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**Various Measures of Underlying Inflation
in Poland 1995–1998**

Warsaw, 1999

Responsibility for the information and views set out in the paper lies entirely with the editor.

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Abstract

As inflation targeting gains popularity policy makers, monetary authorities seek to design a measure of inflation that would be a good indicator of fundamental demand-driven price movements, i.e. the underlying or core rate of inflation. It is widely acknowledged that the Consumer Price Index (which is the simple weighted average of price changes of the set of goods and services comprising the consumers' expenditure basket) is a rather deficient indicator of the "trend" inflation as it is highly volatile, seasonal and contains a lot of noise. 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 supply side.

The paper presents 4 alternative methods of calculating the core inflation most commonly found in the literature: trimmed mean, sample mean percentile, standard deviation trimmed mean and exclusion mean. Using Polish price data from the period 1995:1–1998:7, each measure is calculated at monthly, quarterly and annual frequencies and compared to the 24-month centered moving average of the CPI which is assumed to be the benchmark core inflation. Root mean square error (RMSE) and mean absolute deviation (MAD) of the candidate measure and the benchmark were chosen to be the criteria for choosing the optimal definition – both within each of the 4 groups and across them.

Rather surprisingly, crude methods based on exclusion yielded the best results. Volatility-based exclusion proved most efficient for monthly and quarterly series, whereas excluding broad aggregates (food and energy) turned out optimal for annual series. The paper concludes with highlighting the caveats and fragility of the results as well as stressing the necessity of further research.

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I. Introduction

Since the end of 70s, inflation has become one of the most pronounced concerns of monetary policy in industrialized countries. It has been recognized that inflation is essentially a bad phenomenon that introduces uncertainty, destabilizes economies and hampers growth [1] and offers very few benefits instead.

Therefore, fighting inflation became an issue of highest priority. An ever-increasing number of countries are switching to inflation (or price level) targeting and setting explicit inflation (or price level) goals that are binding for monetary authorities. Failure to meet them implies various penalties including, in the extreme case of New Zealand, removing the central bank's governor from office. Originally those targets have been expressed in terms of the rate of change or the level of the consumer price index – CPI. However, it is also widely acknowledged that the CPI index, which is the weighted average of price movements of the set of goods and services comprising the consumers' expenditure basket, 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 [2]. By how much should the monthly CPI inflation go down or up for the economic agents to be convinced that a new trend has set it? It is difficult to give a precise answer to this very fundamental question even if one looks at developments of annual series.

These questions prompted economists to develop the concept of underlying or core inflation. If monetary authorities are to control the level or movements of prices in the economy, they ought to be able to distinguish between temporary shocks to the price level and 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 underlying 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 supply side. This idea of excluding all shocks with no demand-side provenience stems essentially from the mainstream economics view that "monetary policy works

[1] The last claim is the subject of an ongoing debate and extensive research. While the results are not conclusive for the group of industrialized countries, strong negative relationship has been established between inflation and growth in transition economies.

[2] Bryan and Cecchetti (July 1995) find that in the US seasonality in prices is substantially greater than previous research has indicated.

[3] Unless monetary authorities target price level.

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 index would temporarily or permanently pick up. Now, if the monetary authorities followed the CPI movements closely this would prompt "tightening" action on their side as the targeted variable moved out of the band. But is it really the right policy to pursue? In other 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 text book 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 Polish inflation data. To the best of author's knowledge there exist no published studies concerning core inflation in Poland. This negligence is even more surprising considering that both Hungary and Czech Republic – Poland's Central European OECD fellows have done extensive research on the topic and now regularly publish their measures of underlying inflation along with the plain CPI figures. Consequently this paper constitutes the first empirical account of the issue that is rapidly gaining importance across central banks in most OECD countries [4]. As such it is subject to constant revision and modifications. This paper presents various methods of calculating core inflation involving techniques developed during past couple of years in the countries that are unquestionable leaders in the field: USA and New Zealand [5].

The paper is composed as follows. Section 2 begins with a brief review of theoretical foundations for various methods of calculating core inflation. Section 3 describes empirical distributions of individual price changes during the sample period and provides statistical as well as intuitive justification for using those methods to purge CPI. Sections 4, 5, 6 and 7 explore four such methods: trimmed means, percentiles standard-deviation-trimmed means and exclusion means, respectively. Finally, section 8 concludes with the summary and final remarks.

[4] Especially in the wake of adoption of inflation targeting by many of them.

[5] Most of the statistical research has been done by Bryan and Cecchetti (US) and Scott Roger (New Zealand). Measures of core inflation obtained by structural vector autoregressive model and a set of more fundamental macroeconomic assumptions comprise a group of alternative methods, not considered in this paper. Basic reference in this field is Quah and Vahey (1995) and more recently Claus (1997), both for the United States. Kaczor (1997) constitutes the only attempt at using this latter method for Polish data.

2. 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. *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 Polish data since it is essentially related to constant weights used in the calculation of the CPI in most OECD countries (in contrast with ever-changing relative price structure). Polish Statistical Office belongs to a small 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 [6]. It is the subject of numerous studies done mostly in the context of US price data [7] and since it is essentially different in nature than *noise* it will not be elaborated upon in this paper.

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

\dot{x}_{it} – relative price inflation that represents one-time movements inherent in an individual item and not representative of the core trend.

[6] Cecchetti (1996) gives quality and new goods bias as examples of measurement bias.

[7] See Wynne and Sigalla (1993) and Shapiro and Wilcox (1996) for detailed discussion and actual bias estimates for the US.

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 to those who wish to measure 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

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

this yields the following definition of the aggregate price inflation:

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

In line with the earlier discussion, the assumption is being made that the weighting bias – ω_t is rather insignificant in the Polish 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 [8]. 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 S 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.

[8] 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.

[9] 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.

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 timely measures, that is, indicators available for use in the first instance [9].

Ideal estimators of core inflation should also be robust, 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 feature is good and reliable performance even in extreme settings.

Another desirable characteristic of a good estimator is unbiasedness. 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.

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. Most common techniques of calculating the core rate of inflation typically fall into one of the below categories [10]:

1. Exclusion

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, high their high volatility obscures the general picture of inflation and hence may trigger inappropriate policy actions. A variation of this method introduced in this paper involves excluding certain categories entirely based on the historical volatility of their price series.

2. Trimmed Means

The method of trimmed means has drawn a great deal of attention across central banks in recent years. It is based on systematic exclusion of extreme price movements regardless of the CPI category they fall into. For example, k -% trimmed mean is derived by omitting (or 0-weighting) $k\%$ [11] highest and $k\%$ lowest price movements during the period concerned (month or quarter) and computing the weighted mean of the rest. A special case of a trimmed mean is a median (50% trimmed mean) and a usual CPI index (0% trimmed mean).

[10] The categories as given are not mutually exclusive. One can very well imagine a measure that was calculated using a combination of all of the methods.

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

3. Percentile Method

The k -percentile measure of core inflation is defined as the k^{th} percentile of a weighted distribution of price changes over the given horizon. In particular, median is a 50th percentile. Unlike trimmed means this method does take into account all of the available observations, but makes use of them in a different way than does the simple average.

Methods based on exclusion or adjustment 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 a couple of important questions. 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 two methods described above. Trimmed means and percentiles seem to fulfill the conditions of an efficient use of available price information and practically do not require judgment or discretion.

Sections that follow explore each of the methods separately. Each section contains evaluation made using the same definition of efficiency. 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 Price Changes 1995–1998

To see the rationale for trimming the distribution of price changes in order to arrive at a measure of underlying inflation, let us look at the characteristics of empirical distributions. Figure 1 presents 12-month CPI inflation rates along with the 12-, 24- and 36-month centered moving averages. The bottom panel presents the same set of series for month-to-month inflation.

The author uses centered moving averages of actual "headline" inflation as the benchmark trend, i.e. in fact core inflation. The definition of the underlying benchmark inflation is bound to be subject to criticism, since it is very central to the search of ideal measure of underlying inflation. Centered moving averages are among the most widely used in the literature. As Bryan et al (1997) point out, centered averages come very close to what people have in mind when they think of core inflation. The rationale for using them as the

Figure 1. 12-month CPI Inflation and 12-, 24-, 36-month Centered Moving Average

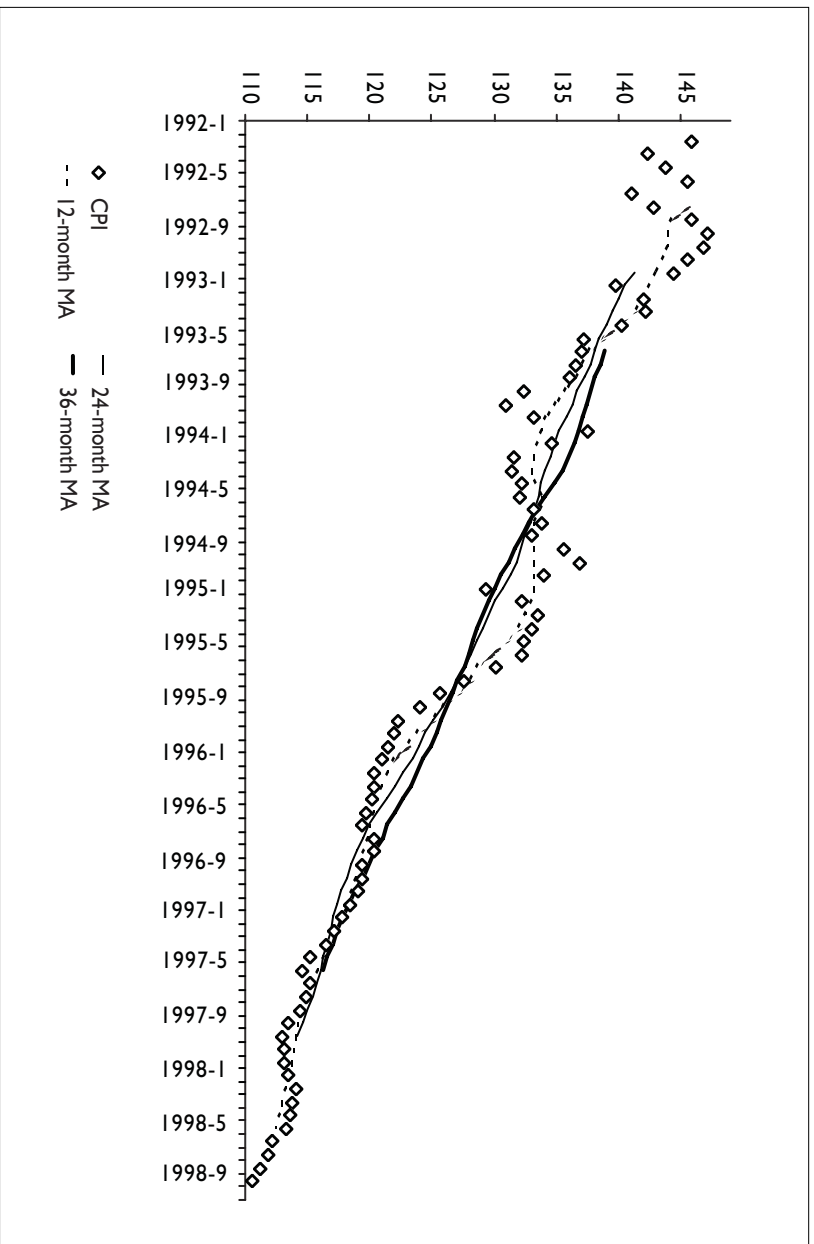
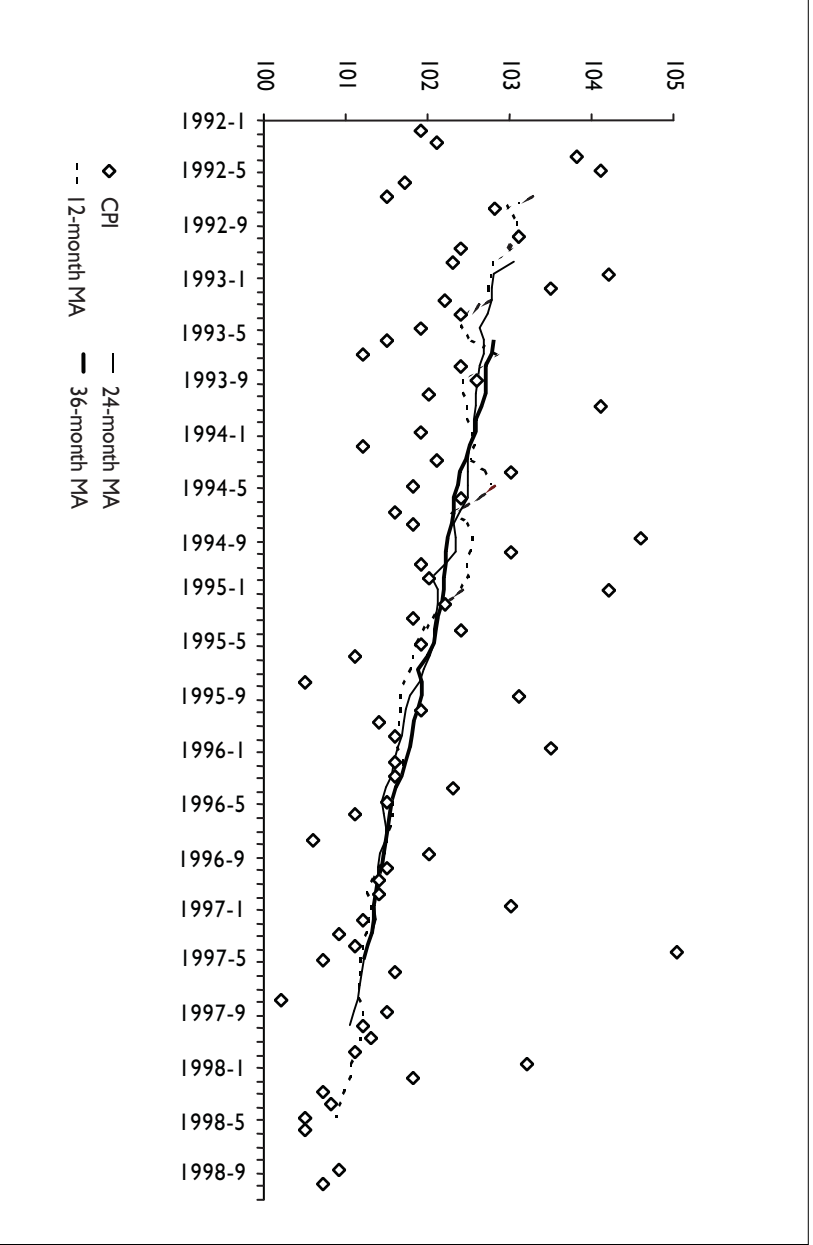


Figure 1a. Month-to-month CPI Inflation and 12-, 24-, 36-month Centered Moving Average



historical [12] approximation for core inflation lies in their ability to reflect longer-term trend in the averaged variable, which is exactly what we want our conceptual underlying inflation to be. More formally, equation (7) in Section 2 implied that by averaging high-frequency inflation rates we get rid of the noise that disappears accumulated over time and get a more accurate estimate of the real price movements.

Figures show how volatile month-to-month or even 12-month CPI inflation is and how moving averages smooth the series out. Choosing the index for the benchmark moving average is another discretionary issue. It is obvious that widening the horizon over which one averages reduces the volatility of the series, however, at a high cost of losing observations. Bryan and Cecchetti (1997) and Cecchetti (1998) use 36-month moving average of actual US CPI inflation and treat it as the best approximation of the trend inflation. In this study, however, the author decided to use the 24-month measure on the grounds that it is sufficiently good an approximation of the Polish trend [13] and allows to use utilize more observations.

From the figures we see that both monthly and annual inflation data contain a great deal of noise as judged against the moving-average approximation of core inflation. Therefore, one commits a substantial error when using the CPI annual headline to make inferences about the current inflation trend.

To get a better picture of the distributions of individual inflation rates of all CPI components within a month, a quarter and a year, it is necessary to calculate descriptive statistics of those distributions. For that purpose the author used the entire sample 1995:1–1998:7 at the level of disaggregation of 205 to 207 items (depending on the year). All descriptive statistics were calculated at monthly, quarterly and annual frequencies ($k=1, 3$ and 12 respectively). Multi-month periods have been obtained by cumulating monthly observation over 3 and 12 months at overlapping intervals, so that the resulting data set contains 43 monthly observations (1995:1–1998:7), 41 quarterly observations (1995:3–1998:7) and 31 annual observations (1995:12–1998:7).

Following most studies in the field and specifically Roger and Cecchetti, the author uses the following definitions of the weighted moments [14]:

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

[12] It is clear that we can only calculate centered moving averages for historical data since for a k -period average at time t we need $k/2$ observations ahead of t .

[13] Surely, any judgment as to the length of the averaging horizon is debatable. However, in the case of transition economies (like the Polish economy during the sample period) it is reasonable to assume that the trend itself is more variable and therefore setting a narrower horizon seems desirable. This notwithstanding, the problem of choosing the right horizon is a rather theoretical issue in this particular case, considering the relatively small differences between the 24- and 36-month measures.

[14] 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.

defines aggregate CPI inflation over the period of $k = 1, 3$ or 12 months calculated as the weighted sum of i components using time-variable weights w_i .

Then the k^{th} weighted moment around the mean (the CPI inflation) is defined as:

$$m_{rt}^k = \sum_i w_{it} (\pi_{it}^k - \Pi_t^k)$$

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

skewness

$$S_t^k = \frac{m_{3t}^k}{[m_{2t}^k]^{3/2}}$$

and kurtosis

$$K_t^k = \frac{m_{4t}^k}{[m_{2t}^k]^2}$$

Table I below shows descriptive statistics of distributions of monthly, quarterly and annual individual inflation rates. For each frequency all available observations have been pooled together and average and median skewness and kurtosis (along with their standard deviation) have been calculated.

Table I. Weighted Skewness and Kurtosis of Price Distributions

		Monthly	Quarterly	Annual
Skewness	Average	0.43	0.33	1.03
	Median	1.61	0.45	0.88
	St. dev	2.90	2.19	1.26
Kurtosis	Average	16.37	11.57	16.42
	Median	14.75	12.02	8.58
	St. dev	11.46	5.86	19.29

The main message that emerges from the table is one of high and persistent positive skewness [15]. This means that during the period of measurement, few unusually large price jumps dominated the inflation process. It is also noteworthy that while there is no correlation between the frequency at which skewness is measured and the average or the median value of the moment, there is a clear negative relationship between the frequency and standard deviation of skewness. This points to the fact that distributions calculated over longer horizons are characterized by less dispersed values of skewness. Therefore, when dealing with the month-to-month calculated inflation data one has to be

[15] 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.

aware not only of high and persistent skewness present in the distributions but also of its relatively highly dispersed values.

The other interesting feature of the distributions is high kurtosis [16]. In all cases kurtosis is well above 3 – the value that characterizes the normal distribution. 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. However, to the best of author's knowledge, Polish inflation data is among the most right-skewed and leptokurtic (fat-tailed). This phenomenon can be fairly easily explained by inherent high seasonality of the data (especially at such a high level of disaggregation) [17].

To get a more intuitive picture of how the distribution really looks like, 43 distributions of monthly individual price changes were standardized [18] and pooled to obtain a histogram. Since there are 204–207 CPI categories, the total number of observations is 8844. The same procedure has been applied to annual data and the resulting histogram can be seen below.

Clearly, empirical distributions do not resemble the Normal very closely. Both monthly and annual distributions have much sharper peaks and fatter tails (symptoms of high kurtosis), although annual distribution visibly less so. Both are also heavily skewed to the right, i.e. there are more unusually high positive observations than there are negative. Vertical bars at -4 and 4 indicate the total frequency of empirical observations that are further away from the mean than 4 standard observations to the left and to the right, respectively (compared with practically 0 for the normal).

The above discussion clearly shows that the distribution of individual inflation rates is very far from Normal regardless of the frequency at which the data is examined. It is persistently skewed to the right and has fat tails.

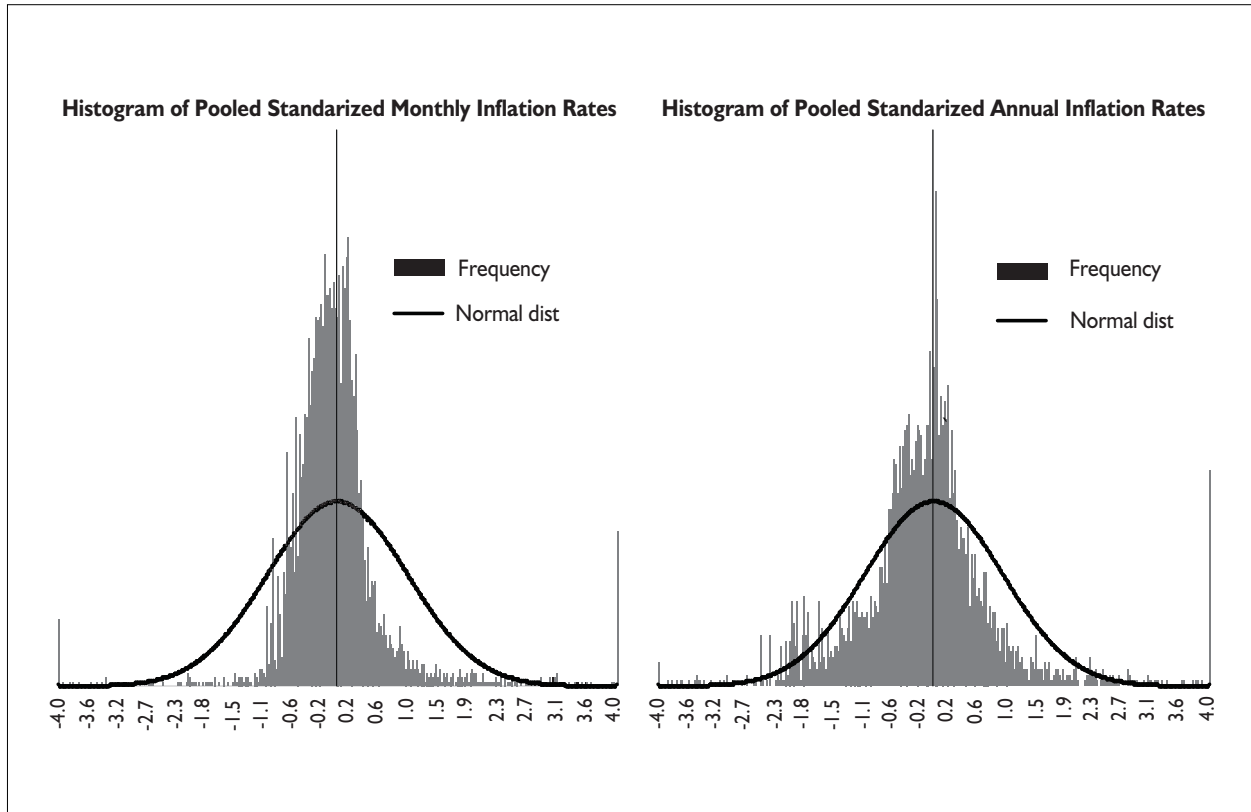
If we think of the distribution of individual inflation rates of all CPI components during, say, one month as being a drawing from the underlying population of all inflation rates during that period, we can redefine our search for core inflation. It then becomes an issue of finding the most efficient estimator of underlying mean.

[16] 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.

[17] There are two very primary and very distinct kinds of seasonality in Polish inflation data – "natural" (weather-induced) and "artificial" (administered-price-related). For a thorough discussion see Koen (1997) and Woźniak (1998).

[18] Means and variances of each month's distribution are different. Standardization ensures that once pooled they yield a meaningful set of observations.

Figure 2 and 3.



A thorough discussion of the statistical rationale of that approach can be found in Roger (1997). For the purpose of this study, the author restricts himself to a brief intuitive explanation.

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 statistic 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 [19] may not be the most efficient in the family of all estimators. 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 weights all the observations equally will tend to give a distorted image of the underlying distribution.

Table I and figures that followed clearly show that the distribution of individual inflation rates is very far from Normal regardless of the frequency at which we it. 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.

4. Trimmed Means

4.1. Intuition

The many weaknesses of a simple sample mean as an estimator of non-normal distributions prompted economists and statisticians to search for a better estimator. Trimmed means are one of the most effective and comprehensive remedies suggested. Their concept relies on the fact that one can substantially reduce the undesirable properties of the sample mean by trimming the distribution of most extreme observations. The intuition is straightforward: if outlier price changes cause the sample average to give a distorted view of the "true" inflation, one is better off if those changes are left out of calculations.

The most systematic method proposed in the literature involves trimming the distribution by a certain percentage, say, t % symmetrically from both sides. T % refers not

[19] Nonetheless, it still remains unbiased.

to the number of observations, but to the weight in the basket, so that $t\%$ -trimmed mean is just a weighted average of $(100-2t)\%$ of the middle observations. If the distribution is symmetrical (like the Normal or close to the Normal), trimming the mean by whatever percentage will leave the sample mean unchanged. However, if it is skewed (which is the case with the price data), trimming will affect the sample mean in that it will discard the most extreme values that pulled the mean up (positive skewness) or down (negative skewness). Figure 2 illustrates how trimming works for those kinds of distributions. (For the purpose of illustrative simplicity the figure shows trimming $t\%$ of the observations, and not $t\%$ of the weight. However, the intuition carries over to the case with trimming by weight).

Bryan et al (1997) carry out a series of illustrative experiments based on artificially generated distributions with varying kurtosis. They find that the trim that yields efficient [20] estimates of the "real" mean increases monotonically with the kurtosis of the underlying population [21]. Hogg (1967) gives a simple rule of thumb concerning the choice of a robust estimator. Inferring from extensive Monte Carlo experiments (on a much wider range of distributions) he suggests that if the distribution is relatively platykurtic (kurtosis between 2 and 4), i.e. close to the Normal, the sample mean performs very well. However, for kurtosis between 4 and 5.5, 25% trimmed mean is better. Finally for relatively leptokurtic distributions (kurtosis > 5.5), sample median (which is a 50% trimmed mean) works best. Those results, however, were not derived analytically and may not apply with equal strength to all distributions. Furthermore, the scheme, as simple as it is, disregards in its suggestions the continuum of intermediate trims that, in a particular distribution setting, may very well be superior to those recommended by Hogg.

Considering that the empirical distribution of price changes in Poland 1995–1998 is heavily skewed and leptokurtic (Table 1), what is the optimal "percentage" of the basket that one should discard from the calculation in order to achieve the best estimators of the underlying mean? Is it the median, as suggested by Hogg, the currently used 0%-trimmed mean, i.e. the headline CPI or some other statistic? Following Bryan et al (1997) and other related studies, the author chose the root mean square error (RMSE) and the mean absolute deviation (MAD) efficiency criteria. The benchmark core inflation is, as noted earlier, the 24-month centered moving average [22].

[20] Authors define efficiency in terms of the Root Mean Squared Error (RMSE) and Mean Standard Deviation (MAD). These definitions will also be used throughout this paper.

[21] Authors caution that results are to be treated as merely illustrative and inherent in the distributions they consider. They are aware of no general analytic results concerning the relationship between the moments of the underlying distribution and the size of the optimal trim.

[22] These two choices (efficiency criteria and the benchmark inflation) have profound consequences for the results obtained in this paper. It may happen that by choosing different set of assumptions, one may obtain different answers. However, the author believes that the bulk of results reported in this paper are rather robust to alternative assumptions.

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

4.2. Finding Efficient Trim

Since monthly, quarterly and annual inflation rates are fundamentally different in terms of information they contain, efficient trims (as well as all estimators of core inflation described later) are found separately for each frequency. The process of finding an efficient trim involves the following steps:

- Distribution of price changes for the given frequency (m , q and a for monthly, quarterly and annual respectively) is sorted in an ascending order together with respective weights.
- Cumulative weight W_{trim} is found by cumulating weights from top and bottom of the sorted distribution, such that.

$$W_{trim} = \sum_{i=1}^{trim} w_i$$

- The set of CPI items associated with i 's that satisfy the inequality:

$$\frac{trim}{100} < W_i < \left(1 - \frac{trim}{100}\right)$$

represent the middle $(100 - 2 * trim)\%$ movements of prices.

- The set as defined above is the trimmed basket of which we compute weighted average. This weighted average is the $t\%$ -trimmed mean.

There are two special border cases in the family of trimmed means. 0% trimmed mean is just a plain weighted average, that is, exactly the CPI and 50% trimmed mean is the median.

In order to find the most efficient trim, the distribution is successively trimmed of 0 to 50% observations (by weight in the basket) and respective weighted averages are calculated. This procedure yields the total of 501 trimmed means for each period (the step increase in the trim is 0.1%). The means are then subtracted from the underlying inflation (i.e. centered 24-month moving average of the actual CPI) and the resulting deviations are used to calculate two measures of efficiency introduced earlier: root mean square error (RMSE) and mean absolute deviation (MAD).

Figure 4 plots the values of RMSE and MAD for monthly, quarterly and annual trimmed means as a function of the trim. We can clearly see that this function is highly nonlinear and in some cases has multiple local minima. A bold vertical line marks the global minimum and the corresponding trim is written on top. RMSE and MAD minimizing trims are as follows [23]:

- For monthly rates – 50% trim yields median,
- For quarterly rates – 48% trimmed mean,
- For annual rates – 46 % trimmed mean.

It should come as no surprise that as we increase the frequency, the efficiency criteria point to lower optimal trims. As indicated by table I, higher-frequency inflation rates are historically characterized by greater kurtosis. Therefore, the empirical result goes well with findings by Hogg (1967) and Bryan et al (1997) as sketched earlier which predict that efficient estimators should discard more observations as kurtosis of the underlying distribution rises.

Another noteworthy message that emerges from the figure is that relatively high-trim means are found to be optimal estimators of trend inflation. Bryan et al (1997) find that the optimal trim for the 1967–1997 US price data distribution is a mere 9%. The key difference, however, that seems to account for the difference is the number of CPI categories used – 36 for the US vs. 207 in this study. The authors carry out a series of robustness checks and conclude that disaggregating the price data into finer categories produces distributions that are more leptokurtic, and therefore require higher-order trims. The data set used in this study is certainly a highly disaggregated one and yields inherently leptokurtic distribution. In the author's view, this is the main reason for the seemingly high optimal trims obtained in the computations.

Figure 5 presents graphical comparisons of trimmed means obtained by minimizing the efficiency criteria along with "headline" inflation and 24-month centered moving average thereof. Clearly, trimmed means are much less volatile than headline CPI and seem to indicate the trend inflation with much less noise.

[23] For quarterly data the trim minimizing RMSE and MAD was 48.4% and 47.6% respectively. For annual data – 46.5% and 45.8%, respectively. However, in terms of integer percentage points they can be rounded to 48% and 46% with just a negligible loss of accuracy.

Figure 4a. Efficiency of Trimmed Mean Estimators: RMSE and MAD – Monthly Inflation

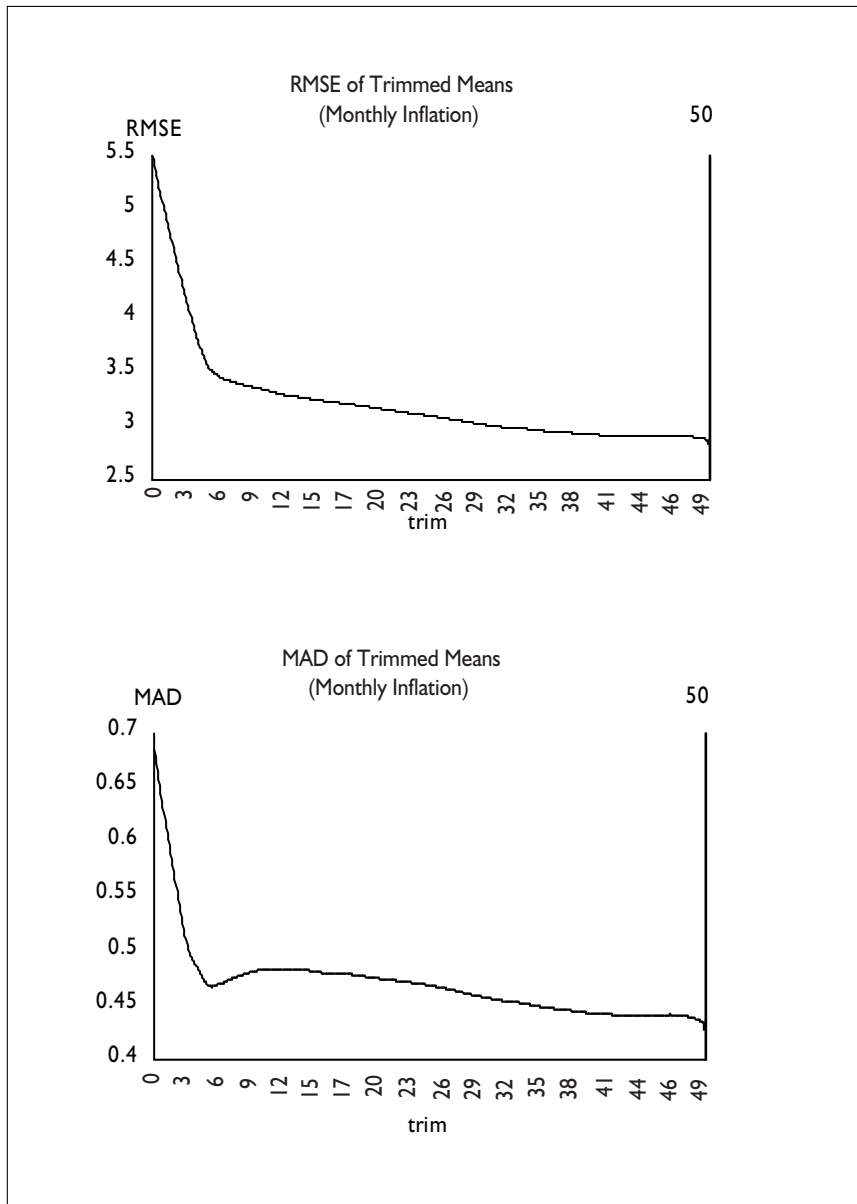


Figure 4b. Efficiency of Trimmed Mean Estimators: RMSE and MAD – Quarterly Inflation

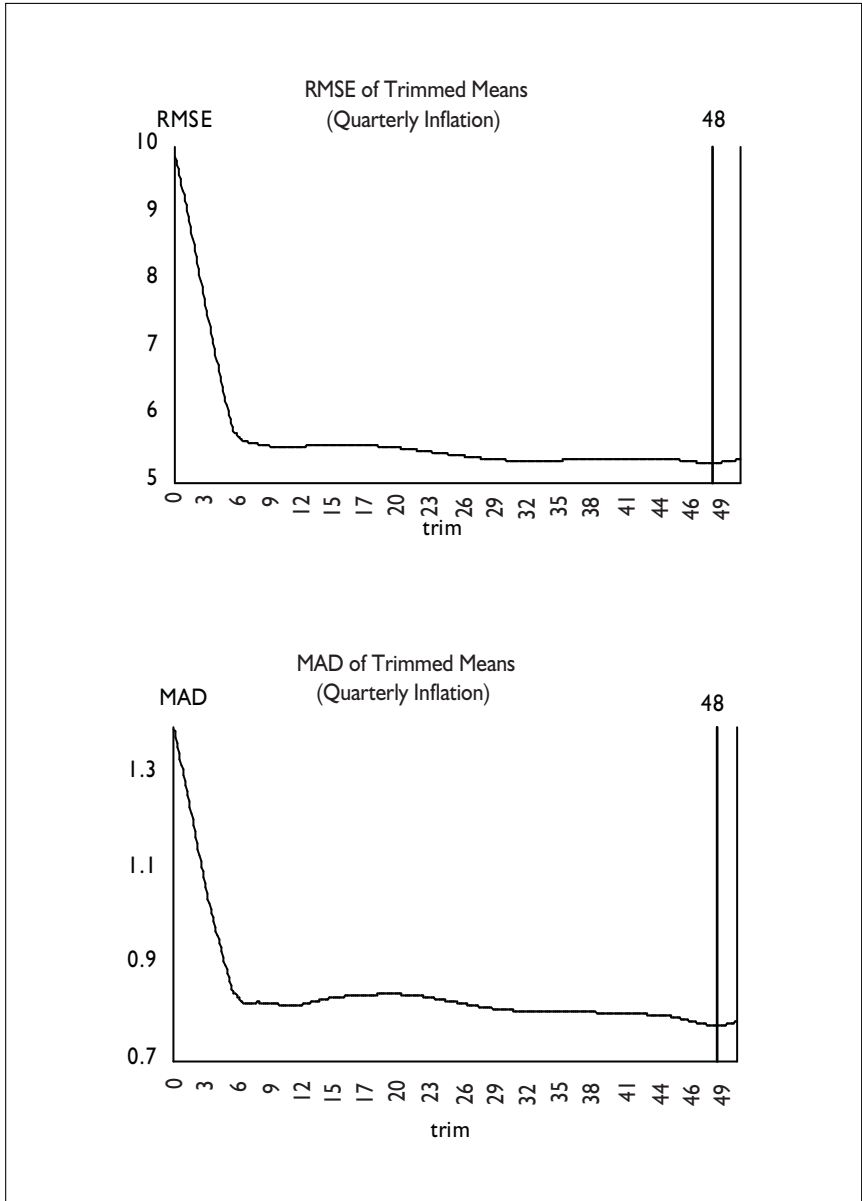


Figure 4c. Efficiency of Trimmed Mean Estimators: RMSE and MAD – Annual Inflation

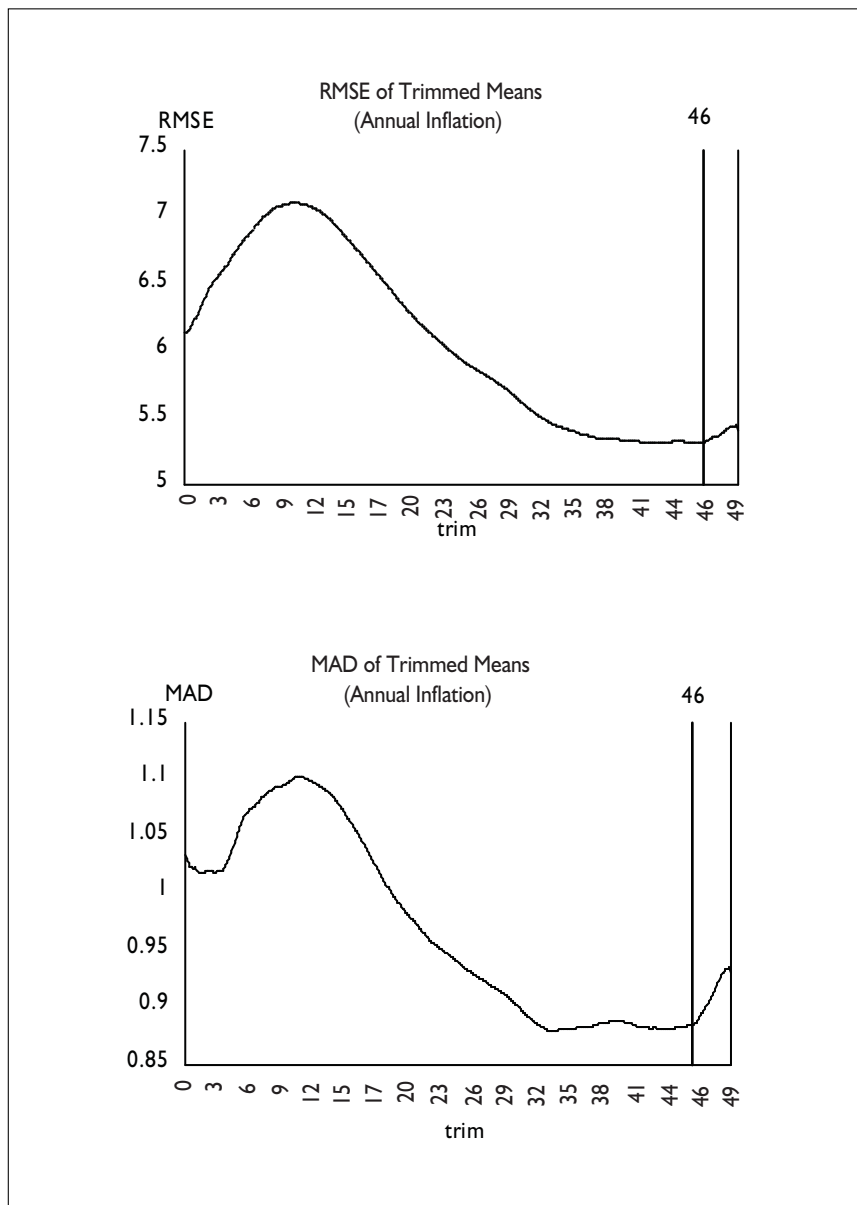


Figure 5a. Efficient Trimmed Means

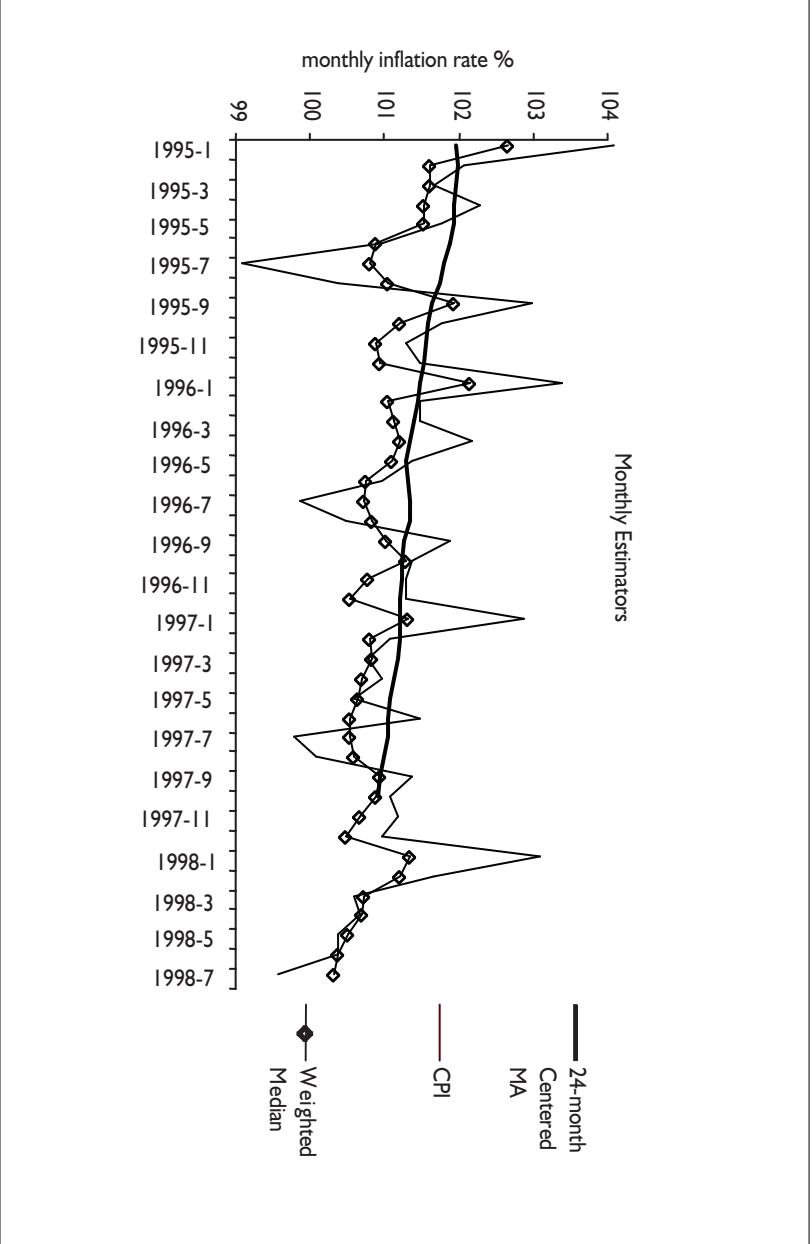


Figure 5b. Efficient Trimmed Means

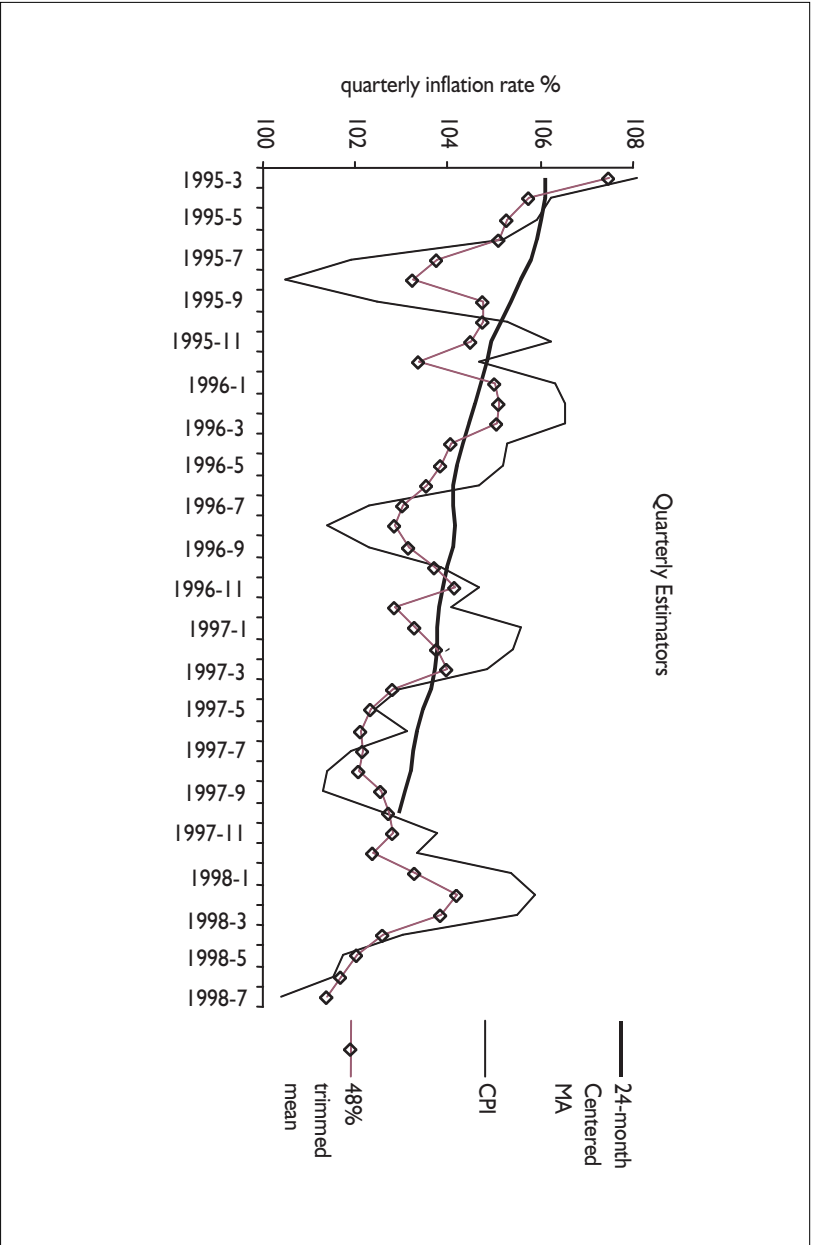
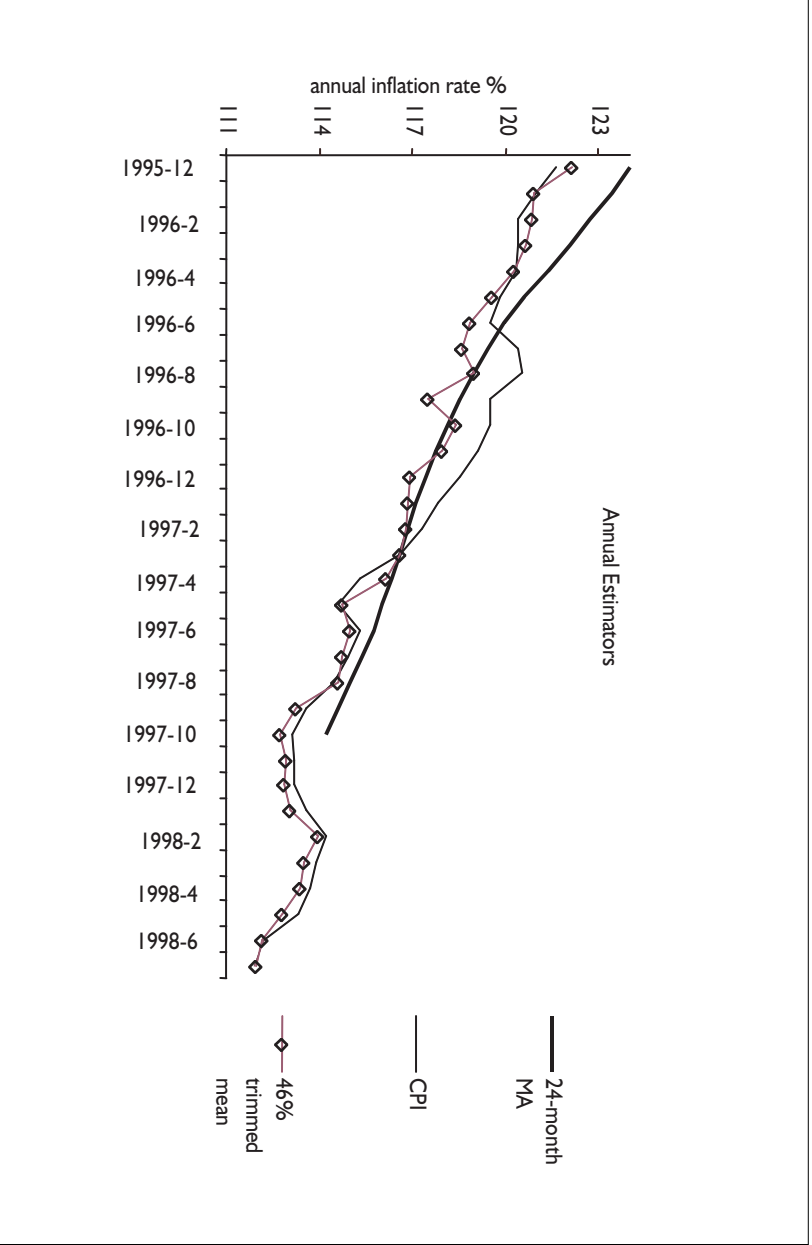


Figure 5c. Efficient Trimmed Means



5. Sample Mean Percentiles

5.1. Intuition

The most crucial idea behind finding the optimal percentile estimator of the underlying mean is that of unbiasedness. The argument made in the literature goes as follows. Since sample means are unbiased, Roger (1997) claims that, by transitivity, the percentile of the empirical distribution that, on average corresponds to the sample mean should also be an unbiased estimator of the population mean [24]. As mentioned earlier, with any symmetric distribution, the 50th percentile will satisfy that condition. For distributions skewed to the right, the corresponding percentile will be above 50, and for those skewed to the left it will be below 50. Throughout this section, the author will label *sample mean percentile* the percentile that corresponds to the sample mean of the empirical distribution. For population, or underlying distributions, the percentile that corresponds to the population mean will be called *population mean percentile*.

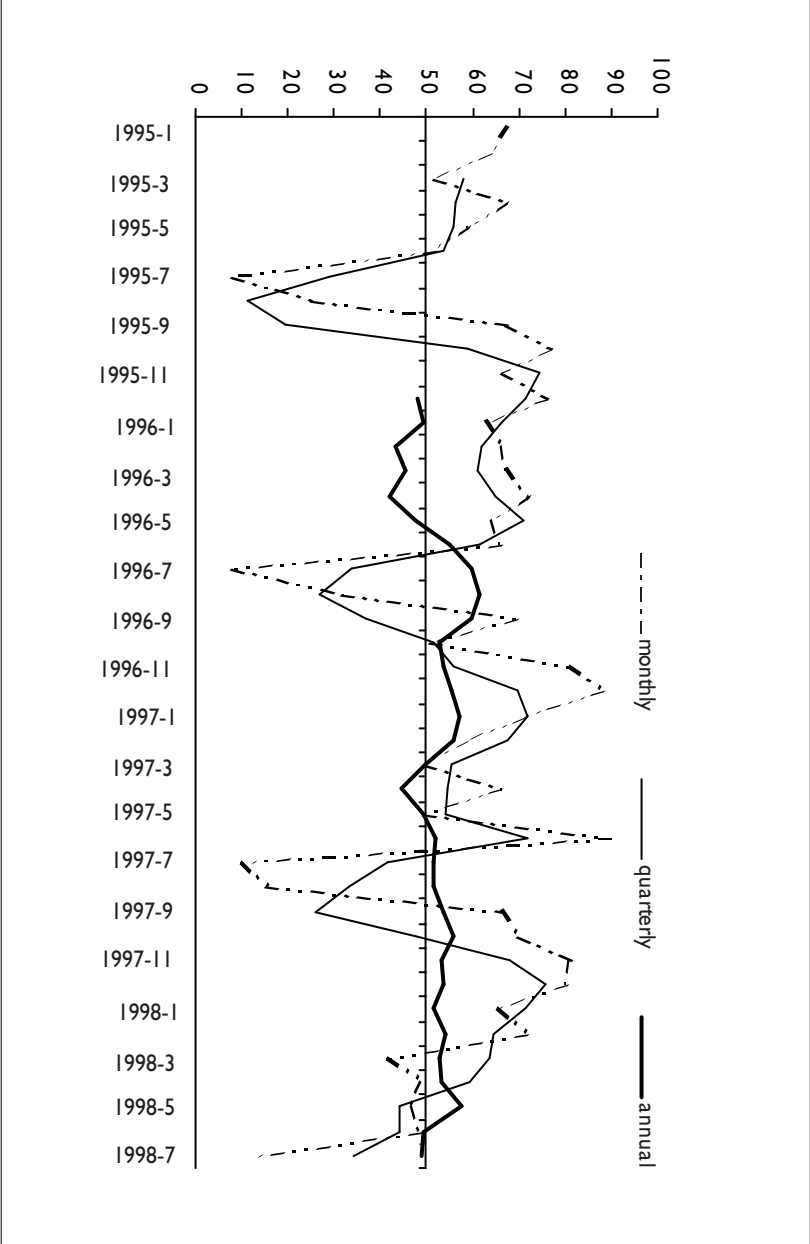
It is obvious that during a particular period, sample mean will not always correspond to the sample median. That is, in terms of the empirical distribution of price changes, plain average of inflation rates of the entire expenditure basket will not be equal to the median price change. Figure 6 plots the sample mean percentiles calculated over the entire sample period for monthly, quarterly and annual data. It is striking that for monthly observations, sample mean can be below the 10th or above the 90th percentile. This means that at times, as little as 10% or, at other times, as much as 90% of the CPI categories [25] experience price changes that are smaller than the recorded CPI. It is also well visible that the series is highly volatile and the volatility decreases with increasing frequency. The annual series stands out as having by far the least variation of all.

Also, monthly and quarterly series are highly seasonal. Summer months (or third quarters) when registered CPI has been historically lowest (due to seasonal positive food supply shock) tend to be characterized by low sample mean percentiles. On the other hand, cumulated administered increases in first 2 or 3 months of the year (or first quarter) produce high positive skewness resulting in high sample mean percentiles.

[24] The claim may not be obvious intuitively but can be proven statistically.

[25] As before, all statements refer to the weight in the basket and not the number of observations.

Figure 6. Sample Mean Percentiles



Mere visual inspection allows to notice that, high volatility notwithstanding, the average sample mean percentile does not change significantly over sample. Figure 7 presents evolution of the average and median sample mean percentiles for each frequency over the available period. Both means and medians can be considered relatively stable and well above 50% inherent in the Normal distribution. Also, they increase visibly for higher-frequency data. However, the main message to be drawn from this table is that of relative stability of sample mean percentiles over time and hence their robustness and suitability for further inference.

5.2. Finding Efficient Percentile

Now, according to the logic outlined above, the claim is that the "appropriately" chosen sample mean percentile for the entire period is an unbiased estimator of the population mean. Prior to making the choice it is worthwhile to look at the approximation of the characteristic "underlying" population. Since the whole analysis is based on the primary assumption that empirical distributions of price changes as we observe them every month (quarter, year) are just particular samples from the underlying population of "core" price movements, the best way to approximate it is to use empirical sample distributions. We do it by pooling all available standardized observations across sections and periods separately for each frequency [27]. This yields three big observation sets; in author's view – big enough to justify inferences about the underlying distribution (the sets contain 8844, 8428, 6556 observations for monthly, quarterly and annual sets, respectively).

Figure 8 plots cumulative distributions of these three sets along with that of the Normal distribution. The figure clearly shows that empirical distributions differ from the Normal, in particular they hit the 50th percentile (or 50% frequency) much sooner than does the Normal. The right panel of the figure provides a close-up of the middle and the most interesting area of the graph. It can be read off the graph that the

[26] First 12 available observations were left out of calculating the average and the median so that observable seasonality does not influence the outcome too much.

[27] Pooling observations without prior normalization would yield a set that contains data from distributions characterized by different means and standard deviations and hence, a rather meaningless information in the context of this section. Normalization ensures that all observations are expressed in the form of deviation from respective means and scaled by the particular standard deviation of the empirical distribution they were drawn from. By pooling we obtain a set that contains essential information about the moments of the distribution of interest which were preserved by virtue of normalization.

Figure 7.

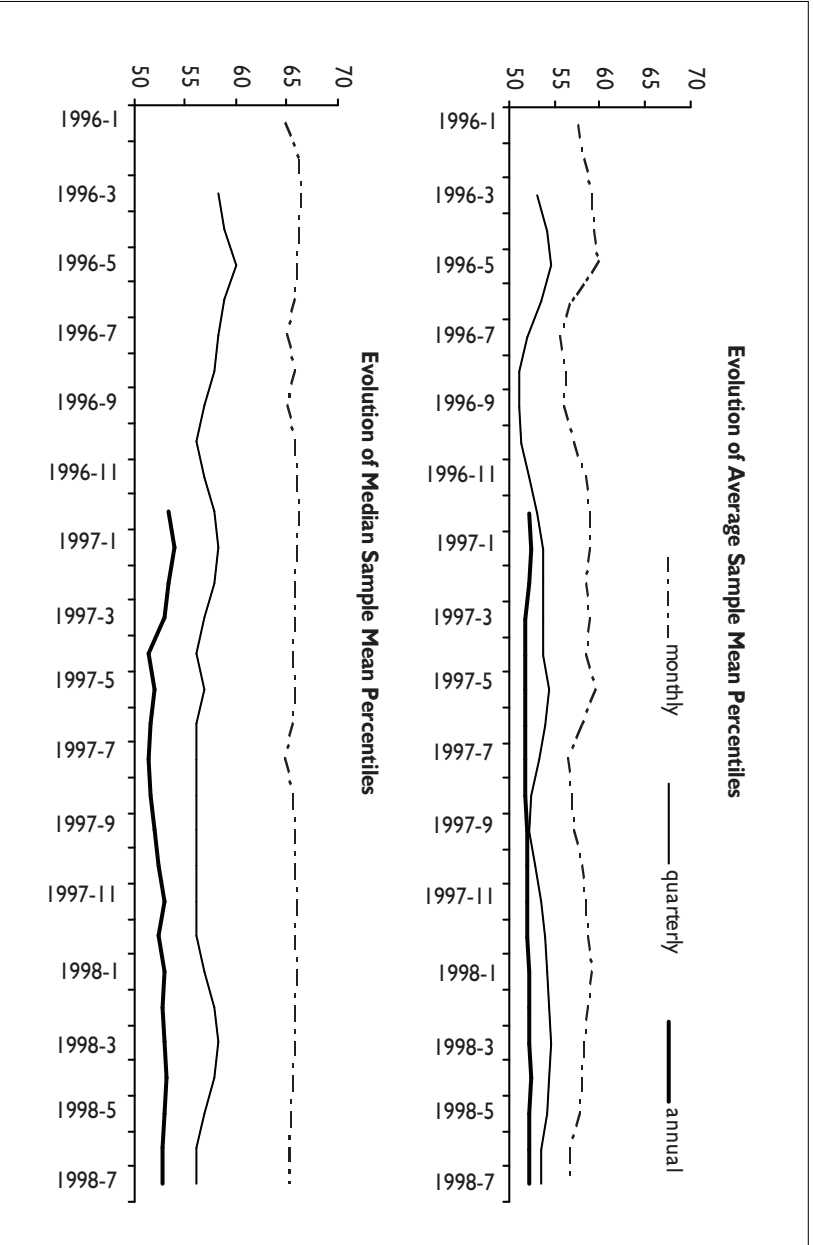
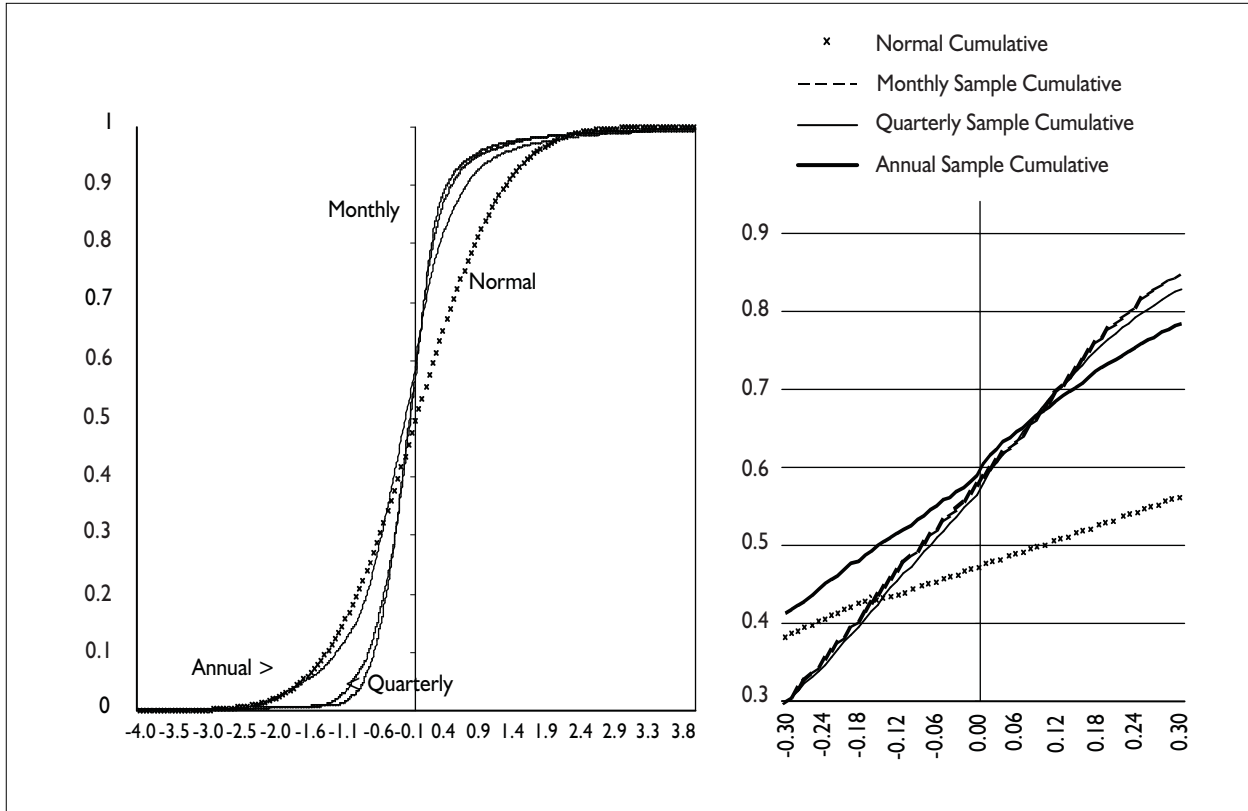


Figure 8. Cumulative Distributions. Sample Distributions vs. Normal



percentile corresponding to the mean of the distribution (marked by a vertical line passing through 0) is somewhat above the 50%, between 55 and 60% depending on the frequency [28].

Table 2 presents detailed results of the search for the percentile corresponding to the population mean – *the population mean percentile*.

Table 2. Estimates of the Population Mean Percentile

Data frequency	Average of sample mean percentiles	Median of sample mean percentiles	Sample mean percentile of the pooled normalized distribution
Monthly	56.9	65.3	58.6
Quarterly	53.6	56.1	58.0
Annual	52.1	52.8	60.4

First two columns present averages and medians of sample mean percentiles calculated earlier for the figures 6 and 7. Third column contains the sample mean percentile of the pooled normalized distribution constructed in a way described above and used to plot figure 8. The results for the two methods differ somewhat reflecting a rather different approach taken in their calculation. The first two columns report averages and medians of the group of individually calculated sample mean percentiles on a month-to-month (or quarter-to-quarter as well as year-to-year) basis. On the other hand, each number in the third column is a sample mean percentile of a single distribution – the pooled normalized distribution composed of the cross-section of all available observations separately for the monthly, quarterly and annual data set.

Although the results of those two methods differ slightly, they all point to population mean percentile being somewhere [29]:

- Between 57 and 59 percentile for the monthly data.
- Between 54 and 58 percentile for the quarterly data.
- Between 52 and 60 percentile for the annual data.

Table 3 below summarizes the final results of the search. As before, the main criteria will be the two measures of deviation from the long-run trend – the 24-month centered moving average, that is RMSE and MAD. Whenever the optimal percentiles minimizing RMSE and MAD were different, an auxiliary criterion was employed. This

[28] Another prove of chronic right skewness.

[29] For the purpose of the calculations medians will be ignored.

is taken from Roger (1997) and measures the average drift of the percentiles from the actual CPI throughout the sample (defined as simple sum of deviations from the CPI divided by the number of observations). The criterion checks whether departures from the CPI index cancel each other out, which would be a very desirable property of any measure of core inflation. Optimal drift would be one that is closest to 0 regardless of the sign. In order to eliminate any bias due to possible seasonality, the drift was calculated as an average over full-year periods [30].

Table 3. Optimal Percentiles

Frequency	Percentile	RMSE	MAD	Average annual drift vs. CPI	Lowest drift occurs at
Monthly	57	2.630	0.360	-0.136	63 (0.015)
	<u>60</u>	<u>2.719</u>	<u>0.339</u>	<u>-0.066</u>	
Quarterly	53	4.894	0.713	-0.26	57 (-0.014)
	<u>57</u>	<u>4.972</u>	<u>0.698</u>	<u>-0.014</u>	
Annual	<u>57</u>	<u>3.623</u>	<u>0.755</u>	<u>0.601</u>	52 (-0.075)

First column of the table gives RMSE- and MAD-minimizing percentiles with their respective values in the second and third column. Average drifts for each percentile can be found in the fourth column. The last column lists specific percentiles that minimize the drift from CPI (along with the value of the drift in the parentheses). For monthly and quarterly data RMSE and MAD criteria give different results and therefore drift criterion was used. Final choices for each frequency were underlined and are graphed in figure 9. The 60th percentile was found to be the most efficient monthly estimator and the 57th percentile – the most efficient annual and quarterly estimator (in the case of quarterly data the 57th percentile is also optimal according to the drift-criterion).

[30] 3 such periods are available in the sample. The author decided to use the most recent which yielded the sample over which we calculate the average drift: 1995:8–1998:7.

Figure 9a. Optimal Percentile Estimators. Monthly Estimators

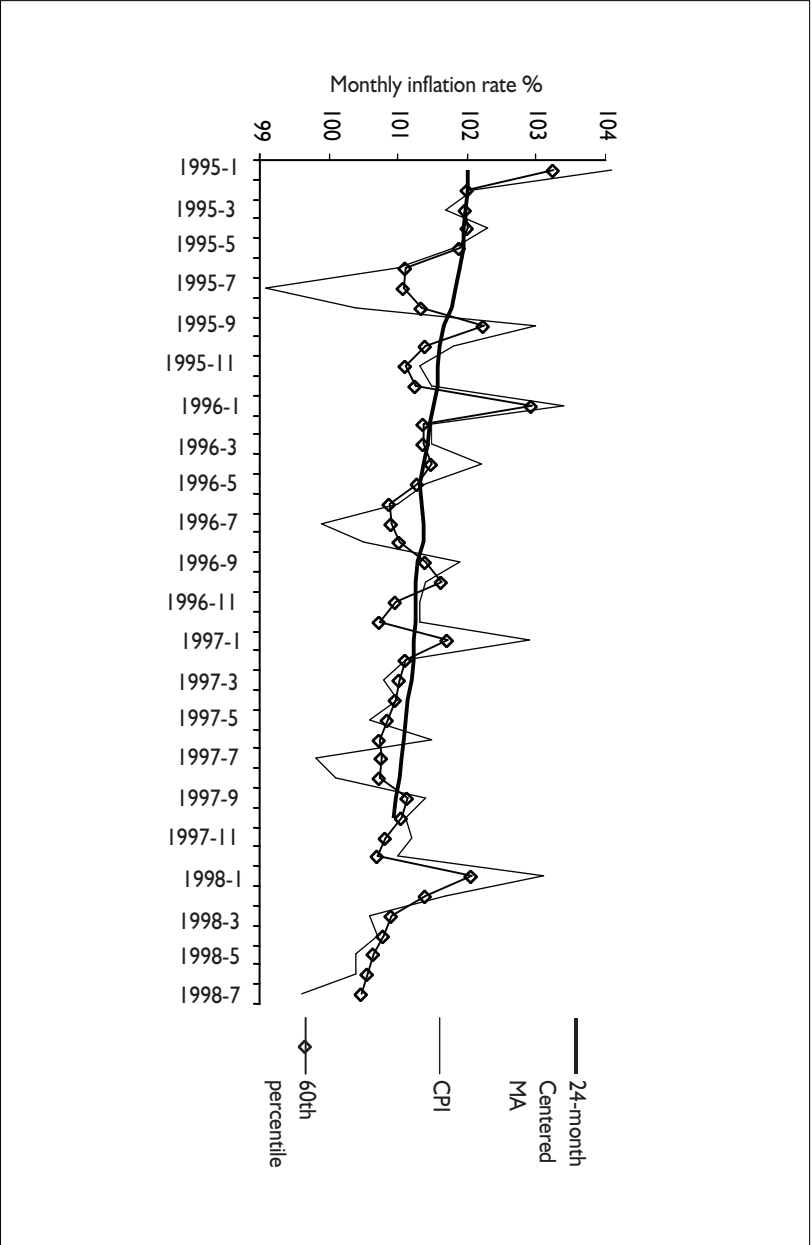


Figure 9b. Optimal Percentile Estimators. Quarterly Estimators

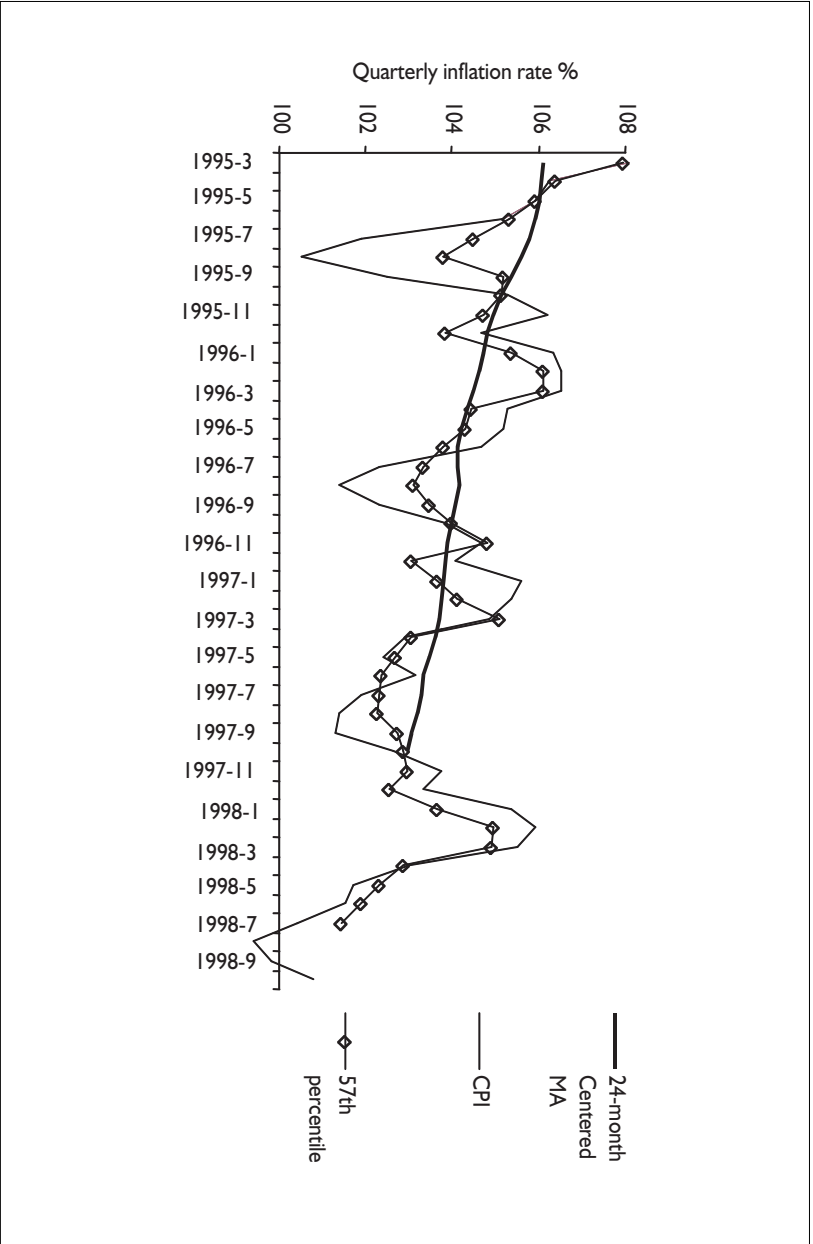
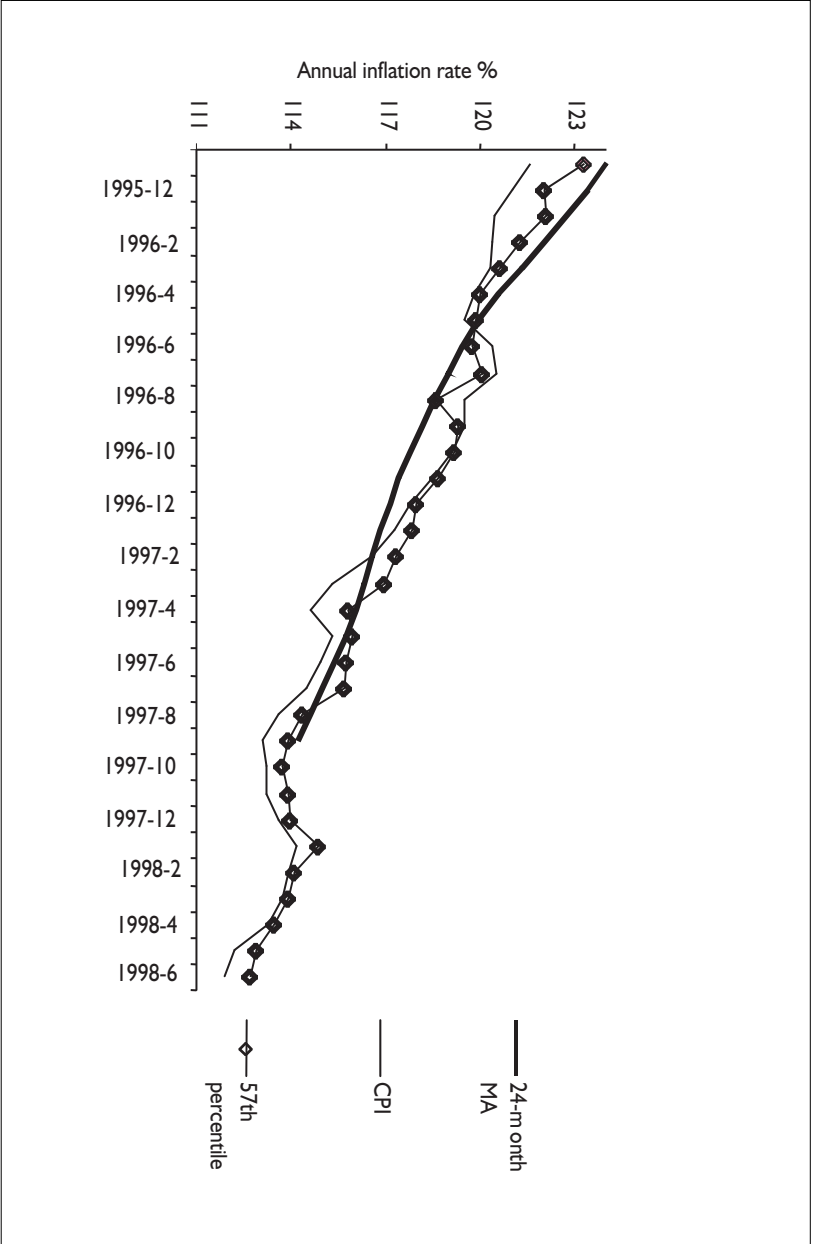


Figure 9c. Optimal Percentile Estimators. Annual Estimators



6. Standard Deviation Trimmed Means

The trimming procedure used in standard-deviation-trimmed means is essentially different from these applied to obtain means trimmed by a certain weight percentage. The idea is to exclude all price movements that are "further" away from the weighted mean of the individual price change distribution in particular period than a given number of standard deviations of that distribution. By doing so one eliminates the influence of extreme price jumps.

The cut-off points suggested in the literature are somewhat arbitrary. The most common practice is to discard all observations above and below 1 to 3 standard deviations from the mean. The justification for this elimination lies in the fact that for any Normally distributed variable:

- 68.2% of observations lies within *one* standard deviation from the mean,
- 95.4% of observations lies within *two* standard deviations from the mean,
- 99.8% of observation lies within *three* standard deviations from the mean.

Therefore, for the purpose of calculating the core price movements, one needs to exclude outlier jumps or falls as determined on a period-by-period basis. With this method it is very possible that items will be discarded asymmetrically. If in any period, inflation is dominated by high price increases without commensurate decreases (i.e. the distribution is positively skewed), the standard deviation trimming will occur at one end of the distribution and will cut off those big jumps leaving all below-the-mean price movements for averaging.

To find optimal core inflation measures using this method, the procedure described above was repeated 6 times for each frequency with varying cut-off points. Beginning with $+ - 3$ standard deviations the author lowered the cut-off point by 0.5 standard deviation (from both sides of the distribution) at a time and finished with the set of $+ - 0.5$ st. deviation around the mean. For each resulting trimmed set of observation the usual weighted average was computed along with the standard efficiency criteria against the 24-month entered average. The results can be found in the table 4 below.

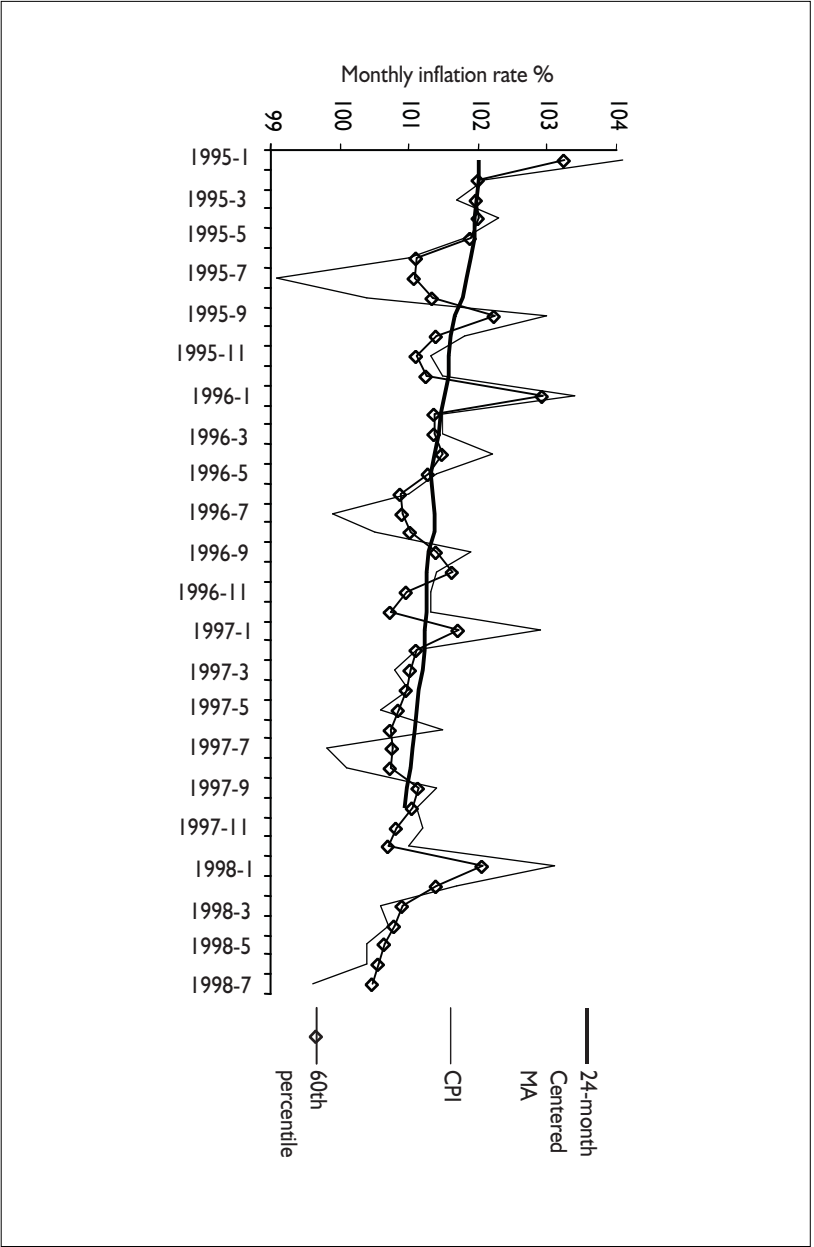
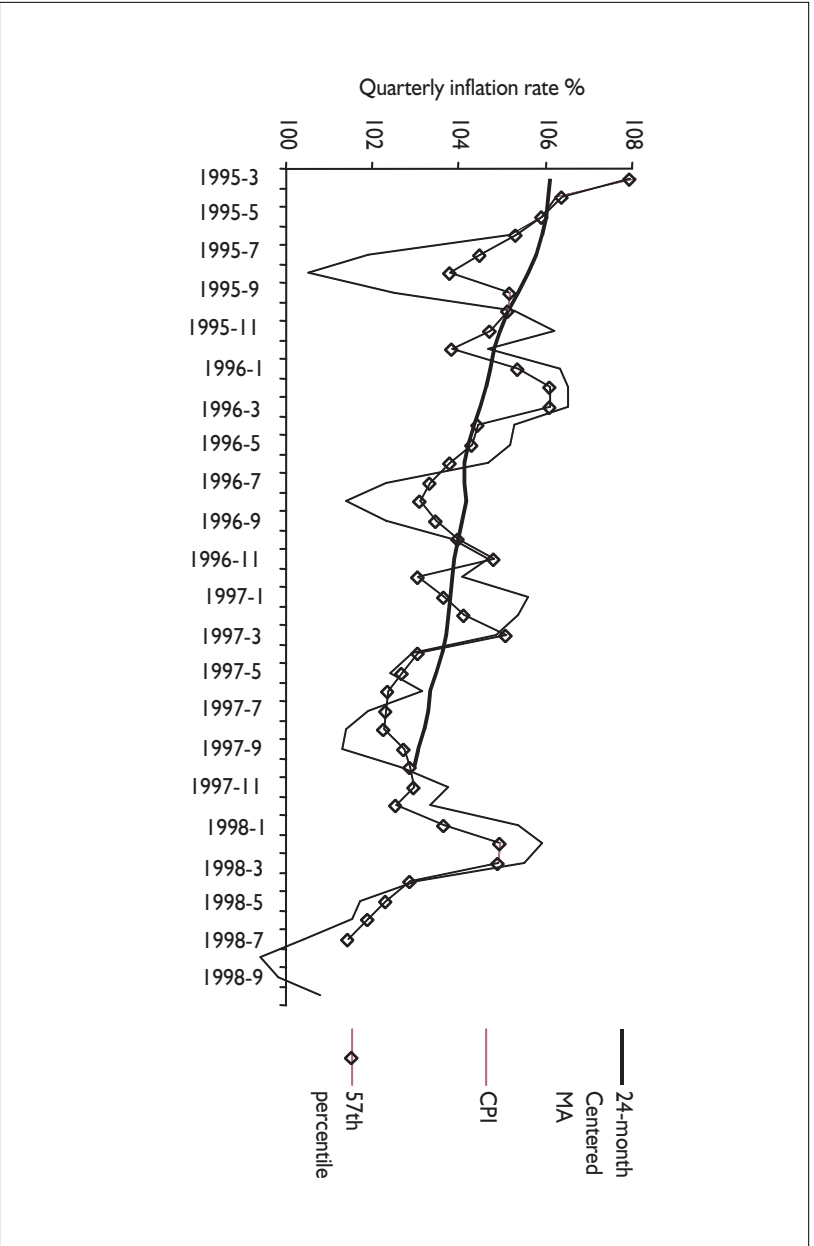


Figure 10a. Optimal Standard-deviation-trimmed Means. Monthly Estimators

Figure 10b. Optimal Standard-deviation-trimmed Means: Quarterly Estimators



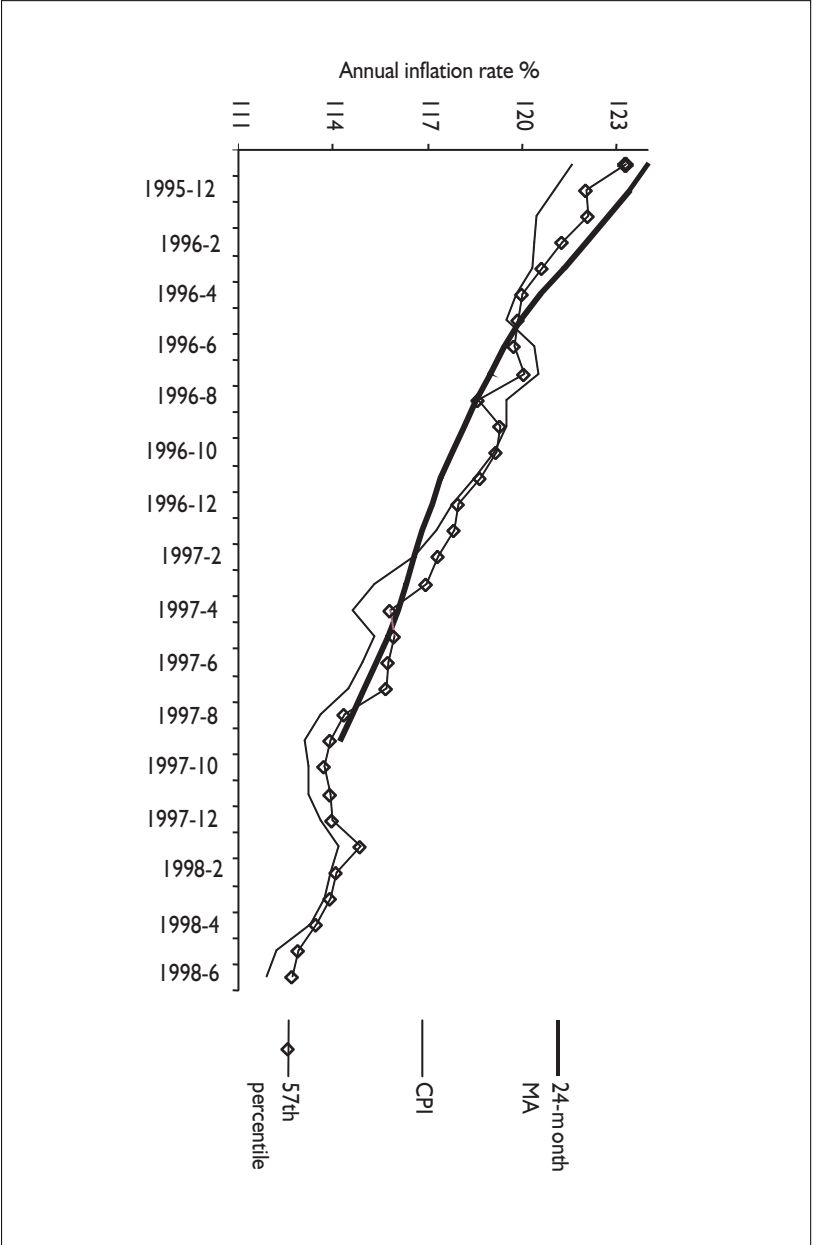


Figure 10c. Optimal Standard-deviation-trimmed Means. Annual Estimators

Table 4. Optimal Standard-deviation-trimmed Means

Data frequency	Cut-off point – of st. deviations	RMSE	MAD	Average annual drift vs. CPI
Monthly	1.0	2.910	0.449	-0.246
	<u>2.5</u>	<u>3.287</u>	<u>0.432</u>	<u>-0.065</u>
Quarterly	1.5	5.133	0.752	-0.178
	<u>2.5</u>	<u>5.152</u>	<u>0.751</u>	<u>0.107</u>
Annual	1.0	4.906	0.828	–

As previously, RMSE and MAD pointed to different estimators for monthly and quarterly data. Likewise, average annual drift was calculated and determined the final choice. 2.5 standard deviations was found to be the optimal threshold for monthly and quarterly data and 1 standard deviation was optimal for annual series. Figure 10 below plots the optimal estimators against the CPI and the 24-month centered moving average.

7. Exclusion Means

7.1. Broad Aggregate Exclusion

The last section is devoted to means that are certainly most widely used across central banks. It is computationally and conceptually the easiest method as well. The technique involves excluding (or zero-weighting) certain categories of goods or services based on the assumption that their price changes are relatively "noisy" i.e. sensitive to transitory phenomena. Consequently it is believed that their price movements carry little valuable information about the trend but rather for the most part reflects relative-price shifts.

Since the 1970s it is customary to include food and energy in this category. Rationale for including food seems pretty clear. Prices of fresh foods, grain or dairy product are particularly prone to rapid seasonal changes as well as all kinds of natural and artificial supply shocks. As for energy prices, it was primarily oil shocks that prompted economists to include them in that category. Roger (1995) points to other, no less important reasons. Prices of energy may not be as volatile as prices of food, but their movements, whenever they occur are rather unlikely to reflect the state of excess demand in the economy. They are with almost no exceptions the result of

classic supply shocks. The same reasoning applies to the group of goods or services whose prices are regulated by government in one way or another, such as utilities, government charges or other items heavily burdened with excise taxes (like tobacco or alcohol in Poland) [31]. Excluding all those items should therefore yield a measure of inflation that is closer to the central tendency reflecting demand pressures present in the economy.

Internationally, the most common sub-groups excluded for the purpose of calculating the core inflation (or an equivalent measure not always explicitly called so) are food and/or energy (United States, Japan, Germany, Canada, Australia, Czech Republic, Hungary), government charges (UK, Australia and New Zealand) and interest costs or rents (UK, Australia and New Zealand).

Despite the fact that the method is very clear and well justified, it also has some serious weaknesses. The practical problem arises when one aims to define categories like food or energy. Is it appropriate to exclude the entire aggregate (with its weight close to 40% in the Polish consumption basket) or single out particular categories, intuitively regarded as highly volatile (like fresh produce or meat)? The other problem lies in the fact that by consistently excluding, say, food from the calculation of the index one runs a risk of losing a potentially important piece of information. When prices of food drift in a slightly different direction than the remainder of the basket the mean calculated without them will give a distorted estimate of the general price movements. Therefore, systematic exclusion of entire aggregates has to be done with caution since the resulting measure of core inflation may be pulled up or down by the bias.

For the purpose of empirical analysis, alternative aggregates –candidates for exclusion were tried out. The available set of 204–207 individual categories offered a very wide range of possible combinations. Common sense narrowed it down to the following 6 broad-aggregate combinations [32]:

1. CPI – energy, fruits and vegetables, meat and meat products,
2. CPI – energy, fruits and vegetables, meat and meat products, bread, cereal and related products,
3. CPI – energy, fruits and vegetables, meat and meat products, bread, cereal and related products, dairy products,
4. CPI – energy and food,

[31] Most of those items (like cigarettes or heating) are characterized by highly inelastic demand and therefore reactively weakly affected by demand squeeze or expansion.

[32] Clearly other combinations involving these or finer categories are possible and are very likely to produce different estimates.

5. CPI – energy, food and regulated items (government charges, utilities, post and telecom services, transportation),

6. CPI – energy and regulated items.

As previously, monthly, quarterly and annual data were analyzed separately. For each of the six above definitions, efficiency criteria: RMSE and MAD were calculated and if they pointed to different optimal series, drift criterion was used to single out the best estimator.

7.2. Volatility-based Exclusion

As noted in the beginning of this section excluding broad aggregates has advantages and disadvantages to it. Clearly, the most serious problem arises when by excluding all food or all energy items we leave out crucial information about the trend movements of prices, i.e. the primary goal of calculating core inflation in the first place. One straightforward remedy is to exclude categories not on the basis of their belonging to one or another category, but rather using the criterion of volatility. After all, it is the volatility that one wants to get rid off by calculating exclusion means. Excluding most volatile categories, regardless of which broad aggregates they fall into, seems a simple and intuitively justified solution.

An important weakness of this method becomes visible when the pattern of volatility is itself changing over time. Then, by excluding categories that were historically highly volatile but for some reason have ceased to be so, one runs a potential danger of voluntarily discarding valuable information while retaining one that can be misleading. Other potential problems with the method concern the definition of volatility, the period over which it is supposed to be measured and the level of disaggregation of individual categories.

As a first step, standard deviations were computed for individual inflation rates of each of the 204 available CPI items [33] over the period set beginning with first 12 available observations up to 43 (for monthly data), 41 (for quarterly data) and 32 (for annual data) observations. The resulting series represent the evolution of volatility of individual CPI categories over time and are indeed relatively stable. This means that volatility is inherent in particular series rather than in specific time periods and one

[33] Since availability varies from 204 to 207 items, the minimum of 204 categories had to be used to ensure the continuity throughout the sample period.

should not run a big inaccuracy risk when extrapolating the past volatility record onto current data.

Not surprisingly, results differ for each frequency reflecting the fact that the very nature of volatility is tied to the time horizon over which the data was accumulated. Table 5 below lists top and bottom 10 categories sorted by volatility as measured by the standard deviation [34].

The table shows very clearly how large an oversimplification one makes when excluding broad aggregates in their entirety. Actual volatility of disaggregated series varies largely within each aggregate [35]. Calculations showed that even food has some components that are more stable than average (like fish or confectionery) while other categories (like various kinds of fees) from outside of the "most suspect" aggregates rather unexpectedly score very high in the ranking.

Accordingly, the author decided to calculate a series of 207 means for each frequency obtained by trimming the set of components according to their volatility. Beginning with the full set of 207 components, the most volatile component (i.e. characterized by highest in-sample standard deviation) was dropped from the set and the mean was calculated as a simple weighted average of the 206 remaining components. The method was applied 207 times and yielded 207 means such that each *mean excluding k components* was averaged over $(207-k)$ least volatile components.

Table 6 below shows the results of the search for the most efficient mean computed using both the method defined above as well as that involving exclusion of broad aggregates introduced earlier. Again, usual efficiency criteria were used supplemented by drift where necessary.

The table shows that for both monthly and annual series, second method of excluding highly volatile components does a much better job reflecting the long-run trend. For quarterly series, simply excluding food and energy yields a better estimator. Figure 11 plots optimal means in both categories along with the CPI and trend.

[34] Table lists only those categories whose weight in the basket was 0.005% and higher during at least one year in the sample.

[35] However, it is clear and the table confirms it that food along with government or government-regulated fees or services are indeed the most volatile groups in the CPI index. On the opposite manufactured household and electronic goods were.

Table 5. Most and Least Volatile CPI Categories

Monthly St.dev.	(95:1–98:7) Categories	Quarterly St.dev.	(95:3–98:7) Categories	Annual St.dev.	(95:12–98:7) Categories
Most volatile categories					
12.33	court and lawyers' fees	23.95	fresh fruits and vegetables	53.14	court and lawyers' fees
11.94	fresh fruits and vegetables	20.46	court and lawyers' fees	22.57	flour
8.03	eggs	18.65	eggs	19.25	eggs
6.29	public radio and tv fee	12.58	animal fats	18.81	sugar
4.96	postal fees	8.58	public radio and tv fee	15.82	animal fats
4.57	hot water	8.24	poultry	15.80	bread
4.49	animal fats	7.89	other household products	13.10	hot water
4.07	electricity	7.64	hot water	13.01	fresh fruits and vegetables
3.83	telephone monthly fee	7.41	postal fees	11.85	rice
3.39	poultry	7.24	flour	11.35	poultry
Least volatile categories					
0.45	kids' clothes	0.98	wine	1.86	men's clothes
0.44	hair and cosmetic care	0.93	cookware	1.69	dormitories and youth hostels
0.42	men's clothes	1.01	dental care	1.66	dental care
0.38	washing machines	0.88	silverware and kitchen utensils	1.48	computer hardware
0.37	silverware and kitchen utensils	0.87	men's clothes	1.44	construction and renovation services
0.37	radio equipment		washing machines	1.38	fish
0.36	cookware	0.79	tv sets	1.34	shoemaker's services
0.35	tv sets	0.73	jewelry	1.34	beer
0.33	jewelry	0.72	radio equipment	1.10	hair and cosmetic care
0.00	hospital and nursing home care	0.00	hospital and nursing home care	0.00	hospital and nursing home care

Figure 11a. Monthly Estimators

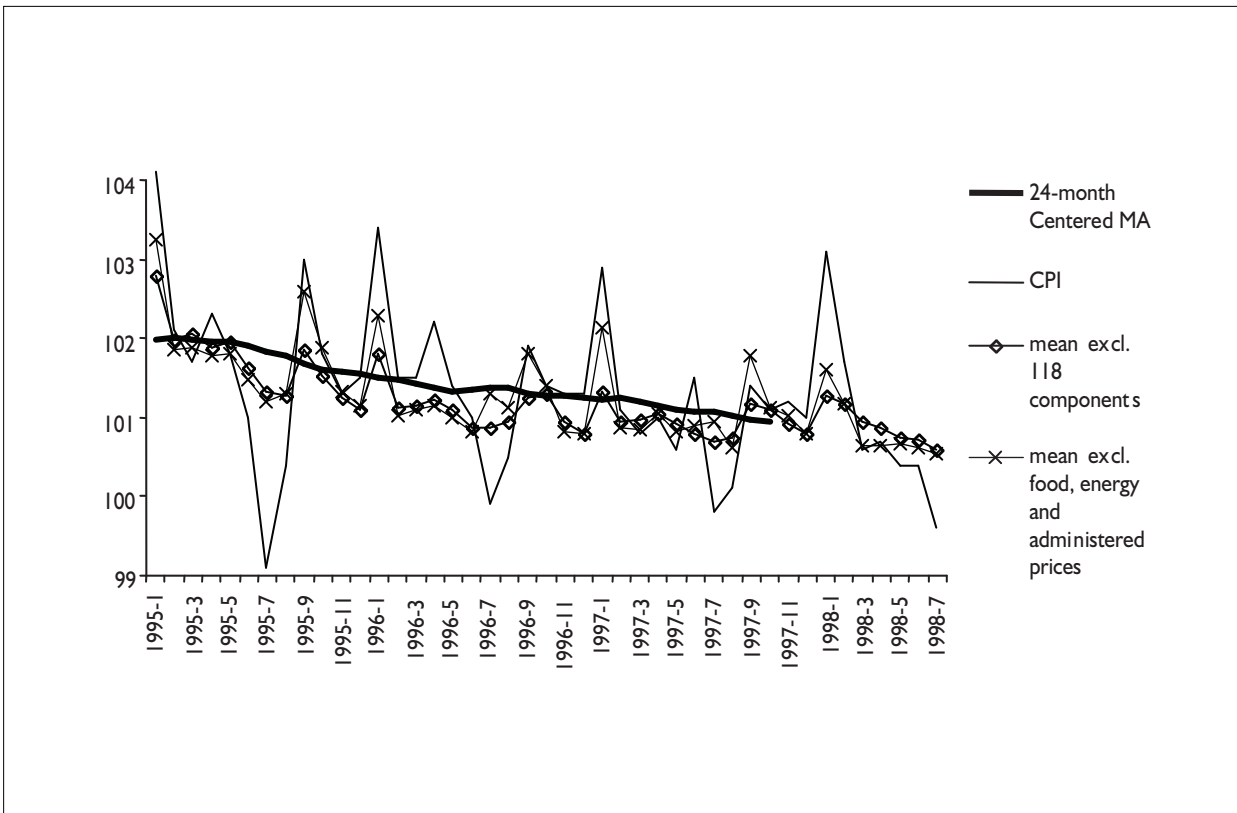


Figure 11b. Quarterly Estimators

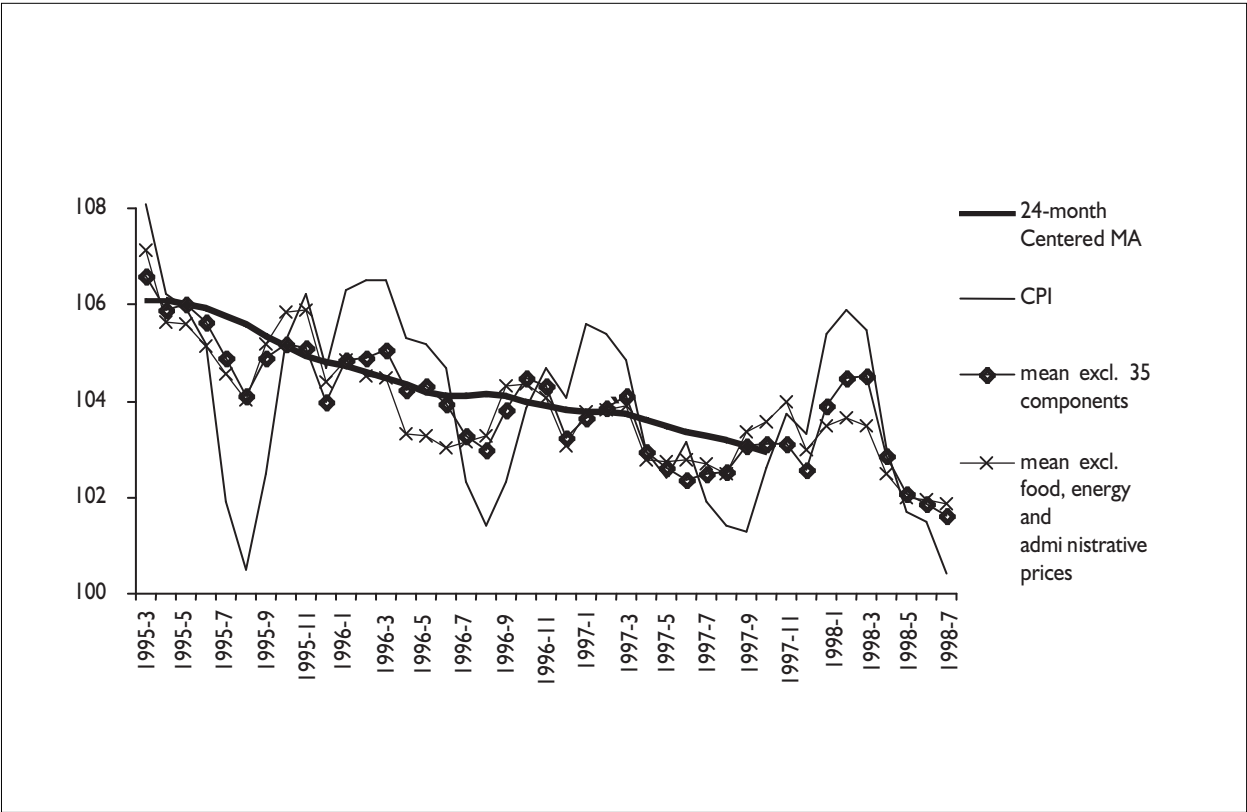


Figure 11c. Annual Estimators

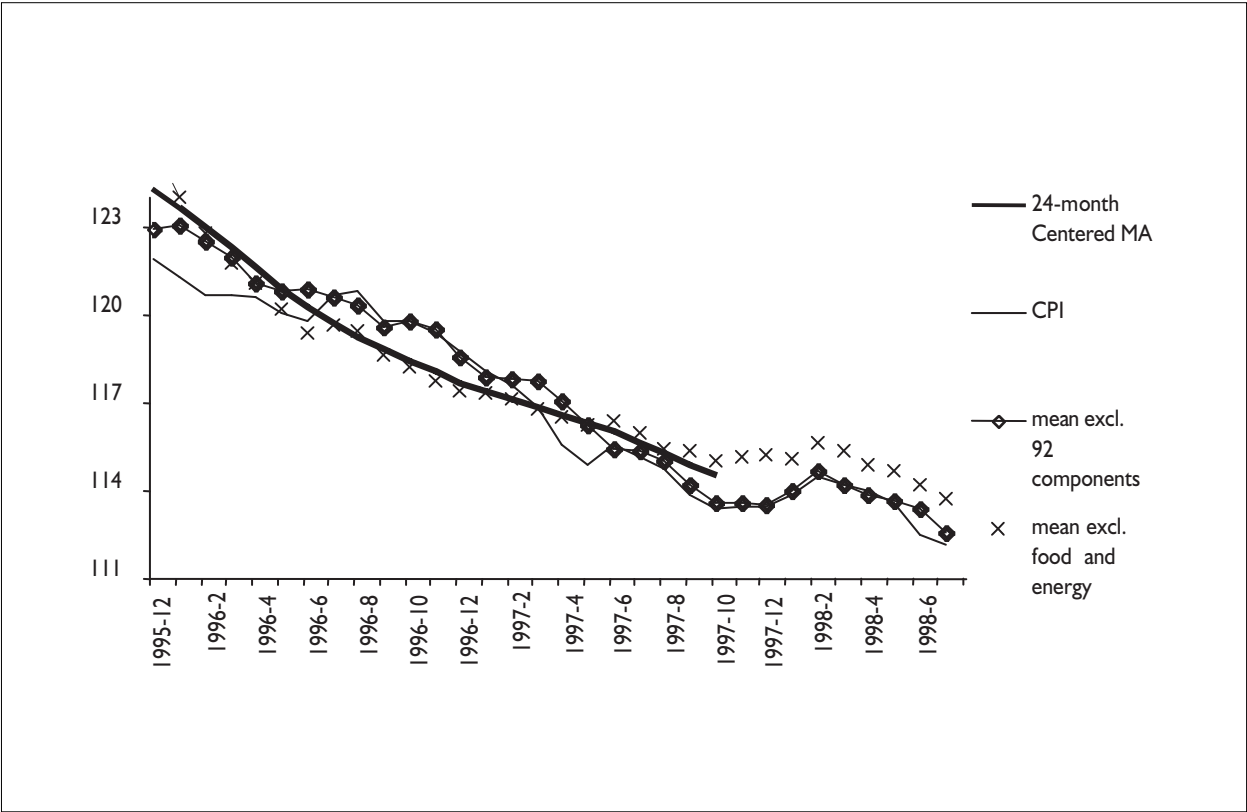


Table 6. Optimal Exclusion Means

	Broad Aggregate Exclusion			Volatility-Based Exclusion				
	Broad categories excluded:	RMSE	MAD	Drift	Number of excluded categories	RMSE	MAD	Drift
Monthly	Mean #5 food, energy and administrative prices	<u>2.779</u>	<u>0.393</u>	<u>0.026</u>	<u>149</u>	<u>1.81</u>	<u>0.281</u>	<u>0.178</u>
	Mean #1 most foods and energy	<u>3.175</u>	<u>0.358</u>	<u>-0.101</u>	<u>118</u>	<u>1.86</u>	<u>0.265</u>	<u>0.126</u>
Quarterly	Mean #5 food, energy and administrative prices	<u>3.99</u>	<u>0.589</u>	<u>-0.121</u>	<u>35</u>	<u>3.352</u>	<u>0.463</u>	
	Mean #1 most foods and energy	<u>4.41</u>	<u>0.580</u>	<u>0.296</u>				
Annual	Mean #4 food and energy	<u>2.347</u>	<u>0.354</u>		<u>92</u>	<u>3.754</u>	<u>0.691</u>	

8. Summary and Conclusions

Table 7 summarizes results obtained in sections 4 through 7 and lists both efficiency criteria computed on the basis of deviations from 24-month centered average. First row presents the baseline performance of the simple headline CPI. It is clear from the table that using any one of the 5 listed methods produces significant efficiency gains. The most efficient estimators for each frequency are typed bold and are underlined.

Rather surprisingly, crude methods based on exclusion yielded the best results. Volatility-based exclusion proved most efficient for monthly and quarterly series, whereas excluding broad aggregates (in this case: food and energy) turned out optimal for annual series. These results are quite different from those obtained by Bryan et al (1997) for the US data, where trimmed means were found to be significantly more efficient than simple-exclusion measures. The reason for that difference again may lie in the different level of disaggregation of CPI components used in both calculations. It is quite likely that if broader components were used, the results would have been quite different, possibly closer to those found in Bryan et al's paper.

It should be noted that, as highlighted in section 7, rules based on simple exclusion suffer from two major deficiencies. If we exclude broad aggregates (such as food and energy from annual data) we risk losing important data that do contain valuable information about the trend. On the other hand, if we exclude items based on their past volatility, we are acting in a rather ad-hoc way and robustness of the resulting estimator (i.e. its sensitivity to "unusual" inflation data) could be severely endangered.

One more possible explanation for the superior performance of exclusion means in our sample may be the steady downward trend in inflation of all CPI aggregates during the entire period under consideration. This constant tendency might have contributed to the results in a major way. The sample used by Bryan et al was 30 years long and included periods of dramatic trend changes during 1967–1997. In this kind of dynamic inflation environment, more robust estimators such as trimmed means and percentiles are very likely to perform much better. In a way, small sample from the steady disinflation period 1995–1998 in Poland used in this paper did not "present" many challenges to the estimator. In other words, if the sample were more diverse and included periods of changing inflation trend, then it is very likely that means based on exclusion would be "penalized" for their lack of robustness and trimmed means and percentile methods would win on the same ground.

Table 7. Comparison of Inflation Estimators: Summary

Class of estimator	Monthly			Quarterly			Annual		
		RMSE	MAD		RMSE	MAD		RMSE	MAD
CPI		5.517	0.656		10.422	1.408		11.357	1.599
Trimmed means	50	2.893	0.437	48	5.322	0.776	46	5.307	0.885
Percentile	60	2.719	0.339	57	4.972	0.698	57	3.623	0.755
St.dev. trimmed means	2.5	3.287	0.432	2.5	5.152	0.751	1	4.906	0.828
Broad-aggregate exclusion	#5	2.779	0.393	#5	3.990	0.589	#4	<u>2.347</u>	<u>0.354</u>
Volatility-based exclusion	118	<u>1.860</u>	<u>0.265</u>	35	<u>3.352</u>	<u>0.463</u>	92	3.754	0.691

Results clearly show that more research is needed in the field. Specifically, it is desirable to lengthen the sample period, re-do the calculations using more aggregated data and changing the definitions of the benchmark inflation. Therefore, this paper should be regarded as an opening voice in the discussion of various measures of underlying inflation in Poland rather than one that is giving conclusive answers and ready recipes.

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comments and suggestions concerning numerous calculations that appear throughout the paper.