THE USE OF ROBUST ESTIMATORS AS MEASURES OF CORE INFLATION

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ABSTRACT

This paper examines robust estimators of core inflation for Belgian historical CPI data, and for euro area Harmonised Indices of Consumer Prices. Evidence of fat tails in the cross-sections of price changes is provided by traditional measures, as well as by a robust measure of the tail weights that is not vulnerable to the masking phenomenon. Trimmed means are considered in the first instance. We introduce a new estimator where the optimal trimming percentage is the lowest percentage for which the hypothesis of normality of the trimmed samples cannot be rejected on the basis of the Jarque-Bera statistic. Two variants are considered one with a constant and one with a time-varying optimal trimming percentage. The latter has a higher breakdown point. Symmetric and asymmetric trimming are considered as well. Another robust estimator, the one-step Huber-type skipped mean, which is less vulnerable to the masking phenomenon, is also examined. It is shown that the robust estimators outperform the traditional core inflation measures found in the literature. However, as traditional measures, they lag rather than lead observed inflation. This was particularly so in the 70s and the 80s when the oil price shocks had substantial second-round effects on Belgian inflation.

Keywords: Inflation, Core inflation, Relative prices, Robust estimators of central tendency
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1 INTRODUCTION

Given the long lags in the transmission mechanism, monetary policy is essentially medium-term oriented. Consequently transitory inflation movements should not have any major impact on monetary policy decisions. This medium-term orientation is, for instance, specified explicitly in the monetary policy strategy of the Eurosystem. As inflation data typically show a considerable degree of short-term volatility, which cannot be controlled by monetary policy actions, there is a need to develop inflation measures that are free of this type of noise. If these 'underlying' or 'core' inflation measures can be successfully constructed, they should in principle provide the monetary authorities with better signals than the observed inflation does.

Although the concept of core inflation is very appealing from this point of view, it does however have one important drawback. Since it has not been well defined from a theoretical point of view, several estimation techniques for the unobservable core inflation component have been proposed but no consensus has been reached on which estimation technique performs best. The different approaches to core inflation are surveyed in Roger (1998) and Wynne (1999). According to Roger (1998) there are two broad concepts of core inflation: '*One concept views core inflation as the persistent component of measured inflation. The second concept views core inflation as the generalised component of measured inflation'*. Examples of approaches belonging to the first group are: univariate smoothing techniques and the multivariate SVAR method first presented in Quah and Vahey (1995). The latter approach excludes from measured inflation the effects of the so-called non-core shock that has been identified in a bivariate VAR with output and inflation as the shock that can have long-term effects on output[1]. The second group consists of techniques that reweight or exclude particular price series in a systematic way (for instance, measures of the well-known 'excluding energy and unprocessed food'-type) or make use of robust estimators such as the median or trimmed means, in order to downweight outliers in the cross-section of price changes in a more flexible way. Measures that make specific adjustments (for instance, the exclusion of the direct effect of a change in indirect taxes on consumer prices) occupy in our view a more intermediate position in this classification. On the one hand these adjustments are made because it is believed that the indirect tax effect on inflation is of a transitory nature. On the other hand it may be argued that some tax increases, for instance excise duties for specific products, do not reflect the generalised component of measured inflation. Practical applications of several of these approaches can be found in BIS (1999) which presents the proceedings of a workshop of central bank model builders on core inflation.

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1 Applications of this approach to Belgian data can be found in Dewachter and Lustig (1997) and in Aucremanne and Wouters (1999).

The aim of this paper is to treat robust estimators[2] only. The remainder of the paper is structured as follows. Section 2 gives a brief overview of the literature on robust estimators as measures of core inflation. Section 3 describes some characteristics of the cross-sectional distribution of Belgian consumer prices. Special attention is paid to a robust method of outlier detection. In Section 4 two estimators are introduced in which the optimal trimming percentage is directly related to the departure from normality. When the trim is progressively increased from zero to 50, the optimal trimming percentage of these estimators corresponds to the percentage that produces the first subsample for which the null hypothesis of normality cannot be rejected on the basis of the Jarque-Bera test statistic. The initial objective was to obtain an optimal trimming percentage that is constant over time. This result has been achieved by using the historical average of the Jarque-Bera as the benchmark. However, as this strategy may have important drawbacks, a second variant using the Jarque-Bera statistic for each month separately is presented too. This optimisation procedure yields a time-varying optimal trimming percentage and has a higher breakdown point. A robust estimator of a completely different type is considered as well: the so-called one-step Huber-type skipped mean. The latter is not vulnerable to the masking phenomenon. Section 5 tries to assess the performance of the estimators discussed in Section 4. Section 6 applies these estimators to euro-area wide Harmonised Indices of Consumer Prices (HICPs). These estimators can easily be constructed for data for which only a limited number of historical observations are available, as is the case for HICP data. Finally, Section 7 presents some conclusions.

[2] Some authors use the wording *limited-influence* estimators or *bounded-influence* estimators instead of robust estimators. We prefer the general term *robust* over the specific terms *limited influence* or *bounded influence* that cover only one aspect of robustness.

2 A BRIEF OVERVIEW OF THE LITERATURE ON ROBUST ESTIMATORS AS MEASURES OF CORE INFLATION

The robust estimators approach to core inflation emphasises the fact that inflation, which is a monetary phenomenon, should ideally measure the increase in the *general* price level. However, in practice this is done using the CPI, which is the weighted mean of prices of *individual* goods and services. Consequently, the CPI measures the increase in the general price level, as well as the changes in *relative* prices. Bryan and Pike (1991) summarise this statistical problem as a signal extraction problem: '*To accurately gauge the economy's current inflationary momentum, we must somehow disentangle the relative price 'noise' from the inflation signal'*. To do so, they propose taking the median of the cross-sectional distribution of price changes as a measure of core inflation. In contrast to the mean, the median has the advantage that it is a measure of central tendency that is largely independent of the data's distribution, in particular its departure from normality. Bryan and Cecchetti (1994) propose the use of statistics of the same type, in particular the weighted median[3] or the 15 p.c. trimmed mean[4]. In contrast to the 'adjustment by exclusion' approach where discretionary judgement is essential when the excluded components are selected, these robust estimators - either the median, or the trimmed means - remove the influence of relative prices in a non-subjective way. This is perhaps their most appealing characteristic.

Bryan and Cecchetti (1994) provide an *economic* rationale for the use of robust estimators of core inflation by relating them to the sticky price model presented in Ball and Mankiw (1995), where firms face menu costs when they wish to adjust their prices. As a consequence, prices are adjusted in response to large shocks only and therefore large shocks have a disproportionately large impact on inflation in the short-run. In that event, the distribution of the relative price changes influences the overall price level. When this distribution is skewed to the right, the price level rises and vice versa. In other words, the model predicts that inflation is positively related to the skewness of relative price changes, as is often observed in practice. Balke and Wynne (2000), however, present a multi-sector general equilibrium model with flexible prices, which provides an alternative explanation for the positive correlation between inflation and the skewness of relative prices changes.

Bryan et al (1997) prefer to be non-committal on the underlying economic model of price-setting behaviour and elaborate instead the *statistical* argument for using robust estimators. They view the monthly observed price changes as small-sample draws from the longer-horizon population whose distribution is unknown. This sampling idea is also discussed in Bryan and Cecchetti (1999). They

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[3] The weighted median is the median whereby the CPI weights are used as the probabilities of the corresponding price changes. In contrast, Bryan and Pike (1991) proposed the unweighted median.

demonstrate that the correlation observed between the sample mean and the sample skewness can be fully explained by the small-sample bias. This finding leads them to conclude that such statistics are not useful in distinguishing sticky from flexible price-setting behaviour in macroeconomic models.

How desirable is it to embed the robust estimator technique of core inflation in a broader economic theory on price dynamics? It certainly is desirable and, seen from this angle, we agree with Zeldes (1994) when he argues that '*(...) the appropriate measure of core inflation must be model-based. Additional work needs to be done deriving the properties of the trimmed mean in more general models of inflation'*. It should be observed, however, that this is not an easy task. Logically, some apects of price stickiness will be part of this story, otherwise it would make no sense to look at the prices of individual CPI components[5]. A fully dynamic specification of the underlying model, as well as the occurrence of aggregate demand shocks in combination with relative price shocks will be other ingredients[6]. Taking aggregate demand shocks explicitly into account is important, as Zeldes (1994) and Bakshi and Yates (1999) pointed out that these shocks may be a source of (chronic) skewness in the distribution of price changes and that it would be misleading to eliminate them from the core inflation measure. Finally, the model should be in line with micro-foundations and micro-evidence in the field of price stickiness and should presumably incorporate some state dependence, whereas many of the dynamically specified New-Keynesian models typically assume time-dependent pricing rules. At the current juncture, we therefore tend to agree with Bakshi and Yates (1999) when they state that the statistical arguments put forward in Bryan et al (1997) are more convincing than the arguments based on economic theory.

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4 After having removed in each tail of the distribution α p.c. of the price changes, the α - p.c. trimmed mean corresponds to the mean of the remaining central (100-2α) p.c. observations. The mean and the median can be considered as special cases of trimmed means, with a trimming percentage of zero and 50 p.c. respectively.

5 See Zeldes (1994) and Ball and Mankiw (1999).

6 The Ball and Mankiw (1995) model is static and considers relative price shocks only. Ball and Mankiw (1994) present a menu cost model that is static too, but incorporates trend inflation. The presence of trend inflation generates endogenous asymmetric price adjustment.

That is why the present paper focuses on the statistical argument, which goes as follows. If the population is normally distributed, the sample mean is an unbiased and efficient estimator of the population mean. However, the population of price changes appears to have fatter tails than the normal distribution, as is suggested by the high kurtosis of the observed samples. The presence of fat tails increases the probability that an observation is drawn from one of the tails of the distribution. Consequently a sample from a leptokurtic distribution is often skewed, even if the underlying distribution is symmetric. In these circumstances, the sample mean is no longer an efficient estimator and estimators that are robust for the departure from normality such as, for instance, the median or trimmed means, perform better, as they are less affected by extreme price changes drawn from one of the tails of the distribution. The approach of Roger (1997) is also explicitly stochastic and this paper mentions that other L-estimators than the median or the trimmed means could be considered as core inflation measures as well[7].

The Bryan et al paper also presents a method of determining the optimal trimming percentage. They therefore examine the entire range of trimmed means, with the trim going from zero to 50 p.c. The trimmed means are then compared with the 36-month centred moving average of actual CPI inflation, which is supposed to represent the trend (or core) inflation and is therefore used as benchmark. The aim is to find the trimming percentage that minimises the gap between both inflation measures. Technically speaking, this gap was measured by the Root Mean Square Error (RMSE) or by the Mean Absolute Deviation (MAD) and the trim that minimised the RMSE was chosen as the optimal trimming percentage. They find that trimming 9 p.c. from each tail minimised the gap between the core inflation measure and the benchmark in the case of US CPI data. Determination of the optimal trim using this method has been applied in several papers[8].

Roger (1997), confronted with a high degree of kurtosis and *chronic* right skewness in the quarterly price changes in New Zealand over the period 1949-1996, was faced with the dilemma between using the sample mean (unbiased, but relatively inefficient in the case of leptokurtic distributions) on the one hand, or the median or trimmed means (relatively efficient, but biased in the case of chronic skewness) on the other. Indeed, the chronic - or average - right skewness indicates that, on average, the observations in the right hand tail of the distribution are further away from the mean than those in the left hand tail. Removing observations from the tails in a symmetric way will in these circumstances result in a core inflation measure that has the tendency to undershoot the observed inflation in a

7 An order statistic is a percentile of a sample. For instance, the first quartile (i.e. the 25th percentile) is an order statistic, and so is the median (i.e. the 50th percentile). An L-estimator is a linear combination of order statistics, in other words, a weighted mean of percentiles. For instance, the 20 p.c. trimmed mean can be seen as a weighted mean in which the observations get weight zero up to the 20th percentile; weight zero above the 80th percentile; and weight 100/60 between the 20th and the 80th percentile. More complex weighting schemes are possible. More complex L-estimators could have a gradual decrease in weights to outlying observations, whereas trimmed means assign a zero weight to outliers.

8 For instance, in Kearns (1998), Bakhshi and Yates (1999), Bryan and Cecchetti (1999b), Meyler (1999), Vega and Wynne (2000).

systematic way and consequently has a negative bias. To overcome this dilemma, Roger proposed the 57th percentile as a measure of core inflation, because this statistic combines the property of being essentially unbiased in the case of data for New Zealand[9], with the efficiency property of robust measures of central tendency in the case of leptokurtic distributions. Other examples of asymmetric trimming are Chatelain, Odonnat and Sicsic (1996), Kearns (1998), Le Bihan and Sédillot (1999), Meyler (1999) and Marques and Mota (2000).

Wynne (1999) points to the fact that European research in this field is confronted with the constraint that HICP data have only been available since January 1995. As he suggested, analysing historical national data is one way of overcoming this problem. In this perspective, the following application to Belgian *national* CPI data can contribute to a certain extent to the European research in this field. As will be argued in the remainder of this paper, determining the number of rejected observations on the basis of robust arguments only, instead of on the basis of trend inflation, may also overcome that problem of data availability.

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[9] The sample mean of the cross-sectional distribution of price changes belonged, on average, to the 57th percentile. On the basis of this evidence, it is assumed that the 'true' population mean also belongs to that percentile. As a consequence, the 57th percentile can be considered as an unbiased estimator of the population mean. Using the 57th percentile can also be interpreted as a case of asymmetric trimming.

3 FAT-TAILED BELGIAN CONSUMER PRICES: 1976.06 - 1999.10

An homogenous CPI-database with a sufficiently detailed disaggregation and a monthly frequency could be constructed fairly easily from June 1976 onwards, when the so-called index with base period 1974-1975 = 100 was introduced. In the remainder of this paper, three different aggregation levels are considered. The first aggregation level ('Level 1') consists of 60 subindices of the CPI, the second aggregation level ('Level 2') corresponds to 52 subindices and the third ('Level 3') to 32 subindices. Table 1 lists all the items included in the COICOP/HICP classification which is currently used for HICP data, as well as their code[10]. For each aggregation level the components are marked with the value 1. At Levels 1 and 3 an additional breakdown is considered for some components[11]. For each aggregation level the CPI at time t can be expressed as a fixed weighted index of all the subindices $I_{i,t}$ of the aggregation level considered[12]:

$$CPI_t = \sum_{i=1}^{n} w_i I_{i,t}$$

$$\text{with each } w_i > 0 \text{ and } \sum_{i=1}^{n} w_i = 1 \qquad (1)$$

In formula (1) n equals 60, 52 and 32 for Level 1, Level 2 and Level 3 respectively. For each of the subindices price changes have been calculated over an horizon h as

$$\Pi_{i,t}^{h} = \frac{I_{i,t}}{I_{i,t-h}} - 1 \qquad (2)$$

Four time horizons have been studied, where h was 1, 3, 6 and 12 respectively. As the databank used starts in 1976.06 for the indices, the total sample size of the price changes decreases as the horizon increases. For 1-month price changes the total sample size is 280, while it is 278, 275 and 269 for 3-month, 6-month and 12-month price changes respectively. The observed inflation at time t over a horizon h corresponds to the weighted mean of the price changes of the different subindices over the same horizon:

$$\Pi_t^h = \sum_{i=1}^{n} w_{i,t}^h \Pi_{i,t}^h \qquad (3)$$

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[10] The historical data considered are of course national CPI data, as HICP data are only available from January 1995 onwards.

[11] At Level 1, these items, which are not part of the standard COICOP classification, are marked with the extension 'part' in the column 'code' of Table 1. At Level 3, the COICOP-component 'Food' (1.100) is broken down in the subcomponents processed and unprocessed food.

[12] It should be noted that during the period considered the CPI has been actualised in 1984, 1991 and in 1998. At these occasions the weights were actualised, as well as the basket of goods and services considered. The indices with different base years have been chain-linked.

where the time-varying weights $w_{i,t}^{h}$ are the fixed weights of formula (1), adjusted for the relative price change of component i:

$$w_{i,t}^{h} = w_i \frac{I_{i,t-h}}{CPI_{t-h}} \tag{4}$$

The weighted mean can be used to calculate the higher order central moments of a cross-section . The central moment of order r is defined as.:

$$m_{r,t}^{h} = \sum_{i=1}^{n} w_{i,t}^{h} \left(\Pi_{i,t}^{h} - \Pi_{t}^{h}\right)^{r} \tag{5}$$

The second central moment, $m_{2,t}^{h}$, is the variance $\left(s_t^h\right)^2$ of the cross-section considered, from which the standard deviation s_t^h is calculated by taking the square root. Both are measures of the dispersion of the cross-sectional distribution. When the third and fourth central moment are scaled by the standard deviation, the skewness S_t^h and the kurtosis K_t^h of the cross-section are obtained:

$$S_t^h = \frac{m_{3,t}^{h}}{\left(s_t^h\right)^3} \tag{6}$$

$$K_t^h = \frac{m_{4,t}^{h}}{\left(s_t^h\right)^4} \tag{7}$$

They are summarised in Table 2, where for each of the aggregation levels and time horizons considered, the historical average and the historical standard deviation of the sample skewness and the sample kurtosis are reported[13]. The skewness gives an idea of the symmetry of the distribution. A symmetrical distribution, as for instance the normal distribution, always has a population skewness of zero. If the population skewness is positive (negative), then the distribution is skewed to the right (left) indicating that the right (left) hand tail is the longest. The kurtosis measures the relative importance of the tails of the distribution. The kurtosis of the normal distribution is 3. Fat-tailed or leptokurtic distributions have a population kurtosis higher than 3, whereas distributions with a population kurtosis lower than 3 have relatively few observations in their tails (platykurtic distributions).

The most striking observation which can be made from Table 2, is that there is a high sample kurtosis in the cross-sections of price changes, indicating that they are very fat tailed. The kurtosis ranges from an average value of 6.4 for 12-month price changes at Level 3 to 37.8 for 1-month price changes at

Level 1 (seasonally adjusted data). The kurtosis tends to decrease for higher horizons h and for higher aggregation levels, while seasonal adjustment has only a rather limited impact on the average kurtosis. Even the lowest average value of kurtosis (6.4) is more than twice the kurtosis of a normal distribution. As far as the skewness is concerned, there is evidence of some degree of right (average) skewness for all the aggregation levels and horizons considered. Far more important than the average value, is, though, the relatively large standard deviation of the sample skewness, which ranges from 1.3 for 12-month price changes at Level 3 to 4.5 for the 1-month price changes at Level 1 (seasonally adjusted data). These high standard deviations reveal more clearly than the average value that the samples are often skewed, as the effect on the average value of months with positive skewness is to a large extent compensated by months with negative skewness.

Skewness and kurtosis can be used to test the null hypothesis of normality by means of the so-called Jarque-Bera statistic, which is defined as:

$$JB_t^h = \frac{n}{6}\left[\left(S_t^h\right)^2 + \frac{1}{4}\left(K_t^h - 3\right)^2\right] \qquad (8)$$

This test statistic was previously proposed by D'Agostino and Pearson (1973). From (8) it can be seen that the population version of the Jarque-Bera statistic of the normal distribution equals zero and that this statistic increases with the departure of either the skewness or the kurtosis from their respective values for the normal distribution. Under the null hypothesis of normality the Jarque-Bera statistic is χ^2 with two degrees of freedom. The 95 p.c. critical value for rejection of the null hypothesis is 5.99, which is far exceeded by the average Jarque-Bera statistic for each aggregation level and each horizon of Table 2. Even for 12-month price changes at Level 3, for which the lowest average Jarque-Bera statistic was recorded, the null hypothesis of normality is rejected in about 50 p.c. of the individual months (136 out of 269 months). For 1-month price changes at Level 1 the null hypothesis can be rejected in all but 1 month.

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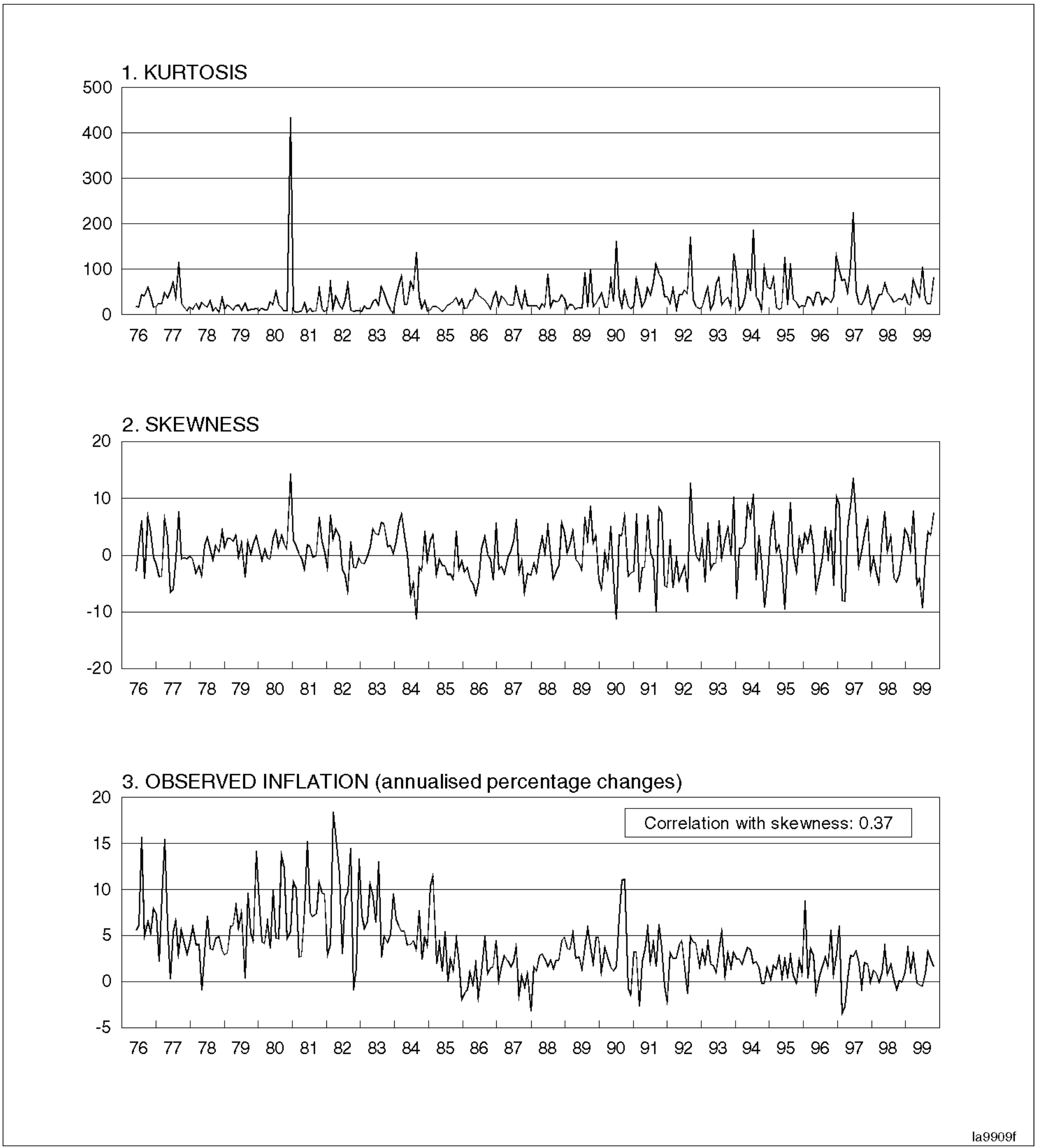
13 The term 'historical' refers to the fact that the average and the standard deviation of S_t^h and K_t^h have been calculated with respect to the time dimension of the data.

FIGURE 1 - Belgian 1-month price changes at Level 1
(seasonally adjusted data)



The findings of Table 2 are illustrated in Figure 1 for 1-month price changes at Level 1. Given the presence of outliers, as is evidenced by the kurtosis, there is also a lot of skewness observed, which typically switches from the right to the left. This switching explains not only the low historical average and the high historical standard deviation of the skewness, but is also an indication of the efficiency loss incurred by the sample mean if the data are not normally distributed. Indeed, the sample mean of price changes of individual goods and services is in a systematic way influenced upwards (downwards) when the skewness is positive (negative): the correlation between sample skewness and sample mean, i.e. observed inflation, is positive and amounts to 0.37. This figure also provides the rationale for the use of robust estimators. By downweighting the influence of outliers these estimators will reduce the switching effect of the outliers on the inflation measure and will consequently be able to reduce the short-term volatility in the inflation data as well.

Although the results with respect to the skewness and the kurtosis, as well as the related Jarque-Bera statistic, provide ample evidence for the presence of outliers in the cross-section of Belgian CPI price changes, it is interesting to note that these measures tend to mask the true importance of the tails as they are themselves constructed in a non-robust way. There are two reasons for this masking phenomenon. Firstly, from formula (5) it can be seen that these measures are based on the distance that separates each individual observation from the mean. It is clear however that the mean itself is influenced by the occurrence of outliers and therefore the distance between an outlier and the true centre of the sample is understated by the measure that is used in (5). Secondly, the skewness and the kurtosis are scaled by the standard deviation (see equations (6) and (7)). In the presence of outliers, though, the standard deviation tends to overstate the true dispersion. Both factors exert a downward influence on the kurtosis, leading to the conclusion that the statistic that is supposed to measure the occurrence of fat tails becomes less effective the fatter the tails are.

To illustrate this masking phenomenon we present two alternative ways of measuring the tail weights. The first one uses the mean and the standard deviation to standardise the data, i.e. the sample mean is subtracted from each individual price change and this difference is subsequently divided by the standard deviation:

$$x_{i,t}^{h} = \frac{\Pi_{i,t}^{h} - \Pi_{t}^{h}}{s_{t}^{h}} \tag{9}$$

This is done for all the months considered. Thereafter, the historical average of the total weight of those standardised price changes which exceed 2.5 in absolute value is calculated. The choice of this critical value is based on the fact that for the standard normal distribution (N(0,1)) the observations with an absolute value exceeding 2.5 only represent a minor weight, or 1.24 p.c. to be precise. These observed weights of standardised price changes exceeding 2.5 in absolute value are reported in Table 2 for each aggregation level and each horizon considered. For seasonally adjusted data, they range from 2.4 to 3.8 p.c., suggesting that more extreme observations are on average recorded for the cross-sections considered than is the case for the standard normal distribution. It is clear however that these measures suffer from the masking phenomenon described above, as the standardisation is based on the mean and on the standard deviation. The same type of measure was therefore calculated using the robust standardisation procedure described in Rousseeuw and Leroy (1987). This procedure replaces the sample mean in formula (9) by the sample median and replaces the standard deviation by the median of absolute deviations from the median, multiplied by a correction factor that equals 1.4826[14]. In so doing, the following standardisation was performed:

$$y_{i,t}^{h} = \frac{\Pi_{i,t}^{h} - \text{med}\left(\Pi_{i,t}^{h}\right)}{1.4826 \text{ med}\left|\,\Pi_{i,t}^{h} - \text{med}\left(\Pi_{i,t}^{h}\right)\right|} \qquad (10)$$

For more information about the median absolute deviation, see Rousseeuw and Croux (1993). The weights of the (robust) standardised price changes exceeding 2.5 in absolute value are also recorded in Table 2 and are far more pronounced than the weights associated with the non-robust standardisation, as they range for seasonally adjusted data from 7.8 p.c. for 12-month price changes at Level 3 to 15.1 p.c. for 1-month price changes at Level 1. The difference between the two types of standardisation increases for shorter horizons. As they have typically more outliers, the masking is more pronounced for the shorter horizons. A similar conclusion can be drawn from a comparison of seasonally adjusted data and data without seasonal adjustment. According to the robust standardisation, the tails of the distribution are significantly fatter for data without seasonal adjustment, whereas hardly any difference can be seen between both types of data in the case of the non-robust standardisation. These results clearly illustrate the importance of the masking phenomenon when non-robust measures are used and emphasise that the masking increases as the tails become fatter.

[14] This correction factor is based on the fact that the measure of dispersion used in formula (10) equals 0.6745 in the case of the standard normal distribution. Consequently, this measure of dispersion is multiplied by the correction factor 1/0.6745 or 1.4826 to obtain 1, which makes the standardisation of formula (10) immediately comparable to the standard normal distribution.

FIGURE 2 - Pooled standardised price changes: cumulative frequency function

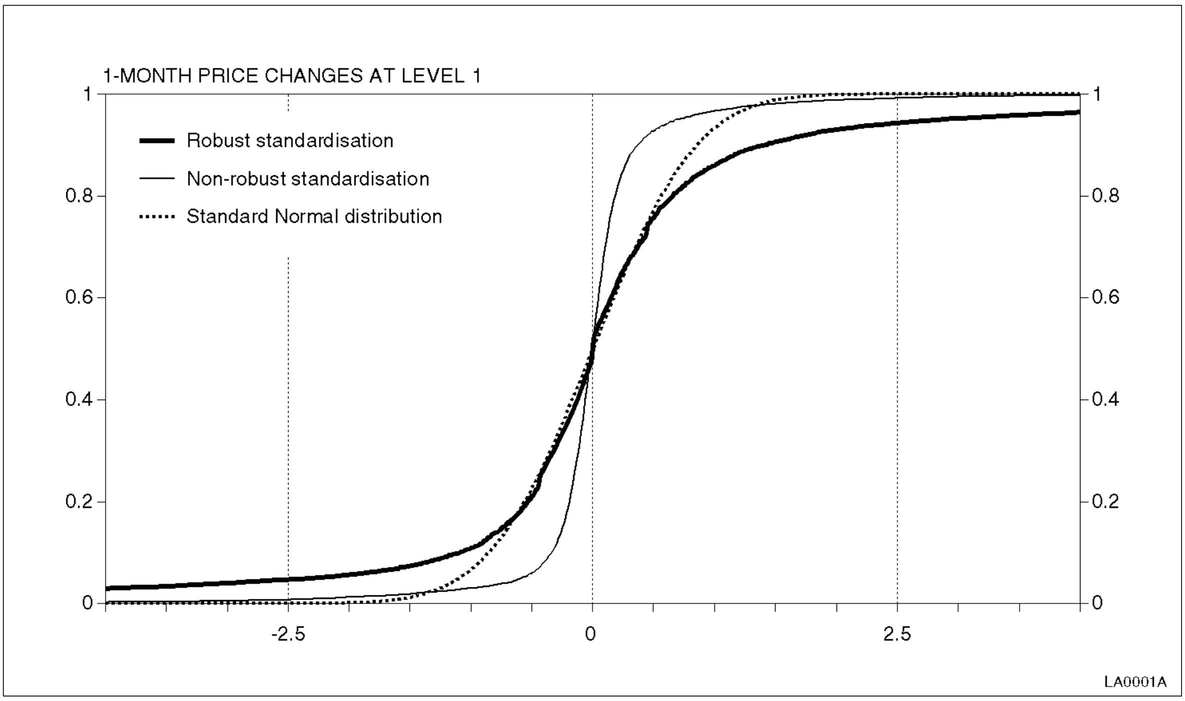


Figure 2 shows for seasonally adjusted 1-month price changes at Level 1 the cumulative frequency function for the two different types of standardised price changes and compares them with the cumulative standard normal distribution. In order to obtain the average image during the period considered, the standardised data of each month have been pooled. Evidently this pooling also explains the smoothness of the observed cumulative curves. The figure shows clearly that the occurrence of fat tails is masked to a large extent by the non-robust standardisation. Outside the central part of the distribution we see that the robustly standardised curve shows the tails that really exist, whereas the classically standardised curve appears to have tails that are nearly as thin as those of the normal distribution. In addition, the figure reveals that the central part of the distribution of the robust standardised price changes is much closer to the standard normal distribution than the central part of the data that have been standardised in a non-robust way. This is so because in the latter case the observations have been scaled by the standard deviation which overstates the true dispersion. The non-robust standardisation overstates therefore the concentration of observations in the centre of the distribution.

4 MAKING DIRECT USE OF THE DEPARTURE FROM NORMALITY TO DETERMINE THE EXCLUDED PRICE CHANGES

Aucremanne (2000) showed that the Bryan et al method for determining the optimal trimming percentage on the basis of the ability to track trend inflation was very unstable in the Belgian case. Therefore a method for determining the optimal trimming percentage was designed that depends directly on the departure from normality of the observed samples. Such a method has the advantage that it aligns the remedy with the problem and re-establishes the link with robust estimation arguments. This idea has also been advanced in Bakhshi and Yates (1999)[15]. Roger (1995), Laflèche (1997) and Johnson (1999) are other examples where the trimming percentage is to some extent a function of the number of outliers. They present core inflation measures that correspond to the weighted average of the cross-sectional distribution of price changes that has been trimmed at each point in time to exclude values farther than 1.5 standard deviations from the mean.

Making direct use of the departure from normality to determine the optimal trimming percentage, we want to rely on robust arguments only. The first question that has to be discussed from this point of view is whether it makes any sense to look for the optimal trimming percentage. Indeed, one could argue that the median, or its asymmetrical variant as proposed in Roger (1997), is a robust estimator with the highest possible breakdown point, making it useless to look for the optimally trimmed mean. The breakdown point measures the vulnerability of an estimator to the occurrence of outliers and can intuitively be understood as the smallest number of observations, expressed in percent of the total sample size, that can cause an arbitrarily large effect on the estimator[16]. With regard to the mean, it is clear that one (very pronounced) outlier is enough to cause an arbitrarily large effect on it. The breakdown point of the mean is therefore $1/n$, which tends to zero as the sample size n increases. Consequently, the mean has an asymptotic breakdown point of zero p.c. It can be shown that the median has a breakdown point of 50 p.c. and that 50 p.c. is the highest breakdown point possible. Intuitively it is clear that it is not possible to handle more than 50 p.c. outliers, because in those cases it becomes impossible to make a distinction between the 'good' and the 'poor' observations. An α - p.c. symmetrically trimmed mean occupies an intermediate position, having a breakdown point of α p.c. For asymmetrically trimmed means the breakdown point is the percentage of unused observations on the left or the percentage of unused observations on the right, whichever is the smallest, or (α-z) p. c. when its central percentile is the (50+z)th percentile.

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15 They state: 'Ideally, therefore, it is the kurtosis of actual price changes that should dictate the optimal trim in reality and not the ability of the resulting trimmed index to approximate some proxy for 'core inflation' (...). In short, the optimal trim should depend on the population kurtosis, and will, in general, vary over time.' (p. 29).

16 A more formal definition can be found in Rousseeuw and Leroy (1987, p. 10) or in Rousseeuw (1997, p. 104).

Generally speaking, the breakdown point measures how well the estimator is protected against the occurrence of outliers. From this point of view, the median is more robust than trimmed means, as it can handle very polluted samples that have up to 50 p.c. outliers (or (50-z) p.c. when its asymmetric variant proposed by Roger is considered), instead of α p.c. for the symmetrically trimmed mean (or (α-z) p.c. for the asymmetrically trimmed mean). However, from Table 2 and Figure 2 of the previous section, it is clear that the number of outliers in the cross-sections of Belgian CPI price changes is probably well below 50 p.c., possibly rendering the use of the median unnecessary. Using the median without considering the trimmed means is as if one opts for an overprotection against outliers, without taking into account the cost of such a strategy. This might be awkward, as it is known that the median is not necessarily the most efficient estimator. Oosterhoff (1994) discusses this trade-off between breakdown point and efficiency in the case of small samples and finds a smaller sampling variance for (heavily) trimmed means than for the median, unless the distribution is strongly 'peaked' at the median. From Figure 2 it appears that the distribution of CPI price changes is not strongly peaked at the median, at least when a robust standardisation is used. Consequently there is some scope left to look for the optimal trimming percentage.

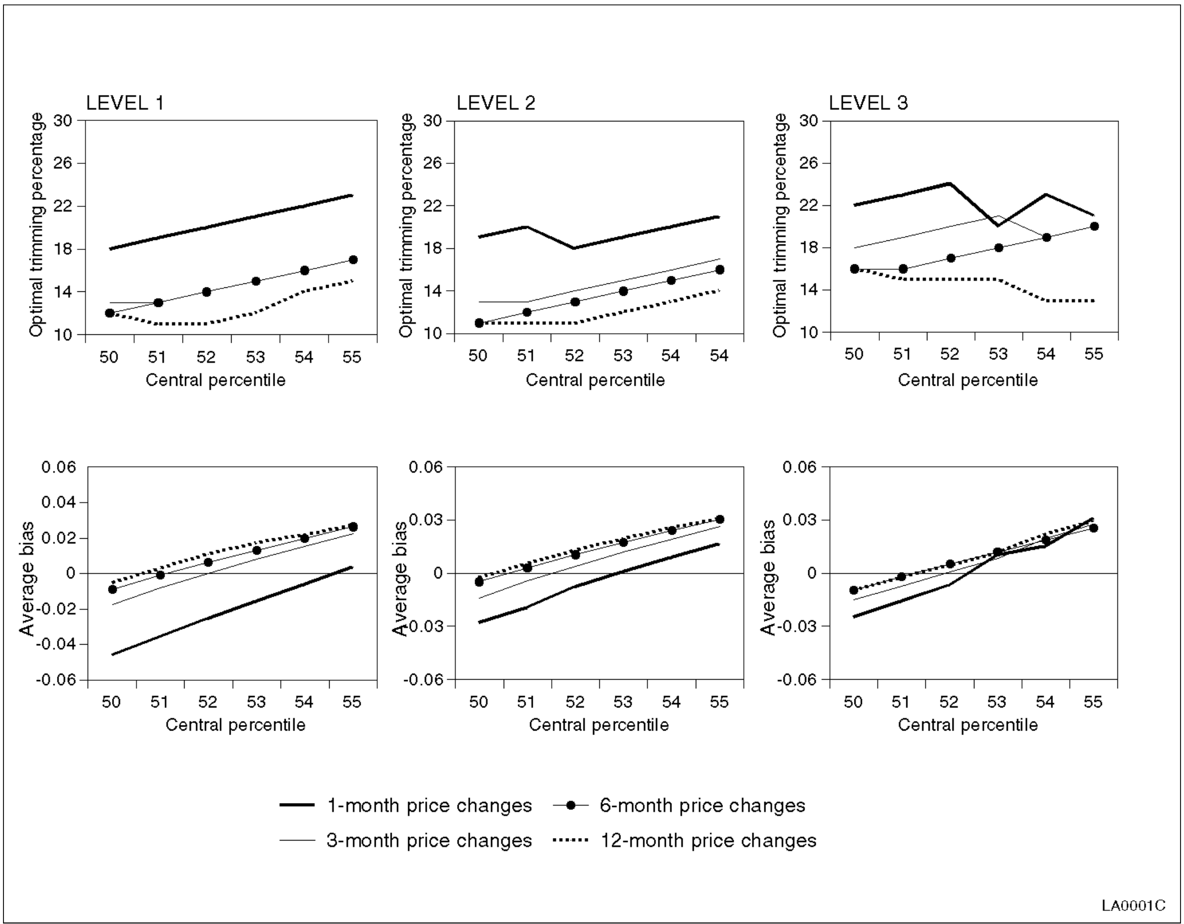
The following optimisation procedure was performed. All the possible trimming percentages between 0 and 50 p.c. were considered. For each trimmed sample, the corresponding mean - i.e. the trimmed mean - and also the corresponding standard deviation, skewness, kurtosis and Jarque-Bera statistic were calculated. It appeared that the Jarque-Bera statistic tends to fall as the trim rises, which means that, by progressively removing the outliers, the remaining central part of the sample increasingly begins to show the characteristics of a normal distribution. This confirms the conclusions drawn from Figure 2, where it was made clear that, when a robust standardisation is used, the central part of the samples resembles the normal distribution. This property made it possible to stop the optimisation procedure at the trimming percentage that produced the first subsample for which the hypothesis of normality was not rejected on the basis of the Jarque-Bera statistic. The 95 p.c. critical value was used, which means that in practice the trim was increased up to the point where the Jarque-Bera statistic of the remaining part of the sample fell just below 5.99. The sensitivity of the results with respect to the critical value used has not been studied.

Two variants of the method were applied. In the first case the Jarque-Bera statistic of all the trimmed distributions was calculated for each individual month of the period considered and these results were subsequently averaged over time. The optimal trimmed mean according to this method is the one for which the historical average of the Jarque-Bera statistic falls below the critical value of 5.99 for the first time. This method, from now on labelled as the 'JB-Average estimator', yields a trimming percentage that is by definition constant for all months considered. From that point of view this estimator does not differ from any other trimmed mean and that is the reason why it is considered in the first instance here. The second variant applies the method to each individual month separately and therefore yields an optimal trimming percentage that varies over time. It is labelled as the 'JB-Monthly estimator'. As will be explained in Section 4.2, this estimator has some conceptual advantages compared with the first variant.

For both estimators the optimisation of the trimming percentage was combined with the determination of the central percentile. As the skewness reported in Table 2 was on average positive for each of the aggregation levels and each of the horizons considered, it seemed useful to allow for asymmetric trimming in order to remedy this chronic right skewness. To do so, the optimisation procedure of the trim was performed for several central percentiles. All percentiles between the 50th and the 60th were considered. Consequently, for each central percentile an optimal trim was obtained on the basis of the Jarque-Bera statistic. Among these, the one that minimises the absolute value of the average difference between the trimmed mean on the one hand and observed inflation on the other hand is chosen. Figure 3 illustrates for the first variant - the use of the historical average of the Jarque-Bera statistic - the two dimensions of the optimisation problem for seasonally adjusted data. Only the results for central percentiles up to the 55th are reported, as it appeared that superior percentiles were not optimal for seasonally adjusted data. The figure is divided into three parts, from the left to the right. Each part corresponds to one of the aggregation levels. Inside each part the results for the four horizons considered are reported. The upper level of each part shows the optimal trimming percentages for the different central percentiles. The optimal trim tends to increase as the percentile increases: often this increase is one for one.

The lower level of the figure shows for each central percentile the historical average of the difference between the trimmed mean and observed inflation. This difference is negative for all the symmetrically trimmed means, which indicates that they tend to underestimate the observed inflation. This result could be expected on the basis of the chronic right skewness of the data and requires some degree of asymmetric trimming. For higher central percentiles the difference increases and becomes positive at some point. The central percentile that minimises the absolute value of the difference indicates the optimal central percentile. In the case of 1-month price changes at Level 1 this corresponds to centring the trimmed mean around the 54th percentile. Finally, combining both levels of the graph, the optimal central percentile and the optimal trim can be obtained: the example described above gives a 22 p.c. trimmed mean centred around the 54th percentile, i.e. a trimmed mean that removes 26 p.c. of the observations from the left-hand tail and 18 p.c. from the right-hand tail.

FIGURE 3 - Optimal trimming percentage and optimal central percentile for the JB-Average estimator (seasonally adjusted data)



4.1 Using the historical average of the Jarque-Bera statistic (the JB-Average estimator)

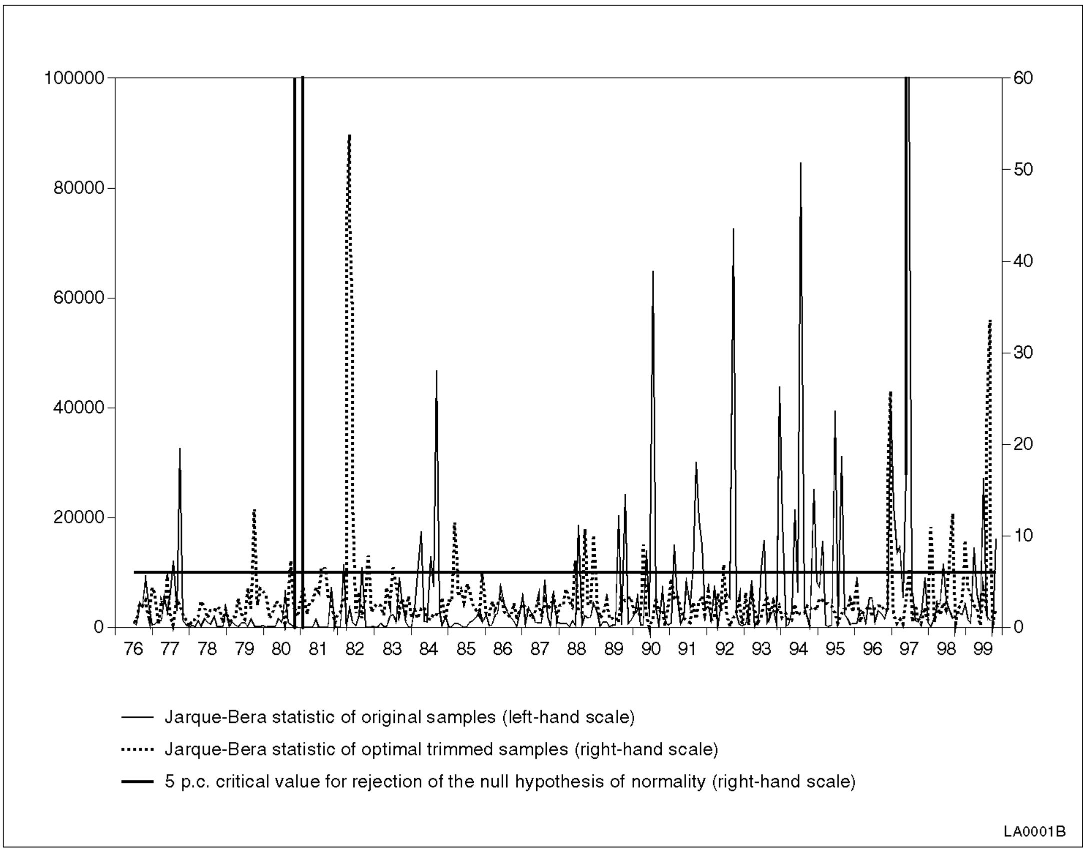
Table 3 presents - for the JB-Average estimator - these optimal combinations (the optimal trimming percentage and the optimal central percentile) for each of the aggregation levels and horizons considered, as well as for data with and without seasonal adjustment. Results are recorded for the whole sample and for three subsamples, i.e. a subsample ending in December 1987 ('Subsample 1'), a subsample starting in January 1988 ('Subsample 2') and a subsample starting in January 1992 ('Subsample 3'). The optimal trim is higher for the shorter horizons, which is in line with the measures of the tail weight reported in Table 2. The optimal trim is, generally speaking, higher for Level 3 than for Levels 1 and 2. This is a somewhat surprising result, since the data in Table 2 suggest that there is less weight in the tails of the distribution for this level than for the two others, although it must be recognised that the differences are rather limited for the robust measure of the tail weights. As was expected, it is in many cases optimal to trim to some extent asymmetrically. The need to do so seems to be somewhat less pronounced for the more recent subsamples.

The optimal trimming percentage is in general higher for data without seasonal adjustment than for seasonally adjusted data. This is in line with the observation made in Table 2 that data without seasonal adjustment have more weight in the tails of the distribution. The optimal central percentile is also higher for data without seasonal adjustment, especially for 1- and 3-month price changes. Both features are related to the observation that for some subindices, prices remain unchanged over a considerable time period and are only revised at regular points - often in the same month each year. Without seasonal adjustment, the corresponding 1-month price changes for these subindices are zero during most of the months, while a relatively large price increase is recorded when prices are adjusted. The latter will probably be excluded by the trimmed mean and, as a result of this, the symmetrically trimmed mean tends to undershoot the observed inflation systematically. This phenomenon is of course less pronounced for seasonally adjusted data, as the seasonal adjustment attributes the price changes that systematically take place in a particular month of the year to all the months of that year. Hence, both the optimal trim and the optimal central percentile will be less pronounced for seasonally adjusted data.

Figure 4 shows the Jarque-Bera statistic of the original monthly samples and of the corresponding optimally trimmed samples for 1-month price changes at Level 1 (seasonally adjusted data). The fact that two different scales were needed for this figure illustrates clearly the reduction of the Jarque-Bera statistic for the trimmed samples, especially for those months where the Jarque-Bera statistic for the original sample was very high. The figure also shows, though, that for some months the Jarque-Bera statistic for the trimmed sample is above the 5 p.c. critical value, typically for those months in which the problems in the original sample were not very pronounced. This might suggest that for these months too much has been trimmed, rather than too little. The intuition behind this is as follows. The Jarque-Bera statistic for the trimmed sample tends to decrease for increasing trims up to a certain point, but increases thereafter as the trim continues to increase and finally heads off to infinity for a 50 p.c. trim[17]. Consequently it may be that for some months too much has been trimmed. Given this observation, it seemed logical to try avoiding these situations by trimming, for each month separately, up to the point where the Jarque-Bera statistic falls under the critical value of 5.99 for the first time.

FIGURE 4 - Reduction of the Jarque-Bera statistic for the JB-Average estimator

(1-month price changes at Level 1, seasonally adjusted data)



[17] The 50 p.c. trimmed mean corresponds to the median (or the central percentile). The corresponding 50 p.c. trimmed sample consists of only one observation. It is obvious that such a "degenerated" sample does not show the characteristics of a normal distribution at all.

4.2 Using the Jarque-Bera statistic for each individual month (the JB-Monthly estimator)

In so doing, an optimal trimming percentage that varies from month to month can be obtained, as was also suggested in Bakhshi and Yates (1999) and Johnson(1999). In addition to the fact that this strategy avoids the 'trimming too much' situation described above, it can also overcome the problem of trimming too little. Indeed, as the monthly trimming percentage can potentially be any number between zero and 50, the method is able to treat very polluted samples that have up to (50-z) p.c. outliers. In other words this method has a breakdown point of (50-z) p.c., whereas the breakdown point of the previous method is lower and corresponds to the optimal trims reported in Table 3, corrected downwards, however, if the central percentile exceeds the 50th. The optimal central percentile of the JB-Monthly estimator has been determined as in the previous method and is, in contrast to the optimal trimming percentage, based on historical averages rather than on monthly data only.

Table 4 gives for the JB-Monthly estimator the *average* of the monthly optimal trimming percentages, for the whole sample as well as for each of the three subsamples. It should be mentioned here that a substantial monthly dispersion around these averages can be observed[18]. In general, substantially less has been trimmed than by the JB-Average estimator. This seems to confirm that trimming too much was indeed a risk for the first method. Following this method, it is no longer optimal to trim more at Level 3 than at Levels 1 and 2, which is in line with the diagnosis made on the basis of Table 2. On average, data without seasonal adjustment continue to require substantially more trimming, as well as a higher central percentile than seasonally adjusted data. The average optimal trimming percentage is in general rather stable from one subsample to another.

4.3 The one-step Huber-type skipped mean

The two estimators discussed in Sections 4.1 and 4.2 have the weakness that the Jarque-Bera statistic on which they rely is vulnerable to the masking phenomenon, as it uses the mean and the standard deviation[19]. Under the null-hypothesis of normality this is not a problem, but under fat-tailed alternatives this may lead to type 2 errors, i.e. not rejecting the null-hypothesis when this hypothesis is not correct. In other words, the Jarque-Bera statistic has a low power under fat-tailed alternatives. Although the iterative nature of the procedure reduces this vulnerability - by progressively removing more observations from the tails of the distribution there is less scope for masking - , it seemed justified to consider an estimator that does not suffer from masking as well. Therefore the one-step Huber-type skipped mean was analysed.

[18] Results of this dispersion are not given here, but can be obtained from the author upon request.
[19] The Jarque-Bera statistic is based on the kurtosis and the skewness, which both make use of the mean and the standard deviation.

This estimator rejects in the first instance all the observations for which the robust standardisation of formula (10) yields a number that exceeds in absolute value some bound and calculates subsequently the mean of the remaining observations. This rejection rule was analysed by Hampel (1985) and yielded the best overall estimators, as they combine a breakdown point of 50 p.c. with the property of being relatively efficient for a wide range of distributions. For more information about this method and other M-estimators[20], see Hampel et al (1986). We consider here a bound of 2.5, as was the case in Section 3. Alternative values have not been considered. The method was applied to each month separately, resulting in a time-varying rejection of observations, as was the case in Section 4.2. Table 5 records for the whole sample and for each of the three subsamples *half of the average* weight of the rejected observations. Reporting only half of the weights makes this table to some extent comparable to Tables 3 and 4, where the trimming percentages, which typically correspond to half the weight of the rejected observations, are recorded. As for the JB-Monthly estimator, a substantial monthly dispersion around the average values recorded in Table 5 is typically observed. In general this estimator rejects fewer observations than the JB-Monthly estimator. The average weights of the rejected observations for the three subsamples are very similar to those for the whole sample.

[20] Least square estimators minimise the sum of squared residuals, and are a cornerstone of classical statistics. The one-dimensional least square estimator of location is the mean. M-estimators are a class of estimators where the squared residuals are replaced by another function of the residuals. The use of M-estimators as core inflation measures is an interesting area for further research, as much work has been done on constructing M-estimators that are as robust as possible on the one hand, but still fairly efficient on the other hand.

5 ASSESSING THE PERFORMANCE OF THE ESTIMATORS CONSIDERED

A first assessment of the estimators constructed in Section 4 is made on the basis of the two evaluation criteria presented in Sections 5.1 and 5.2 respectively. The first criterion tests whether the estimators are unbiased. It is indeed desirable that they should not systematically understate or overstate observed inflation. The second criterion examines the reduction in volatility that is obtained by the different core measures, in order to quantify the efficiency gain. For each criterion, the three estimators of Section 4 are examined, as well as two other robust estimators that are straightforward: the median and its asymmetric variant proposed by Roger (1997), i.e. a particular percentile higher than the 50th. That particular percentile was chosen to minimise the average difference between the estimator considered and the observed inflation. The results for this estimator, from now on labelled as the 'Central percentile estimator', are recorded in Table 6. By construction, its trimming percentage always equals 50. Subsequently we present a more economic interpretation of the estimators that performed best according to the two first tests. In Section 5.3 the list of excluded components is examined and the robust estimators are compared with core inflation measures of the 'systematic exclusion' or 'systematic reweighting' type. Section 5.4 examines the direction of the long-term causality between observed and core inflation, a test suggested by Marques et al (2000).

5.1 **Are the estimators unbiased?**

For each of the five estimators considered, the upper level of Table 7 gives the average difference between the estimator on the one hand and observed inflation on the other. As estimators with different time horizons are mutually compared, the original results for the different estimators have been compounded to obtain a 12-month horizon for all of them. Not surprisingly, this difference is very small for the robust estimators that were constructed in an asymmetric way[21] and systematically negative for the two symmetric estimators, the median and the one-step Huber-type skipped mean[22]. For the symmetric estimators this negative bias is quite frequently statistically significant at the 95 p.c. level. The bias is more pronounced for the shorter horizons and for data which have not undergone seasonal adjustment, thus confirming the findings of Tables 3, 4 and 6 that in these cases more asymmetry is needed.

Only using the average difference is however a poor test of the unbiasedness of the estimators. Any estimator that has nearly the same average as the observed inflation will pass this test, even if it shows a different trend. A second test was therefore performed as well. Following Marques et al (2000), we tested whether the estimator is cointegrated with observed inflation, applying the double restriction

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[21] Indeed, it was precisely this difference that was used as the benchmark when determining the optimal degree of asymmetry.

that the cointegration vector should have a unitary coefficient and no constant term[23]. To do so, the Augmented Dickey Fuller (ADF) test for a unit root in the difference between the estimator and observed inflation was performed, with 13 lags and no constant term in the test equation of each estimator[24]. The ADF-statistics are reported in the lower level of Table 7. According to MacKinnon (1991), the 95 p.c. critical value for rejection of the null hypothesis of a unit root is minus 1.94.

The results confirm the findings of the previous test that the asymmetric estimators are unbiased, while some of the symmetric estimators are biased, although the latter can only be verified for a smaller number than could be expected on the basis of the first test. For seasonally adjusted data, the null-hypothesis of a unit root cannot be rejected for the median in the cases of 1-month price changes at Level 1 and 2 and for the one-step Huber-type skipped mean in the case of 1-month price changes at Level 3. For data which have not been seasonally adjusted, non-rejection of the null hypothesis occurred for the two symmetric estimators in all cases where 1- or 3-month price changes were used, except for the one-step Huber-type skipped mean using 3-month price changes at Level 3. Overall, we can conclude that the estimators that were constructed in an asymmetric way are indeed unbiased and that there is increasing evidence of a bias in the symmetric estimators when the shorter horizons are considered, especially for data which have not been seasonally adjusted.

Table 8 gives the results of identical tests for the second subsample, starting in January 1988. From this table it is clear that the negative differences for the symmetric estimators are less pronounced than for the whole sample, though they are still statistically significant in most of the cases. Some of the asymmetric estimators show positive differences which are statistically significant, especially for the shorter horizons and for data without seasonal adjustment. These findings illustrate that the optimal degree of asymmetry may be lower if only the more recent subsamples are taken as the benchmark, as was already seen in Tables 3, 4 and 6. A similar conclusion can be drawn from the ADF-test. The hypothesis of a unit root can now be rejected for all the symmetric estimators that make use of seasonally adjusted data. When data that have not been seasonally adjusted are examined, the null hypothesis can also be rejected for the three one-step Huber-type skipped means making use of 3-month price changes and for the median in the case of 3-month price changes at Level 3.

It is possible that the observed instability in the bias is the result of less chronic right skewness in the low inflation environment of Subsample 2. This would indeed be the outcome of sticky price models[25] in a strict sense or of models where, according to Roger's terminology, some prices are adjusted

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22 Although this estimator is able to remove different weights in each tail of the distribution, it is by definition centred around the median. Asymmetric variants have not yet been considered.

23 The two other conditions specified by Marques et al will be discussed in section 5.4.

24 With this number of lags the residuals of the test equations appeared to be white noise. Marques *et al* use instead the Johansen cointegration test. For more information on this test, see Johansen (1995).

25 See Ball and Mankiw (1994), Zeldes (1995), Bakshi and Yates (1999).

infrequently because they are either regulated, infrequently sampled or refer to seasonal goods[26]. Studying this chronic right skewness and more particularly examining whether it is correlated with trend or expected inflation, seems to be an important issue for further research. It possibly allows to fill the gap between the statistical and economic approaches to some extent and can also lead to more powerful core inflation measures by endogenising the degree of asymmetry in the robust estimators used.

5.2 Volatility reduction

Table 9 provides a volatility measure for observed inflation and for the five estimators considered. As we are typically interested in short-term volatility, we have used the standard deviation of the first difference of observed inflation (or the estimator) as our measure, instead of the standard deviation of observed inflation (or the estimator) itself. For observed inflation this volality measure is:

$$\mathrm{Vol}\left(\Pi^h\right) = \left[\frac{1}{m-1}\sum_{t=2}^{m}\left(\Delta\Pi_t^h - \frac{1}{m-1}\sum_{t=2}^{m}\Delta\Pi_t^h\right)^2\right]^{1/2} \tag{11}$$

with m the total number of months. This measure can also be defined for each of the estimators considered (by replacing Π_t^h in (11) by the estimator E_t^h considered), as well as for the price changes of individual components (by replacing Π_t^h in (11) by $\Pi_{i,t}^h$).

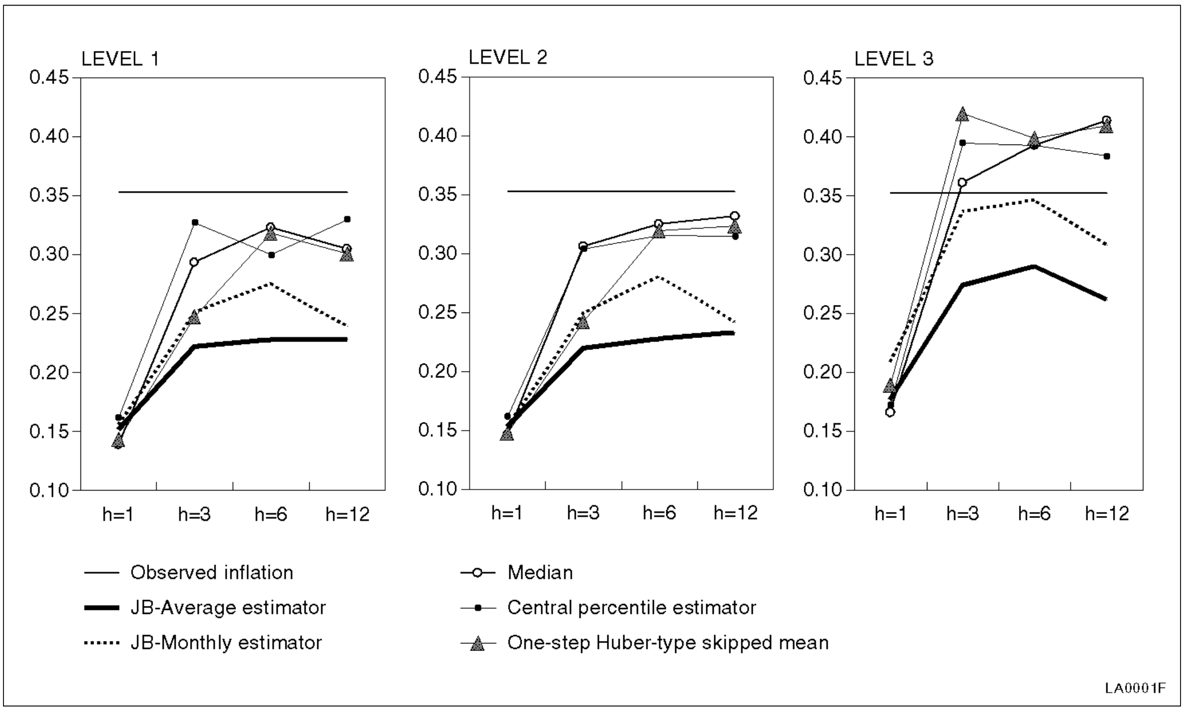
In order to be able to compare the original volatility for the different horizons, Π_t^h and E_t^h have been annualised before being put into formula (11)[27]. In so doing, the volatility measure for observed inflation shows clearly that price changes are typically more volatile when they are calculated over shorter horizons, even when seasonally adjusted data are used. The volatility of each of the five robust estimators is in many cases significantly below that of observed inflation. This confirms the idea that a substantial efficiency gain can be obtained by making use of robust estimators. The largest volatility reduction is obtained for the shortest horizon. The smallest volatility is, however, typically obtained for the robust estimators making use of 12-month price changes. As 12-month price changes can be considered as 12 compounded 1-month price changes, the robust estimators that make use of 12-month price changes are in fact the result of two techniques: compounding (or smoothing) and, subsequently, robust estimation. From this, it seems fair to allow for the same degree of smoothing in the case of robust estimators that make use of price changes over shorter horizons, and Π_t^h and E_t^h

[26] See Roger (2000a and 2000b).
[27] In contrast to compounding, annualising does not smooth the original results.

have therefore also been compounded before being put into formula (11). The results of this approach are recorded in Table 10. All data have now the same benchmark, i.e. the volatility of observed inflation for 12-month price changes. We select the estimator with the lowest volatility as the one with the largest efficiency gain.

In fact the maximisation of the efficiency gain from robust estimation (and subsequent compounding) depends on three factors: the type of estimator used, the horizon of the price changes and the aggregation level. Figure 5 illustrates the relative importance of each of these dimensions for the volatility of the compounded estimators in the case of seasonally adjusted data. As far as the first dimension is concerned, the choice of the estimator is important for the longer horizons. For these horizons, a substantially higher efficiency gain is obtained for the two estimators that optimise the trimming percentage on the basis of the Jarque-Bera statistic. This confirms the idea put forward in the beginning of Section 4 that there was some scope to look for the ideal trim. However, for 1-month price changes all estimators produced similar efficiency gains and all the estimators yielded their best result for this horizon, regardless of the aggregation level considered. The horizon of the price changes therefore seems to be the most important dimension. For seasonally adjusted 1-month price changes, the median yielded the highest volatility reduction and the one-step Huber-type skipped mean also performed very well at Levels 1 and 2. From the previous section we know however that both are biased. Among the unbiased estimators making use of seasonally adjusted 1-month price changes, the JB-Average estimator performed best at Level 1, the JB-Monthly estimator at Level 2 and the central percentile estimator minimised the volatility at Level 3. As far as the aggregation level is concerned, some efficiency gain is obtained from examining more disaggregated data, especially when going from Level 3 to Level 2.

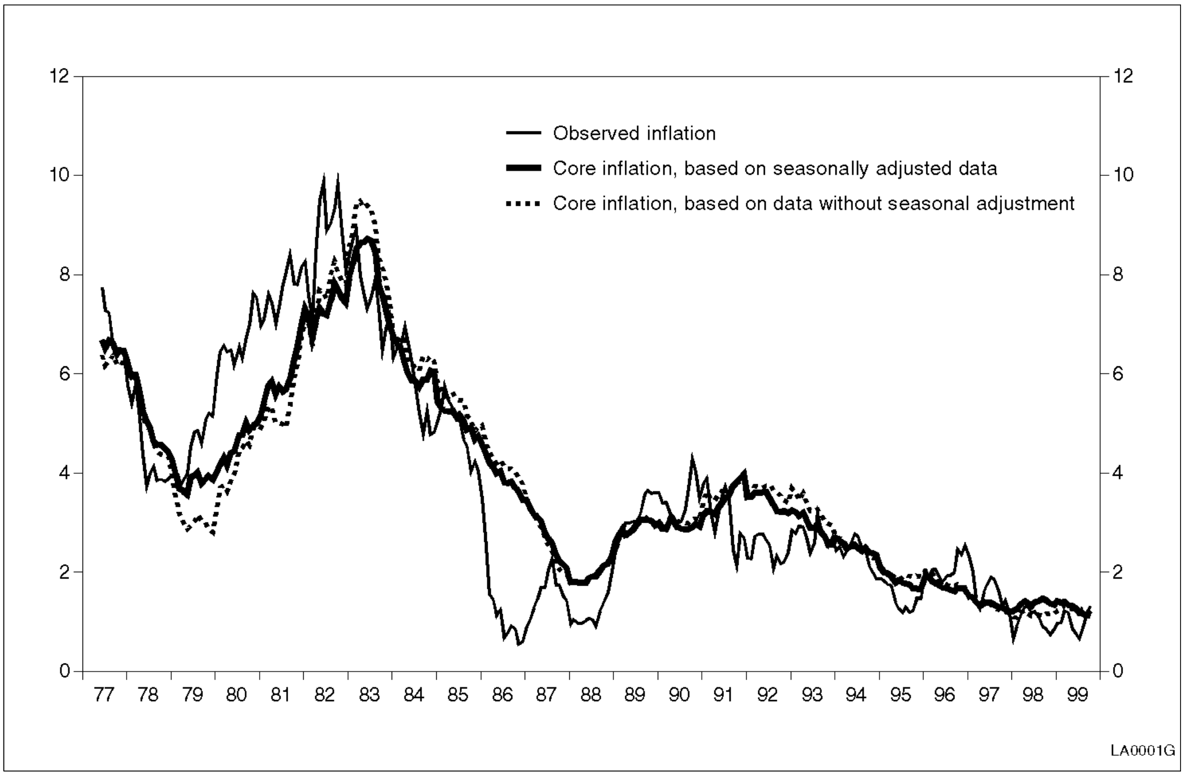
FIGURE 5 - Volatility of observed inflation and volatility of the robust estimators
(compounded results for seasonally adjusted data)



Summarising this assessment, the best results are achieved by applying robust estimators on 1-month price changes at Level 1 and compounding the results subsequently. In order to obtain an unbiased core inflation measure, asymmetric estimators are preferable, although there were indications of some instability in the optimal degree of asymmetry. For this reason, neither the one-step Huber-type skipped mean nor the median are the most suitable for Belgian data. Among the unbiased estimators based on 1-month price changes at Level 1, the JB-Average estimator maximised the efficiency gain for data both with and without seasonal adjustment, but the differences between it and the two other asymmetric estimators are small. Given this observation, the JB-Monthly estimator or even the central percentile estimator are interesting alternatives. They both have the advantage of having a higher breakdown point. As this property may be very important for the out-of-sample performance of the estimators, we prefer the JB-Monthly estimator over the JB-Average estimator. For 1-month price changes, volatility is systematically minimised when seasonally adjusted data are used. Using this type of data does however carry the disadvantage that the core inflation measure will change each time a new observation becomes available. Figure 6 shows, for the JB-Monthly estimator of core inflation, the differences between using data with and without seasonal adjustment.

FIGURE 6 - The JB-Monthly estimator of Belgian core inflation

(compounded results for 1-month price changes at Level 1, percentage changes)



5.3 Examination of excluded products and comparison with core inflation measures of the 'systematic exclusion' or 'systematic reweighting' type

Table 11 shows the frequency with which the different components are excluded by the JB-Monthly estimator. Many of the items that are at the top of this list are often associated with volatility, which suggests that the estimator does what it is supposed to do, i.e. reducing the volatility by rejecting outliers. The products that are often rejected correspond to a considerable extent to those removed by the core inflation measure that systematically excludes unprocessed food and energy (the 'XUE-measure'). There are two important differences, though, between the JB-Monthly estimator and the XUE-measure. Firstly, of all the items that are systematically removed by the XUE-measure, not one is always rejected by the JB-Monthly estimator. Even the most frequently excluded item, fresh vegetables, is not removed in 27 out of 280 months, while, for instance, electricity or meat are retained quite frequently by the JB-Monthly estimator. Secondly, for the products that are systematically incorporated into the XUE-measure, all are at some time rejected by the JB-Monthly estimator. Even the items rentals for housing and household textiles, that are the most frequently retained products, are rejected by the JB-Monthly estimator in 16 months, while a fair number of items that are retained by the XUE-measure are rejected in more than a quarter of the months by the JB-Monthly estimator. From this it is clear that the JB-Monthly estimator is much more flexible in excluding products from the core inflation measure and therefore has a greater potential. Moreover no discretionary judgement is required when the excluded components are selected. There appears to be more correspondence between the products excluded by the JB-Monthly estimator and those excluded by the X14-measure, which systematically removes the 14 most volatile products[28].

Two other core inflation measures are considered as well. What they have in common is that they downweight the volatile products more gradually, whereas the XUE- and X14-measures typically either systematically exclude or include a particular product. Both measures use the short-term volatility of a particular component, as defined in Section 5.2. Inspired by Johnson (1999), the double-weighted core inflation measure (the 'DW-measure') uses the product of the CPI weights and the reciprocal of short-term volatility as new weights[29]. The DW-measure can formally be defined as:

$$DW_t = \frac{\sum_{i=1}^{n} \frac{w_{i,t}^{12}}{Vol\left(\Pi_i^{12}\right)} \Pi_{i,t}^{12}}{\sum_{i=1}^{n} \frac{w_{i,t}^{12}}{Vol\left(\Pi_i^{12}\right)}} \qquad (12)$$

The core inflation measure that is based on the volatility weighting scheme (the 'VW-measure') is a variant of the so-called neo-Edgeworthian index discussed in Wynne (1999). The VW-measure reweights the components by the reciprocal of the short-term volatility defined above[30] and can be defined as:

$$VW_t = \frac{\sum_{i=1}^{n} \frac{1}{Vol\left(\Pi_i^{12}\right)} \Pi_{i,t}^{12}}{\sum_{i=1}^{n} \frac{1}{Vol\left(\Pi_i^{12}\right)}} \qquad (13)$$

Table 12 gives the results of the test of sections 5.1 and 5.2 for the JB-Monthly estimator and for the four alternative core inflation measures presented in this section. All the core inflation measures considered are roughly unbiased over the whole sample period, although there are some indications of a systematic negative bias for the VW-measure. As far as the volatility reduction is concerned, the JB-Monthly estimator using seasonally adjusted data performs best during the whole sample, though the difference with the DW-measure is small. It is also interesting to note that the volatility reduction for the JB-Monthly estimator is rather close to that of the 35-month moving average of observed inflation,

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[28] This core inflation measure systematically excludes all the components at Level 1 for which the volatility measure (11), based on 12-month price changes, was higher than 5 times the corresponding volatility of observed inflation. For Belgian data, this was the case 14 products.

[29] Johnson (1999) uses the reciprocal of the historical standard deviation of relative price changes instead of the short-term volatility measure defined in section 5.2.

[30] The neo-Edgeworthian index in its original form uses the reciprocal of the variance as its weighting scheme.

although this average was not used as benchmark when the JB-Monthly estimator was constructed. Even the JB-Monthly estimator that uses data that have not been seasonally adjusted performs relatively well. The volatility reduction of the traditional XUE-measure is substantially less pronounced, which is, given the observations made on the basis of Table 11, not surprising at all. The other asymmetric robust estimators (JB-Average and Central Percentile) outperform the XUE-measure as well. From this point of view, the choice of the robust estimation technique used is less important than choosing between the XUE-measure on the one hand and robust estimation on the other. The latter result appears to be quite robust with respect to the reference period used, as it is confirmed for the second subsample.

5.4 **Endogeneity of observed inflation and exogeneity of core inflation**

This section examines the direction of the long-term causality between core and observed inflation and is entirely based on Marques et al (2000). On top of having an unbiased estimator, these authors emphasise the fact that it is desirable, from a monetary policy perspective, for the long-run causality to go from core inflation to observed inflation and not in the other direction. They formalised two conditions to test this property. Given the fact that the different core inflation measures discussed in the previous Section are cointegrated with observed inflation, an error correction mechanism (ECM) must exist either for observed or core inflation or for both. These ECMs can be written as:

$$\Delta\Pi_t = \sum_{j=1}^{\ell} a_{1,j}\Delta\Pi_{t-j} + \sum_{j=1}^{p} b_{1,j}\Delta E_{t-j} - \beta_1\left(\Pi_{t-1} - E_{t-1}\right) + \varepsilon_{1,t} \tag{14}$$

$$\Delta E_t = \sum_{j=1}^{q} a_{2,j}\Delta\Pi_{t-j} + \sum_{j=1}^{r} b_{2,j}\Delta E_{t-j} - \beta_2\left(E_{t-1} - \Pi_{t-1}\right) + \varepsilon_{2,t} \tag{15}$$

In equations (14) and (15), E_t refers to one of the core inflation measures considered.

The first condition requires that observed inflation converge in the long-term to core inflation. Technically speaking, this condition states that observed inflation must not be weakly exogenous, which corresponds to testing whether the coefficient β_1 in equation (14) is significantly different from zero. In that case, positive (negative) differences between observed and core inflation in the previous period will have a downward (upward) effect on the change of observed inflation in the current period. In other words, observed inflation is attracted by core inflation. The second condition requires that core inflation should not be attracted by observed inflation. We therefore tested whether core inflation is (at least) weakly exogenous, i.e. that the coefficient β_2 in equation (15) is not significantly different from zero[31].

Table 13 gives the results of these tests for the whole sample, as well as for subsample 2. For the whole sample, the condition that observed inflation should not be weakly exogenous is rejected for all the core inflation measures considered, as well as the condition that core inflation should be weakly exogenous. From this we may conclude that core inflation was attracted by observed inflation instead of observed inflation being attracted by core inflation. All the core inflation measures considered have this reversed long-term causality in common. This result reduces their relevance for monetary policy purposes quite considerably. It means that core inflation is lagging rather than leading, whereas monetary policy should in principle look forward. From Figure 6 the endogeneity of core inflation can be visually verified for the JB-Monthly estimator, especially during the aftermath of the second oil shock (1979-1982) and when oil prices dropped significantly (1985-1986). These shocks first had an impact on observed inflation, but gradually their effects were passed through to core inflation via so-called second- and third-round effects.

However, as the sensitivity to oil price movements has significantly lessened in recent years for industrial countries in general[32], and in Belgium in particular[33], and as these shocks themselves were less pronounced and less persistent, it seemed justifiable to check the direction of the causality for the second subsample, starting in January 1988. From Table 13 it can be seen that during this subsample observed inflation was indeed not weakly exogenous, whereas core inflation was. For this subsample the long-run causality worked in the right direction, re-establishing the relevance of core inflation measures of this type for monetary policy purposes. The experience of the 70s and the 80s shows, though, that the core inflation measure can never be the only policy indicator, and that observed inflation has to be analysed as well. In particular, if the differences between the two measures persist, one should be aware of the risk that this may sooner or later have second-round effects on core inflation. Mio and Higo (1999) also warn that large relative price movements located in the tails of the distribution may sometimes contain information for future core inflation.

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[31] According to Marques *et al* (2000), strong exogeneity of core inflation – not only β_2, but also all the $a_{2,j}$ coefficients of equation (15) are zero – may prove to be too strong.

[32] OECD(1999) illustrates this decrease of oil dependence for the OECD area (pp. 8-9).

[33] In 1994 the so-called "health index", that excludes oil products, as well as alcoholic beverages and tobacco from the CPI, has been introduced as the reference index for the indexation of wages.

6 APPLICATION TO HICP DATA FOR THE EURO AREA

The robust estimators of Section 4 can easily be applied to data which cover only a limited time period, as is the case for HICPs. The results of such an application on HICPs for the euro area as a whole are reported in this section. The national dimension of HICP data has not been examined. Vega and Wynne (2000) report results from exploiting this dimension of the data, but it appeared that pooling the national data did not yield any additional efficiency gains. As in the Belgian case, three aggregation levels and four horizons are considered. The aggregation levels are described in Table 14. The first level ("Level 1") consists of 66 components and is the highest level of breakdown for which data are available from January 1995 onwards[34]. The second level ("Level 2") and the third level ("Level 3") have 53 and 33 components respectively and are almost identical to the second and the third level in the Belgian case.

From Table 15 it can be seen that the cross-sections of euro area price changes considered are fat-tailed. According to the robust standardisation, the weights in the tails of the distribution are rather similar to those observed in the Belgian case. The average kurtosis and consequently also the average Jarque-Bera statistic tend to be lower than in the Belgian case, although they are often far above the corresponding values for a normal distribution. The 12-month price changes for Level 3 do however form an exception: with an average kurtosis of 3.8 and an average Jarque-Bera statistic of 4.5, this cross-section does not seem fundamentally different from the normal distribution. However, the robust standardisation does provide evidence of fat tails, which illustrates the importance of the masking phenomenon in this case. On the basis of the average skewness, there is less evidence of chronic right skewness than in the Belgian case. For some cross-sections the average skewness is even negative.

Table 16 reports, in a similar way to the Belgian case, the results of the optimisation procedure for the JB-Average and JB-Monthly estimators, as well as half the weight of the excluded observations for the one-step Huber-type skipped mean. From this table it is clear that, in contrast to the Belgian case, symmetric trimming nearly always provides the best results. In the few cases where asymmetric trimming was better, the smallest degree of asymmetry was already sufficient. These findings are in line with the fact that there was little evidence of chronic right skewness reported in Table 15. However, it should be noted that these conclusions are based on the average situation during the sample considered, which may, given its shortness, not be sufficiently representative. For the same reason it was difficult to test the unbiasedness of the estimators.

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[34] A more detailed breakdown of HICP data (80 components) is only available from January 1996 onwards.

As far as the optimal trimming percentage is concerned, the following comments on Table 16 will concentrate on two differences between the euro area results and the Belgian results. These differences can be interpreted as illustrations of some weaknesses of the estimators making use of the Jarque-Bera statistic. Firstly, in a few cases the JB-Average estimator trimmed less than the JB-Monthly estimator, particularly for 12- and 6-month price changes in seasonally adjusted data at Level 3. This is due to the low breakdown point of the JB-Average estimator. As in these cases the historical average of the Jarque-Bera statistic is either below 5.99 or only marginally above this value, the corresponding JB-Average estimators do not trim at all or trim only moderately. Consequently they have a very low breakdown point, i.e. zero and 2 p.c. respectively. From the fact that the corresponding JB-Monthly estimators trimmed on average more than these JB-Average estimators, it can be deduced that the latter broke down effectively, at least for some months during the sample considered. In those months the JB-Average estimator trimmed too little, which contrasts with the Belgian case where the 'trimming too much' situation prevailed. The fact that the JB-Average estimators for the HICP data of the euro area are only based on a relatively short historical period has certainly contributed to their vulnerability.

Secondly, it should be noted that for some cross-sections the one-step Huber-type skipped mean removes on average more observations than the JB-Monthly estimator does. This is so for nearly all the cross-sections at Level 3 and for some cross-sections at Level 2. This contrasts with the Belgian results were the one-step Huber-type skipped mean removed systematically less than the JB-Monthly estimator. This result for the euro area data could be seen as an indication that the JB-Monthly estimator effectively suffers from masking. It should be recognised though that a comparison of the removed sample fractions of the JB-Monthly estimator on the one hand and the one-step Huber-type skipped mean on the other will typically also depend on the critical values used (5.99 and 2.5 respectively). The sensitivity of the outcome of this comparison to changes in these values has not been examined.

FIGURE 7 - The one-step Huber-type skipped mean estimator of euro area core inflation
(compounded results for 1-month price changes of Level 1, percentage changes)

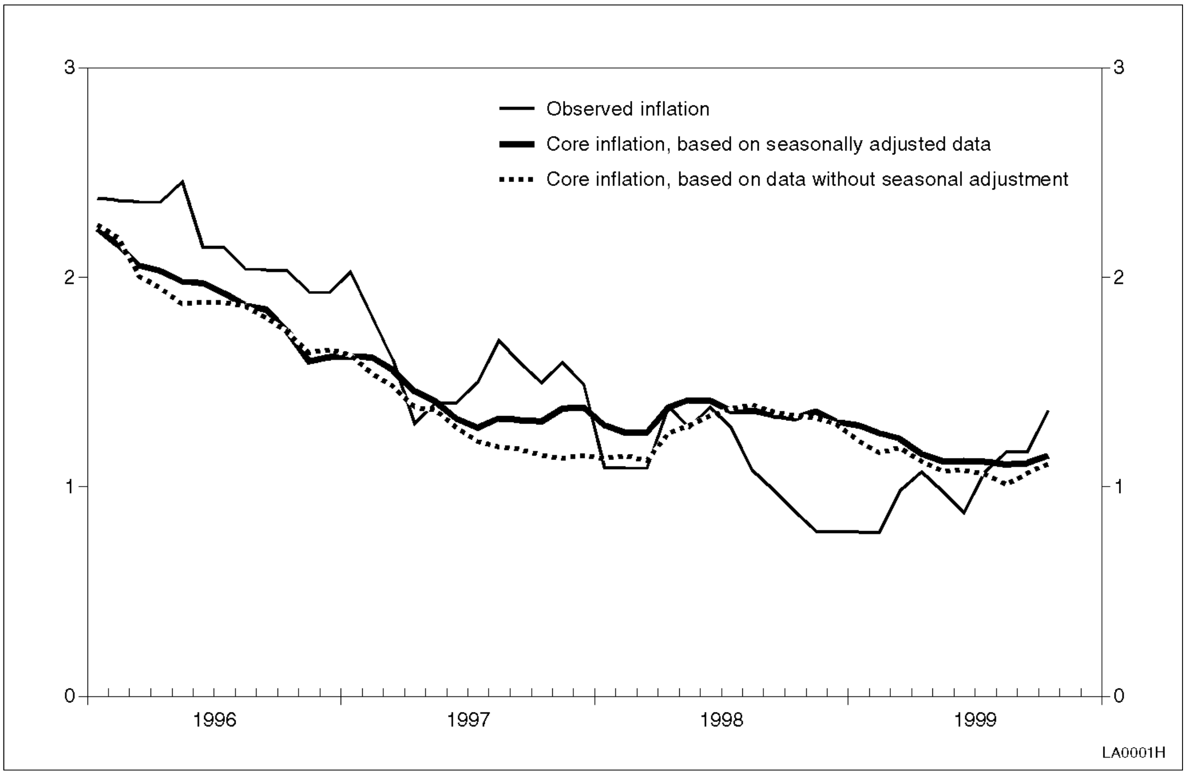

Table 17 reports, in a similar way as in the Belgian case, the volatility and the volatility reduction for the compounded results of the estimators considered. The largest efficiency gains are obtained for robust estimators that make use of 1-month price changes at Level 1[35]. For 1-month price changes at Level1 the differences between the different estimators are small, as was seen in the Belgian case. For seasonally adjusted data the one-step Huber-type skipped mean performed best, followed by the JB-Average estimator and the JB-Monthly estimator. For data without seasonal adjustment the efficiency gain of the one-step Huber-type skipped mean was only slightly smaller than that of the JB-Average estimator. Given its higher breakdown point and its protection against masking, the one-step Huber-type skipped mean may be preferable for both types of data. The two resulting compounded core inflation measures are shown in Figure 7. From Table 18 it can be seen that the robust estimators clearly outperform the XUE-measure, as in the Belgian case. The other core inflation measures produce similar efficiency gains as the one-step Huber-type skipped mean, in particular the VW-measure. However, the latter seems to be characterised by a negative bias.

[35] When applying the Bryan et al method to euro area data, Vega and Wynne (2000) also obtained the largest efficiency gain with 1-month price changes that are subsequently compounded and when data at the lowest level of aggregation are used (80 components in their paper).

7 CONCLUSIONS

In this paper several robust estimators of core inflation are examined for Belgian CPI data covering the period from June 1976 to October 1999, and for euro area HICPs for the period from January 1995 to October 1999. Evidence of fat tails in the cross-sections of price changes is provided by traditional measures, such as the kurtosis, as well as by a robust measure of the tail weight that is not vulnerable to the masking phenomenon. The latter is more reliable. Three aggregation levels, four time horizons over which the price changes have been calculated, as well as data with and without seasonal adjustment are considered. The sensitivity of the results to these three dimensions is examined.

We have considered trimmed means in the first instance, as many other authors in this field apply this type of robust estimator. Instead of determining the trimming percentage on the basis of the ability to track trend inflation as suggested by Bryan et al (1997), the optimal trim was determined on the basis of the departure from normality of the observed samples. In so doing, the lowest percentage for which the hypothesis of normality of the trimmed samples cannot be rejected on the basis of the Jarque-Bera statistic was chosen. Two variants of this method are considered. The JB-Average estimator determines the optimal trimming percentage on the basis of the historical average of the Jarque-Bera statistic and yields a trimming percentage that is constant over the whole period. The JB-Monthly estimator uses the Jarque-Bera statistic for each individual month and produces a time-varying optimal trimming percentage. Having a higher breakdown point, the latter is more robust. In both cases symmetric and asymmetric trimming are considered, by allowing for the possibility that the central percentile of the trimmed means is higher than the 50th. As both methods based on the Jarque-Bera statistic are to a certain extent vulnerable to the masking phenomenon, a robust estimator of a different type is examined as well: the so-called one-step Huber-type skipped mean. This estimator has a high breakdown point too. The use of other M-estimators has not yet been considered, but this appears to be an interesting area for further research.

A first assessment of the estimators considered is made on the basis of two evaluation criteria: unbiasedness and volatility reduction. Only in the Belgian case did trimmed means with higher central percentiles perform markedly better than symmetrically trimmed means. As far as volatility reduction is concerned, the largest efficiency gain was typically produced for 1-month price changes at the most disaggregated level, at least if the results are compounded over the last 12 months. In that case the differences in efficiency between the estimators are relatively small. Among the Belgian unbiased estimators, the largest efficiency gain was obtained by the JB-Average estimator, but the more robust JB-Monthly estimator was nearly as efficient. Given its higher breakdown point, we prefer the latter. For euro area data, the one-step Huber-type skipped mean combined the largest efficiency gain with the properties of having a high breakdown point and being protected against masking. That is why it was chosen for euro area data. This (symmetric) estimator was not the most suitable for Belgian data, as it turned out to be biased. Asymmetric variants of this estimator have not yet been considered. When the compounded results for 1-month price changes are considered, the efficiency gain is somewhat more pronounced for seasonally adjusted data than for data without seasonal adjustment. However, the disadvantage of using adjusted data is that the core inflation measure will change each time a new observation becomes available.

For both types of data, the volatility reduction of the robust estimators is more pronounced than that of the traditional core inflation measure, which systematically excludes the price changes of unprocessed food and energy. Applying the test suggested by Marques et al (2000), it was found that Belgian observed inflation was weakly exogenous over the whole sample, while Belgian core inflation was not. All the core inflation measures considered have this reversed long-term causality in common. This result reduces their relevance for monetary policy purposes quite considerably. It means that core inflation is lagging rather than leading, whereas monetary policy should in principle look forward. This finding is essentially due to the second- and third-round effects in the aftermath of the second oil shock (1979-1982) and when oil prices dropped sharply in 1985-1986. For the more recent period, starting in January 1988, the long-run causality worked in the right direction, re-establishing the relevance of core inflation measures for monetary policy purposes. The experience of the 70s and the 80s shows, though, that the core inflation measure can never be the only policy indicator. A similar exercise was not possible for the euro area, as the time period for which HICP data are available is too short to yield reliable results for this type of cointegration analysis.

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Table 1 - Aggregation levels considered: Belgian historical data

CODE	DESCRIPTION	LEVEL 1 60 compo-nents	LEVEL 2 52 compo-nents	LEVEL 3 32 compo-nents
1.000	FOOD AND NON-ALCOHOLIC BEVERAGES			
1.100	Food			
foodproc	*Processed food*			1
1.110	Bread and cereals	1	1	
1.140	Milk, cheese and eggs	1	1	
1.150	Oils and fats	1	1	
1.180	Sugar, jam, honey, syrups, chocolate and confectionery			
1.18 part	*Sugar*	1		
1.18 part	*Jam, honey, syrups, chocolate and confectionery*	1		
1.190	Food products n.e.c.	1	1	
1.200	Non-alcoholic beverages			
1.210	Coffee, tea and cocoa	1	1	
1.220	Mineral waters, soft drinks and juices	1	1	
foodunp	*Unprocessed food*			1
1.120	Meat	1	1	
1.130	Fish	1	1	
1.160	Fruit	1	1	
1.170	Vegetables including potatoes and other tubers		1	
1.17 part	*Fresh vegetables, excluding potatoes and other tubers*	1		
1.17 part	*Potatoes and other tubers*	1		
1.17 part	*Tinned vegetables*	1		
2.000	ALCOHOLIC BEVERAGES AND TOBACCO			
2.100	Alcoholic beverages	1	1	1
2.110	Spirits			
2.120	Wine			
2.130	Beer			
2.200	Tobacco	1	1	1
3.000	CLOTHING AND FOOTWEAR			
3.100	Clothing	1	1	1
3.110	Clothing materials			
3.120	Garments			
3.130	Other articles of clothing and clothing accessories			
3.140	Dry-cleaning, repair and hire of clothing			
3.200	Footwear, including repairs		1	1
3.2 part	*Footwear, excluding repairs*	1		
3.2 part	*Footwear, repairs*	1		
4.000	HOUSING, WATER, ELECTRICITY, GAS AND OTHER FUELS			
4.100	Actual rentals for housing	1	1	1
4.300	Regular maintenance and repair of the dwelling	1	1	1
4.310	Products for the regular maintenance and repair of the dwelling			
4.320	Services for the regular maintenance and repair of the dwelling			
4.400	Other services relating to the dwelling	1	1	1
4.500	Electricity, gas and other fuels			
4.510	Electricity	1	1	
4.520	Gas	1	1	
4.530	Liquid fuels	1	1	
4.540	Solid fuels	1	1	
4.550	Hot water, steam and ice			

Table 1 - continued

CODE	DESCRIPTION	LEVEL 1	LEVEL 2	LEVEL 3
5.000	FURNISHINGS, HOUSEHOLD EQUIPMENT AND ROUTINE MAINTENANCE OF THE HOUSE			
5.100	Furniture, furnishings and decorations , carpets and other floor coverings and repairs	1	1	1
5.110	Furniture and furnishings			
5.120	Carpets and other floor coverings			
5.130	Repair of furniture, furnishings and floor coverings			
5.200	Household textiles	1	1	1
5.300	Heating and cooking appliances, refrigerators, washing machines and similar major household appliances, including fittings and repairs			
5.312	Major household appliances whether electric or not and small electric household appliances	1	1	
5.330	Repair of household appliances	1	1	
5.400	Glassware, tableware and household utensils	1	1	1
5.500	Tools and equipment for house and garden	1	1	1
5.600	Goods and services for routine household maintenance			
5.610	Non-durable household goods	1	1	
5.620	Domestic services and home care services		1	
5.62 part	*Domestic services*	1		
5.62 part	*Home care services*	1		
6.000	HEALTH: Medical and pharmaceutical products, therapeutic appliances and equipment and medical services[1]		1	1
6 part	*Medical and pharmaceutical products*	1		
6 part	*Therapeutic appliances and equipment*	1		
6 part	*Medical services*	1		
6 part	*Hospital services*	1		
7.000	TRANSPORT			
7.100	Purchase of vehicles	1	1	1
7.110	New and second-hand motor cars			
7.123	Motor cycles and bicycles			
7.200	Operation of personal transport equipment			1
7.210	Spare parts and accessories	1	1	
7.220	Fuels and lubricants	1	1	
7.230	Maintenance and repairs	1	1	
7.240	Other services in respect of personal transport equipment	1	1	
7.300	Transport services	1	1	1
7.310	Passenger transport by railway			
7.320	Passenger transport by road			
7.330	Passenger transport by air			
7.340	Passenger transport by sea and inland waterway			
7.350	Other purchased transport services			
7.360	Combined tickets			
8.000	COMMUNICATIONS	1	1	1
8.100	Communications			
8.110	Postal services			
8.123	Telephone and telefax equipment and services			

Table 1 - continued

CODE	DESCRIPTION	LEVEL 1	LEVEL 2	LEVEL 3
9.000	RECREATION AND CULTURE			
9.100	Equipment and accessories, including repairs			1
9.11-9.13	*Equipment for the reception, recording and reproduction of sound and pictures* *Photographic and cinematographic equipment and optical instruments* *Data processing equipment*	1	1	
9.14-9.18	*Other major durables for recreation and culture* *Games, toys and hobbies, equipment for sport, camping and open-air recreation* *Recording media for pictures and sound* *Gardening* *Pets*	1	1	
9.190	Repair of equipment and accessories for recreation and culture	1	1	
9.200	Recreational and cultural services	1	1	1
9.300	Newspapers, books and stationery	1	1	1
9.400	Package holidays	1	1	1
10.000	EDUCATION - commonly paid by consumers in Member States	1	1	1
11.000	HOTELS, CAFES AND RESTAURANTS	1	1	1
11.100	Catering			
11.110	Restaurants and cafés			
11.120	Canteens			
11.200	Accommodation services			
12.000	MISCELLANEOUS GOODS AND SERVICES			
12.100	Personal care			1
12.110	Hairdressing salons and personal grooming establishments	1	1	
12.120	Appliances, articles and products for personal care	1	1	
12.200	Personal effects n.e.c.	1	1	1
12.400	Insurance	1	1	1
12.420	Insurance connected with the dwelling - Contents insurance			
12.440	Insurance connected with transport - Car insurance			
12.500	Banking services n.e.c.	1	1	1
12.600	Other services n.e.c.	1	1	1

[1] Including medical services, as national CPI data are considered.

Table 2 - Measures of the departure from normality in the cross-section of belgian cpi price changes (1976.06 - 1999.10)

	LEVEL 1				LEVEL 2				LEVEL 3			
	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
SEASONALLY ADJUSTED DATA												
SKEWNESS												
Historical average	0.5	0.6	0.5	0.5	0.2	0.3	0.3	0.3	0.4	0.5	0.5	0.6
Historical standard deviation	4.5	4.4	4.0	3.8	3.5	3.2	3.0	2.7	2.3	1.7	1.4	1.3
KURTOSIS												
Historical average	37.8	35.3	32.6	29.2	23.7	20.2	19.3	16.6	11.8	7.9	6.6	6.4
Historical standard deviation	39.9	30.7	29.5	32.3	32.2	13.1	14.1	12.4	42.6	14.2	9.1	7.4
JARQUE-BERA STATISTIC												
Historical average	7195.9	5152.9	4520.8	4464.6	3269.3	1099.0	1087.5	794.3	2537.7	319.4	139.5	99.6
WEIGHT IN THE TAILS OF THE DISTRIBUTION[1]												
Non-robust standardisation	3.3	3.1	2.8	3.1	3.8	3.6	3.3	3.4	3.6	3.1	2.7	2.4
Robust standardisation	15.1	12.4	11.1	9.2	15.0	12.8	11.2	9.6	14.8	11.4	9.7	7.8
UNADJUSTED DATA												
SKEWNESS												
Historical average	0.4	0.6	1.0	0.5	0.3	0.2	0.5	0.3	0.6	0.5	0.6	0.6
Historical standard deviation	4.6	4.7	4.0	3.8	3.4	3.1	2.7	2.7	2.4	2.1	1.7	1.3
KURTOSIS												
Historical average	39.6	40.1	35.2	28.8	21.9	19.4	17.4	16.6	11.4	9.6	7.9	6.4
Historical standard deviation	35.8	43.2	30.5	30.1	13.8	12.1	11.8	12.3	15.4	14.2	8.0	7.5
JARQUE-BERA STATISTIC												
Historical average	6745.7	8312.8	5079.8	4053.6	1286.6	982.1	815.8	791.5	443.5	348.1	134.9	100.0
WEIGHT IN THE TAILS OF THE DISTRIBUTION[1]												
Non-robust standardisation	3.4	3.[illegible]	3.1	3.0	3.9	4.0	3.8	3.5	3.6	3.2	3.2	2.4
Robust standardisation	19.5	16.0	12.2	9.4	19.6	16.3	12.7	9.7	18.0	14.4	10.6	7.8

[1] Historical average of the weights of standardised price changes exceeding 2.5 in absolute value. The corresponding weight for the standard normal distribution equals 1.24.

Table 3 - The JB-Average estimator: optimal trimming percentage and optimal central percentile

			Seasonally adjusted data		Data without seasonal adjustment	
			Optimal trimming percentage	Optimal central percentile	Optimal trimming percentage	Optimal central percentile
Level 1	**h=1**	Sample	22	54	29	60
		Subsample 1	23	55	30	60
		Subsample 2	17	52	26	58
		Subsample 3	14	52	26	58
	h=3	Sample	14	52	24	56
		Subsample 1	15	52	23	56
		Subsample 2	13	52	23	55
		Subsample 3	12	51	23	54
	h=6	Sample	13	51	15	52
		Subsample 1	12	51	15	52
		Subsample 2	14	51	15	52
		Subsample 3	12	51	15	52
	h=12	Sample	11	51	11	51
		Subsample 1	11	51	12	50
		Subsample 2	10	51	10	51
		Subsample 3	10	51	10	51
Level 2	**h=1**	Sample	19	53	27	59
		Subsample 1	23	54	28	60
		Subsample 2	18	52	25	57
		Subsample 3	12	51	25	57
	h=3	Sample	14	52	21	54
		Subsample 1	15	52	21	55
		Subsample 2	12	51	23	54
		Subsample 3	12	51	22	53
	h=6	Sample	12	51	13	51
		Subsample 1	11	50	14	52
		Subsample 2	12	51	13	51
		Subsample 3	12	51	13	51
	h=12	Sample	11	50	11	50
		Subsample 1	12	50	12	50
		Subsample 2	9	50	9	50
		Subsample 3	10	50	10	50
Level 3	**h=1**	Sample	24	52	31	56
		Subsample 1	25	53	28	56
		Subsample 2	18	51	29	55
		Subsample 3	19	51	29	55
	h=3	Sample	20	52	22	53
		Subsample 1	17	52	17	52
		Subsample 2	20	52	24	53
		Subsample 3	18	51	25	52
	h=6	Sample	16	51	17	52
		Subsample 1	16	51	17	52
		Subsample 2	19	51	21	53
		Subsample 3	8	50	16	52
	h=12	Sample	15	51	15	51
		Subsample 1	15	52	15	52
		Subsample 2	7	51	6	50
		Subsample 3	3	51	3	51

Table 4 - The JB-Monthly estimator: historical average of the monthly optimal trimming percentages and optimal central percentile

			Seasonally adjusted data		Data without seasonal adjustment	
			Average optimal trimming percentage	Optimal central percentile	Average optimal trimming percentage	Optimal central percentile
Level 1	**h=1**	Sample	11	53	20	58
		Subsample 1	12	53	22	59
		Subsample 2	9	52	18	56
		Subsample 3	9	52	18	56
	h=3	Sample	9	52	14	54
		Subsample 1	10	52	16	55
		Subsample 2	9	52	12	53
		Subsample 3	8	51	12	52
	h=6	Sample	8	51	10	52
		Subsample 1	8	51	11	52
		Subsample 2	7	51	9	52
		Subsample 3	7	51	9	52
	h=12	Sample	6	50	6	50
		Subsample 1	6	50	6	50
		Subsample 2	6	51	6	51
		Subsample 3	6	51	6	51
Level 2	**h=1**	Sample	10	52	19	57
		Subsample 1	12	53	20	58
		Subsample 2	9	51	16	55
		Subsample 3	9	51	16	55
	h=3	Sample	9	52	13	53
		Subsample 1	10	52	15	54
		Subsample 2	8	51	11	52
		Subsample 3	8	51	11	52
	h=6	Sample	7	51	9	52
		Subsample 1	8	51	10	52
		Subsample 2	6	51	8	51
		Subsample 3	6	51	8	51
	h=12	Sample	6	50	6	50
		Subsample 1	6	51	6	50
		Subsample 2	6	50	6	51
		Subsample 3	5	50	5	50
Level 3	**h=1**	Sample	9	51	11	52
		Subsample 1	9	52	11	53
		Subsample 2	9	51	11	52
		Subsample 3	9	51	12	52
	h=3	Sample	8	51	7	51
		Subsample 1	7	51	7	51
		Subsample 2	9	52	7	51
		Subsample 3	8	51	6	51
	h=6	Sample	6	51	6	51
		Subsample 1	6	51	6	51
		Subsample 2	6	51	7	52
		Subsample 3	5	51	7	52
	h=12	Sample	5	51	5	51
		Subsample 1	6	51	6	51
		Subsample 2	4	51	4	51
		Subsample 3	4	51	4	51

Table 5 - The one-step Huber-type skipped mean: half the weight of the rejected observations
(historical averages)

			Seasonally adjusted data	Data without seasonal adjustment
Level 1	**h=1**	Sample	8	10
		Subsample 1	8	10
		Subsample 2	7	10
		Subsample 3	8	10
	h=3	Sample	6	8
		Subsample 1	6	8
		Subsample 2	6	8
		Subsample 3	7	8
	h=6	Sample	6	6
		Subsample 1	6	6
		Subsample 2	5	6
		Subsample 3	5	6
	h=12	Sample	5	5
		Subsample 1	5	5
		Subsample 2	5	5
		Subsample 3	5	5
Level 2	**h=1**	Sample	8	10
		Subsample 1	8	10
		Subsample 2	7	10
		Subsample 3	8	10
	h=3	Sample	6	8
		Subsample 1	6	8
		Subsample 2	6	8
		Subsample 3	7	8
	h=6	Sample	6	6
		Subsample 1	6	6
		Subsample 2	5	6
		Subsample 3	5	6
	h=12	Sample	5	5
		Subsample 1	5	5
		Subsample 2	5	5
		Subsample 3	4	4
Level 3	**h=1**	Sample	7	9
		Subsample 1	7	8
		Subsample 2	8	10
		Subsample 3	8	10
	h=3	Sample	6	7
		Subsample 1	5	6
		Subsample 2	6	8
		Subsample 3	6	8
	h=6	Sample	5	5
		Subsample 1	4	5
		Subsample 2	5	6
		Subsample 3	5	6
	h=12	Sample	4	4
		Subsample 1	4	4
		Subsample 2	4	4
		Subsample 3	4	4

Table 6 - The central percentile estimator

			Seasonally adjusted data		Data without seasonal adjustment	
			Trimming percentage	Optimal central percentile	Trimming percentage	Optimal central percentile
Level 1	**h=1**	Sample	50	56	50	63
		Subsample 1	50	57	50	64
		Subsample 2	50	55	50	62
		Subsample 3	50	55	50	61
	h=3	Sample	50	55	50	59
		Subsample 1	50	56	50	59
		Subsample 2	50	54	50	58
		Subsample 3	50	53	50	56
	h=6	Sample	50	53	50	55
		Subsample 1	50	54	50	56
		Subsample 2	50	52	50	54
		Subsample 3	50	52	50	54
	h=12	Sample	50	54	50	54
		Subsample 1	50	55	50	55
		Subsample 2	50	52	50	52
		Subsample 3	50	52	50	52
Level 2	**h=1**	Sample	50	56	50	62
		Subsample 1	50	57	50	63
		Subsample 2	50	54	50	61
		Subsample 3	50	54	50	60
	h=3	Sample	50	54	50	58
		Subsample 1	50	55	50	59
		Subsample 2	50	53	50	57
		Subsample 3	50	52	50	55
	h=6	Sample	50	52	50	55
		Subsample 1	50	53	50	56
		Subsample 2	50	51	50	54
		Subsample 3	50	51	50	53
	h=12	Sample	50	53	50	53
		Subsample 1	50	55	50	55
		Subsample 2	50	51	50	51
		Subsample 3	50	51	50	51
Level 3	**h=1**	Sample	50	54	50	58
		Subsample 1	50	54	50	59
		Subsample 2	50	53	50	57
		Subsample 3	50	52	50	57
	h=3	Sample	50	53	50	55
		Subsample 1	50	53	50	55
		Subsample 2	50	53	50	56
		Subsample 3	50	52	50	55
	h=6	Sample	50	52	50	54
		Subsample 1	50	53	50	54
		Subsample 2	50	52	50	54
		Subsample 3	50	50	50	54
	h=12	Sample	50	54	50	54
		Subsample 1	50	54	50	55
		Subsample 2	50	52	50	52
		Subsample 3	50	51	50	51

Table 7 - Unbiasedness of the estimators - compounded data, whole sample (1976.06 - 1999.10)

	LEVEL 1				LEVEL 2				LEVEL 3			
	h=1	**h=3**	**h=6**	**h=12**	**h=1**	**h=3**	**h=6**	**h=12**	**h=1**	**h=3**	**h=6**	**h=12**
HISTORICAL AVERAGE OF DIFFERENCE BETWEEN THE ESTIMATOR AND OBSERVED INFLATION[1]												
Seasonally adjusted data												
JB-Average	0.04	0.03	0.10	0.05	0.03	0.07	0.12*	-0.03	-0.07	0.02	-0.01	-0.01
JB-Monthly	0.06	0.02	0.00	-0.02	-0.01	0.05	0.03	-0.01	-0.06	-0.01	0.00	0.01
Median	-0.50*	-0.33*	-0.22*	-0.19*	-0.46*	-0.28*	-0.16*	-0.16*	-0.37*	-0.26*	-0.14*	-0.23*
Central percentile	0.00	0.03	0.01	0.03	0.04	0.01	-0.01	0.00	0.02	0.01	0.00	0.04
One-step Huber-type skipped mean	-0.44*	-0.30*	-0.18*	-0.09	-0.40*	-0.25*	-0.13	-0.07	-0.40*	-0.22*	-0.14*	-0.12
Data without seasonal adjustment												
JB-Average	0.09	0.10	0.04	0.06	0.12	-0.01	-0.01	0.07	0.02	0.07	0.03	-0.01
JB-Monthly	0.08	0.01	0.04	-0.01	0.07	0.00	0.08	0.00	-0.04	-0.04	-0.02	0.02
Median	-1.33*	-0.76*	-0.37*	-0.18*	-1.27*	-0.69*	-0.33*	-0.15*	-0.99*	-0.48*	-0.31*	-0.23*
Central percentile	0.09	0.08	0.01	0.04	0.02	0.03	0.05	0.01	0.02	-0.03	0.01	0.04
One-step Huber-type skipped mean	-1.11*	-0.61*	-0.26*	-0.08	-1.04*	-0.54*	-0.22*	-0.05	-0.76*	-0.32*	-0.25*	-0.12
STATIONARITY OF DIFFERENCE BETWEEN THE ESTIMATOR AND OBSERVED INFLATION: THE AUGMENTED DICKEY FULLER TEST STATISTIC[2]												
Seasonally adjusted data												
JB-Average	-2.28	-2.48	-3.09	-2.80	-2.33	-2.51	-3.04	-2.80	-2.09	-2.30	-2.57	-2.26
JB-Monthly	-2.24	-2.50	-2.96	-2.86	-2.26	-2.45	-2.97	-2.92	-2.28	-2.38	-2.82	-2.59
Median	-1.89*	-1.99	-2.32	-2.81	-1.89*	-2.02	-2.46	-2.70	-1.97	-2.01	-2.61	-2.53
Central percentile	-2.34	-2.35	-2.77	-2.95	-2.38	-2.26	-2.66	-3.08	-2.25	-2.25	-2.98	-2.68
One-step Huber-type skipped mean	-1.96	-2.08	-2.47	-3.00	-1.98	-2.14	-2.46	-2.69	-1.79*	-2.19	-2.63	-2.40
Data without seasonal adjustment												
JB-Average	-2.06	-2.20	-2.58	-2.65	-2.05	-2.15	-2.53	-2.65	-1.96	-2.10	-2.44	-2.39
JB-Monthly	-1.99	-2.07	-2.45	-2.61	-2.00	-2.09	-2.49	-2.68	-1.98	-2.24	-2.67	-2.56
Median	-1.18*	-1.39*	-2.13	-2.73	-1.23*	-1.42*	-2.29	-2.70	-1.33*	-1.71*	-2.15	-2.57
Central percentile	-2.17	-2.10	-2.56	-2.98	-2.11	-2.12	-2.59	-3.04	-1.86	-2.07	-2.33	-2.75
One-step Huber-type skipped mean	-1.34*	-1.60*	-2.24	-2.87	-1.36*	-1.66*	-2.20	-2.77	-1.48*	2.01	-2.15	2.50

1 Differences which are statistically significant at the 95 p.c. level are marked with an asterisk (*).
2 The 95 p.c. critical value for rejection of the null hypothesis of a unit root is -1.94. The estimators for which the null hypothesis could not be rejected at the 95 p.c. critical value are marked with an asterisk (*).

Table 8 - Unbiasedness of the estimators - compounded data, subsample 2 (1988.01 - 1999.10)

	LEVEL 1				LEVEL 2				LEVEL 3			
	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
HISTORICAL AVERAGE OF DIFFERENCE BETWEEN THE ESTIMATOR AND OBSERVED INFLATION[1]												
Seasonally adjusted data												
JB-Average	0.14*	0.04	0.06	0.00	0.14*	0.08*	0.09*	-0.03	0.08	0.03	0.01	0.00
JB-Monthly	0.17*	0.05	-0.01	-0.07*	0.13*	0.09*	0.01	-0.05	0.01	-0.03	-0.04	-0.01
Median	-0.24*	-0.13*	-0.10*	-0.12*	-0.18*	-0.08*	-0.04	-0.07*	-0.15*	-0.14*	-0.07	-0.12*
Central percentile	0.13*	0.13*	0.06	0.08*	0.18*	0.13*	0.05	0.07	0.09*	0.02	0.03	0.10*
One-step Huber-type skipped mean	-0.20*	-0.12*	-0.10*	-0.11*	-0.14*	-0.07	-0.05	-0.08	-0.11*	-0.11*	-0.10*	-0.09*
Data without seasonal adjustment												
JB-Average	0.20*	0.12*	0.02	0.00	0.24*	0.08	0.00	0.04	0.09*	0.07*	0.00	0.01
JB-Monthly	0.23*	0.11*	0.04	-0.07*	0.27*	0.13*	0.09*	-0.05	0.00	-0.08*	-0.06*	-0.01
Median	-0.82*	-0.45*	-0.23*	-0.10*	-0.76*	-0.36*	-0.18*	-0.06	-0.57*	-0.28*	-0.19*	-0.11*
Central percentile	0.22*	0.13*	0.08	0.08*	0.23*	0.14*	0.11*	0.07	0.13*	-0.02	0.00	0.11*
One-step Huber-type skipped mean	-0.62*	-0.32*	-0.17*	-0.11*	-0.52*	-0.24*	-0.11*	-0.07	-0.41*	-0.16*	-0.21*	-0.09*
STATIONARITY OF DIFFERENCE BETWEEN THE ESTIMATOR AND OBSERVED INFLATION: THE AUGMENTED DICKEY FULLER TEST STATISTIC[2]												
Seasonally adjusted data												
JB-Average	-2.65	-2.61	-2.47	-2.58	-2.67	-2.60	-2.48	-2.70	-2.92	-2.92	-2.44	-2.76
JB-Monthly	-2.62	-2.62	-2.41	-2.46	-2.74	-2.65	-2.40	-2.63	-3.09	-3.02	-2.33	-3.09
Median	-2.42	-2.70	-2.73	-2.52	-2.58	-2.87	-2.82	-3.03	-2.58	-2.75	-2.63	-2.96
Central percentile	-2.78	-2.76	-2.73	-2.95	-2.71	-2.73	-2.86	-3.07	-2.78	-2.96	-2.55	-2.26
One-step Huber-type skipped mean	-2.58	-2.58	-2.69	-2.37	-2.78	-2.74	-2.70	-2.48	-2.96	-2.79	-2.66	-2.20
Data without seasonal adjustment												
JB-Average	-2.33	-2.57	-2.65	-2.57	-2.24	-2.62	-2.61	-2.57	-2.75	-2.83	-2.89	-2.59
JB-Monthly	-2.21	-2.53	-2.69	-2.45	-2.15	-2.47	-2.62	-2.16	-2.55	-2.72	-2.61	-2.83
Median	-1.19*	-1.62*	-2.57	-2.62	-1.19*	-1.80*	-2.73	-3.02	-1.52*	-2.17	-2.35	-2.95
Central percentile	-2.28	-2.46	-2.65	-2.80	-2.29	-2.40	-2.63	-2.94	-2.69	-2.97	-2.68	-2.35
One-step Huber-type skipped mean	-1.47*	-1.99	-2.56	-2.35	-1.52*	-2.20	-2.75	-2.45	-1.80*	-2.81	-2.28	-2.13

[1] Differences which are statistically significant at the 95 p.c. level are marked with an asterisk (*).
[2] The 95 p.c. critical value for rejection of the null hypothesis of a unit root is -1.94. The estimators for which the null hypothesis could not be rejected at the 95 p.c. critical value are marked with an asterisk (*).

Table 9 - Volatility of observed inflation and the robust estimators - original data, whole sample (1976.06 - 1999.10)

	LEVEL 1				LEVEL 2				LEVEL 3			
	h=1	**h=3**	**h=6**	**h=12**	**h=1**	**h=3**	**h=6**	**h=12**	**h=1**	**h=3**	**h=6**	**h=12**
VOLATILITY[1]												
Seasonally adjusted data												
Observed inflation	3.63	1.38	0.69	0.35	3.63	1.38	0.69	0.35	3.63	1.38	0.69	0.35
JB-Average	1.52	0.68	0.42	0.23	1.47	0.69	0.42	0.23	1.64	0.85	0.52	0.26
JB-Monthly	1.59	0.67	0.44	0.24	1.49	0.67	0.45	0.24	2.04	1.09	0.64	0.31
Median	1.36	0.72	0.51	0.30	1.46	0.71	0.50	0.33	1.61	0.91	0.60	0.41
Central percentile	1.78	0.76	0.48	0.33	1.63	0.75	0.48	0.31	1.77	1.03	0.60	0.38
One-step Huber-type skipped mean	1.33	0.67	0.48	0.30	1.34	0.68	0.47	0.32	1.75	0.91	0.64	0.41
Data without seasonal adjustment												
Observed inflation	4.83	1.79	0.78	0.35	4.83	1.79	0.78	0.35	4.83	1.79	0.78	0.35
JB-Average	2.14	0.93	0.49	0.22	2.18	0.90	0.49	0.22	2.66	1.25	0.64	0.27
JB-Monthly	2.21	0.99	0.57	0.24	2.24	0.98	0.58	0.24	3.35	1.63	0.79	0.32
Median	1.59	0.98	0.60	0.30	1.56	1.02	0.65	0.31	1.97	1.32	0.83	0.43
Central percentile	2.16	1.24	0.66	0.32	2.17	1.19	0.71	0.31	2.75	1.39	0.83	0.40
One-step Huber-type skipped mean	1.61	0.98	0.62	0.28	1.63	0.98	0.60	0.31	2.31	1.47	0.87	0.41
VOLATILITY REDUCTION[2]												
Seasonally adjusted data												
Observed inflation	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
JB-Average	41.76	49.52	60.23	64.91	40.41	49.89	59.95	66.16	45.20	61.99	74.50	74.23
JB-Monthly	43.72	48.89	63.80	67.93	40.90	48.65	65.47	68.63	56.12	79.13	91.99	87.47
Median	37.53	52.42	73.21	86.47	40.31	51.74	71.35	94.10	44.27	65.97	86.52	117.44
Central percentile	49.02	55.33	69.06	93.61	44.93	54.12	68.92	89.33	48.66	75.02	86.55	108.91
One-step Huber-type skipped mean	36.75	48.70	68.69	85.27	36.92	49.28	67.12	91.74	48.24	66.21	92.30	116.22
Data without seasonal adjustment												
Observed inflation	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
JB-Average	44.25	51.78	62.61	62.54	45.15	50.14	63.14	63.47	54.98	69.84	81.46	76.19
JB-Monthly	45.71	55.22	72.46	66.79	46.38	54.87	73.77	68.15	69.41	90.74	100.74	90.33
Median	32.90	54.48	76.40	84.05	32.30	56.92	83.19	88.00	40.70	73.73	106.17	122.01
Central percentile	44.64	68.90	84.52	92.19	44.88	66.60	91.03	86.74	56.85	77.29	105.83	114.10
One-step Huber-type skipped mean	33.31	54.79	79.13	78.60	33.82	54.73	76.75	87.20	47.89	81.96	112.02	115.16

[1] Measured as the standard deviation of the first difference of observed inflation (or the estimator in question).
[2] Volatility expressed as a percentage of the volatility of the corresponding observed inflation measure.

Table 10 - Volatility of observed inflation and the robust estimators - compounded data, whole sample (1976.06 - 1999.10)

	LEVEL 1				LEVEL 2				LEVEL 3			
	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
VOLATILITY[1]												
Seasonally adjusted data												
Observed inflation	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35
JB-Average	0.15	0.22	0.23	0.23	0.15	0.22	0.23	0.23	0.18	0.27	0.29	0.26
JB-Monthly	0.16	0.25	0.27	0.24	0.15	0.25	0.28	0.24	0.21	0.34	0.35	0.31
Median	0.14	0.29	0.32	0.30	0.15	0.31	0.32	0.33	0.17	0.36	0.39	0.41
Central percentile	0.16	0.33	0.30	0.33	0.16	0.30	0.32	0.31	0.17	0.39	0.39	0.38
One-step Huber-type skipped mean	0.14	0.25	0.32	0.30	0.15	0.24	0.32	0.32	0.19	0.42	0.40	0.41
Data without seasonal adjustment												
Observed inflation	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35
JB-Average	0.17	0.25	0.22	0.22	0.17	0.24	0.22	0.22	0.20	0.36	0.32	0.27
JB-Monthly	0.19	0.33	0.32	0.24	0.19	0.33	0.31	0.24	0.23	0.53	0.40	0.32
Median	0.15	0.39	0.32	0.30	0.15	0.40	0.33	0.31	0.16	0.49	0.55	0.43
Central percentile	0.18	0.49	0.36	0.32	0.18	0.45	0.40	0.31	0.23	0.50	0.49	0.40
One-step Huber-type skipped mean	0.16	0.37	0.34	0.28	0.16	0.38	0.30	0.31	0.20	0.50	0.54	0.41
VOLATILITY REDUCTION[2]												
Seasonally adjusted data												
Observed inflation	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
JB-Average	42.94	62.90	64.67	64.91	43.55	62.35	64.54	66.16	50.12	77.67	82.25	74.23
JB-Monthly	44.09	71.16	77.99	67.93	43.43	70.78	79.54	68.63	59.37	95.59	98.25	87.47
Median	39.44	83.18	91.57	86.47	41.37	86.87	92.15	94.10	47.02	102.47	111.39	117.44
Central percentile	46.06	92.86	85.09	93.61	46.01	86.32	89.53	89.33	49.00	112.07	111.33	108.91
One-step Huber-type skipped mean	40.69	70.28	90.31	85.27	41.91	68.87	90.69	91.74	53.64	119.08	113.09	116.22
Data without seasonal adjustment												
Observed inflation	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
JB-Average	49.29	70.49	63.15	62.54	49.64	68.68	62.85	63.47	57.44	101.00	90.56	76.19
JB-Monthly	53.03	94.16	90.04	66.79	53.52	94.00	87.54	68.15	66.53	150.70	112.45	90.33
Median	41.34	109.62	90.32	84.05	41.40	113.50	94.08	88.00	46.75	138.08	157.16	122.01
Central percentile	50.52	139.97	102.60	92.19	50.52	127.38	113.15	86.74	64.21	142.18	139.82	114.10
One-step Huber-type skipped mean	44.59	104.57	96.28	78.60	44.93	107.86	86.23	87.20	57.48	142.73	152.69	115.16

[1] Measured as the standard deviation of the first difference of observed inflation (or the estimator in question).
[2] Volatility expressed as a percentage of the volatility of observed inflation.

Table 11 - JB-Monthly estimator: products excluded
(1-month price changes at Level 1, seasonally adjusted data)

Code	Description	Frequency of exclusion by the JB-Monthly estimator		Exclusion by XUE[1]	Exclusion by X14[2]
		Number of months	As a percentage of total number of months		
1.17 part	Fresh vegetables	253	90.4	yes	yes
1.17 part	Potatoes and other tubers	239	85.4	yes	yes
4.530	Liquid fuels	231	82.5	yes	yes
1.160	Fruit	224	80.0	yes	yes
1.210	Coffee, tea and cocoa	192	68.6		yes
7.220	Fuels and lubricants	184	65.7	yes	yes
1.130	Fish	148	52.9	yes	yes
6 part	Hospital services	142	50.7		
9.400	Package holidays	135	48.2		yes
9.11-9.13	Equipment for the reception, recording and reproduction of sound and pictures	132	47.1		
4.520	Gas	132	47.1	yes	yes
9.14-9.18	Other major durables for recreation and culture	122	43.6		
4.540	Solid fuels	108	38.6	yes	
1.220	Mineral waters, soft drinks and juices	98	35.0		
2.200	Tobacco	91	32.5		
8.000	Communications	86	30.7		yes
1.150	Oils and fats	85	30.4		
12.500	Banking services n.e.c.	83	29.6		yes
4.400	Other services relating to the dwelling	79	28.2		yes
1.17 part	Tinned vegetables	76	27.1	yes	
1.18 part	Jam, honey, syrups, chocolate and confectionery	74	26.4		
1.140	Milk, cheese and eggs	63	22.5		
12.110	Hairdressing salons and personal grooming establishments	62	22.1		
5.610	Non-durable household goods	58	20.7		
7.300	Transport services	58	20.7		yes
10.000	Education	57	20.4		
6 part	Therapeutic appliances and equipment	55	19.6		
4.510	Electricity	54	19.3	yes	
6 part	Medical and pharmaceutical products	54	19.3		
7.240	Other services in respect of personal transport equipment	54	19.3		yes
7.210	Spare parts and accessories	54	19.3		
5.330	Repair of household appliances	52	18.6		
1.18 part	Sugar	52	18.6		

Table 11 - continued

Code	Description	Frequency of exclusion by the JB-Monthly estimator		Exclusion by XUE[1]	Exclusion by X14[2]
		Number of months	As a percentage of total number of months		
9.300	Newspapers, books and stationery	50	17.9		
2.100	Alcoholic beverages	49	17.5		
12.600	Other services n.e.c.	48	17.1		
12.120	Appliances, articles and products for personal care	46	16.4		
1.110	Bread and cereals	45	16.1		
1.190	Food products n.e.c.	44	15.7		
5.312	Major household appliances whether electric or not and small electric household appliances	44	15.7		
9.190	Repair of equipment and accessories for recreation and culture	44	15.7		
12.400	Insurance	43	15.4		
6 part	Medical services	43	15.4		
5.100	Furniture, furnishings and decorations, carpets and other floor coverings and repairs	41	14.6		
7.230	Maintenance and repairs	41	14.6		
3.2 part	Footwear, repairs	39	13.9		
3.2 part	Footwear, excluding repairs	34	12.1		
7.100	Purchase of vehicles	32	11.4		
12.200	Personal effects n.e.c.	31	11.1		
9.200	Recreational and cultural services	31	11.1		
1.120	Meat	29	10.4	yes	
5.62 part	Domestic services	26	9.3		
5.62 part	Home care services	25	8.9		
11.000	Hotels, cafés and restaurants	23	8.2		
5.500	Tools and equipment for house and garden	21	7.5		
4.300	Regular maintenance and repair of the dwelling	20	7.1		
3.100	Clothing	19	6.8		
5.400	Glassware, tableware and household utensils	19	6.8		
4.100	Actual rentals for housing	16	5.7		
5.200	Household textiles	16	5.7		

1 CPI, excluding unprocessed food and energy.
2 CPI, excluding the 14 most volatile products.

Table 12 - Comparison with other core inflation measures

	JB-Monthly estimator (Compounded results of 1-month price changes)		**Other core inflation measures** (12-month price changes)				**35-month centred moving average**
	Seasonal-ly adjusted data	Data without seasonal adjust-ment	XUE[1]	X14[2]	DW[3]	VW[4]	
<u>WHOLE SAMPLE</u>							
Unbiasedness							
Average difference with observed inflation[5]	0.06	0.08	0.12	-0.04	-0.08	-0.21*	-0.07
Stationarity of difference with observed inflation[6]	-2.24	-1.99	-2.50	-2.69	-2.21	-2.33	-3.12
Volatility reduction[7]	44.09	53.03	66.02	52.38	45.63	49.52	37.16
<u>SUBSAMPLE 2</u>							
Unbiasedness							
Average difference with observed inflation[5]	0.17*	0.23*	0.14*	-0.03	-0.03	-0.26*	-0.01
Stationarity of difference with observed inflation[6]	-2.62	-2.21	-2.45	-2.53	-2.45	-2.04	-3.16
Volatility reduction[7]	36.33	36.57	54.11	37.63	31.26	32.19	35.10

1 CPI, excluding unprocessed food and energy.
2 CPI, excluding the 14 most volatile products.
3 CPI, reweighted by the product of the CPI weights and the reciprocal of short-term volatility.
4 CPI, reweighted by the reciprocal of short-term volatility.
5 Differences which are statistically significant at the 95 p.c. level are marked with an asterisk (*).
6 Augmented Dickey-Fuller test statistic. The 95 p.c. critical value for rejection of a unit root is -1.94.
7 Volatility expressed as a percentage of the volatility of observed inflation.

Table 13 - Exogeneity of core inflation

	Observed inflation	**Core inflation**
	Not weakly exogenous $(b_1 \neq 0)$	**Weakly exogenous** $(b_2 = 0)$
<u>WHOLE SAMPLE</u>		
JB-Monthly estimator		
Seasonnally adjusted data	Weakly exogenous	Not weakly exogenous
Data without seasonal adjustment	Weakly exogenous	Not weakly exogenous
Other core inflation measures[1]		
XUE	Weakly exogenous	Not weakly exogenous
X14	Weakly exogenous	Not weakly exogenous
DW	Weakly exogenous	Not weakly exogenous
VW	Weakly exogenous	Not weakly exogenous
<u>SUBSAMPLE 2</u>		
JB-Monthly estimator		
Seasonnally adjusted data	Not weakly exogenous	Weakly exogenous
Data without seasonal adjustment	Not weakly exogenous	Weakly exogenous
Other core inflation measures[1]		
XUE	Not weakly exogenous	Weakly exogenous
X14	Not weakly exogenous	Weakly exogenous
DW	Not weakly exogenous	Weakly exogenous
VW	Not weakly exogenous	Weakly exogenous

[1] For definitions of these core measures, see Table 14.

Table 14 - Aggregation levels considered: HICP data for the euro area

CODE	DESCRIPTION	LEVEL 1 66 components	LEVEL 2 53 components	LEVEL 3 33 components
1.000	FOOD AND NON-ALCOHOLIC BEVERAGES			
1.100	Food			
foodproc	*Processed food*			1
1.110	Bread and cereals	1	1	
1.140	Milk, cheese and eggs	1	1	
1.150	Oils and fats	1	1	
1.180	Sugar, jam, honey, syrups, chocolate and confectionery	1	1	
1.190	Food products n.e.c.	1	1	
1.200	Non-alcoholic beverages			
1.210	Coffee, tea and cocoa	1	1	
1.220	Mineral waters, soft drinks and juices	1	1	
foodunp	*Unprocessed food*			1
1.120	Meat	1	1	
1.130	Fish	1	1	
1.160	Fruit	1	1	
1.170	Vegetables including potatoes and other tubers	1	1	
2.000	ALCOHOLIC BEVERAGES AND TOBACCO			
2.100	Alcoholic beverages		1	1
2.110	Spirits	1		
2.120	Wine	1		
2.130	Beer	1		
2.200	Tobacco	1	1	1
3.000	CLOTHING AND FOOTWEAR			
3.100	Clothing	1	1	1
3.110	Clothing materials			
3.120	Garments			
3.130	Other articles of clothing and clothing accessories			
3.140	Dry-cleaning, repair and hire of clothing			
3.200	Footwear, including repairs	1	1	1
4.000	HOUSING, WATER, ELECTRICITY, GAS AND OTHER FUELS			
4.100	Actual rentals for housing	1	1	1
4.300	Regular maintenance and repair of the dwelling		1	1
4.310	Products for the regular maintenance and repair of the dwelling	1		
4.320	Services for the regular maintenance and repair of the dwelling	1		
4.400	Other services relating to the dwelling	1	1	1
4.500	Electricity, gas and other fuels			1
4.510	Electricity	1	1	
4.520	Gas	1	1	
4.530	Liquid fuels	1	1	
4.540	Solid fuels	1	1	
4.550	Hot water, steam and ice	1	1	

Table 14 - continued

CODE	DESCRIPTION	LEVEL 1	LEVEL 2	LEVEL 3
5.000	FURNISHINGS, HOUSEHOLD EQUIPMENT AND ROUTINE MAINTENANCE OF THE HOUSE			
5.100	Furniture, furnishings and decorations , carpets and other floor coverings and repairs	1	1	1
5.110	Furniture and furnishings			
5.120	Carpets and other floor coverings			
5.130	Repair of furniture, furnishings and floor coverings			
5.200	Household textiles	1	1	1
5.300	Heating and cooking appliances, refrigerators, washing machines and similar major household appliances, including fittings and repairs			
5.312	Major household appliances whether electric or not and small electric household appliances	1	1	
5.330	Repair of household appliances	1	1	
5.400	Glassware, tableware and household utensils	1	1	1
5.500	Tools and equipment for house and garden	1	1	1
5.600	Goods and services for routine household maintenance			
5.610	Non-durable household goods	1	1	
5.620	Domestic services and home care services	1	1	
6.000	HEALTH: Medical and pharmaceutical products and therapeutic appliances and equipment - paid by the consumer and not reimbursed	1	1	1
7.000	TRANSPORT			
7.100	Purchase of vehicles		1	1
7.110	New and second-hand motor cars	1		
7.123	Motor cycles and bicycles	1		
7.200	Operation of personal transport equipment			1
7.210	Spare parts and accessories	1	1	
7.220	Fuels and lubricants	1	1	
7.230	Maintenance and repairs	1	1	
7.240	Other services in respect of personal transport equipment	1	1	
7.300	Transport services	1	1	1
7.310	Passenger transport by railway			
7.320	Passenger transport by road			
7.330	Passenger transport by air			
7.340	Passenger transport by sea and inland waterway			
7.350	Other purchased transport services			
7.360	Combined tickets			
8.000	COMMUNICATIONS		1	1
8.100	Communications			
8.110	Postal services	1		
8.123	Telephone and telefax equipment and services	1		

Table 14 - continued

CODE	DESCRIPTION	LEVEL 1	LEVEL 2	LEVEL 3
9.000	RECREATION AND CULTURE			
9.100	Equipment and accessories, including repairs			1
9.110-9.130	Sum of the 3 following items		1	
9.110	Equipment for the reception, recording and reproduction of sound and pictures	1		
9.120	Photographic and cinematographic equipment and optical instruments	1		
9.130	Data processing equipment	1		
9.140-9.180	Sum of the 5 following items		1	
9.140	Other major durables for recreation and culture	1		
9.150	Games, toys and hobbies, equipment for sport, camping and open-air recreation	1		
9.160	Recording media for pictures and sound	1		
9.170	Gardening	1		
9.180	Pets	1		
9.190	Repair of equipment and accessories for recreation and culture	1	1	
9.200	Recreational and cultural services	1	1	1
9.300	Newspapers, books and stationery	1	1	1
9.400	Package holidays	1	1	1
10.000	EDUCATION - commonly paid by consumers in Member States	1	1	1
11.000	HOTELS, CAFES AND RESTAURANTS		1	
11.100	Catering			1
11.110	Restaurants and cafés	1		
11.120	Canteens	1		
11.200	Accommodation services	1		1
12.000	MISCELLANEOUS GOODS AND SERVICES			
12.100	Personal care			1
12.110	Hairdressing salons and personal grooming establishments	1	1	
12.120	Appliances, articles and products for personal care	1	1	
12.200	Personal effects n.e.c.	1	1	1
12.400	Insurance	1	1	1
12.420	Insurance connected with the dwelling - Contents insurance			
12.440	Insurance connected with transport - Car insurance			
12.500	Banking services n.e.c.	1	1	1
12.600	Other services n.e.c.	1	1	1

Table 15 - Measures of the departure from normality in the cross-section of HICP price changes of the euro area (1995.01 - 1999.10)

	LEVEL 1				LEVEL 2				LEVEL 3			
	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
SEASONALLY ADJUSTED DATA												
SKEWNESS												
Historical average	0.2	0.2	0.1	-0.3	0.2	0.3	0.2	-0.2	0.0	-0.1	-0.2	-0.3
Historical standard deviation	3.5	2.7	2.0	1.7	3.6	2.7	2.1	1.7	2.4	1.3	0.9	0.5
KURTOSIS												
Historical average	22.6	17.9	15.1	12.4	23.7	18.5	15.4	12.3	11.7	6.4	5.1	3.8
Historical standard deviation	21.3	12.3	7.3	7.1	22.5	12.8	7.7	7.4	14.3	5.2	2.2	1.1
JARQUE-BERA STATISTIC												
Historical average	2422.8	1091.3	588.8	406.4	2163.0	952.3	506.4	332.9	413.0	61.8	17.4	4.5
WEIGHT IN THE TAILS OF THE DISTRIBUTION[1]												
Non-robust standardisation	3.6	3.9	3.3	2.7	3.4	3.8	3.5	3.0	2.6	1.7	1.8	2.0
Robust standardisation	14.9	14.6	13.6	12.6	14.5	14.2	14.1	12.2	11.2	10.2	10.6	8.8
UNADJUSTED DATA												
SKEWNESS												
Historical average	0.0	0.3	-0.1	-0.3	0.2	0.3	-0.1	-0.2	0.3	0.1	0.0	-0.3
Historical standard deviation	3.5	2.3	2.1	1.7	3.7	2.5	2.2	1.7	4.7	3.0	2.0	0.5
KURTOSIS												
Historical average	24.9	17.4	15.3	12.3	27.3	19.3	16.8	12.2	30.6	16.6	9.6	3.8
Historical standard deviation	12.3	6.3	5.1	7.0	13.9	7.5	5.5	7.4	20.9	13.4	9.0	1.1
JARQUE-BERA STATISTIC												
Historical average	1862.9	736.1	528.9	403.2	1841.1	761.2	526.3	330.4	1757.6	543.6	189.3	4.5
WEIGHT IN THE TAILS OF THE DISTRIBUTION[1]												
Non-robust standardisation	3.2	3.7	3.8	2.7	2.9	3.4	3.7	2.9	2.1	2.1	1.8	2.0
Robust standardisation	20.1	17.7	15.3	12.6	17.5	15.6	14.0	12.1	19.6	17.1	14.7	8.9

[1] Historical average of the weights of standardised price changes exceeding 2.5 in absolute value. The corresponding weight for the standard normal distribution equals 1.24.

Table 16 - Euro area: the JB-Average estimator

		Seasonally adjusted data		Data without seasonal adjustment	
		Optimal trimming percentage	Optimal central percentile	Optimal trimming percentage	Optimal central percentile
Level 1	**h=1**	11	50	18	51
	h=3	13	50	18	50
	h=6	11	50	12	50
	h=12	8	50	8	50
Level 2	**h=1**	11	50	16	51
	h=3	13	50	15	50
	h=6	10	50	10	50
	h=12	7	50	7	50
Level 3	**h=1**	15	50	16	51
	h=3	3	50	3	50
	h=6	2	50	4	50
	h=12	0	50	0	50

Euro area: the JB-Monthly estimator

		Seasonally adjusted data		Data without seasonal adjustment	
		Average trimming percentage	Optimal central percentile	Average trimming percentage	Optimal central percentile
Level 1	**h=1**	10	50	11	50
	h=3	9	50	9	50
	h=6	8	50	9	50
	h=12	6	50	6	50
Level 2	**h=1**	8	50	9	50
	h=3	9	50	7	50
	h=6	8	50	9	50
	h=12	6	50	6	50
Level 3	**h=1**	6	51	7	51
	h=3	3	50	3	50
	h=6	3	50	3	50
	h=12	2	50	2	50

Euro area: the one-step Huber-type skipped mean
(half the weight of the rejected observations, historical averages)

		Seasonally adjusted data	Data without seasonal adjustment
Level 1	**h=1**	7	10
	h=3	7	9
	h=6	7	8
	h=12	6	6
Level 2	**h=1**	7	9
	h=3	7	8
	h=6	7	7
	h=12	8	6
Level 3	**h=1**	6	10
	h=3	5	9
	h=6	5	7
	h=12	4	4

Table 17 - Euro area: volatility of observed inflation and robust estimators - compounded data, whole sample (1995.01 - 1999.10)

	LEVEL 1				LEVEL 2				LEVEL 3			
	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
VOLATILITY[1]												
Seasonally adjusted data												
Observed inflation	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14
JB-Average	0.05	0.08	0.10	0.10	0.06	0.08	0.10	0.10	0.08	0.13	0.14	0.14
JB-Monthly	0.06	0.12	0.12	0.11	0.06	0.10	0.11	0.11	0.09	0.14	0.15	0.13
Median	0.06	0.13	0.14	0.18	0.05	0.13	0.18	0.18	0.07	0.16	0.20	0.20
Central percentile	0.06	0.13	0.14	0.18	0.05	0.13	0.18	0.18	0.07	0.16	0.20	0.20
One-step Huber-type skipped mean	0.05	0.14	0.11	0.14	0.05	0.10	0.12	0.13	0.07	0.14	0.18	0.23
Data without seasonal adjustment												
Observed inflation	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14
JB-Average	0.05	0.13	0.11	0.10	0.06	0.16	0.11	0.10	0.09	0.15	0.14	0.14
JB-Monthly	0.06	0.19	0.11	0.11	0.07	0.22	0.12	0.11	0.10	0.19	0.16	0.13
Median	0.06	0.17	0.20	0.17	0.07	0.20	0.24	0.19	0.07	0.32	0.21	0.19
Central percentile	0.07	0.17	0.20	0.17	0.08	0.20	0.24	0.19	0.07	0.32	0.21	0.19
One-step Huber-type skipped mean	0.05	0.25	0.14	0.14	0.07	0.25	0.18	0.14	0.08	0.22	0.19	0.22
VOLATILITY REDUCTION[2]												
Seasonally adjusted data												
Observed inflation	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
JB-Average	37.27	58.52	70.41	72.61	40.87	56.43	71.99	72.65	56.98	94.12	95.87	100.00
JB-Monthly	40.02	82.85	80.63	78.16	42.14	69.38	77.29	75.62	63.98	97.21	104.21	94.36
Median	41.79	91.74	101.47	123.26	36.64	89.68	124.30	129.36	51.13	111.65	138.90	137.72
Central percentile	41.79	91.74	101.47	123.26	36.64	89.68	124.30	129.36	51.13	111.65	138.90	137.72
One-step Huber-type skipped mean	33.78	98.92	78.74	99.79	35.30	71.22	86.88	93.17	51.39	97.69	128.31	158.38
Data without seasonal adjustment												
Observed inflation	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
JB-Average	36.76	91.77	78.95	71.49	39.38	112.13	75.96	71.65	62.60	103.80	98.66	100.00
JB-Monthly	42.66	135.89	79.22	74.44	45.84	152.40	84.05	73.93	72.53	131.97	112.49	94.55
Median	43.01	116.93	136.82	120.55	52.52	141.64	170.05	130.95	50.89	227.29	147.57	136.28
Central percentile	47.72	116.93	136.82	120.55	53.02	141.64	170.05	130.95	50.45	227.29	147.57	136.28
One-step Huber-type skipped mean	36.77	172.80	94.88	101.16	45.62	172.54	127.92	95.48	53.34	154.66	130.41	154.96

[1] Measured as the standard deviation of the first difference of observed inflation (or the estimator in question).
[2] Volatility expressed as a percentage of the volatility of observed inflation.

Table 18 - Euro area: comparison with other core inflation measures

	One-step Huber-type skipped mean (compounded results of 1-month price changes)		**Other core inflation measures** (12-month price changes)			
	Seasonally adjusted data	Data without seasonal adjustment	XUE[1]	X15[2]	DW[3]	VW[4]
Unbiasedness						
Average difference with observed inflation	-0.02	-0.08	0.09	0.09	0.06	-0.31
Volatility reduction[5]	33.78	36.77	69.98	41.61	40.70	35.72

1 CPI, excluding unprocessed food and energy.
2 CPI, excluding the 15 most volatile products.
3 CPI, reweighted by the product of the CPI weights and the reciprocal of short-term volatility.
4 CPI, reweighted by the reciprocal of short-term volatility.
5 Volatility expressed as a percentage of the volatility of observed inflation.