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Trimmed Means of the CPI as Indicators of Core Inflation for Costa Rica

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Trimmed Means of the CPI as an Indicator of Core Inflation for Costa Rica

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Abstract

This study presents an evaluation of trimmed-mean inflation series calculated from Costa Rican data following the methodology of Bryan, Cecchetti and Wiggins (1997) and of Roger (1997), which entails the calculations of trimmed means centered in an estimator of the population mean percentile. It was found that the historical distribution of price changes in Costa Rica is highly leptokurtic and right-skewed, the mean percentile being estimated at percentile 60th. Trimmed-mean series were calculated by centering on the percentiles 50th to 70th and by using trimming percentages from 0% to 49%. In order to choose a trimmed-mean indicator for core inflation, the series obtained were evaluated through unbiasedness tests, forecasting ability tests and indicators of adequacy of fit to a measure of trend inflation. Most unbiased series were found to be centered around the estimated mean percentile. The series resulting from centering on the mean percentile (60th) and trimming 30% of the weight on the left of the distribution and 10% on its right presents the best fit to the trend among the group of 24 unbiased series that showed the highest forecasting ability. This trimmed-mean series fits better to the trend inflation than an exclusion measure currently in use (the ISI, for its Spanish acronym), and its variability is lower.

Key words: Core inflation, Trimmed means, Mean percentile.

JEL codes: C46, E30.

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Medias truncadas del IPC como un indicador de inflación subyacente para Costa Rica

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Palabras clave: Inflación subyacente, Medias truncadas, Percentil de la media.

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1. Introduction

Most people associate inflation with price increases. However, not all price increases are inflation. Some prices rise simply because of good become scarcer. For example, oil prices could rise due to falls in the level of reserves. This type of price increases are called relative price increases and they should not be considered inflation. For inflation to occur there must be a widespread and sustained increase in the price level.

An oil price increase may occur when oil becomes relatively scarcer, but it could also reflect a general upward trend in all price ranges of the economy, in the latter case, it would be part of an inflationary process. It could be said, then, that a consequence of inflation is the increase in the price of individual goods and services. However, it is not possible to experience individual increases or increases in small samples and easily discern whether it is inflation or changes in relative prices

Month after month, analyst and authorities at central bank wait for the new inflation data. However, the simple observation that CPI could generate confusion between changes in relative prices and inflation. The number of monthly CPI changes often shows jumps or falls that are far from the inflation trend.

Changes in the CPI, particularly monthly changes, usually contain noise, since they could be a consequence of seasonal behavior, regulatory issues, weather factors, etc. Hence, the inference of inflation trends from high-frequency variations in the CPI can produce significant biases and high volatility with respect to the long-term trend. The factors that explain this behavior are typically associated with the supply side, so in general, they cannot be controlled by monetary policy actions.

In view of the aforementioned, it is recommended that the monetary authorities have periodic follow-up instruments to monitor the behavior of the inflation trend and react as soon as possible to unwanted deviations from its target. Since they are a guide to the early implementation of monetary policy changes, these instruments should exclude supply shocks that cause sporadic price changes and should, therefore, essentially reflect demand pressures in the longer term.

How should the monthly change in the CPI be interpreted? How useful is this information about potential turning points in the underlying trend of inflation? While the CPI is a good indicator of changes in the cost of living, it is not necessarily accurate for core inflation, so a central bank should be able to tell when some variation in prices is sustained and generalized to optimally manage its monetary policy.

Such questions have led to the implementation of several measures of core inflation. The most common one results from excluding the most volatile items (typically food and energy). However, these indicators cannot be considering robust if there is no certainty that atypical price shocks will not affect the other components of CPI. Nor are they particularly efficient in the use of information since the excluded components, however volatile, also contain trend information that is not being captured.

These critics to this widespread measure of core inflation have led large number of central banks to complement the monitoring of core inflation with more systematic statistical methods to reduce the noise in the high frequency variations of price rates. One of the methodological approaches that have gained acceptance is the so-called limited-influence estimators, within which several variants of trimmed means and percentiles based on statistical average are located. Among the central banks that publish an indicator of core inflation based on a variant of limited-influence indicators are the Bank of the Republic in Colombia[1], Bank of Guatemala, the National Bank of Poland, the Bank of Brazil, the Reserve Bank of Australia, the Bank of Canada and the Federal Reserve Bank of Cleveland, for the U.S. economy

This paper estimates and evaluates limited-impact indicators to supplement the traditional measures of core inflation in Costa Rica. Its aim is essentially to make the most of high frequency information generated by the National Institute of Statistics and Censuses (INEC) for the early identification of changes in the inflation trend. These indicators seek to overcome the robustness and efficiency limitations of current core inflation indicator used by the Central Bank.

The paper is organized as follows: section 2 presents the theoretical justification for the use of limited-influence indicators when there is evidence that the population distribution of price changes is not normal. Later, Section 3 reviews the characteristics of the empirical distribution of price changes in Costa Rica with the aim of clarifying the shape of the population distribution. Then, section 4 presents methodological details for the calculation of limited-influence indicators used in the study. Section 5 presents the evaluation results of the trimmed-mean measures. A population estimate of the average percentile is identified; based on it, asymmetrically truncated indicators are built. One of these truncations will be chosen to be used as an indicator of core inflation after carrying out unbiasedness tests, tests of forecasting ability and measuring its ability to fit an indicator of trend inflation. Section 6 presents the main conclusions. Sections 7 and 8 are devoted to references and annexes respectively.

2. Why limited-influence indicators?

There is no doubt that inflation, understood as monetary phenomenon, is difficult to quantify, especially when it comes to information inferred from high-frequency sampling. As mentioned above, the traditional CPI contains short-term noise, originating from supply factors that do not correspond to inflationary pressures from a monetary source. In consequence, central banks often make use of so-called core inflation to guide monetary policy decisions. Such indicators seek to eliminate the distorting influence of extreme volatility associated with non-monetary factors. The importance of such measurements is that monetary policy should not react to price movements arising from these shocks.

[1] They use the so-called core 20 CPI, which excludes 20% of the most extreme variations of each period.

However, there is no general agreement as to what core inflation indicator is better. Roger (1997) mentions three characteristics that an inflation indicator should offer to make it less prone to the abovementioned distortions:

- ***Timeliness.*** The practical utility of the measure would be limited if it were not available on time or if it were subject to revisions over extended periods.

- ***Robustness and unbiasedness.*** The measure must clear out the type of distortion that is required and not show a different trend to that of the series from which it is derived. Failure to meet these two characteristics would lead to unwanted biases in implementing the monetary policy and eventually to lose the credibility that is needed from the public.

- ***Replicability.*** To build credibility, it is clear that the measurement of core inflation should allow verification or replication by any other agent different from its original source. Otherwise, it would be a weak indicator of monetary policy performance and a poor guide to anchor expectations and, thus, the determination of wages and prices.

That same author, but in an earlier paper (Roger, 1995), presents a review of the most common methods for measuring core inflation based on the information contained in the Consumer Price Index (CPI). Some of these methods are:

- **Adjustment by smoothing.** It applies some type of statistical filter to remove the effects of deterministic seasonality. Since it eliminates only deterministic effects, the method lacks robustness, because it is unable to eliminate stochastic shocks on prices. Apart from this, it may not be a method that stands out for its opportunity. The filtering methods involve some sort of average between price change observations of past and present, leading to some delay in identifying the trend.

- **Adjustment by exclusion.** It consists of reducing the domain of the CPI, excluding the components that, in the opinion of specialists, are most likely to present unwanted volatilities or to exhibit extreme and unrepresentative price movements (e.g. seasonal agricultural goods and energy products). An indicator of core inflation currently published by The Central Bank of Costa Rica (the ISI, for its Spanish acronym) is calculated through this method.

  It is reasonable to question whether this method complies with all the features mentioned above as desirable for an indicator of core inflation. Unless it can be assumed that the components stored in the calculation will not eventually show distorting shocks, such indicators do not meet the property of robustness. Generally, the exclusion criterion is based on historical volatility indicators, which is not a guide to ensure the absence of outliers in the future. Additionally, even when achieving accuracy on the exclusion, the question remains on up to what extent components should be excluded, which potentially introduces elements of arbitrariness[2]. While this reduces the likelihood of bias, it potentially extends the magnitude of the submission.

- **Specific adjustments.** This method involves modifying recorded price changes in order to eliminate the influence of certain events considered atypical from the aggregate measure. Its main advantage lies in leaving space for evidence in determining what price movements are exceptional. Paradoxically, this advantage becomes, at the same time, the main weakness, since the high discretionary component of the resulting indicator curtails its replicability, as well as its transparency.

Since the above methods does not meet all of the desired characteristics for a measure of core inflation, several authors (e.g. Koenker and Bassett, 1978; Bryan et al, op.cit;, Diewert 1995, Roger 1995 and Cecchetti, 1996) have suggested a variety limited-influence indicators to achieve greater robustness without sacrificing reproducibility or opportunity.

The base for these proposals comes from the evidence that points to a pattern of historical distributions of changes in prices to move away from normality. In most cases reported in the literature, such distributions show high levels of kurtosis and, although less frequently, also have many cases of asymmetries, especially to the right of the distribution.

The problem can be visualized if one considers the distribution of prices of goods in the CPI of a specific month as a particular sample taken from an underlying population distribution of price changes. Thus, the variations of each month would be random samples taken from an aggregate population distribution. The sample distribution usually differs from population distribution for several reasons. One of these, perhaps the most natural, is the simple fact that the sample is, by definition, a portion of the total price changes occurring in the economy. Suppose the price of electricity rises sharply and abruptly in a specific month and that such product is included in the CPI. That variation will change the distribution of sample products of that indicator, making it very different from the typical distribution that would have otherwise. In this case, the distribution would be particularly asymmetrical to the right and would be considered a bad sample for having been drawn from a non-representative distribution of the typical distribution or population distribution.

As mentioned above, robust indicators of central tendency should not be very influenced by unusual sampling distributions. If the true population distribution cannot be observed, the analyst is limited to estimating the population mean from samples of price changes. However, in statistical terms, the criterion for choosing an estimator of the population mean should be based on three highly desirable properties: unbiasedness, efficiency and robustness.

It is well known that when observations are randomly drawn from a population whose distribution is normal, the sample mean is an unbiased estimator, as well as the most efficient (minimum variance), of the first moment of the distribution. But separation from normality turns the sample mean into an inefficient estimator and one not as robust as a wide variety of other estimators.

[2] It should be noted that the indicator used in Costa Rica, excludes the measurement of historically volatile components to the point where, according to criteria of goodness of fit, it was determined that best approached the Baxter-King filter for the CPI inflation. See Saborío, Solano and Solera (2002).

In particular, when the population distribution tends to be leptokurtic, the sample average will be very sensitive to changes in the sample, resulting in high variance especially in small samples. Bryan et al, op.cit. discuss how this leads to loss of efficiency with increasing population kurtosis.

With population data whose distribution shows high kurtosis, (very long tails) random samples drawn from it will be very likely to select an observation located in one of these tails without choosing a counterpart at the other end to provide a balance, even if the population distribution is symmetrical. Based on this insight, studies as early as Yule (1911) show that in such cases the sample median is a more efficient estimator of the population mean than the sample mean. Note also that the median is an extreme form of truncation of the distribution, which means that the trimmed means are also more efficient estimators when the population distribution -from which samples are drawn- is leptokurtic[3].

Roger (1997) points out that if the population distribution is known, we can find an estimator that may prove more efficient than all others. On the other hand, if the population distribution is unknown, it is more appropriate to focus on the property of robustness. A robust estimator may not be the most efficient, but it will rarely show poor performance in this area.

The question that arises then is what degree of kurtosis should the population distribution show so that the media ceases to be a more efficient estimator than the median or trimmed mean? Hogg (1967) provides a simple scheme for selecting efficient estimators depending on the degree of kurtosis of the distribution. The study was based on a large number of Monte Carlo experiments where various measures applied to a wide range of frequency distributions were tested; the recommendation is as follows:

- If the kurtosis is between 2 and 4, the sample mean estimator is recommended.
- With kurtosis between 4 and 5.5, a 25% trimmed mean performs well.
- If the kurtosis is greater than 5.5, it is recommended to use the sample median.

The findings of Hogg are confirmed by other authors. Koenker and Bassett op.cit compare the variances of the sample mean, median, trimmed means 10% and 25%, and other more complex indicators (statistical L) as estimators of the population mean for a specific number of different distributions. These authors conclude that the more leptokurtic the distribution is, an efficient estimator should put less weight on extreme observations at the time of sampling. They also confirm that the sample mean is not a particularly robust estimator when the population is not normally distributed and that limited-influence estimators, such as trimmed means or the median, are robust to a wide range of leptokurtic distributions.

Bryan et al, op.cit., using repeated experiments, show how the gain in efficiency of trimmed-mean estimators increases, in relation to sample means, when population kurtosis rises.

[3] An additional class of estimators with non-uniform weighting scheme are known as statistical L (see for example David 1981 and Judge et al 1988). These are not discussed in this document, but are basically linear combinations of order statistics. They are more complex than trimmed means in the sense that the weight assigned to non-truncated components is decreasing (often non-linearly) as the observations are more extreme.

In addition, as noted by Roger (1997), finding an efficient and robust estimator of the population mean necessarily involves looking at the characteristics of the empirical distribution. *"What can be said a priori is that even if the mean is the most efficient estimator, it is unlikely to be particular robust"* (Roger, 1997, pp. 9).

3. Characteristics of the distribution of price changes

3.1. Data used in the study

Before going into detail on the characteristics of the historical distribution of price changes in Costa Rica, it is important to give a brief description of the basic data and the treatment that has been given to it in this paper.

The database covers from January 1995 to February 2011 and corresponds to the price indexes of the CPI components. The period includes a change in the CPI calculation basis (July 2006) when the basket of goods and services included was changed. However, this study includes data for all of the products in each basket in each period. In this way we worked with 264 series of 139 observations each for the period from January 1995 to July 2006 and 292 series of 55 observations each, for the period from August 2006 to February 2011.

For data analysis, the following notation was defined:

- Monthly inflation rate of a single component along a horizon k

$$\pi_{it}^{k} = \frac{1}{k} ln \left(\frac{p_{it}}{p_{i\ t-k}} \right) \tag{1}$$

  Where p_{it} is the level of the *i-th component rate* at period *t.*

- Average monthly inflation over a horizon k

$$\Pi_{t}^{k} = \sum_{i} \omega_{it} \pi_{it}^{k} \tag{2}$$

  Where ω_{it} corresponds to the relative weight of each component in period t. Note that, being the arithmetic average rate, these weights can vary to reflect changes in relative prices[4].

It is important to note that analysis was carried out for various overlapping horizons of one, three, twelve, twenty and thirty-six months, in other words: $k = \{1,3,12,24,36\}$.

[4] If the weights are fixed, such as the CPI in Costa Rica, and are denoted as r_i, the aggregate price level is defined as $P_t = \sum r_i p_{it}$ and it can be demonstrated that, in such case, the change in aggregate price level is calculated as a weighted sum of individual changes. In such case $\omega_{it} = r_i \left(p_{it} \quad p_{i\ t-1} \right)$.

3.2. Moments of the distribution of price changes

There is abundant literature documenting distributions in prices changes which tend to move away from normality. There are also numerous theoretical justifications to expect non-normal distributions[5]. To verify this result, this section provides an analysis of the characteristics of the distribution of price movements in Costa Rica, which closely follows the presentation by Roger (1997) for New Zealand data.

Table 1 shows statistics for the first two sample moments scaled according to the mean and the median, kurtosis and coefficient of asymmetry of each cross-sectional distribution of price changes in CPI components for overlapping horizons $k = 1,3,12,24,36$ [6].

The figures suggest a typically non-normal distribution. In particular, it highlights the high and very volatile kurtosis, especially from high-frequency variations. The average kurtosis for monthly and quarterly data is 54 and 38, with standard deviations of about 40 and 30 respectively.

Although expected, another point is that the kurtosis decreases as k increases, in other words, as the variations are of lower frequency. In addition to displaying large tails, the sampling distribution of price changes has a marked asymmetry to the right. For monthly and quarterly data the means of the coefficient of asymmetry are 0.70 and 0.54 with standard deviations of 4.6 and 3.8 respectively. As in the case of the kurtosis, the volatility tends to decrease with decreasing frequency of calculated price changes.

[5] Roger (2000) offers an extensive compilation of this literature.
[6] If each component has a different weight, $h - th$ moment, with respect to the media, is defined as $m_{ht}^{k} = {}_{i}\,\omega_{it}\ \pi_{it}^{k} - \Pi_{t}^{k}\ {}^{h}$. Thus, asymmetry A_t^k and kurtosis C_t^k are, respectively, the third and fourth scaled moment. $A_t^k = m_{3t}^k \quad m_{2t}^k\ {}^{3/2}, C_t^k = m_{4t}^k \quad m_{2t}^k\ {}^{2}$

Table 1

Summary of statistics for cross-section distributions of Price changes of the CPI products (annualized rate), Jan 1995 - Feb 2011

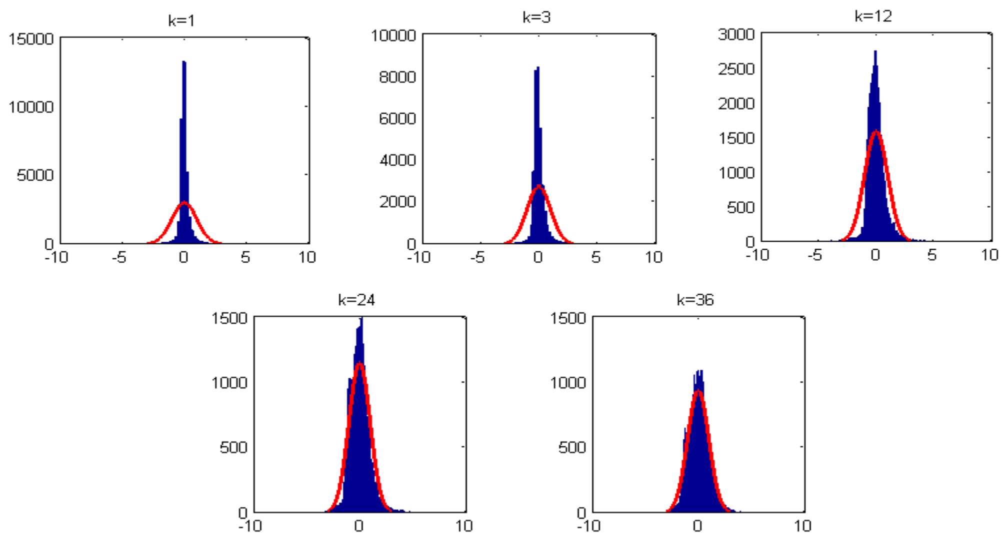
		Mean	Median	Std. Desv.	Kurtosis	Skew
Mean	**Monthly**	10,15	8,07	53,46	53,54	0,70
	Quarterly	10,17	8,84	28,01	37,82	0,54
	Annual	10,14	9,56	11,03	15,45	0,81
	Biennial	10,01	9,83	6,64	6,23	0,33
	Triennial	9,84	9,86	5,16	4,96	0,11
Median	**Monthly**	10,63	7,74	50,45	41,39	0,77
	Quarterly	10,42	8,64	27,31	28,73	0,70
	Annual	10,08	9,17	10,85	12,48	1,11
	Biennial	9,66	9,65	6,57	5,46	0,36
	Triennial	9,30	9,37	5,04	4,49	0,05
Std. Desv.	**Monthly**	5,86	3,16	11,32	40,08	4,64
	Quarterly	4,70	3,27	5,94	30,94	3,76
	Annual	3,19	2,98	1,79	9,89	1,88
	Biennial	2,36	2,29	1,09	2,70	0,74
	Triennial	1,65	1,71	0,55	1,85	0,58

SOURCE: authors' elaboration

To better illustrate these characteristics of the sampling distribution of price changes, Figure 1 plots the histograms for the historical observations of changes in goods prices of CPI for $k = \{1,3,12,24,36\}$. Given that the average of the changes may vary over time, the cross-section distribution in each case is shown normalized (measured standard deviations from the mean). In each case the standard normal distribution is superimposed to compare the departure from normality.

Figure 1

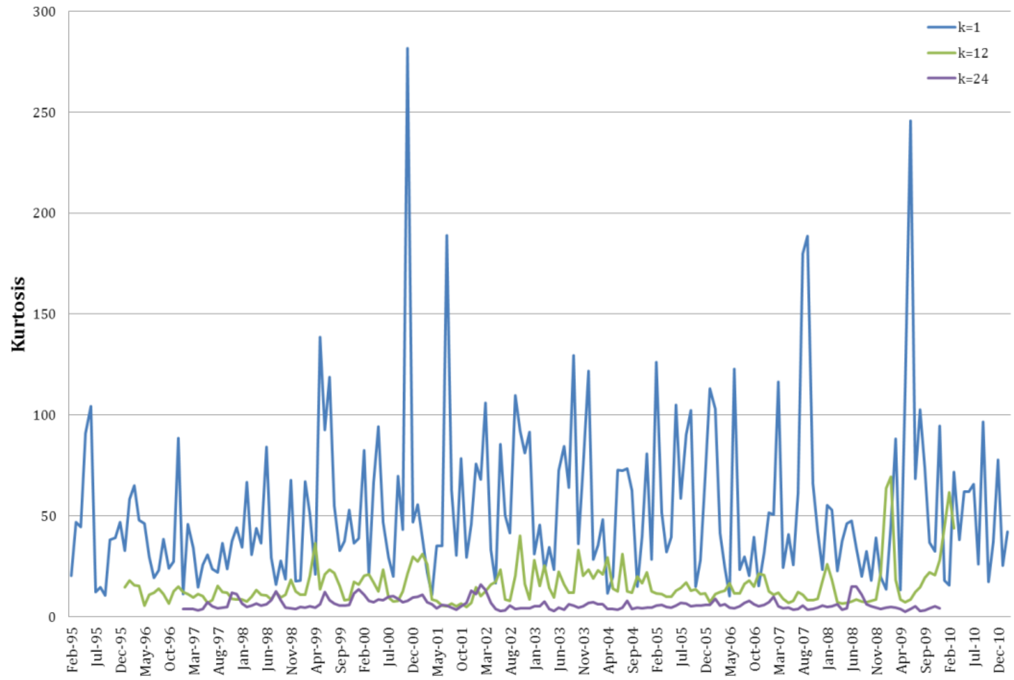
Distribution of standardized price variations of CPI products vs. Standard normal distribution.
Feb 1995 - Feb 2011



SOURCE: authors' elaboration

Figure 2 shows the evolution of the scaled fourth moment around the mean of the sampling distribution of price changes for monthly, annual and biennial variations. Clearly, kurtosis drops as k increases.

Figure 2
Kurtosis of distribution of CPI changes for monthly, annual and biennial variations. Feb 1995 - Feb 2011.



SOURCE: authors' elaboration

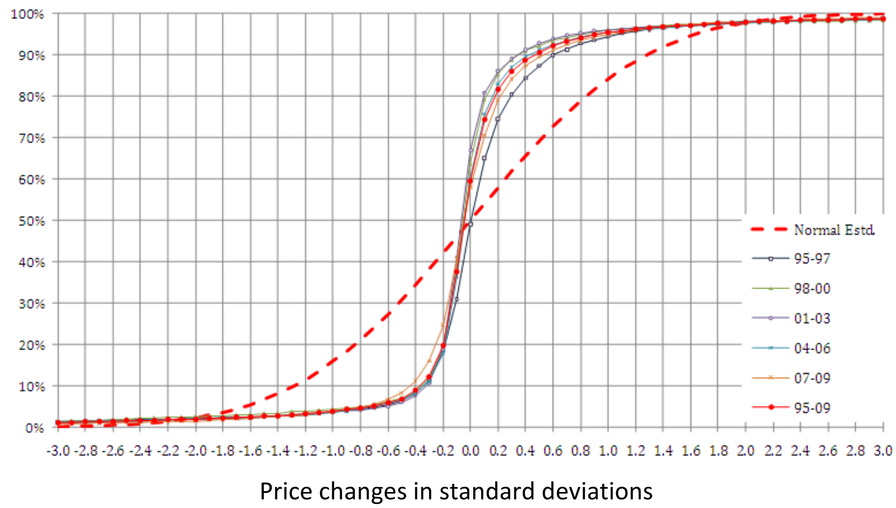
It is possible that in Figure 1, the tendency towards positive asymmetry observed in the data of Table 1 is not clearly illustrated. Figure 3 plots the cumulative frequency distribution of monthly price changes for various sub periods of a 3-year span with the corresponding standard normal cumulative distribution (dashed line). In all sub periods, it is clear that the cumulative distribution crosses zero at levels above 50% probability, reflecting the marked asymmetry to the right previously reported.

In sum, historical evidence points to a distribution of price changes that is leptokurtic and skewed to the right. This result is not exceptional in those reported in similar studies elsewhere. Bryan et al, op.cit. presented similar results for the U.S. case, with a sample of monthly data covering from January 1967 to April 1994. Roger (1997), using quarterly data from New Zealand and a sample from the second quarter 1949 to the fourth in 1996, also reported large tails and marked positive asymmetry [7].

[7] New Zealand figures correspond to average levels of kurtosis and asymmetry of 7.2 and 0.7 respectively for quarterly frequency data (k=3).

Figure 3

Accumulated frequency distribution of monthly price changes for 3-year periods.



SOURCE: authors' elaboration

Despite the different averages of inflation in each of these periods of 36 months, the shape of the distribution is basically the same. Also note that change of base for the CPI occurred in mid-2006 did not have any sizable effect on the shape of the distribution, either.

The highlighted features expose potential sources of noise in the measurement of inflation using the CPI as a high frequency indicator. Specifically, the large tails in the distribution generate a high probability of observing extreme variations in one of the tails that are not offset by extreme variations in the other when taking a sample of monthly variations in a particular period, causing the sample mean to be potentially biased and highly volatile in repeated sampling.

The economic interpretation of these features of the distribution of changes has been explained on the grounds of inflexibility in the price adjustment, especially in the short term. Setting prices is costly, this is the premise of all models of menu costs that result not-quite flexible prices in the aggregate.

The price setters will adjust them only if their desired price lies outside the limits set by menu costs. This, delays the moment of the change and causes that, in each period, prices are changed at a rate higher than necessary, which leads to extreme observations in the normal distribution (large tails).

As for the theoretical origin of the asymmetry, Ball and Mankiw (1995) argue that price setters who want increases tend to make price adjustments more often than those who prefer a decrease. Such behavior would lead to a positive relationship between asymmetry and inflation. The argument of the menu cost model indicates that those who want a decrease in real prices, in order to avoid incurring costs by adjusting nominal prices will let overall inflation do its job. By keeping nominal prices unchanged, increases in general price levels will eventually reduce the real relative price on their products.

Another type of explanation for the presence of asymmetries in the distribution of price changes is offered by Roger (2000) and includes the rarity of adjustments due to the existence of government regulations (regulated prices) and the seasonal nature of some goods. When there are regularities or seasonalities that determine the time of adjustment, there will inevitably be extreme changes. The same author shows that both asymmetry and kurtosis will be high, even when a percentage of the prices as low as 4% is subject to infrequent adjustments

If all prices were fully flexible, we would expect the distribution of changes to be normal. This is clear when observing that by the extension of the reference frequency in the changes, that is, allowing more time for adjustments, both the kurtosis and the asymmetry tend to decrease in the historical data of Costa Rica.

Knowing the problems that the use of averages leads to when the population distribution is not normal, and with evidence that points to serious departure from this assumption for the distribution of price changes in Costa Rica, especially for high frequency data, the question is: what kind of solution is feasible to adopt to maximize the benefit from the monthly data on prices when trying to bring changes in the inflation trend?

Bryan et al, op. cit. identifies two options: On one hand, to explicitly model the behavior of price setters, for which there is abundant theoretical literature, as well as to estimate the changing rules of price setting. The other option suggested is to treat such rules of state-dependent adjustment as a statistical sampling problem. To this end, monthly (or quarterly) distributions of price changes of CPI products would be considered as small random samples from a population distribution of lower frequency. This will be called stochastic approach of core inflation.

Theoretically such a population distribution would tend to symmetry and so it is assumed by these authors. However, for the Costa Rican case, the evidence indicates that positive asymmetry still remains, even with very low frequency data and it is independent from the data sample used. So, as discussed below, assuming symmetry and using trimmed means centered on the mean of the distribution leads to a systematic underestimation of the inflation trend.

This brings us closer to the alternative approach of Roger (1997), who deals directly with the problem of the lack of symmetry taking the percentile of the mean of the distribution as an estimate of underlying inflation. This paper adopts such methodology, focusing on skewed truncations, calculating the percentile of the mean, but also in nearby percentiles.

4. Approaches to measuring core inflation

4.1. Percentile of the mean

In discussing the relative efficiency of the sample mean versus other estimators of the population mean, statistics texts often assume that each alternative measure is unbiased, or, at worst, a consistent estimator. The implicit assumption in this analysis is that the population distribution is symmetric. But, we have seen that this is not the case of the empirical distribution being treated.

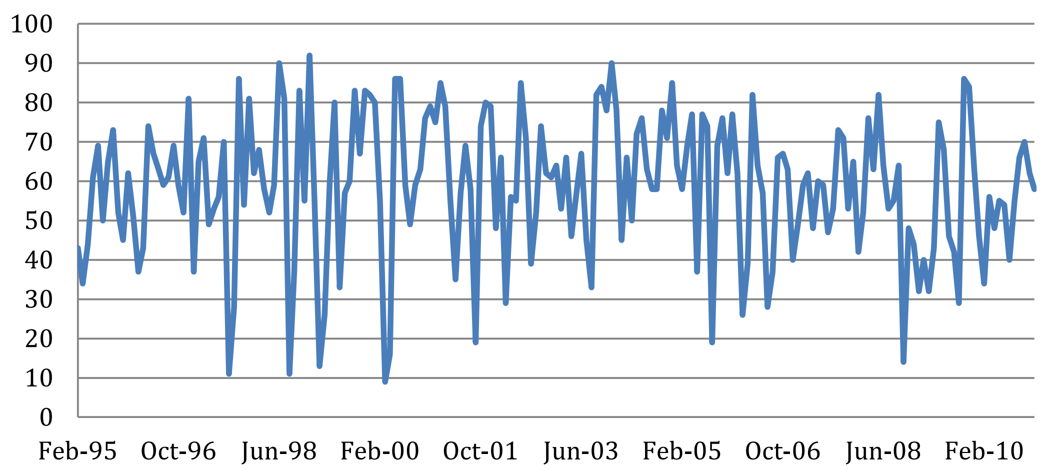
Roger (1997) addresses the problem pragmatically. The author argues that for distributions whose mean exists, the observation ordered in the lowest level will consistently be a downwards biased estimator, while the observation ordered in the highest level will be systematically biased upward. So, the order statistics (a percentile) will be located in any position between these two, which on average is an unbiased estimator of the population mean.

It is clear that for symmetric distributions, the observation corresponding to the 50th percentile, or median, is an unbiased estimator of the population mean. But for right skewed distributions, the percentile for the population mean will be higher. So, Roger argues that the problem reduces to find the percentile that corresponds to the average population distribution.

Figure 4 shows the evolution of the percentile, where the weighted sample mean of the distribution of monthly changes at the product level is located. The volatility of this series shows how unrepresentative of the mass distribution the weighted average is. There have been months when it has been averaging just over 10% of total price changes, while, some other times, it has been higher than 90%. More than the simple coefficient of asymmetry, this illustrates the extent to which the weighted average could be pulled away from the central mass of price changes, due to variations located in the tails of the distribution.

Figure 4

Estimated mean percentile for the distribution of price changes. Feb 1995 - Feb 2011



SOURCE: authors' elaboration

There is a potential difficulty when adopting the approach suggested by Roger (1997). If the shape of population distribution varies with time, the percentile in which the mean is located would also depend on time. If there is a positive association between the level of asymmetry in the distribution and the level of inflation and certain fixed percentile is used to estimate the population mean in periods of rising inflation, the inflation trend would systematically be underestimated. In periods of falling inflation, by contrast, it would be overestimated.

From Figure 4, it is not possible to ascertain any trends or cyclical behavior in the location of the percentile of the mean. This is a first indication against the asymmetry of the distribution systematically depending on the levels of inflation.

Now, if we consider the distribution of price changes in a specific month as a particular random sample taken from a characteristic or population distribution; then, comparing the distributions of various periods may help to approximate the population distribution.

Table 2 shows the average and median percentile of the weighted average for monthly changes at the product level in sub-periods of four years in length. As shown, there are no significant changes over time. So, we can conclude that the asymmetry in the distribution of price changes does not depend on time; it seems relatively stable at levels close to average throughout the period.

Table 2

Estimated mean percentile, product-level data

	Monthly data	
	Average of sample mean percentile	Median of sample mean percentile
95-98	56,4	59,0
99-02	60,6	61,5
03-06	64,6	66,5
07-10	54,8	53,0
Jan 95-Feb 11	58,6	60,0

SOURCE: authors' elaboration

Although the evidence just shown suggests some stability in the shape of the distribution of price changes, the still unanswered question is what percentile of the sampling distribution is suitable for use as an estimator of the population mean. While the information contained in Table 2 suggests that it should be somewhere between 54 and 64, the decision should be based on a more precise numerical quantification.

Roger (1997) suggests calculating the implied inflation rate associated with each percentile and use these levels to get a percentage or bias rate over the corresponding level of change in the CPI. Table 3 shows the percentage of bias for the total sample (January, 1995 to February, 2011) and for two sub samples from each basket (January 1995 to July 2006 and August 2006 to February 2011).

Table 3
Rates of drift in price levels associated with different percentiles of the distribution of monthly changes, relative to the CPI
Annualized product-level data.

		Jan 95 - Feb 11		Enero 95 - Julio 06		Agosto 06 - Febrero 11	
		Average % change	Average annual % drift vs CPI	Average % change	Average annual % drift vs CPI	Average % change	Average annual % drift vs CPI
	Total CPI	11.07	0.00	12.14	0.00	8.41	0.00
	55	9.45	-1.46	9.98	-1.94	8.14	-0.26
	56	9.76	-1.19	10.28	-1.68	**8.47**	**0.05**
	57	10.07	-0.90	10.58	-1.41	8.82	0.38
	58	10.37	-0.63	10.85	-1.16	9.17	0.70
	59	10.67	-0.36	11.13	-0.91	9.52	1.03
Percentile	**60**	**11.00**	**-0.06**	11.40	-0.63	9.88	1.37
	61	11.30	-0.22	11.73	-0.37	10.24	1.70
	62	11.63	0.51	**12.03**	**-0.10**	10.63	2.06
	63	11.97	0.82	12.35	0.19	11.00	2.41
	64	12.32	1.14	12.69	0.50	11.38	2.76
	65	12.66	1.45	13.01	0.78	11.78	3.13

SOURCE: authors' elaboration

As shown, when variations are calculated on a monthly basis, the lowest bias (in absolute value) for inflation is reached by taking the 60th percentile for the total sample and the 62th for the sub-sample from January 1995 to July 2006. For the period between August 2006 and February 2011, the percentile with the lowest deviation is the 56th. In short, the 60th percentile seems a reasonable estimate of population percentile of the mean for monthly variations.

4.2. Symmetric trimmed means and asymmetric trimmed means of the CPI

This brief section outlines the procedure for calculating inflation measures by the symmetrically-trimmed-mean approach, that is, centered on the 50th percentile of the distribution, and by the asymmetrically-trimmed-mean approach, that is, centered on percentile different from the 50th.

The well-known method of symmetrical truncation basically consists of ordering sample variations, delete (truncate) the tails of the distribution and averaging the remainder. However, the CPI, being a weighted average, requires some elaboration. To calculate the weighted average truncated to α% in the period t, the sample of changes in the components $\pi_{1t}, \pi_{2t}, \dots, \pi_{nt}$, is ordered in ascending (or descending) order, along with its associated weights $\omega_{1t}, \omega_{2t}, \dots \omega_{nt}$. Then, $\Omega_i \equiv \sum_{j=1}^{i} \omega_{jt}$ is defined as cumulated sum of the weight of components ordered from 1 to i-th. Now, the set of observations to average for the truncation of the α%, which we will call Ψ_α, would be composed of the i-components such that $\frac{\alpha}{100} < \Omega_i < 1 - \frac{\alpha}{100}$. Thus, the weighted average truncated to α% in the period t would be:

$$\bar{\pi}_{\alpha t} = \left(\frac{1}{1 - 2\frac{\alpha}{100}} \right) \sum_{i \in \Psi_\alpha^a} \omega_{it} \pi_{it} \qquad (3)$$

But there must be some set of criteria for choosing a value for the truncation percentage α that is used to generate a series of reference trimmed mean.

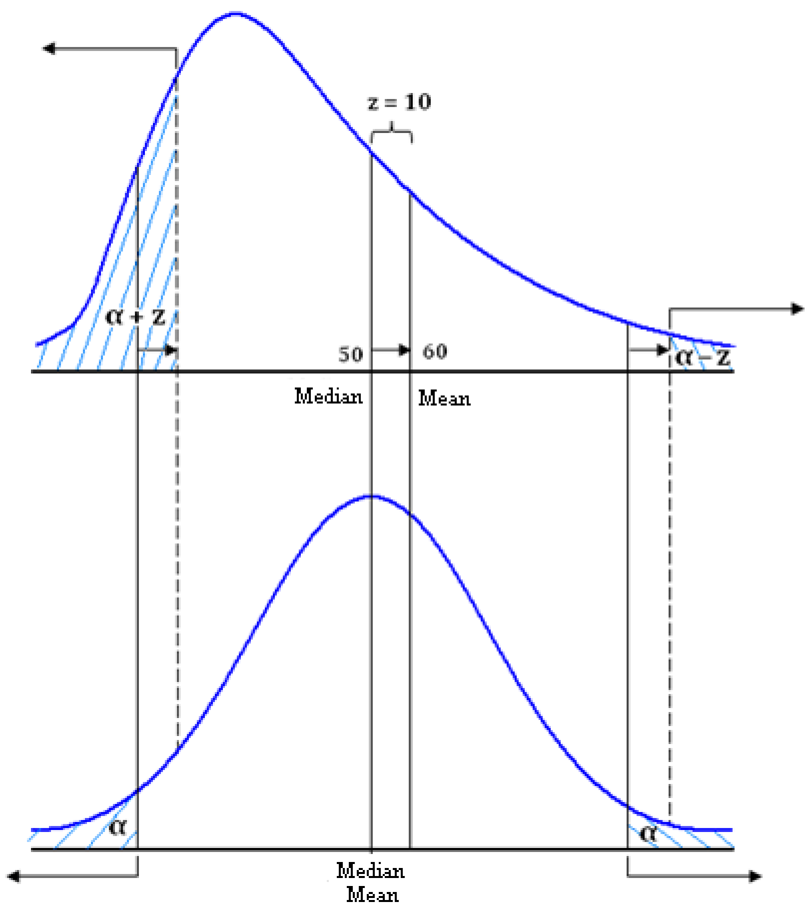
On the other hand, the asymmetric truncation method proposed by Roger (1997) simultaneously addresses the problems of inefficiency of the sample mean, generated by high kurtosis, and systematic bias in the symmetric trimmed means caused by the asymmetry. The trimmed-mean method has been used in different countries. See, among others, Roger (1997), Bryan and Cechetti (2001), Laflèche (1997), Mio and Higo (1999) and Jaramillo (1998).

To apply the approach of Roger (1997), first we must have estimated the average percentile of the population distribution, which is denoted as ρ, which has already been done in section 4.1. To calculate the asymmetrically truncated weighted average to α% at time t, the sample of component variations $\pi_{1t}, \pi_{2t}, \ldots, \pi_{nt}$ is ordered in an ascending way together with its weights $\omega_{1t}, \omega_{2t}, \ldots \omega_{nt}$. Later, $\Omega_i \equiv \sum_{j=1}^{i} \omega_{jt}$ is defined as the accumulated sum of component weights sorted from 1 to *i-th.* Now, the set of observations to average for the asymmetric truncation of α% would be composed by the *i*-components, such that $\frac{\alpha+z}{100} < \Omega_i < 1 - \frac{\alpha-z}{100}$, where z = ρ -50. Such set will be denoted as Ψ_α^a. This defines the weighted average asymmetrically truncated at α% in the period t as:

$$\bar{\pi}_{\alpha t}^{a} = \left(\frac{1}{1 - 2\frac{\alpha}{100}} \right) \sum_{i \in \Psi_\alpha^a} \omega_{it} \pi_{it} \qquad (4)$$

The procedure is illustrated in Figure 5.

Figure 5
Asymmetric trimmed centered on the mean percentile



The following section presents the results of the calculation of the inflation of trimmed means series and the evaluation process to which they were subjected.

5. Calculation and evaluation of trimmed means for Costa Rica

As mentioned above, the distribution of price changes of CPI components shows a higher kurtosis than the normal distribution. In these cases, one can show an estimator of the population mean which provides more weight to central changes in the distribution is more efficient than the sample mean. The trimmed means are a clear examples of this type of estimators of the population mean. In fact, Bryan et al, op. cit, show that, in general, the more leptokurtic the distribution of price changes, the greater should be the optimal truncation.

However, it must be remembered that the considerations on Bryan et al, op.cit. originate from a distribution of symmetric price changes. If, however, this distribution is not only leptokurtic but also has a positive skewed as in the case of Costa Rica, an unbiased estimator of the population mean should truncate the left tail more than the right tail. This is because in a right-skewed distribution, a certain percentage of changes in higher prices contributes more to inflation than that same percentage of changes in lower prices.

Given the above, Marques and Mota (2000) argue that the ideal middle of the distribution must be above the 50th percentile because, otherwise, actual inflation would systematically be underestimated. In addition, according to Roger (1997) the optimum truncation should be asymmetric and should be focused on the average percentile.

In section 4.1 it was found that, for the Costa Rican case, the 60th percentile is a good indicator of the mean percentile of the distribution of change prices of the CPI. However, this study we do not rule out the possibility that the optimal truncation is centered on a different percentile. For this reason, we analyzed the resulting inflation series of truncations made with a center between the 50th and the 70th percentile, considering truncations from 0% to 49% for each percentile[8]. It is important to remember that in the event that a center of distribution different from the 50th is considered, a percentage $\alpha + z$ is truncated in the left tail and $\alpha - z$ in the right tail, where α denotes the truncation and z is the difference in percentage points between the percentile considered as the center and the 50th percentile. It is clear that when the distribution is centered in the 50th percentile, z is zero and any resulting truncation would be symmetrical. On the other hand, if the distribution is centered at a different percentile than the 50th, any truncation would be asymmetric. In particular, truncations centered in the 60th percentile correspond precisely to the methodology proposed by Roger (1997). Henceforth, whenever the center is mentioned, we will be referring to the percentile in which the truncation exercise is focused. Also, to facilitate the reference to the series, the percentile in which the truncation is centered will be mentioned first, followed by the truncation percentage α. For example, the series 55-18 results from a truncation centered on the 55th percentile, with an α of 18%.

[8] Of these, the series centered on the 50th percentile with truncation zero is excluded, since it represents CPI inflation itself.

In addition, the list of series whose properties are analyzed also includes the core inflation rate (ISI) and centered moving averages of CPI inflation for 12, 24 and 36 months. In total, 1053 series were analyzed: 1049 truncations, the ISI and the three moving averages.

Finally, note that all products in the CPI basket were considered for the calculation of the different inflations for the entire period between January 1995 and February 2011.

5.1. References on evaluation of trimmed mean indicators

This section presents a brief review of some reference studies in which exercises are performed for evaluating the properties of measures of core inflation.

In terms of general desirable properties, Roger (1997) suggests that measures of core inflation should be calculated in real time, robust, unbiased and verifiable. Meanwhile, Wynne (1999) proposed six criteria to be met by such indicators: to be calculable in real time, easily understood by the public, have prospective orientation (forward-looking), supported by economic theory, with a verifiable performance history and that its history does not change every time a new observation is added.

In terms of choice and evaluation methodologies of indicators, Marques, Neves and Sarmento (2000) criticize that the comparison of measures of core inflation trend measures remains the sole criterion of choice of the indicator. This is because there is no guarantee that these measures of reference are the best estimate for the real trend of core inflation and therefore, this approach ensures that the indicator that best approximates the reference series is the one that best approximates the core inflation. They discuss the importance of including the trend series in testing unbiasedness, since if it is biased with respect to inflation, it makes no sense to use them as benchmarks for comparing the performance of other indicators.

Furthermore, these authors propose conditions to be met by any potential indicator of core inflation. Thus, assuming that inflation rate is integrated of order 1, they suggest three essential conditions:

i) Both measures of inflation should not show divergent trends.
ii) The measure of inflation should act as an attractor of inflation, i.e., inflation should, in the long run converge to core inflation.
iii) The inflation rate should not be an attractor for core inflation.

These conditions can be verified through an Error Correction Model. Using this methodology, Marques and Motta (2000) find that, in the case of Portugal, the asymmetric trimmed mean to 10% centered on the 51.5th percentile shows the desired characteristics. Mankikar and Paisley (2004) apply this approach to indicators in the UK and find that exclusion measures perform better than other indicators, including the trimmed-mean. However, this evaluation method is limited only to non-stationary inflation series.

Rich and Steindel (2005) suggest the following four performance criteria for an indicator of core inflation:

i) Transparency in the construction
ii) Similarity in the means of the indicators of inflation and of core inflation
iii) Ability to adjust the trend of core inflation
iv) Forecast Ability[9].

The ability to adjust the trend of inflation is measured, as usual, using indicators such as the root mean square error (RMSE). The model used to analyze the predictive capacity is particularly interesting:

$$\pi_{t+h} - \pi_t = \alpha_h + \beta_h \ \pi_t^* - \pi_t \ + \varepsilon_{t+h} \tag{5}$$

where π_t the CPI inflation at time *t* and π_t^* is the estimated monthly core inflation at time *t*. This model was proposed by Cogley (2002) and has been widely used for evaluation of core inflation[10].

Brischetto and Richards (2006) performed an empirical analysis of the performance of trimmed means and an exclusion index (similar to ISI) as indicators of long-term inflation in Australia, USA, Japan and the Euro area. Essentially, these authors use four criteria of comparison. First, they calculate the standard deviation of changes in monthly and quarterly inflation as a measure of persistence of the indicators over time. Second, unbiasedness tests are performed with reference to inflation measured by consumer price rates. Third, they analyze the adjustment of indicators to trend inflation measures. In particular, comparisons were made against the moving average of inflation in 25 months in the case of Japan, USA and the Euro zone, and a moving average of 9 quarters for the case of Australia. Finally, they analyzed the ability to predict inflation over short periods . According to these authors, despite the rationality of core inflation indicators, they are based on long-term inflation; it is most useful for purposes of economic policy, and central banks can forecast inflation for periods of three to six months. In this sense, we calculated the mean square error of inflation with respect to the indicator lags and tested for causality in the Granger sense between the proposed indicators. They conclude that trimmed mean indicators perform better as measures of core inflation than the exclusion rates.

In a more recent study, Bermingham (2009) considers core inflation indicators used for USA and assesses their fit to trend measures and their ability to forecast official inflation (with a model equal to that of Rich and Steindel, 2005), but also applies two additional criteria: the ability of the estimator to predict changes in the direction of inflation and a measure of agreement. According to the author, an important property of inflation is to indicate whether there are inflationary pressures in the economy through calculation of an inflation gap similar to the output gap. The degree to which core inflation indicators predict correctly the sign of the inflation gap is used as an

[9] One of the first studies to propose the evaluation of the forecasting ability as a criterion for the selection of underlying inflation was Laflèche (1997).

[10] See, among others, Hogan, Johnson and Laflèche (2001) and Clark (2001).

estimate of the concordance. They conclude that it is very difficult to distinguish the core inflation measures because of their similar performances.

In summary, three criteria that are repeated in most evaluation exercises of core inflation measures can be distinguished: unbiasedness tests that include measures of trend inflation, verification of the ability to adjust to these measures and some kind of evaluation of the forecasting ability as an indicator of prospective orientation.

5.2. Criteria for evaluation

The objective of the evaluation exercise is to identify truncations that generate inflation series that meet a number of desirable properties. Drawing on of CPI inflation, unbiasedness tests, tests of forecasting capability and the ability to fit a trend measure of such inflation series were used as selection criteria.

Bryan and Cechetti (1994) indicate that long-term inflation; is a component of the change in prices, expected to persist within different time horizons. To take this into account, unbiasedness tests were performed based on the equation suggested for this purpose by Cogley (2002):

$$\pi_t - \pi_{t-i} = \alpha_i + \beta_i \ \pi^*_{t-i} - \pi_{t-i} \ + \varepsilon_t \tag{6}$$

where π_t is the inflation measured by the CPI at time t y π^*_{t-i} is the monthly inflation estimated at the time $t-i$. The unbiasedness feature is checked if the joint hypothesis $\alpha_i = 0$ y $\beta_i = 1$ is not rejected. This test was performed for horizons $i = 1, 6, 12$ and 24 months.

For its part, the forecasting capability test used was the proposal by Diebold and Mariano (1995). This test compares two forecasts for a series and allows determining if one of them incorporates all relevant information of the alternative forecast, based on a null hypothesis of equal predictive power. The annex describes the test methodology. First predictions were generated from the regression proposed by Cogley (2002) and used by Rich and Steindel (2005) and Bermingham (2009), among others:

$$\pi_{t+h} - \pi_t = \alpha_h + \beta_h \ \pi^*_t - \pi_t \ + \varepsilon_{t+h} \tag{7}$$

In this case, π_{t+h} is a mobile window forecast for horizon h, obtained with a window size of at least 11 years. Again, h = 1, 6, 12 and 24 month horizon values were used Once the forecasts from all series of trimmed means were generated, the test was performed considering each possible pair of forecasts[11]. It should be noted that using the deviation from core inflation to predict the change in inflation over the next h periods corresponds to the intuition that if this deviation identifies price changes that are expected to eventually disappear, the underlying inflation measure used should by definition be useful to give an idea of the expected reversal in inflation.

[11]That is, for each forecast tests were applied considering the null hypothesis of equal predictive power with each other 1051 forecasts.

The evaluation of the fit to the trend of inflation was carried out in two steps. First, a reference series for the trend was defined. A widely used reference (among others by Bryan et al, op. cit) is a centered moving average of 24 months. But in the literature this series are often taken as a measure of the trend of inflation, but we could not find widespread evaluation of its properties. For this reason, the test of unbiasedness described above was applied evidencing that it is an unbiased estimate of CPI inflation. The second step, once the moving average of 24 months has defined as the indicator of the trend inflation, was to compare the fit to it that other inflation truncated series have. For this, we computed the root mean square error (RMSE), the mean absolute deviation (MAD) and root mean square error ratio (RMSER) for all series studied[12].

5.3. Evaluation results

First, we must point out that a large majority of the series analyzed, including inflation, proved to be stationary according to the Phillips-Perron test with both constant and constant and trend. This rules out the possibility of using the evaluation criteria of Marques and Mota (2000), based on a methodology applicable only to series with a unit root.

To identify the most appropriate truncation to represent the measure of core inflation in the case of Costa Rica, unbiasedness was the first verified feature, ruling out the series of trimmed mean inflation deemed to be biased with respect to the CPI inflation, according to the test described in Section 5.2.

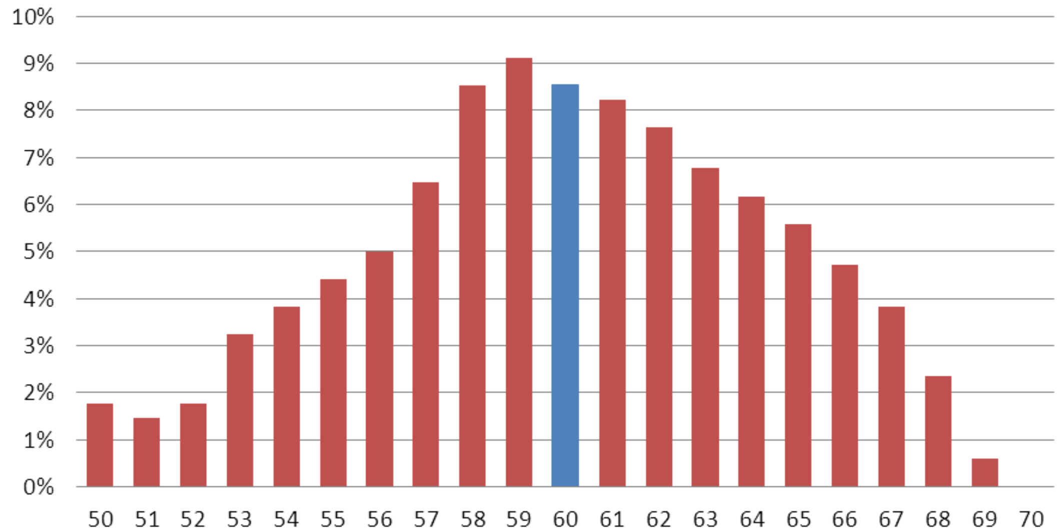
Then, the forecasting ability of each series was analyzed by the Diebold and Mariano (1995) test, for horizons of 6, 12 and 24 months. As a result, truncations whose forecasts were systematically surpassed by the resulting forecasts from the other truncations were no longer considered.

Having identified the series that were unbiased and with better forecasting capability, we examined the extent to which these series fit several sets of unbiased trends and selected the middle percentile and the percentage of truncation that resulted in a better adjustment.

Of the 1053 series under analysis, 202 passed the test of unbiasedness for horizons of 6, 12 and 24 months. Among these series are the moving averages of 24 and 36 months as well as the ISI. Furthermore, as shown in Figure 5, we found that, centers close to the 60th percentile, estimated as the mean, accumulate the majority of the total unbiased trimmed measures for a horizon of 24 months.

[12] $RMSE = \sqrt{\frac{1}{N}\sum_{j}^{N}\left(\pi_{\alpha j}-\Pi_j^*\right)^2}$ y $DAM = \frac{1}{N}\sum_{j}^{N}\left|\pi_{\alpha j} - \Pi_j^*\right|$ Where N is the number of valid observations in each comparison comparación, where $\pi_{\alpha j}$ is the measure of trend inflation and Π_j^* is a measure of core inflation.

Figure 6
Share of unbiased trimmed mean indicators, by percentile
24 months horizon



SOURCE: authors' elaboration

The latter is consistent with the literature that contends that the percentile of the mean is a better estimator of the population mean than the sample mean for distributions such as price changes in the CPI. This result is an argument in favor of using the percentile of the mean estimate as the middle for truncations, as suggested by Roger (1997). Note that less than 2% of the total unbiased series are symmetrical trimmings (centered at the 50th percentile), and correspond to trimming levels of $\alpha \leq 6$.

Having identified the 202 unbiased series, the forecasting ability of each was analyzed with respect to the rest by Diebold and Mariano's test, whose null hypothesis shows equally predictive power in each pair of series. Truncations whose forecasts were not surpassed by forecasts of any other unbiased truncation were selected for horizons of 24 and 12 months and were overtaken by less than 1% at a horizon of 6 months. This resulted in the choice of the group 24 series of trimmed mean inflation shown in Table 6, which also includes data for the CPI (see appendix). About a third of the selected trimmed series corresponds to percentiles centered around the percentile ±2pp around the 60th percentile, estimated as the mean. In addition, this group of 24 truncations does not include symmetrical truncation.

Now, according to Diebold and Mariano test, we could not find a series whose forecast of inflation was better than that of another of the 24, for any horizon, so they can be thought as having comparable predictive capacity. However, all of them are better predictors of the CPI inflation than the ISI at a horizon of 24 months.

Once identified the unbiased trimmed series that are better at forecasting, their ability to approximate the trend of inflation was contrasted. Table 4 shows statistics for goodness of fit of the CPI, the ISI and the 10 series of asymmetric means with the best fit. It also includes data for the unbiased best-fitting symmetric mean. The calculations correspond to annualized data and are found on descending order with respect to the RMSE calculated with respect to the 24-month moving average.

Table 4
Fit of trimmed-mean indicators to trend inflation measures

	CMA 24 months		CMA 36 months	
	RMSE	MAD	RMSE	MAD
CPI	6.28	4.82	6.22	4.54
Series 50-06 (symmetric)	4.72	3.77	4.74	3.68
ISI	3.76	2.93	3.90	2.92
Series 64-40	3.66	2.76	3.71	2.68
Series 56-16	3.66	3.03	3.69	3.00
Series 56-15	3.66	3.01	3.64	2.92
Series 61-21	3.66	2.84	3.72	2.77
Series 65-39	3.65	2.69	3.72	2.64
Series 64-39	3.64	2.73	3.74	2.71
Series 58-17	3.64	2.91	3.63	2.83
Series 57-16	3.64	2.95	3.62	2.87
Series 57-17	3.61	2.96	3.64	2.92
Series 60-20	3.60	2.84	3.66	2.77

SOURCE: authors' elaboration

As can be seen, of all the trimmed mean series, the one that best approximate the trend series used as reference is the asymmetric of the 60-20, that is, the result of eliminating of 30% of the left tail and 10% of the right tail of the distribution of price changes, centered on the percentile of the mean. It should be noted that this truncation is what produces the minimum RMSE of all the trimming centered on the percentile of the mean.

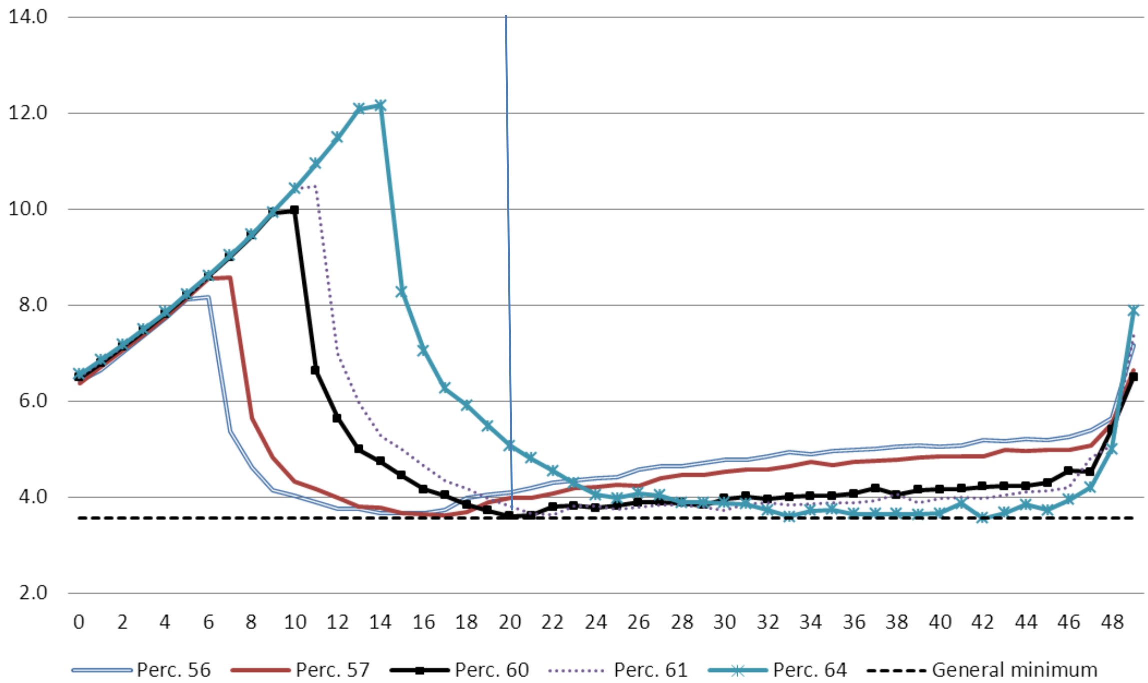
The resulting RMSE from the 60-20 truncation is very similar to the minimum RMSE for all 1049 trimming considered[13], as shown in Figure 7, which plots the RMSE according to the trend measure for all centered truncations of various reference percentiles. The figure also illustrates that for percentiles close to the mean, the percentages of trimming that generate the minimum RMSE are located between 15% and 22% and are much closer to the general minimum.

[13] Which occurs in series 64-42, with an RECM of 3,56.

Figure 7

Raíz del error cuadrático medio por porcentaje de truncamiento, para varios centros

Datos anualizados, con referencia a la media móvil de 24 meses



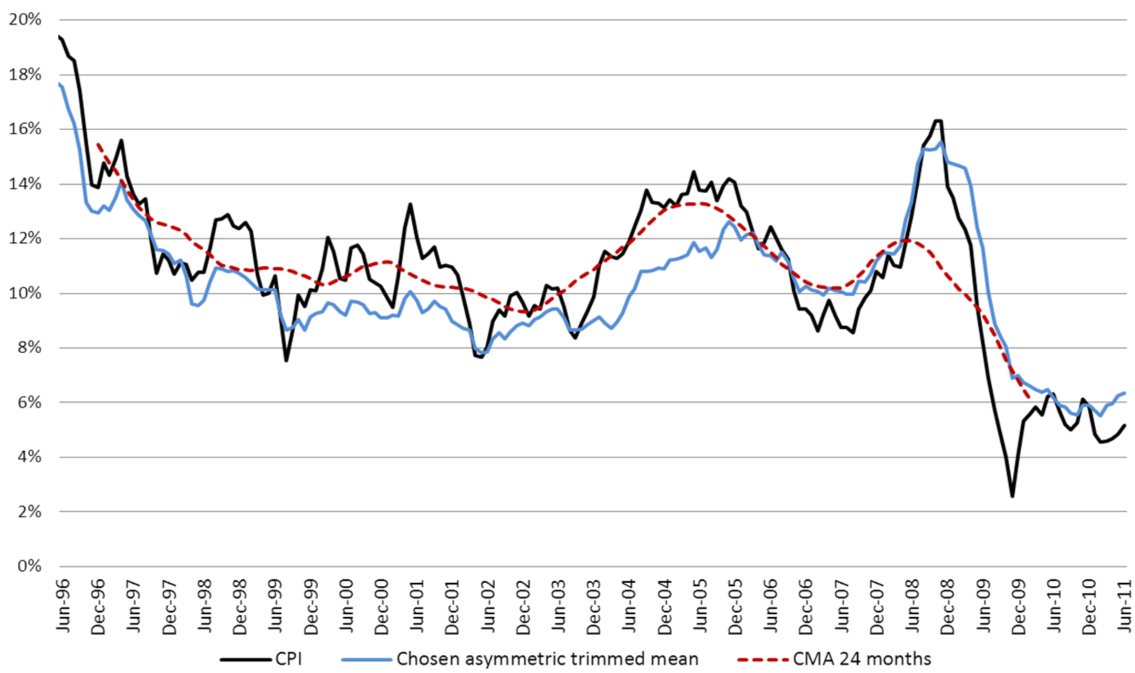
SOURCE: authors' elaboration

Since core inflation measures aim at eliminating the most volatile component of the inflation indicator, it is expected that its variability is lower than that of the CPI inflation series from which they are constructed. Table 5 of the Annex shows the relative variance of the estimator of asymmetric trimmed means in relation to that of CPI. The calculation corresponds to the ratio $\xi_a = \frac{\sigma_p}{\sigma_a}$, where σ_a is the standard deviation of the CPI and σ_p the corresponding standard deviation of the core inflation indicator. Levels are shown for the total sample (Jan,1995-Feb, 2010) and for 4 subperiods. Levels below 1 indicate less volatility of the indicator constructed with asymmetric truncations. It can be seen that all the inflation series resulting from truncations have lower volatility than the CIR, and that, in general, the percentile truncations close to the mean show lower volatility.

In general, the series of trimmed mean inflation listed in tables 4 and 5 show similar properties with the 60-20 series, performing specially well in the fit to the inflation trend. To obtain that series, the truncation is centered on the the mean percentile, so that the suitability of its calculation has theoretical support, as discussed in section 4. In addition, the truncation rates associated with each side of the distribution (30% left and 10% right) facilitate the communication of the calculation method, which helps ensure the conditions of "transparency" and replicability that some authors consider essential in a core inflation indicator. In summary, it is considered that the inflation rate resulting from the 60-20 trimming is the series with the most suitable characteristics to be used as another indicator of core inflation in Costa Rica.

Figure 8 shows the evolution of the series of the 60-20 trimmed mean inflation, together with the CPI inflation and the trend indicator of inflation. It can be seen that since late 2006, the inflation of optimal truncation has consistently been placed above the CPI inflation, with an average difference of 1.1 pp. since October of that year. In August 2011, annual inflation recorded by the CPI is 5.25%, while the core inflation indicated by the optimal truncation is at 5.94%. The complete set of values can be found in Table 7 of the Annex.

Figure 8
Asymmetric trimmed-mean inflation vs. CPI inflation[1].
Annual variations.



[1] Centering on the 60th percentile, trimming 30% from the left and 10% from the right.

SOURCE: authors' elaboration.

6. Conclusions

The analysis of data shows that the historical distribution of price changes in Costa Rica is clearly different from a normal distribution, since it is highly leptokurtic and asymmetric to the right. High kurtosis causes the sample mean to be an inefficient estimator of the population mean . Meanwhile, the chronic right skewness will introduce a systematic downward bias if the symmetric trimmed means are used as estimators of core inflation. It was estimated that, for monthly data, the average percentile is 60th.

We performed an evaluation process of 1051 trimmed means, besides the CIR and three measures of core inflation. In line with recent literature on the subject, unbiasedness and forecasting ability tests were carried out, as well as a test on the ability to reproduce the trend of inflation.

It was found that about one fifth of the series of trimmed mean inflation can be considered unbiased estimators of CPI inflation, with most of them concentrated around the estimated mean percentile . This illustrates the appropriateness of using the percentile of the mean as the center for asymmetric trimmed series, as proposed by Roger (1997). In contrast, the vast majority of symmetric trimmed series was biased. It should be noted that the 24-month moving average can also be considered unbiased, so its use as an indicator of the trend of inflation in Costa Rica is not objectionable.

From the unbiased series of trimmed mean, 24 of them show greater ability to forecast CPI inflation than the rest of unbiased series, including the ISI, but the same forecasting capability tests among themselves. Of this group of 24 series, the truncation that best fits the trend of inflation is just the best fit within the centered truncations in the percentile of the mean. It results from truncating 30% to the left and 10% to the right from the distribution of changes in prices, centering on the 60th percentile. In addition, the indicator of fit for this truncation is very close to the general minimum for the 1052 considered series. Additionally, asymmetric truncations with better fit to the trend showed much better fit and less variability than the ISI, with the lowest variabilities corresponding to truncations centered near the mean percentile.

Overall, the trimmed mean series with better fit to the trend considered at the end of the evaluation exercise agree on the location of core inflation in relation to the CPI. The inflation series resulting from the optimal truncation indicates that since late 2006, core inflation has consistently been above the one registered by the CPI.

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8. Annex

Table 5

Volatility of the trimmed-series related to the CPI

series standard deviation /CPI standard deviation

	1995-1998	1999-2002	2003-2006	2007-2010	**Jan-1995-Feb-2011**
CPI	1.00	1.00	1.00	1.00	**1.00**
Series 50-06	0.63	0.45	0.66	0.74	**0.64**
ISI	0.64	0.48	0.69	0.83	**0.72**
Series 64-40	0.74	0.41	0.48	0.80	**0.67**
Series 56-16	0.61	0.42	0.49	0.64	**0.57**
Series 56-15	0.62	0.47	0.52	0.64	**0.59**
Series 61-21	0.72	0.49	0.58	0.74	**0.67**
Series 65-39	0.76	0.42	0.52	0.81	**0.69**
Series 64-39	0.73	0.38	0.49	0.82	**0.67**
Series 58-17	0.66	0.50	0.55	0.68	**0.62**
Series 57-16	0.64	0.48	0.53	0.66	**0.60**
Series 57-17	0.63	0.43	0.51	0.66	**0.59**
Series 60-20	0.70	0.47	0.56	0.72	**0.65**

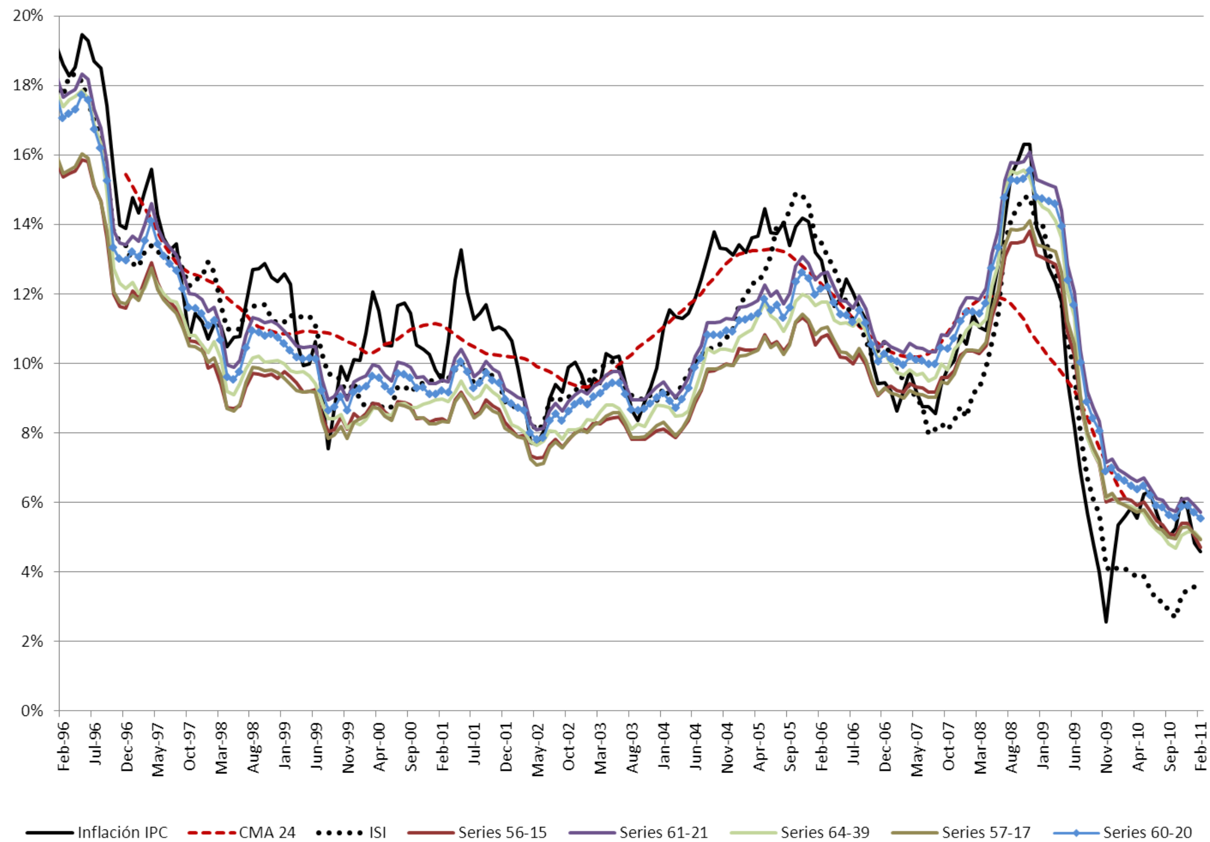
SOURCE: authors' elaboration

Table 6
Selected series throughout Diebold and Mariano's Test

	h = 24 meses		h = 12 meses		h = 6 meses	
	Serie predice mejor	Otras series predicen mejor	Serie predice mejor	Otras series predicen mejor	Serie predice mejor	Otras series predicen mejor
Series 55-14	38	0	1	0	1	0
Series 56-15	38	0	3	0	1	0
Series 56-16	29	0	0	0	0	1
Series 57-16	42	0	7	0	1	0
Series 57-17	28	0	0	0	0	1
Series 58-17	44	0	12	0	1	0
Series 59-18	43	0	14	0	0	0
Series 60-19	37	0	10	0	0	0
Series 60-20	18	0	0	0	0	2
Series 61-20	29	0	8	0	0	0
Series 61-21	12	0	0	0	0	2
Series 62-21	29	0	6	0	0	0
Series 62-22	11	0	2	0	1	2
Series 63-22	19	0	5	0	0	0
Series 63-37	29	0	1	0	31	0
Series 64-34	73	0	0	0	12	0
Series 64-39	59	0	1	0	15	0
Series 64-40	16	0	2	0	11	0
Series 65-35	53	0	0	0	2	2
Series 65-39	80	0	1	0	77	0
Series 66-38	24	0	1	0	20	0
Series 66-41	11	0	1	0	10	0
Series 67-37	65	0	2	0	2	0
Series 68-38	10	0	3	0	1	0
ISI	0	113	0	0	0	0

SOURCE: authors' elaboration

Figure 9
Selected inflation series. Feb 1996- Feb 2011.



SOURCE: authors' elaboration.

Diebold and Mariano Test (1995)

The test is applicable to non-quadratic loss functions to multihorizon forecasts and errors that are not white noise or normally distributed. It is based on the following loss function:

$$d_t = (r_t^1 - r_t^2)$$

where r_t^1 and r_t^2 are the squared forecast errors of two forecasts for inflation, π_t^{*1} and π_t^{*2} respectively. The null hypothesis of equal predictive power of the two forecasts would imply that $E\ d_t = 0$. The alternative hypothesis is that forecast 2 is better than 1.

Assuming stationarity in covariance, among other regularity conditions, the process given by $T^{1/2}$ (d $-\mu$) converges in distribution to $N(0, 2\pi f_d(0))$, where f_d is the spectral density of d_t.

The statistics of the test is:

$$DM = \frac{\bar{d}}{(2\pi \hat{f}_d(0)/T)^{1/2}} \sim N(0,1)$$

where $\hat{f}_d(0)$ is a consistent estimator of $f_d(0)$ and $\bar{d}$ is the sample mean of d_t.

Table 7
Optimum symmetric trimmed-mean inflation[1]

Jan-96	17.69%	Jan-00	9.26%	Jan-04	9.14%	Jan-08	11.47%
Feb-96	17.06%	Feb-00	9.33%	Feb-04	8.92%	Feb-08	11.47%
Mar-96	17.18%	Mar-00	9.63%	Mar-04	8.71%	Mar-08	11.43%
Apr-96	17.29%	Apr-00	9.59%	Apr-04	8.96%	Apr-08	11.72%
May-96	17.71%	May-00	9.34%	May-04	9.28%	May-08	12.73%
Jun-96	17.57%	Jun-00	9.19%	Jun-04	9.87%	Jun-08	13.34%
Jul-96	16.73%	Jul-00	9.71%	Jul-04	10.16%	Jul-08	14.77%
Aug-96	16.20%	Aug-00	9.67%	Aug-04	10.80%	Aug-08	15.27%
Sep-96	15.26%	Sep-00	9.58%	Sep-04	10.80%	Sep-08	15.25%
Oct-96	13.33%	Oct-00	9.28%	Oct-04	10.82%	Oct-08	15.30%
Nov-96	13.00%	Nov-00	9.30%	Nov-04	10.94%	Nov-08	15.55%
Dec-96	12.96%	Dec-00	9.11%	Dec-04	10.91%	Dec-08	14.79%
Jan-97	13.20%	Jan-01	9.10%	Jan-05	11.22%	Jan-09	14.74%
Feb-97	13.05%	Feb-01	9.20%	Feb-05	11.25%	Feb-09	14.66%
Mar-97	13.52%	Mar-01	9.16%	Mar-05	11.32%	Mar-09	14.58%
Apr-97	14.11%	Apr-01	9.81%	Apr-05	11.42%	Apr-09	13.95%
May-97	13.43%	May-01	10.06%	May-05	11.86%	May-09	12.40%
Jun-97	13.08%	Jun-01	9.74%	Jun-05	11.53%	Jun-09	11.67%
Jul-97	12.86%	Jul-01	9.30%	Jul-05	11.68%	Jul-09	10.03%
Aug-97	12.67%	Aug-01	9.43%	Aug-05	11.31%	Aug-09	8.88%
Sep-97	12.16%	Sep-01	9.72%	Sep-05	11.60%	Sep-09	8.42%
Oct-97	11.61%	Oct-01	9.51%	Oct-05	12.35%	Oct-09	8.05%
Nov-97	11.58%	Nov-01	9.43%	Nov-05	12.62%	Nov-09	6.90%
Dec-97	11.44%	Dec-01	8.97%	Dec-05	12.43%	Dec-09	7.00%
Jan-98	11.09%	Jan-02	8.85%	Jan-06	11.97%	Jan-10	6.73%
Feb-98	11.23%	Feb-02	8.71%	Feb-06	12.15%	Feb-10	6.61%
Mar-98	10.65%	Mar-02	8.65%	Mar-06	12.19%	Mar-10	6.48%
Apr-98	9.62%	Apr-02	8.00%	Apr-06	11.76%	Apr-10	6.37%
May-98	9.54%	May-02	7.81%	May-06	11.40%	May-10	6.48%
Jun-98	9.75%	Jun-02	7.86%	Jun-06	11.39%	Jun-10	6.21%
Jul-98	10.44%	Jul-02	8.34%	Jul-06	11.19%	Jul-10	5.91%
Aug-98	10.93%	Aug-02	8.55%	Aug-06	11.52%	Aug-10	5.85%
Sep-98	10.88%	Sep-02	8.35%	Sep-06	11.16%	Sep-10	5.62%
Oct-98	10.80%	Oct-02	8.61%	Oct-06	10.55%	Oct-10	5.56%
Nov-98	10.83%	Nov-02	8.81%	Nov-06	10.06%	Nov-10	5.89%
Dec-98	10.74%	Dec-02	8.92%	Dec-06	10.26%	Dec-10	5.91%
Jan-99	10.57%	Jan-03	8.82%	Jan-07	10.12%	Jan-11	5.72%
Feb-99	10.37%	Feb-03	9.05%	Feb-07	10.05%	Feb-11	5.53%
Mar-99	10.16%	Mar-03	9.13%	Mar-07	9.94%	Mar-11	5.60%
Apr-99	10.12%	Apr-03	9.34%	Apr-07	10.20%	Apr-11	5.67%
May-99	10.14%	May-03	9.44%	May-07	10.10%	May-11	5.98%
Jun-99	10.12%	Jun-03	9.43%	Jun-07	10.07%	Jun-11	6.08%
Jul-99	9.20%	Jul-03	9.11%	Jul-07	9.96%	Jul-11	6.03%
Aug-99	8.65%	Aug-03	8.66%	Aug-07	9.97%	Aug-11	5.94%
Sep-99	8.74%	Sep-03	8.65%	Sep-07	10.45%		
Oct-99	9.03%	Oct-03	8.68%	Oct-07	10.42%		
Nov-99	8.65%	Nov-03	8.84%	Nov-07	10.70%		
Dec-99	9.15%	Dec-03	9.02%	Dec-07	11.20%		

[1] Centering on the 60th percentile, trimming 30% from the left and 10% from the right.
SOURCE: authors' elaboration.