“Measuring core inflation as the common trend of prices”

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Measuring core inflation as the common trend of prices*

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Abstract: In recent years, many central banks have adopted inflation targeting policies starting an intense debate about which measure of inflation to adopt. The literature on core inflation has tried to develop indicators of inflation which would respond only to "significant" changes in inflation. This paper defines a measure of core inflation as the common trend of prices in a multivariate dynamic model, that has, by construction, three properties: it filters idiosyncratic and transitory macro noises, and it leads the future level of headline inflation. We also show that the popular trimmed mean estimator of core inflation could be regarded as a proxy for the ideal GLS estimator for heteroskedastic data. We employ an asymmetric trimmed mean estimator to take account of possible skewness of the distribution, and we obtain an unconditional measure of core inflation.

1. Introduction

In recent years, many central banks have adopted inflation targeting policies starting an intense debate about which measure of inflation to adopt. This debate reflects the suspicion that standard inflation indexes might give a misleading picture of the "real" level of inflation. Standard indexes might be too "nervous" in the sense of not discriminating (i) idiosyncratic from generalised price shocks and (ii) temporary from permanent shocks. If this is so, the conduct of monetary policy would be obviously impaired.

The literature on core inflation has tried to develop "less nervous" indicators of inflation which would respond only to "significant" changes in inflation. Many alternative approaches have been proposed and all of them are concerned with noise filtering. But the definitions of what is noise do

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differ, reflecting a lack of consensus about what should be measured and why
not use standard indexes.

Since the literature on core inflation has been largely motivated by the
literature on inflation targeting, it will be useful to consider the relationship
between them.

An inflation targeting regime requires two different measures of
inflation. The first measure is the inflation target itself, which defines policy
objectives and might help co-ordinating agents' expectations. The target must
be credible, easily understandable and its history should not change as new
information arrives – conditions that would not be met if the target were
defined in terms of an econometric model.

The second measure of inflation is the core inflation which shows
inflation trends over the short-run and, thus, whether policy is on track. It is
not necessary that the "core" possesses the same characteristics of the
"target". Rather, it must reflect effective changes in inflation: (i) it should
discriminate between idiosyncratic and generalised movements in prices; (ii)
it should discriminate between temporary and persistent movements in prices;
and (iii) it should lead the probable short-run trend of inflation. (The literature
frequently assumes that the indicator should discriminate supply from demand
shocks. This is not so obvious for us and we will not require this ability from
the indicator. We are interested on movements in inflation, whatever their
sources.)

These are not arbitrary characteristics. Without such an indicator it is
more probable that monetary policy will be highly volatile since it will be
continuously reacting to noise and will not be pre-emptive. Thus, the key
words for us are: generality, persistency and lead-power.

Targets and Core are different things but the literature tends to treat
them as one. In this paper we are interest on core inflation exclusively as an
indicator of inflation or, more to the point, as an indicator of whether policy is
on track. This means that the definition of the indicator will depend on the

1 "Surprisingly, precise definitions of [core inflation] are rarely provided." (Bryan & Cecchetti (1999), pg 1)
"In general, core inflation tends to be defined in terms of the particular method used to construct a practical
measure rather than in terms of what the measure is trying to capture." (Roger (1998), pg 1)
"I evaluate the competing merits of the different approaches [to measure core inflation], and argue that a
common shortcoming is the absence of a well-formulated theory of what these measures of inflation are
supposed to be capturing." Wyne (1999, pg 2)
2 "At the Fed, I can assure you, we never thought of the exchange rate as a source of 'noise'. Far from being
statistical marginalia, we thought of both supply shocks and exchange-rate movements as raising important
policy issues." Blinder (1997, pg. 160)
definition of the target. Many different indexes might serve as the basis for
the target: consumer price indexes, wholesale price indexes etc. But, once the
target has been defined, the indicator should suggest whether policy concerning
that target is on track. In 1999 Brazil moved to an inflation target
regime where the target inflation rate is the IPCA\textsuperscript{3}. So, for us, core inflation
will mean core IPCA\textsuperscript{4}.

Section 2 briefly reviews the existing approaches to measuring core
inflation. Section 3 presents our measure of core inflation and section 4
considers whether this measure is an effective lead of the corresponding
headline index. Section 5 concludes.

2. The main approaches in the literature

The literature presents four main approaches to compute core inflation\textsuperscript{5}.

(i) The most traditional approach is the “ex. food and energy”. This
amounts to pre-specifying a fixed group of products that will be
systematically excluded from the computation of the inflation core. The
reason for the exclusion is usually the fact that the prices of these products are
“too volatile”. But since relative volatilities can change, you must be
somewhat prescient to employ this approach effectively. In fact, there is not
much to be said in favour of this approach except that it is simple.

(ii) By far, the most popular current approach to compute core inflation
are the trimmed estimators proposed most notably by Bryan and Cecchetti in
several papers\textsuperscript{6}. The problem is the following. Price indexes are an average of
individual prices. If the distribution of prices at a given moment were normal,
the arithmetic mean of observed prices would be an efficient estimator of the
general price level. There is, however, reasonable international evidence that
the cross-sectional distribution of prices is not normal, rather, it appears to be
asymmetric and leptokurtic (fat tails)\textsuperscript{7}. If the distribution is leptokurtic, the
literature recommends trimming the sample to estimate the mean, which
produces an improvement in the efficiency of the estimator.

\textsuperscript{3} IPCA (Índice de Preços ao Consumidor Ampliado) is a consumer price index.
\textsuperscript{4} We will not discuss traditional sources of bias in consumer price indexes such as quality and substitution
bias.
\textsuperscript{5} We present the main issues briefly. For more complete reviews the reader may consult Roger (1998) or
Wyne (1999).
\textsuperscript{6} See the bibliography.
\textsuperscript{7} Menu-costs are a possible rationalisation of these characteristics, but the trimming approach does not depend
on it.
The main criticism to the trimming approach is that it is not obvious how to compute the optimal amount of trimming and approximate measures might not be robust\(^8\).

(iii) Trimmed estimators can deal with the problem of efficiency but they do not address the problem of discriminating permanent from transitory shocks. Dealing with the persistence issue leads to the third approach: smoothing. Cogley (1998) suggests employing an exponentially smoothing filter.

This procedure will filter away temporary shocks and give a better idea of the current inflation trend, but it does not address the problem of efficiency mentioned before.

(iv) None of the above approaches makes much use of economic theory to define core inflation. Quah and Vahey (1995) use the structural vector autoregression approach to construct measures of core inflation that draws on economic theory. They estimate a bi-variate VAR consisting of inflation and output and they define core inflation as the component of inflation that has no long-run impact on output.

One problem with this approach is that identifying assumptions are always debatable. For instance, the idea that in the long run the price level does not affect output would probably be much less debatable than Quah and Vahey's hypothesis that inflation does not affect output in the long run\(^9\).

3. The common trend model

The main hypothesis behind our approach, and probably behind the other measures of core inflation, is that price changes of all products share one common trend, which is the "real" inflation level\(^10\). However, this common trend cannot be directly observed due to idiosyncratic product price fluctuations and transitory macro fluctuations.

The markets for each product react to macro and specific shocks and the resulting price fluctuations can be decomposed into two parts. The first is common to all products and the other is specific to each product. The latter

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\(^8\) See Bakhshi and Yates (1999).
\(^9\) Wyne (1999) also makes this point. Blix (1995) assumes that the price level does not affect output in the long-run.
\(^10\) More than one trend of price changes can only be justified by improbable persistent relative productivity gains or persistent changes in preferences. Even tradable and non-tradable products can have different paths only temporarily, since it is not realistic to assume persistent real exchange rate valuation or devaluation.
reflects the specific conditions of each market — such as the price elasticity to supply and demand shocks, or, maybe, the costs of price adjustment — and should be discarded from the core inflation measure. Notice that, since market characteristics differ, there is no reason to expect that the idiosyncratic components will share the same distribution. In particular, the distribution of their standard deviations might be quite dispersed.

Even if we eliminate the idiosyncratic components, there is still the problem that macro shocks could have transitory as well as persistent effects on inflation. Common movements of products’ prices can be decomposed into one component that will disappear within one period, and another one that will persist for the following periods. Since the first component will disappear fast, it should not affect long run expectations or outcomes and, thus, it should be discarded from the core inflation measure.

Finally, monetary authorities can only affect the future level of inflation and their actions must be pre-emptive. If they are to react to what is likely to happen instead of to what has already happened, the core must lead the near future level of inflation.

Thus, our measure of core inflation should have three properties: (a) it should estimate general or common price fluctuations discarding idiosyncratic product price fluctuations; (b) it should estimate only persistent price movements discarding transitory macroeconomic effects; and (c) it should lead the future level of inflation.

Core inflation, as defined by (a) and (b), can be related to the common trend ($\mu_t$) of product prices ($\pi_{it}$) measured by the following dynamic multivariate model where the errors are heteroskedastic.

$$\pi_{it} = \mu_t + e_{it} \quad e_{it} \sim (0, \sigma_i^2) \quad i=1...N \quad (1)$$

$$\mu_t = \mu_{t-1} + \xi_t \quad \xi_t \sim (0, W)$$

In this model, idiosyncratic noises are represented by ($e_{it}$) which has specific volatility ($\sigma_i^2$), and the macro transitory component is represented by ($\xi_t$). The model was estimated using monthly data for the period [July 1994, 

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11 It is important to draw the distinction between persistent and permanent shocks to inflation, but it may be empirically difficult to estimate both shocks with any precision, especially in small samples like ours which contains only about 60 observations. In this paper we will be concerned only with permanent shocks and we will ignore persistent shocks.

12 Representing the idiosyncratic and macro transitory components as non correlated noises is the simplest way to separate components. More complex proprieties of those components would be very difficult to estimate given the size of our data sample and the number of dependent variables.
January 2000]. This is a very short sample but previous data can not be used since price dynamics in Brazil changed with the Real Plan of 1994\textsuperscript{13}.

This model cannot be estimated using standard procedures. First, the dependent variable space dimension is very large\textsuperscript{14}. Second, the dimension of this space changes with the change in the definition of IPCA which occurred in August 1999. Finally, there are too many volatilities to estimate and they can change through time.

Our approach to estimation was inspired by Cecchetti and Cogley; it combines the trimmed mean and the smoothing approaches. In the next section we analyse a simplified static version of model (1) where we connect the estimator of heteroskedastic data with the trimmed mean estimator. In the following section we insert the trimmed estimator in the dynamic model\textsuperscript{15}.

### 3.1 The static model

To motivate the trimmed mean approach as proxy for standard GLS estimator for heteroscedastic data let consider one static version for model (1). In a static framework, our main hypothesis implies that the price changes of all products ($\pi_i$) must share the same common level ($\mu$). This suggests modelling ($\pi_i$) as (2)\textsuperscript{16}, which is a simplified version of model (1).

\begin{align*}
\pi_i &\sim N(\mu, \sigma_i^2) \quad (2)
\end{align*}

This is an heteroskedastic model and the most efficient estimator of ($\mu$) is Generalised Least Squares:

\begin{align*}
E(\mu) &= (\sum \sigma_i^{-2})^{-1} \sum_j \sigma_i^{-2} \pi_j = \left(\sum \delta_j\right)^{-1} \sum \delta_j \pi_j \quad (3)
\end{align*}

Headline indexes are simple means of product prices and thus are not the most efficient estimators of ($\mu$). In fact we do not know the volatilities ($\sigma_i^2$) and it is an empirical question whether feasible GLS\textsuperscript{17} is still efficient. In our context, there are also other difficulties. As market conditions change...

\textsuperscript{13} Fiorencio and Moreira (2000).
\textsuperscript{14} 350 products before July 1999 and 512 after.
\textsuperscript{15} Headline inflation ($\pi_t$) is defined as the weighted mean of the changes in the price of products ($\pi_t$), but can be defined as the simple mean of these changes where each product is repeated proportionally to its weight. For convenience, we use the latter form.
\textsuperscript{16} The normal distribution is assumed specially because the price of each product is the result of simple means over a large set of elements.
\textsuperscript{17} Calculated with the estimated volatilities.
through time, probably do the volatilities; and as the composition of the index changes, the estimation of \((\sigma^2_t)\) becomes more precarious, even admitting its stability. Given these problems, we will look for a substitute to GLS and will introduce two assumptions.

First, we take the absolute value of the observed deviation \(|\pi_i - \mu|\) as a proxy for product price volatility \((\sigma^2_t)\). Second, we use a very simple weighting function, one that gives weight zero to observations that are beyond a certain critical point on the tails of the distribution and weight one to the others (\(\delta=1\) if \(\sigma_j<\sigma^*\) and 0 if \(\sigma_j>=\sigma^*\)). These two assumptions produce the trimmed mean as a substitute for the GLS estimator.

\[
g({\pi_i}_{1\alpha}) = \sum_{i \in I(a)} \pi_{it}, \quad I(\alpha,d) = \{i; \alpha < (j/N < 1-\alpha)\}, \quad \pi_{it(1)} < \ldots < \pi_{in(n)} \quad (4)
\]

If the distribution \((\phi_i)\) for each product has proper variances as (2) the observed distribution \(Z={\pi_i, .. \pi_n}\) of prices of all products in one month would have fat tail, and it is more probable that prices on the tails come from distributions with high variance than from distributions with low variance. Given the mentioned hypothesis trimmed mean discards prices that are under percent \((\alpha)\) and over percent \((1-\alpha)\) is a proxy to the GLS estimator.

If the price distribution is skewed, the trimmed mean can be biased. To take account of this possibility, we will consider an asymmetric trimmed mean estimator where the right-hand side coefficient is \((1-\alpha-d)\).

In this section we consider the problem of estimating the common price movement in a static framework. In this framework we will assume that if we adjust the individual price \((\pi_{it})\) by the moving average \((\pi^*_t)\) of inflation \((\pi_t)\), the distribution of \((\pi_{it} - \pi^*_t) = \z_{it} \sim \phi_i\) will be independent of time. Then, our adjusted data can be considered as realisations of the random variable \((z_i)\), which has known volatilities \((\sigma^2_t)\).

Given that GLS is the most efficient estimator, it is an empirical matter how far the trimmed mean is from it. In this framework, \((z_{it} = \pi_{it} - \pi^*_t)\) has known distribution \(\phi_i={z_{i1}, .. z_{in}}\)\(^{18}\). Using this data – the distribution of adjusted product price changes – we can calculate \((\sigma^2_t)\), the efficiency of the GLS estimator, and some descriptive statistics of the headline (IPCA) index \((z = N^{-1} \sum_i z_i)\). Table 2 shows that the IPCA distribution is right skewed and leptokurtic.

\(^{18}\) We use only data for the period [7/1994,7/2000] due the redefinition of the basket occurred after 8/2000
As already mentioned, market conditions for each product determine its volatility. As these conditions differ among products, we usually observe a very large dispersion of the volatilities. Table 1 shows that, in our sample, the volatilities vary from less than 1 to more than 20.

Table 1: Percents of the distribution of \((\sigma^2_i)\)

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>10%</th>
<th>30%</th>
<th>50%</th>
<th>70%</th>
<th>90%</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.57</td>
<td>1.41</td>
<td>2.03</td>
<td>2.65</td>
<td>5.09</td>
<td>12.77</td>
<td>23.10</td>
</tr>
</tbody>
</table>

Since we know the distribution of \((z_i \sim \phi_i)\), we can sample from it and conduct a Monte Carlo experiment to estimate the efficiency of the trimmed estimator. Steps 1-3 below were repeated 10000 times to calculate the mean and the other moments of \(g(\{\pi_i\}, \alpha)\) for each value of the grid of the trimming level \((\alpha)\).

1. Sample \(\pi_i(s) \sim \phi_i\) \(i = 1..n\)
2. Compute \(\pi(s|\alpha,d) = g(\pi_i(s), \alpha, d)\)
3. Sum \(\pi(s|\alpha,d)\) and the other moments \(\pi(s|\alpha,d)^m m=2,3,4\)

The standard deviation of the GLS estimator for this data set is (0.129). Graphs 1 and 3 show the standard deviation of the trimmed estimator calculated as a function of \((\alpha,d)\) where the simple mean corresponds to the \((\alpha = d = 0)\) case. Graph 2 shows the p-value of the test of estimation bias.
These results indicate that: (i) a larger (α) implies greater efficiency and greater probability of bias; (ii) a larger asymmetry coefficient (d) implies less efficiency and less probability of bias; (iii) trimming could double efficiency compared to the non-trimming case; (iv) the efficiency of the trimmed mean estimator is comparable to the efficiency of the GLS estimator although we do not know the volatility of the changes in the price of each product.

This exercise shows that, for our data set, we can use the trimmed mean to estimate the common level of inflation (μ) without much efficiency loss. It should be stressed that the GLS estimator requires the estimation of more than 300 parameters, whereas the trimmed mean involves only 2 parameters, and that the trimmed mean can be calculated using only data for each month. This means that we do not need hypothesis about the stability of the volatilities and that we can work with a data set where the number of components changes.

3.2 Estimation of the common trend

Now we turn to our full model (1) which allows the common level (μ) to follow a random walk. This is one possible way to discriminate between transitory and permanent shocks that affect all products jointly and that cannot be estimated using synchronic data. Core inflation is defined as \( m_t = E(\mu_t) \), the expected value of the common trend. This measure discards idiosyncratic and macro noises, as required.
\[
\pi_{it} = \mu_t + \epsilon_t \quad \epsilon_t \sim (0, \sigma^2_t) \quad i=1\ldots N \quad (1)
\]

\[
\mu_t = \mu_{t-1} + \xi_t \quad \xi_t \sim (0, W)
\]

The common trend is close to a mean of \((\pi_{it})\), so its variance should be smaller than the idiosyncratic shocks' variances \((\sigma^2_t)\). If we assume that it is much smaller and define the common trend innovation variance as a proportion of the common trend variance \((W=(1/f-1)V(\mu_{t-1}|t-1))^{19}\), it can be shown\(^{20}\) that core inflation follows:

\[
m_t = f m_{t-1} + (1-f) \left( \sum_i \sigma^2_i \right)^{-1} \sum_i \sigma^2_i \pi_i \equiv f m_{t-1} + (1-f) g(\{\pi_i\}_t, \alpha, d) \quad (5)
\]

Where the last factor is exactly the GLS estimator of the common level of the price variation in month \(t\). Since the trimmed estimator was a good substitute for GLS in the static case, we will assume without test\(^{21}\), that it will be a good for each in the dynamic case too. So, we will substitute the last factor in (5) by the trimmed mean estimator of the common level.

Given \(\psi = \{\alpha, d, f\}\), we have a family of core inflation measures \((m_t(\psi))\) indexed by \(\psi\), each of them with a specific degree of trimness and smoothness. The maximum likelihood estimator of \(\psi\) is, in this case, equivalent to minimising \(\sum (E(\pi_{it}|t-1)-m_{t-1}(\psi))^2\), which is not exactly our objective\(^{22}\). The future level of inflation can be measured, each month, by the mean inflation over the next \(h\) months \((x_t(h))^{23}\). To emphasise the leading character of core inflation, we propose to estimate \(\psi\) by minimising\(^{24}\):

\[
\text{LS}(\psi) = \sum (x_t(h)-m_t(\psi))^2 \quad (7)
\]

As this function could have more than one extreme value, we need a weighing function for the members of the core inflation family \(\{m_t(\psi)\}\) to obtain unconditioned results. So, we introduce a new, and last, hypothesis and assume that \((x_t(h) - m_t(\psi))\) follows a normal distribution\(^{25}\):

\[
x_t(h) - m_t(\psi) \sim N(0, \sigma^2) \quad (7.1)
\]

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19 This is the proportional variance dynamic bayesian model of West and Harrison (1997).
20 See the appendix.
21 We have no data for this test.
22 We want to have a good local trend and not a good one period forecast. The latter approach produces core measures with low leading capacity too.
23 \(x_t(h) = (h+1) \sum_{i=0}^{\infty} \pi_{ti}\) Where \(\pi_t\) is the headline IPCA index.
24 An alternative definition for \((p_t(h))\) would be to consider the centred moving average as Bryan and Cecchetti do. We show bellow that our definition gives better results.
25 This is a somewhat strong hypothesis, since Table 2 shows that the distribution of IPCA is leptokurtic and skewed. However, \(p_t(h)\) is an average and its distribution should tend to the normal distribution.
Using (7.1) we can obtain one weight for each of the members of our family of core \( \{m_t(\psi)\} \) using the likelihood (8) to obtain this weighted function (9). We use (10) to calculate a measure of core inflation that does not depend on \( (\psi) \).

\[
p(\psi|\Omega) \propto -0.5(\sum_t (x_t(h) - m_t(\psi))^2/T)^{-1/2} \tag{8}
\]

\[
w_\psi = \frac{p(\psi|\Omega)}{\int_\psi p(\psi|\Omega)} \tag{9}
\]

\[
E(m|\Omega) = \frac{\int_\psi p(\psi|\Omega)m_t(\psi)}{\int_\psi p(\psi|\Omega)} = \int_\psi w_\psi m_t(\psi) \tag{10}
\]

Considering the size of the data sample and the actual characteristics of the Brazilian economy we choose \( h=6 \). Results are conditional on this value, which is \textit{ad hoc}, but, we hope, will not greatly affect the basic results. Empirical results were done using a grid on \( (\psi) \) space and calculating the value of \( \{w_t(\psi_i), m_t(\psi_i)\} \) for all grid points.

The mode is defined as \( \psi_i^* = \text{argmax}_i p(\psi_i|\Omega) \).

Given that \( (x_t(h)) \) is observed only up to \( h \) months before the last month in the sample, model (7.1) is estimated without the last \( h \) months. In spite of this, it should be stressed that we can calculate up-to-date values of core inflation \( \{m_t(\psi)\} \) that do not depend on \( (h) \).

To isolate the effects of trimming, asymmetric trimming, and smoothing, we estimated restricted versions of the model and calculated the \( \psi \) that minimises (8) or, which is the same, that maximises (9) for each case. To evaluate the effect of of future mean of inflation we estimated \( (\psi) \) using the loss function \( \text{LS}^*(.) \) that has the same especificition of \( \text{LS}(.) \) but \( (x_t(h)) \) is substituted by centred moving average\(^{27} \) \( (y_t(h)) \).

The results in table 3 suggest that: (i) asymmetric trimming has a small impact on the likelihood; (ii) trimming by itself has a larger effect on the likelihood than smoothing by itself; (iii) current IPCA is a bad lead of future inflation; and (iv) we get the worst leading capacity when the core is estimated using the centred moving average of inflation.

\(^{26}\) Where \( \Omega \) is the information set.

\(^{27}\) \( y_t(h) = (2h+1)^{-1} \sum_{i=-m}^{m} \pi_{t+i} \)
The unconditioned results were done using the same grid for (ψ) space and equations (10-12). The function \( w(.) \) given by (10) is an approximation for the estimator distribution. The graphs 4-6 show the parameter marginal distribution for the 3 models, only trimmed, trimmed and smoothing, and symmetric trimmed and smoothing.

\[
\begin{align*}
\text{Graph 4: Only trim Model: Marginal Distribution of} \\
\end{align*}
\]

\[
\begin{align*}
(\alpha|\Omega) &
\end{align*}
\]

\[
\begin{align*}
(\delta|\Omega) &
\end{align*}
\]
Graphs 4-6 suggest that: (i) for all versions of the model, \((\alpha|\Omega)\) and \((\alpha+d|\Omega)\) have more than one mode, which does not recommend estimating the components of \(\psi\) by maximum likelihood; (ii) the \((\Omega)\) distribution has a nicer behaviour than the others; (iii) mode points change with model version, indicating that parameters must be estimated jointly.

Graphs 7-10 below show the path of each measure of core inflation\(^{28}\). We notice that: (i) only trimming smooths the path, as it should, since idiosyncratic components are discarded; (ii) the common trend between (IPCA, IPA, INCC) is somewhat volatile; (iii) the unconditional and trim&smooth estimator are very similar, which means that the core measures calculated using either estimators are also similar.

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\(^{28}\) Graph 8 presents a measure of core inflation that will be discussed more fully in the next section. Briefly, it is the common trend between IPCA and two other Brazilian price indexes, IPA and INCC.
Graph 7: IPCA and one version of core inflation
Unconditioned: only smooth

Graph 8: IPCA and one version of core inflation
MLE: trim and smooth

Graph 9: IPCA and unconditional (smooth&trim)
The graphs reflect the process of inflation reduction that started with the Real Plan of July 1994, as they should. Our measure of core inflation suggests that price stability could be rejected before the second half of 1997 and that the major devaluation of January 1999 had a significant impact on trend inflation. Price stability is again rejected throughout 1999. The different measures also suggest that by late 1998 the economy might be heading for deflation if policy were maintained. This helps explaining why the January 1999 devaluation did not have an even larger impact on inflation.

4. Does our measure of core inflation lead headline inflation?

Our measure of core inflation satisfies, by construction, the proprieties we mentioned above: it discards idiosyncratic and macro noises, and it is also forward-looking in the sense that it was constructed with an eye at tracking the h-step ahead moving average of inflation. But we do not know whether it is also forward-looking in the more usual sense of being a lead of headline inflation. Is it a good leading indicator? How does it compare with other leads? To answer these questions we compare the forecast capacity of our core inflation measure with a data set of non consumer prices, using a model of attraction and a standard lead model. For all cases we forecast inflation 6 months ahead.

Cecchetti (1990) suggested a multivariate dynamic model to estimate the common trend between aggregate indexes. We estimate a standard
common trend model\textsuperscript{29} with IPCA and two complementary indexes IPA\textsuperscript{30} and INCC\textsuperscript{31} to serve as a benchmark; we call it the "3 variable model".

The data is the set of IPA and INCC components. They are sub-price indexes of IGP\textsuperscript{32} that is the other main indicator of inflation in Brazil\textsuperscript{19}. The 105 components of the IPA&INCC data-set represent a very diversified set of products, from agricultural inputs, to raw materials, to investment products. This data set is "complementary" to IPCA in the sense that it has a higher probability of containing information not included in IPCA, since their components have other kind of products, and are measured with another methodology\textsuperscript{34}.

The attraction model (13) checks whether the deviation between current inflation and the selected indicator ($v_t^m$) is relevant to forecast the deviation between future and current inflation ($\pi_t$). When current inflation is above (bellow) ($v^m$), it should tend to be decreasing (increasing), which means that we should not reject the hypothesis that $\beta(0,1]$.

$$\pi_{t+6} - \pi_t = \alpha_k + \beta_k(v_t^m - \pi_t) + u_{t+6}$$
$$u_t = \rho u_{t-1} + e_t \quad e_t \sim N(0, \sigma^2_k) \quad (13)$$

As we are forecasting h-months ahead and the model has no dynamics, residuals tend to be auto-correlated. So equations were estimated with an AR(1) process for errors. This model was estimated for each of our measures of core inflation, and for each component of the IPA&INCC data set and we calculated their log likelihoods (LLH). Table 4 condenses the 109 results, ordering them in descending order of (LLH) and eliminating the intermediate lines.

Table 4 shows that: (i) only two of the 105 components of the IPCA&INCC data set have a better – although not significant – forecast capacity than our selected measure of the core, but one of them gives non-sense results ($\beta<0$); (ii) the unconditional trim&smooth and the MLE version have almost the performance; (iii) the results for the presented leads are almost

\textsuperscript{29} $x_{it} = B_{it} + D_{it} + e_{it} \quad e_{it} \sim N(0, \Sigma); \quad \mu_i = \mu_{i+1} + \xi_t \quad \xi_t \sim N(0, \nu_{it}); \quad z_{it} = \phi y_{it-1} + \xi_{it} \quad \xi_{it} \sim N(0, \nu)$, estimated using STAMP

\textsuperscript{30} IPA (Índice de Preços no Atacado) is wholesale price index.

\textsuperscript{31} INCC (Índice Nacional da Construção Civil) is a price index for housing construction.

\textsuperscript{32} IGP (Índice Geral de Preços) is a measure of "general" price level.

\textsuperscript{33} IGP is composed of 3 sub-price indexes: IPA, the production price index of industrialised products which includes 67 elements; INCC, the price index of construction which includes 38 elements; and IPC, the consumer price index.

\textsuperscript{34} IPCA is mostly measured at shopping points, and IPA & INCC are calculated from producer price lists.
the same considering the likelihood scale, but are significantly better than the other leads that have $\text{LLK} \in (52.9, 54.7)$.

Table 4: Comparison between leads variables (attraction model)

<table>
<thead>
<tr>
<th>Variable</th>
<th>LLH</th>
<th>$\beta$</th>
<th>T($\beta$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPA – Agricultural machines</td>
<td>56.895</td>
<td>-0.110</td>
<td>-2.85</td>
</tr>
<tr>
<td>INCC – Food at the workplace</td>
<td>56.350</td>
<td>0.144</td>
<td>2.61</td>
</tr>
<tr>
<td>Unconditional : Trim and Smooth</td>
<td>56.262</td>
<td>0.580</td>
<td>2.71</td>
</tr>
<tr>
<td>MLE : Trim and Smooth</td>
<td>55.799</td>
<td>0.553</td>
<td>2.51</td>
</tr>
<tr>
<td>Unconditional: only Trim</td>
<td>55.657</td>
<td>0.653</td>
<td>2.48</td>
</tr>
<tr>
<td>Centred mean</td>
<td>55.528</td>
<td>0.456</td>
<td>2.30</td>
</tr>
<tr>
<td>3 Index model</td>
<td>55.361</td>
<td>0.717</td>
<td>2.32</td>
</tr>
<tr>
<td>IPA-OG – Sugar</td>
<td>55.306</td>
<td>-0.051</td>
<td>-2.22</td>
</tr>
<tr>
<td>IPA-OG – Pharmaceutical products</td>
<td>55.239</td>
<td>0.046</td>
<td>2.10</td>
</tr>
<tr>
<td>IPA-OG – Rubber</td>
<td>55.216</td>
<td>-0.050</td>
<td>-2.16</td>
</tr>
<tr>
<td>IPA-OG – Fertilisers</td>
<td>55.202</td>
<td>-0.048</td>
<td>-2.18</td>
</tr>
<tr>
<td>INCC – Stone</td>
<td>55.124</td>
<td>0.109</td>
<td>2.04</td>
</tr>
<tr>
<td>Unconditional: only symmetric Trim</td>
<td>54.712</td>
<td>0.548</td>
<td>1.94</td>
</tr>
<tr>
<td>All others index</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPA-OG – Tissue, Clothing, Shoes</td>
<td>52.908</td>
<td>-0.019</td>
<td>-0.25</td>
</tr>
</tbody>
</table>

Table 3 and table 4 show that the best measure for core is the unconditionated and unrestricted measure. It is interesting verify if this variable ($y$) is sufficient to lead future inflation given each of the other variables of IPA&INCC data set ($v^n$), and if these others variables ($v^n$) are sufficient given ($y$). Model (14) explain future inflation by ($v^n$) using a dynamic relation, and our measure of core ($y$). Using this model we can test two hypothesis: 1) $H_0: \left( \delta_m = 0 \right) | v^n \right)$ using t-student test; and 2) $H_0: \left( \lambda_{1m} = ... = \lambda_{pm} = 0 \right) | y$ using one F-test.

$$\pi_t = \alpha_m + \delta_m y_{t-6} + \sum_k \eta_{km} \pi_{t-k} + \sum_k \lambda_{km} v^m_{t-k} + u_t \quad u_t = \rho_k u_{t-1} + e_t \quad e_t \sim \text{N}(0, \sigma_k^2) \quad \text{(14)}$$

Table 5: Comparison between lead variables (lead model)

<table>
<thead>
<tr>
<th>Variable</th>
<th>P-value</th>
<th>S</th>
<th>T((\delta))</th>
<th>(\delta)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPA-OG – Flour etc</td>
<td>0.02</td>
<td>.0303</td>
<td>2.56</td>
<td>.793</td>
</tr>
<tr>
<td>IPA-OG – Agricultural machines</td>
<td>0.02</td>
<td>.0679</td>
<td>2.25</td>
<td>.723</td>
</tr>
<tr>
<td>IPA-OG – Rubber</td>
<td>0.03</td>
<td>.0629</td>
<td>2.75</td>
<td>.883</td>
</tr>
<tr>
<td>IPA-OG – Tissue (natural)</td>
<td>0.04</td>
<td>.0403</td>
<td>2.22</td>
<td>.722</td>
</tr>
<tr>
<td>IPA-OG – Fertilisers</td>
<td>0.08</td>
<td>.0379</td>
<td>3.21</td>
<td>.989</td>
</tr>
<tr>
<td>IPA-OG – Paper etc</td>
<td>0.10</td>
<td>.0333</td>
<td>2.13</td>
<td>.699</td>
</tr>
</tbody>
</table>

Table 5 condenses the 105 results, ordering then in ascending order of p-value. Only 5 variables cannot be excluded without loss of information.
Although we have not presented all tests, in all 105 cases, we can not exclude core inflation given the others lead variables, and its coefficient has reasonable values.

This analysis does not consider that variables can lead when used in combination. With the IPA&INCC data-set, it would be a bit hard to consider all $2^{105}$ combinations of variables. Naturally, it is possible to construct a lead index using canonical correlation between future inflation and the data-set of components of IPA&INCC and theirs lags. But this is another theme.

Just to make a first description of the IPA&INCC data-set, we make the canonical decomposition of the correlation matrix between all their 105 components. The first eigenvalue has about 74% of all variation suggesting that a lot of “linear” information is organised along just one direction. The 6 variables of table 5 are the sub-set of IPA&INCC which separately adds more information to the forecast of inflation. Using this sub-set we repeat the same exercise and the first eigenvalue responds for 90% of all variation, which suggests that is not probable that analysis with more than one variable could be successful.

5. Conclusion

In this paper we build on work by other authors to develop a measure of core inflation or, more precisely, of core IPCA. We combine and extend their work in some ways. First, we define a measure of core inflation as the common trend of a multivariate dynamic model, that has, by construction, three properties. It filters idiosyncratic and transitory macro noises, and it leads the future level of headline inflation. Second, we show that the popular trimmed mean estimator of core inflation could be regarded as a proxy for the ideal GLS estimator for heteroskedastic data. Third, we employ an asymmetric trimmed mean estimator to take account of possible skewness of the distribution. Fourth, we obtain an unconditional measure of core inflation. This is a potentially important step given the “unpleasant” shape of some likelihood functions.

We have, at least, one non resolved methodological issue. The unpleasant behaviour of marginal densities reflects the original unpleasant behaviour of the loss function (7). This function has many local minima, making it difficult to choose among them. The use of (7.1) was an extreme alternative to consider all of them jointly. One interesting issue might be to
define a more adequate model to weight the members of the core inflation family.

Our main results are: (i) the trimmed and smoothed estimator produces the best measure of core inflation for our data set; (ii) smoothing by itself does contribute to the results but less than trimming by itself; (iii) our measures of core inflation constructed with reference to a forward moving average of inflation are good leads of headline inflation when compared with other price indexes and with the core estimated using the centred moving average of inflation; (iv) the unconditional and MLE estimators are similar.

It is obvious that the same approach could be applied to other data sets that share the same proprieties of IPCA: a large number of components, heteroskedasticity, and one common trend.

It should be stressed that the size of our sample is a big limitation. The Real plan is a break on Brazilian price dynamics, and the sample after July 1994 has only about 60 months, with a continued trend of inflation reduction. So there is not enough price variability information to produce robust results.

We emphasise that there is no single measure of core inflation that is best for all possible uses. The measure we develop could neither be employed as an inflation target nor be used to discriminate supply from demand shocks. But it might be helpful as a means of checking whether a given policy is on track.

Finally, our measure of core inflation suggests that the Real Plan of July 1994 did not obtain price stability before the second half of 1997\textsuperscript{35} and that the major devaluation of January 1999 had a significant impact on trend inflation.

\textsuperscript{35} We obtain almost the same results in Fiorencio and Moreira (2000) using a different methodology.
Appendix

Let:

\[ \pi_{it} = F \mu_t + e_t \quad e_t \sim (0, V_t) \quad F = (1, 1, \ldots, 1), \quad i = 1 \ldots N \]

\[ \mu_t = \mu_{t-1} + \xi_t \quad \xi_t \sim (0, W) \quad W = (1/f-1)V(\mu_{t-1}|t) \]

Using the Dynamic Bayesian model we have:

\[ (\mu_t|t) \sim (m_t, C_t) \]

\[ (\mu_t|t-1) \sim (a_t, R_t) \]

where

\[ a_t = m_{t-1} \]

\[ R_t = C_{t-1} + W = C_{t-1}/f \]

\[ A_t = R_t F Q_t^{-1} \]

\[ Q_t = F R_t F^T + V \quad \text{if the idiosyncratic errors are dominant} \]

\[ C_t = R_t A_t Q_t A_t^T = R_t - R_t F Q_t^{-1} Q_t (R_t F Q_t^{-1})' = R_t - R_t F V^{-1} F' R_t = R_t (1 - R_t \gamma) = C_{t-1}/f(1 - \gamma C_{t-1}/f) \]

\[ \gamma = F V^{-1} F' = \sum_i \frac{1}{V_i} \]

\[ \lim_{t \to \infty} C_t = f(1-f)/\gamma \Rightarrow \lim_{t \to \infty} R_t = (1-f)/\gamma \]

\[ m_t = a_t + A_t (\pi_{it} - F' a_t) = m_{t-1} + R_t F V^{-1} (\pi_{it} - F' m_{t-1}) = \]

\[ = m_{t-1} (1 - R_t F V^{-1} F) + R_t F V^{-1} \pi_{it} = m_{t-1} (1 - (1-f)/\gamma) + (1-f) \frac{1}{\gamma} \sum_i \frac{\pi_{it}}{V_i} = \]

\[ = f m_{t-1} + (1-f) \frac{1}{\gamma} \sum_i \frac{\pi_{it}}{V_i} \]
Bibliography


22. West and Harrison (1997) “Bayesian Forecasting and Dynamic models” Spring Verlag