ISSN 1518-3548

BANCO CENTRAL DO BRASIL

A Data-Rich Measure of Underlying Inflation for Brazil

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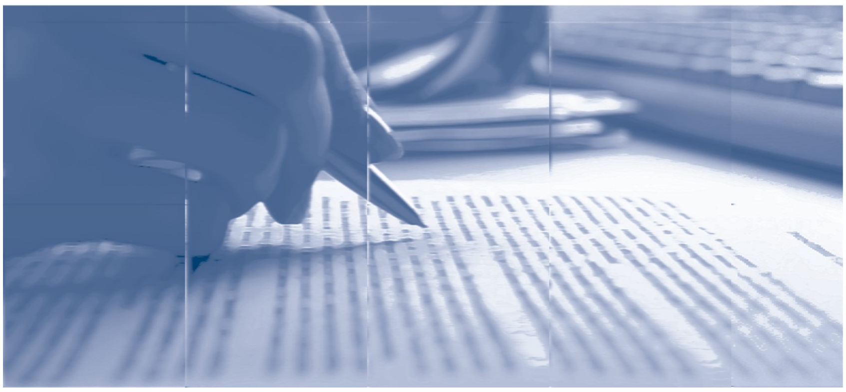
January 2020

Working Papers



516

ISSN 1518-3548
CGC 00.038.166/0001-05

Working Paper Series	Brasília	no. 516	January	2020	p. 1-31

Working Paper Series

Edited by the Research Department (Depep) – E-mail: workingpaper@bcb.gov.br

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Non-technical summary

Underlying inflation measures play a central role both in the conduct of monetary policy and in academic literature, as they represent a clearer picture of inflation, which is less susceptible to noise. Such measures, also called core inflation, are designed to represent the persistent part of inflation, therefore more closely tracking its trend. There is also some consensus that, given the complexities of inflation dynamics, it is advisable to follow a set of measures that tend to be complementary.

In this paper, we develop a still unexplored measure in Brazil using information from various sources, many of which regularly monitored by the Banco Central do Brasil (BCB). Such information – coming from prices, economic activity, monetary and financial indicators – is condensed into the FC core measure, by using a technique called Generalized Dynamic Factor Model (GDFM).

This technique allows considering not only the specific information of each month, as in the case of usual exclusion core measures, but also series dynamics, i.e., their joint behavior over time. By discarding sharp changes in specific items, exclusion methods may involuntarily ignore early signals of changes in trend inflation, which should not happen with the FC core measure.

A further advantage of the present measure is that it can be updated as soon as new data is released, instead of depending exclusively on the monthly CPI figures (in Brazil, the IPCA), as is the case with traditional core inflation measures. This feature is useful when abrupt shifts in inflation occur, as for example during 2018 temporary halt in the transportation sector.

Summing up, the resulting FC underlying inflation measure shows good performance in usual evaluation criteria. Particularly, it does not fluctuate a lot, is unbiased and displays relatively good forecasting performance compared to other measures of trend inflation. Therefore, the measure may complement the information set of the BCB in the analysis of inflation dynamics.

Sumário Não Técnico

Na condução da política monetária, assim como na literatura acadêmica, é reconhecido o papel central que as medidas de inflação subjacente desempenham, ao refletirem uma imagem mais limpa da inflação, menos suscetível a ruídos. Tais medidas, também chamadas de núcleo de inflação, procuram representar o componente mais persistente da inflação, acompanhando mais de perto a sua tendência. Também há certo consenso de que, diante das complexidades da dinâmica inflacionária, é recomendável acompanhar um conjunto de medidas, que tendem a se complementar.

Neste artigo é desenvolvida uma medida ainda não explorada no Brasil, que utiliza informações de diversas fontes, muitas das quais regularmente acompanhadas pelo Banco Central do Brasil. Esta informação – proveniente de dados de preços, de atividade econômica, monetários e variáveis financeiras – é condensada no chamado núcleo FC, utilizando-se a técnica de Modelo Generalizado de Fatores Dinâmicos (GDFM, em inglês).

Esta técnica permite que se leve em conta não apenas a informação específica de cada mês, como no caso dos núcleos por exclusão, mas também a dinâmica das séries – isto é, seu comportamento conjunto ao longo do tempo. Ao descartarem mudanças fortes de itens específicos, os núcleos por exclusão podem, involuntariamente, ignorar sinais de mudança de tendência na inflação, o que não ocorreria no núcleo FC.

Outra vantagem dessa medida é que ela pode ser atualizada à medida que novos dados são publicados, ao invés de depender exclusivamente dos dados contidos no IPCA do mês, como é o caso nos núcleos tradicionais. Esta característica é útil em momentos de mudanças bruscas na inflação, como foi o caso do episódio da paralisação dos caminhoneiros em 2018.

Conclui-se que o núcleo FC resultante possui boa performance em quesitos usualmente testados. Em particular, verificam-se uma baixa variabilidade, ausência de viés e uma boa capacidade de previsão em relação a outras medidas de tendência da inflação. Portanto, trata-se de uma medida que pode complementar o conjunto de informação do Banco Central do Brasil na análise da dinâmica inflacionária.

A Data-Rich Measure of Underlying Inflation for Brazil[*]

Vicente da Gama Machado[**]

Raquel Nadal[**]

Fernando Ryu Ramos Kawaoka[***]

Abstract

This paper proposes a new measure of underlying inflation for Brazil based on a generalized dynamic factor model (GDFM). The approach summarizes a wide set of indicators, which the Banco Central do Brasil (BCB) regularly monitors in its assessment of the inflation scenario, such as data on prices, activity, financial and monetary variables. Differently from most core inflation approaches, the model takes account of the time series dimension – by extracting the lower frequency component – as well as the cross-section dimension and is able to handle end-of-sample unbalances. To our knowledge, it is the first application of this procedure for Brazil. The resulting series exhibits lower variability, unbiasedness and a relatively good forecasting performance compared to various other measures of trend inflation. Overall, the findings suggest the novel underlying inflation measure may be an important complement to the information set used by the BCB.

Keywords: Core inflation, Dynamic Factor Model, Monetary Policy

JEL Classification: C32, E31, E32, E52

[*]We thank Francisco Figueiredo, Pedro Castro, Alisson Curatola, Euler Mello, Carlos Viana de Carvalho, seminar participants at the BCB and an anonymous referee for valuable comment and suggestions.

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1. Introduction

The general purpose of an underlying inflation measure is to identify changes in the inflation dynamics, particularly relevant in monetary policy analysis, out of an otherwise volatile headline index. This is most commonly obtained by excluding some volatile prices - either entire groups such as food and energy or using a statistical criterion such as trimmed means. Another common approach is to weigh components of the price index according to their relative volatility.

Yet one limitation of these approaches is that they generally do not consider the time dimension of price developments[2], neglecting potentially useful information in data movements over time. Energy prices, for example, are very volatile, but can at times have relatively large persistence. By mechanically excluding price groups which have persistent dynamics, early signals of changes in inflation may also be undesirably removed. Indeed, the performance of traditional exclusion core measures have been under criticism[3], despite their widespread utilization by central banks and market participants.

Another limitation of the traditional core inflation metrics is that they do not take advantage of information other than the inflation series itself and its subcomponents. For instance, wholesale prices or activity indicators may contain important information on price pressures which could be used to obtain an improved measure of core inflation.

This paper presents the FC core measure[4], a novel underlying measure of inflation for Brazil based on a dynamic common factors model presented by Cristadoro et al. (2005). Taking into account a large number of variables, many of which the Banco Central do Brasil (BCB) actually pays close attention to, the procedure considers both the time-series and the cross-section dimensions of the panel. In other words, the leading and lagging relationships among several economic variables are exploited, generating a smoothed underlying measure of inflation without phase shifts, a typical (undesirable) feature of historical moving averages.

[2] Core inflation measures based on volatility and/or persistence weighting actually do consider the time series dimension, but this comes at the cost of imposing backward-lookingness to the measure.

[3] Bean (2006) and Bullard (2011) offer interesting policymakers' views. Walsh (2011) argues food inflation should not be excluded from core measures, particularly in lower income countries, given its higher share and persistence. In Brazil, da Silva Filho & Figueiredo (2011) document the shortcomings of traditional core inflation measures, especially regarding bias and their performance in forecasting inflation.

[4] Short for "Núcleo de fatores comuns" in Portuguese.

It is worth emphasizing the FC can be updated more frequently than usual monthly measures of core inflation, allowing the assessment of the effect of specific data releases on the underlying inflation estimate.[5] A more frequently updated measure of underlying inflation may be particularly beneficial for policymakers in periods with higher uncertainty.

This seems to be the first application of a dynamic factor model to build an underlying inflation measure for Brazil[6]. The resulting FC exhibits many of the desirable properties of a core inflation measure, such as unbiasedness; the ability to track the inflation trend; and good forecasting performance. Moreover, the FC features a relatively high sensitivity to the business cycle. Therefore, it is a promising complement to the information set for monetary policy analysis in Brazil.

The rest of the paper is organized as follows. Section 2 briefly presents the related literature, while Section 3 describes the methodology for generating the underlying inflation measure. In Section 4, data is presented and the specifications of the dynamic factor model used to construct FC are discussed. Section 5 compares FC's performance with other core inflation measures, and Section 6 concludes.

2. Literature review

There is a large literature about core inflation measures, which is not surprising given their clear importance for policymakers and market participants.[7] In Brazil, the main core inflation measures are the ones developed by the BCB for the IPCA[8]. There are currently four exclusion-based measures (Ex-0, Ex-1, Ex-2 and Ex-3); two trimmed mean measures (MA and MS); and a double-weighted core measure (DP). [9]

[5] This is a clear advantage compared to traditional exclusion-based core inflation measures, in which new information is only incorporated, by definition, when new inflation data is released. Section 5.3 illustrates this feature with a real-time example.

[6] A core inflation measure for Brazil based on common factors was presented at the VIII Annual Inflation Targeting Seminar of the BCB by André Minella and Tomie Sugahara, but no subsequent paper was found.

[7] Wynne (2008) and Clark (2001) discuss conceptual issues and compare usual core inflation measures.

[8] IPCA – Extended National Consumer Price Index; the official CPI used in Brazil.

[9] Ex-0 is obtained by the exclusion of the Food-at-home and Administered Prices groups, while Ex-1 excludes 10 out of 16 items from the Food-at-home group, plus domestic fuels and vehicle fuels. Ex-2 excludes volatile items from Industrial and Food-at-home groups, from services and the whole Administered prices group. Ex-3 is similar to Ex-2, but excludes the whole Food-at-home group. The trimmed mean measure (MA) excludes

Figueiredo (2001) and da Silva Filho & Figueiredo (2014) provide a review of the main core measures and conclude that, although there is no clear superior core measure, the MS seems to reflect inflation trends slightly better than the others. Nonetheless, according to da Silva Filho & Figueiredo (2011), it is noteworthy these measures have shown poor performance in predicting inflation.

The construction of core inflation measures using weights coming from measures of persistence for each subcomponent of IPCA is another line of research in Brazil (da Silva Filho & Figueiredo, 2015; Machado & Figueiredo, 2017). Ferreira et al. (2017), in a similar fashion, add persistence by considering moving averages in the weighting scheme.

A related literature covers potential candidates for predicting inflation. Phillips Curve models and their variations, which include measures of economic activity, asset prices, and/or monetary aggregates,[10] have shown mixed results depending on countries and time span. Stock & Watson (2008), for example, provide a comprehensive review for the US using Phillips Curve, while Atkeson & Ohanian (2001) show NAIRU based inflation forecasts are generally less accurate than a naïve model.

These mixed results, according to Cecchetti, Chu & Steindel (2000), can be attributed to the use of variables which individually have poor performance in predicting inflation. This, together with the development of greater computational power, has inspired high dimensional models such as dynamic factor models and shrinkage methods. For Brazil, some papers have explored large datasets for forecasting inflation, such as Figueiredo (2010), Garcia et al. (2017) and Marçal & Silva (2018).

This paper seems to be the first to apply a dynamic factor approach to build an underlying inflation measure for Brazil. The framework is mainly based on Cristadoro et al. (2005).

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items whose monthly inflation stands, in the distribution, above the 80 percentile or below the 20 percentile. The remaining 60% are used to calculate the final monthly change. The smoothed trimmed mean indicator (MS) follows the same procedure of the MA, with a difference: before eliminating the tails, the components with infrequent changes are smoothed out. The double-weighting core measure (DP) adjusts the original expenditure weights of each item according to its relative volatility, a procedure that downweighs more volatile components.

[10] Stock & Watson (2001) and Nicoletti (2001).

Other country studies have presented underlying inflation measures using a similar approach, as for example Giannone & Matheson (2007); Amstad, Potter & Rich (2017); and Amstad, Huan & Ma (2018). Some central banks actually release similar measures of underlying inflation as part of their communication, such as the Bank of Canada (see Khan, Morel & Sabourin, 2013), and the New York Fed (see Amstad, Potter & Rich, 2017). This work is also connected to a literature estimating common factors of disaggregated inflation series, which includes Neves, Marques & da Silva (2001); Boivin et al. (2009); Reis & Watson (2010); and Stock & Watson (2016).

3. Theoretical Background

The methodology follows closely similar measures developed by Cristadoro et al. (2005) for the Euro Area and Amstad, Potter & Rich (2017) for the US, which rely on the generalized dynamic factor model (GDFM) developed by Forni et al. (2000). The model uses only a few factors to summarize relevant information from a large dataset.

Let $X_t = [x_{1t}, x_{2t}, \ldots, x_{Nt}]$ be a vector of time series and x_{1t} be the monthly inflation measured by the IPCA. x_{1t} can be decomposed as the sum of a signal $x^*_{1,t}$ – the variable of interest – and a noise component e_{1t}, which captures idiosyncratic shocks, short-run dynamics and measurement error:

$$x_{1t} = x^*_{1t} + e_{1t}. \tag{1}$$

Key to the analysis is the estimation of x^*_{1t} using information from X and from the dynamic factor model. The framework begins with a traditional factor model flavor: each variable x_{jt} from the dataset can be described as the sum of two unobserved components: a common component χ_{jt} and an idiosyncratic component ξ_{jt}. The common component is formed by a small number q of factors which capture the co-movement between the selected variables, working as proxy for the fundamental shocks that drive the behavior of inflation.

The idiosyncratic component is driven by specific shocks[11]. Hence, x_{jt} can be described as follows:

$$x_{jt} = \chi_{jt} + \xi_{jt} = \sum_{h=1}^{q} \sum_{k=0}^{s} b_{jhk} u_{ht-k} + \xi_{jt}. \tag{2}$$

In equation (2), u_{ht} represents the common factors and b_{jhk} denotes the coefficients of the k^{th} lag of factor h for variable j. Using spectral decomposition, the common component χ_{jt} can be decomposed into short-run and long-run components χ_{jt}^{S} and χ_{jt}^{L}, by aggregating waves of periodicity larger or smaller than the critical threshold of 12 months:[12]

$$\chi_{jt} = \chi_{jt}^{S} + \chi_{jt}^{L}. \tag{3}$$

Equation (3) summarizes the idea of time-series and cross-section smoothing, mentioned before. The main interest here is to obtain χ_{1t}^{L}, or the long-run common component of monthly inflation, whose estimation departs from usual factor models and rely on the generalized factor model developed by Forni et al. (2000).

The estimation procedure is divided in three steps (Forni et al., 2000). First, the spectral density matrix of the common and idiosyncratic components is estimated by a dynamic principal component analysis (Brillinger, 1981). The number of common factors is identified at this stage, allowing for the estimation of a covariance structure of the long-run component.

In the second step, the resulting variance-covariance matrices generate estimates of so-called static factors by a method of generalized principal components. In the final step, the measure of underlying inflation $\hat{\chi}_{1t}^{L}$ arises as a projection of the leads and lags of the

[11] These shocks have typically a local or sectoral nature, which monetary policy should ideally not react to, although they may at times be important enough to affect aggregate IPCA.
[12] This cut-off frequency was selected because inflation is relatively insensitive to changes in the reference rate in the short run, due to existing lags in monetary policy transmission.

estimated static factors.[13] Such a procedure exploits the superior information embedded in the cross-sectional dimension, leading to a reasonably good smoothing without the need for a large window. In other words, this procedure removes regularly observed volatility out of monthly inflation, without incurring in phase shift, which is inevitable in temporal smoothing techniques such as moving averages, for example.

The framework is also able to deal with end-of-sample unbalances, often referred to as "ragged-edge". This is done by re-estimating the covariance matrices and realigning the variables based on the most updated series to obtain estimated forecasts $\hat{\chi}^{*}_{T+h}$. Such forecasts are then used to replace missing data and to get the forecasts χ_{T+h} back from the original alignment.

4. Data

It is not clear which criteria should be used to select series to be included in the dataset. In the case of the NY Fed Underlying Inflation Gauge (UIG), Amstad, Potter & Rich (2017) state their selection is based on the experience of the NY Fed staff or on judgment.

Cristadoro et al. (2005) list three conditions for the selection of the series: 1) the chosen series must be driven by the same factors that drive core inflation; 2) a large amount of series must be selected, in order to minimize the influence of idiosyncratic noise; and 3) there should be a mix of leading, lagging and coincident series with respect to the factors. The authors then use these criteria to check whether the overall dataset is adequate for the methodology, but no specific test is applied to individual series.

As in Amstad, Potter & Rich (2017), this paper first selects series that are routinely used by the BCB to analyze and forecast headline inflation. Given the absence of formal tests for the inclusion/exclusion of individual series to/from the dataset, the results obtained with this set are afterwards compared with two other different datasets: one with price data, only, and other that uses a pre-selection criterion based on Granger causality tests, motivated by

[13] At the end of the sample, the measure must be obtained using only the contemporaneous and lagged factors.

the discussion in Boivin & Ng (2006)[14]. Appendix 1 lists the series included in the three baseline datasets.

Since the algorithm requires a balanced panel at the beginning of the sample, the start date for model estimation is determined by the shortest series on the set (December 2006).

Only seasonally adjusted versions of the datasets are used in FC estimation.[15] The seasonal adjustment is performed with the X-13 ARIMA-SEATS software, using general specifications for outlier detection, ARIMA model identification and calendar effects adjustment. Appendix 1 indicates, for each series, the chosen specification. Outliers were identified only as part of the estimation of seasonal factors and were not removed from the series. As in both Cristadoro et al. (2005) and Amstad, Potter & Rich (2017), the series are stationarized and standardized.[16]

Differently from Cristadoro et al. (2005), the seasonal adjustment and the standardization are performed recursively to generate a pseudo real-time series that uses only the subset of data available at each point of time. Real-time *vintages* of the series are not available and thus only the most recent *vintages* are used to construct the pseudo real-time datasets. It is important to notice that most price data in Brazil do not undergo revisions, except for changes in weights, which affect price aggregates periodically.

[14] According to Boivin & Ng (2006), the inclusion of every available indicator that could have an impact on inflation in dynamic factor models does not come without risks. Their results suggest factors estimated using more data do not necessarily lead to better forecasting results. The quality of the data must be taken into account, with the use of more data increasing the risk of "leakage of noise" into the estimated factors.

[15] Cristadoro et al. (2005) pre-treat the series in order to remove outliers and seasonality. Outliers are identified using the Tramo-Seats procedures and seasonality is identified using seasonal dummies and seasonal dummies interacted with a trend. The series are differenced or log-differenced in order to achieve stationarity if necessary. Finally, since the model is not scale-independent, the series are standardized by using z-score. The seasonal adjustment is not performed recursively for the real-time tests. The same is probably true for the identification of outliers and standardization, even though the authors do not explicitly state it.
It is interesting to note that Cristadoro et al. (2005) decide to seasonally adjust the series, even though they state that their choice of cut-off frequency – 1 cycle per 12 months – should eliminate seasonality. A similar point is made by Amstad, Potter & Rich (2017) when they decide to use the 1 cycle per 12 months cut-off frequency, but, in their case, no pre-treatment is performed except for the standardization. They further argue this is done to prevent revisions stemming from the seasonal adjustment procedure.

[16] This process further requires we impose an average value for the measure of underlying inflation, which is done separately from the estimation of factors. This average value matches the historical average of IPCA.

5. Results

In this section, different configurations of FC are presented and its baseline version is assessed against traditional BCB core inflation measures in terms of forecast accuracy, bias, and adherence to economic cycles.

5.1 Comparing different configurations of FC

The first estimated version of the FC was constructed using more than 500 price and non-price series, including the entire hierarchy of IPCA subcomponents. At this stage, there was no formal pre-selection criteria for the inclusion of the series. Nevertheless, many of the series were not much relevant for inflation dynamics, which generated an underlying measure with low performance in terms of smoothing and inflation forecasting when compared to current BCB measures. For practical reasons, a smaller subset with 118 series was constructed, mainly excluding IPCA subcomponents that present a relatively low weight and/or have infrequent changes (such as courses and some regulated prices).

The next step consisted on using a pre-selection scheme in order to improve the performance of the FC (Boivin & Ng, 2006). To do so, bivariate Granger causality tests between each candidate variable and the IPCA were applied considering different lag specifications. Three thresholds for the p-values of Granger tests were used: 1%, 5% and 10%. The tests were run using the full sample.

On preliminary tests[17], the dataset generated with the 1% threshold was superior to the other two datasets and was thus adopted. A few other series, not necessarily selected by any of the Granger tests, were also added to the dataset based on judgment, given that they seem natural candidates as inflation drivers. The real minimum wage, the unemployment rate and inflation indicators released by Fundação Getulio Vargas (FGV), such as the inflation monitor at closing IPCA collection day and the consumer price index (IPC) of the fourth week of the month, were the main series selected by judgement. At the end, the baseline dataset consisted of 45 series.

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[17] More specifically, the mean absolute errors of different datasets against measures of trend inflation were compared.

This baseline dataset contains much fewer series than the ones used by Cristadoro et al. (2005) and Amstad, Potter & Rich (2017)[18], which may reflect idiosyncratic features of the Brazilian inflation process. Nevertheless, this smaller dataset still contains forward looking series (such as expectations), and coincident and lagged variables, allowing the FC to have the desirable level of intertemporal smoothing.

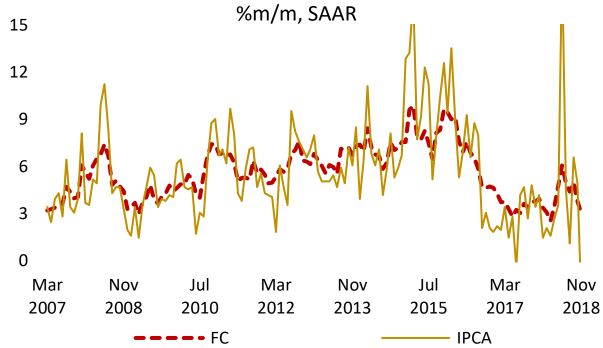
Among the selected price variables, there are series for producer and consumer inflation, including consumer indices other than the IPCA, commodity price indices, inflation expectations series from the Focus survey[19], percentiles and other core measures of the IPCA, and some IPCA subcomponents. Amid the non-price variables, there are labor-market series (number of admissions, dismissals, wages and unemployment), industrial activity series, money aggregates, fiscal, and external sector series.

The baseline model used 4 factors with 6 lags and a cut-off frequency of 12 months ($\pi/6$). Fluctuations of frequency higher than 1 cycle/year were discarded, as they capture mainly short-term dynamics and seasonality. These choices are broadly in line with Cristadoro et al. (2005) and Amstad, Potter & Rich (2017).[20]

Figure 1 compares the seasonally adjusted annualized rate (SAAR) of monthly FC to IPCA since March 2007, and clearly shows the intertemporal and cross-sectional smoothing provided by the core measure.

Figure 1 - FC and IPCA

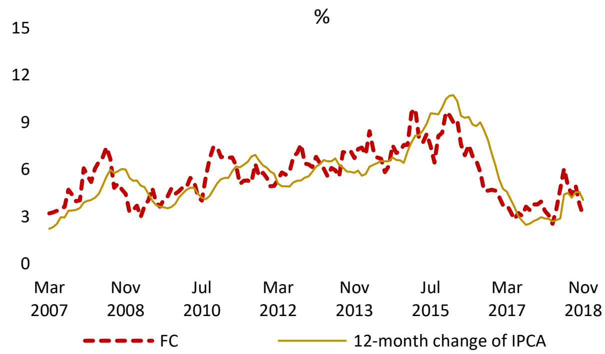
%m/m, SAAR



[18] Their dataset contains 450 and 339 series, respectively.
[19] Survey conducted by the BCB among professionals.
[20] For more on the selection decisions, see also the discussion on Table 1.

Figure 2 compares the 12-month percentage change of IPCA inflation with the monthly SAAR FC. It is noteworthy the FC anticipates large changes of IPCA, such as its downward trend after the 2008 financial crisis and its upward trend along 2015. Although both measures represent trend inflation, this occurs because the FC does not carry as much past information as does the 12-month change of IPCA. This result reinforces FC potential for the assessment of inflation dynamics.

Figure 2 - SAAR FC and 12m IPCA



Figures 3, 4 and 5 show the FC estimated with different datasets and specifications. Figure 3 compares three alternatives: one based on a mixed dataset, without Granger pre-selection, containing 118 series; another based on a dataset containing only price series (89 series, as shown in the Appendix); and the last one with pre-selected variables (the baseline FC). Figure 4 compares the baseline FC measure, which uses 4 factors, to the versions that use 2 and 6 factors; while Figure 5 shows, along with the baseline FC, a version with 12 lags instead of 6, and a version with a cut-off frequency of 6 months ($\pi/3$).

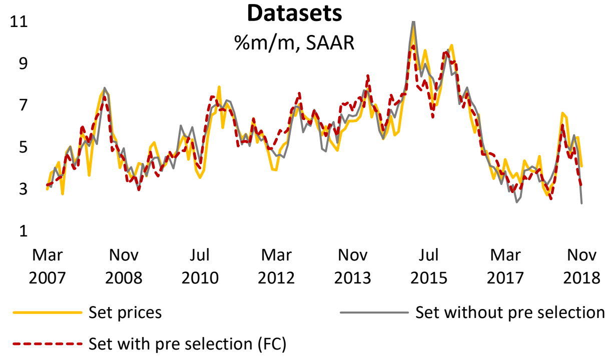


Figure 3 - FC Estimates Using Different Datasets

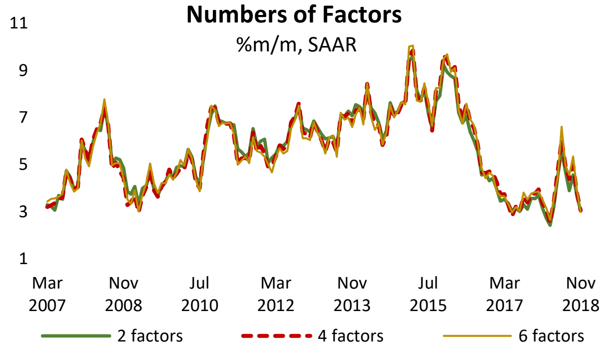


Figure 4 - FC Estimates Using Different Numbers of Factors

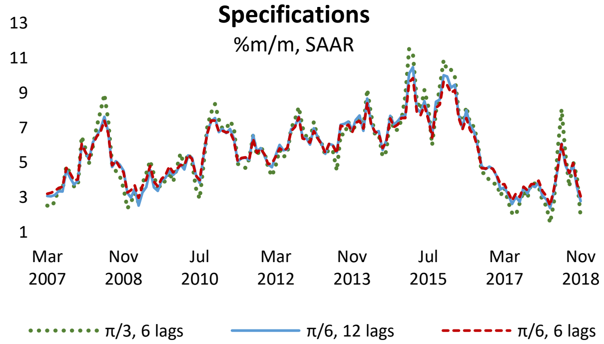


Figure 5 - FC Estimates Using Different Specifications

Changes in the number of factors do not produce visible changes to the FC measures. The use of longer lags or of a higher cut-off frequency seems to generate more volatile series, while the dataset that contains only price series generates a less volatile core measure in terms of standard deviation.

Table 1 compares these different versions of the FC based on their deviation from several measures of IPCA trend inflation.[21] Deviations are computed in annualized percentage points and expressed in terms of mean absolute error (MAE).

Table 1 – MAE of monthly SAAR FC versions, from 12/2006 to 11/2018

p.p.

	MA+3	MA+6	MA+12	MA13	MA25	MA37
4 factors (baseline FC)	1.26	1.36	1.26	0.74	0.72	0.81
2 factors	1.19	1.36	1.23	0.72	0.65	0.73
6 factors	1.23	1.38	1.25	0.74	0.71	0.82
12 lags	1.33	1.38	1.31	0.78	0.79	0.91
π/3	1.47	1.46	1.47	0.95	1.03	1.16
Set of prices	1.37	1.42	1.37	0.79	0.82	0.95
Set without Granger selection	1.24	1.38	1.29	0.73	0.78	0.92

In accordance with Table 1, the baseline FC shows the lowest errors, together with the FC estimated with 2 and 6 factors. Nonetheless, a Diebold-Mariano test for the MAE of these 3 specifications shows no evidence they are different in terms of matching IPCA trend measures. The alternative with 4 factors was the chosen to represent the FC core because it explains a greater share of variance, while allowing for more degrees of freedom. Similar choice was carried out by Cristadoro et al (2005).

5.2 Comparison to other core measures

Three desirable properties of a core inflation measure are unbiasedness; capacity to explain a substantial amount of future variation in trend inflation, producing more accurate forecasts than those generated by the headline inflation measure; and good sensitivity to economic cycles, reflecting the cyclical component of aggregated demand that reacts to monetary policy.

[21] The chosen measures of trend IPCA inflation were the 3-month moving average (MMA) of IPCA 3 months ahead (MA+3); 6MMA of IPCA 6 months ahead (MA+6); the annual changes of IPCA 12 months ahead (MA+12); the centered moving average (CMA) of 13 months (MA13); the CMA of 25 months (MA25); the CMA of 37 months (MA37).

To assess FC's performance against other core measures regarding these properties, several methods can be applied. To any evaluation, however, it is particularly important that the forecast exercise reflects a realistic setting (Amstad, Potter & Rich, 2017). In this section, statistical features of FC and of core inflation measures currently used by the BCB are compared always by means of their pseudo real time *vintages*.[22] Figure 6 compares the final estimate of FC, which incorporates the full sample, to its pseudo real time version.

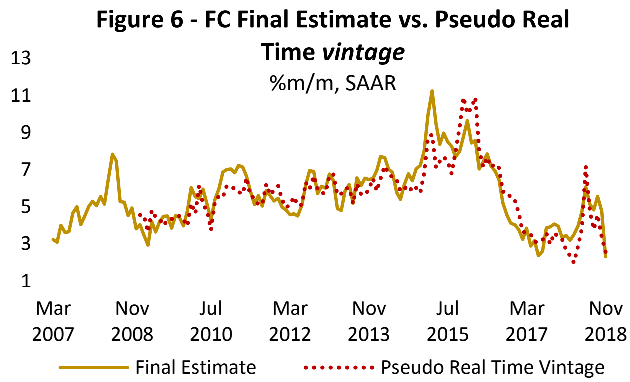


Figure 6 also draws attention to the presence of revisions in the FC series. These revisions arise mainly due to changes induced by seasonal adjustment, standardization of the series and model estimation.[23] Traditional core measures, on the other hand, are less prone to revisions, which are limited to those caused by the seasonal adjustment process. Quantitatively, FC revisions were found to be higher than those from other core measures, although they are not biased when averaged over the whole sample.

In this regard, it is worth noting the signal of FC *vintages*, expressed as seasonally adjusted annualized rates (SAAR), switched between acceleration and deceleration in 17% of the months between January 2009 and November 2018.[24] Regarding the 3-month moving average (3MMA) version of the FC *vintages*, the signal switched between acceleration and deceleration in 13% of the months. These FC stability statistics cannot be fairly compared

[22] For each month of the sample, seasonally adjusted series were produced, and the last observation was collected, generating pseudo real time *vintages*.
[23] Note that series revision is not a big issue here, since most price series in Brazil do not undergo historical revisions.
[24] The balance includes cases where the signal was neither acceleration nor deceleration in at least one of the *vintages*. Changes up to 0.10 percentage point were classified as having "stability".

with similar statistics obtained for other usual core measures, since they are revised only due to the seasonal adjustment process, while FC is also revised due to re-estimation and information set change (ragged-edge). Nonetheless, for the MS core inflation, the signal switched between acceleration and deceleration in 15% of the months, which is very similar to the figure obtained for the FC. This percentage drops to 5% when the 3MMA version of MS is considered.

Table 2 summarizes the mainly descriptive statistics of pseudo real time *vintages* from FC and core inflation measures currently tracked by the BCB (which are detailed in footnote 9), generated for January 2009 to November 2018. A moving average version of each measure is also tested, as this is shown to improve the performance of the traditional core measures.

Table 2 – Descriptive Statistics for Core Inflation Measures - 01/2009 to 11/2018

%, SAAR

		Mean	Median	Maximum	Minimum	Std. Dev.	Correlation with IPCA annual changes	Correlation with IPCA monthly changes
Monthly change	IPCA	5.78	5.47	18.97	-2.60	3.30	0.54	1.00
	Ex-0	5.43	5.43	12.01	-0.05	2.39	0.51	0.64
	Ex-1	5.63	5.47	17.46	-2.01	2.62	0.57	0.80
	Ex-2	6.04	6.45	11.06	-0.29	2.41	0.62	0.60
	Ex-3	5.97	6.30	11.34	-0.61	2.30	0.58	0.57
	DP	5.72	5.91	10.37	0.71	2.15	0.73	0.81
	MS	5.63	5.48	9.87	2.02	1.87	0.85	0.73
	MA	4.99	4.96	9.10	0.02	1.96	0.70	0.79
	FC	5.76	5.81	10.26	2.47	1.76	0.75	0.78
3MMA change	IPCA	5.78	5.62	14.34	0.92	2.59	0.72	1.00
	Ex-0	5.42	5.62	8.83	1.50	1.86	0.68	0.73
	Ex-1	5.63	5.36	13.10	0.74	2.03	0.74	0.89
	Ex-2	6.08	6.40	9.42	0.93	2.18	0.69	0.67
	Ex-3	6.01	6.51	9.07	1.24	2.04	0.67	0.64
	DP	5.72	6.05	9.36	1.63	1.91	0.84	0.88
	MS	5.63	5.70	9.50	2.55	1.76	0.91	0.84
	MA	4.99	5.04	8.46	1.26	1.75	0.82	0.87
	FC	5.76	5.80	9.47	2.79	1.68	0.82	0.89

According to Table 2, the FC measure more closely matches the average of the IPCA monthly changes, while the MA is the one with the largest difference to the IPCA in this respect. The FC also shows the lowest variance and the second largest correlation with IPCA annual changes. Regarding 3MMA versions of the measures, it is interesting to note the FC does not seem to benefit much in terms of variability, which indicates this additional smoothing may not be necessary. The moving average naturally lowers the variance of other measures, but the FC still shows the smallest standard deviation.

The next step consisted in assessing whether the BCB traditional core measures and the FC display the desirable properties of a core inflation measure. To assess bias, the following regression was estimated for each measure and a given horizon h:

$$\pi_{t+h} - \pi_t = \alpha_h + \beta_h(\pi_t - \pi_t^m) + \varepsilon_{t+h}, \tag{4}$$

where π_{t+h} is the annual change of IPCA headline inflation 12-month ahead; π_t is the monthly SAAR IPCA; and π_t^m is either the monthly or the 3MMA SAAR of each core inflation measure[25]. Unbiasedness is indicated by $\alpha_h = 0$. If α_h is higher (smaller) than zero, then variations of core inflation tend to overstate (understate) future changes in the headline inflation. As the core inflation measures aim to track trend inflation, the term $(\pi_t - \pi_t^m)$ in (4) can be interpreted as the transitory component of the monthly inflation at time t; or a deviation to be reverted as temporary effects dissipate over time. When the transitory component is completely filtered by the core measure, then $\beta_h = -1$. If β_h is negative but less than (greater than) one in absolute value, then the deviation between headline inflation and the measure of core inflation is overstating (understating) the magnitude of subsequent changes in inflation, and thus the current transitory deviation in inflation (Amstad, Potter & Rich, 2017).

Table 3 summarizes the results of the estimations of equation (4), from January 2009 to November 2018.

[25] Equations were estimated by OLS with correction for residuals autocorrelation (HAC – Newey-West).

Table 3 – Bias test[1/]

	Monthly change		3MMA change	
	$\alpha_{12} = 0$	$\beta_{12} + 1 = 0$	$\alpha_{12} = 0$	$\beta_{12} + 1 = 0$
Ex-0	0.27	0,30***	0.26	0.13
	(0.234)	(0.096)	(0.198)	(0.110)
Ex-1	0.17	0.18	0.18	-0.20
	(0.242)	(0.126)	(0.193)	(0.144)
Ex-2	-0.33	0,20**	-0,39*	0,18*
	(0.212)	(0.082)	(0.204)	(0.103)
Ex-3	-0.27	0,19**	-0,35*	0.14
	(0.200)	(0.075)	(0.189)	(0.092)
MA	0,92***	-0.15	0,92***	-0.21
	(0.212)	(0.107)	(0.209)	(0.134)
MS	0.18	0.00	0.17	0.00
	(0.201)	(0.095)	(0.200)	(0.130)
DP	0.06	-0.10	0.04	-0.10
	(0.215)	(0.122)	(0.207)	(0.161)
FC	0.14	0.08	0.17	0.10
	(0.195)	(0.084)	(0.199)	(0.117)

1/ ***, **, * denote statistically significant coefficients at the 1%, 5% and 10% level.

At the 5% level, the null hypothesis of $\alpha_{12} = 0$ is rejected only for the MA core inflation measure[26]. The hypothesis of $\beta_{12} = -1$ is rejected for the monthly variations of Ex-0, Ex-2 and Ex-3 core measures, which indicates overestimation of the transitory deviation in inflation[27]. For all other core measures, including FC, no significant bias in forecasting future variations of the IPCA headline is found. Nevertheless, it is important to notice that the absence of bias found for the FC is partially explained by its construction, as mentioned in footnote 16.

To assess the capacity of core inflation measures to explain a substantial amount of the future variation in inflation and their ability to track trend headline inflation, the alternative core inflation measures were directly compared to various moving averages of the

[26] The MA underestimation bias probably reflects its calculation procedure. This measure is obtained by symmetrically trimming the tails of the distribution of IPCA changes, which is, in fact, asymmetric to the right.
[27] The overestimation of the transitory deviation by the Ex-0, Ex-2 and Ex-3 measures reflects the exclusion of administered prices with lower volatility.

IPCA, either centered (CMA) or forward looking. These deviations are presented in terms of MAE in Table 4.

Table 4 – MAE of Core Inflation Measures - 01/2009 to 11/2018

%, SAAR

		MA3 at t+3	MA6 at t+6	MA12 at t+12	CMA13	CMA25	CMA37
Monthly change	Ex-0	2.06	2.11	1.90	1.74	1.68	1.69
	Ex-1	2.07	2.06	1.82	1.64	1.57	1.56
	Ex-2	1.99	1.94	1.79	1.51	1.37	1.46
	Ex-3	1.99	1.91	1.71	1.52	1.34	1.39
	MA	1.88	1.80	1.69	1.31	1.31	1.43
	MS	1.72	1.65	1.54	0.98	0.90	1.13
	DP	1.74	1.67	1.58	1.17	1.16	1.32
	FC	1.60	1.49	1.45	0.89	0.69	0.83
3MMA change	Ex-0	1.89	1.87	1.61	1.34	1.20	1.15
	Ex-1	1.77	1.72	1.53	1.13	1.03	1.13
	Ex-2	1.99	1.87	1.65	1.36	1.14	1.23
	Ex-3	1.95	1.81	1.55	1.36	1.07	1.16
	MA	1.83	1.77	1.65	1.13	1.07	1.21
	MS	1.77	1.63	1.53	0.89	0.76	1.04
	DP	1.67	1.68	1.54	0.98	0.91	1.10
	FC	1.66	1.53	1.50	0.86	0.69	0.81

According to Table 4, for monthly changes, the FC shows the best performance in terms of forecasting and smoothing, followed by the DP and MS measures. Overall the MAEs are smaller when the usual core measures are presented in 3MMA.[28] Even in this case, the FC performance is still the best performing measure. Table 4 also confirms the relatively good performance of the MS in comparison with other BCB core measures, in line with da Silva Filho & Figueiredo (2014).

[28] Interestingly, this effect is not clearly present for MS and FC measures. This happens because these measures already bring some smoothing technique in their calculation methodologies.

The forecasting performance of the core measures can also be measured by computing out-of-sample MAEs from the estimations of equation (4), as shown in Table 1. It is worth emphasizing this test compares the forecasting performance of a "bias-corrected" version of each core inflation measure, instead of the measure itself.[29] Table 5 exhibits the MAEs from this exercise.

Table 5 – MAE of Core Inflation Measures with bias correction – 01/2009 to 11/2018

%, SAAR

	Monthly change	3MMA change
Ex-0	1.86	1.64
Ex-1	1.82	1.59
Ex-2	1.80	1.80
Ex-3	1.72	1.72
MA	1.56	1.56
MS	1.56	1.62
DP	1.64	1.67
FC	1.60	1.83

The results from Table 5 are comparable to the ones exhibited in the "MA12 at t+12" column from Table 4. The correction benefited mainly the MA measure, which starts to figure between the cores with the best performance. In this particular case, the FC is no longer competitive.

Sensitivity of the FC measure to economic activity is also tested. The exercise consists in running, with quarterly data, the following Phillips Curve[30] for the FC and for other competing core measures π_t^m:

$$\pi_t^m = \alpha\pi_{t-1} + \beta E(\pi_{t+4}) + (1-\alpha-\beta)\pi_t^* + \gamma h_{t-i} + \varepsilon_t \tag{5}$$

[29]As Rich & Steindel (2005) postulate, a good core inflation measure should be simple and easily understandable by the "public". In this sense, core inflation numbers themselves should work as a reliable measure of future inflation; not an adapted version of them.

[30] Since the exercise involves a hybrid NK Phillips curve, we estimate the regressions using the generalized method of moments (GMM) as a solution to the endogeneity problem. The following instruments were included: lagged inflation from 1 to 4 quarters, lagged output gap, lagged IC-Br and a proxy for supply shocks (difference from producer prices to a consumer price index).

where π_{t-1} represents the lagged headline IPCA; π_{t+4} represents 12-month ahead IPCA expectations from the Focus Survey, and π_t^* denotes foreign inflation measured by changes in the Commodities Index – Brazil (IC-Br) in R$ units. The output gap, denoted by h_{t-i}, was built with a combination of the industrial capacity utilization gap and the unemployment gap, both obtained using HP filtration.

Table 6 – Sensitivity to Economic Cycles[1/]

	γ	R^2
Ex-0	0.24***	0.78
	(0.118)	
Ex-1	0.07	0.84
	(0.113)	
Ex-2	0.44***	0.80
	(0.153)	
Ex-3	0.48***	0.75
	(0.133)	
MA	0.18**	0.83
	(0.106)	
MS	0.00	0.85
	(0.079)	
DP	0.12	0.86
	(0.083)	
FC	0.23***	0.83
	(0.073)	

1/ ***, **, * denote statistically significant coefficients at the 1%, 5% and 10% level.

Focusing on parameter γ, Table 6 shows the Ex-0, Ex-2, Ex-3, MA and FC core measures have a statistically significant response to movements in activity at the 5% level.[31] For the FC, this result comes as no-surprise, given that activity variables are present in its formulation. Therefore, the FC measure performs well when compared to other core measures. The only two measures which are clearly superior in this criterion are Ex-2 and Ex-3, which BCB (2018a) already showed to display good adherence to economic cycles.

[31] A simple correlation analysis between each core inflation series and the measure of output gap shows qualitatively similar results.

5.3 Assessing the effects of specific data releases

As mentioned in the introduction, an important feature of the FC core measure is that it allows for the assessment of the current stance as new data arrives. This section illustrates this FC feature using as an example data from June 2018. In this month, a particular shock coming from a temporary halt in the truck transportation sector caused a spike in monthly inflation.[32]

Despite the transitory nature of the shock, which affected mainly food prices, some effect on underlying inflation was expected to arise. While the June reading of exclusion-based core measures were only available after the IPCA release, the FC measure could be previously estimated.

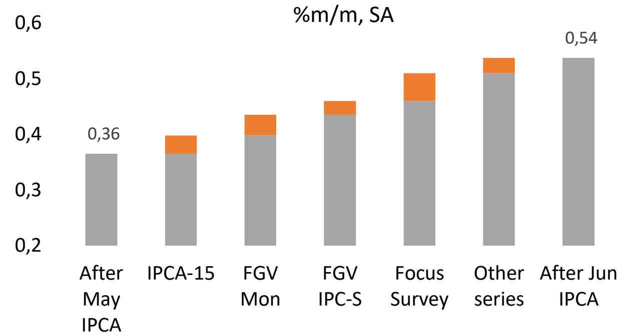
In this exercise, the path of June 2018 FC measure between May and June 2018 IPCA releases is estimated (Figure 7). The orange bars show the impact of additional data on the intermediate estimates of the FC, focusing on the release of key inflation indices, such as the IPCA-15[33], IPC-S and inflation monitor, from FGV, and the 12-month-ahead expectation of the IPCA inflation, from Focus Survey.

It is worth noting that the total impact from these developments was relatively smaller on the FC than on other core measures. In seasonally adjusted terms, the average of the seven core measures followed by the BCB rose from 0.16 in May to 0.42 in June.

Therefore, as we have shown, the FC allows for a real-time assessment of underlying inflation (particularly important during a period of sharp rise in prices) while at the same time providing a relatively smoother picture of it.

[32] For more details on the particular effects, see BCB (2018b).
[33] Flash estimate of IPCA that considers an overlapping sampling period.

Figure 7 - Jun/18 FC sensitivity to new data



6. Conclusions

This paper presents the FC, a novel measure of underlying inflation for Brazil based on a GDFM. The procedure considers both the time series and the cross-section dimensions of the dataset, achieving at the same time volatility reduction and smoothness without imposing a phase shift, a common feature in historical moving average procedures. Another important advantage is that FC benefits from the real-time data flow, since it can be updated whenever an important piece of new information is available. It is worth noting the FC summarizes information from a large number of indicators, which are actually part of the BCB information set. As a minor limitation to this novel underlying measure of inflation, it is not as easily verifiable and understandable by the public as traditional exclusion methods, since it requires a specific model and a fair amount of economic variables. Also, compared to traditional exclusion methods, the FC is subject to higher revisions, although they have not shown to be relevant in a long-term perspective, and more importantly, are not biased.

After testing several alternative datasets and model parameterizations, the resulting FC exhibited unbiasedness in relation to the IPCA; and a good accuracy in predicting several metrics of headline trend inflation compared to a random walk process and to traditional BCB core inflation measures. Besides these desirable properties, FC still showed good sensitivity to economic cycles, as its fluctuations are well explained by changes in the output gap. According to tests implemented in this paper, none of the traditional core measures currently observed by the BCB meets so well all these properties at once. Therefore, the FC seems to be a promising complement to monetary policy analysis by the BCB, providing an early, non-noisy signal of inflation changes.

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Appendix 1: List of series

Table A.1 - List of series used in the pre-selected set version

"Without pre-selection" set	Price Set	Pre-selected Set	**Prices**	Seas Adjustment	Unit	Start Date
Y	Y	Y	IPCA	Mult	pch	Dec-99
Y	Y	Y	IPCA15	Mult	pch	Apr-00
Y	Y	Y	FGV-Monitor W4	Add	pch	Jan-06
Y	Y	Y	FGV-Monitor Ponta W4	Add	pch	Dec-06
Y	Y	Y	FGV-IPCS W4	Mult	pch	Mar-04
Y	Y	Y	FGV-IPCS Regional W4	Add	pch	Jan-06
N	Y	Y	Bakery	Mult	pch	Dec-99
N	Y	Y	Oils and fats	Mult	pch	Dec-99
N	Y	Y	Cleaning Articles	Mult	pch	Dec-99
N	Y	Y	Household Articles	Mult	pch	Dec-99
Y	Y	Y	Furnishings and Utensils	Mult	pch	Dec-99
N	Y	Y	Menswear	Mult	pch	Dec-99
Y	N	Y	IPA-Broad Producer Price Index W3	Mult	pch	Dec-99
Y	N	Y	FOCUS Survey W4	Add	pch	Jan-03
N	N	Y	IPCA Percentile 55	Add	pch	Dec-99
N	N	Y	IPCA Percentile 74.5	Add	pch	Dec-99
N	N	Y	IPCA Percentile 81	Add	pch	Dec-99
N	N	Y	FOCUS Survey 12M03	No	pch	Jan-02
N	N	Y	FOCUS Survey 12M04	No	pch	Jan-02
N	N	Y	FOCUS Survey 12MS03	No	pch	Jan-02
N	N	Y	FOCUS Survey 12MS04	No	pch	Jan-02
			Real Variables			
Y	N	Y	FGV Industry IE Survey	Auto	pch	Jan-01
Y	N	Y	FGV Industry Stocks	Auto	pch	Jan-01
Y	N	Y	FGV Consumer IE Survey	Auto	pch	Sep-05
Y	N	Y	PIM Industrial Production - IT	Auto	pch	Jan-02
Y	N	Y	Goods Import	Auto	pch	Jan-00
Y	N	Y	Domestic Public Debt - Federal	Auto	pch	Jan-00
Y	N	Y	External Public Debt - Federal	Auto	pch	Jan-00
Y	N	Y	Public Sector Debt - % GDP	Auto	chg	Dec-01
Y	N	Y	Central Government Expenditures	Auto	pch	Jan-00
			Labor			
Y	N	Y	CAGED Dismissal Construction	Auto	pch	Jan-04
Y	N	Y	CAGED Dismissal Commerce	Auto	pch	Jan-04
Y	N	Y	CAGED Income Admission	Auto	pch	Jan-03
Y	N	Y	Minimum Wage	Auto	pch	Jan-03
Y	N	Y	Unemployment Rate	Auto	pch	Jan-03
			Financial Variables			
Y	N	Y	ICBR-Commodity Index Brazil - Total	No	pch	Dec-99
Y	N	Y	ICBR Agriculture	No	pch	Dec-99
Y	N	Y	ICBR Metals	No	pch	Dec-99
Y	N	Y	ICBR Energy	No	pch	Dec-99
Y	N	Y	CRB Index	No	pch	Dec-99
Y	N	Y	Exchange rate (R$/Dollar)	No	pch	Dec-99
Y	N	Y	Exchange rate (R$/Euro)	No	pch	Jan-00
Y	N	Y	360-day Pre-DI Swap rate	No	chg	Jan-00
			Money variables			
Y	N	Y	Money Stock: M4	Auto	pch	Jan-00
Y	N	Y	Expanded Monetary Base	Auto	pch	Jan-00

Table A.2 - List of series used in the other 2 versions

"Without pre-selection" set	Price Set	Pre-selected Set	Prices	Seas Adjustment	Unit	Start Date
Y	Y	N	FGV-Monitor Week1	Add	pch	Jan-06
Y	Y	N	FGV-Monitor W2	Add	pch	Jan-06
Y	Y	N	FGV-Monitor W3	Add	pch	Jan-06
Y	Y	N	FGV-Monitor Ponta W1	Add	pch	Dec-06
Y	Y	N	FGV-Monitor Ponta W2	Add	pch	Dec-06
Y	Y	N	FGV-Monitor Ponta W3	Add	pch	Dec-06
Y	Y	N	FGV-IPCS W1	Mult	pch	Mar-04
Y	Y	N	FGV-IPCS W2	Mult	pch	Mar-04
Y	Y	N	FGV-IPCS W3	Mult	pch	Mar-04
Y	Y	N	FGV-IPCS Regional W1	Add	pch	Jan-06
Y	Y	N	FGV-IPCS Regional W2	Add	pch	Jan-06
Y	Y	N	FGV-IPCS Regional W3	Add	pch	Jan-06
N	Y	N	Foods and Beverages	Mult	pch	Dec-99
Y	Y	N	Food at Home	Mult	pch	Dec-99
N	Y	N	Cereals, leguminous and oilseeds	Mult	pch	Dec-99
N	Y	N	Flour and pastes	Mult	pch	Dec-99
N	Y	N	Tubers, roots and vegetables	Mult	pch	Dec-99
N	Y	N	Sugar and derivates	Mult	pch	Dec-99
N	Y	N	Greens and Vegetables	Mult	pch	Dec-99
N	Y	N	Fruits	Mult	pch	Dec-99
N	Y	N	Meats	Mult	pch	Dec-99
N	Y	N	Fish	Mult	pch	Dec-99
N	Y	N	Industrialized Meats and Fish	Mult	pch	Dec-99
N	Y	N	Poultry and Eggs	Mult	pch	Dec-99
N	Y	N	Milk and derivates	Mult	pch	Dec-99
N	Y	N	Beverages and Infusions	Mult	pch	Dec-99
N	Y	N	Tinned foods and Jams	Mult	pch	Dec-99
N	Y	N	Salt and Condiments	Mult	pch	Dec-99
Y	Y	N	Food away from home	Mult	pch	Dec-99
N	Y	N	Housing	Mult	pch	Dec-99
Y	Y	N	Charges and Maintenance	Mult	pch	Dec-99
N	Y	N	Rent and Taxes	Mult	pch	Dec-99
N	Y	N	Repairs	Mult	pch	Dec-99
Y	Y	N	Fuels and Energy	Mult	pch	Dec-99
N	Y	N	Fuels (domestic)	Mult	pch	Dec-99
N	Y	N	Residential Eletric Power	Mult	pch	Dec-99
N	Y	N	Furniture	Mult	pch	Dec-99
N	Y	N	Utensils and Decorations	Mult	pch	Dec-99
N	Y	N	Items of Bed, Table and Bath	Mult	pch	Dec-99
Y	Y	N	Electroeletronic Devices	Mult	pch	Dec-99
N	Y	N	Household Appliances and Equipment	Mult	pch	Dec-99
N	Y	N	TV sets, Stereos, and Computers	Mult	pch	Dec-99
Y	Y	N	Repairs and Maintenance	Mult	pch	Dec-99
N	Y	N	Wearing Apparel	Mult	pch	Dec-99
Y	Y	N	Clothes	Mult	pch	Dec-99
N	Y	N	Women's clothing	Mult	pch	Dec-99
N	Y	N	Children's wear	Mult	pch	Dec-99
Y	Y	N	Footwear and Accessories	Mult	pch	Dec-99
Y	Y	N	Jewelry and Bijoux	Mult	pch	Dec-99
Y	Y	N	Tissues and Haberdashery	Mult	pch	Dec-99
Y	Y	N	Transportation	Mult	pch	Dec-99
N	Y	N	Public Transportation	Mult	pch	Dec-99
N	Y	N	Personal Vehicle	Mult	pch	Dec-99
N	Y	N	Fuels (vehicle)	Mult	pch	Dec-99
N	Y	N	Health and Personal Care	Mult	pch	Dec-99
Y	Y	N	Pharmaceutical and Optical Products	Mult	pch	Dec-99
N	Y	N	Pharmaceutical Products	Mult	pch	Dec-99
N	Y	N	Optical Products	Mult	pch	Dec-99
Y	Y	N	Health Services	Mult	pch	Dec-99
N	Y	N	Medical and Dental Services	Mult	pch	Dec-99
N	Y	N	Hospital and Laboratory Services	Mult	pch	Dec-99
N	Y	N	Health Care	Mult	pch	Dec-99
Y	Y	N	Personal Care	Mult	pch	Dec-99
N	Y	N	Personal Hygiene	Mult	pch	Dec-99
N	Y	N	Personal Expenses	Mult	pch	Dec-99
Y	Y	N	Personal Services	Mult	pch	Dec-99
Y	Y	N	Recreation, Smoke and Photography	Mult	pch	Dec-99
N	Y	N	Recreation	Mult	pch	Dec-99
N	Y	N	Smoke	Mult	pch	Dec-99

N	Y	N	Photography and Filming	Mult	pch	Dec-99
N	Y	N	Education	Mult	pch	Dec-99
Y	Y	N	Courses, Reading and Stationery Items	Mult	pch	Dec-99
N	Y	N	Regular Courses	Mult	pch	Dec-99
N	Y	N	Reading	Mult	pch	Dec-99
N	Y	N	Stationery Items	Mult	pch	Dec-99
N	Y	N	Another Courses	Mult	pch	Dec-99
Y	Y	N	Communication	Mult	pch	Dec-99
Y	N	N	IPA-Broad Producer Price Index W1	Mult	pch	Dec-99
Y	N	N	IPA-Broad Producer Price Index W2	Mult	pch	Dec-99
Y	N	N	FOCUS Survey W1	Add	pch	Jan-03
Y	N	N	FOCUS Survey W2	Add	pch	Jan-03
Y	N	N	FOCUS Survey W3	Add	pch	Jan-03
			Real Variables			
Y	N	N	FGV Industry IC Survey	Auto	pch	Jan-01
Y	N	N	FGV Industry ISA Survey	Auto	pch	Jan-01
Y	N	N	FGV Consumer IC Survey	Auto	pch	Sep-05
Y	N	N	FGV Consumer ISA Survey	Auto	pch	Sep-05
Y	N	N	IBC-BR	Auto	pch	Jan-03
Y	N	N	PIM Industrial Production - Intermediate Goods	Auto	pch	Jan-02
Y	N	N	PIM Industrial Production - K	Auto	pch	Jan-02
Y	N	N	PIM Industrial Production - Durable Goods	Auto	pch	Jan-02
Y	N	N	PIM Industrial Production - Non Durable Goods	Auto	pch	Jan-02
Y	N	N	PMC Retail trade - Restricted	Auto	pch	Jan-03
Y	N	N	PMC Retail trade - Expanded	Auto	pch	Jan-03
Y	N	N	EPE	Auto	pch	Jan-00
Y	N	N	Savings	Auto	pch	Jan-00
Y	N	N	Current Account	Auto	lin	Jan-00
Y	N	N	Goods Export	Auto	pch	Jan-00
Y	N	N	Terms-of-trade	Auto	pch	Jan-00
Y	N	N	Domestic Public Debt - States	Auto	pch	Jan-00
Y	N	N	Domestic Public Debt - Cities	Auto	pch	Jan-00
Y	N	N	External Public Debt - States	Auto	pch	Jan-00
Y	N	N	External Public Debt - Cities	Auto	pch	Jan-00
Y	N	N	Internal Public Sector Debt - % GDP	Auto	chg	Dec-01
Y	N	N	IRPF	Auto	pch	Jan-00
Y	N	N	IRPJ	Auto	pch	Jan-00
Y	N	N	PIS/PASEP	Auto	pch	Jan-00
Y	N	N	CLPJ	Auto	pch	Jan-00
Y	N	N	Total Revenue	Auto	pch	Jan-00
Y	N	N	Above the Line Primary	Auto	lin	Jan-00
Y	N	N	Primary BCB	Auto	lin	Dec-01
			Labor			
Y	N	N	CAGED Admission	Auto	pch	Jan-04
Y	N	N	CAGED Admission Transformation	Auto	pch	Jan-04
Y	N	N	CAGED Admission Construction	Auto	pch	Jan-04
Y	N	N	CAGED Admission Commerce	Auto	pch	Jan-04
Y	N	N	CAGED Admission Services	Auto	pch	Jan-04
Y	N	N	CAGED Dismissal	Auto	pch	Jan-04
Y	N	N	CAGED Dismissal Transformation	Auto	pch	Jan-04
Y	N	N	CAGED Dismissal Services	Auto	pch	Jan-04
Y	N	N	CAGED Balance	Add	pch	Jan-04
Y	N	N	CAGED Balance Transformation	Add	pch	Jan-04
Y	N	N	CAGED Balance Construction	Add	pch	Jan-04
Y	N	N	CAGED Balance Commerce	Add	pch	Jan-04
Y	N	N	CAGED Balance Services	Add	pch	Jan-04
Y	N	N	CAGED Income Admission - Services	Auto	pch	Jan-04
Y	N	N	CAGED Income Dismissal	Auto	pch	Jan-03
Y	N	N	CAGED Income Dismissal - Services	Auto	pch	Jan-04
			Financial Variables			
Y	N	N	IBOVESPA Stock Index	No	pch	Jan-00
Y	N	N	Selic Interest rate	No	chg	Jan-00
Y	N	N	EMBI	No	pch	Jan-00
			Money variables			
Y	N	N	Money Stock: M1	Auto	pch	Jan-00
Y	N	N	Money Stock: M2	Auto	pch	Jan-00
Y	N	N	Money Stock: M3	Auto	pch	Jan-00