ANALYSIS OF CORE INFLATION INDICATORS IN UKRAINE

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1 INTRODUCTION

Since the end of the 1970s fighting inflation became an issue of highest priority in most countries. Targeting inflation, whether direct (in the form of the Direct Inflation Targeting strategy) or indirect, in the majority of cases implies aiming to achieve a specific rate of annual growth of the Consumer Price Index (CPI), i.e. the index that measures the percentage change in the cost of a variety of goods and services comprising the consumers' basket. As such, it is publicized and well known and the target itself is therefore transparent and well understood. However, it is also widely acknowledged that the CPI is a rather deficient indicator of the "trend" inflation especially if measured at high frequencies such as quarters or months. Monthly or quarterly series are usually highly volatile, seasonal and contain a lot of noise. Given the insufficient knowledge of the nature of transmission processes, monetary authorities need some firm guidelines that would help shape their policy to produce the targeted rate of inflation. Most importantly, they need to distinguish between movements in inflation that are transitory and those that are symptoms of the persistent drift of prices. Roger (1995) notes that as long as perceived CPI changes reflect one-time shocks to the general price level (such as for example, a change in the tax rate), or one-off shifts in relative prices, they should not provoke any action on the part of monetary authorities[3].

Therefore, the ideal measure of core inflation should account for the long-term trend movements in prices that reflect the state of demand in the economy and discard various one-off shocks coming from the supply side. This idea of excluding all shocks with no demand-side provenience stems essentially from the mainstream economics view that "monetary policy works primarily through its influence over demand pressures in the economy" (Roger 1995). Therefore one can only hold monetary authorities accountable for inflation that arises from those pressures, i.e. inflation whose elements lie within their direct influence. To see why this is a reasonable setup, one might think of a frequently exploited example of bad harvest caused by unfavorable weather. Rise in prices resulting from smaller-than-usual supply would certainly raise food prices and the entire CPI would pick up temporarily. Now, if the monetary authorities followed the CPI movements closely this would prompt a "tightening" action on their part as the targeted variable moved out of the band. But is it really the right policy to pursue? In other

[3] *Unless monetary authorities target price level*

words, is the registered rise in inflation a sign of the permanent trend or is it just reflecting a temporary shift in relative prices?

This simple example is to provide intuition for what is not at all a trivial problem. How to filter out transitory noise out of price data and construct a measure that can serve as an appropriate guideline for monetary authorities? This paper aims to shed some light on the answers to this complex question in the context of Ukrainian inflation data. Inflation developments in Ukraine have been highly unpredictable in recent years: annual deflation prevailed in the second half of 2002, after which inflation was on a steady rise in 2003 and is now back to moderate levels at 7-8% on an annual basis. High volatility of the CPI inflation makes it more difficult for the Ukrainian policymakers to filter out transitory short-term fluctuations and correctly predict the inflation trend. Core inflation constitutes a potential answer to this problem. It provides the authorizes with a more stable and reliable measure of inflation and is thus a highly desirable policy tool in Ukraine.

In view of the absence of one widely accepted theoretical definition of core inflation, methods of calculating core inflation have proliferated in last 2 decades. Each of them renders itself further to parameterization and owing to numerous values for these parameters, the resulting population of core inflation estimates is virtually infinite. To the extent that all series differ slightly or significantly in the way they filter the data, it is necessary to find a statistical method that reflects core price movements in a relatively most efficient and robust way. In this paper we suggest a complete and methodologically coherent technique of comparing and choosing between various core inflation indicators and then apply it to the Ukrainian inflation data.

The paper is composed as follows. Chapter 2 reviews most important conceptual issues related to core inflation as well as introduces 5 statistical methods of estimating core inflation indicators. Chapter 3 presents and analyzes descriptive statistics of empirical distributions of disaggregated CPI in Ukraine and provides further rationale for using statistical techniques of estimating core inflation. Chapter 4 introduces the 3 criteria used in evaluating core inflation indicators and applies them to the population of empirical series of Ukrainian core inflation indicators. These criteria allow to single out optimal core inflation series for each method separately as well as indicate the series that can be considered the optimal indicator within the entire population of core inflation series. Finally, chapter 5 concludes with summary and recommendations.

2 CORE INFLATION – THEORY AND PRACTICE

2.1 General considerations

Literature suggests two general broad categories of problems that arise when one deals with typically collected price data. Using the terminology borrowed from econometrics they will be labeled *noise* and *bias*.

Noise refers to all transitory shocks that are assumed to add up to zero in the long run, but exert temporary and noticeable influence on prices in the short run (especially when data is reported at high frequencies such as month or quarter). This category encompasses all kinds of shocks that originate in the supply side of the economy, such as seasonal phenomena, broadly defined resource shocks as well as shocks related to exchange or tax rate changes or any other shocks inducing shifts in relative prices. As indicated earlier all these shocks cancel out when one looks at a longer horizon but introduce undesirable fluctuations at high frequencies. Eliminating *noise* will be the primary focus of this study.

Bias in the context of price data is usually thought of as being either *weighting bias* or *measurement bias.* The former is rather unlikely to play a substantial role in the Ukrainian data since it is essentially related to infrequent adjustment of consumption weights. The Ukrainian Statistical Office belongs to a group of statistical agencies that carry out expenditure surveys every year and adjust the weights accordingly. Therefore, the bias that arises as constant weights do not account for relative price shifts, may be harmlessly neglected. *Measurement bias* refers to actual errors in measuring individual prices[4]. It is the subject of numerous studies done mostly in the context of US price data[5] and since it is essentially different in nature than *noise* it will not be elaborated upon in this paper.

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[4] *Cecchetti [1996] gives quality and new goods bias as examples of measurement bias.*

[5] *See Wynne and Sigalla[1993] and Shapiro and Wilcox[1996] for detailed discussion and actual bias estimates for the US.*

Cecchetti (1996) gives a simple formalized accounting framework wrapping up the preceding discussion in formulas. Following his notation, we define:

(1) $\dot{p}_{it} = \dot{P}_t + \dot{x}_{it}$ is the rate of change in the price of an individual CPI item – i

According to the formula it is composed of

$\dot{P}_t$ -the trend movement and the best approximation of the underlying inflation and

-relative price inflation that represents one-time movements inherent in an individual

$\dot{x}_{it}$ item and not representative of the core trend.

Now, the regular "headline" CPI is just the weighted average of all the items:

(2) $\pi_t \equiv \sum_i w_{it}\dot{p}_{it}$ where w_{it}'s represent expenditure basket weights and add up to unity for each t.

or, combining (1) and (2)

(3) $\pi_t = \dot{P}_t + \sum_i w_{it}\dot{x}_{it}$

The second term in (3) is of most interest from the point of view of measuring core inflation. It represents the cluster of noise (n_t) and bias (b_t) that is attached to the "real" inflation period by period for all t's. Writing more explicitly:

(4) $\pi_t - \dot{P}_t = \sum_i w_{it}\dot{x}_{it} = n_t + b_t$

where noise or n_t has zero mean and is stationary and bias b_t can be further decomposed into a constant (μ_b) and a zero-mean transitory component (ω_t):

(5) $b_t = \mu_b + \omega_t$

If we define inflation of an individual item i over k periods as

(6) $\dot{p}_{it}^k = \dfrac{p_{it+k} - p_{it}}{p_{it}}$

this yields the following definition of the aggregate price inflation:

(7) $\pi_t^k = \dot{P}_t^k + \mu_b + \sum_{j=1}^k \left(\omega_{t+j} + n_{t+j}\right)$

In line with the earlier discussion, the assumption is being made that the weighting bias - ω_t is rather insignificant in the Ukrainian price data. As for the measurement bias represented by the constant term - μ_t , it might very well be present in the data, however, it will not be discussed in this paper[6]. It follows from the definition of the noise (in particular from zero mean assumption) that when the number of elements (k) in the right-hand side sum in (7) is sufficiently large, n_t*'s* cancel each other out and the whole summation collapses to zero. In the context of inflation rates this means that with the change of frequency from monthly to 12-monthly, π_t should get closer to $\dot{P}_t^k$ which represents the core inflation.

From (7) it is also clear that taking averages of inflation over longer periods will do the job too as high-frequency noise averaged over longer time horizon is likely to move closer to zero. However, averaging inflation rates in order to approximate trend price movements is not a good option for policy makers who need <u>timely</u> measures, that is, indicators available for use in the first instance.[7]

Ideal estimators of core inflation should also be <u>robust</u>, i.e. relatively insensitive to particular cases (or, in the context of this study, individual price distributions). Robust estimators may not be optimal for every single situation, but their useful feature is good and reliable performance even in extreme settings.

Another desirable characteristic of a good estimator is <u>unbiasedness.</u> It is clear that any good measure of core inflation must hit the "real" core inflation on average. Otherwise, it will tend to mislead us and either over- or understate the core price movements.

2.2 Core inflation: econometric vs. statistical approach

To come up with a measure of inflation that comprises all these characteristics and ends up being a transparent and coherent measure, is not an easy task. Econometric methods (e.g. Eckstein, 1981 and Quah and Vahey, 1995) offer a very interesting and rigorous approach to core inflation calculation.

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[6] *The measurement bias should not weaken the conceptual framework of the analysis presented in this paper since as a constant it does not interact with the time-variable noise.*

[7] *It is obvious that averages will fail as timely measures as one needs some "future" (t>0) observations in order to calculate a contemporaneous (i.e. t=0) measure.*

Eckstein who is considered the father of the term itself[8] defined core inflation in the following way:

"The core rate of inflation can be viewed as the rate that would occur on the economy's long-term growth path, provided the path were free of shocks, and the state of demand were neutral in the sense that markets were in long-run equilibrium. The core rate reflects those price increases made necessary by increases in the trend costs of the inputs to production (Eckstein, 1981, p.8)"

To accompany this theory, Eckstein presented a multi-equation model that produced a core inflation series for the US during the 1960 and 1970s. A more rigorous approach was taken by Quah and Vahey (1995) who defined core inflation as

"the component of headline inflation that has no effect on output in medium and long run (Quah and Vahey, 1995, p. 1130)"

Core inflation is thus interpreted as an "output-neutral" inflation and extracted from the bivariate VAR with inflation and output.

Both methods imply the necessity to use econometrics in order to produce an estimate of core inflation series. This triggers all the well-known consequences such as extreme sensitivity of results to the length of the sample, in particular to its first and last observation as well as pervasive revisions of history (changing of core inflation series) every time the system is re-estimated. Moreover, econometric methods rely on complex[9] models with the use of many other macroeconomic variables (such as GDP or industrial output) which protracts the process of producing core estimates and leaves to entire modeling process open to revisions (every time the GDP estimates are revised).

To be useful for monetary policy, core inflation indicators must be final and available in a timely manner (ideally together with conventional CPI). Therefore, it is not surprising that no central banks use the econometrically generated core inflation series as their official core inflation indicator. When it comes to the active use of core inflation in communicating with the market and setting the parameters of monetary policy the focus is on statistical methods. In spite of the many drawbacks they suffer from (see, for example Wozniak, 2002 or Wynne, 2002), they offer the best techniques of generating core inflation in a reliable and timely manner, with

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8 *Eckstein (1981) first used the term "core inflation" in a coherently defined and elaborated way.*

9 *Particularly in the case of the Eckstein's model.*

no revisions of historical observations and are relatively easy to communicate to the general public.

The statistical methods of calculating core inflation refer directly to the concept of extracting the trend through noise reduction (see 2.1). Most commonly used techniques typically fall into 3 broad categories:

1) Exclusion- based methods

This method relies on the idea of removing certain categories of goods or services from the index. These categories typically include portions or entirety of food and energy aggregates in the consumer basket. The rationale for excluding these items from the calculation of underlying inflation stems from the fact that historically movements in these prices have had much more to do with supply-side transitory shocks (often reversible) rather than the fundamental state of demand in the economy. Additionally, their high volatility obscures the general picture of inflation and hence may trigger inappropriate policy actions.

2) Trimmed means

Trimming involves calculating the core series as a weighted average with reduced or zero weights applied to extreme price movements. However, unlike exclusion (where zero-weighing is applied to specific aggregates), statistical methods are “component-blind”, in that they modify the weights regardless of the CPI category that the affected CPI component belongs to. The resulting core inflation indicator is calculated as the weighted average of the inner, stable core of the distribution.

Ordinary trimmed means

The most common category within this group are *ordinary trimmed means*. Calculating simple trimmed means involves discarding (or zero-weighing) a certain percentage of CPI components (based on their share in the basket) from both ends of the distribution of individual inflation rates and computing the weighted average of the rest. Symmetric trims zero-weigh the same percentage at both ends so that k% trimmed mean eliminates k/2 %[10] highest and k/2% lowest price movements during the period concerned and takes the weighted mean of the middle (100-k)%. Asymmetric means distribute the trim asymmetrically. A special case of a trimmed mean is

[10] *Where percentages refer to basket weights rather than the number of categories.*

the usual CPI (0% trimmed mean) and percentiles that are 100% trimmed means (specifically, median is a symmetric 100% trimmed mean). Thus, ordinary trimmed means are characterized by 2 parameters: total trim (t) and the asymmetry of trimming (a).

Means trimmed according to the distance from the center of the distribution

In the case of this type of trimmed means, the criterion for trimming is the distance from the center of the distribution of cross-sectional price changes. In simple terms, this method eliminates all the components whose prices changed much more or much less than the average.

The new weight system changes every month and can be written as follows:

$$(7)\ \tilde{w}_i = \begin{cases} w_i \text{ for } \forall_i \pi_t^i \le \mu_t + \tau V_t \\ 0 \text{ for } \forall_i \pi_t^i > \mu_t + \tau V_t \end{cases} \text{ where}$$

μ_t is the center of the price change distribution during a particular month t defined for example as the weighted mean,

τ is a non-negative number,

V_t is the volatility measure of individual inflation indices during time t, for example, variance of the cross-section distrubution.

In the re-weighting process items with unrepresentative price changes are zero-weighted and items with price changes close to the average are left with the original weight.

Means trimmed according to price stability

The trimming criterion used here refers to volatility. This method aims at reducing noise by eliminating those components whose variance ratio (to the variance of the CPI) is higher than some cut-off threshold. The implied new weight structure is as follows:

$$(8)\ w_i^{***} = \begin{cases} w_i \text{ for } \forall_i \dfrac{\sigma_i^2}{\sigma_\pi^2} < \gamma \\ 0 \text{ for } \forall_i \dfrac{\sigma_i^2}{\sigma_i^2} > \gamma \end{cases} \quad \text{where}$$

γ is a non-negative number

σ^2 stands for the variance of individual items of the basket (in numerator) or the aggregate CPI (in denominator).

3) Variance-weighted means

The main principle of calculating variance-weighted means is to reduce noise by substituting completely or augmenting consumption-related weights with weights proportional to volatility. The system of re-weighting implies that no items are zero-weighted (which was the case in all 4 preceding methods), but instead, basket elements are given weights inversely proportional to their volatility. Four different types of variance weighted means will be calculated in this paper with the following new weight systems[11]:

Type I: Complete substitution with reciprocal of individual variances $w_i^1 = \dfrac{1/\sigma_i^2}{\sum_{i=1}^{N} 1/\sigma_i^2}$ (9)

Type II: Partial substitution in which consumption weights remain but are augmented (multiplied) by reciprocal of individual variances $w_i^2 = \dfrac{\dfrac{w_i}{\sigma_i^2}}{\sum_{i=1}^{N} \dfrac{w_i}{\sigma_i^2}}$ (10)

Type III: Partial substitution with reciprocal of variances of relative price changes: π_i - π^{CPI} $w_i^3 = \dfrac{w_i \dfrac{1}{\sigma_{(\pi_i - \pi),i}}}{\sum_{i=1}^{N} \dfrac{w_i}{\sigma_{(\pi_i - \pi),i}}}$ (11)

[11] *All weight structures presented below are scaled to unity.*

Type IV : Partial substitution: weights remain but are augmented (multiplied) by the ratio of the CPI variance to individual variances: $w_i^4 = \frac{w_i \frac{\sigma_{cpi}^2}{\sigma_i^2}}{\sum_{i=1}^{N}\left(w_i \frac{\sigma_{cpi}^2}{\sigma_i^2}\right)}$ (12)

Applying such alternative weighting systems ensures that each CPI component gets a weight proportional to the quality and strength of the inflation signal it carries. The contribution of volatile items to the index is reduced while that of stable items is magnified. The end result is a core inflation indicator that indicates the trend inflation movement to a much bigger extend than does the CPI which contains a lot of noise coming from volatile items.

Methods based on crude exclusion (method 1) are very good in that they are concise, simple, and offer a very appealing alternative to the conventional CPI. Their widespread use as indicators of trend inflation does, however, raise of couple of important objections. To the extent that the ideal measure of core inflation should make use of all available price information about long-run inflation trends, is permanent exclusion of food and energy prices always justified? In other words, is it always the case that those price movements convey no such information? Certainly not, and it seems logical to try to construct a measure of underlying inflation that would make use of valuable price information in a more flexible way without automatically discarding specific CPI categories like the first two methods described above. Trimmed means and variance weighted means (methods 2 and 3) seem to fulfill the conditions of an efficient use of available price information and are based to a smaller extent on ad-hoc judgment and discretion.

Throughout the paper several terms will be used interchangeably. Core inflation will be sometimes called underlying or trend inflation. CPI inflation will be referred to as “headline” rate inflation or simply, conventional rate of inflation.

3 EMPIRICAL DISTRIBUTIONS OF DISAGGREGATED CPI

3.1 Description of the data

To date, core inflation for Ukraine has been estimated by Petrik and Polovnyov (2002, 2003). However, their analysis concerns only monthly inflation rates which, due to seasonality, are a much less important measure of inflationary pressures than annual rates. In their 2002 paper Petrik and Polovnyov calculated one exclusion-based indicator for the period 1999:1-2002:5 while their 2003 study includes 3 basic indicators (exclusion, trimmed mean and a median) as well as a moving average and covers the period of 1999:1-2003:4.

Our study is fundamentally different in that we make use of annual inflation rates and apply various theoretical criteria to make a choice of an optimal core inflation indicator for Ukraine. Our analysis also covers the extended sample: we made use of a monthly inflation series for the period 1997:1-2004:5 which yielded 78 annual inflation observations covering the period 1997:12-2004:5.

We decide to work with annual data since annual changes of the CPI became the standard measure of inflation worldwide. Inflation targets are also expressed in annual terms and the annual inflation rate is the primary focus of the financial market. It is somewhat surprising that the Statistical Office and the National Bank of Ukraine do not publish annual inflation rates on a regular basis and instead use some other indices, such as previous month =100 or Dec of the previous year =100). Due to the pervasive seasonality of such indices and in line with clear trend to use the annual inflation rates, we will make use of the annual inflation data and calculate core inflation on an annual basis.

Before calculating core inflation series it is advisable to check descriptive statistics of the Ukrainian data. As mentioned above, our dataset is composed of 85 CPI categories and 89 monthly observations from January 1997 until May 2004. All descriptive statistics were calculated at an annual frequency (k=12). Annual observations on price changes have been obtained by cumulating monthly observations over 12 months at overlapping intervals, so that the resulting data set contains 78 monthly observations: from December 1997 through May 2004.

Following most studies in the field and, specifically, Roger and Cecchetti, we use the following definitions of the weighted moments.[12]

If

$$\Pi_t^k = \sum w_{it} \pi_{it}^k$$

defines aggregate CPI inflation over the period of k = 12 months calculated as the weighted sum of all components using time-variable weights w_{it} , then the r^{th} weighted moment around the mean (the CPI inflation) is defined as:

$$m_{r\,t}^k = \sum_i w_{it} \left(\pi_{it}^k - \Pi_t^k \right)^r$$

and coefficients of skewness and kurtosis which are scaled third and fourth central moments, respectively:

$$S_t^k = \frac{m_{3t}^k}{\left[m_{2t}^k \right]^{3/2}} \qquad K_t^k = \frac{m_{4t}^k}{\left[m_{2t}^k \right]^2}$$

skewness[13] and kurtosis[14]

Figure 1 shows the developments of weighted (defined above) and unweighted (conventional) descriptive statistics of distributions of annual individual inflation rates. The average and median empirical skewness amounts to 1.59 and 1.25, respectively. In the case of weighted skewness the values are: 1.23 and 0.78. In all cases the empirical skewness exceeds the value of 0 characteristic of the Normal distribution.

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[12] *Conventional moments implicitly put equal weights on all observations and therefore give a distorted view of the distribution of price changes. When weighted moments are calculated, the standard CPI becomes just the first central moment.*

[13] *Skewness characterizes the degree of asymmetry of a distribution around its mean. Positive skewness indicates a distribution with an asymmetric tail extending toward more positive values. Negative skewness indicates a distribution with an asymmetric tail extending toward more negative values.*

[14] *Kurtosis characterizes the relative peakedness or flatness of a distribution compared with the normal distribution. Positive kurtosis indicates a relatively peaked distribution while negative kurtosis a relatively flat distribution.*

The situation looks similar with kurtosis. The average and median unweighted kurtosis are 15.23 and 13.94, while the respective values of the weighted kurtosis are 9.26 and 7.36. It is much more than '3' which characterizes the Normal distribution.

The departure of empirical distributions from the Normal is further confirmed if the normalized observations on individual components are pooled to form one population equal to 6630 (85 components times 78 observations). This empirical distribution is presented in Figure 2 and contrasted with the Normal distribution. The figure makes clear that the empirical distribution has higher kurtosis (as evidenced by much fatter tails) and is skewed to the right (as evidenced by more observations in the right far-end of the tail compared with the left one). Positive skewness suggests that during most periods few unusually large price jumps dominated the inflation process. On the other hand, the presence of fat distribution tails as detected by high kurtosis implies that random draws from such a distribution are likely to yield "unrepresentative" values.

Similar studies for other countries confirm the presence of both positive skewness and high kurtosis in inflation data. For monthly U.S. CPI data Bryan and Cecchetti [1998] report with a very slight positive average skewness (0.25), and a kurtosis of 11.44 over the 1970-97 period. Using quarterly data for New Zealand, Roger (1997) finds that the average skewness is 0.7 and kurtosis 7.2. Wozniak (2002) estimated the descriptive statistics on the monthly sample 1991:2001:12 of the 78-element-dataset and obtained empirical values of 2.21 (unweighted skewness) and 16.53 (unweighted kurtosis)[15].

3.2 Additional rationale for using the statistical approach

If we think of the distribution of individual inflation rates of all CPI components during, say, one month as being a drawing from the underlying population of all inflation rates during that period, we can redefine our search for core inflation. It then becomes an issue of finding the most efficient estimator of the underlying mean. A thorough discussion of the statistical rationale of that approach can be found in, among many, Roger (1997) and Wozniak (2002). For the purpose of this study we provide only a brief intuitive explanation.

[15] *Respective values were higher for more disaggregated datasets*

Since we treat the observed individual inflation rates as a sample from the underlying population that is of interest to us, we should condition our estimate on the type of population we are drawing from. Basic statistics tells us that in the case of the Normal distribution, the best and the most efficient estimator of the population mean is the sample mean. However, if we are not sure about the shape of the distribution or if we know it is not normal, then sample average may not be the most efficient in the family of all estimators[16]. Specifically, if the underlying distribution is skewed and leptokurtic, one is more likely to get a sample distribution that contains observations that are unrepresentative for the central tendency. Therefore, simple average which weighs all the observations equally will tend to give a distorted image of the underlying distribution.

Figures 1 and 2 clearly show that the distribution of individual inflation rates is very far from the Normal. It is persistently skewed to the right and has fat tails. Hence, it is easy to see that sample mean (be it weighted or unweighted) will be pulled away from the "true" central tendency by extreme observations.

Conventional headline inflation (CPI) takes account of many shocks and disturbances that are unrepresentative of the long run trend. In calculating the CPI (as with any simple weighted mean), equal importance (albeit no equal weight) is given to each observation. While this is the right method of calculating the central tendency of the sample drawn from the Normally distributed population, it may not always be optimal if the distribution departs from the Normal. Statistical methods of calculating core inflation presented in the chapter 2 constitute the response to these problems. Calculation of exclusion-based methods, trimmed mean as well as variance-weighted means implies re-weighting the CPI basket so that volatile items (that are most likely to be found in the tails of the distributions) are downplayed and stable components are given relatively higher weights. Hence, estimates of core inflation with the use of statistical techniques embody not only the postulates of the theory of core inflation (provide a clear inflation trend) but solve some statistical deficiencies of the conventional CPI, as well.

16 *Nonetheless, it still remains unbiased.*

4 Evaluation of core inflation indicators

4.1 Criteria used for evaluating core inflation indicators

The process of evaluation of various competing core inflation indicators will be carried out with help of 3 criteria most frequently used in the literature:

- Unbiasedness, "attraction" and exogenity - the UAE criterion
- Deviation from the trend - the DT criterion
- Stability – the ST criterion

4.1.1 Unbiasedness, "attraction" and exogenity (UAE)

This complex criterion was first proposed by Freeman (1998) and then augmented by a group of economists from the Central Bank of Portugal[17]. The conditions that constitute this criterion refer to 3 properties that any good core inflation estimate should posses if it is to be helpful for monetary authorities:

- Core inflation series should be unbiased with respect to the CPI.
- CPI should fluctuate around core inflation, i.e. core inflation should "attract" the CPI.
- Core inflation should be (strongly) exogenous with respect to the CPI.

These properties have been formalized in a set of 3 conditions (see for example Marques, P. D. Neves and da Silva, 2000). In the notation below π^c refers to core inflation and π to CPI inflation:

<u>Condition 1) Unbiasedness</u>

π^c and π are cointegrated with unitary coefficient, i.e. $(\pi^c - \pi)$ is stationary and the coefficient α in the regression

$\pi_t = \alpha + \beta * \pi^c_t + u_t$ (13)

is insignificant

<u>Condition 2) "Attraction"</u>

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[17] *See for example Marques, Neves and da Silva (2000) and Marques, Neves and Sarmento (2000)*

There exists an error correction representation for π given by $(\pi^c_{t-1} - \pi_{t-1})$, i.e. $\gamma \neq 0$ in the equation:

$$\Delta\pi_t = \sum_{j=1}^{n} \alpha_j \Delta\pi_{t-j} + \sum_{j=1}^{m} \beta_j \Delta\pi^c_{t-j} + \gamma(\pi_{t-1} - \pi^c_{t-1}) + \varepsilon_t \qquad (14)$$

Condition 3) Exogeneity

π^c should be weakly (strongly) exogenous with respect to π, i.e. λ (as well as all thetas -θ_j) should be equal to zero in the following equation:

$$\Delta\pi^c_t = \sum_{j=1}^{r} \delta_j \Delta\pi^c_{t-j} + \sum_{j=1}^{s} \theta_j \Delta\pi_{t-j} + \lambda(\pi^c_{t-1} - \pi_{t-1}) + \eta_t \qquad (15)$$

We consider that a core inflation series fulfills this criterion if it satisfies all the 3 conditions. Thus, the UAE criterion has a discreet, zero-one character: the series either fulfills it (1) or does not (0).

4.1.2 Deviation from the trend (DT)

This criterion was first formalized by Cecchetti (1996) and applied most extensively in the core inflation literature. It refers to *minimizing deviations from trend inflation.* Cecchetti points out that what central bankers are looking for in inflation figures are timely estimates of a long-term trend in general price level. Therefore, core inflation series that tracks this trend closely should also be considered a good inflation measure for monetary policymakers.

Two assumptions are crucial in order to evaluate core inflation series using this criterion. First, one needs to define the trend series and the function to be minimized. The trend series has been conventionally defined as a centered moving average of the CPI inflation while the deviation function is commonly taken to be the root mean squared error (RMSE) or mean absolute deviation (MAD).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2} \quad (16) \qquad\qquad MAD = \frac{1}{N}\sum_{i=1}^{N}\left|(x_i)\right| \quad (17)$$

where x_i is the deviation from the benchmark trend.

Unlike the UAE criterion, the DT criterion is continuous in that the core series can exhibit the feature of trend tracking to varying degrees. The series with minimum deviation is assigned 1 while all the other series are assigned values from the range (0, 1).

4.1.3 The stability criterion (ST)

This criterion follows from the basic postulate that a core rate of inflation should be characterized by lower volatility than the CPI. Within the population of competing core inflation indicators, those that are most stable, are also the ones that are potentially the most attractive for policy makers (provided of course, they fulfill the previous 2 criteria).

In our study we will use two most intuitive measures of stability: standard deviation of levels and first differences of core inflation series. As was the case with the DT criterion, the stability criterion is also a continuous one. The highest value of 1 is assigned to the most stable series, while all the remaining indicators are assigned values from the range of (0,1)

The final evaluation

Each of the 3 criteria evaluates the population of core inflation indicators in an independent way by assigning values from the range [0;1] in the case of the UAE criterion or (0;1] in the case of the DT and ST criteria. We base the final selection on the sum of the 3 criteria, which assigns each indicator a value from the range (0;3] and orders the entire population accordingly.

4.2 Ordinary Trimmed Means

As explained in section 2.2, ordinary trimmed means are weighted averages of the inner “core” of the distribution. Each month the cross-section distribution of individual price changes is trimmed of a certain percentage of the basket from the left and right tail of the distribution. The sum of the trimmed share of the basket is the total trim parameter (t), while the percentage of the total trim that is trimmed from the left tail constitutes the asymmetry parameter (a). If only integers are considered for both parameters (1 to 100), the population of trimmed means equals 10,000 (100 x 100). Within this population one can single out special cases. All the trimmed means with the parameter t set to 100 are percentiles and specifically the one with a=50 is the median. In addition all the trimmed means with a=50 are symmetric trimmed means which eliminate the same percentage of the basket weight for both tails of the distribution.

4.2.1 UAE criterion applied to ordinary trimmed means

Applying the UAE criterion to the population of 10,000 trimmed means, involves checking the unbiasedness of the core inflation indicators. In line with 4.1 this requires testing whether the deviation of core inflation from the CPI is stationary and zero-mean. This is done by testing the $(\pi^c - \pi)$ for the presence of a unit root and then testing the significance of α in equation (13).

"Attraction" property is tested by testing the null hypothesis of the insignificance of the error correction mechanism (ECM) in equation (14). This test is only applied to the unbiased indicators, i.e. those that passed the "unbiasedness" test.

The third stage involves testing whether core inflation is exogenous with respect to headline inflation. This is done by testing the joint significance of the CPI terms in the Granger causality-type equation (15). This test is only applied to the unbiased core inflation series that possess the "attraction" property as evidenced by the ECM term.

Figure 3 presents the trimmed means that fulfill all the 3 conditions of the UAE criterion. Out of 10,000 analyzed trimmed means only a small fraction turned out to satisfy the UAE criterion. They are are centered around the 48th percentile and comprise trims of 71-100%. The group contains also several means centered on the 47^{th} percentile (trims from 93-100%) and 49^{th} percentile (trims ranging from 85 to 100%) as well as on the 50^{th} percentile (trims 95% and 96%). In particular the means centered on the 50^{th} percentile with trims 95-96% are very close to the weighted median of the distribution (whose parameters are t=100, a=50).

4.2.2 DT criterion applied to ordinary trimmed means

As noted in section 4.1 the DT criterion requires setting the form of the deviation function as well as the series which is to serve as a benchmark trend. We check the sensitivity of results by assuming two alternative forms of the deviation function: root mean squared error (RMSE) and the mean average deviation (MAD), i.e. equation (16) and (17) in 4.1, respectively.

The selection of the benchmark trend is a problematic issue. As some studies show that the results are sensitive to the specific form of the benchmark trend (e.g. Wozniak 1999, Kearns 1998, Meyler, 1999), we take a rigorous approach to choosing it. We assume the best benchmark to be centered moving averages of headline inflation. Out of the many variants of the averaging horizons we choose 25 means: from a 12-month moving average to a 36-month moving average. We select the optimal moving average by applying the UAE criterion to all the 25 moving averages. It turns out that only one moving average fulfills of the 3 conditions of this criterion. It is the 32-month centered moving average. This series will serve as a benchmark trend in all subsequent applications of the DT criterion.

In order to better interpret the results, we transform the deviation function in a way that it assigns higher values to the series that exhibit lower deviation and all values are contained in the range (0;1]. This is done by a simple monotonic transformation (shown here for the MAD function):

$$p(MAD(t,a)) = \frac{(MAD(t,a))^{-1}}{\max\left((MAD(1 \le t \le 100, 1 \le a \le 100))^{-1}\right)} = (MAD(t,a))^{-1} \min(MAD(1 \le t \le 100, 1 \le a \le 100))$$

where MAD(t,a) is the value of the MAD function of a particular trimmed mean with parameters (t,a). The values of the p function (transformed deviation function) for all the analyzed ordinary trimmed means is presented in figure 4.

Quite surprisingly the means that exhibit the lowest deviation from the trend are concentrated around the small trims and small values of the asymmetry parameters. We can also notice a band going through all symmetric trims (a=50), however, the value of the deviation function for trimmed means with lowest asymmetry parameters exceeds that of the symmetric trims. The single trimmed mean that deviates from the trend the least is the trimmed mean with parameters (1,1), marked with a white dot in the figure.

4.2.3 ST criterion applied to ordinary trimmed means

In this paper we assume two alternative forms of the stability criterion: one that uses the standard deviation of the inflation rates and another one, that uses the standard deviation of first differences of inflation rates, i.e. the month-to-month changes in annual dynamics.

Analogously to the DT criterion, the continuous character of the ST requires transforming the volatility function so that the resulting function assigns higher values to more stable series and all values are contained in the range (0;1].

If V(t,a) is the value of the volatility function (e.g. standard deviation) for a particular trimmed mean with the parameters *(t,a)*, the transformation function *p* has the following form

$$p(V(t,a)) = \frac{\left(V(t,a)\right)^{-1}}{\max\left(V\left(1 \le t \le 100, 1 \le a \le 100\right)^{-1}\right)} = \left(V(t,a)\right)^{-1} \min\left(V\left(1 \le t \le 100, 1 \le a \le 100\right)\right)$$

The function is monotonic and assigns the value of 1 to the trimmed mean with the lowest volatility of all and values close to 0 to the most volatile trimmed means.

Figure 5 presents the values of the *p* function applied to standard deviation of both levels and first differences of inflation rates (stability function I and II, respectively). Changing the argument of the stability function changes the results. In the case of levels, the group of optimal trimmed means forms a ‘cloud’ with trims ranging from 60 to 80% and asymmetries ranging from 5-20%. In the case of first differences the cloud is ‘blurred’ somewhat and spreads to higher trims and asymmetries (trims up to 100% and asymmetries between 0 and 30%). The optimal means are tm(69,11) and tm(100,21) - a 21st percentile, for stability functions defined on levels and first differences, respectively.

4.2.4 Final evaluation of ordinary trimmed means

To come up with a final evaluation of the population of trimmed means, we summed up the values assigned by each of the 3 analyzed criteria for all 10,000 trimmed means. Simple summation is naturally subject to criticism, as it implies that the properties checked for by each of the 3 criteria (i.e. unbiasedness-attraction-exogenity, tracking the trend and low volatility) are equally important. This might not always be the case, but seems the most natural assumption to be made when neither theory nor practice indicates clearly the prioritized features of a core inflation indicator. Hence, the final evaluation of the core series will be made based upon the sum of the values assigned by each of the 3 criteria.

Figure 6 presents the results of this evaluation. Clearly, due to the fact that only relatively few trimmed means fulfilled the UAE criterion, scores on this criterion turned out decisive. The optimal trimmed mean was thus chosen from the subgroup of the series fulfilling the UAE criterion and the final choice depended on the sum of the values assigned by the two latter criteria. Trimmed mean trimming 71% of the basket of which 48% from the left tail of the distribution turned out the optimal trimmed mean in the light of the analysis. Other means that came close were the remaining means that scored '1' on the UAE criterion, i.e. means with relatively high trims centered on the 47^{th}, 48^{th}, 49^{th} and 50^{th} percentiles.

This result is robust to the form of the deviation function (RMSE or MAD) or the argument of the stability function (levels of first differences). The optimal trimmed mean along with the CPI is presented in Figure 8.

4.3 Means trimmed according to the distance from the center of the distribution

As follows from the description in 2.2, means trimmed according to the distance from center of the distribution, are characterized by 2 parameters. The first one refers to the exact definition of the center of the price change distributions and the second one sets the threshold for zero-weighting components. In terms of the definition of modified weights (equation 7), we need to define μ which is going to be our benchmark inflation rate and τ which determines the width of the band around the center within which price changes are considered moderate and are given its full consumption weight in the new weighting system. The permitted deviation band is defined in terms of the unweighted standard deviation of the distribution in a particular month.

The main difference between this type of trimming and the ordinary trimming presented in 4.2 is that trimming need not occur at all here when the distribution is relatively condensed and there are no dispersed observations, while in the case of ordinary trimmed means, the distribution is always trimmed regardless of its shape.

In our study we considered 4 alternative definitions of the center of the distribution: weighted mean (equivalent to the CPI), unweighted mean as well as weighted and unweighted median. For the parameter τ, we investigated 100[18] possible values equally spaced between 0 and 1: 0.01, 0.02, 0.03, …, 0.99, 1. These values correspond to eliminating all the components whose distance from the center is larger than 1/100 of a standard deviation up to eliminating all the components further away from the center than 1 standard deviation. Accordingly, the population of means trimmed according to this method is 400 (4 definitions of μ times 100 values for τ)

The analysis will proceed analogously to that in the preceding subsection. Unlike in the previous case, however, we will not present all the intermediate results and instead we will focus on the final evaluation. Figure 9 presents the sum of points scored by each mean in the process of applying the three previously analyzed criteria: UAE, DT(RMSE), ST(CPI levels). The figure graphs four lines (each for an alternative definition of the distribution center) as a function of the τ parameter. Results were robust to changing the stability function in the ST criterion, however, the deviation function did matter for the final result. Thus, figure 9 contains two graphs: upper one for the evaluation with the use of the RMSE function and lower one plotting the results obtained with the use of the MAD function. In both cases the optimal indicator was estimated by trimming around the weighted mean, i.e. the conventional CPI. The optimal mean eliminates all components whose price changes deviated more than 1/10 or 1/4 of a standard deviation from the CPI (for RMSE and MAD, respectively).

Figure 10 presents both series along with the CPI.

[18] *We also checked values higher than 1, but they yielded series with worse characteristics*

4.4 Means trimmed according to price stability

Rationale for calculating this type of trimmed means stems from acknowledging that individual CPI components are characterized by a different strength of the "inflation signal" and this strength is not directly related to consumption weights. Stable CPI components, i.e. those whose price changes are moderate, contain much more information about the trend than those whose price changes are very dispersed. Therefore, if a core inflation indicator is to reflect a inflation trend, it is advisable to eliminate the influence of volatile, "noisy" items. However, unlike in the case of previous methods, where only the cross-section properties of the data were exploited, this technique makes use of the time-series dimension of the data as well. In particular, it assigns new weights based on the volatility of the time series of CPI components: components whose variance has been high are excluded from the new basket, while those who were stable become part of the basket.

In our study, we define volatility in terms of the ratio of a variance of an individual component to the variance of the CPI inflation during a particular period of time (equation 8). If this ratio exceeds a parametrized value - γ, the item is zero-weighted. We investigate 30 possible values for this parameter equally spaced between from $\gamma=1.05$ and $\gamma=2.5$[19]. The first one corresponds to the situation in which all items with variance higher than the variance of the aggregate CPI get discarded from the basket. The last one sets the threshold much higher: only those items that are 2.5 times more volatile than the CPI are assigned a zero weight.

In addition to the threshold parameter γ, we consider 2 alternative ways of defining volatility: one based on levels of price changes, another one based on first differences of price changes. Horizon of measuring variance in our study ranges from 12 to 36 months. Thus, the total population of means trimmed according to the price stability criterion is 1500 (2 volatility definitions x 30 values for parameter γ x 25 different time horizons).

Figure 11 presents the results of the evaluation of means trimmed according to price stability. The figure contains only means estimated with the use of variance on first differences of inflation since this definition yielded visibly better results than those estimated with the use of variance on levels of inflation. The series that scored highest were the ones calculated with

[19] *We also checked values higher than 2.5, but they yielded series with worse characteristics.*

the value of γ=1.1 and the longest variance horizon: 36 months. This result is robust to changing the standard assumptions in DT and ST criteria.

Figure 12 presents the optimal trimmed mean in this category along with the CPI.

4.5 Variance-weighted means

Variance weighted means exploit the signal-noise properties of the disaggregated CPI components to an even higher extent than do means trimmed according to price stability. While the trimmed means implied a rigid system of either discarding or including the components based on analysis of their volatility, variance weighted means offer a more gradual and sophisticated approach. The weighting system is modified in a continuous manner allowing for weights of more stable components to be expanded and weights of more volatile components to be reduced. Instead of assigning zero or full weights, this method implies adjusting weights by factors inversely proportional to individual variances.

In our study we will investigate 4 systems of weights' re-adjustments described by equations 9, 10, 11 and 12. Furthermore, analogously to means trimmed according to price stability, we will use two alternative arguments of the volatility function (variance), namely: levels and first differences of price changes of individual components. The width of the variance horizon will vary from 12 to 36 months. This parameterization produces 200 different variance weighted means (2 volatility definitions x 4 weight adjustment systems x 25 time horizons).

Figure 13 presents the results of the evaluation of variance-weighted means. It has to be mentioned that none of the 200 variance weighted means fulfilled the UAE criterion in an analyzed sample. Hence the values presented in the figure are sums of respective scores from the DT and ST criteria. In order to retain the clarity of the figure we present only 2 variants of variance-weighted means that scored consistently highest scores throughout the evaluation process. First, when we applied the RMSE function in the DT criterion, means estimated on first differences with the weight adjustment system described by equation 12 (variant I), turned out the best. When MAD was used instead, the lead was taken by means based on levels of price changes and the adjustment system described by equation 11 (variant II). The sum of evaluation criteria scores for indicators estimated according to those two methods are plotted in figure 12 against the width of the variance horizon.

The figure indicates that in both cases, optimal means are calculated with a wide moving window: maximum allowed, 36 months (RMSE) or 32 months (MAD). Also common for both variants presented in the figure is the weight adjustment method that augments the consumption weights of individual CPI components with the measure of their volatility relative to the volatility of the aggregate CPI.

Figure 14 presents these two variance weighted means along with the CPI.

4.6 Exclusion-based means

This is the single most frequently applied method of calculating core inflation among central banks. In fact, when most people think of core inflation they think of some indicator that is calculated by permanent exclusion of specific broad aggregates, like food, energy or fuel. Exclusion-based means imply a zero-one re-adjustment system and exploit only a cross-section dimension of data on price changes: components that are considered volatile and “noisy” are eliminated from the basket while the rest retains their original consumption weight. The crucial issue in estimating the core inflation indicator according to this method concerns the selection of components to be excluded. Traditionally they included food and energy due to the fact that their short term movements in the past reflected supply-side transitory shocks rather than fundamental state of the demand in the economy. However, the exclusion-based method does not formalize the selection process (there are no formal criteria to guide the researcher) and hence the decision is rather arbitrary and relies on subjective judgment. The excluded goods or services typically fall into 3 categories:

- Administratively controlled items; prices are controlled directly by the Government or indirectly through the Government agencies or local authorities and are adjusted upwards in a discreet (one-off) manner (e.g. electricity in most countries)
- Items whose price contains a high share of indirect taxes (e.g excise); movements of such prices are typically triggered by tax changes and are not demand-driven (e.g. alcohol, tobacco)
- Items whose price changes contain a significant seasonal component prices or are shaped by other clear supply-side effects. (e.g. fuel, unprocessed food).

For the purpose of calculating exclusion-based means we singled out the following "candidate" categories to be excluded (consumption weight used in 2003/04 in brackets):

1. All food (63.5%);
2. Raw food: meat, eggs, butter, sugar, flour, bread, potatoes, vegetables, berries (28.7%)
3. Fuel (0.5%);
4. Tobacco (1.3%);
5. Alcohol (2.0%);
6. Public utilities (9.3%);
7. Communications (1.5%);
8. Transport (2.7%);

Components so defined were excluded from the CPI basket in different 56 combinations. Consequently, we calculated 56 series of exclusion-based means in which the total weight of excluded components ranged from several to over 80%. The process of evaluation of these indicators revealed that none of them fulfilled all three conditions of the UAE criterion. Also, the results were robust with respect to the form of the stability function (criterion ST), but not to the form of the deviation functions. Thus, 2 different series can be considered optimal in this category. When RMSE was used as a deviation function, the best evaluation score was registered for the mean excluding raw food (2) and the communication services (7) results (the total weight of excluded elements: 30.2%). However, when the MAD function was used, the optimal indicator turned out to be the mean calculated without raw food(2), fuel(3), public utilities(6), alcohol (5) and tobacco (4) (total weight of excluded components amounts to 41.8%).

Both series are presented in Figure 15.

4.7 Aggregate evaluation

So far we have applied the UAE, DT and ST criteria to each method separately in order to identify the parameters that characterize the optimal series within each of the 5 methods. Each evaluation procedure resulted in selecting one (4.2 and 4.4) or two (4.3, 4.5, 4.6) series that perform the best so that the subgroup of optimal indicators contains 8 series. However, the evaluation values (sums of the scores on 3 criteria) cannot be used outside of a particular method. They are incomparable due to the fact that the scores on DT and ST have been scaled (divided) by the maximum within-method value of the score (see 4.2.2 and 4.2.3) so that the domain of values ranges from 0 to 1. Therefore, the group of 8 optimal series will undergo the same evaluation procedure once again.

Figure 16 presents the result of this evaluation for each of the 4 possible combination of assumptions:

1. RMSE used in DT and stability I (levels) used in ST
2. RMSE used in DT and stability II (first differences) used in ST
3. MAD used in DT and stability I (levels) used in ST
4. MAD used in DT and stability II (first differences) used in ST

Each of the 8 lines indicates one optimal series while on the x- axis the four observations refer to the 4 combinations of assumptions in the sequence presented above. The series are numbered from 1 to 8 and denote the following core inflation indicators:

1. Ordinary trimmed mean with the parameters (71, 48) - see section 4.2
2. Mean trimmed according to the distance form the CPI with th parameter τ=0.1 – see section 4.3
3. Mean trimmed according to the distance form the CPI with th parameter τ=0.25 – see section 4.3
4. Mean trimmed according to price stability with parameters γ=1.15 and h=36 – see section 4.4
5. Variance-weighted mean with the weight adjustment described by equation 12 and parameter h=36 – see section 4.5
6. Variance-weighted mean with the weight adjustment described by equation 11 and parameter h=32 – see section 4.5
7. Exclusion-based mean without raw food and communication services – see section 4.6

8. Exclusion-based mean without raw food, fuel, public utilities, alcohol and tobacco – see section 4.6.

Figure 16 makes clear that the first 3 indicators: the ordinary trimmed mean and the two means trimmed according to the distance from the CPI outperform by far the remaining core inflation series. In particular, the means trimmed according to the distance from the CPI take the lead in all 4 cases: when stability function I (levels) is used the mean with value of τ=0.25 turns out to be the best, while the use of stability function II (first differences) implies that the best mean is the one with τ=0.1. However, both series take the two leading places in each of the 4 “rankings”.

This result might be viewed as somewhat surprising especially in what concerns the trimmed mean with τ=0.1. This mean implies that any price changes that differ from the CPI by more than a mere 10% of the standard deviation in the respective month, get eliminated from the index. Because the band is so narrow, what we are left with is several price changes immediately around the CPI. Hence, it comes at no surprise that the resultant series is very close to the CPI. On the other hand, another trimmed mean (favored when the MAD function was applied) looks much more reasonable. In the process of calculating it, the basket is cleaned off all the elements whose price changes exceeded one-quarter of the standard deviation. Figure 10 suggest that it is rather stable, behaves fairly well and clearly indicates the trend.

Another potentially good core inflation indicator is the ordinary trimmed mean. The differences in the total score (Fig 16) are very small between first 2nd and a 3rd indicator, therefore this trimmed mean is almost equally recommendable. Out of practical reasons, however, it might be possible to use the parameters that are more likely to be accepted by the public, i.e. asymmetry parameter equal to 50 (instead of 48) and the total trim equal to 70% (instead of 71%). This mean is very close to the optimal one (71,48).

5 Summary and conclusions

In this paper we analyzed a sizeable population of core inflation indicators for Ukraine and evaluated them according to standard criteria postulated in the literature. The investigated population included not only all the statistical methods that are used among central bankers but also some new or modified ones that have not been formalized before, but contain elements of the previously applied approaches (such as means trimmed according to price stability). Due to the parametrization of the methodology, we obtained a sizable population of 12156 series that can be considered comprehensive and complete.

The population of core inflation series was evaluated using a set of 3 criteria each of which refers to the desirable properties of a core inflation indicator. Altogether, these criteria ensure that the indicator that will score high in the ranking will

- Be unbiased,
- Have the attraction property, i.e. it will "pull in" the CPI whenever it drifts away from it
- Be exogenous with respect to the CPI,
- Will track the trend inflation well
- Will be stable in terms of both levels and first differences.

Our analysis revealed that 3 core inflation indicators stand out in the optimality ranking. The first two trim all the price changes that are further away from the CPI than 1/10 and 1/4 of a standard deviation. A third one trims 34.08% of the basket form the left tail of the distribution and 36.92% from the right tail of the distribution. Due to the fact that the first one is rather close to the CPI, our recommendation points to the other 2 indicators. They are presented in figure 17 together with the CPI.

Both core inflation series perform well in reducing volatility of the original series, albeit indicator II seems to do a better job: it is much smoother and filters out the noise more efficiently.

Although indicator I dropped below zero for one month in 2002, we can say that both series did well in terms of treating the deflation period. The conventional CPI indicated that this period lasted for 7 months (second half of 2002 and early 2003), while the core indicators did not register this phenomenon at all (series II) or barely pointed to it (series I) in September 2002. Thus, we consider that both indicators passed this text very well.

It has to be mentioned that while ordinary trimmed means are used by many central banks (e.g. Bank of England, National Bank of Poland), the other types of trimmed means, and particularly, the means trimmed according to deviation from the CPI, have not been used officially, to the best of our knowledge, in any central bank. Thus, if the National Bank of Ukraine decides to introduce core inflation to its official indicators, for practical reasons, it might be easier to start with ordinary trimmed means. Furthermore, all of the trimmed means used at central banks are symmetric means, even though some authors (Marques et al. 2000, Wozniak 2001) suggest that asymmetric trimmed means might be more efficient. For simplicity, we might suggest that the trimmed mean, instead of parameters (71, 48) might be also calculated with the simpler parameters (70,50) to produce a very similar result.

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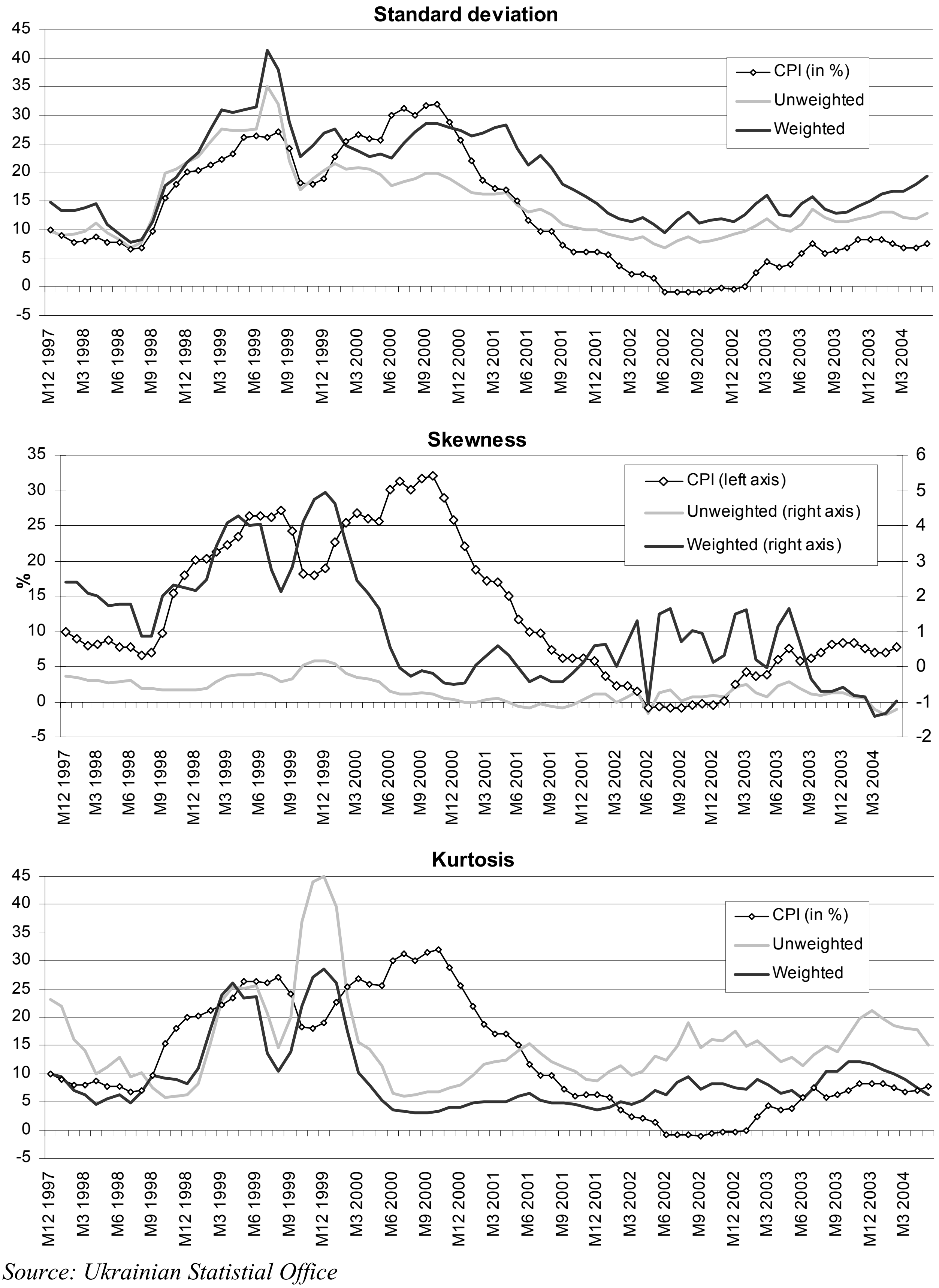
Figure 1. Descriptive statistics of disaggregated distributions of Ukrainian annual CPI data (78 components)



Source: Ukrainian Statistial Office

Figure 2. Cumulated empirical distribution of annual price changes of CPI components

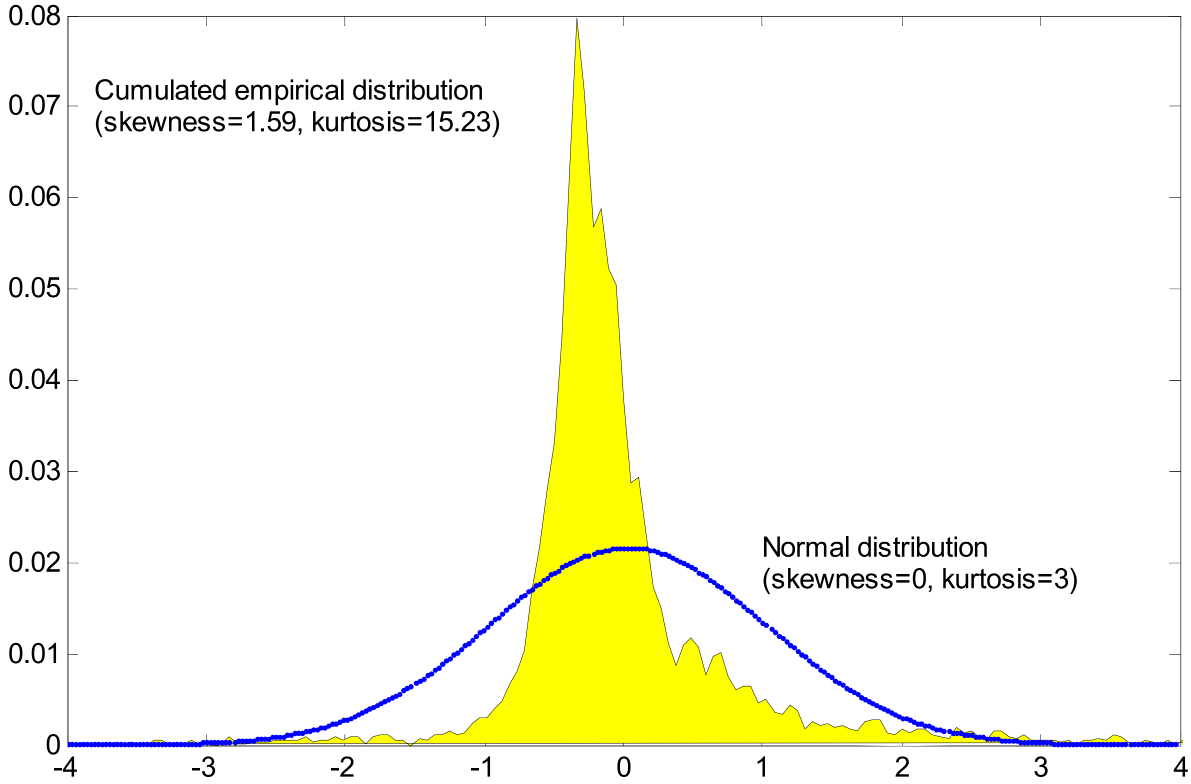


Figure 3. Ordinary trimmed means satisfying the UAE criterion

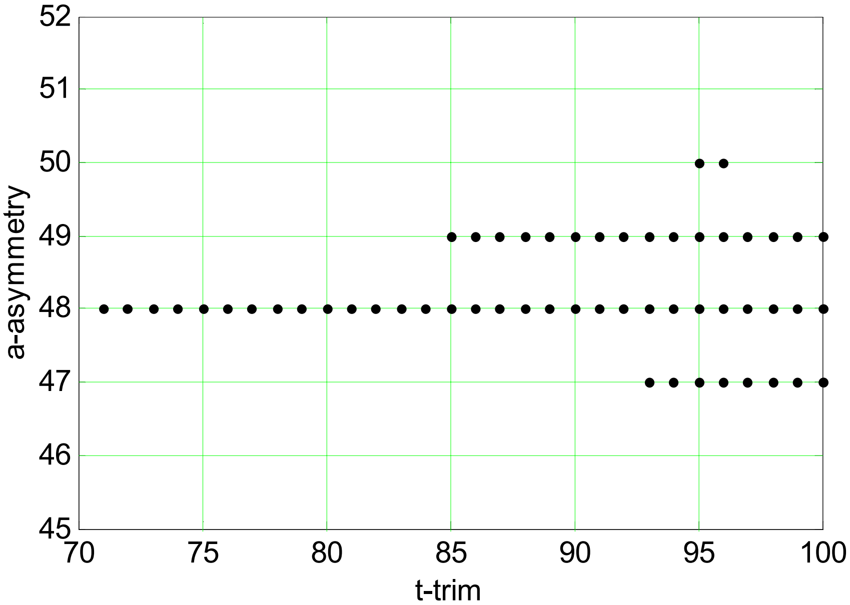


Figure 4. Trimmed means according to the deviation from the trend criterion

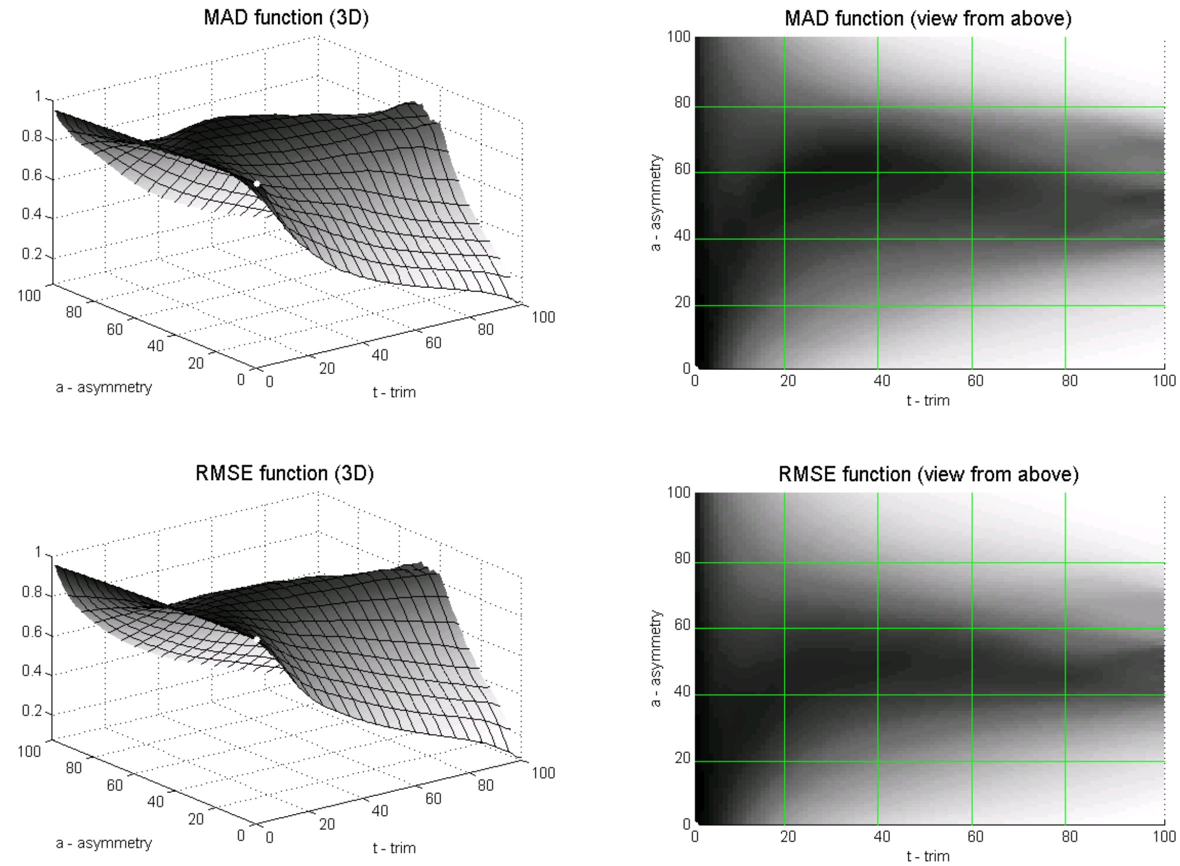


Figure 5. Ordinary trimmed means evaluated according to the stability criterion

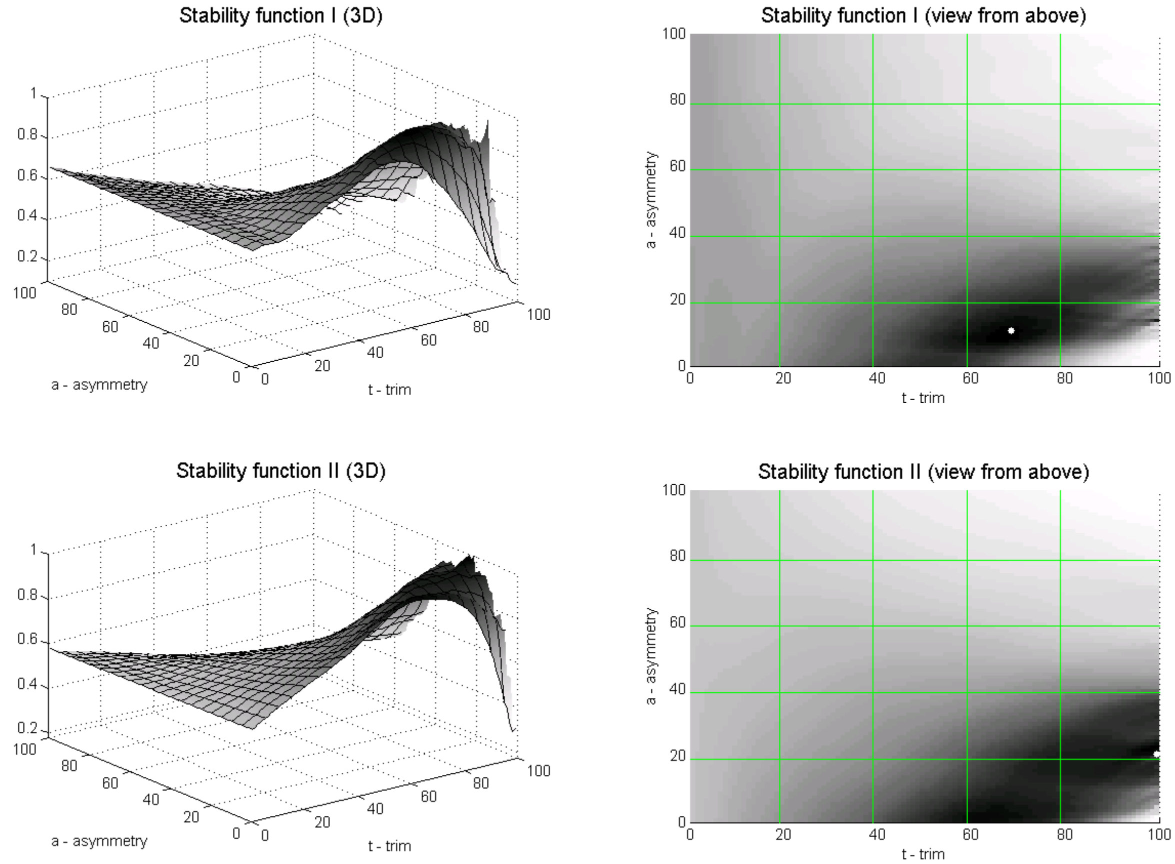
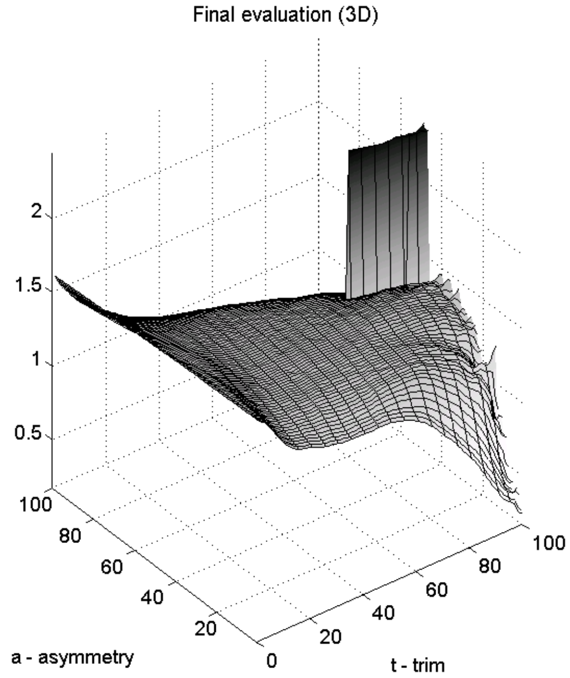


Figure 6. Final evaluation of ordinary trimmed means



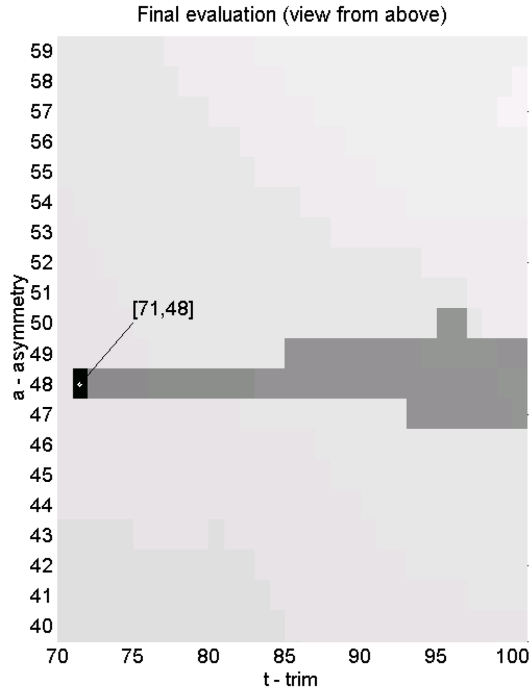


Figure 8. Optimal ordinary trimmed mean and the CPI

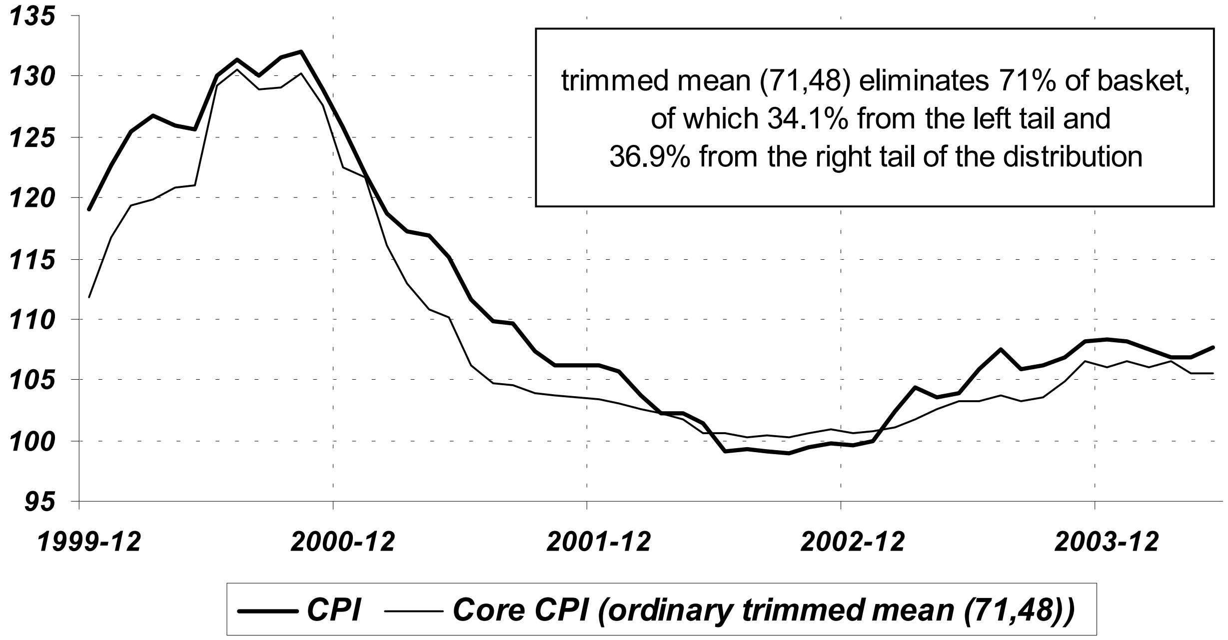


Figure 9. Final evaluation of means trimmed according to the distance from the center of the distribution

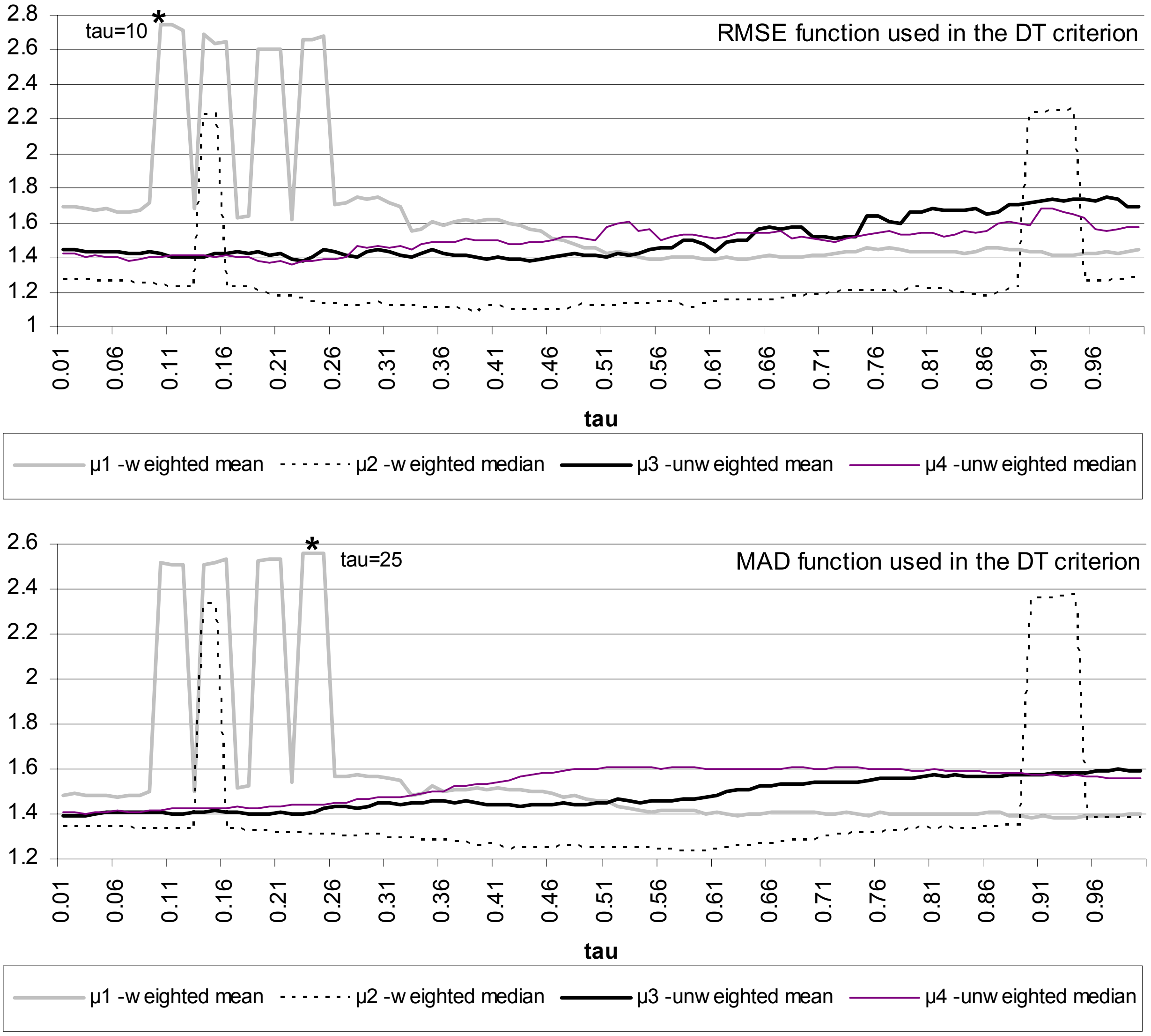


Figure 10. Optimal trimmed means according to the distance from the center of the distribution and the CPI

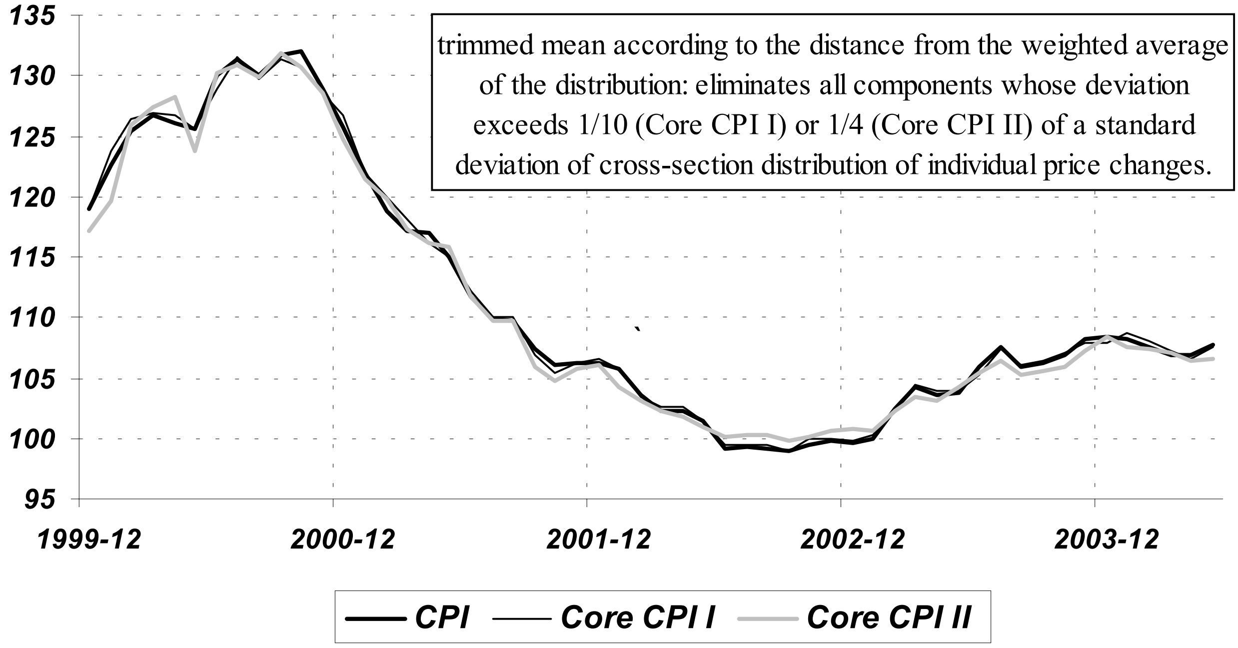


Figure 11. Final evaluation of means trimmed according to price stability

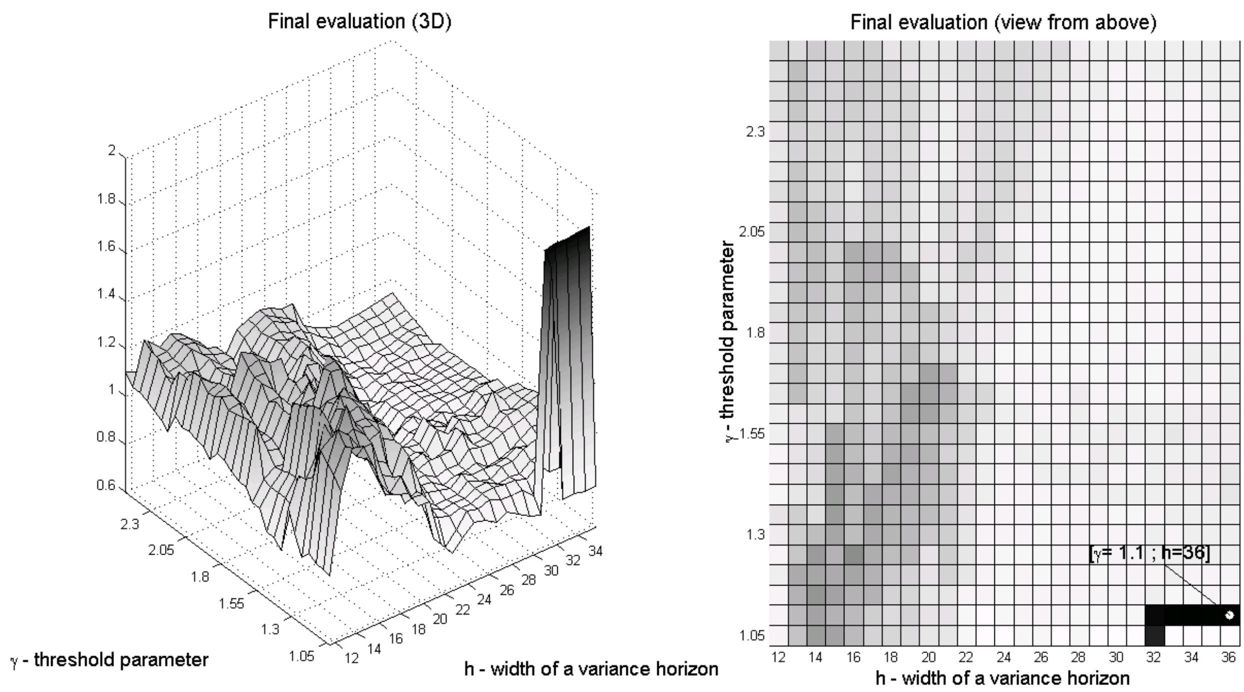


Figure 12. Optimal trimmed mean according to price stability and the CPI

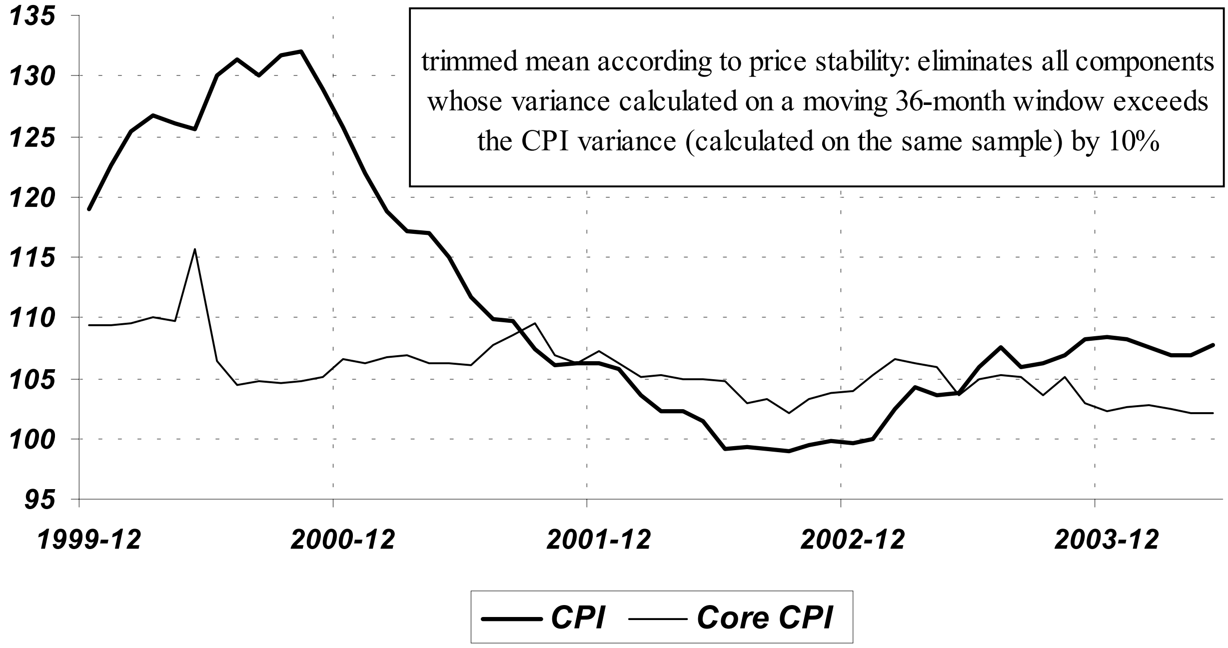


Figure 13. Final evaluation of variance-weighted means

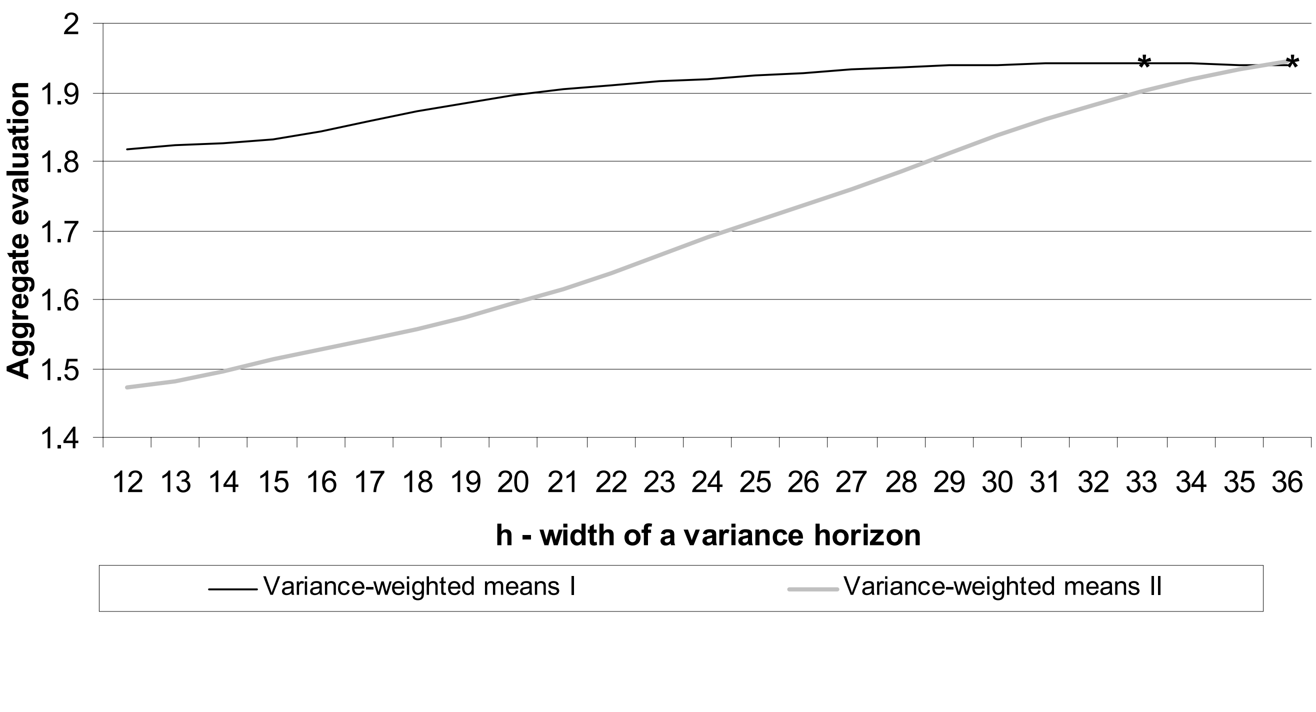


Figure 14. Optimal variance-weighted means and the CPI

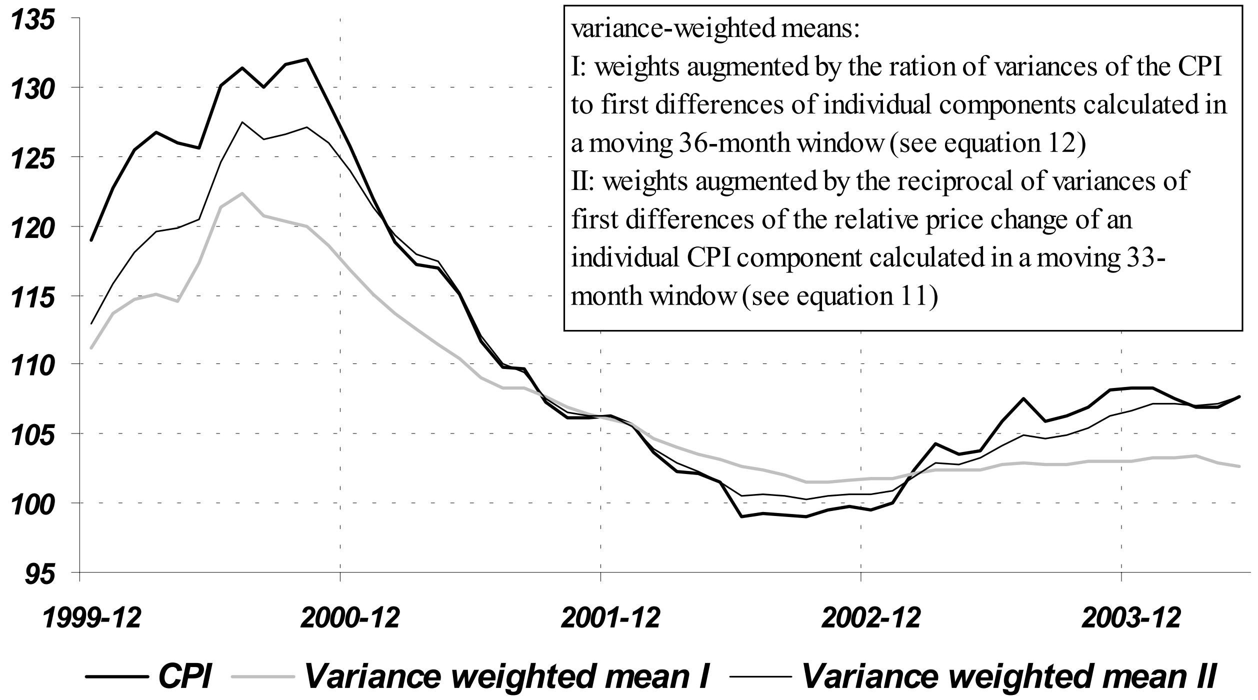


Figure 15. Optimal exclusion-based means and the CPI

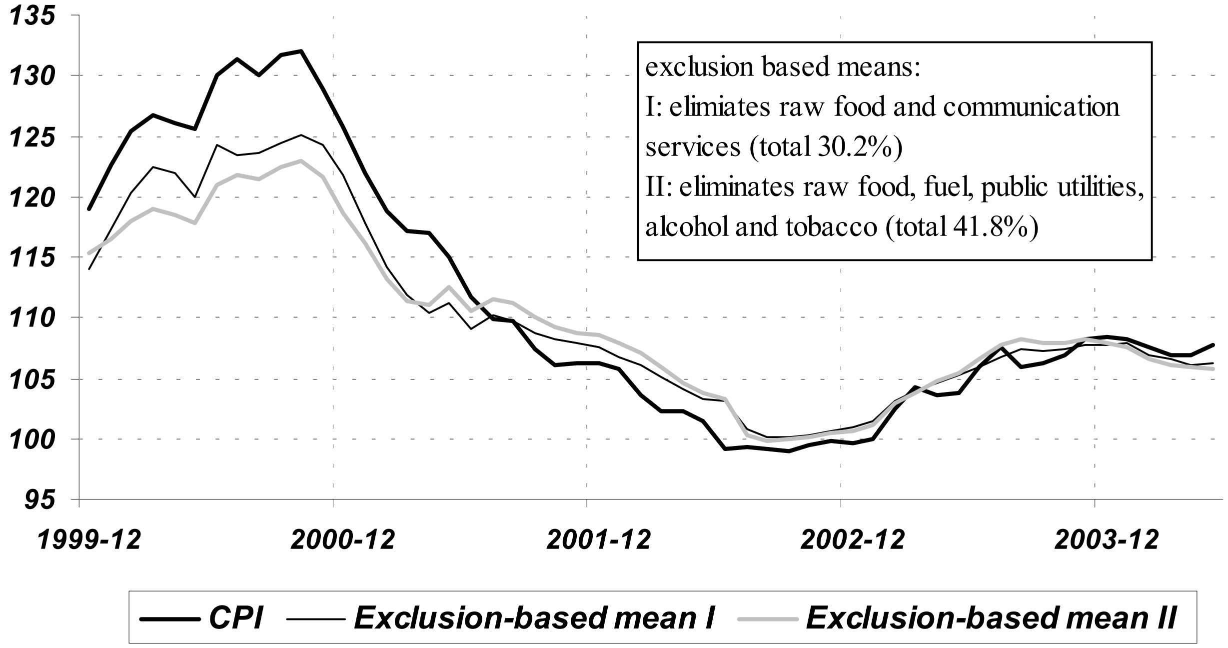


Figure 16. Final evaluation of optimal core inflation indicators

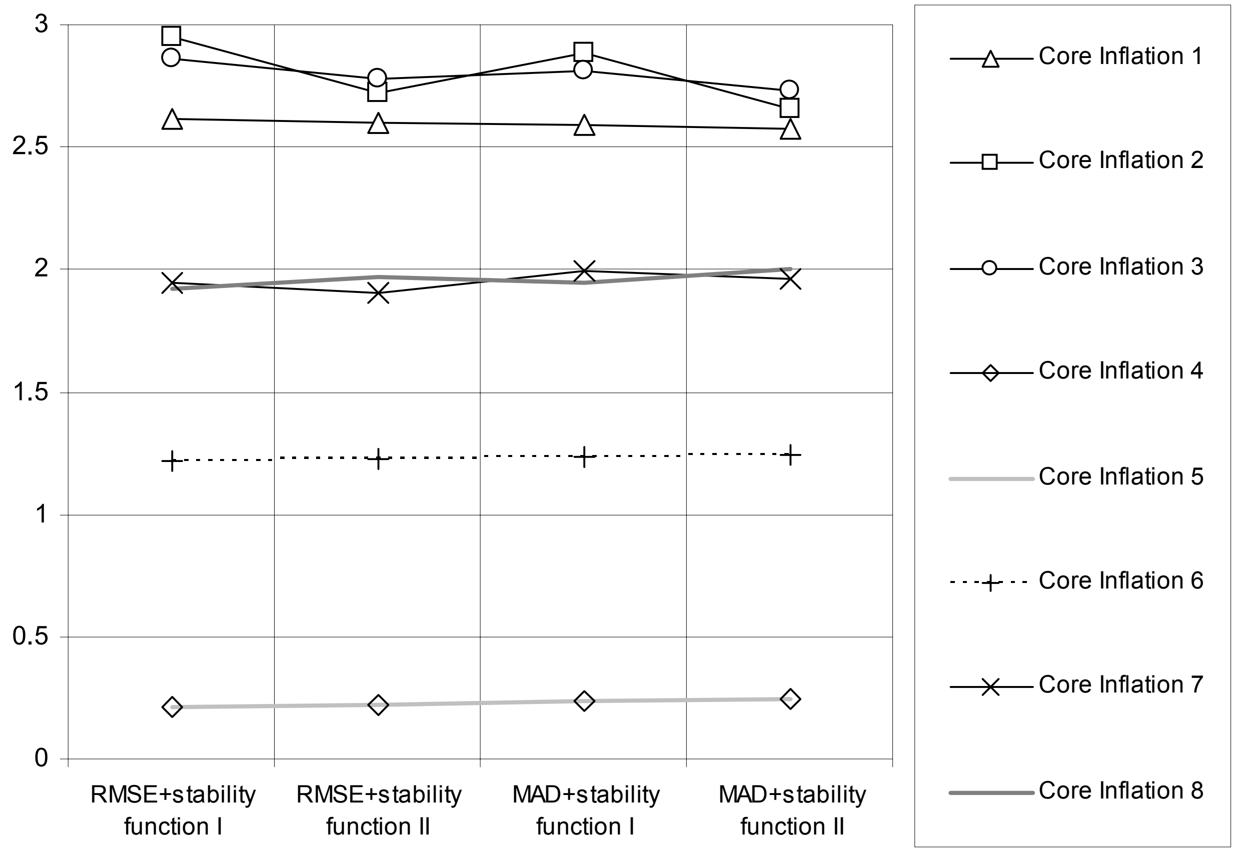


Figure 17. Optimal Core Inflation Indicators for Ukraine.