NATIONAL BANK OF KAZAKHSTAN

A New Core Inflation Indicator for Kazakhstan

Monetary Policy Department
Economic Study №2026-6
Working Paper

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March 2026

NBRK – WP – 2026 – 6

ISSN: 2789-150X

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Abstract

The Consumer Price Index (CPI) is the measure of inflation followed by policymakers and market participants in Kazakhstan. However, due to its volatility, the CPI series is not a reliable measure of the underlying trend in inflation. This makes it difficult for policymakers to make informed decisions about monetary policy. In addition, the annual inflation measures that are used policymakers are lagging indicators and hence miss turning points in the inflation rate. Thus, policymakers employ the measure of "core" inflation that excludes certain volatile components, such as fruits and vegetables from the CPI calculation. However, this measure has limitations when it comes to capturing turning points. This paper proposes a new approach to estimating core inflation index for Kazakhstan by utilizing cross-sectional and dynamic links between prices and non-price variables in a large dataset. We estimate two indicators of core inflation for Kazakhstan that have some attractive statistical properties in contrast to traditional measures of core inflation.

Keywords: Core Inflation, Dynamic Factor Model, Monetary Policy, Inflation Forecast

JEL code: C32, E31, E37, E52

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Table of contents

1. Introduction

In August 2015, the National Bank of Kazakhstan (NBK) adopted an inflation-targeting monetary policy regime with the aim of maintaining price stability. Since 2023, the NBK has aimed to keep the year-on-year inflation rate at 5%.[2] Changes in the consumer price index (CPI) are the primary indicator of inflation used for policy analysis by the government and businesses. However, CPI data tend to be highly volatile, making it an unreliable gauge of the underlying inflation trend. This makes it difficult for policymakers and market participants to make informed decisions. For example, in August 2008 the annual inflation rate reached 20,1% then fell to 9,5% in December of that year, and finally reached 6,3% in August 2009. A similar pattern can be seen in 2015-2016 and in 2022-2023. The excessive volatility of headline inflation is a challenge for efficient monetary policy decision-making. Therefore, researchers and policymakers are searching for an underlying[3] measure of inflation that reflects the long-term and persistent component of headline inflation.

Following the practice of many countries, policy makers in Kazakhstan use a measure of core inflation known as the core consumer price index (CCPI-FE and CCPI-FER). The CCPI-FE index stands for core inflation, which excludes prices for fruits, vegetables, and energy, while the CCPI-FER index excludes regulated prices in addition to fruits, vegetables, and energy. The CCPI-FE and CCPI-FER are derivative price indices from the CPI, reflecting the long–term dynamics of price changes that are not affected by supply and demand shocks caused by random factors. This approach assumes that temporary changes in the aggregate price index are related to the volatility of its sub-components. Consequently, the core inflation indicator does not take into account the most volatile goods and services, such as food and energy. Another strategy proposed by Bryan and Cecchetti (1994) is based on the use of truncated averages and medians, in which the most volatile components are excluded from the basket regardless of the sectors to which they belong. Both methods of estimating the sustainable long-term component of inflation have different identified limitations. First, exclusion methods assume that the source of temporary changes in the cumulative series of inflation remains unchanged over time. Second, both exclusion and truncation strategies focus solely on cross-dimensional data and ignore potentially useful information about data dynamics over time. Third, annual inflation figures, although smoothed, require shifting monthly inflation figures back in time, since annual inflation is the sum of the previous twelve months. Consequently, these annual indicators are lagging indicators of monthly inflation and do not take into account turning points. Further, the traditional core inflation figures are published with some delay.[4] Finally, research shows that traditional core inflation indicators remain too volatile and subject to temporary and industry shocks, so they cannot serve as a reliable indicator of long-term inflation

[2] https://www.nationalbank.kz/ru/news/monetary-policy-strategy/rubrics/2010
[3] The terms “core” and “underlying” are used interchangeably in the paper.
[4] The CCPI-FE and CCPI-FER for Kazakhstan are released by the Bureau of National Statistics one week after the CPI release.

(Cogley (2002); Rich and Steindel (2007)). We also find that both the CCPI-FE and CCPI-FER are just as volatile as the CPI.

In this regard, the NBK uses a variety of alternative methods to estimate core inflation during the monetary policy decision-making process. The study by Orlov and Seidakhmetov (2023) analyzes the statistical properties and the relationships between various core inflation indicators and other macroeconomic variables. The authors identify 63 different estimates of core inflation and recommend using the median estimate of the calculation group, which has become the basis of the NBK's Forecasting and Policy Analysis System (FPAS).

This paper aims to construct an additional new measure of core inflation for Kazakhstan using a large panel of data that contains price, financial, and real variables. We assume that a few common factors explain most of the variation in the panel. We derive our core estimate by projecting the long-term persistent component of monthly inflation onto these common factors. Our goal is to construct an indicator for inflation that captures the trend component of monthly inflation and provides timely signals of future turning points in inflation. Hence, we filter out idiosyncratic and short-term sector-specific volatilities from the panel to extract the long-run common component of inflation. Methodologically, our estimation strategy closely follows that of Cristadoro et al. (2005), Amstad et al. (2017) и Banbura and Bobeica (2020), who study cross-sectional and dynamic links between price and non-price variables in a large panel of data to estimate an underlying or core measure of inflation. We estimate two indicators of core inflation for Kazakhstan that have some attractive statistical properties in contrast to traditional measures of core inflation. These new core inflation indicators are smoother, less volatile, and have better forecasting ability.

The main difference between this paper and Cristadoro et al. (2005) and Amstad et al. (2017) lies in the input data used to estimate the measure of "core" inflation. Cristadoro et al. (2005) use euro area aggregates of price data and consumer prices comprise only 10% of the data set. [5] Our data set, as will be discussed later in detail, uses mostly consumer prices. Furthermore, unlike Amstad et al. (2017), we use only individual item price data in the estimation. By excluding component aggregates at any level of aggregation, we allow only individual item prices to affect our estimate of the "core" inflation. In contrast to Orlov and Seidakhmetov (2023), who also consider a dynamic factor model to estimate core inflation, this paper introduces three extensions. First, the method is supplemented by isolating the long-run common component using spectral decomposition (Brockwell and Davis, 1987) of the common component. Second, this article utilizes a larger data panel, as it incorporates disaggregated prices for goods and services along with additional non-price data. Third, the application of the Forni et al. (2005) method allows us to avoid end-point problems when using a symmetric centered filter to obtain an equivalent of yearly inflation. Similar to Amstad et al. (2017), we construct two indicators of core inflation for Kazakhstan. The first includes only

[5] Consumer and producer prices together constitute 31% of the data set.

price data for the consumer basket, while the second incorporates real, financial, and other price data in the estimation.

The remainder of the paper is structured as follows. Section 2 describes the methodology used in the estimation of the Core Inflation Indicator. Section 3 provides details of the data we use in our estimation. In Section 4, we discuss the results of the estimates and compare the new estimates of core inflation with the traditional measures. Section 5 analyzes the forecast performance of the estimated indicators and compares it to those of the traditional measures. In Section 6, we evaluate the stability of our estimated indicators using a recursive estimation. Finally, Section 7 presents our conclusions.

2. Methodology

This paper follows Cristadoro et al. (2005) and Amstad et al. (2017) to estimate the Core Inflation Indicator (CII) and applies the Generalized Dynamic Factor Model (GDFM) developed by Forni et al. (2000), Forni and Lippi (2001), and Forni et al. (2005). In the following, we provide the methodology and estimation procedure used to obtain the CII.

We assume that the data can be represented by the sum of two unobservable components:

$$X_t = X_t^* + e_t, \quad (2.1)$$

where X_t is a vector of N series such that $X_t = [x_{1,t}, x_{2,t}, \dots, x_{N,t}]$, X_t^* is a signal that drives the underlying behavior of the data and e_t captures idiosyncratic shocks, short-run dynamics, and measurement errors. Let us assume that $x_{1,t}$ denotes the monthly inflation rate, then $x_{1,t}^*$ is the common component of the monthly inflation rate. To estimate $x_{1,t}^*$, we use the GDFM methodology, which allows us to represent $x_{i,t}$ as the sum of stationary, uncorrelated and unobservable components, $\chi_{i,t}$ and $\xi_{i,t}$. The former denotes the common component and captures a high degree of co-movement between variables in the panel, while the latter denotes the idiosyncratic component, specific to each variable. The common component, $\chi_{i,t}$, is driven by a small number of common factors that underlie the dynamics of the inflation rate. Then, we can rewrite the equation 2.1 for each variables as:

$$x_{i,t} = \chi_{i,t} + \xi_{i,t} = \sum_{h=1}^{q} \sum_{k=0}^{s} \lambda_{i,h,k}\, f_{h,t-k} + \xi_{i,t}, \quad (2.2)$$

Where the common component, $\chi_{i,t}$, is defined by some small number of, q, common factors, $f_{h,t}$, which are loaded with different coefficients and come with different lag structures, with the maximum lag s. Further, following Cristadoro et al. (2005), the common component, $\chi_{i,t}$, can be decomposed into a long-run (persistent) component, $\chi_{i,t}^L$, and a short-run component, $\chi_{i,t}^S$, based on the spectral decomposition of the data. The spectral decomposition allows the representation of the time-series data in the frequency domain. Then, the long- and short-run components can be extracted on the basis of a given cut-off frequency. We set a cut-off frequency of $\frac{\pi}{6}$, that corresponds to the periodicity of 12 months for the following reasons. First, the literature on monetary policy transmission mechanisms demonstrates that changes in current monetary policy affect inflation at a horizon of one year and more (Havranek and Rusnak, 2013; Chernyavskiy, 2017; Andrus, 2025). Second, it allows us to compare our estimated CII with the year-on-year inflation rate, which is monitored by central banks in the monetary policy decision making process. Third, the choice of this periodicity allows us to remove seasonal effects. Hence, the equation 2.2 can be rewritten as follows:

$$x_{i,t} = \chi_{i,t}^{L} + \chi_{i,t}^{S} + \xi_{i,t} = x_{i,t}^{*} + e_{i,t}. \quad (2.3)$$

In the equation 2.3, $x_{i,t}^{*} = \chi_{i,t}^{L}$ is the common long-run component of variable i, while $e_{i,t} = \chi_{i,t}^{S} + \xi_{i,t}$ denotes short-run and idiosyncratic movements, respectively. We eliminate short-run and idiosyncratic shocks as they represent high-frequency changes, measurement errors, and variable-specific shocks that only affect a particular sector. Although these shocks might account for a considerable share of volatility in monthly inflation series, they represent little interest for long-run inflation dynamics. The main idea behind the CII is that it unveils long-run inflation movements and serves as a signal for policy intervention by the NBK.

To compare our estimate of the CII with the year-on-year inflation rate, we smooth out the annualized long-run common component of inflation, $\chi_{i,t}^{L}$, using a symmetric, centered, moving average filter. To avoid end-point filtering problems, we follow Forni et al. (2005) and use forecast values of $\chi_{i,t}^{L}$ for up to 6 months in the smoothing process. For a more detailed discussion of common component forecasts, seeForni et al. (2005) and Cristadoro et al. (2005).

3. Data

The consumption basket in the CPI at the highest level of disaggregation (8-digit level) consists of 508 products and services. For the majority of individual prices (332 items), the data span from January 2011 to September 2025. For twenty (20) items, the available data start from December 2015 or January 2016, and for the remaining items (156) the available data start from January 2021. Then we obtained the monthly inflation series by transforming the data in the following way:

$$\pi_t^i = 100\left(\frac{P_t^i}{P_{t-1}^i} - 1\right), \quad (3.1)$$

where P_t^i denotes the price index for item *i* in the basket in period *t*. The mean value of the entire data set is 0,78% with the standard deviation of 1,66%. The fully available subset has the mean and standard deviation equal to 0,75% and 1,73%, respectively. Cauliflower has the highest mean price inflation (2,58%) among all item prices, while medical masks have the lowest (-0,86%). In total, four variables in the CPI have negative mean inflation. Cucumbers and smoked sausage are the most volatile and least volatile goods, with standard deviations of 22,54% and 0,44%, respectively. The average correlation of all goods with headline inflation is 48%. Six items in the basket have a correlation with headline inflation of 77% and above.[6] Gasoline inflation has an average correlation of 6%.[7] Finally, 21 items are

[6] These items are (ordered by correlation): Toothbrush, men's socks, men's undershirts, bleaches, men's underwear, shoe polish.
[7] Correlation coefficients for gasoline AI-92, AI-95, and AI-98 are 0,07, 0,07, and 0,04, respectively.

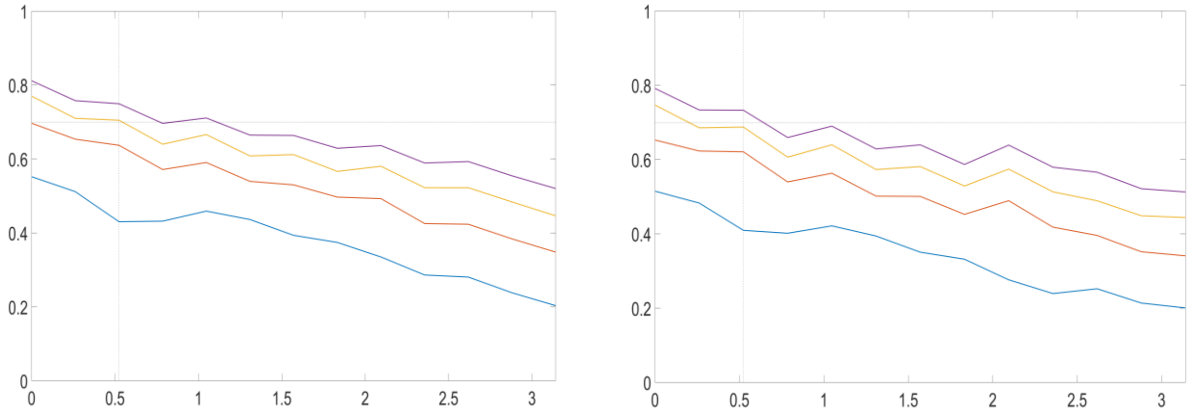
negatively correlated with headline inflation. In addition to the price indices data in the consumption basket, we employ various data on real, financial, and other price indices. There are 48 additional variables with observations that span from January 2011 to September 2025 as well. The complete list of variables used in the estimation is given in the Appendix. All domestic data were obtained from the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan and the NBK. Foreign data such as inflation in Russia, the US, the EU, and China are obtained from corresponding sources.

To obtain the CII we employ 332 item price indices out of 508 that are used in the construction of the CPI in Kazakhstan and the CPI itself. The main reason is that the GDFM method requires a balanced panel of data. As mentioned above, price indices for only 332 items in the basket are fully available for the period of interest. First, we estimate the CII using the consumption basket prices data only, then, we estimate the CII using all nominal and real variables available.[8] Therefore, we can analyze whether other real and nominal macroeconomic variables disclose additional information. As stated above, we are interested in the long-run common component, $\chi_{i,t}^{L}$, of inflation. Hence, we refer to the dynamic principal component analysis described in Brillinger (1981) to compute the spectral density of common components at different frequencies. Then, we discard high-frequency parts and focus only on low-frequency parts (threshold frequency of $\frac{\pi}{6}$). We set a cut-off frequency of $\frac{\pi}{6}$ that corresponds to a periodicity of 12 months and higher because the effect of monetary policy changes on expected inflation come into force only after one year. Furthermore, eliminating low frequencies allows us to remove seasonal effects. Figure 1a and Figure 1b illustrate the share of variance explained by the first four dynamic common factors for the panel with consumption basket prices only and the panel with all data, respectively. The first line from the bottom denotes the variance of the panel explained by the first common factor at each frequency from 0 до π (on x-axis). The second line represents the cumulative share of variance by the first two common factors, and so on. The vertical grid line corresponds to the frequency of $\frac{\pi}{6}(\approx 0{,}52)$ and the horizontal grid line indicates 70% of variance explained. The first four common factors explain on average 77% and 75% of variance at periodicities greater than one year for the consumption basket price panel and the full data panel, respectively.

[8] Hereinafter we refer to the former as the CII-P and to the latter as the CII-F.

Figure 1: Share of variance explained by the first four common factors

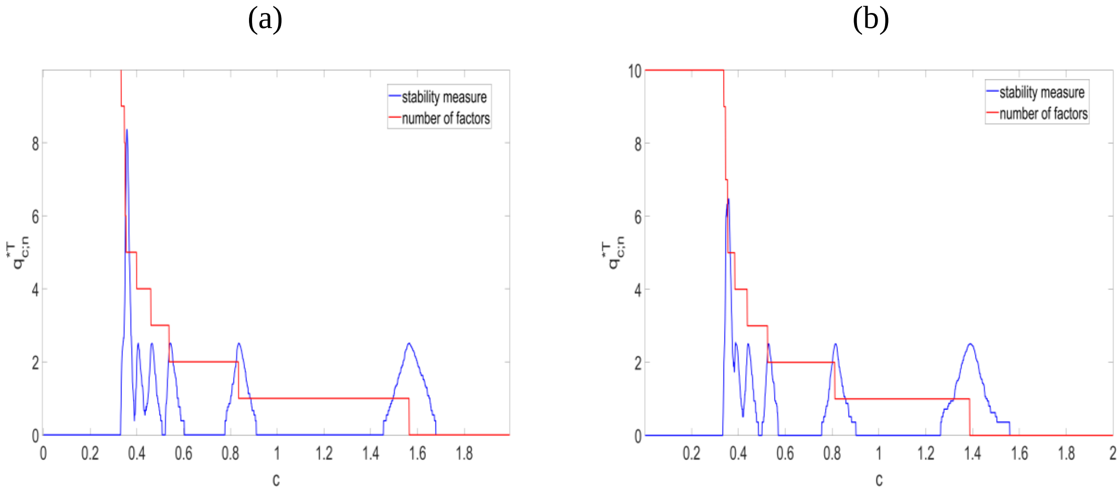
(a) (b)



4. Estimation results

Following common practice in the factor model literature, we standardize each monthly inflation series before the estimation. Hence, each variable in our transformed series has zero mean and unit variance. With regard to the number of factors, the literature on DFM supports the choice of a small number of factors that explain macroeconomic dynamics (Watson (2004); Gianone et al. (2004); Cristadoro et al. (2005); Amstad et al. (2017)). Then, to determine the exact number of factors we refer to Hallin and Liska (2007) and Forni (2000). The analysis based on the methodology of Hallin and Liska (2007) identifies three dynamic factors (q = 3) for both indicators, CII-P (Figure 2a) and CII-F (Figure 2b). The vertical axis of the figure ($q_{c;n}^{*T}$) represents the number of factors, while the horizontal axis (c) – the interval between 0 and 2, within which the stability of the number of factors is determined. According to the authors, in practice, the number of factors is determined by the second stability interval associated with a particular number of factors. In Figure 2 the stability interval is determined by the segment on which the stability measure is adjacent to the x-axis. For the CII-P and CII-F, these stability intervals, [0.51-0.52] and [0.49-0.50], coincide with three factors ($q_{c;n}^{*T} = 3$) on the y-axis of Figure 2a and Figure 2b, respectively.

Figure 2: Number of factors



In addition, following the practical criterion of Forni (2000), we again identify three factors (q = 3) for the CII-P and three factors (q = 3) for CII-F.[9] Hence, the analysis for Kazakhstan does not support the view of Amstad et al. (2017) on the relevance of only one factor for price data. We choose three factors for the CII-P and the CII-F in our further analysis.

Figure 3 depicts year-on-year measures of headline inflation and estimates of the core inflation, CII-P and CII-F, with different number of factors for the period between July 2011 and September 2025[10]. Visual examination of the figure reveals several conclusions. First, there is almost no difference between the estimates of the CII-P using one, two, and three factors. Three exceptional periods, where we observe a slight disparity between the indicators are 2015-2016, 2019-2020, and 2024-2025. In 2015-2016 the CII-P and CII-F with two and three factors are estimated to be above the CII-P with one factor and in 2019-2020 the estimates with three factors seem to better capture the COVID-19 effect than the estimates with one and two factors. In 2020, core inflation estimates with three factors were, on average, higher than in 2019, whereas this trend is not observed in estimates with fewer factors. Finally, in 2024-2025 the estimates with three factors start to increase in April 2024, while the estimates with fewer factors tend to decrease until August 2024. At the same time, the CII-P and CII-F with three factors are higher than the estimates with one or two factors, reaching their peak in June 2025 at 10,35% and 10,38%, respectively. Second, the estimated CII-P and CII-F are smoother and appear to be less volatile than the headline inflation. Third, the estimated indicators appear to be leading indicators of headline inflation in Kazakhstan. We discuss the statistical properties of inflation measures later below.

[9] The number of factors is chosen based on the assigned minimum of the explained variance by the additional factor. We follow Forni (2000) and set the minimum limit to 5%.

[10] Year-on-year inflation is defined as $100(\frac{P_t}{P_{t-12}} - 1)$, while year-on-year core inflation is the annualized common component of CPI smoothed using centered symmetric 13-term moving average..

Figure 3: CII-P and CII-F with different number of factors

(a) (b)

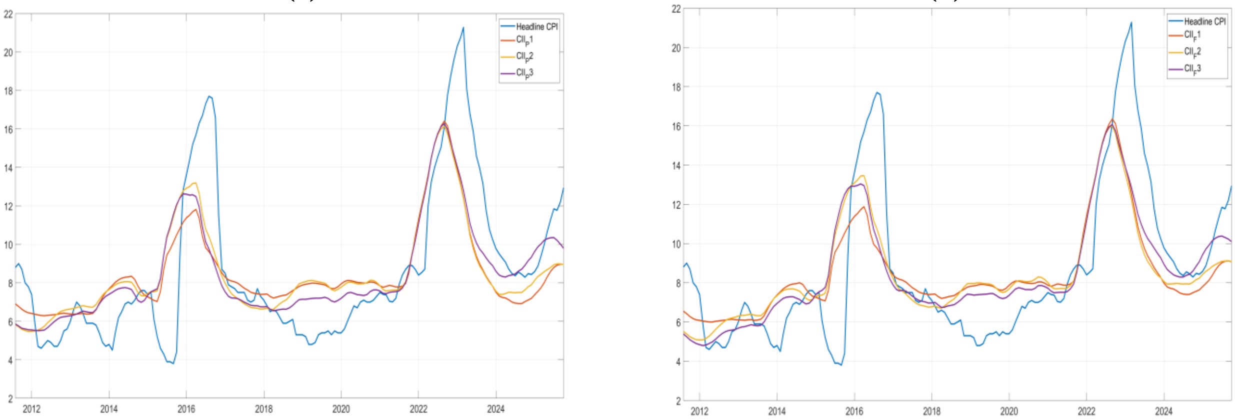


Figure 4 depicts the CII-P and CII-F estimates alongside the CPI and the traditional measure of core inflation, CCPI-FER between July 2011 and September 2025. The dynamics of CII-P and CII-F coincide throughout the entire period, with only minor differences in values. Furthermore, unlike the CPI, both the CII-P and CII-F remained above the 4-6% inflation target in 2019. In 2019, the CPI decreased, reaching a minimum of 4,80% in February and March. As shown in Figure 5a, this decline comes from the paid services component of the CPI, while the food and non-food components did not experience any decline in 2019. In particular, Figure 5b shows that the price indices for electricity, heating, gas, wastewater disposal, and cold water show an abrupt decline in 2019.[11] This highlights one of the problems with the CPI, discussed in Bryan and Cecchetti (1993), related to transitory noise in the CPI due to sector-specific shocks. However, our estimated core inflation indices do not suffer from this issue, since the methodology allows us to eliminate sector-specific shocks. Another case of sector-specific shock can be observed in 2013, when wastewater disposal and cold water prices increased significantly. Further, reforms in the housing and utilities sector, initiated at the end of 2023, led to a significant increase in regulated service prices.[12] Both periods of growth in regulated services significantly impacted the inflation level, whereas the estimated core inflation indicators smooth out these temporary and idiosyncratic shocks.

Between January 2012 and September 2025 the CII-P and CII-F experienced five different phases.[13] The first phase, which begins in January 2012 and ends in May 2014, is characterized by the gradually increasing estimates from 4,8-5,5% to 7,3-7,8%, while headline inflation fluctuated between 4,5% and 7%. The CII-P and CII-F at the beginning of the first phase were well below the target corridor for inflation.[14] In the second phase, from April 2015 to December 2016, which corresponds to the economic crisis of 2015 in Kazakhstan, the indicators increased dramatically and fast reaching 12,63% (the CII-P) in November 2015[15] and 13,04%

[11] All these prices are regulated by the government.

[12] In 2024 and for the first nine months of 2025, prices grew on average by: 25% and 15% for electricity, 30% and 20% for heating, 33.6% and 28.5% for water disposal, and 36% and 85% for cold water.

[13] We refer to the estimates with three factors

[14] he National Bank of Kazakhstan set the inflation target corridor of 6-8% for 2011-2017, 5-7% for 2018, 4-6% for 2019-2022, and 5% starting from July 2023.

[15] The local maximum value of the CII-P then remains until February 2016.

(the CII-F) in February 2016. The increase in the headline inflation started only in September 2015 and reached its maximum in July 2016. The third stage, January 2017 - December 2019, is characterized by stable indicators levels around 6,97% for the CII-P and 7,22% for the CII-F, while the CPI clearly experienced a declining trend until March 2019. In the fourth phase, from January 2020 to March 2024, the estimated indicators experienced the effects of two overlapping shocks: the COVID-19 lockdown in late March 2020 and geopolitical events in the region in late February 2022. During the COVID-19 period, the core indicators were around 7,5-7,7%, well above the target of 4-6%. In addition, the military conflict in the region exacerbated economic conditions and led to a further increase in the indicators. The estimates show that the CII-P and CII-F reached their maximum of 16,3% and 16,1%, respectively, in August 2022. Then they started to decline sharply slowing down to 8,1% and 8,4%, respectively, in March 2024. For the headline inflation, again, visually significant changes started only in March 2022 capturing the effect of the geopolitical shock. It reached its maximum of 21,3% in February 2023 and then declined to 9,1% in March 2024. Finally, the fifth phase, which began in April 2024, is characterized by an acceleration of core inflation indicators amid external and domestic shocks, reaching a peak of 10,35% for the CII-P and 10,38% for the CII-F in June 2025. The headline inflation showed acceleration only in December 2024. As of September 2025, the core inflation estimates have slowed slightly and stand at 9,8% and 10,1%, respectively.

Figure 4: CII-P and CII-F with 3 factors

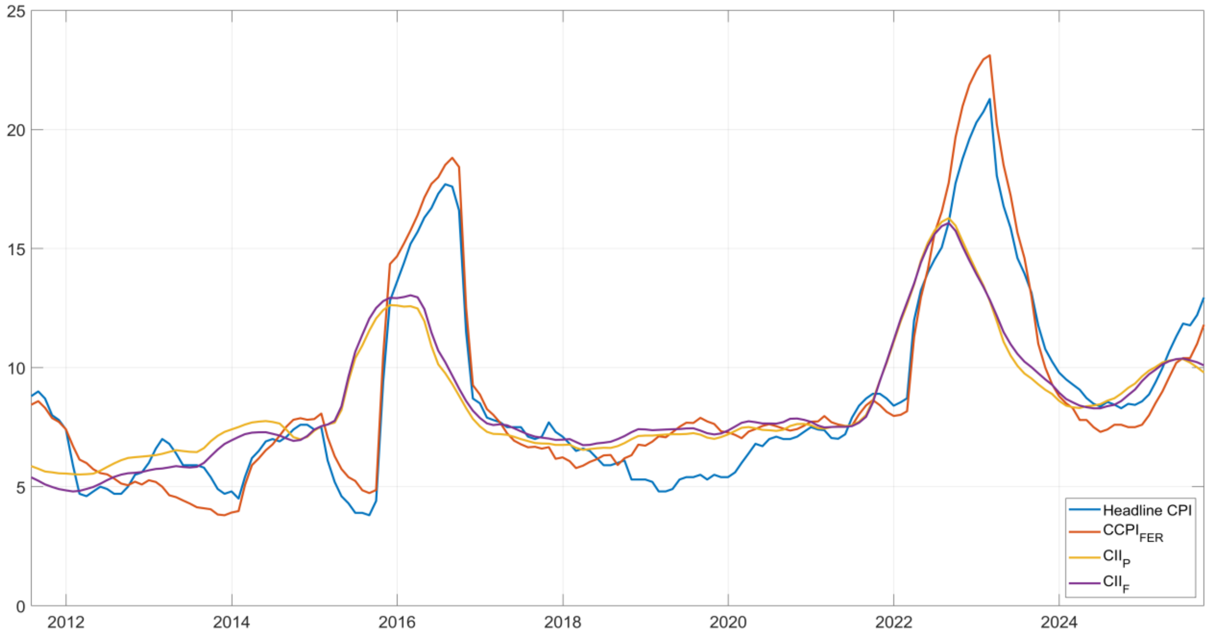
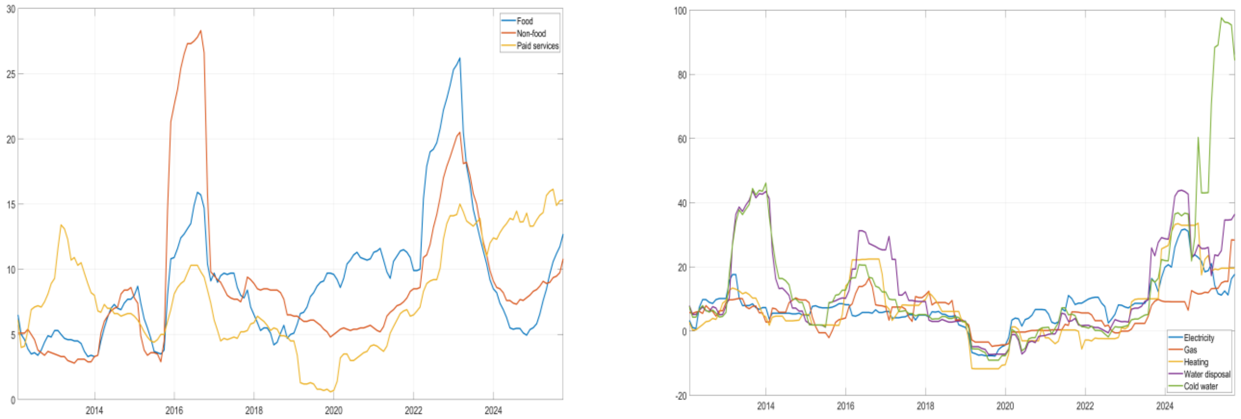


Figure 5: Sector-specific shocks issue

(a) CPI: main components (b) Paid services: individual prices



To analyze the statistical properties of the estimated CIIs in more detail, we provide summary statistics of the inflation measures in Table 1. The estimated CIIs are less volatile than the headline and core inflation series. The standard deviations of the year-on-year change in CII-P and CII-F are 2,47% and 2,59%, respectively, while the standard deviation of the yearly CPI and CCPI-FER are 3,96% and 4,32%, respectively. Moreover, the volatility of the annualized month-on-month change in the estimated CII-P and CII-F is less than those of the headline and traditional core measures. Despite its definition and purpose, core inflation is slightly more volatile than headline inflation. [16] In addition, Table 1 shows that headline and core inflation are almost identical with a correlation coefficient of 0,97 and 0,91 for the yearly and annualized monthly changes, respectively. The correlation coefficient of the CIIs with the yearly headline inflation is quite high as well (0,75 and 0,76 for the CII-P and CII-F, respectively). Next, the cross-correlation analysis shows that the yearly CII-P and CII-F are leading indicators of headline inflation in contrast to the CCPI-FER, which is found to be a coincident indicator. The year-on-year values of CII-P and CII-F lead the CPI by three and two months. In addition, the year-on-year changes in the CII-P and CII-F are coincident indicators of the monthly CPI, while the yearly CPI and CCPI-FER are lagging indicators.

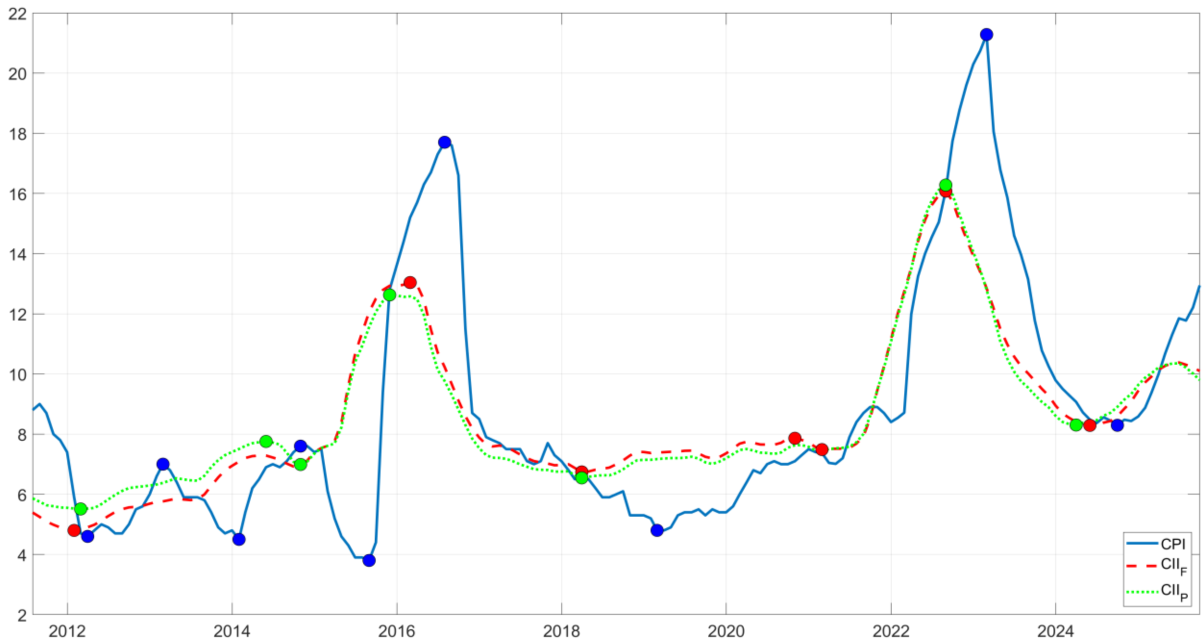
[16] According to the Methodology for calculating the core consumer price index, there are three variants for calculating the BCPI. The first excludes fruits and vegetables; the second excludes fruits and vegetables, gasoline, and coal; and the third additionally excludes diesel fuel, housing and utility services, rail transport, and communication services. This article uses the second and third calculation options.

Table 1: Summary statistics for July 2011-September 2025

	CPI		CCPI		CII-P		CII-F	
	y/y	*m/m*	*y/y*	*m/m*	*y/y*	*m/m*	*y/y*	*m/m*
Mean, %	8,64	8,41	8,85	8,59	8,52	8,52	8,52	8,52
Maximum, %	21,28	62,40	23,12	70,44	16,28	23,05	16,07	22,56
Minimum, %	3,80	-1,20	3,80	0,72	5,40	3,78	4,71	3,19
Std. dev., %	3,96	7,26	4,32	7,48	2,47	3,19	2,59	3,24
Corr. with CPI y/y	1	0,37	0,97	0,39	0,75	0,64	0,76	0,66
Max. corr. Lag	0	4	0	4	3	3	2	3
Corr. with CPI m/m	0,37	1	0,35	0,91	0,54	0,75	0,53	0,73
Max. corr. lag	-4	0	-4	0	0	0	0	0

Figure 6 demonstrates that the estimated indicators can provide early signals of turning points. We applied the Bry and Boschan (1971) algorithm to identify turning points in the CII indicators and the CPI using historical data. The analysis shows that the CII indicators lead the CPI (by three to five months) in identifying significant turning points, such as July 2016, February 2023, and September 2024. Additionally, the CII indicators capture the post-COVID acceleration of inflation in 2021. A possible reason for the estimates in failing to identify the August 2015 turning point is that they had already begun to rise as early as November 2014.

Figure 6: Turning points analysis



5. Forecasting performance

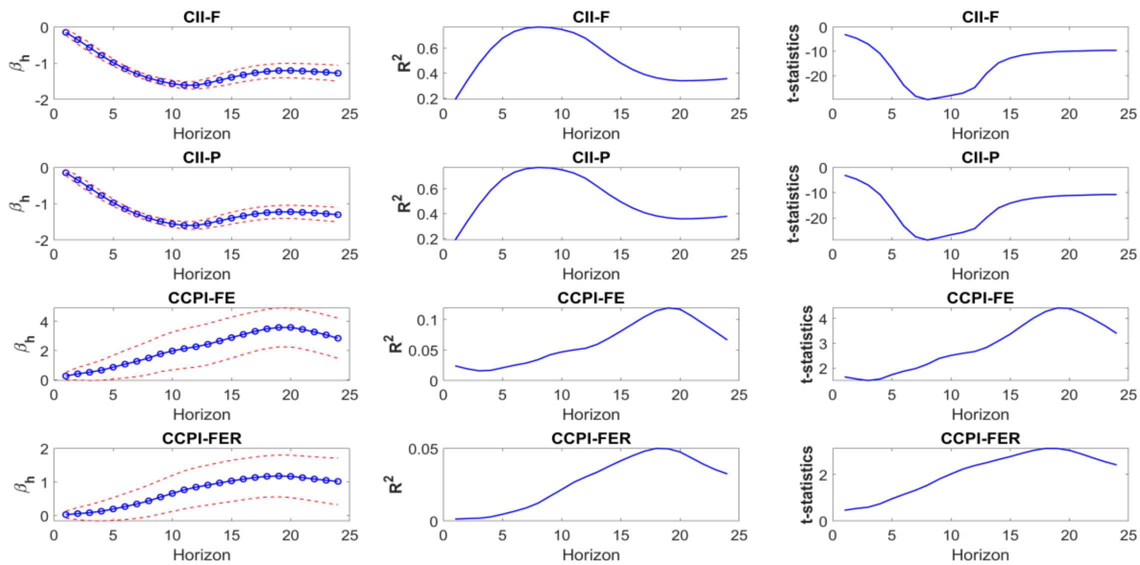
Our final test of the estimated core inflation indicators evaluates the forecast performance of the indicators. We follow Clark (2001) and Cogley (2002) to analyze the predictive ability of our estimated core indicators. In particular, we estimate the following regression:

$$\pi_{t+h} - \pi_t = \alpha_h + \beta_h(\pi_t - \pi_t^*) + \epsilon_{t+h}, \quad (5.1)$$

where π_t^* denotes the estimated core inflation indicator. The term $(\pi_t - \pi_t^*)$ on the right-hand side can then be interpreted as the core deviation. Equation 5.1 states that when the current inflation is above (below) the core inflation, the future inflation should fall (rise). The construct of the equation supposes that the deviation coefficient, β_h, should be negative. We evaluate in-sample and out-of-sample performance of various core inflation measures. For the in-sample forecasting exercise, we estimate 5.1 for horizons from one month to two years, $h = 1,\ldots,24$. We are, particularly, interested in the estimates of β_h and the explanatory power of the core inflation measures.

Figure 7 depicts the results of the estimation. The first column, with dotted blue lines, shows the estimated coefficient for β_h with a 90% confidence interval given in dashed red lines.[17] The estimates of β_h the CII-P and CII-F are all negative and statistically significant at the one percent significance level (column three of Figure 7) at all horizons. It suggests that the core deviation measured by $(\pi_t - \pi_t^*)$, successfully dissipates over time when we use our estimated core inflation indicators. The R^2statistics, reported in the second column, reveal that the CII-P and CII-F explain a substantial amount of the variation in future inflation. For the one-year-ahead forecast (h = 12) the R^2 is equal to 68% for both indicators. The maximum value of the R^2 for the CII-F (77%) and the CII-P (77%) is reached on the horizon of six months. For a two-year horizon (h = 24) both indicators explain around 36-38% of future inflation variation. The estimates for CCPI-FE and CCPI-FER have a wrong sign (positive) and are not statistically different from zero for some periods. In addition, they explain almost zero percent variation in future inflation. Hence, both traditional core inflation indicators are argued to be not satisfactory predictors of future inflation.

Figure 7: In-sample forecasting performance



[17] The confidence intervals are computed from heteroskedasticity and autocorrelation consistent (HAC) estimates of the standard errors.

For the out-of-sample forecasts evaluation, we estimate equation 5.1 recursively and make a one-year ahead, h = 12, forecasts of headline inflation. In particular, we first estimate equation 5.1 for the period between January 2011 and April 2017 to make forecasts for April 2018, and then add one month to the estimation to forecast the value for May 2018 and so on until September 2025. We then compare the RMSE for various core inflation measures for the whole forecasting sample and two sub-samples. The first sub-sample is characterized by a relatively stable inflation period and includes the period between April 2018 and December 2019. The second sub-sample includes the remaining volatile periods between January 2020 and September 2025 affected by multiple shocks. [18] For the out-of-sample forecasts evaluation, we also estimate a simple AR(1) process for headline inflation, π_{t-h}, and include it in the RMSE analysis. Table 2 reports the RMSE for one-year-ahead out-of-sample CPI forecasts. The results show that the CII-F has the lowest RMSE when we consider the whole sample (4,76) and the sample with overlapping crises (5,32). Both the CII-F and the CII-P outperform all other measures for the entire sample and the crisis period. The RMSE for the CII-P is the second lowest after the CII-F in these periods. However, interestingly, for the relatively stable and low inflation period, the CII-P (1,98) slightly outperforms the CII-F (2,12), but the RMSEs for both indicators are inferior to the AR(1) specification (0,67). Forecast analysis shows that the estimated core inflation indicators generally perform better than the traditional core inflation measures. However, the performance of the estimated core inflation measures during the stable and relatively low inflation periods needs further analysis, since a simple backward-looking forecast performs better in a stable environment

Table 2: Out-of-sample forecasting performance in RMSE

	CII-F	CII-P	CCPI-FE	CCPI-FER	π_{t-12}
2018-2025	**4,76**	4,96	5,52	*5,55*	5,25
2018-2019	2,12	1,98	2,90	*3,11*	**0,67**
2020-2025	**5,32**	5,56	6,10	*6,11*	5,98

6. Stability of the CIIs

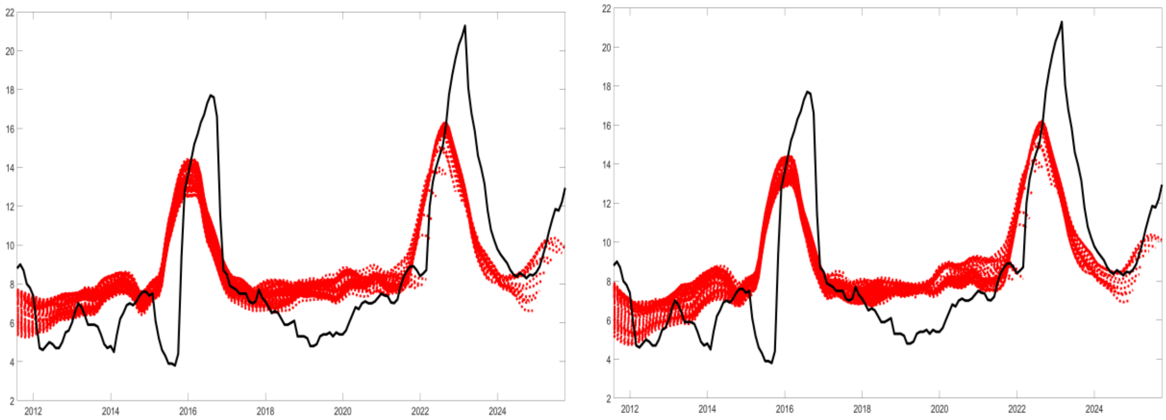
To assess the stability of our estimated indicators, we analyze historical revisions to CII-P and CII-F when new observations are included. We again estimate the core indicators up to October 2016 and add one new observation at each step to generate new estimates. In total, we have 108 estimates for each core indicator. It would have been more insightful to compare the scale of revisions to the core indicators during the stable, non-crisis periods with the revisions during the crisis period. However, the available data span does not allow us to perform this exercise. We do not have enough series with stable periods since the CPI experienced three-four distinctive shocks between 2011 and 2025. Hence, our analysis of the revisions of the estimates can be attributed to the study of stability during crisis periods. Figure 8a and Figure 8b depict the recursively estimated CII-P and CII-F, respectively. In

[18] The COVID-19 pandemic that started in 2020, the Russian invasion of Ukraine in 2022, and domestic sectoral and external shocks.

addition, each plot also shows the year-on-year inflation rate. The results suggest that the overall stability of the estimates, except for some isolated cases, is satisfactory for both indicators. Revisions to the estimates are largely related to the level, but not to the turning points of the estimates. This suggests that our estimated core indicators provide a reliable signal for a possible change in trend inflation.

Figure 8: Stability of the CIIs

(a) CII-P (b) CII-F



7. Conclusion

To conclude, this paper attempts to construct an indicator of "core" inflation for Kazakhstan. We employ a large panel of monthly series of 381 variables that include individual prices of the consumer basket in Kazakhstan and other real and nominal variables to develop two new core inflation indicators for Kazakhstan. The CII-P is based only on consumer basket prices, while the CII-F is estimated using additional real, financial, and price data. In contrast to the literature, our analysis shows three dynamic factors for the estimated core indicators. We show that our estimated core indicators have some attractive statistical properties in contrast to traditional measures. The CII-P and the CII-F are smoother and less volatile than the CCPI-FE and CCPI-FER. Unlike traditional measures, our estimated indicator allows us to include a broad set of real and nominal variables that convey additional information not present in the price data. Furthermore, the new measures of core inflation are coincident indicators of the monthly inflation and thus do not miss the turning points. The latter property is of particular interest to policymakers. The CIIs are largely consistent with the monetary policy interventions except for the later period. The estimated CII-P and CII-F outperform traditional measures of core inflation in the in-sample and out-of-sample forecasts of future headline inflation. The results hold for the whole sample, the stable period, and the overlapping crisis period. Finally, the analysis shows that our estimated indicators are stable and provide a reliable signal of trend developments in the inflation series.

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Appendix

CPI basket items (MoM % change)		
1. All items	2. Polished ground rice	3. Premium wheat flour
4. Semolina	5. Buckwheat	6. Oatmeal
7. Barley	8. Millet	9. Wheat bread made from premium flour
10. Wheat bread made from first grade flour	11. Vermicelli	12. Noodles
13. Buns	14. Gingerbread	15. Elbow macaroni
16. Cakes	17. Cupcakes	18. Sugar cookies
19. Dough	20. Cereal flakes (breakfast cereals))	21. Waffles
22. Horse meat with bones	23. Horse meat (zhaya)	24. Porridge
25. Mutton with bones	26. Chicken	27. Horse meat (kazy)
28. Chicken breasts	29. Beef liver	30. Chicken legs
31. Semi-smoked sausage	32. Sausages	33. Boiled sausage
34. Ground meat	35. Canned stewed meat	36. Uncooked smoked sausage
37. Fresh or chilled fish	38. Frozen fish	39. Semi-finished meat products of small size
40. Canned fish delicacies	41. Ultra-pasteurized, sterilized milk	42. Red caviar
43. Cream	44. Condensed milk with sugar	45. Pasteurized milk
46. Concentrated milk without sugar	47. Yogurt	48. Baby milk powder
49. Fermented horse milk (kumiss)	50. Baked yogurt (ryazhenka)	51. Sour cream
52. Processed cheese	53. Brine cheese	54. Curd mass, cheese
55. Unsalted butter	56. Vegetable butter (spread)	57. Cottage cheese 5-9 % fat content
58. Sunflower seed oil	59. Olive oil	60. Margarine
61. Grapes	62. Bananas	63. Apples
64. Lemons	65. Pears	66. Oranges
67. Nuts (hazelnuts, almonds, cashews, walnuts)	68. Sunflower seeds	69. Dried fruits for compote
70. Raisins	71. Canned fruits	72. Dried apricots
73. White cabbage	74. Onion	75. Frozen berries
76. Carrots	77. Cucumbers	78. Beets
79. Garlic	80. Sweet pepper	81. Tomatoes
82. Peas	83. Beans Фасоль	84. Potatoes
85. Natural, canned, pickled vegetables	86. Canned green peas	87. Pickles
88. Salted and pickled mushrooms	89. Potato chips	90. Canned corn
91. Granulated sugar	92. Refined sugar	93. Frozen natural vegetables
94. Candies glazed with chocolate	95. Candies non-glazed with chocolate	96. Caramel
97. Chocolate	98. Fruit jellies	99. Chewing gum
100. Ice cream	101. Ground red pepper	102. Nut paste
103. Other spices	104. Mayonnaise	105. Ground black pepper
106. Ready-made seasonings and sauces	107. Vinegar	108. Yeasts
109. Dry broths	110. Salt, except extra	111. Tomato ketchup
112. Coffee beans, ground	113. Black tea	114. Instant coffee

115. Semi-finished products for the manufacture of cocoa-based beverages	116. Mineral water	117. Green tea
118. Non-carbonated drinks	119. Carbonated drinks	120. Drinking water
121. Vegetable juices	122. Vodka	123. Fruit juices
124. Champagne, sparkling wines	125. Beer with alcohol content	126. Ordinary, fine cognacs
127. Cigarettes with a filter	128. Cotton fabrics	129. Men's light coat
130. Men's two-piece suit	131. Men's jeans	132. Men's jacket (windbreaker)
133. Men's top shirt	134. Men's jumper	135. Men's trousers made of woolen, woolen fabrics
136. Men's socks	137. Men's underpants	138. Men's sports suit
139. Women's light coat	140. Women's two-piece suit	141. Men's T-shirt
142. Women's jeans	143. Blouse	144. Skirt
145. Women's dress	146. Bra	147. Nightgown
148. Women's jumper	149. Women's tights	150. Women's trousers
151. Women's T-shirt	152. Light jacket for school-age children	153. Women's sports suit
154. Girl's dress made of all kinds of fabrics	155. Girl's skirt made of all kinds of fabrics	156. Suit for school-age children
157. Suit, set for preschool children	158. Children's trousers	159. Top shirt for boys
160. Children's sports suit	161. Children's jumper	162. Blouse for girls
163. Children's underpants	164. Socks, knee socks for children	165. Tights for children
166. Crawlers	167. Baby jumpsuit	168. Children's T-shirt
169. Women's hats, berets	170. Knitted children's hat	171. Men's hats, caps
172. Women's fur hat	173. Scarves	174. Men's fur hat
175. Men's winter boots	176. Men's running shoes	177. Waist belts
178. Home shoes for adults	179. Women's low-heeled leather shoes	180. Men's sandals, summer shoes
181. Children's sneakers	182. Girl's shoes	183. Women's high-heeled shoes
184. Water-based paints	185. Wall tile	186. Dry building mixes
187. Cement	188. Liquefied gas (in cylinders)	189. Linoleum
190. Firewood	191. Table	192. Coal
193. Chair	194. Bedroom furniture set	195. Wardrobe
196. Electric chandelier	197. Wool carpet, with the addition of wool, silk	198. Sofa bed
199. Pillow	200. A set of bed linen	201. Carpet synthetic
202. Plaids made of artificial and woolen fabrics	203. Terry towels	204. Quilted blanket
205. Curtains	206. Tablecloth'	207. Tulle
208. Washing machine	209. Vacuum cleaner	210. Roll-up curtains
211. Kitchen stove	212. Electric heater	213. Microwave oven
214. Iron	215. Electric kettle	216. Air conditioner
217. Glass	218. Tea cup with saucer	219. Electric grinder
220. Kitchen knife	221. Kazan	222. Dinner plate
223. Ironing board	224. Electric drill	225. Plastic bucket
226. Batteries	227. Hammer	228. Electric lamp
229. Washing powder	230. Bleachers	231. Laundry soap
232. Shoe polish	233. Dish-washing detergent	234. Cleaning products for bathtubs, sinks
235. Medical syringes	236. Cotton-wool	237. Corvalol, 25 ml

238. Blood pressure measuring devices	239. Bicycle for adults	240. Eyeglasses
241. Tires for a passenger car	242. Oil filter for passenger car	243. Children's bike
244. Gasoline Euro-92	245. Gasoline Euro-95, Euro-96	246. Gasoline Euro-98
247. Engine oil	248. Telephone set	249. Diesel fuel
250. USB flash drive	251. Soft toys	252. Camera
253. Soccer ball	254. Roller skates	255. Board Games
256. School notebook	257. Ballpoint pen	258. Pet food
259. Sketchbook	260. A4 paper	261. A set of colored pencils
262. Electric hair dryer	263. Shampoo	264. Electric Shaver
265. Soap	266. Baby soap	267. Toothpaste
268. Toothbrush	269. Toilet paper	270. Deodorant
271. Sanitary pads	272. Baby diapers	273. Hair dye
274. Women's bag	275. Satchel, student's backpack	276. Wristwatches
277. Baby strollers	278. Umbrella	279. Suitcases, travel bags
280. Dry cleaning of men's suits	281. Repair of men's shoes	282. Fitting clothes
283. Rental housing	284. Wallpapering work	285. Repair of women's shoes
286. Wastewater disposal, per 1 cubic meter	287. Cold water, per 1 cubic meter	288. Laying tiles
289. Housing maintenance	290. Electricity	291. Intercom
292. Central heating	293. Refrigerator repair (compressor motor replacement))	294. Gas
295. Medical services in an ambulance station	296. Initial doctor's appointment	297. Washing machine repair (heating element replacement)
298. General urine analysis	299. X-ray	300. General blood test
301. Massage of the cervical-collar area	302. Physiotherapy treatment	303. Medical support staff services
304. Day hospital treatment	305. Technical inspection	306. Sanatorium services
307. Commuter train travel	308. Travel by city bus	309. Car wash
310. Travel by intercity bus	311. Sending parcels	312. Taxi fare
313. Cable TV services	314. Cellular communication services	315. Phone subscription fee
316. Printing photos	317. Services of photographers	318. Music education classes
319. Theater services	320. Vacation in Turkey	321. Cinema services
322. Higher education	323. Lunch at the restaurant	324. Secondary education
325. Men's haircut	326. Manicure	327. Hotel accommodation
328. Car insurance	329. Card maintenance services	330. Visit to the sauna
331. Burial	332. Document copying	333. Payment fees
Real, financial, other price data		
334. Industrial production	335. Mining	336. Manufacturing
337. Agriculture	338. Construction	339. Retail trade
340. Wholesale trade	341. Transport	342. Transportation services
343. Communication	344. Fixed capital formation	345. Short-term economic index
346. Manufacturing prices	347. Construction prices	348. Intermediate goods prices
349. Fuel and energy goods prices	350. Rolled ferrous metal prices	351. Non-durable goods prices
352. Capital goods prices	353. Durable goods prices	354. Industrial services prices
355. Housing prices	356. Nominal income	357. Real income
358. Brent crude oil price	359. Nominal exchange rate Tenge/USD	360. Nominal exchange rate Tenge/Euro

361. Nominal exchange rate Tenge/Renminbi	362. Nominal exchange rate Tenge/Ruble	363. Monetary base, M0
364. Narrow money, M1	365. Money supply, M2	366. Savings of population, national currency
367. Loans to businesses, short-term	368. Loans to businesses, long-term	369. Consumer loans, short-term
370. Consumer loans, long-term	371. Interest rates on loans to businesses	372. Interest rates on loans to consumers
373. Interest rates on deposits for businesses	374. Interest rates on deposits to consumers	375. TONIA
376. FEDRATE	377. CPI, Russia	378. CPI, US
379. CPI, EU	380. CPI, China	381. FAO

Figure: Shares of components in the data