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Eurilton Araujo

Antonio Fiorencio

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Eurilton Araújo*
Ibmec

Antonio Fiorencio**
Ibmec and UFF

* Corresponding author. Ibmec. Av. Rio Branco, 108,12º. Rio de Janeiro, RJ. Brazil. 22.040-001. ejunior@ibmecrj.br. Phone: 55-21-3806-4123. fax: 55-21-2232-3253.
** Ibmec and UFF; fiorencio@ibmecrj.br. Financial support from CNPq is gratefully acknowledged.

Frequency Domain Analysis of Core Inflation Measures for Brazil

Abstract: This paper analyses the frequency domain properties of two well-known measures of core inflation: the trimmed mean estimator and the SVAR estimator. It also investigates whether a small modification of the trimmed mean estimator enhances its capacity of filtering high-frequency noise. We find that the two versions of the trimmed estimator are rather similar. They work as imperfect approximations for low pass filters. The SVAR estimator, however, is quite different from both of them. It emphasizes intermediate frequencies rather than low frequencies.

Key words: core inflation, frequency domain, trimmed estimator, SVAR.

1 – Introduction

In recent years many central banks adopted inflation targets as a framework to the conduct of monetary policy. It is critical for these central banks to continuously evaluate inflationary trends to set monetary policy appropriately.

The trimmed estimator of core inflation is widely regarded as a useful indicator of "underlying inflation"[1]. The rationale for the use of trimmed estimators of core inflation is by now well known. Price indexes are an average of individual prices. The arithmetic mean of observed prices is an efficient estimator of the general price level if the distribution of prices at a given moment is normal. But the international evidence suggests that the cross-sectional distribution of prices is leptokurtic (and asymmetric) making the trimmed mean a more efficient estimator of central position. The optimal degree of trimming is usually chosen minimising the mean squared error from the trimmed mean to a centred moving average of inflation.

But, even though trimmed estimators of core inflation have become quite popular, they have been criticised for lacking economic rationale[2]. Another approach states that central banks should be concerned with demand driven price movements and that is what core inflation should measure. The structural vector auto-regression (SVAR) approach uses economic theory to impose identification restrictions on a standard VAR model. The main problem here, of course, is to find compelling and credible restrictions.

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[1] Bryan & Cecchetti, and co-authors, suggested the trimmed estimator of core inflation in several papers – see References. Roger (1998), Bakhshi &Yates (1999) and Wyne (1999) review the main issues.
[2] Quah & Vahey (1995).

We want to assess these two measures of core inflation from a policy-oriented point of view. A central bank would not want to change its policy stance in reaction to a shock that would fade away within its targeting horizon anyway. In other words, central banks must filter away high frequency inflation shocks to get a picture of trend inflation.

We analyse the frequency domain properties of the trimmed estimator and of the SVAR estimator of core inflation. In particular, we want to check whether they filter away high frequency noise and thus serve as good indicators of “trend inflation”. We also suggest a minor modification of the trimmed estimator that might enhance its capacity of filtering high frequency noise. Specifically, we construct our alternative proxy by applying a 1-year low-pass filter to the inflation series, instead of applying a moving-average filter.

This paper is organized as follows. Section 2 presents the data we use. Section 3 analyses the frequency domain properties of the two alternative trimmed mean estimators of core inflation. Section 4 analyses the SVAR estimator. Section 5 offers conclusions.

2 – The Data

The data for inflation are the monthly percentage changes of IPCA at the item level of aggregation[3]. The data for activity is the level of industrial production[4]. All data are for the period 8/94-6/02[5].

[3] IPCA is the Extended Consumer Price Index computed by IBGE – Brazilian Institute of Geography and Statistics, a governmental agency. It is a weighted average of equivalent indexes for nine metropolitan areas and two municipalities. There were 47 items in the index until July 1999 and there 52 now.

[4] The data for industrial production comes from IPEADATA, under the mnemonic *ipeadata 1736265156*, and the seasonality was already filtered.

[5] In July 1994, Brazil launched the Real Plan and brought monthly inflation rates down from almost 50% to

Figure 1 plots the IPCA[6] series (continuous line).

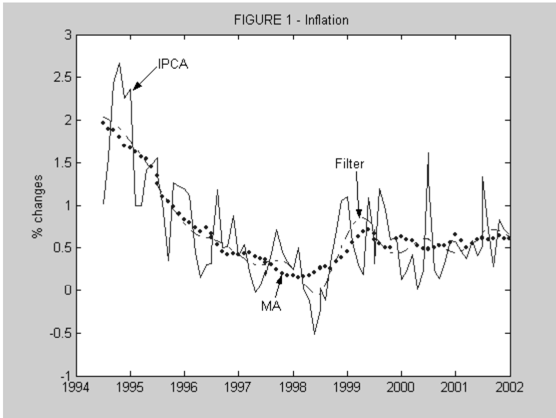
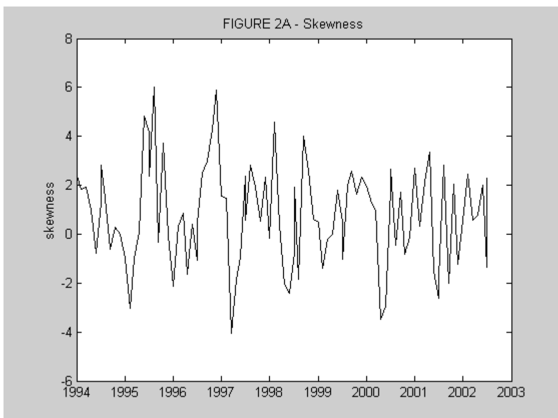
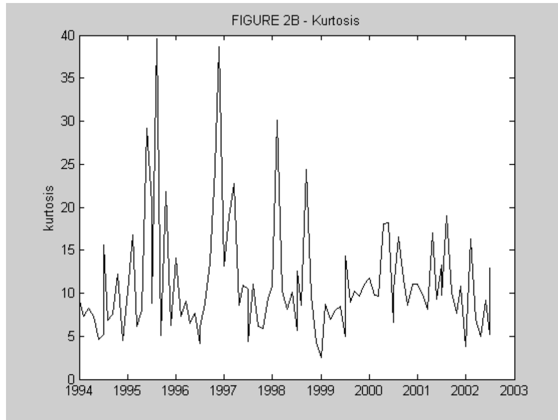


Figure 2 shows that IPCA displays the positive skewness and the excess kurtosis typical of this kind of data. Mean skewness and kurtosis of IPCA are, respectively 0.76 and 10.0, and monthly variation is large.



less than 1%. In January 1999, Brazil could no longer sustain its currency peg, it let the Real float and a few months later joined the group of countries adopting an inflation target framework for the conduct of monetary policy. At the time of writing, the Brazilian Central Bank (BCB) sets inflation targets for a horizon of about two and a half years. The target is set for a headline consumer price index (IPCA) with a symmetric band and no escape clauses. In June 2002 the BCB altered the previously established target for 2003 and fixed the target for 2004.

[6] When there is no risk of confusion we will refer to the percentage change in IPCA simply as IPCA.



We now analyse the frequency domain properties of the inflation series. Any time series $\{x_t\}$ can be represented by its spectral density, which is given by: $f_x(\omega) = \frac{1}{2\pi}\sum_{k=-\infty}^{+\infty}\gamma_x(k)\exp(-i\omega k)$, where $\gamma_x(k)$ is the auto-covariance function of order k and the letter i denotes the complex number unit.

The spectrum is just the Fourier Transform of auto-covariance functions. In the bivariate case, we have the cross-spectrum given by: $f_{xy}(\omega) = \frac{1}{2\pi}\sum_{k=-\infty}^{+\infty}\gamma_{xy}(k)\exp(-i\omega k)$, where $\gamma_{xy}(k)$ is the cross-covariance function of order k. The Greek letter ω denotes the angular frequency associated with cycles of periodicity given by $\frac{2\pi}{\omega}$. The spectrum and the cross-spectrum are estimated non-parametrically by Smoothing methods[7].

For instance, consider the univariate process $\{x_t\}$. The sample periodogram, which is the sample analogue of $f_x(\omega)$, can be computed as follows $\hat{f}_x(\omega) = \frac{1}{2\pi}\sum_{j=-T+1}^{T-1}\hat{\gamma}_x(j)\exp(-iwj)$.

[7] For more details related to estimation procedures, see Hamilton (1994).

$\hat{\gamma}_x(j)$ are sample auto-covariance functions based on a sample of T observations, satisfying the condition $\hat{\gamma}_x(l) = \hat{\gamma}_x(j)$ for $l = -j$.

A Kernel estimator averages the sample periodogram over different frequencies and can be constructed as $\sum_{m=-h}^{h} k(\omega_{j+m}, \omega_j)\hat{f}_x(\omega_{j+m})$.

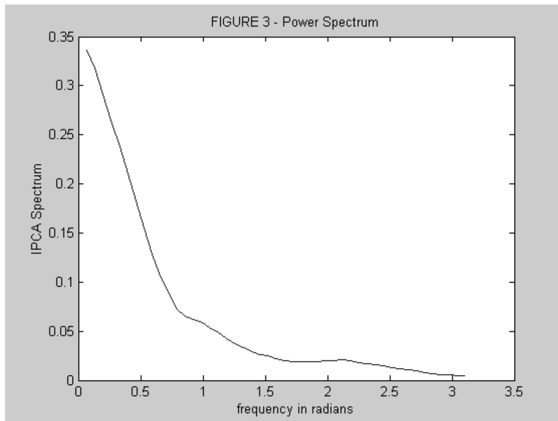
The Kernel $k(\omega_{j+m}, \omega_j)$ assigns weights to each frequency considered. Hamilton (1994) recommended the use of the Kernel $k(\omega_{j+m}, \omega_j) = \frac{h+1-|m|}{(h+1)^2}$.

Since we are interested in the relationship between alternative cores and IPCA inflation in the frequency domain, it is necessary to discuss a mathematical object, based on cross-spectrum that summarizes this relationship.

The relationship between the input series $\{x_t\}$ and the output series $\{y_t\}$ of a system is measured by the Transfer Function, which is defined by the ratio $\frac{f_{xy}(\omega)}{f_x(\omega)}$. As any complex number, the Transfer Function has a modulus, often called gain and an angle, usually known as phase.

We will show the Transfer Function gains associated with IPCA inflation, as input series and the cores we intend to study, as output series.

Figure 3 shows the power spectrum of IPCA. The spectrum was estimated using the recommended kernel with smoothing parameter h equal to 10. The spectrum shows the standard shape of the spectral density of a macroeconomic time series, characterized by concentrating mass in the low frequency range. The decay pattern is not so fast though. Almost 70 per cent of the spectral mass is concentrated in the range defined by zero and 0.79 radians, which corresponds to cycles with periodicity of approximately more than eight months. To eliminate the high-frequency components of IPCA, we apply to it a 1-year low-pass filter. The filtered series is shown as the broken line in Figure 1.



The low-pass-filter is a special case of a band-pass-filter with the passing band defined from zero up to a specified frequency. We now briefly describe the band-pass-filter.

Generally, the Ideal Band Pass Filter is the artefact used to extract particular frequency components associated with a given series. The Ideal Band Pass Filter is just a linear transformation of the data, which does not change the data within a specified frequency band and eliminates all other frequency components.

A filtered series can be represented as follows $x_t^F = B(L)x_t$, where the polynomial $B(L)$ is given by $B(L) = \sum_{h=-\infty}^{+\infty} b_h L^h$ with the condition $b_h = b_{-h}$ being satisfied.

The Ideal Band Pass Filter is an infinite moving average and the weights can be computed according to the following formulas: $b_0 = \frac{f_2 - f_1}{\pi}$ and $b_h = \frac{\sin(f_2 h) - \sin(f_1 h)}{\pi h}$ for $h = \pm 1,2,3,...$

The specified frequency band is given by $[f_2, f_1]$.

Therefore, to apply the Ideal Band Pass Filter, one needs an infinite amount of data. For this reason, some sort of approximation is needed.

Christiano and Fitzgerald (2001) study optimal linear approximations to the unachievable Ideal Band Pass Filter. They define weights for a linear combination involving all data points in the sample. Their recommended weights vary with the time index and are not symmetric. Therefore, one does not loose data points though the first year and last year of filtered data are poorly estimated.

Our low-pass-filter is built according to Christiano and Fitzgerald (2001) and we decide to discard the first six and last six values generated by their algorithm, since they are poorly estimated and the series length is the same as the six-month centred moving average of IPCA, which facilitates comparison.

Figure 1 also shows the six-month centred moving average of IPCA as the dotted line. The fact that moving averages tend to eliminate high frequency components is evident in the figure.

Before computing the two core inflation measures under study in this paper, we perform standard unit root tests for the industrial production index and IPCA inflation. Tests give strong support to the presence of a unit root in the industrial production series.

For instance, allowing for the presence of a constant and a time trend, with lag length equals to 6, the ADF statistics is –3.2211 and the critical value at 5% significance level is –3.4608. With lag length equals to 8, the ADF statistics is –2.9466, the critical value at 5% level is –3.4620. With leg length equals to 12, the ADF statistics is –2.2612, the corresponding critical value is –3.4645 at 5%. Phillips-Perron and KPSS tests also supported the non-stationary nature of the industrial production index.

On the other hand, unit root tests give mixed evidence concerning the existence of a unit root on the IPCA inflation series. Overall, tests indicate that inflation is stationary, but again this is not strongly supported by all tests performed. For instance, allowing for a constant, which seems to be the best specification for IPCA inflation, this series is stationary according to the ADF test, with lag length equal to 10, chosen by looking at the AIC criterion. The test statistics is –3.5280 with 5% critical value equal to –2.8967. The Phillips-Perron test supported the absence of a unit root for inflation since the test statistics computed equals –3.3138 and the 5% critical value is –2.8929. However, the KPSS LM statistics points to the rejection of the null, which in this case is absence of unit root, since the statistics computed is 0.7113 and the 5% critical value is 0.4630.

3 – Trimmed Mean Estimators of Core IPCA[8]

To facilitate comparison with other studies, we compute a simple measure of core inflation: an asymmetric trimmed (weighted) average of percentage changes in the prices of individual products. The degree of trimming is chosen to minimise the mean squared

[8] Measures of core inflation for Brazil have been calculated by Bryan & Cecchetti (2001), Fiorencio & Moreira (2000), Figueiredo (2001), Moreira & Migon (2001), Picchetti & Kanczuk (2001).

error of the trimmed estimator from a six-month centred moving average of IPCA[9]. We call this estimator the MA-core. Since moving averages reduce high-frequency noise, the MA-core targets a measure of trend inflation.

We also compute an alternative measure of core inflation. We continue to use an asymmetric trimmed mean estimator, but we choose the degree of trimming by minimising the mean squared error from the trimmed estimator to a 1-year low-pass filtered IPCA[10]. We call this estimator the F-core. The motivation for computing this alternative core is rather obvious. Since inflation targets are set for specific horizons, it is interesting to evaluate inflation prospects at those frequencies. The low-pass filter allows a better definition of the frequencies of interest than does the MA filter.

Figure 4 shows the mean squared error of the MA-core and of the F-core as a function of the degrees of trimming. The optimal MA-core trims 33% of the right tail and 22% of the left tail, whereas the optimal F-core trims 36% of the right tail and 22% of the left tail. The MA-core attains a lower minimum than that of the F-core: 7.0 and 7.8, respectively.

The optimal degrees of trimming are quite similar for both estimators. They remain similar when we change the window of the moving average and when we consider a symmetric trimming. We only got markedly different results when we chose a very short window for the moving average, one month on each side. But this is too short, of course.

[9] We tried different windows for the moving-average and a symmetric trimmed mean. With one exception mentioned bellow, results were not qualitatively different.

[10] The choice of 1-year for the cutting frequency is arbitrary. We have not yet experimented with other cutting frequencies for the low-pass filter but intend to do so.

FIGURE 4 - Triming points

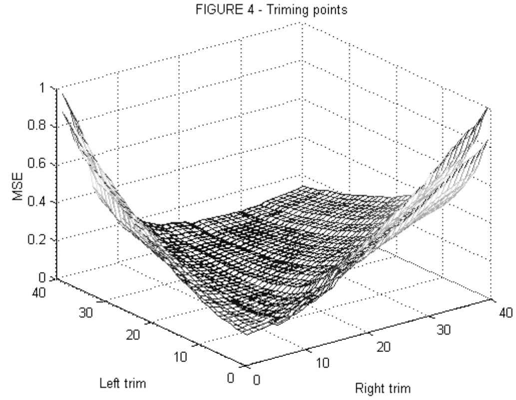


Figure 5 shows the IPCA series (continuous line), the MA-core (broken line) and the F-core (dotted line). The difference between the two core measures is hardly discernible.

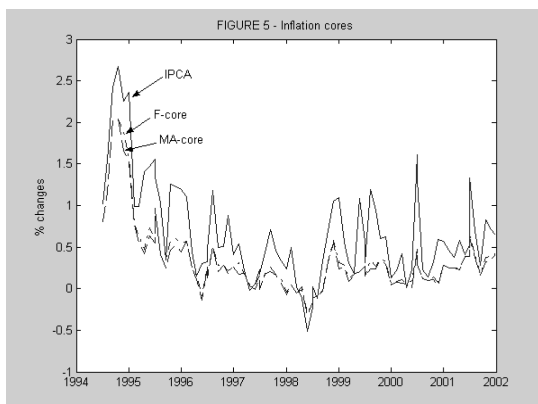
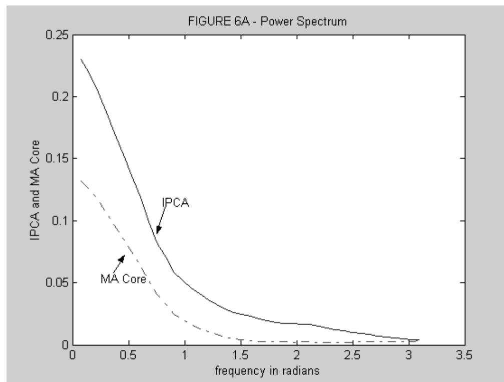


FIGURE 5 - Inflation cores

We now turn to the frequency domain properties of the two trimmed estimators of core inflation. Figure 6A shows the power spectrum of IPCA and of the MA-core. Figure

6B shows the power spectrum of IPCA and of the F-core[11]. As is well known, the variance of a series is the area under its spectrum. The figures show the expected reduction in the variance of the series produced by the two filters.



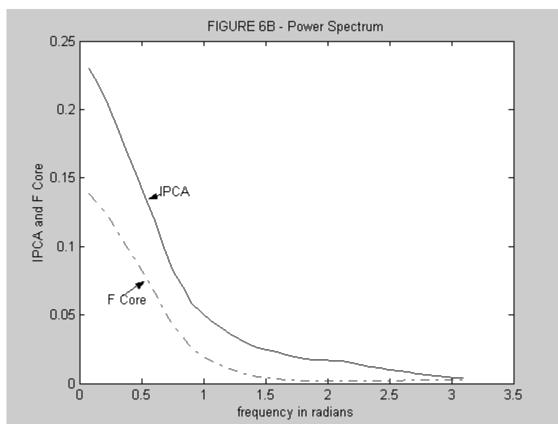
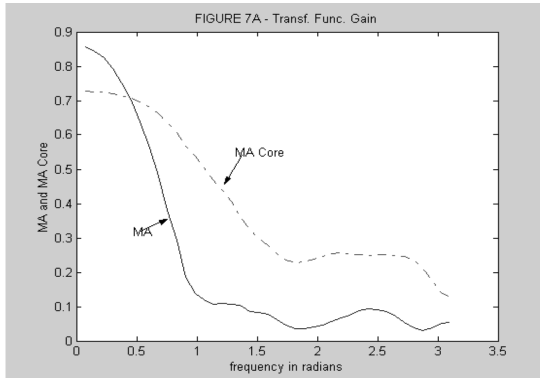
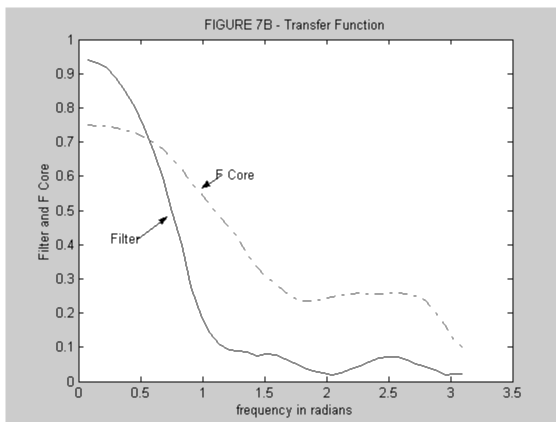


Figure 7A compares the transfer function gains of the MA-core with the transfer function of the moving average itself. Figure 7B does the same for the F-core and the

[11] The two power spectra of IPCA are not identical because they were estimated on different data samples, since the MA-core loses 6 observations on each end of the sample.

low-pass filter. The figures show that both cores reduce high-frequency noise much less than their ideal counterparts.





The contribution of cycles associated with the frequency band $[\omega_1, \omega_2]$ to total variance is given by the following integral $\frac{1}{\pi}\int_{\omega_1}^{\omega_2} f_x(\omega)d\omega$. All frequencies belong to the interval $[0,\pi]$ and $f_x(\omega)$ stands for the spectrum of the series being studied.

Tables 1,2 and 3 assess quantitatively the contribution of different frequency bands to total variance for IPCA inflation, MA-Core and F-Core.

Table 1 – IPCA Inflation

Periodicity	Frequency	Variance	Percentage of Variance
All Cycles (Total)	$0 \le \omega \le \pi$	0.3664	100
$T \ge 12$	$0 \le \omega \le 0.5236$	0.2737	74.7
$6 \le T \le 12$	$0.5236 \le \omega \le 1.0472$	0.0482	13.17
$T \le 6$	$1.0472 \le \omega \le \pi$	0.0444	12.13

Table 2 – MA Core

Periodicity	Frequency	Variance	Percentage Variance	$\frac{Var(Core)}{Var(IPCA)}$
All Cycles (Total)	$0 \le \omega \le \pi$	0.1760	100	0.48
$T \ge 12$	$0 \le \omega \le 0.5236$	0.1399	79.51	0.51
$6 \le T \le 12$	$0.5236 \le \omega \le 1.0472$	0.0244	13.85	0.51
$T \le 6$	$1.0472 \le \omega \le \pi$	0.0117	6.64	0.26

Table 3 – F Core

Periodicity	Frequency	Variance	Percentage Variance	$\frac{Var(Core)}{Var(IPCA)}$
All Cycles (Total)	$0 \le \omega \le \pi$	0.1828	100	0.50
$T \ge 12$	$0 \le \omega \le 0.5236$	0.1460	79.89	0.53
$6 \le T \le 12$	$0.5236 \le \omega \le 1.0472$	0.0254	13.89	0.52
$T \le 6$	$1.0472 \le \omega \le \pi$	0.0114	6.22	0.26

The main conclusion from this section is that using a low-pass filter or a moving-average to proxy for trend inflation produces similar cores. The optimal degrees of trimming do not change much and the spectrum of the F-core is not superior to the spectrum of the MA-core, in the sense of having much less power at high frequencies. The MA-core has the advantage of being simpler to compute. Of course, these are empirical results that may or may not apply to other data sets.

4 – A SVAR Core of IPCA

The SVAR methodology is based upon Quah and Vahey (1995). It amounts to an application of the Blanchard and Quah identification strategy to define a measure of the underlying inflation. Core Inflation is defined as the component of measured inflation that has no long-run effect on output. We call this estimator the S-core. Behind that definition is the idea that central bankers should be concerned only with inflation related to demand shocks.

To implement that notion of core inflation, one needs to impose restrictions on a Vector Auto-Regression (VAR) system involving the growth of industrial production and the inflation rate.

Let us denote the growth of industrial production by Δy_t and the inflation rate by π_t. Consider the vector $x_t = (\Delta y_t \;\; \pi_t)^T$ and the structural shocks ε_1 and ε_2.

The reduced form VAR can be written as :

$$\Delta y_t = A_{11}(L)\Delta y_{t-1} + A_{12}(L)\pi_{t-1} + e_{1t}$$

$$\pi_t = A_{11}(L)\Delta y_{t-1} + A_{12}(L)\pi_{t-1} + e_{2t}$$

The VAR is estimated in its reduced form and is used to compute the residuals e_1 and e_2. Using our data set, we chose to estimate a VAR with lag length equal to six for two reasons. First, we did not have a long data set. Second, we want to capture as much as possible the dynamics of the system.

We choose the lag length comparing AIC criteria for various lag lengths going from two to nine. The R^2 for the first equation was 0.2695 and the R^2 for the second was 0.6368. Tables 4 and 5 summarize the estimated VAR.

Table 4
First Equation: Industrial Production Growth is the dependent variable

Variable	Coefficient	*t* Statistics
Constant	0.004401	1.07992
IP Growth (-1)	-0.361597	-3.18276
IP Growth (-2)	0.049629	0.43382
IP Growth (-3)	0.051546	0.44838
IP Growth (-4)	0.021803	0.19048
IP Growth (-5)	-0.169934	-1.51854
IP Growth (-6)	-0.123277	-1.17199
IPCA Inflation (-1)	-0.001295	-0.19855
IPCA Inflation (-2)	-0.003924	-0.51417
IPCA Inflation (-3)	0.013489	1.79814
IPCA Inflation (-4)	-0.012895	-1.72948
IPCA Inflation (-5)	0.012448	1.69665
IPCA Inflation (-6)	-0.012243	-2.04318

Table 5
Second Equation: IPCA Inflation is the dependent variable

Variable	Coefficient	*t* Statistics
Constant	0.118146	1.65017
IP Growth (-1)	-2.798083	-1.40194
IP Growth (-2)	-4.255435	-2.11745
IP Growth (-3)	-1.517366	-0.75133
IP Growth (-4)	-0.590151	-0.29349
IP Growth (-5)	-1.194244	-0.60748
IP Growth (-6)	-0.270651	-0.14647
IPCA Inflation (-1)	0.644527	5.62570
IPCA Inflation (-2)	-0.251644	-1.87709
IPCA Inflation (-3)	0.195367	1.48242
IPCA Inflation (-4)	-0.147717	-1.12777
IPCA Inflation (-5)	0.182482	1.41577
IPCA Inflation (-6)	0.163035	1.54883

The vector x_t can be written in a moving average representation according to: $x_t = \sum_{j=0}^{\infty} C(j)\varepsilon_{t-j}$. The moving average representation associated with the residuals is: $x_t = I + \sum_{j=1}^{\infty} B(j)e_{t-j}$. The identity matrix is denoted by the letter *I*. The Greek ε_{t-j} and e_{t-j} denote vectors stacking structural shocks and residuals respectively.

Comparing both moving average representations, it is not hard to show that the structural shocks and the residuals are related by the following equations:

$$e_{1t} = c_{11}(0)\varepsilon_{1t} + c_{12}(0)\varepsilon_{2t}$$

$$e_{2t} = c_{21}(0)\varepsilon_{2t} + c_{22}(o)\varepsilon_{2t}$$

Since the residuals are obtained via reduced form estimation, to recover the structural shocks one need to know the coefficients $\{c_{ij}(0)\}$.

The variance-covariance matrix of residuals gives three conditions that are related to the variances of the two residuals and to the covariance between them. These conditions involve the four unknowns $\{c_{ij}(0)\}$, two known variances and a known covariance. But we still have four unknowns and only three equations.

Using the Blanchard and Quah strategy for identification, one can impose a restriction that the long-run impact of one shock in one of the variables is zero. So, one can impose that the first shock will not have any effect on output in the long run. That restriction implies a fourth equation involving $c_{11}(0)$ and $c_{21}(0)$ and known quantities which came from the reduced form estimation.

The four equations just described are:

$$Var(e_1) = c_{11}(0)^2 + c_{12}(0)^2$$

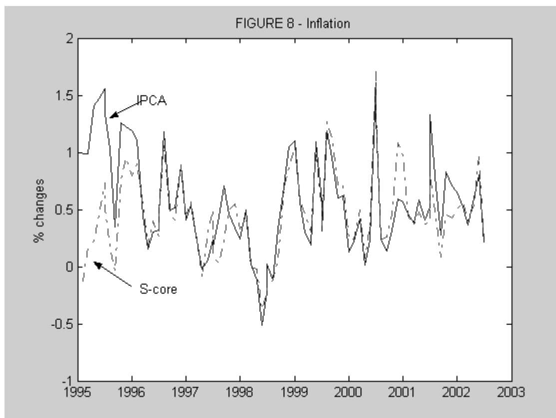
$$Var(e_2) = c_{21}(0)^2 + c_{22}(0)^2$$

$$\mathrm{cov}(e_1, e_2) = c_{11}(0)c_{21}(0) + c_{12}(0)c_{22}(0)$$

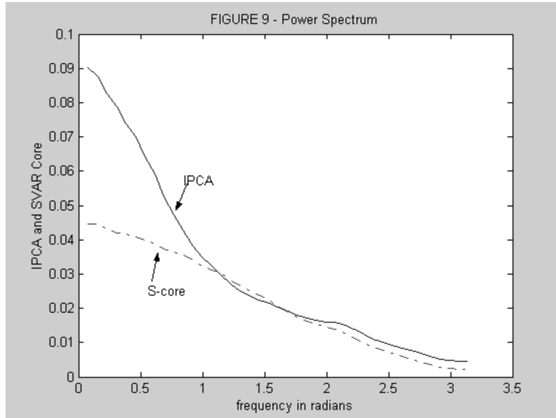
$$0 = c_{11}(0)[1 - \sum_{k=0}^{p} a_{22}(k)] + c_{21}(0)[\sum_{k=0}^{p} a_{12}(k)]$$

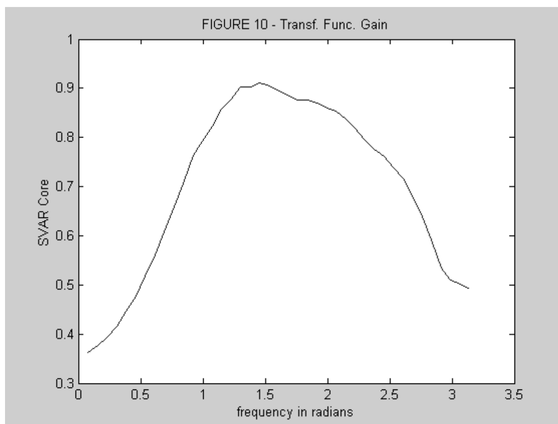
Finally, we will have four unknowns and also four equations. By solving that system, one is able to find the matrix $C(0)$. Knowing the residuals and the inverse matrix of $C(0)$, it is straightforward to recover the structural shocks. After that step is completed, the process for inflation can be written as a function of the structural shocks as following: $\pi_t = \sum_{j=0}^{p} c_{21}(j)\varepsilon_{1t-j} + \sum_{j=0}^{p} c_{22}(j)\varepsilon_{2t-j}$. Here we are assuming that we are truncating the infinite moving average representation, using the same lag length employed in the estimation of the reduced form system. The SVAR measure of core inflation is: $\sum_{j=0}^{p} c_{21}(j)\varepsilon_{1t-j}$.

Figure 8 shows that the S-core is able to track the observed IPCA well, especially after the second half of 1995. Figure 9 shows the spectrum of the S-core[12] and Figure 10 shows its transfer function, which is markedly different from the transfer functions of the MA-core and the F-core. We see that the S-core does not give a high gain to the low frequencies. This is not surprising since the S-core is not built to be close to any type of smoother. It is the middle frequencies that are being highlighted by the SVAR procedure.



[12] The same comments concerning the change of scale in the spectrum of IPCA made with respect to Figure 6 apply here. The SVAR procedure implied a loss of 12 months of observations.





Tables 6 and 7 assess quantitatively the contribution of different frequency bands to total variance for IPCA inflation and S-Core. Of course, we are taking into account that we lost 12 months of observations by estimating the SVAR Core. Therefore, we recomputed the figures for IPCA inflation in order to compare them with the ones related to the S-Core.

Table 6 – IPCA Inflation

Periodicity	Frequency	Variance	Percentage of Variance
All Cycles (Total)	$0 \le \omega \le \pi$	0.2	100
$T \ge 12$	$0 \le \omega \le 0.5236$	0.1359	67.98
$6 \le T \le 12$	$0.5236 \le \omega \le 1.0472$	0.0209	10.45
$T \le 6$	$1.0472 \le \omega \le \pi$	0.0431	21.57

Table 7 – S Core

Periodicity	Frequency	Variance	Percentage Variance	$\frac{Var(Core)}{Var(IPCA)}$
All Cycles (Total)	$0 \le \omega \le \pi$	0.1432	100	0.71
$T \ge 12$	$0 \le \omega \le 0.5236$	0.0904	63.14	0.64
$6 \le T \le 12$	$0.5236 \le \omega \le 1.0472$	0.0146	10.23	0.59
$T \le 6$	$1.0472 \le \omega \le \pi$	0.0381	26.63	3.25

The tables show that the S-Core introduces more volatility associated with high frequency cycles and it reduces overall volatility by less than the previous two core estimators considered. The variance associated with periodicity of more than one year is lower when compared to IPCA but not as lower as in the cases of the MA-Core and F-Core.

5 – Conclusions

Many central banks look at different measures of core inflation in order to define their policy stances. In this paper we performed an empirical evaluation of two popular measures of core inflation: two versions of the trimmed mean estimator and the SVAR estimator of core inflation. Specifically, we investigated the frequency domain properties of these estimators.

We found that the differences between the two versions of the trimmed estimator are minor. The MA-core and the F-core series are similar and, naturally, so are their spectra and transfer functions. It will be interesting to test whether this similarity is dependent on the specific cutting frequency (1 year) that we arbitrarily chose. The MA-core has the advantage of being easier to compute. The F-core has the advantage of a greater precision in the definition of what is meant by “trend” inflation. This greater precision might be important if the similarity between the two estimators does depend on the chosen cutting frequency.

The differences between the two trimmed estimators on the one hand and the SVAR estimator on the other hand are considerable. The S-core aims at separating demand from supply shocks to inflation whereas the MA-core and the F-core aim at separating high frequency from low frequency movements. This difference in objectives translates clearly into differences on their frequency characteristics. The S-core highlights intermediate frequencies whereas the MA-core and the F-core emphasize low frequencies.

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