Observation errors or idiosyncratic measurement
4. No relationship between lagged error terms in either transition equation or measurement (no serial correlation).

The formation of a baseline dynamic factor model can be described as follows,

$$x_t = C_0 f_t + e_t , \qquad e_t \sim N(0, R)$$

$$f_t = \sum_{j=1}^{P} A_j f_{t-j} + u_t , \qquad u_t \sim N(0, Q_0)$$

Where the first equation is the observation (measurement) equation, the second equation is the transition (process or state) equation. The second equation enables the unobserved factors f_t to evolve according to the VAR(p) process. Both equations do not include trend or intercept terms. Before estimation, the data x_t should be standardized (scaled and centered) and stationary. The system's matrices are;

- $\boldsymbol{n}$: number of series in x_t
- $\boldsymbol{x_t}$**:** $n\ x\ 1$ vector of observed series at time t, some missing observations are possible.
- $\boldsymbol{f_t}$**:** $r\ x\ 1$ vector of factors at time t
- $\boldsymbol{C_0}$**:** $n\ x\ r$ observation (measurement) matrix
- $\boldsymbol{e_t}$**:** $n\ x\ 1$ idiosyncratic part
- $\boldsymbol{A_j}$: $r\ x\ r$ state transition (process or state) matrix at lag j
- $\boldsymbol{Q_0}$**:** $r\ x\ r$ state covariance matrix
- $\boldsymbol{R}$: $n\ x\ n$ observation (measurement) covariance matrix.

After converting it to State Space (stacked, VAR (1)) form, this model may be estimated using the Expectation Maximization (EM) algorithm and a classical form of the Kalman filter;

$$x_t = CF_t + e_t , \qquad e_t \sim N(0, R)$$

$$F_t = AF_{t-1} + u_t , \qquad u_t \sim N(0, Q_0)$$

where x_t, e_t and R are as in the first equation, and the other matrices are as follows;

- $\boldsymbol{F_t}$: $rp\ x\ 1$ vector of stacked factors at time t:

  $F_{rpx1} = \left(f_t', f_{t-1}', \dots \dots \dots, f_{t-p}'\right)' = \left(f_{1t} \dots, f_{rt}, \dots, f_{1,t-1}, \dots, f_{1,t-p}, \dots, f_{r,t-p}\right)'$

- $\boldsymbol{C}$: $n\ x\ rp$ observation matrix:

  $C_{nxrp} = (C_0, 0, \dots, 0)$, where 0 $n\ x\ r$ matrices of zeros for each factor lag. Only the first $n\ x\ r$ terms are non-zero.

- $\boldsymbol{A}$: $rp\ x\ rp$ vector of stacked state transition matrix:

  $$A_{(rp\ x\ rp)} = \begin{pmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I_1 & 0 & \dots & 0 & 0 \\ 0 & I_2 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & I_{p-1} & 0 \end{pmatrix}$$, where 0/ I is $r\ x\ r$ zero/identity matrices

  This matrix consists of 3 parts:

  - The top $r\ x\ rp$ part provides dynamic relationships captured by $(A_1, \dots \dots, A_p)$.
  - $A[(r+1): rp, 1: (rp-1)]$ constitute an $(rp-r)\ x\ (rp-r)$ identity matrix mapping all lagged factors to their known values at times t.
  - The rest of $A[(rp-r+1): rp, (rp-r+1): rp]$ is an $r\ x\ r$ matrix of zeros.

- $\boldsymbol{u_t}$: $rp\ x\ 1$ vector at time t:

  $u_{t\ (rp\ x\ 1)} = (u_t', 0', \dots \dots \dots, 0'\ )'$, where 0 is a $r\ x\ 1$ vector of zeros.

- $\boldsymbol{Q}$: $rp\ x\ rp$ state covariance matrix:

  $$Q_{(rp\ x\ rp)} = \begin{pmatrix} Q_0 & \dots & 0 & 0 \\ 0 & \dots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & 0 & 0 \end{pmatrix}$$, where 0 is $r\ x\ r$ zero matrices.

  The top $r\ x\ r$ part gives the contemporaneous relationships.

Principal components analysis (PCA) is used to produce the initial system matrices for this model's estimation using the EM technique, which is found to be suitable for a large number of series (n), as described in Doz et al. (2011 & 2012). Since the dataset used in this paper to construct an underlying inflation indicator includes 153 disaggregated price series in CPI, this method is entirely appropriate. In addition, since the dataset used to build underlying inflation has missing data from time to time due to the exclusion and inclusion of some of the subgroups in the CPI basket, missing data is another issue that should be considered. In this respect, it is essential to note that the two-step estimation procedure using the Kalman filter significantly solves the problem of missing values. For these reasons, the dynamic factor model is preferred as a methodology, and the approach of Doz, Giannone, and Reichlin (2011) is adopted to construct an underlying inflation measure for Turkey.

CHAPTER 5

ESTIMATION RESULTS

This chapter presents all the findings regarding estimating underlying inflation based on the dynamic factor model (DFM). The first part describes the inflation rates of the DFM with headline and other core inflation indicators. The next part evaluates the performance of the DFM and compares it with other core indicators.

Before interpreting the estimation results, the determination of the model structure is explained. First, to determine the number of factors for the model, a scree plot[9] can be used by looking for a kink point in the plot[10]. Alternatively, the number of factors can be chosen according to Bai and Ng's (2002) criteria[11]. Based on these criteria, 3 factors are estimated because more than 3 factors do not add much to the model's explanatory power. After selecting the number of the factors, the lag order of the factor-VAR of the transition equation is estimated.

The lag order is set to 4 according to the information criteria. Therefore, a dynamic factor with three factors and four lags is estimated. First-factor model estimates are used in this analysis. Furthermore, before estimating, the stationarity of the data series should be provided. For this reason, each series is standardized to have zero mean and unit variance, as is typical procedure in the literature on factor models. As a result, the estimation results are not comparable with the headline and the traditional and alternative underlying inflation measures. To this end, the regression analysis is created with the monthly price change of the CPI as the dependent variable and the standardized estimated DFM as the independent variable. Then, to make the DFM

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[9] The scree plot for this analysis can be seen in Appendix C.

[10] A mathematical procedure for the determination of the kink is proposed by Onatski (2010).

[11] See Appendix C.

comparable with the other measures, the standardized series derived from the analysis is multiplied by the coefficient of the DFM in the regression, and then the coefficient term is added to this series.

In the figures used in this chapter, the colors red, black, blue, dark blue, and grey represent the CPI, DFM, B, C, and D indicators, respectively. In addition, the colors purple, green, orange, pink, and yellow represent the weighted median, the volatility-based indicators, SATRIM, the median, and the indicator based on principal component analysis, respectively. It should also be noted that all underlying inflation indicators are seasonally adjusted.

5.1 Inflation of DFM

This section provides an interpretation of the DFM based on monthly inflation rates. A narrative explanation based on annual inflation is not preferred because annual inflation rates include base effects that make them challenging to interpret. Turkey is a country where inflation is not very stable, and especially after September 2018, there have been exchange rate shocks that have made the inflation series more volatile. Therefore, base effects can be seen in annual inflation. However, the exact figures used in this section for annual inflation can be found in Appendix D.

The monthly underlying inflation indicator based on the dynamic factor approach and seasonally adjusted monthly CPI is illustrated in Figure 1. This figure shows that DFM is less volatile than the headline inflation, as expected from an underlying inflation indicator. Specifically, especially before September 2018, DFM showed very smooth behavior while headline CPI inflation fluctuated. However, it is also seen that DFM exhibits similar patterns to the CPI, particularly in September 2018, December 2021, January 2023, July 2023, and August 2023. Except for January 2023, these periods are when a high increase happens in the exchange rate. There is high monthly inflation in January 2023. This significant increase is due to the adjustments in the minimum wage and tax, as well as the beginning of the year. January is a month where time-dependent pricing behavior is prevalent, and the year 2023 is the high inflationary period. This situation results in higher price-setting behavior. It should also be noted that although the DFM follows a similar pattern to the CPI during these periods, DFM has lower values during these periods, especially in December 2021, July 2023, and August

2023. After periods of high inflation, the DFM shows a stable outlook in contrast to the headline inflation, which makes it a reliable indicator of underlying inflation.

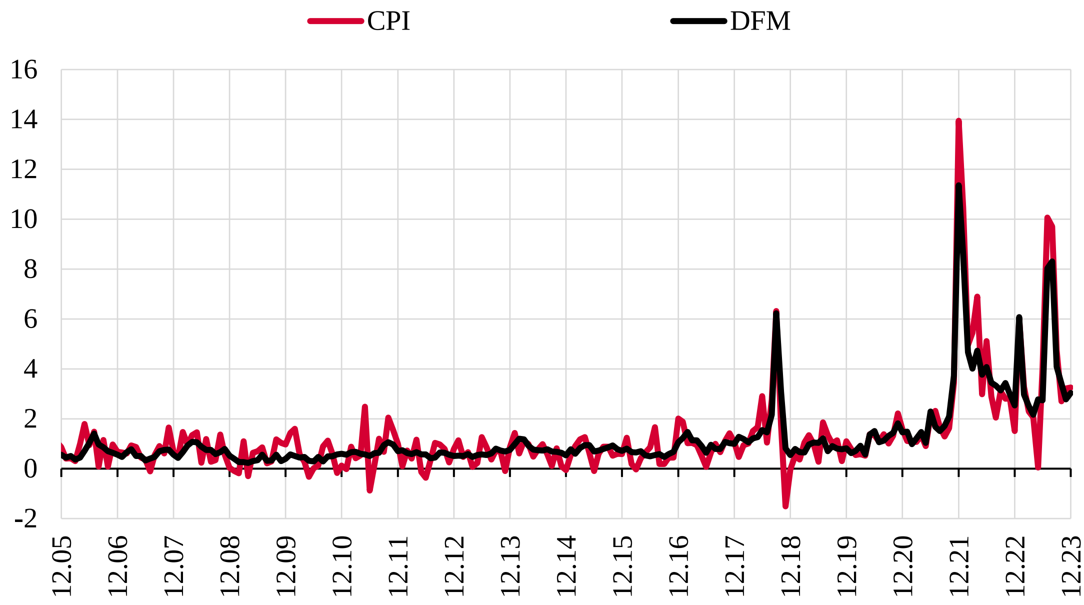

Figure 1: Monthly Inflation of CPI and DFM (Seasonally Adjusted)

Figure 2 compares the monthly inflation of underlying inflation indicators based on permanent exclusions with DFM. This comparison is vital for analyzing DFM's behavior, as the B, C, and D indices are the most commonly used underlying inflation indicators. The figure shows that DFM behaves similarly to the measures based on the permanent exclusion method. However, it is crucial to note that DFM appears less volatile than these indicators, except during periods of high inflation. In other words, DFM has a more stable outlook, while other indicators show fluctuations, especially after the periods following the high inflation periods.

When the periods between September 2018 and December 2021 is considered, it is seen that DFM is less volatile than B, C, and D measures, which exhibit fluctuations. The high inflation of the B, C, and D indices during shocks is due to their relatively high weight of core goods compared to the CPI. The primary determinant of the core goods inflation dynamics is the exchange rate. This situation is because it includes the prices of relatively less labor-intensive products with a high share of imported inputs. As a result, the B, C, and D indices show sharp declines in the periods following enormous exchange rate appreciation, but the DFM shows a more stable outlook. It is also important to note that DFM has lower values during periods of high inflation.

In addition, the comparison of DFM monthly inflation with other underlying measures of inflation, namely WM, V_1, V_1.5, V_2, V_2.5, SATRIM, median, and PC1, is shown in Figure 3. As in the previous figure, the behavior of DFM is very similar to that of the other measures. However, unlike the B, C, and D indices, the other underlying inflation indicators do not show sharp declines in the periods following large exchange rate appreciations. However, although these measures show a more stable outlook than the permanent exclusion-based underlying inflation measures, the DFM is more stable than these measures. For instance, looking at the period between December 2021 and January 2023, the other indicators show lower values than the DFM. In other words, the monthly price changes of the DFM are not as volatile.

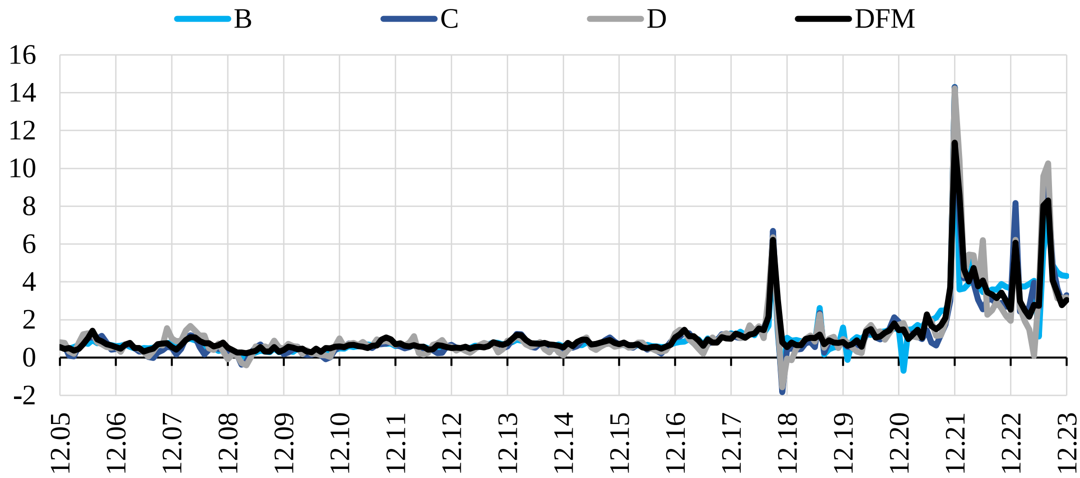

Figure 2: Monthly Inflation of Permanent Exclusion Based Underlying Inflation Indicators and DFM (Seasonally Adjusted)

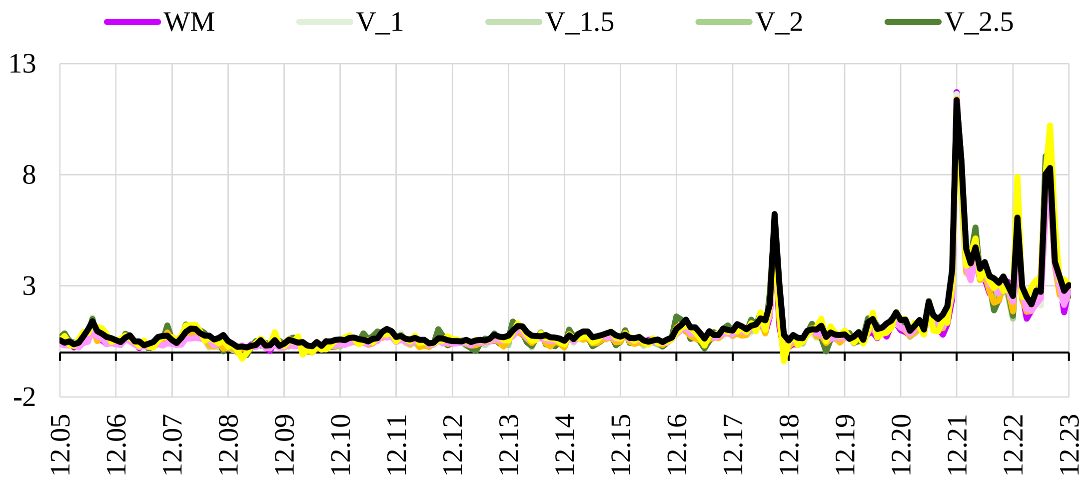

Figure 3: Monthly Inflation of Other Underlying Inflation Indicators and DFM (Seasonally Adjusted)

Analyzing the behavior of DFM during shock periods is also important. Figure 4 displays the monthly inflation rates of CPI, permanent exclusion-based underlying inflation indicators, and DFM during shock periods. In September 2018, the monthly inflation rates of DFM, B, C, and D indicators were similar and very close to the monthly headline inflation. However, in December 2021, DFM experienced the lowest monthly price changes. Additionally, the monthly inflation rates of indicators B, C, and D were similar to the headline rate. In July 2023, the monthly inflation rate was lower than indices C and D but higher than that of indicator B. Finally, a similar trend to July 2023 was observed in August 2023, with the monthly inflation rate of index B being the lowest and DFM having lower values compared to indices C and D. Although indicator B appears less volatile due to lower values in July and August 2023, it had higher values in December 2021. A good underlying inflation indicator should be stable and consistent across different periods. Therefore, the DFM index appears more stable and consistent than the B, C, and D indices during shock periods.

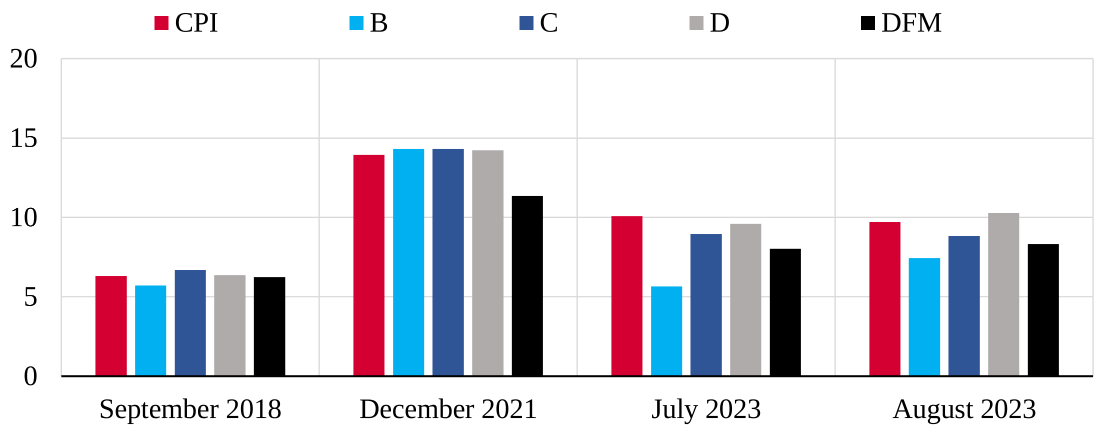

Figure 4: Monthly Inflation of CPI, Permanent Exclusion Based Underlying Inflation Indicators, and DFM during Shock Periods (Seasonally Adjusted)

Furthermore, Figure 5 compares the monthly inflation of CPI, other underlying inflation indicators, and DFM during shock periods. The figure shows that in September 2018, DFM had the highest monthly inflation rate among the other underlying inflation indicators, which was very close to the headline inflation rate. However, it is important to note that the inflation rates were very similar that month. In December 2021, DFM had a lower value than WM and V_1 but a higher value than the others. In July 2023, while the median had the lowest value, V_2.5 had the highest value, and DFM had values very close to the rest of the indicators. Lastly, when August

2023 is analyzed, it is seen that DFM has a value that is very close to V_2 and V_2.5, while PC1 has the highest value. Overall, when analyzing the behavior of DFM during the shock periods, it is consistent and less volatile compared to the other indicators. As underlying inflation indicators should remain stable over time, it can be observed that DFM possesses this characteristic.

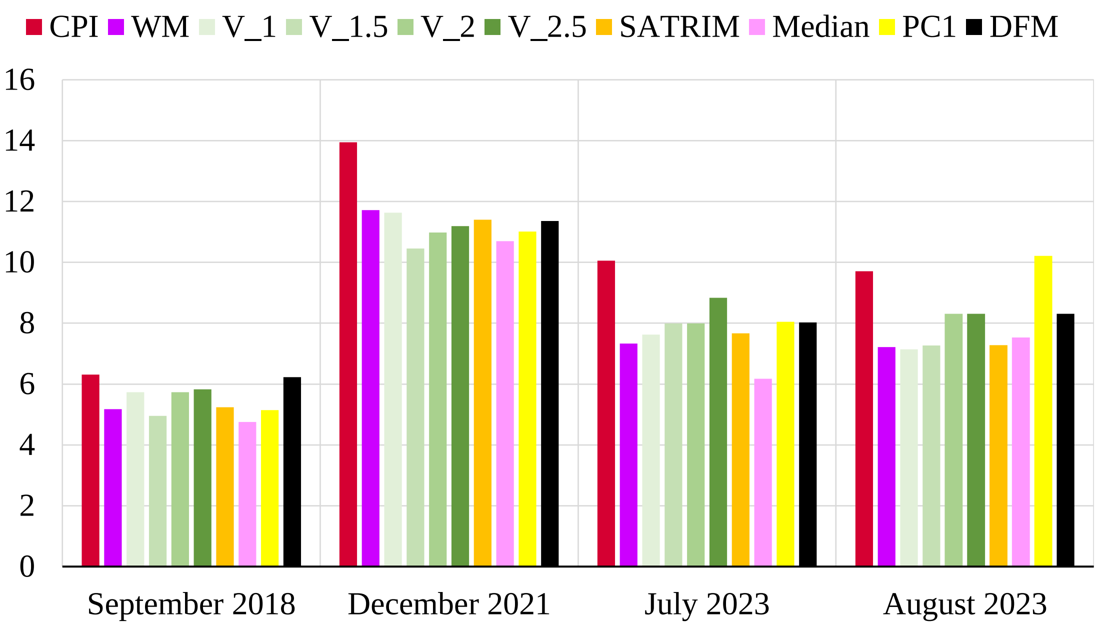

Figure 5: Monthly Inflation of CPI, Other Underlying Inflation Indicators, and DFM during Shock Periods (Seasonally Adjusted)

5.2. Evaluation of the Underlying Inflation Measures in Turkey

As there is no specific way of defining and measuring core inflation, it is challenging to evaluate core indicators empirically. In the literature, there are different methods for assessing core indicators. This section provides a comparative analysis of the performance of core measures. Several criteria are used to evaluate their informativeness and predictive power for analyzing headline inflation. These criteria are chosen because they are the most commonly used in the literature. These criteria check whether the measures are dynamically correlated with the CPI inflation, less volatile than CPI inflation, able to monitor trend inflation efficiently, have predictive ability, and are unbiased. Hence, the empirical assessment of various core inflation indicators focuses on these properties, as discussed below. After the evaluations, whether DFM is a suitable indicator for measuring the underlying inflation trend will be addressed.

5.2.1. Dynamic Correlation Analysis

A measure of the variables' co-movement is the dynamic correlation. Croux, Forni, and Reichlin (2001) utilized it to evaluate the relationship between headline inflation and the fundamental metrics. Tekatlı (2010) also considers the dynamic correlation analysis as an evaluation criterion for the Turkish CPI data. A dynamic correlation analysis can help evaluate how the core measures and inflation relate to each other in different periods. Therefore, dynamic correlation analysis is conducted in this paper.

Table 5: Dynamic Correlation of the Headline Inflation and Inflation of the Underlying Inflation Indicators

	3 Months	**6 Months**	**1 Year**	**3 Years**	**5 Years**	**8 Years**	**10 Years**	**12 Years**	**15 Years**
B	0.18	0.31	0.38	0.49	0.49	0.53	0.58	0.66	0.78
C	0.36	0.47	0.52	0.57	0.57	0.60	0.65	0.73	0.84
D	0.48	0.60	0.66	0.69	0.68	0.71	0.74	0.80	0.89
WM	0.48	0.58	0.64	0.69	0.68	0.70	0.73	0.78	0.87
V_1	0.41	0.50	0.58	0.65	0.65	0.67	0.71	0.77	0.86
V_1.5	0.43	0.54	0.62	0.68	0.68	0.70	0.73	0.79	0.87
V_2	0.46	0.59	0.64	0.69	0.69	0.71	0.74	0.80	0.88
V_2.5	0.46	0.60	0.66	0.71	0.71	0.73	0.76	0.81	0.88
SATRIM	0.58	0.69	0.72	0.76	0.75	0.76	0.78	0.83	0.89
Median	0.39	0.46	0.51	0.56	0.56	0.59	0.63	0.70	0.82
PC1	0.32	0.45	0.52	0.58	0.59	0.62	0.66	0.73	0.84
DFM	0.38	0.47	0.54	0.58	0.59	0.62	0.66	0.72	0.83

Dynamic correlation[12] of the CPI and the core measures for the different periods are provided in Table 5. The findings can be interpreted as the headline inflation and core measures inflation's short-, medium-, and long-term relationships.. 3 months to 1 year can be read as short-term, 3-8 years, and 10-15 years as medium and long term, respectively. Also, dynamic correlation analysis for these periods is shown in Table

[12] Seasonally adjusted monthly inflation series are used to conduct this analysis.

6[13]. According to this analysis, all the core indicators are positively related to the headline inflation at all horizons examined, and the core indicators are more closely related to the headline inflation over time. When the core indicators are compared, DFM has a better relation with the headline than B, C, median, and PC1 for all the horizons examined.

Table 6: Dynamic Correlation in Short-Run, Medium-Run and Long-Run

	Short Term	**Medium Term**	**Long Term**
B	0.29	0.51	0.68
C	0.45	0.58	0.74
D	0.58	0.70	0.81
WM	0.57	0.69	0.79
V_1	0.50	0.66	0.78
V_1.5	0.53	0.68	0.79
V_2	0.56	0.70	0.81
V_2.5	0.57	0.71	0.82
SATRIM	0.67	0.76	0.83
Median	0.45	0.57	0.72
PC1	0.43	0.59	0.75
DFM	0.46	0.60	0.73

5.2.2. Volatility

One of the main reasons for constructing and using core inflation measures is to address the volatility of headline inflation. Therefore, headline inflation does not accurately indicate the actual inflation process. The main goal in developing the core inflation measures is to reduce excess volatility arising from variations in subcomponents' prices. A reliable core inflation indicator should exhibit more stability and lower volatility than headline inflation. This criterion is considered essential by many studies in the literature.

[13] Short-term, medium-term and long-term correlation is calculated by taking the averages of given time periods in Table 6. In other words, averages of dynamic correlation of 3 months to 1 year show short term analysis, averages of dynamic correlation of 3 years to 8 years show medium-term analysis and averages of dynamic correlation of 10 years to 15 years show long term analysis.

Table 7: Volatility of Monthly Inflation of the Underlying Inflation Measures

2005-2023	Mean	Standard Deviation	Coefficient of Variation
CPI	1.25	1.76	1.40
B	1.18	1.49	1.26
C	1.13	1.62	1.43
D	1.20	1.73	1.44
WM	0.97	1.33	1.37
V_1	1.00	1.33	1.33
V_1.5	1.03	1.35	1.32
V_2	1.07	1.42	1.33
V_2.5	1.09	1.46	1.33
SATRIM	0.99	1.36	1.37
Median	0.98	1.28	1.31
PC1	1.16	1.51	1.31
DFM	1.22	1.45	1.19

Many studies examine the mean and the standard deviation of the monthly and annual inflation of the core measures for a specific period to evaluate the volatility. The coefficient of variation is also commonly presented. It measures the dispersion of data points around the mean. Furthermore, for annual inflation, Armour (2006) utilizes the mean-absolute change, and Catte and Slok (2005) propose the standard deviation of the first difference as an indicator of high-frequency volatility. This paper considers monthly inflation's mean, standard deviation, and coefficient of variation as a volatility measure. Additionally, the mean absolute deviation and the standard deviation of the change in annual inflation are also reported for annual inflation data.

Table 7 shows the statistics for monthly inflation. According to the table, similar to the other core indicators, the DFM's mean and standard deviation are lower than the overall inflation. When considering the coefficient of variation, the DFM has the lowest value among the core inflation indicators. This situation indicates that the DFM provides the most precise estimate. The same results are observed when these statistics are examined for annual inflation, as shown in Table 8 below. Specifically, DFM has a lower mean and standard deviation than headline inflation and has the lowest coefficient of variation value. Moreover, DFM has a lower value than the CPI when considering the first difference's mean absolute and standard deviations. As a result, DFM satisfies the primary criterion, and it appears to be a more stable indicator than headline inflation.

Table 8: Volatility of Annual Inflation of the Underlying Inflation Measures

2005-2023	Mean	Standard Deviation	Coefficient of Variation	Mean Abs. Dev. of First Difference	Std. Dev. of First Difference
CPI	16.15	17.63	1.09	1.34	2.73
B	15.06	16.56	1.10	0.79	1.93
C	14.34	16.11	1.12	0.96	2.15
D	15.44	17.28	1.12	1.22	2.63
WM	12.18	13.63	1.12	0.75	1.83
V_1	12.57	13.79	1.10	0.75	1.78
V_1.5	12.98	14.51	1.12	0.82	1.76
V_2	13.51	14.90	1.10	0.90	1.98
V_2.5	13.90	15.17	1.09	0.94	2.05
SATRIM	12.45	14.21	1.14	0.79	1.87
Median	12.32	13.75	1.12	0.70	1.68
PC1	14.58	16.09	1.10	0.87	1.88
DFM	15.69	16.32	1.04	0.86	1.94

5.2.3. Tracking the Trend Inflation and Efficiency

The headline inflation is not good at providing reliable information regarding the underlying inflation trend due to its susceptibility to various shocks that create volatility. Therefore, core inflation indicators should track the trend more closely than headline inflation. However, the inflation trend is imperceptible, and it can be estimated in different ways. Therefore, trend inflation or benchmark inflation should be defined first. While Dolmas (2005), Rich and Steindel (2005) use Baxter-King (1999) bandpass filter, Bryan and Cecchetti (1993), Bryan, Cecchetti, and Wiggins

(1997), and Clark (2001) use a centered moving average of the headline. Additionally, Atuk and Ozmen (2009b) prefer to use the centered moving average of the headline inflation for the Turkish CPI data. That is why the centered moving average of the headline inflation is used in this paper. A centered moving average is the moving average of a given number of values centered around a specific period[14]. Root mean square error (RMSE) and mean absolute deviation (MAD) are considered for the efficiency criteria[15].

Although generally, the 18, 24, and 36-month centered moving averages of the monthly CPI inflation are used as the benchmark series, this paper also reports the statistics for shorter periods because the benchmark value increases when the long-term average is taken due to high headline inflation values during shock periods. Recently, the Turkish economy experienced exchange rate shocks in the last quarter of 2018 and 2021, as well as in the third quarter of 2023. A centered moving average of a longer period raises the benchmark values. Therefore, inflation values that remain relatively stable outside of these shocks differ quietly from the benchmark. When a shorter period is included in this calculation, non-shock periods become more compatible with inflation realizations. Thus, the benchmark series is created from 4, 6, 8, and 10-month centered moving averages of monthly headline inflation and the 12, 24, and 36-month averages.

Low root mean square error (RMSE) values indicate that the simulated and observed data are close to each other, demonstrating better accuracy. Therefore, a lower RMSE indicates better model performance and greater accuracy. A dataset's mean absolute deviation (MAD) provides the average distance between each data point and the mean. MAD provides insight into the variability of a dataset. A small MAD indicates that most data values are close to the mean. Hence, it is vital to aim for lower values of RMSE and MAD to increase efficiency. Table 9 and Table 10 summarize the

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[14] For example, to compute 24-month centered moving average, 12-month forecasts and backcasts of the series are required to acquire the statistics for the tails of the series.

[15] Root Mean Squared Error is computed by using the following formula $RMSE = \sqrt{\frac{1}{n}\sum_1^n(\pi_t - \pi_t^{trend})^2}$, Mean Absolute Deviation is computed by using the following formula $MAD = \frac{1}{n}\sum_1^n | \pi_t - \pi_t^{trend}|$, where π_t represents the seasonally adjusted monthly inflation of the core measure and π_t^{trend} indicates the monthly trend or benchmark inflation.

computed efficiency measures for the core indicators. Table 9 shows RMSE values of different core indicators, and Table 10 demonstrates MAD values of core inflation indicators under different benchmarks. When the 4-month centered moving averages are taken as the benchmark, DFM has the lowest root mean square error and mean absolute deviation. This case shows that DFM is the most efficient indicator in this setup. Even though DFM does not have the lowest value, considering other periods, it has very low values. Also, it is crucial to note that DFM consistently has low values for shorter and longer periods, while other core indicators have different values depending on the period.

Table 9: Root Mean Square Error of the Underlying Inflation Indicators under Different Benchmarks

	RMSE 4	RMSE 6	RMSE 8	RMSE 10	RMSE 12	RMSE 24	RMSE 36
B	0.92	0.91	0.94	0.89	0.87	0.96	1.00
C	0.96	1.04	1.13	1.10	1.05	1.11	1.11
D	0.98	1.10	1.17	1.14	1.09	1.20	1.21
SATRIM	0.76	0.81	0.99	0.86	0.83	0.93	0.92
WM	0.78	0.83	1.01	0.87	0.85	0.93	0.92
V_1	0.80	0.84	0.98	1.10	0.84	0.92	0.91
V_1.5	0.73	0.78	0.95	1.07	0.79	0.88	0.87
V_2	0.76	0.83	0.99	1.12	0.84	0.96	0.94
V_2.5	0.78	0.85	0.99	1.13	0.85	0.97	0.95
Median	0.74	0.79	0.95	0.80	0.78	0.86	0.85
PC1	0.81	0.87	0.98	0.87	0.83	0.89	0.89
DFM	0.72	0.80	0.94	0.83	0.79	0.90	0.92

Overall, when evaluating all periods, DFM appears to be a better measure than those based on the permanent exclusion method, even if B indices have lower values occasionally. The indicators based on the period-by-period exclusion method do not appear efficient when 8, 10, and 12-month centered moving averages are taken as benchmark values. Median, PC1, and DFM have lower values among the core indicators. When comparing these three, DFM appears to be the most efficient due to its consistently low values across all periods. Therefore, DFM can be considered a better indicator than other core indicators in tracking the inflation trend.

Table 10: Mean Absolute Deviation of the Underlying Inflation Indicators under Different Benchmarks

	MAD 4	MAD 6	MAD 8	MAD 10	MAD 12	MAD 24	MAD 36
B	0.42	0.39	0.42	0.35	0.33	0.35	0.36
C	0.45	0.46	0.54	0.51	0.49	0.52	0.49
D	0.47	0.51	0.58	0.54	0.52	0.56	0.54
SATRIM	0.41	0.43	0.52	0.47	0.46	0.49	0.47
WM	0.42	0.43	0.51	0.46	0.46	0.47	0.45
V_1	0.43	0.43	0.51	0.58	0.46	0.48	0.46
V_1.5	0.40	0.43	0.52	0.60	0.46	0.49	0.48
V_2	0.41	0.44	0.53	0.61	0.47	0.51	0.49
V_2.5	0.41	0.44	0.53	0.61	0.47	0.51	0.49
Median	0.41	0.42	0.50	0.44	0.44	0.45	0.43
PC1	0.39	0.40	0.50	0.43	0.42	0.45	0.43
DFM	0.35	0.36	0.47	0.38	0.37	0.40	0.38

5.2.4. Predictive Ability and Unbiasedness

Underlying inflation indicators are expected to have some predictive power for movements in headline inflation. In-sample and out-of-sample forecasting ability can be analyzed to test the predictive ability of the core measures. Core measures should provide valuable insights about the headline inflation within the sample. Policymakers must consider both current and future inflation when making decisions. Therefore, core inflation indicators should be able to explain the headline inflation and help forecast future inflation. Various methods are used in the literature to measure forecasting ability. This paper follows the model that Cogley (2002) proposes to evaluate the predictive ability of the core measures.

Cogley (2002) presents a model to analyze a core indicator's predictive ability. The model examines whether the current deviation between the core measure and the headline inflation can explain the deviation of current inflation from future inflation. Monthly data is used in the regression:

$$\pi_{t+h} - \pi_t = \alpha + \beta(\pi_t - \pi_t^{core}) + \varepsilon_t$$

Where π_t represents the monthly inflation of the CPI index and π_t^{core} denotes the indicator of core inflation. Furthermore, ε_t shows the error, and h demonstrates the period. According to the model, headline inflation should grow if current inflation is below the core and fall if it is above it, given that the core inflation represents the underlying inflation trend. In other words, this model adopts the idea that if the core indicator recognizes transient price fluctuations, then a deviation in the core inflation indicator should indicate a reversal in headline inflation. Additionally, β reflects the coefficient measure, which indicates how accurate the core inflation deviation is in estimating the extent of the inflationary transitory component. β with an absolute value higher (lower) than one implies that the magnitude of the present temporary inflation is understated (overstated) by the present core inflation divergence.

Table 11: Regression R Squares of the Sample Before September 2018

Horizon: Months	**1**	**2**	**3**	**6**	**12**	**18**	**24**
B	0.43	0.49	0.48	0.41	0.47	0.43	0.41
C	0.39	0.38	0.35	0.33	0.38	0.40	0.32
D	0.38	0.35	0.33	0.22	0.27	0.32	0.25
WM	0.41	0.46	0.44	0.35	0.46	0.44	0.42
V_1	0.39	0.43	0.43	0.34	0.46	0.43	0.39
V_1.5	0.37	0.42	0.41	0.31	0.42	0.43	0.36
V_2	0.36	0.41	0.39	0.30	0.39	0.45	0.35
V_2.5	0.36	0.41	0.38	0.27	0.36	0.42	0.35
SATRIM	0.41	0.46	0.45	0.35	0.45	0.45	0.42
Median	0.40	0.44	0.42	0.36	0.50	0.44	0.38
PC1	0.37	0.42	0.39	0.33	0.39	0.37	0.32
DFM	0.40	0.40	0.40	0.33	0.46	0.42	0.35
Sample	2005M3 2018M8	2005M4 2018M8	2005M4 2018M8	2005M8 2018M8	2006M2 2018M8	2006M8 2018M8	2007M2 2018M8
Obs.	162	161	160	157	151	145	139

This regression assesses the predictive power of different core inflation indicators. The horizon is expressed in terms of months. Two approaches are preferred when constructing this regression for Turkey. The first one is constructed using the sample from before September 2018, as the Turkish economy experienced frequent shocks after this period. The second one is constructed using the whole sample, but there are dummies for the months of significant exchange rate change: September 2018, December 2021, January 2022, July 2023, and August 2023.

Table 11 reveals the regression R squares of the sample before September 2018, and Table 12 shows the averages of these regression R squares for different periods. Similarly, Table 13 represents regression R Squares of the whole sample with the dummies, while averages of these regression R squares for different periods are shown in Table 14. Each entry presents the R square values for different periods resulting from the regression of future deviations of headline inflation on current deviation from core inflation. Horizon is in terms of months.

When considering the predictive ability of the core indicators in the sample before September 2018, DFM has an average R square of 0.38 for the horizons of 1-6 months, 0.41 for the horizons of 12-24 months, and 0.39 for the horizons of 1-24 months. DFM appears to have higher R square values than C, D, V_2, V_2.5, and PC1. This situation indicates that DFM demonstrates better forecasting power than these core indicators. Additionally, R square values of V_1.5 are not significantly different from that of DFM. B exhibits the highest predictive power among the core inflation indicators, while WM, SATRIM, and Median also have high R square values.

When examining the predictive power of the core indicators used in the whole sample, DFM has an average R square of 0.78 for the horizons of 1-6 months, 0.74 for the horizons of 12-24 months, and 0.76 for the horizons of 1-24 months. DFM exhibits better predictive power than C, D, V_2.5, and PC1. In the second approach, the median has the highest R square value, followed by WM, V_1, and SATRIM has the highest values. However, it is essential to note that in the second approach, the R square values of the other core measures are not entirely different from those of DFM. In other words, DFM has considerably similar R square values to other core measures that have higher predictive power than DFM.

Table 12: Averages of Regression R Squares of the Sample Before September 2018

Horizon	1-6 Months	12-24 Months	1-24 Months
B	0.45	0.43	0.44
C	0.36	0.37	0.36
D	0.32	0.28	0.30
WM	0.41	0.44	0.42
V_1	0.40	0.42	0.41
V_1.5	0.38	0.40	0.39
V_2	0.36	0.40	0.38
V_2.5	0.36	0.38	0.37
SATRIM	0.42	0.44	0.43
Median	0.40	0.44	0.42
PC1	0.38	0.36	0.37
DFM	0.38	0.41	0.39

Table 13: Regression R Squares of the Whole Sample

Horizon	1 Month	2 Months	3 Months	6 Months	12 Months	18 Months	24 Months
B	0.71	0.85	0.83	0.76	0.79	0.70	0.72
C	0.69	0.81	0.79	0.73	0.76	0.69	0.71
D	0.67	0.79	0.78	0.65	0.72	0.66	0.69
WM	0.75	0.87	0.86	0.74	0.77	0.71	0.73
V_1	0.73	0.86	0.84	0.76	0.77	0.71	0.73
V_1.5	0.72	0.85	0.83	0.75	0.76	0.71	0.72
V_2	0.71	0.85	0.82	0.74	0.75	0.70	0.72
V_2.5	0.70	0.84	0.82	0.73	0.75	0.70	0.72
SATRIM	0.74	0.86	0.86	0.75	0.77	0.71	0.73
Median	0.73	0.86	0.85	0.76	0.79	0.72	0.74
PC1	0.66	0.82	0.80	0.74	0.77	0.68	0.72
DFM	0.71	0.84	0.83	0.75	0.78	0.70	0.73
Obs.	226	225	224	221	215	209	203

Table 14: Averages of Regression R Squares of the Whole Sample

Horizon	1-6 Months	12-24 Months	1-24 Months
B	0.79	0.73	0.76
C	0.76	0.72	0.74
D	0.72	0.69	0.71
WM	0.80	0.74	0.77
V_1	0.80	0.74	0.77
V_1.5	0.79	0.73	0.76
V_2	0.78	0.72	0.76
V_2.5	0.77	0.72	0.75
SATRIM	0.80	0.74	0.77
Median	0.80	0.75	0.78
PC1	0.75	0.72	0.74
DFM	0.78	0.74	0.76

Unbiasedness is another significant evaluation criterion for core indicators. Unbiasedness is particularly crucial when using core indicators to predict the path of CPI inflation (Heath et al., 2004). In the long run, a core inflation indicator is expected to be unbiased concerning headline inflation. Precisely, although core measures and headline inflation may diverge in the short run, these divergences should disappear in the long run, and the mean of core inflation is expected to be the same as that of CPI inflation. In order to test this argument, some studies concentrate solely on the unconditional means of core inflation indicators and headline inflation over various periods and then analyze their similarity. For instance, Clark (2001) presents the average rate of inflation for both the headline and core indicators by using US price data with a period of over 30 years and explores that the unconditional means of the headline and core indicators are not the same, but very similar to each other. Other studies examine the unbiasedness of the core indicators using various specifications. In order to illustrate, according to Bryan and Cechetti (1994), headline inflation can be decomposed as the following equation:

$$\pi_t = \pi_t^{core} + \vartheta_t$$

where, π_t stands for the headline inflation, π_t^{core} demonstrates the underlying inflation and ϑ_t shows a transitory disturbance term, a relative price shock at a certain period. According to the equation, the underlying and the headline inflation should not differentiate without relative price shock. Hence, a core measure should be unbiased with respect to the headline inflation if it is a good proxy for underlying inflation. If the equation above is taken into account, Bryan and Cecchetti's definition implies:

$$\pi_t^{core} = E(\pi_{t+h}|I_t),$$

where E shows the expectations operator and I_t presents information about inflation over time. Additionally, joint restrictions of the coefficients $\alpha = 0$ and $\beta = 1$ can be tested empirically by using the equation to analyze the unbiasedness of core indicators. According to the different empirical studies, the unbiasedness measure of core inflation indicators varies depending on the different sample periods[16]. Hence, testing for unbiasedness in different sample periods is generally preferred to control for system changes or considerable shifts in the inflation process.

In order to test the unbiasedness of DFM, the equation is estimated for both the pre-September 2018 sample and the entire sample, and the periods are also taken to be the same as in the previous analysis, from 1 to 24. In Appendix E, the F-statistics are reported concerning the joint parameter restrictions of $\alpha = 0$ and $\beta = 1$. When the equation results are estimated with the sample before September 2018, the null hypothesis of joint limitation cannot be rejected for all the periods considered. Therefore, it can be stated that DFM is an unbiased estimator.

The test results change depending on the time horizon when considering the equation with a full sample. If the time horizon (h) is taken to be 18 and 24, the null hypothesis of joint restriction is rejected. However, the null hypothesis cannot be rejected if the time horizon is 1 to 12. As a result, since the time horizon of 12[17] is generally preferred for unbiased tests in the literature, it can be stated that DFM has the property of unbiasedness.

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[16] For detail, see Catte and Slok (2005), Amstad et al. (2014) and Rich and Steindel (2005).

[17] See Rich and Steindel (2007), Amstad et al. (2014).

5.3. Evaluation of Dynamic Factor Model Approach as an Underlying Inflation Indicator

A comparative analysis of the performance of the core indicators according to different criteria is presented in this section. Following these analyses, the DFM is assessed to determine whether or not it is a good core indicator. Firstly, like other core indicators, DFM is positively related to headline inflation at all horizons examined and is more closely associated with headline inflation as time passes. Secondly, statistics such as mean, standard deviation, coefficient of variation, and so forth are calculated to measure the volatility of the core indicators. According to these statistics, DFM seems to be a more stable indicator than headline inflation, similar to others. Thirdly, when tracking the trend of inflation is examined, DFM has consistently low values of RMSE and MAD over all periods, so it is good at monitoring the trend of inflation and appears efficient. Finally, like other core indicators, DFM has some predictive power for movements in headline inflation, and depending on the different periods, it is unbiased. As a result of these criteria examined above, the dynamic factor approach is a good application in defining the core inflation. It can, therefore, be a good alternative to the other core measures.

CHAPTER 6

CONCLUSION

Academics, central bankers, and various economic agents frequently consider underlying inflation, which does not include the prices of CPI categories with volatile fluctuations. The rationale is that since headline inflation is subject to unusual price changes, it may not provide accurate information about the inflation process. Policy-makers cannot affect inflation and economic activity in the short term, so they aim to comprehend the shifts in inflation patterns and the medium- and long-term dynamics of inflation. Therefore, volatile price changes should be removed from the CPI.

In Turkey, there are various underlying inflation measures such as B, C, and D indicators, SATRIM, the median, etc. However, academic studies show that since underlying inflation is unobservable, there is no single indicator for it. Thus, it is recommended that various underlying inflation measures should be frequently monitored in order to perceive accurate information regarding inflation behavior in the economy over time. Additionally, other underlying inflation measures do not consider the time series and cross-sectional dimensions of price changes in the CPI.

This study introduces a new measure of underlying inflation based on a dynamic factor model for Turkey using disaggregated prices from the Turkish CPI at the 5-digit level. This approach is preferred in this study because it considers information about price changes of sub-indices in the CPI from both the time-series and cross-sectional dimensions. Therefore, the persistent part of the CPI was extracted and dates back to 2005. A comparative performance analysis of DFM with other commonly used underlying inflation indicators for the Turkish economy is also provided. To this end, some criteria are applied to the measures to assess their informativeness and usefulness for the analysis of overall inflation. The requirements are selected primarily to test their predictive ability and to understand the information content of each underlying inflation measure.

This work contributes to the literature by providing a new indicator for underlying inflation. The definition of underlying inflation has become increasingly important, especially during high inflation periods. Although traditional measures of underlying inflation are available, the DFM can provide a different perspective on tracking inflation dynamics. Additionally, in Turkey, there is no widely used model-based approach for measuring underlying inflation. Other central banks also use dynamic factor-based approaches to monitor underlying inflation. For example, the New York Federal Reserve Bank uses the UIG and MCT indicators, which have two different factor models that serve as underlying inflation indicators. Therefore, the DFM adopts a similar technical perspective by using the dynamic factor model with 5-digit level sub-indices of the CPI to extract accurate information about the inflation process. This method aims to isolate the persistent inflation component by filtering out temporary changes in headline inflation. Based on the performance criteria analyzed in this paper, the DFM is a valuable indicator of underlying inflation. It tracks the inflation trend, strongly correlates with overall inflation, and exhibits predictive power. Therefore, it is a suitable alternative to other measures of underlying inflation. These findings are essential for policymakers, who rely on measures of underlying inflation to comprehend target inflation trends and anticipated inflation fluctuations.

In order to develop the analysis presented in this paper, the dynamic factor model approach can be extended by using not only the sub-indices of the CPI but also a wide range of nominal, real, and financial variables, which is similar approach to the New York FED UIG approach. Thus, the analysis can consider data beyond the price changes of the sub-indices of the CPI and include a large number of additional series. In addition, as an alternative approach, a dynamic factor with time-varying parameters can be adopted that is similar to the recently used indicator, the New York FED MCT indicator. In this way, a smoother data series can be generated. These ideas are left for future work.

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APPENDICES

A. TURKISH SUMMARY / TÜRKÇE ÖZET

Enflasyonun ana eğilimi, akademisyenler, merkez bankacıları ve ekonomi analistleri tarafından, TÜFE'de dalgalı hareketler gösteren kalemlerin fiyatlarını dışarıda bırakan bir enflasyon ölçüsü olarak yaygın bir şekilde kullanılmaktadır. Bunun nedeni ise, manşet enflasyonun fiyatlarda olağandışı değişikliklere maruz kalması sebebiyle enflasyon süreci hakkında doğru bilgi vermemesidir. Politika yapıcılar, enflasyonu ve ekonomik aktiviteyi kısa vadede etkileyememektedirler, bu nedenle orta ve uzun vadede enflasyon eğilimlerindeki değişiklikleri ve gelecekteki enflasyon dinamiklerini anlamayı amaçlamaktadırlar. Bu nedenle, oynak hareketlilik gösteren fiyat değişimleri TÜFE'den çıkarılmalıdır.

Literatürde, enflasyonun ana eğilimini ölçmenin kesin bir yolu olmadığı savunulmaktadır. Bu nedenle, enflasyonun ana eğilimini ölçmek için çeşitli yöntemler bulunmaktadır. Robert J. Gordon 1975 yılında, halen en yaygın kullanılan göstergelerden biri olan gıda ve enerji hariç enflasyonu tanıtmıştır. Kalıcı dışlama temelli yöntemler olarak adlandırılan bu yöntem 1970'lerden beri kullanılmaktadır. Bu yöntemin ana fikri, tüketici fiyat endeksi sepetindeki bazı alt sınıfları dışlayarak enflasyonu elde etmektir. Bunlardan en yaygın kullanılanı gıda ve enerji gruplarının tüketici fiyat endeksinden çıkarılmasıdır. Ayrıca, alternatif bir ölçüm olarak Bryan (1991) medyan fiyat değişiminin kullanılmasını önermektedir. Bu yöntem, geçici göreli fiyat hareketlerinin manşet enflasyon üzerindeki etkisini azalttığı için basit ve kullanışlı bir gösterge olarak kabul edilmektedir. Ayrıca, parasal enflasyonu hem kısa hem de uzun vadede izlemek için doğrudan bir yol sağlamaktadır. Bu yöntemlere ek olarak, literatürde enflasyonun ana eğilimini ölçmek için yaygın olarak kullanılan yöntemlerden biri de sınırlı etki tahmincileridir. Bu tahmincilerin altında yatan ana fikir, aşırı fiyat değişimlerinden etkilenmeyen bir çekirdek gösterge oluşturmaktır. Bryan ve Cecchetti (1994) ve Bryan, Cecchetti ve Wiggins (1997) çekirdek enflasyon göstergesi olarak ağırlıklı medyan ve kırpılmış ortalama gibi sınırlı etki tahmincileri önermişlerdir. Bu tür tahminciler basitçe fiyat değişiklikleri dağılımının kuyruklarından belirli bir yüzdeyi çıkarmakta ve ardından kalan kalemlerin fiyat değişikliklerinin ağırlıklı ortalamasını hesaplamaktadır. Diğer bir ifade ile, temel olarak enflasyon oranları sınıflar arası/alt sınıf dağılımının kuyruklarına düşen kalemlerin çıkarılması yöntemidir. Ayrıca, wavelet kullanılması enflasyonun ana eğilim ölçütü oluşturmak için kullanılan bir diğer yöntemdir. Bu yöntemle, enflasyonun en oynak bileşenleri atılmaktadır. Türkiye için Akkoyun ve diğ. (2011), bir yıllık dönemde tamamlanan enflasyon serilerindeki kısa vadeli dalgalanmaları dışlamak amacıyla wavelet ve band-pass filtreleri birleştiren iki aşamalı bir yaklaşım kullanmaktadır. Bunlara ek olarak, Berkmen (2002), Türkiye fiyat serileri için, dağılımın belirli kuyruklarını çıkararak TRIM olarak adlandırılan kırpılmış ortalama oluşturmuştur. Çalışmada, kırpılmış ortalamaların istatistiksel olarak daha etkin enflasyon tahmincileri sağladığı bulunmuştur. Ancak, bu ölçüt mevsimsel kalemlerle uğraşırken sinyal ve gürültüyü ayırt etmekte başarısız olmaktadır. Bu dezavantajın üstesinden gelmek için Atuk ve Özmen (2009a) Türkiye için yeni bir çekirdek enflasyon ölçütü olan SATRIM, mevsimsellikten arındırılmış kırpılmış ortalama enflasyonu tanıtmıştır. SATRIM'in farklı zaman dilimlerinde trend izleme yeteneği açısından TRIM ölçütünden daha iyi performans gösterdiğini ortaya koymuşlardır. Ayrıca, Atuk ve Özmen (2009b) Türkiye 'de farklı yöntemlere dayalı olarak yaygın olarak kullanılan diğer enflasyon temel göstergelerini (ağırlıklı medyan, SATRIM, oynaklığa dayalı göstergeler vb.) tanımlamakta ve bu göstergelerin performanslarını yansızlık, oynaklığın azaltılması, trend izleme yeteneği ve tahmin yeteneği gibi önceden belirlenmiş kriterlere göre karşılaştırmaktadır.

Literatürde, modele dayalı yaklaşımlar enflasyon göstergesinin oluşturulmasında yaygın olarak kullanılan bir diğer yöntemdir. Faktör modeline dayalı bir enflasyon ana eğilim göstergesi oluşturulmasına ilişkin literatürdeki ünlü çalışmalardan biri New York Federal Rezerv Bankası'na (FRBNY) ait olan Enflasyon Ana Eğilim Göstergesi'dir (UIG). Amstad ve diğerleri (2014) dinamik faktör modelleri kullanarak ABD'de 1995 yılına kadar uzanan enflasyonun kalıcı bileşenini tahmin etmek için

UIG'i oluşturmuştur. Bu makale, enflasyon ana eğilim göstergesi için iki yöntem sunmaktadır. İlk yöntem, tüketici fiyat endeksinin yalnızca alt bileşenlerini içeren 'yalnızca fiyatlar' kullanılarak oluşturulan göstergedir. İkinci yöntemde ise TÜFE alt bileşenlerinin yanı sıra çeşitli nominal, reel ve finansal değişkenleri de içeren 'tam veri seti' kullanılarak oluşturulan göstergedir. UIG, ABD'deki geleneksel çekirdek enflasyon ölçütleriyle karşılaştırıldığında, UIG'in üç önemli özelliği ön plana çıkmaktadır. İlk olarak, UIG hem yatay kesit hem de zaman serisi boyutlarından alt bileşenlerin fiyat değişimlerine ilişkin bilgileri kullanabilmektedir. İkinci olarak, çok sayıda ek seri de dahil olmak üzere alt bileşenlerin fiyat değişimlerinin ötesindeki verileri dikkate alabilmektedir. Üçüncü olarak, farklı zaman dilimlerinde tahmin hassasiyeti testlerinde geleneksel çekirdek enflasyon göstergelerinden daha iyi performans göstermiş ve enflasyondaki dönüm noktalarına ilişkin daha zamanlı ve daha kesin bir sinyal vermiştir. Bu çalışma, ABD enflasyonuna ilişkin mevcut literatüre katkıda bulunmakta ve para politikası yapıcıları ve uzun vadeli yatırımcılar için erişilebilir olan geleneksel temel enflasyon ölçümlerine alternatif sunmaktadır. Türkiye için Tekatlı (2010), TÜFE enflasyonunun alt bileşenleri ile bir faktör modeli kullanarak yeni bir çekirdek enflasyon göstergesi önermektedir. Bu yeni gösterge, aylık göreli fiyat değişimlerinin manşet enflasyondan ve kendine özgü dinamiklerden arındırılmasıyla elde edilmektedir. Analizde TÜFE enflasyonunun on iki alt bileşeni kullanılmıştır. Daha sonra, oluşturulan Fcore adlı çekirdek göstergenin performansı ve kullanışlılığı, H ve I çekirdek göstergeleri ile karşılaştırılarak incelenmiştir. Çalışma, her bir çekirdek göstergenin enflasyon trendini takip etme, manşet enflasyonla kısa ve orta vadeli ilişki ve öngörü yeteneği açısından oldukça iyi performans gösterdiğini ima etmektedir. Sonuçlar, bu yeni göstergenin güvenilir bir çekirdek enflasyon ölçütü ve politika analizi için değerli bir araç olduğuna işaret etmektedir. Ancak bu gösterge TÜFE'nin 12 alt bileşeni kullanılarak hesaplanmakta ve düzenli olarak izlenmemektedir.

Literatürde enflasyonun ana eğilimi, enflasyonun kalıcı bir bileşeni olarak tanımlanmaktadır. Diğer bir deyişle, normal ekonomik koşullar altında beklenen fiyat değişim oranını gösterir, bu da kaynak kullanımının enflasyonu etkilemediği anlamına gelir. Türkiye 'de birçok ana eğilim göstergesi bulunmaktadır. En yaygın kullanılanlar kalıcı dışlamaya dayalı ölçütler, değişken kalemlerin dönemsel olarak dışlanmasına dayalı ölçütler, ağırlıklı medyan (WM), mevsimsellikten arındırılmış kırpılmış ortalama (SATRIM), medyan ve temel bileşen analizine dayalı göstergelerdir. Bu göstergeler farklı metodolojilere dayanmaktadır.

Kalıcı Dışlama Metodu: Belirli kalemlerin TÜFE sepetinden kalıcı olarak çıkarılması en popüler ve yaygın yöntemdir. Kalıcı dışlama yönteminin kullanılmasının birincil faydası, hesaplama ve kamuoyu ile iletişim kolaylığıdır. Ayrıca, bu yöntem herhangi bir varsayım veya sınırlama gerektirmez ve herhangi bir revizyona gerek yoktur. Dolayısıyla, kamuoyu tarafından kolayca anlaşılabilir ve kabul edilebilir. Ancak, bu tür önlemler enflasyon serilerindeki tüm arz şoklarını ve oynaklığı ortadan kaldırmada tam olarak etkili değildir, çünkü kapsam dışı bırakılan kalemler sabittir ve veri gerçekleşmesi ile güncellenmez.

Dönem Bazında Oynak Kalemlerin Dışlanması: Bu yöntemin amacı, oynak kalemleri belirlemek ve fiyat değişimlerinin ortalama fiyat değişimlerinden önemli ölçüde daha oynak olduğu dönemlerde bu kalemleri hariç tutmaktır. Detaylandırmak gerekirse, öncelikle tüm endekslerin mevsimsellikten arındırılmış aylık enflasyonunun standart sapması ve ortalaması beş basamaklı toplulaştırma düzeyinde her ay için hesaplanmaktadır. Daha sonra, tüm endekslerin aylık enflasyonu, hesaplanan standart sapma ve tüm örneklemin ortalaması ile karşılaştırılır. Kullanılan eşiğe göre ortalamanın 1, 1,5, 2 veya 2,5 standart sapmasının dışında kalan kalemler oynak kalemler olarak tanımlanmaktadır.

Ağırlıklı Medyan (WM): Ağırlıklı medyan, kırpılmış ortalamanın farklı bir şekli olarak kabul edilir. Belirli bir dönem için, dağılımın her iki kuyruğu da çıkarılır, böylece sıralanmış mevsimsellikten arındırılmış fiyat değişikliklerinin yalnızca 50. yüzdelik dilimi verilerde yer alır.

Mevsimsel Olarak Düzeltilmiş Kırpılmış Ortalama (SATRIM): Öncelikle her bir serinin mevsimsellikten arındırılmış aylık enflasyonları, TÜFE'deki karşılık gelen ağırlıklarıyla birlikte sıralanır. Kırpma yüzdesi, sıralanan serilerin kümülatif ağırlıklarına göre belirlenir. Daha sonra, dağılım kuyrukları belirlenen yüzdeye göre simetrik olarak kırpılır ve kalan serilerin ağırlıklı ortalaması hesaplanarak belirli bir dönem için kırpılmış ortalama enflasyon belirlenir.

Medyan: Medyan, sıralı veri serilerinin orta noktasını temsil eder. Çekirdek enflasyon göstergesi olarak medyan, beş basamaklı toplulaştırma düzeyinde mevsimsellikten arındırılmış aylık enflasyondan hesaplanmaktadır.

Temel Bileşen Analizi: Temel bileşen analizi (PCA), büyük veri setlerinin boyutluluğunu azaltmak için sıklıkla uygulanan bir boyutluluk azaltma tekniği yöntemi olarak kabul edilir. Bu yöntem, büyük bir değişken kümesini, büyük kümedeki bilgilerin çoğunu kaybetmeden daha küçük bir kümeye dönüştürür.

Bu tezde, enflasyon ana eğilim göstergesi oluşturmak için yöntem olarak dinamik faktör modeli uygulanmıştır. Bu yöntemin seçilmesinin nedeni, B, C, vb. gibi yaygın olarak kullanılan ve kalıcı dışlama yöntemine dayanan çekirdek enflasyon ölçütlerinin aksine, herhangi bir veri serisini dışlamadan veri serilerindeki ortak dalgalanmaları yakalayan az sayıda değişkeni ayıklamasıdır. Kalıcı dışlama yöntemine dayanan bu ölçümlerin bir dezavantajı, enflasyonun alt bileşenlerinin farklı, zamanla değişen kalıcılığının zaman boyutunu dikkate almamasıdır. Örneğin, enerji ve gıda fiyatları son derece oynak olsa da, bunları enflasyonun ana eğilimine ilişkin bir ölçütten çıkarmadan önce değişimlerinin kalıcılığını değerlendirmek önem arz etmektedir. Bu bağlamda, dinamik faktör modeli hem fiyatların yatay kesit dağılımından hem de münferit fiyatların zaman serisi özelliklerinden elde edilen bilgilerin birleşik bir çerçevede bir araya getirilmesini sağlamaktadır. Diğer bir deyişle, dinamik faktör modeli, enflasyonun ana eğilim göstergesini oluştururken yatay kesit ve zaman serisi boyutlarından gelen alt grup fiyat değişimlerine ilişkin bilgileri kullanmaktadır.

Enflasyon ana eğilim göstergesini oluşturmak için 5 basamaklı toplulaştırma düzeyinde mevsimsellikten arındırılmış aylık fiyat değişimleri kullanılmıştır. Aylık fiyat değişimleri hesaplanmadan önce, ARIMA modeli kullanılarak her bir endeks değerine mevsimsel düzeltmeler uygulanmaktadır. Bu analizde kullanılan mevsimsel düzeltme yöntemi, model tabanlı bir mevsimsel düzeltme yöntemi olan TRAMO/SEATS'dir. 5 basamaklı toplulaştırma düzeyinde, 2024 yılı itibariyle 143 alt grubun fiyatları bulunmaktadır. Ancak her yıl alt grupların bir kısmı sepete eklenirken bir kısmı sepetten çıkarılmaktadır. Bu nedenle, 5 basamaklı düzeydeki alt grupların sayısı bir yıldan diğerine değişebilmektedir. Bu analizde, önceki yıllarda hariç tutulan alt gruplar da dahil olmak üzere en kapsamlı veri seti kullanılmaktadır. Sonuç olarak, bu çalışmada 153 alt grup kullanılmaktadır. Aylık enflasyon serisi Şubat 2005'te başlamakta ve Aralık 2023'te sona ermektedir. Bu dönem, 2003 baz yılı fiyat endeksi Ocak 2005'ten itibaren yayınlandığı için seçilmiştir.

Dinamik faktör modelleri tipik olarak durum uzayı formunda formüle edilir ve çeşitli çözüm algoritmalarıyla birlikte Kalman filtresi kullanılarak tahmin edilebilir. Literatürde en yaygın kullanılan algoritmalar, sağlam sayısal özellikleri nedeniyle Beklenti Maksimizasyonu (EM) algoritması (Doz vd., 2012) ve Banbura ve Modugno'nun (2014) popüler karma frekans genellemesidir. Bu tez, Doz, Giannone ve Reichlin'in (2011) dinamik faktör modeli yaklaşımını takip etmektedir. Bu çalışma zaman serileri paneli büyük olduğunda (n büyük olduğunda) dinamik faktör modelindeki faktörlerin iki aşamalı tahmininin tutarlılığını kanıtlamaktadır. İlk adımda, temel bileşenler üzerinde sıradan en küçük kareler (OLS) temelinde modelin parametrelerini tahmin etmektedirler. İkinci adımda, faktörleri Kalman filtresi aracılığıyla tahmin etmektedirler. Kısaca, Doz, Giannone & Reichlin'in (2011) iki aşamalı tahmin yaklaşımı, daha büyük veri kümeleri üzerindeki aşırı etkinliği nedeniyle bu makale için seçilmiştir.

Bu tezde, model için faktör sayısını belirlemek amacıyla yamaç grafiği kullanılarak grafikte bir bükülme noktası aranabilir. Alternatif olarak, faktör sayısı Bai ve Ng (2002) kriterlerine göre de seçilebilir. Bu kriterlere dayanarak 3 faktör tahmin edilmiştir, çünkü 3'ten fazla faktör modelin açıklayıcı gücüne fazla bir katkı sağlamamaktadır. Faktör sayısı seçildikten sonra, geçiş denkleminin faktör-VAR'ının gecikme sırası tahmin edilir. Gecikme sırası bilgi kriterlerine göre 4 olarak belirlenmiştir. Dolayısıyla, 3 faktörlü ve 4 gecikmeli bir dinamik faktör tahmin edilmiştir. Bu analizde birinci faktör modeli tahminleri kullanılmıştır. Ayrıca, faktör modeli literatüründe standart bir uygulama olduğu üzere, tahmin öncesinde veriler durağanlığı sağlamak için dönüştürülmüş ve her seri sıfır ortalama ve birim varyansa sahip olacak şekilde standardize edilmiştir. Bu durum tahmin sonuçlarını manşet ve geleneksel enflasyon ana eğilim göstergeleri ile karşılaştırılabilir olmamasına yol açmaktadır. Dinamik faktör analizinden çıkan sonuçların karşılaştırılabilir olması amacıyla, bağımlı değişken olarak TÜFE'nin aylık fiyat değişimi ve bağımsız değişken olarak DFM'nin standardize edilmiş tahmini ile oluşturulan regresyon analizi kullanılmıştır. Daha sonra, analizden elde edilen standartlaştırılmış seriler regresyondan elde edilen DFM katsayısı ile çarpılmakta ve daha sonra bu seriye katsayı terimi eklenmektedir.

Enflasyonun ana eğilimini tanımlamanın ve ölçmenin kesin bir yolu olmadığından, ana eğilim için oluşturulan göstergeleri ampirik bir ortamda değerlendirmek kolay olmamaktadır. Literatürde ana eğilim göstergelerini değerlendirmek için farklı yöntemler bulunmaktadır. En yaygın olarak kullanılan kriterler bu tezde DFM'nin enflasyonun ana eğilimini ölçmek için uygun bir gösterge olup olmadığı konusunda değerlendirilmektedir. Bu kriterler, göstergelerin TÜFE enflasyonu ile dinamik olarak ilişkili olup olmadığını, TÜFE enflasyonundan daha az oynak olup olmadığını, trend enflasyonu izleyip izleyemediğini ve etkin olup olmadığını, öngörü yeteneğine sahip olup olmadığını ve yansız olup olmadığını kontrol etmektedir.

İlk olarak dinamik korelasyon analiz edilmektedir. Dinamik korelasyon, değişkenler için birlikte hareketin bir ölçüsüdür. Farklı zaman dilimleri için TÜFE ve çekirdek ölçümlerin dinamik korelasyonu incelenmiştir. Bu analize göre, tüm ana eğilim göstergeleri incelenen tüm zaman dönemlerinde manşet enflasyonla pozitif ilişkili olup göstergelerin zaman içinde manşet enflasyonla daha yakından ilişkili olduğu görülmektedir. Ana eğilim göstergeleri karşılaştırıldığında, DFM incelenen tüm dönemler için B, C, medyan ve PC1'e kıyasla manşet enflasyonla daha iyi bir ilişkiye sahip olduğu görülmektedir.

Güvenilir bir ana eğilim göstergesi, manşet enflasyona kıyasla daha fazla istikrar ve daha düşük oynaklık sergilemelidir. Bu kriter, literatürdeki pek çok çalışma tarafından gerekli görülmektedir. Bu çalışmada oynaklık ölçütü olarak aylık enflasyon için ortalama, standart sapma ve değişim katsayısı dikkate alınmıştır. Ayrıca, yıllık enflasyon verileri için ortalama mutlak sapma ve yıllık enflasyondaki değişimin standart sapması da raporlanmaktadır. Analiz sonuçları diğer göstergelerde olduğu gibi, DFM'nin ortalaması ve standart sapması manşetten daha düşük olduğunu göstermektedir. Değişim katsayısı dikkate alındığında, DFM çekirdek enflasyon göstergeleri arasında en düşük değere sahiptir. Bu durum DFM'nin en hassas tahmini sağladığını göstermektedir. Bu istatistikler yıllık enflasyon için incelendiğinde de aynı sonuçlar gözlenmektedir. Spesifik olarak, DFM manşet enflasyondan daha düşük ortalama ve standart sapmaya sahiptir ve aynı zamanda en düşük değişim katsayısı değerine sahiptir. Ayrıca, ortalama mutlak sapma ve birinci farkın standart sapması dikkate alındığında, DFM TÜFE'den daha düşük bir değere sahiptir. Sonuç olarak, DFM birincil kriteri karşılamaktadır ve manşet enflasyona göre daha istikrarlı bir gösterge olarak görünmektedir.

Manşet enflasyon, oynaklık yaratan çeşitli şoklara karşı duyarlılığı nedeniyle enflasyonun ana eğilimine ilişkin güvenilir bilgi sağlama konusunda iyi olmamaktadır. Bu nedenle ana eğilim göstergelerinin enflasyon eğilimini manşet enflasyona kıyasla daha fazla bileşen olarak takip etmesi gerekmektedir. Ana eğilim göstergeleri enflasyon trendini yakalamalıdır. Ancak trend enflasyon gözlemlenemez ve farklı şekillerde tahmin edilebilir. Bu nedenle öncelikle trend enflasyonunun tanımlanması gerekmektedir. Dolmas (2005), Rich ve Steindel (2005) ve Baxter-King (1999) bant geçiş filtresini kullanırken, Bryan ve Cecchetti (1993), Bryan, Cecchetti ve Wiggins (1997) ve Clark (2001) bant geçiş filtresini kullanmaktadır. Ayrıca, Atuk ve Özmen (2009b), Türkiye TÜFE verileri için manşet enflasyonun merkezli hareketli ortalamasını kullanmayı tercih etmektedir. Bu nedenle bu çalışmada manşet enflasyonun merkezli hareketli ortalaması kullanılmıştır. Merkezi hareketli ortalama, belirli bir süre etrafında merkezlenen belirli sayıda değerin hareketli ortalamasıdır. Verimlilik kriterleri için ortalama karekök hata (RMSE) ve ortalama mutlak sapma (MAD) dikkate alınır. Gösterge seri olarak genellikle aylık TÜFE enflasyonunun 18, 24 ve 36 aylık merkezli hareketli ortalaması kullanılsa da bu raporda daha kısa dönemlere ilişkin istatistikler de raporlanmaktadır. Çünkü şok dönemlerinde yüksek manşet enflasyon değerleri nedeniyle uzun vadeli ortalama alındığında gösterge değer artmaktadır. Türkiye ekonomisi 2018 yılının son çeyreği ve 2021 yılının son çeyreğinde ve 2023 yılının üçüncü çeyreğinde döviz şokları yaşamıştır. Daha uzun vadeli merkezli hareketli ortalama, trend olarak hesaplanan değeri yükseltmektedir. Dolayısıyla bu şokların dışında nispeten istikrarlı kalan enflasyon değerleri trend olarak belirlenen değerden oldukça farklılaşıyor. Bu hesaplamaya daha kısa bir zaman dilimi dahil edildiğinde şoksuz dönemler enflasyon gerçekleşmeleriyle daha uyumlu hale gelmektedir. Böylece trend olarak hesaplanan değerler, 12, 24 ve 36 aylık ortalamalara ek olarak aylık manşet enflasyonun 4, 6, 8 ve 10 aylık merkezli hareketli ortalamalarından oluşturulmaktadır. DFM, tüm zaman aralıklarında sürekli olarak RMSE ve MAD değerleri düşük olması nedeniyle en verimli gibi görünmektedir. Bu nedenle DFM'nin enflasyon eğilimini takip etme açısından diğer göstergelere göre daha iyi bir gösterge olduğu düşünülebilir.

Ana eğilim göstergelerinin manşet enflasyondaki hareketler üzerinde bir miktar tahmin gücüne sahip olması beklenmektedir. Örneklem içi ve örneklem dışı tahmin yeteneği, göstergelerin tahmin yeteneğini test etmek için kullanılabilmektedir. Politika yapıcıların karar verirken hem mevcut hem de gelecekteki enflasyonu dikkate almaları önem arz etmektedir. Bu nedenle ana eğilim göstergelerinin manşet enflasyonu açıklayabilmesi ve gelecek enflasyonun tahmin edilmesine yardımcı olması gerekmektedir. Tahmin yeteneği için literatürde çeşitli yöntemler kullanılmaktadır. Bu makale, Cogley'in (2002) temel ölçümlerin tahmin yeteneğini değerlendirmek için önerdiği modeli takip etmektedir. Cogley (2002) sunduğu modelde ana eğilim göstergesi ile manşet enflasyon arasındaki mevcut sapmanın, mevcut enflasyonun gelecekteki enflasyondan sapmasını açıklayıp açıklayamayacağını incelenmektedir. Türkiye için bu regresyon oluşturulurken iki yaklaşım tercih edilmektedir. Türkiye ekonomisinin bu dönemden sonra sık sık şoklar yaşaması nedeniyle ilki Eylül 2018 öncesindeki örneklem kullanılarak oluşturulmuştur. İkincisi ise örneklemin tamamı kullanılarak oluşturulmuştur ancak döviz kurunun büyük oranda değiştiği aylar olan Eylül 2018, Aralık 2021, Ocak 2022, Temmuz 2023 ve Ağustos 2023 için kukla değişkenler kullanılmıştır. Eylül 2018 öncesi örneklemdeki göstergelerin tahmin gücü dikkate alındığında, DFM'nin ortalama R karesi 1-6 aylık ufuklar için 0, 38, 12-24 aylık dönem için 0,41 ve 12-24 aylık dönem için 0,39'dur. DFM'nin C, D, V_2, V_2.5 ve PC1 ile karşılaştırıldığında daha yüksek R kare değerlerine sahip olduğu görülmektedir. Bu durum DFM'nin bu göstergelere göre daha iyi tahmin gücü taşıdığını göstermektedir. Ek olarak, V_1.5'in R kare değerleri DFM'ninkinden önemli ölçüde farklılaşmamaktadır. Çekirdek enflasyon göstergelerinden B en yüksek tahmin gücüne sahipken, WM, SATRIM ve Medyan da yüksek R kare değerlerine sahiptir.

Tarafsızlık, enflasyon ana eğilim göstergeleri için bir diğer önemli değerlendirme kriteridir. Tarafsızlık, özellikle TÜFE enflasyonunun seyrini tahmin etmek için temel göstergeleri kullanırken önem arz etmektedir (Heath ve diğerleri, 2004). Uzun vadede çekirdek enflasyon göstergesinin manşet enflasyona göre tarafsız olması beklenmektedir. Spesifik olarak, her ne kadar kısa vadede çekirdek göstergeler ile manşet enflasyon farklılaşsa da uzun vadede bu farklılıklar ortadan kalkıp ana eğilim göstergesinin ortalamasının TÜFE enflasyonu ile aynı olması beklenmektedir. Bu durumu test etmek amacıyla bazı çalışmalar, yalnızca ana eğilim göstergelerinin ve manşet enflasyonun çeşitli zaman dilimlerindeki koşulsuz ortalamalarına odaklanmakta ve daha sonra benzerliklerini analiz etmektedir. Örneğin Clark (2001), 30 yılı aşkın bir zaman dilimine ait ABD fiyat verilerini kullanarak hem manşet hem de ana eğilim göstergeleri için ortalama enflasyon oranını sunmakla birlikte manşet ve ana eğilim göstergelerin koşulsuz ortalamalarının çok benzer olduğunu fakat aynı olmadığını göstermektedir. DFM'nin tarafsızlığını test etmek amacıyla denklem hem Eylül 2018 öncesi örneklem hem de tam örneklem için tahmin edilmiş ve zaman dilimleri de bir önceki analizde olduğu gibi 1'den 24'e kadar aynı olacak şekilde alınmıştır. Denklemin sonuçları Eylül 2018 öncesi örneklemle tahmin edildiğinde, ortak kısıtlamaya ilişkin sıfır hipotezi, dikkate alınan tüm zaman dilimleri için reddedilmemektedir. Dolayısıyla DFM'nin tarafsız bir tahminci olduğu söylenebilmektedir. Denklem tam örneklemle ele alındığında test sonuçları zamana bağlı olarak değişmektedir. Zaman ufku (h) 18 ve 24 olarak alınırsa ortak kısıtlamaya ilişkin sıfır hipotezi reddedilmektedir. Ancak zaman ufku 1'den 12'ye kadar alınırsa sıfır hipotezi reddedilmemektedir. Sonuç olarak literatürde tarafsız test için genellikle 12 zaman ufku tercih edildiğinden DFM'nin tarafsızlık özelliğine sahip olduğu değerlendirilmektedir.

Özetle, ana eğilim göstergelerin performansının farklı kriterlere göre karşılaştırmalı bir analizi sunulmuştur. Öncelikle, diğer ana eğilim göstergeleri gibi DFM'nin de incelenen tüm ufuklarda manşet enflasyonla pozitif ilişkili olduğu ve zaman geçtikçe manşet enflasyonla daha yakından ilişkili olduğu görülmektedir. İkinci olarak, ana eğilim göstergelerin oynaklığının ölçüsü olarak ortalama, standart sapma, değişim katsayısı vb. istatistikler hesaplanmaktadır. Bu istatistiklere göre DFM diğerlerine benzer şekilde manşet enflasyona göre daha istikrarlı bir gösterge olmaktadır. Üçüncüsü, enflasyon trendinin takibi incelendiğinde, DFM'nin RMSE ve MAD değerlerinin tüm zaman dilimlerinde sürekli olarak düşük olduğu, dolayısıyla enflasyon trendini takip etmede iyi olduğu ve etkili olduğu görülmektedir. Son olarak, diğer temel göstergeler gibi DFM de manşet enflasyonundaki hareketleri tahmin etme gücüne sahiptir ve farklı zaman dilimlerine bağlı olarak tarafsız olma özelliğine sahiptir. Yukarıda incelenen bu kriterler sonucunda dinamik faktör yaklaşımının çekirdek enflasyonun tanımlanması açısından iyi bir uygulama olduğu görülmektedir. Bu nedenle diğer ana eğilim göstergelerine iyi bir alternatif olma özelliği taşımaktadır.

Sonuç olarak, Türkiye'de B, C ve D göstergeleri, SATRIM, medyan ve benzeri gibi çeşitli temel enflasyon ölçütleri bulunmaktadır. Ancak akademik çalışmalar, enflasyonun ana eğiliminin gözlemlenemez olması nedeniyle tek bir gösterge olmadığını göstermektedir. Bu nedenle, zaman içinde ekonomideki enflasyon davranışına ilişkin doğru bilginin algılanabilmesi için farklı enflasyon göstergelerinin sıklıkla izlenmesi önerilmektedir. Ayrıca, geleneksel enflasyon göstergeleri TÜFE'deki fiyat değişimlerinin hem yatay kesit hem de zaman serisi boyutlarını dikkate almamaktadır. Bu çalışma, enflasyonun ana eğilimine ilişkin yeni bir gösterge sunarak literatüre katkıda bulunmaktadır. Özellikle yüksek enflasyon dönemlerinde enflasyonun ana eğiliminin tanımlanması giderek daha önemli hale gelmektedir. Enflasyonun ana eğilimine ilişkin geleneksel göstergeler mevcut olsa da DFM enflasyon dinamiklerinin izlenmesinde farklı bir bakış açısı sağlamaktadır. Ayrıca, Türkiye’de enflasyonun ana eğilimini ölçmek için yaygın olarak kullanılan model bazlı bir yaklaşım bulunmamaktadır. Diğer merkez bankaları da enflasyonun ana eğilimini izlemek için dinamik faktör bazlı yaklaşımlar kullanmaktadır. Örneğin, New York Federal Rezerv Bankası, enflasyonun ana eğilimi olarak iki farklı faktör modeline sahip UIG ve MCT göstergelerini kullanmaktadır. Bu nedenle DFM, enflasyon süreci hakkında doğru bilgi elde etmek için TÜFE'nin 5 basamaklı alt bileşenleri ile dinamik faktör modelini kullanarak benzer bir teknik perspektif benimsemektedir. Bu yöntemin amacı, manşet enflasyondaki geçici değişimleri filtreleyerek enflasyonun kalıcı bileşenini elde etmektir. Bu çalışmada incelenen performans kriterlerine göre, DFM enflasyonun temeline ilişkin faydalı bir göstergedir. Enflasyon eğilimini takip etmekte, genel enflasyonla güçlü bir korelasyona sahip ve tahmin gücü sergilemektedir. Bu nedenle, diğer ana eğilim göstergelerine uygun bir alternatiftir. Bu bulgular, enflasyonun ana eğilimine ilişkin ölçümlere güvenen politika yapıcılar, akademisyenler ve analistler için önem taşımaktadır.

B. 5-DIGIT CODES and NAMES of the SUBGROUPS in CPI BASKET

	5 Digit Code	Name of the Subgroups in CPI Basket
1	01111	Rice
2	01112	Flours and other cereals
3	01113	Bread
4	01114	Other bakery products
5	01115	Pasta products and couscous
6	01116	Other cereal products
7	01122	Beef and veal
8	01124	Lamb
9	01125	Poultry
10	01126	Other meat and edible offal
11	01127	Dried, salted, or smoked meat
12	01131	Fresh or chilled fish
13	01133	Other preserved or processed fish and seafood-based preparations
14	01143	Other milk products
15	01144	Cheese
16	01145	Eggs
17	01151	Butter
18	01152	Margarine and other vegetable fats
19	01153	Other edible oils
20	01161	Fresh or chilled fruit
21	01162	Dried fruit and nuts
22	01171	Fresh or chilled vegetables other than potatoes and other tubers
23	01172	Potatoes
24	01174	Dried vegetables, other preserved or processed vegetables
25	01175	Canned or processed vegetables
26	01181	Sugar
27	01182	Jams, marmalades, and honey
28	01183	Confectionery products, chocolates and cacao
29	01184	Edible ice and ice cream
30	01190	Other food products n.e.c.
31	01211	Coffee
32	01212	Tea
33	01213	Cacao and powdered chocolate
34	01221	Mineral or spring waters
35	01222	Soft drinks

36	01223	Fruit and vegetable juices
37	02110	Alcoholic beverages
38	02121	Wine from grapes
39	02130	Beer
40	02201	Cigarettes
41	02202	Other tobacco products
42	03110	Fabrics
43	03121	Garments for men
44	03122	Garments for women
45	03123	Garments for children
46	03124	Garments for baby
47	03130	Other articles of clothing
48	03140	Dry cleaning, repairing, and hiring of clothing
49	03211	Footwear for men
50	03212	Footwear for women
51	03213	Footwear for infants and children
52	03220	Repair and hire of footwear
53	04111	Actual rentals paid by tenants
54	04310	Materials for the maintenance and repair of the dwelling
55	04410	Water supply
56	04420	Waste garbage
57	04510	Electricity
58	04521	Natural gas
59	04522	Liquefied hydrocarbons
60	04530	Liquid fuels
61	04540	Solid fuels
62	05111	Kitchen furniture
63	05112	Bedroom furniture
64	05113	Dining and living room furniture
65	05120	Carpets, rugs, and other floor coverings
66	05200	Home textile
67	05311	Refrigerators, freezers, and fridge freezers
68	05312	Clothes washing machines, clothes drying machines, and dishwashing machines
69	05313	Cookers and heaters
70	05314	Air conditioners
71	05315	Other large appliances
72	05320	Small electrical appliances
73	05330	Repair of household appliances
74	05401	Glassware, crystal-ware, ceramic ware and chinaware
75	05402	Cutlery, flatware, and silverware
76	05403	Non-electric kitchen utensils and articles
77	05521	Miscellaneous small tool accessories
78	05522	Hand and garden tools

79	05611	Cleaning and maintenance products
80	05612	Other non-durable small household articles
81	05621	Other domestic services and household services
82	05622	Cleaning services
83	06110	Pharmaceutical products
84	06120	Other medical products n.e.c.
85	06131	Corrective eyeglasses and contact lenses
86	06132	Other therapeutic appliances and equipment
87	06212	Specialist practice
88	06220	Dental services
89	06231	Services of medical analysis laboratories and x-ray centers
90	06232	Nursing and midwifery services
91	06300	Hospital services
92	07111	New diesel motorcars
93	07113	New gasoline motor cars
94	07114	Capacity 2000cc vehicles
95	07120	Motorcycles
96	07130	Bicycles
97	07210	Spare parts for personal transport equipment
98	07220	Petrol
99	07230	Maintenance and repair of personal transport equipment
100	07240	Other services of personal transport equipment
101	07311	Passenger transport by underground and tram
102	07312	Passenger transport by train
103	07321	Passenger transport by local bus
104	07322	Taxi fees
105	07323	Passenger transport between cities
106	07330	Passenger transport by plane
107	07340	Passenger transport by sea
108	07360	Other purchased transportation services
109	08100	Postal services
110	08200	Equipment of telephone and telefax equipment
111	08300	Services of telephone and telefax equipment
112	09111	Television
113	09112	Radio, CD player, and other electro-acoustic instruments
114	09120	Photographic and cinema equipment, optical instruments
115	09130	Computers
116	09141	Filled cassettes, disks and diskettes
117	09142	Empty cassettes, discs, and diskettes
118	09150	Repair of audio-visual, photographic, and information-processing equipment
119	09220	Musical instruments
120	09310	Toys and celebration articles
121	09320	Equipment for sport

122	09340	Products for pets
123	09350	Veterinary and other services for pets
124	09410	Recreational and sporting services
125	09421	Photographic services
126	09422	Other cultural services
127	09430	Game of chance
128	09510	Books
129	09520	Newspapers and magazines
130	09540	Stationery and drawing materials
131	09600	Package tours
132	10100	Primary education
133	10200	Secondary education
134	10300	Post-secondary and pre-university education
135	10400	Tertiary education
136	10500	Education is not definable by level
137	11101	Restaurants and food services
138	11102	Cafes and beverage services
139	11201	Hotels and other accommodation services
140	11202	Accommodation services of other establishments
141	12111	Hairdressing for men
142	12112	Hairdressing for women
143	12120	Electric appliances for personal care
144	12130	Articles for personal hygiene and wellness, esoteric products, and beauty products
145	12310	Jewelry, clocks and watches
146	12321	Travel goods
147	12322	Other personal effects n.e.c.
148	12400	Social services
149	12520	Insurance connected with the dwelling
150	12530	Insurance connected with health
151	12540	Motor vehicle insurance
152	12620	Legal services and accountancy
153	12700	Other fees and services

C. OPTIMAL NUMBER OF FACTORS

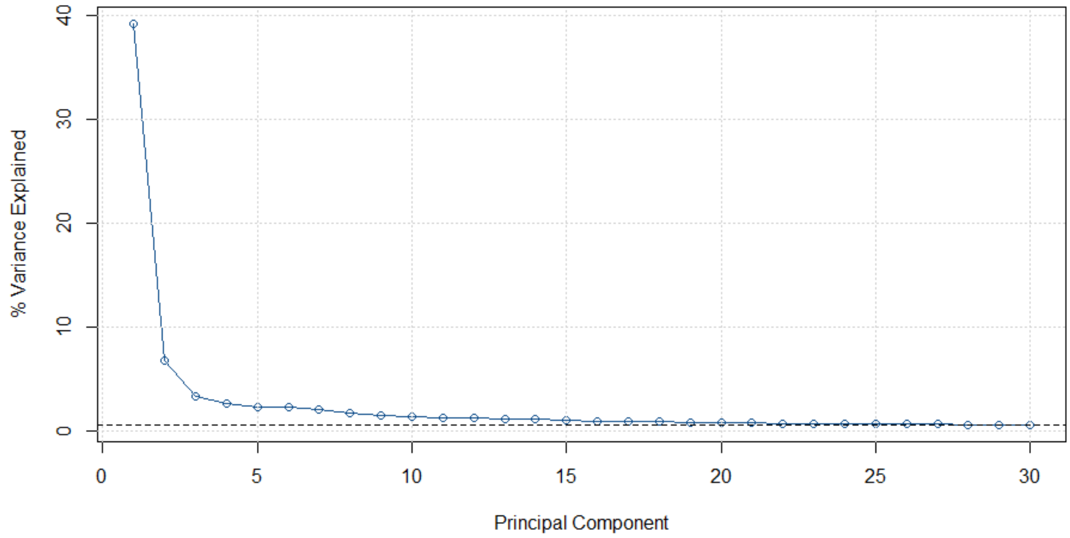

Figure 6: Optimal Number of Factors from a Kink Point in the Screeplot

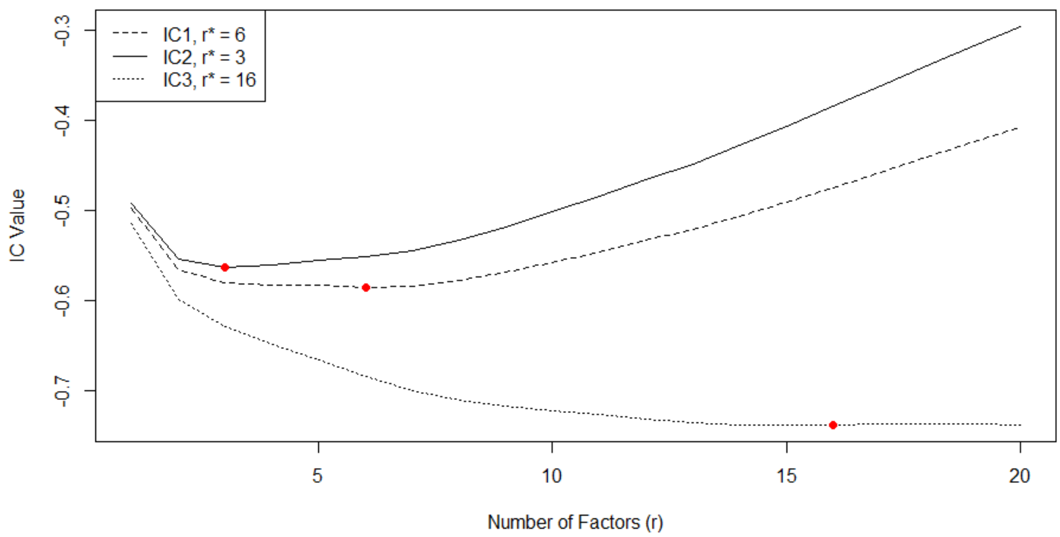

Figure 7: Optimal Number of Factors from Bai and Ng (2002) Criteria

D. ANNUAL DFM RESULTS

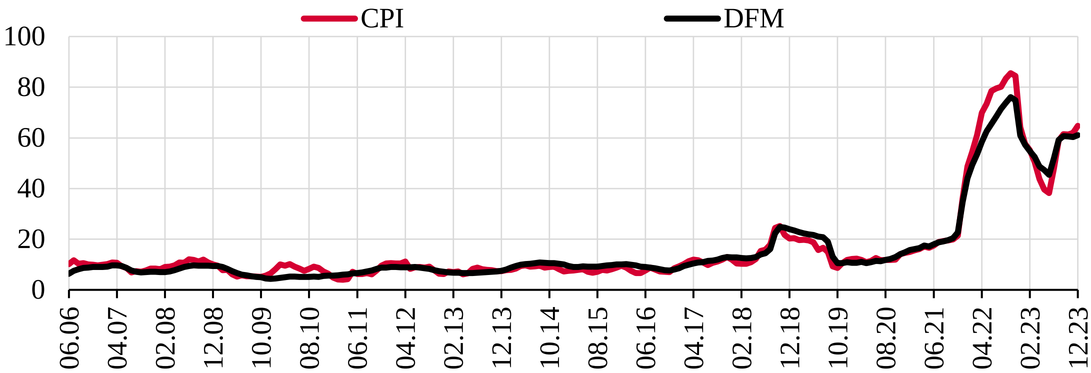

Figure 8: Annual Inflation of CPI and DFM

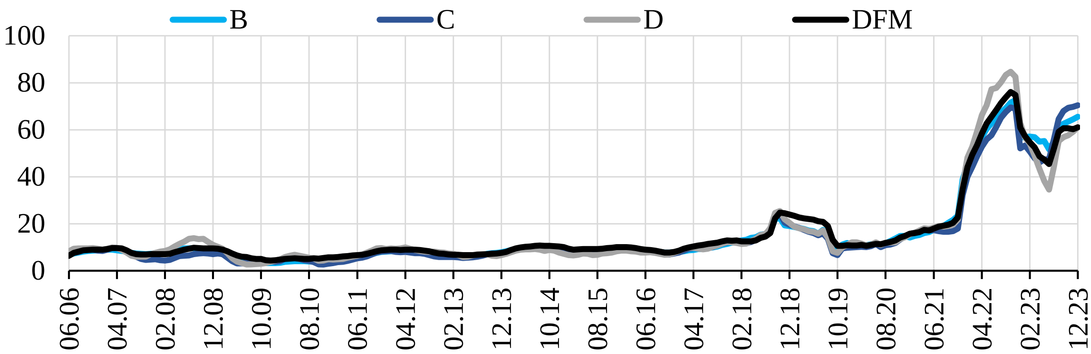

Figure 9: Annual Inflation of the Permanent Exclusion Based Underlying Inflation Indicators and DFM

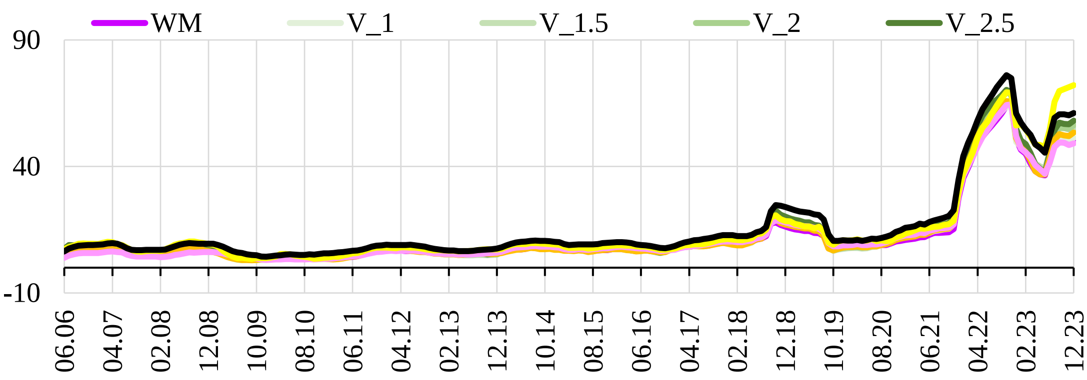

Figure 10: Annual Inflation of the Other Underlying Inflation Indicators and DFM

E. UNBIASEDNESS TEST RESULTS

Table 15: F-Statistics for the Sample Before September 2018

Horizon	1	2	3	6	12	18	24
Unrestricted SSR	50.39	55.56	58.60	57.58	58.47	51.41	58.84
Restricted SSR	50.66	55.97	59.16	58.35	59.61	52.44	60.22
q	2	2	2	2	2	2	2
n	162	161	160	157	151	145	139
k+1	3	3	3	3	3	3	3
F-Stat	0.44	0.58	0.75	1.03	1.44	1.43	1.59

The horizon is expressed in terms of months. In the context of this model, q represents the number of restrictions, k represents the number of regressors in the unrestricted model, and n represents the number of observations.

Table 16: F-Statistics for the Whole Sample

Horizon	1	2	3	6	12	18	24
Unrestricted SSR	129.34	127.53	146.26	181.40	190.07	207.84	220.10
Restricted SSR	129.34	127.54	146.26	182.56	193.74	216.44	236.28
q	2	2	2	2	2	2	2
n	226	225	224	221	215	209	203
k+1	3	3	3	3	3	3	3
F-Stat	0.00	0.01	0.00	0.70	2.04	4.26	7.35

The horizon is expressed in terms of months. In the context of this model, q represents the number of restrictions, k represents the number of regressors in the unrestricted model, and n represents the number of observations.

G. THESIS PERMISSION FORM / TEZ İZİN FORMU

(Please fill out this form on computer. Double click on the boxes to fill them)

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