Identification of Monetary Policy Shocks and Their Effects: FAVAR Methodology for the Brazilian Economy*

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Abstract

This paper applies the factor-augmented vector autoregressive (FAVAR) methodology to analyze the impact of monetary policy shocks on the Brazilian economy, using 125 monthly series for the period between January 1995 and September 2009. Overall, the results obtained were consistent with the economic theory and no price puzzle was observed. The paper also compared the FAVAR with VAR methodologies, concluding that the results were very similar under both methodologies and that the gain of using the FAVAR methodology is very limited when Brazilian data are used to study the effects of monetary shocks.

Keywords: FAVAR, Monetary Policy, Principal Component.

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1. Introduction

In recent years, there has been a worldwide effort to promote institutional changes that increase formalization and transparency in the conduct of monetary policy. An example of this change is the increasing number of countries operating under inflation targeting regimes. While in 2000 only 11 countries had adopted inflation targeting, in 2010 this number increased to 26 (Roger, 2010). In Brazil, this trend became apparent through the creation of the Central Bank's Monetary Policy Committee (COPOM – *Comitê de Política Monetária do Banco Central*) in 1996 and the adoption of a flexible exchange rate system and inflation targeting in 1999. These changes were particularly significant because they consolidated a pattern of economic stabilization after a long period of runaway inflation. Due to this new economic environment and institutional framework, monetary policy has resumed its role as an instrument used to promote short-term adjustments.

Not surprisingly, interest in studying the policy transmission mechanism has been growing. This is justified, as explained in Bernanke and Mihov (1998), because the efficient measurement of policy effects is crucial to their precise development by policymakers. At the same time, Christiano et al. (2000) emphasize that empirical studies are used to assist in the selection of alternative quantitative general equilibrium models.

Thus, this paper is designed to contribute to the advancement of the study of monetary policy via an empirical analysis by examining Brazilian data using the methodology proposed in BBE (2005),[1] which is known as the factor-augmented vector autoregressive (FAVAR) methodology. This methodology differs from the methods that are traditionally used in that it considers a much richer information set, approaching the information set used by the monetary authorities. This richer information set is due to the inclusion of common factors extracted from a set of macroeconomic series in the VAR.

This study used monthly series covering the post-Real period from January 1995 to September 2009. The FAVAR approach generated results consistent with the economic theory. For example, in opposition to Minella (2003), a negative monetary shock caused a decrease in the price level. Thus, there was no evidence of a price puzzle. Moreover, in comparing this methodology with the vector autoregressive (VAR) framework that is usually employed, it was possible to conclude that the informational gain caused by adding the factor model is not substantial. This result probably emerges because it is impossible to capture the information contained in the extensive set of Brazilian macroeconomic series considered in this work by using only a few factors.

The next section presents a brief review of the existing literature on monetary policy, emphasizing the identification of its shocks and their impacts on macroeconomic variables. Section 3 describes the FAVAR methodology that will be used

[1]Bernanke et al. (2005) will be referenced in the remainder of the text as BBE (2005).

during the empirical test, focusing on its econometric particularities in relation to other methods and the benefits resulting from these particularities. Section 4 presents the empirical results obtained. Finally, Section 5 presents the principal conclusions of this paper.

2. Literature Review

Since the work of Bernanke and Blinder (1992) and Sims (1992), the VAR has become the standard methodology used in the analysis of monetary policy shocks and in measuring their effects upon macroeconomic variables. The recurrent application of the VAR in this literature is due to its simplicity. As elucidated in BBE (2005), this method can provide acceptable results, indicating the dynamic responses of variables that are important to monetary policy shocks without the need to estimate the entire macroeconomic model.

Despite the advantages of VAR, this methodology has come under criticism. For example, there is no consensus among economists as to which method should be used to identify these policy shocks. The choice of different identification methods has distinct implications for the dynamic responses of the variables to the shocks.

Christiano et al. (2000) present a discussion of the different identification schemes existing in the literature. According to the authors, it is quite common to adopt the recursive hypothesis, in which the monetary policy shock is orthogonal to the information set utilized by the monetary authority. Under this assumption, it is necessary to classify the variables included in the VAR into three groups. The first of them consists of variables that comprise the monetary authority's information set and that respond to a policy shock with the delay of at least one time period. The second group includes only the operational monetary policy instrument. Finally, the third group consists of the variables that respond to the shocks contemporaneously.

Also according to Christiano et al. (2000), under the recursive hypothesis, there are three identification schemes that provide benchmarking. The first uses short-term interest rates as the policy instrument. This choice is based on institutional arguments. The second scheme adopts bank reserves other than those obtained by loans as an operational tool. Christiano and Eichenbaum (1992) justify the use of this instrument, arguing that changes in this variable reflect exogenous monetary policy shocks without the interference of money demand shocks. Finally, the last scheme considers the ratio bank reserves other than those obtained through loans to total reserves as a policy instrument. Strongin (1995) proposed this measure based on the argument that the demand for total reserves is completely inelastic with respect to short-term interest rates and that therefore, a monetary policy shock initially changes only the total reserve composition.

Despite being commonly adopted, the recursive hypothesis limits the existence of simultaneity in the determination of the model variables. Thus, there are studies that utilize structural VAR, abandoning the assumption that the monetary authority only analyzes variables that are predetermined in relation to the monetary policy shock. Using such methods, it is no longer possible to isolate the shock by using OLS. For this purpose, it is necessary to make other assumptions. BBE (2005) explain that some studies impose contemporaneous restrictions (or in other words, matrix restrictions that relate the structural shocks to the VAR error), while other ones impose restrictions on the impulse response format for longer time horizons. Those identification schemes have also been criticized. One criticism is that contemporaneous restrictions are arbitrary because there is no consensus on which one(s) should be adopted. On the other hand, long-term restrictions are criticized for not always generating plausible results for short-run dynamics. According to Faust and Leeper (1997), this only happens when the structure of the economy conforms to a set of strong restrictions.

Another criticism of the use of VAR is that this methodology only considers unanticipated changes in monetary policy. As pointed out by Sims and Zha (1998), most policy changes are systematic. That is, they are responses to variations in the state of the economy. The VAR does not consider this systematic component and therefore underestimates the effect of monetary policy.

In view of this last criticism, it is interesting to note the existing debate on the source of the monetary policy shock. Christiano et al. (2000) highlight that the systematic component is typically formalized by estimating a reaction function and that the equation error that relates it to the policy instrument is usually considered the shock.

There are three main ways to interpret these shocks. The first one is as a preference shift on the part of the monetary authority, as exemplified by a change in political power. This causes an alteration in the relative weights of the variables in the reaction function. The second interpretation was proposed by Ball (1995) and Chari et al. (1998). These studies argue that the monetary authority tends to avoid the social costs of frustrating agents' expectations and that a change in these expectations can lead to an exogenous shock. Finally, the third interpretation of a shock is the presence of measurement errors in the series used for decision-making, as observed by Bernanke and Mihov (1995) and Hamilton (1997).

Another problem with the use of VAR is that some of the results obtained are not consistent with the initial theoretical hypothesis, of which the price puzzle is the principal one. The result observed in many studies that employ the VAR is that a contractionary monetary shock is followed by a future increase in inflation.[2] Sims (1992) provides an explanation for the price puzzle based on the fact that the VAR does not include series that capture future inflationary pressure. On this basis, the contractionary shock should be a response to this pressure and, as such, it is only able to partially contain the future increase in price levels. Some studies, such as those by Sims (1992), Bernanke and Mihov (1998) and Christiano

[2]The term "price puzzle" was introduced by Eichenbaum (1992). Minella (2003) finds evidence in favor of a price puzzle for Brazilian data as well.

et al. (2000), indicate that one can eliminate the price puzzle via the inclusion of variables such as commodity prices. Furthermore, the increase in inflation after a contractionary monetary shock is consistent with some theoretical models. Barth and Ramey (2001), for example, develop a model in which monetary contraction causes an increase in the marginal costs for firms, which in turn is passed on to prices.[3]

Despite the existence of theoretical models that explain the counterintuitive relationship between a contractionary monetary shock and inflation, and of studies capable of inverting that relationship by including another price series, one must consider that the price puzzle explanation proposed by Sims (1992) provides evidence of the main problem with using VAR, which is the use of a limited information set. It is common knowledge that the monetary authority uses a very broad information set. The Monetary Policy Committee meeting minutes, for example, highlight the evolution of a large number of macroeconomic variables. This is in accord with Svensson (2002), who states that the system of inflation targeting, rather than involving mechanical decisions regarding the policy instrument, is based on an elaborate decision-making process that requires the thorough analysis of a large amount of information. In Bernanke and Boivin (2003), Bernanke, the current Federal Reserve chairman, argues that the FOMC uses hundreds of variables in its decision-making. Although not all of the monitored series are included in the reaction function, they aid in the prediction of the variables that are directly considered in the decision-making. The fact that the policymaker bears the cost of obtaining such information reveals the importance of a rich information set (Bernanke and Boivin, 2003).

The preservation of degrees of freedom requires that the VAR include a reduced number of variables. BBE (2005) highlight that, generally, no more than eight variables are included.[4] Therefore, it is unlikely that this methodology is able to include all of the information used by the central banks. Thus, it is necessary to consider that the results obtained using this methodology can be biased due to the omission of relevant variables. In particular, the systematic component of the monetary policy changes can be confused with the shocks, resulting in dynamic responses that do not match those that have been predicted by the more usual macroeconomic models.

Aiming to resolve the problem with the use of VAR, BBE (2005) combine VAR analysis with factor analysis (FAVAR) to identify monetary policy shocks and their effects. In including factor analysis, it is possible to use a much larger number of economic series without the loss of degrees of freedom because only the

[3]Other studies presenting theoretical explanations for the positive relationship between interest rates and inflation include Beaudry and Devereus (1995) and Fuerst (1992).

[4]There are works that are able to increase the number of variables used by applying Bayesian VARs. One example is Leeper et al. (1996), which are able to include up to 20 variables in the VAR. Bánbura et al. (2008) estimate a VAR with 131 series by using the Bayesian contraction method.

factors extracted from the series set are directly included in the VAR. BBE (2005) use a panel with 120 monthly macroeconomic series covering the period from January 1959 to August 2001. Problems such as the price puzzle were attenuated, corroborating the argument presented in Sims (1992).

The use of FAVAR in the literature on the impacts of the monetary policy shocks represents a major advance over the use of the VAR as traditionally applied.[5] One primary advantage of FAVAR, highlighted in BBE (2005), is that it is possible to obtain impulse responses for all variables used, and not just those directly included in the VAR. Another advantage is that it is not necessary to specify a series as a proxy for a theoretical concept. BBE (2005) highlight an example of this advantage by showing that the concept of "economic activity" does not need to be represented by the industrial production series or real GDP. The use of the series is not exclusive, and other ones such as employment and sales can also be included. It is therefore not necessary to rely on arbitrary choices.

These advantages become clearer with the presentation of the model used to estimate FAVAR, demonstrating the possible benefits of employing this methodology for Brazil. The next section presents that model and describes the econometric procedures adopted to obtain the results of this study.

3. Methodology

3.1 Model

The FAVAR used by BBE (2005) considers that there is an $M \times 1$ vector of observable economic variables (Y_t) and also a $K \times 1$ vector of unobservable factors (F_t). In this study, the vector Y_t initially includes only the Central Bank's monetary policy instrument. This instrument is considered to be exogenously determined by the monetary authority. Note that K must be small to preserve degrees of freedom, because it will be included in the VAR. The dynamics of (F_t, Y_t) is given by

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \upsilon_t \tag{1}$$

where $\Phi(L)$ is a lag polynomial of order d. In principle, this polynomial may contain restrictions, as in a structural VAR. The υ_t error has a zero mean and a covariance matrix Q.

It should be noted that it is possible for equation (1) to be reduced to a traditional VAR should all the terms of the polynomial $\Phi(L)$ that relate Y_t and F_{t-1} be null. However, if this is not the case, the correct model will be a FAVAR model, and the omission of the factors in the model (that is, the estimation of a

[5]Other papers that use the same methodology are: Boivin et al. (2008) and McCallum and Smets (2007).

VAR) will generate biased estimates of the coefficients, jeopardizing the analyses made afterwards.

The fact that F_t is not observable prevents the direct estimation of (1). However, because the factors are forces that interfere with the state of the economy, one expects it to be possible to estimate them using a set of macroeconomic series that can be grouped into an $N \times 1$ vector denominated x_t. According to BBE (2005), N must be big enough to make it possible to improve the quality of the estimation of F_t. The equation that relates X_t to F_t and to Y_t is as follows:

$$X_t' = \Lambda^f F_t' + \Lambda^y Y_t' + e_t' \tag{2}$$

where Λ^f is an $N \times K$ matrix of factor loadings, Λ^y is an $N \times M$ vector and e_t is an $N \times 1$ vector of zero mean errors. Equation (2) shows the idea that F_t is the force that guides the common dynamics of X_t (Bernanke et al., 2005).

The next section introduces the data used in this work, which will contribute to an easier understanding of the estimation method of equation (2). The estimation method will be presented in subsection 3.3.

3.2 Data

The choice of the series was based on BBE (2005), adjusting for the availability of these series for Brazil. Production, price, money, consumption, income, credit and employment series were used. Monthly series were used for the period between January 1995 and September 2009.

Initially, the additional inclusion of expectations for the principal macroeconomic variables was considered because, as discussed in the literature review, the monetary authority monitors the agents' expectations and tends to avoid the social cost of frustrating them. However, these series have only been available for Brazil from 2001 onwards, and it was therefore not possible to use them in this study. Another point worth mentioning is that household consumption, investment and unemployment series are non-existent at the national level with monthly periodicity. Thus, it was not possible to include series that specifically capture these aspects of the economy.

The database used contains 125 macroeconomic series. As a caveat regarding the availability of the data, we should note that although we exceeded the 120 series used in BBE (2005), the database for this study reflects fewer economic concepts. Moreover, BBE (2005) consider series including 512 observations, while the series for this study contains only 177.

The ADF unit root test was performed on all series followed by the transformations to make them stationary. The series with a seasonal component were seasonally adjusted, and the nominal series were deflated by the Brazilian CPI (IPCA). The choice of the IPCA was due to the fact that the Central Bank of Brazil uses this series as reference for the inflation target. The appendix contains a list of all the variables used in this study, stating which transformations were made in each case.

3.3 Estimation

In BBE (2005), the system (1) (2) is estimated using two distinct approaches. The first one uses the two-stage principal component analysis. The second method uses only one stage, employing a Bayesian approach in which equations (1) and (2) are estimated simultaneously using likelihood techniques based on Gibbs sampling.[6]

The results obtained in BBE (2005) suggest that, besides being a computationally simpler estimation method, the two-stage principal component analysis is superior to the second method. The responses of the variables to the shock presented the expected signal and magnitude for the two-stage specification, while the specification using the Bayesian method generated inaccurate responses for some series (apart from not eliminating the price puzzle, for instance). BBE (2005) suggest that the policy shock was probably not well identified. To further analyze the difference between the two methods, BBE (2005) generated factors using the same identification scheme for both. The estimation using principal component analysis continued to yield more plausible results. Thus, we concluded that the superiority of the first method was due to the way in which the estimate was made and not to the identification scheme adopted.

The estimation via two-stage principal component analysis is performed as follows. In the first stage, the factors are estimated by (2) using principal components. In this way, the space generated by the components, $C_t = (F_t', Y_t')$, is obtained. However, the element of interest is $\hat{F}_t$, the portion of the space generated by $\hat{C}_t$ that is not generated by Y_t.[7] The second stage consists in estimating the VAR via (1) using $\hat{F}_t$ instead of F_t. It is then possible to obtain $\hat{\Phi}(L)$. Once the VAR is estimated, it is possible to obtain the impulse response functions for both the factors and the original series.

To perform the factor estimation, it is necessary to develop an identification scheme. Since in the principal component estimation the factors are derived entirely from the observation equation (2), it is sufficient to directly restrict the factors such that $F^{i'}F^i/T = I$, so that it becomes possible to identify the factors in a unique way.

A second point concerns the identification scheme adopted to determine the VAR innovation; in the case of the model adopted in this study, this refers to the innovation in monetary policy. As with BBE (2005), a recursive hypothesis is adopted in which the policy instrument is ordered last in the VAR estimation.

[6] These techniques were developed by Geman and Geman (1984), Gelman and Rubin (1992) and Carter and Kohn (1994). See BBE (2005) for a discussion about the application of the method in a FAVAR.

[7] Later, it will be explained how $\hat{F}_t$ was obtained.

However, it should be noted that this imposes the restriction that the factors cannot contemporaneously respond to a monetary policy innovation. As such, it is important to use $\hat{F}_t$ and not $\hat{C}_t$.

To obtain the free factors from the policy instrument effect, the BBE (2005) procedure is followed, discriminating between "fast-moving" and "slow-moving" variables. The "fast-moving" series are characterized as very sensitive to economic shocks and contemporary news. The "slow-moving" series are basically predetermined in the current period.[8] Examples of "slow-moving" variables include production and price series, while examples of "fast-moving" variables include interest rate and exchange rate series as well as financial markets series.[9] Subsequently, K factors are also estimated via principal component analysis using only the "slow-moving" variable group. The next step is to estimate the regression:

$$\hat{C}_t = b_{F^s}\hat{F}_t^S + b_Y Y_t + e_t \tag{3}$$

Finally, $\hat{F}_t = \hat{C}_t - \hat{b}_Y Y_t$ is constructed, and the VAR is estimated using $\hat{F}_t$ and Y_t. It should be noted that because the factors are estimated using principal components, they are orthogonal. Thus, the way in which the factors are ordered in the VAR is not relevant to the process of obtaining the impulse responses.

Number of factors

The literature on multivariate analysis proposes several criteria for determining the appropriate number of factors for a series set. Many empirical studies, for example, adopt the method proposed in Bai and Ng (2002).[10] However, none of the criteria considers that the factors will be included in the VAR and that therefore, there are restrictions imposed due to the loss of degrees of freedom. As such, this study estimated the VAR using four and six factors so as to compare the results.

The choice regarding the number of factors was based on several considerations. The first was that generally, as previously mentioned, no more than eight variables are included in the VAR in empirical studies. Additionally, the availability of series for Brazil restricts the study to the post-Real Plan period. The reduced number of observations further increases the need to estimate a parsimonious model.

Initially, the choice was to follow BBE (2005) and estimate the FAVAR using three and five factors. However, the three factors with the largest eigenvalues explained only 33% of the variability of set X_t. After our inclusion of the fourth

[8] See Uhlig (2008) for a critique of this distinction between fast- and slow-moving variables.

[9] Appendix A includes the list of series used and the classification of the series as "fast-moving" and "slow-moving". See BBE (2005) for a more detailed explanation of the criteria used to classify the variables.

[10] Bai and Ng (2002) propose penalty functions that consider both the size of the cross-section and the temporal dimension of the database. The resulting criteria are variations on the information criteria commonly used in the time-series literature (AIC and BIC), which tend to overestimate the appropriate number of factors.

factor, the percentage of variance explained increased to 38%. It was thought that the loss of degrees of freedom in the VAR estimation would be offset by the increase in the explanatory power of the factors. Therefore, we chose to use four and six factors.

Even with six factors, the explanatory power of the variability in the dataset was only 46%. This result is similar to that obtained by Ortega (2005), who also estimates factors via principal component analysis for macroeconomic series for Brazil in the post-Real Plan era and isolates five factors that explain 46% of the variability.[11]

Impulse response

The response function of the driving factors for the monetary policy instrument was obtained using the Cholesky decomposition method. The standard error of the estimates was calculated using the Monte Carlo method with 1,000 repetitions and not in an analytical form based on asymptotic results. This choice was made because of the reduced number of observations in the series.

Based on the impulse response functions of the factors, it was possible to obtain the impulse response function for all of the series included in X_t. It should be noted that because $K < N$ factors were used and because the impulse response functions of the factors are orthogonalized with respect to the monetary policy instrument, it was not possible to retrieve a variable X_{it} as a function of the factors through the matrix of factor loadings obtained via principal component estimation. To obtain the impulse response, the variable of interest, X_{it} was written as a linear combination of the VAR variables:

$$X_{it} = \alpha_1 \hat{F}_{1t} + \alpha_2 \hat{F}_{2t} + \cdots + \alpha_K \hat{F}_{Kt} + u_t \tag{4}$$

Subsequently, the impulse response function for each variable was obtained as the linear combination of those factors. Since the factors are themselves orthogonal, in order to construct the confidence interval a weighted sum of the response factors' variance was calculated using the weights α_j^2. The variable of interest was projected in the space generated by the factors so as to obtain the estimates of the weights α_j.

[11] Ortega (2005) also uses factor analysis to extract the information contained in an extensive set of Brazilian macroeconomic data with the objective of analyzing monetary policy. However, the use of these factors in Ortega (2005) is not the same as the one in this work. In Ortega (2005) the factors are used as instruments in a forward-looking Taylor rule and, in the VAR, only as additional regressors. Moreover, the period considered in Ortega (2005) is from January 1995 to January 2004, thus being a subset of the period considered in this work.

4. Empirical Results

4.1 FAVAR

The main results of the FAVAR estimation are presented in Figures 1-3. Each figure shows the responses of a selection of macroeconomic variables to a shock of one standard deviation in the Selic rate, which is the monetary policy instrument in Brazil. The figures also include 90% confidence intervals. Figure 1 shows the FAVAR results estimated using four factors, whereas Figure 2 shows the results for the model with six factors.

The FAVAR estimated with four factors included three lags. Although the information criteria indicate that the best model should include only two lags, it was necessary to add one more to obtain residuals that are not serially correlated.[12] The results for the principal variables were generally consistent with the theory in terms of signal and duration. After a contractionary monetary policy shock, there is a drop in industrial production, which reaches a minimum two months after the monetary contraction. The effect becomes null after three more months, which is consistent with the long-term neutrality of money. Minella (2003), estimating a VAR for the period between September 1994 and December 2000, obtained evidence of a more persistent production response that returned to zero only after 20 months. Ortega (2005) obtained a result similar to that of Minella (2003), estimating both a pure VAR and a VAR with dynamic factors and considering monthly series for the period between January 1995 and January 2004.

The IPCA behavior was also as expected, and the absence of the price puzzle should be highlighted. There is a drop in the inflation rate as a result of the shock to the Selic rate. The negative effect reaches its peak at three months, and at the end of the sixth month, the response returns to zero. This result is more consistent with theoretical models than that obtained by Minella (2003) and Ortega (2005), who found evidence in favor of a price puzzle.[13] As a result, we can conclude that four factors are able to capture sufficient information to indicate that the price behavior follows that predicted by the theory. Furthermore, it should be noted that, in terms of magnitude, the impact on production is shown to be superior to the impact on inflation.

The monetary base suffers a contraction after the shock. This result is quite reasonable and evidences the absence of a liquidity puzzle, which often appears in empirical studies using VARs. It should be noted that the monetary base response was more erratic than the other ones. In observing Figure 1, we can also note that the contractionary shock causes a reduction in installed capacity utilization, an increase in the unemployment rate and a drop in real revenue from industry and energy consumption, which is often used as a measure of economic activity. All these results are consistent with the expectations based on the monetary contrac-

[12] The inclusion of more lags did not change the format of the impulse responses.
[13] Minella (2003) used the IGP-DI series and not the IPCA series.

tion impact theory.

The FAVAR estimation with six factors also included three lags. The results were very similar to those achieved using the estimated model with four factors in terms of signal, duration and magnitude. Figure 3 illustrates the results based on the two FAVAR estimation processes so that they can be better compared. It is clear that the paths for the IPCA response, the monetary base, the unemployment rate and installed capacity utilization in the long term are less erratic over time in the FAVAR estimation with six factors. This suggests that there is an informational gain associated with increasing the number of factors.

Despite the reasonability of the results obtained, it is important to discuss the inaccuracy of the estimates. In the case of the four-factor model as well as the six-factor model, the results for the variables for inflation, installed capacity utilization and unemployment rate were not significant for all periods. The results for the six-factor FAVAR were even more imprecise; the energy consumption and monetary base figures were also not significant. Additionally, the other variables showed significant responses only for the initial three months.

The lack of precision of these results may have more than one explanation. Something that probably contributed to this was the limited number of observations in the series, which not only impacts the variability of the estimated VAR coefficients, but also prevents the inclusion of more factors in the model. To solve this problem, it would be necessary to expand the study period. However, this would have required that fewer series be used because many series in the database were initiated in the second half of 1994. Moreover, the series would present a structural break due to the regime shift.

4.2 VAR-FAVAR comparison

One way to evaluate the informational contribution of the factors is to compare the results obtained using FAVAR with those obtained using small-scale VAR. However, to accurately measure that marginal contribution, the estimation process proposed by BBE (2005) should be followed. It is important to recognize that FAVAR is not a purely factorial model: it also includes a vector of observable variables. Thus, the observable series generally included in the VAR can be included in Y_t. These are an industrial production series as a measure of real activity, a prices series and an exchange series. The exchange series was included because of its importance in the analysis conducted by the monetary authority, especially in the context of inflation targeting. Taylor (2000) argues that the impact of the exchange rate on inflation positively depends on the persistence of inflation. Conversely, Calvo and Reinhart (2000), using VAR, show that the pass-through is greater for emerging countries. Thus, in Brazil, the monetary authority should make an effort to respond to fluctuations in the exchange rates so as to contain the pass-through.

In comparing the VAR results with and without including $\hat{F}_t$, it is possible to evaluate the advantages of considering a broader information set. On this basis, three VARs were estimated, one including only Y_t, another also including $\hat{F}_t$ with one factor and, finally, one containing $\hat{F}_t$ with two factors. It is important to mention that when we include observable variables besides the policy instrument, the ordering of these variables becomes relevant considering that the recursive hypothesis was adopted and there is no guarantee of orthogonality between them. Therefore, to compare the VAR with the FAVAR, benchmark ordering was considered: industrial production, price series, exchange rate and, finally, interest rates. To conduct the FAVAR estimation, the factors were added just before the interest rate because they were constructed from prices, production and exchange series, as well as series that respond most quickly to an interest rate shock.

The results are shown in Figures 4-7. All VARs include three lags. One observes that the VAR estimated without any factors yields impulse responses for inflation and production very similar to those obtained in the FAVARs in terms of signal. However, although the result was similar for industrial production in terms of duration, the impact of the contractionary shock was more persistent in the VAR.

The response of the exchange rate also showed the expected format. In response to a contractionary monetary shock, the exchange rate increased. This was followed by slight depreciation until the impact returned to zero. This behavior reveals the existence of overshooting, which is a fairly common phenomenon in the empirical literature on exchange rates.[14] It was not possible to compare the exchange rate response obtained using VAR and FAVAR because the exchange rate projection coefficients in the space generated by the factors were all insignificant and it was therefore considered inappropriate to use the exchange rate impulse response obtained using the FAVAR.

The inclusion of one and two factors in the VAR changed the results very little, as seen in Figure 7. The inclusion of factors only slightly increased the magnitude and duration of the impact of monetary contraction on the inflation rate. The absence of alterations in the results based on the inclusion of these factors may be related to their low explanatory power; together, they explain only 26% of the variability in the series set. It is interesting to note that even the responses indicated by the VAR without factors were not significant. This, in turn, corroborates the explanation that the reduced number of observations contributed to the imprecision of the results.

4.3 Robustness

The exercise of comparing the VAR and FAVAR estimations showed that the marginal contribution of the information contained in the factors was very small. This result may be related to the low explanatory power of the six larger eigenvalues factors. As already discussed, the first four factors explain 38% of the

[14]It is worth highlighting that the exchange rate only became flexible after the fifth year of the period under consideration.

variability of the database used, and the first six explain 46%.

This percentage is low when compared to those obtained by other studies using empirical factors. Sargent and Sims (1977), for example, are able to explain 80% of the variability of a set of macroeconomic series for the U.S. using only two factors. Stock and Watson (2005) point out that other empirical studies can explain much of the variability of a set of macroeconomic data using approximately two factors, giving Stock and Watson (1999, 2002) and Giannoni et al. (2005) as examples.

One possible cause of the low explanatory power of the factors is the low quality of the series used. Boivin and Ng (2003) discuss the idea that because the factor analysis theory is based on asymptotic results, it is always better to use all available series. The study concludes that not all series are informative and that the inclusion of these series is costly because they can have errors that are highly correlated to the others, which reduces the estimators' efficiency because it tends to reduce the common components.

Boivin and Ng (2003) suggest that macroeconomic variables should be separated into categories and that, within each category, the series should be sorted based on the importance of their common components. Ideally, the series used in the factor estimation should be the well-classified series in each category. When one expands the set to include series with low common components, the average common component size tends to decrease, and the possibility of correlated errors tends to increase. Therefore, there is a point at which the inclusion of more series of the same class only adds noise, reducing the factors' explanatory power.

In view of Boivin and Ng's results (2003), one can conclude that there is a trade-off involved in the decision to include the series in the dataset. In the Brazilian case, this trade-off is even more critical given the absence of series with monthly periodicity to represent different economic aspects. It is thus necessary to include redundant series to approach the hypothesis that a large number of series is used.

Aiming to increase the efficiency in the estimation of the factors, a procedure was adopted following the logic proposed by Boivin and Ng (2003). The series were divided into four categories: economic activity, prices, interest rate, and money. Table 1 shows the cumulative percentage variability explained by the first three factors for each category. Note that the three factors have low explanatory power, except in the interest rate category.

Table 1
Cumulative variability proportion explained by the factors including all the series

Number of factors	Credit	Prices	Activity	Money	Interest rate
1	0.3367	0.4331	0.2444	0.2391	0.6737
2	0.5227	0.6182	0.3313	0.4341	0.8716
3	0.6555	0.711	0.3953	0.5666	0.9780

Next, the series were ordered based on the importance of their common components. The classification was determined by analyzing the weight of each series in building the first principal component. The weights assigned to the credit series for the construction of the first factor were very similar. The same was true for the money category. Therefore, none of the series from these two groups was discarded. For prices, economic activity, and interest rate, it was possible to identify series that could be classified as noisy.[15] These series were eliminated from each category until the first component of each category was constructed by assigning similar weight to all series. Even with the elimination of the noisy series, three factors continued to explain less than 80% of the variability of each category except in the case of the interest rate.

Table 2
Cumulative proportion of the variability explained by the factors without the noisy series

Number of factors	Credit	Prices	Activity	Money	Interest rate
1	0.3367	0.5135	0.3816	0.2391	0.8393
2	0.5227	0.6884	0.4955	0.4341	0.9723
3	0.6555	0.7743	0.5604	0.5666	0.9996

Finally, the factors were recalculated for all categories together, without the noisy series, for a total of 88 series. The first six factors explained 67% of variability, indicating a gain of approximately 20% over the results using the original database. This result is similar to that obtained by Ortega (2005), which explained 67% of the variability using five factors after eliminating series with low common components. The FAVARs were then reestimated with four and six factors for this subset of the database. However, the results were very similar to the original ones in terms of magnitude, duration, and signal. Even with the gain in explanatory power, the factors still explain very little as compared to the results obtained for macroeconomic series from other countries.

When analyzing the subset of the database free from redundant series, we note that together, the price and production series represent over 60% of the dataset. On this basis, one more robustness exercise was carried out, which consisted in estimating factors using only price series and production series. FAVARs were then estimated including those factors in addition to the policy instrument, monetary base, and exchange rate series. As in the VAR-FAVAR comparison exercise, benchmark ordering was used. The first series were the production factors, fol-

[15] "Noisy series" is the term used by Boivin and Ng (2003) to denote the series that add no information and hence reduce the explanatory power of the factors by adding noise to the estimation. The appendix with the list of series used identifies which series were classified as noisy.

lowed by the price factors and finally, the Selic rate, and monetary base. Two FAVARs were estimated, one including two production factors and two prices and another one including three of each factor. The goal of this new estimation was to evaluate whether a price series and a production series provide a good representation of these two economic concepts or whether there is something to be gained in looking for more series in the same group, particularly disaggregated series.

The IPCA and industrial production responses to a contractionary monetary shock are presented in Figures 8-9 for two and three factors, respectively. Figure 10 shows a comparison between the two results. Not much difference is observed in the industrial production response based on the inclusion of an additional factor for each category. However, when analyzing the IPCA response, we note that it is more persistent in the specification with two factors. Thus, in comparing this last result with all of the other estimates, we note that the industrial production and IPCA responses indicated no relevant changes.

The FAVARs were also estimated considering only the period after June 1999. The motivation for restricting the period was the exchange rate regime shift in 1999 and the adoption of the inflation targeting system in the second half of that year. However, the impulse response functions did not change significantly and also became more imprecise, probably due to the reduction in the number of observations.

Uhlig (2008) pointed out a possibility for the high explanatory power of the factors in a comment about Boivin et al. (2008). The author argues that the high explanatory power of few factors found by Boivin et al. (2008) (and by most of the literature) would be the result of the fact that many of the variables in the dataset present autocorrelation coefficients that are close to one. Uhlig (2008) shows, by using a simulated dataset, that if this is the case in a finite sample, these large correlations might be interpreted as a comovement instead. The author then concludes that the high explanatory power of the factors might be consistent with an environment with no comovement at all among the variables or with an environment in which few factors explain the dynamics of the model, but with an explanatory power lower than expected once we control for these correlations. Therefore, it might be the case that once other papers control for these high correlations they would find results similar to ours, in which the factors explain a much lower fraction of the variability of the data.

5. Conclusions

This work used the FAVAR methodology proposed in BBE (2005) to study the effects of a monetary policy shock on the Brazilian economy since 1995. The purpose of using this method was to match the information set included in the empirical analysis as well as possible to that available to the monetary authorities. In addition, FAVAR eliminates the need to rely on arbitrary choices regarding which series to include. The factor estimation was performed using principal component analysis, due to its good performance in other empirical studies and its computational simplicity.

The results obtained were consistent with the existing theory regarding the impact of contractionary monetary shocks. The variables used as a measure of activity responded negatively to the shock, and that impact became null after a few months, consistent with long-term currency neutrality. Additionally, the lack of a price puzzle or liquidity puzzle deserves to be highlighted. Although consistent with the economic theory, the results were inaccurate. Two possible explanations are the size of the series used and the low explanatory power of the factors when compared with those used in studies performed on data from other countries. It is interesting to note that the loss of information by reducing the dataset to six factors persisted even after the elimination of series that did not add information.

When comparing the FAVAR method with the traditional VAR method, we observe that there was no change in the response of the principal variables. Thus, we conclude that the marginal contribution of the information regarding the factors was low. However, although it captured little information, the FAVAR was still able to at least reproduce the results obtained through the small-scale VAR estimation in terms of signal, magnitude, and duration.

The results of this work indicate that the price puzzle found by Minella (2003) and Ortega (2005) cannot necessarily be credited to the limited information set used in the estimation of the VAR. The evidence found in favor of this puzzle can be a particularity of the periods analyzed in these works. Thus, it is interesting to apply the FAVAR methodology using the same periods considered in Minella (2003) and in Ortega (2005), as a way to test if the origin of the price puzzle is actually the omission of relevant variables. However, it is necessary to point out that the number of observations used both in Minella (2003) and Ortega (2005) is small, 76 and 109, respectively. This, in turn, can jeopardize the efficiency of the FAVAR methodology.

Future research should focus on the inclusion of series that capture the international scenario given the importance of those considerations for emerging economies such as Brazil. In this context, it will be interesting to test the performance of a factor model in capturing external information and thus providing more information to the FAVAR. Furthermore, in including a series of external economies, it will also be possible to analyze the transmission mechanism of international shocks to Brazil, reproducing the work of Mumtaz and Surico (2009) for the UK.

Although the results for the U.S. economy supports the superiority of the two-step approach when compared to the Bayesian methodology, future research should analyze whether, given limitations found in the estimation using the Brazilian data, the Bayesian approach is more useful to analyze policy shocks in countries that suffer from serious data limitations.

Another relevant aspect to be considered in future research on this issue is the ability to concentrate information within a dataset using few factors. Principal component analysis was not very effective in focusing on the information from the database used. As a result, other methods of factor estimation should be considered, as should more rigorous procedures for identifying series that only introduce noise into the estimation.

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A. Appendix A

Legend used for transformations

(1) No change; (2) First difference; (4) Logarithm; (5) First difference of the logarithm

Series	Name	Unit	Transformation
Money growth***			
1	M0 - expanded monetary base - mean	Real - million	5
2	M0 - monetary base - mean	Real - million	5
3	Term deposits - mean	Real - million	5
4	Sight deposits - monthly	Real - million	5
5	Savings Deposits - mean	Real - million	5
6	M0 - monetary base - currency issued - mean	Real - million	5
7	M0 - monetary base - bank reserves - mean	Real - million	5
8	M1 - end of period	Real - million	5
9	M2 - new concept - end of period	Real - million	5
10	M3 - new concept - end of period	Real - million	5
11	M4 - new concept - end of period	Real - million	5
Consumption and sales			
12	Real revenues - industry*(N)	index	5
13	Default - t-4 (N)	index	1
14	Electric Energy Consumption	Gwh	5
15	CEE - other sectors (N)	Gwh	5
16	CEE - commerce (N)	Gwh	5
17	CEE - industry	Gwh	5
18	CEE - households (N)	Gwh	5
19	Apparent Consumption - gasoline - mean - qt/day (N)	Barrel (thousand)	5
20	AC - petroleum derivatives - mean - qt/day	Barrel (thousand)	5
21	AC - ethanol fuel - mean - qt/day (N)	Barrel (thousand)	5
22	AC - fuel oil - mean - qt/day (N)	Barrel (thousand)	5
23	AC - diesel oil - mean - qt/day (N)	Barrel (thousand)	5
24	AC - LPG - mean - qt/day (N)	Barrel (thousand)	5
25	Domestic Sales- trucks	units	5
26	Domestic Sales- buses (N)	units	4
27	Domestic Auto-sales	units	5
28	Sales- light commercial vehicles (N)	units	5
29	Domestic Sales- automotive vehicles (N)	units	5
30	SPC - number of queries (N)	units	5
Credit			
31	Credit operations to the Public Sector	Real - million	5
32	CO to the Public Sector - federal government	Real - million	5
33	CO to the Public Sector - state and municipal governments	Real - million	5
34	CO to the Private Sector - industry	Real - million	5
35	CO to the Private Sector - housing	Real - million	5
36	CO to the Private Sector - rural	Real - million	5
37	CO to the Private Sector - commerce	Real - million	5
38	CO to the Private Sector - individuals	Real - million	5
39	CO to the Private Sector - other services	Real - million	5
40	CO to the Private Sector	Real - million	5
Employment			
41	Personnel Employed - industry * (N)	index	5
42	Hours worked - industry *	index	1
43	Wage bill - industry - RJ	index	5
44	Employed Population - Industry - RJ (N)	index	5
45	Unemployment Rate - MASP (N)	%	5
46	Unemployment Rate - hidden - MASP (N)	%	5

Series	Name	Unit	Transformation
Price			
47	Commodities - general - price	Real - million	5
48	IGP-DI - general	index	5
49	INCC - general	index	5
50	IPA source - general	index	5
51	IPC - general	index	5
52	IPCA - general	index	5
54	IPCA - food and beverages	var % (a.m.)	1
55	IPCA - housing	var % (a.m.)	1
56	IPCA - health personal care	var % (a.m.)	1
57	IPCA - transport	var % (a.m.)	1
58	IPCA - regulated prices	var % (a.m.)	1
59	IPCA - market prices	var % (a.m.)	1
60	INPC - general	index	5
61	INPC - food and beverages	var % (a.m.)	1
62	INPC - household items	var % (a.m.)	1
63	INPC - personal expenses (N)	var % (a.m.)	1
64	INPC - housing	var % (a.m.)	1
65	INPC - health personal care	var % (a.m.)	1
66	INPC - transport	var % (a.m.)	1
67	IPA - EP - finished goods	index	5
68	IPA - EP - finished goods - consumer goods	index	5
69	IPA - EP - finished goods - consumer goods - supplies (N)	index	5
70	IPA - EP - finished goods - consumer goods - fuels (N)	index	5
71	IPA - EP - finished goods - durable goods	index	5
72	IPA - EP - finished goods - capital goods	index	5
73	IPA Source - processing industry	index	5
74	IPA Source - agricultural products (N)	index	5
75	IPA Source - industrial products	index	5
76	INPC - clothing (N)	var % (a.m.)	1
77	IPA - EP - intermediate goods	index	5
78	IPA - EP - raw materials (N)	index	5
79	IPCA - household items	var % (a.m.)	1
80	IPCA - personal expenses (N)	var % (a.m.)	1
81	IPCA - marketables	var % (a.m.)	1
82	IPCA - clothing (N)	var % (a.m.)	1
83	IPCA - unmarketables	var % (a.m.)	1
Production			
84	Industrial Production - general industry - quantum*	index	5
85	IP - processing industry - quantum*	index	5
86	IP - intermediate goods - quantum*	index	5
87	IP - consumer goods - quantum*	index	5
88	IP - consumer durables - quantum*	index	5
89	IP - non-durable goods - quantum* (N)	index	5
90	IP - automobiles - quantum	index	5
91	IP - capital goods - quantum*	index	5
92	IP - non-metallic mineral - quantum	index	5
93	IP metals, excluding machinery and equipment - quantum (N)	index	5
94	IP - machinery and equipment - quantum	index	5
95	IP - mining - quantum*	index	5
96	IP - food - quantum	index	5
97	IP - beverages - quantum (N)	index	5
98	IP - tobacco - quantum (N)	index	5
99	IP - footwear and leather goods - quantum	index	5
100	IP - wood - quantum	index	5
101	IP - pulp, paper and paper products - quantum	index	5
102	IP - pharmaceutical - quantum	index	5
103	IP - rubber and plastic - quantum	index	5
104	IP - civil construction inputs - quantum	index	5
105	IP - perfumes, soaps, and cleaning products - quantum	index	5
106	IP - other chemicals - quantum	index	5
107	IP - metallurgy - quantum	index	5
108	IP - machinery, electrical equipment and material - quantum	index	5
109	IP - other transportation equipment - quantum	index	5
110	IP - electrical equipment and material, communications - quantum	index	5
111	IP - furniture - quantum	index	5
112	IP - textile - quantum	index	5
113	IP - clothing and accessories - quantum	index	5
114	IP - petroleum and alcohol refining - quantum (N)	index	5
115	Installed Capacity Utilization* (N)	(%)	1
Wage and income			
116	Payroll - general industry (N)	index	5
117	Real Minimum Wage (N)	Real	5
118	Real Average Income - salaried - main job (N)	index	5

Series	Name	Unit	Transformation
Interest rate			
119	Interest Rate- CDB**	% (a.m.)	5
120	Interest Rate- CDI/Over**	% (a.m.)	5
121	Interest Rate- TJLP** (N)	% (a.m.)	5
122	Interest Rate- TR**	% (a.m.)	5
123	Interest Rate- Over/SELIC**	% (a.m.)	5
Other			
124	Closing mean Ibovespa (N)	index	5
125	Exchange Rate		

(*)Seasonally adjusted series published by the institution.
(**)Not seasonally adjusted.
(***)"Rapid response" Series.
(N) *Noisy series.*

B. Appendix B

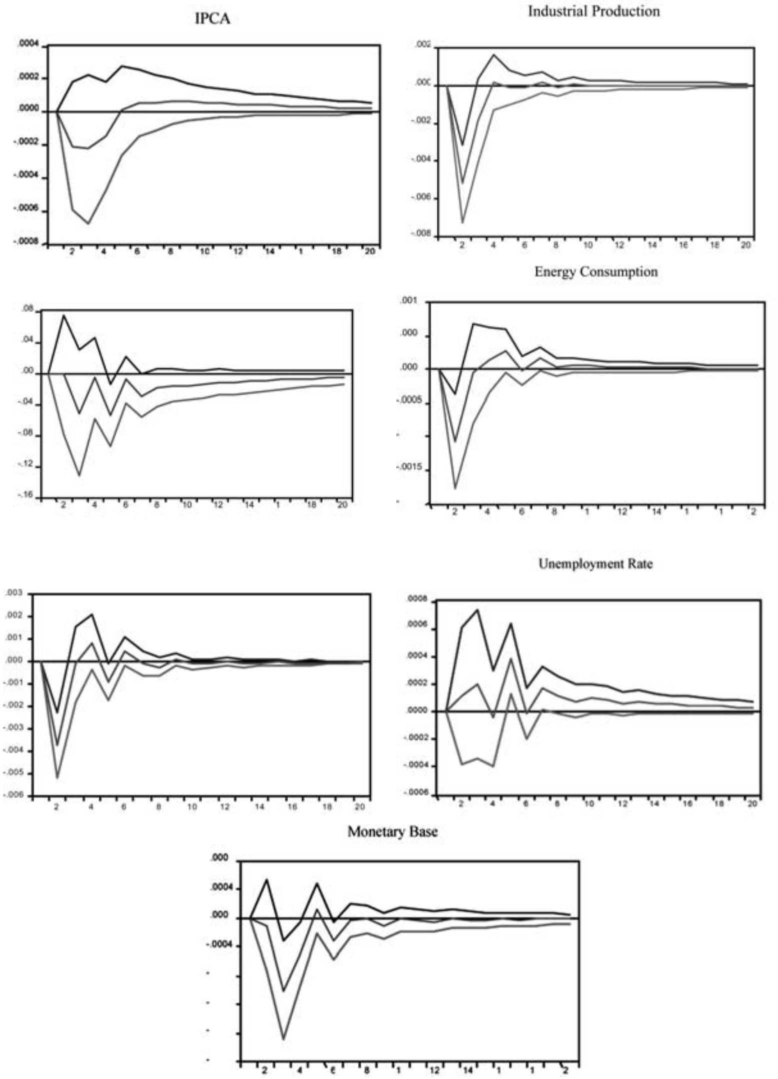

Figure 1
FAVAR with four factors

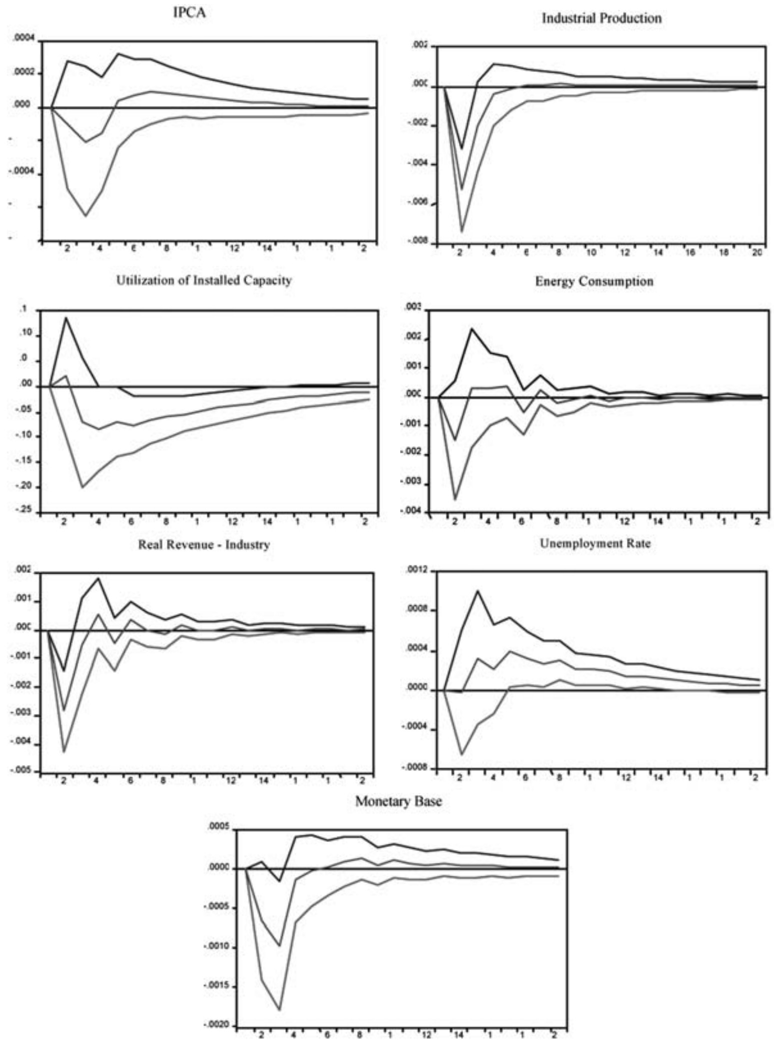

Figure 2
FAVAR with six factors

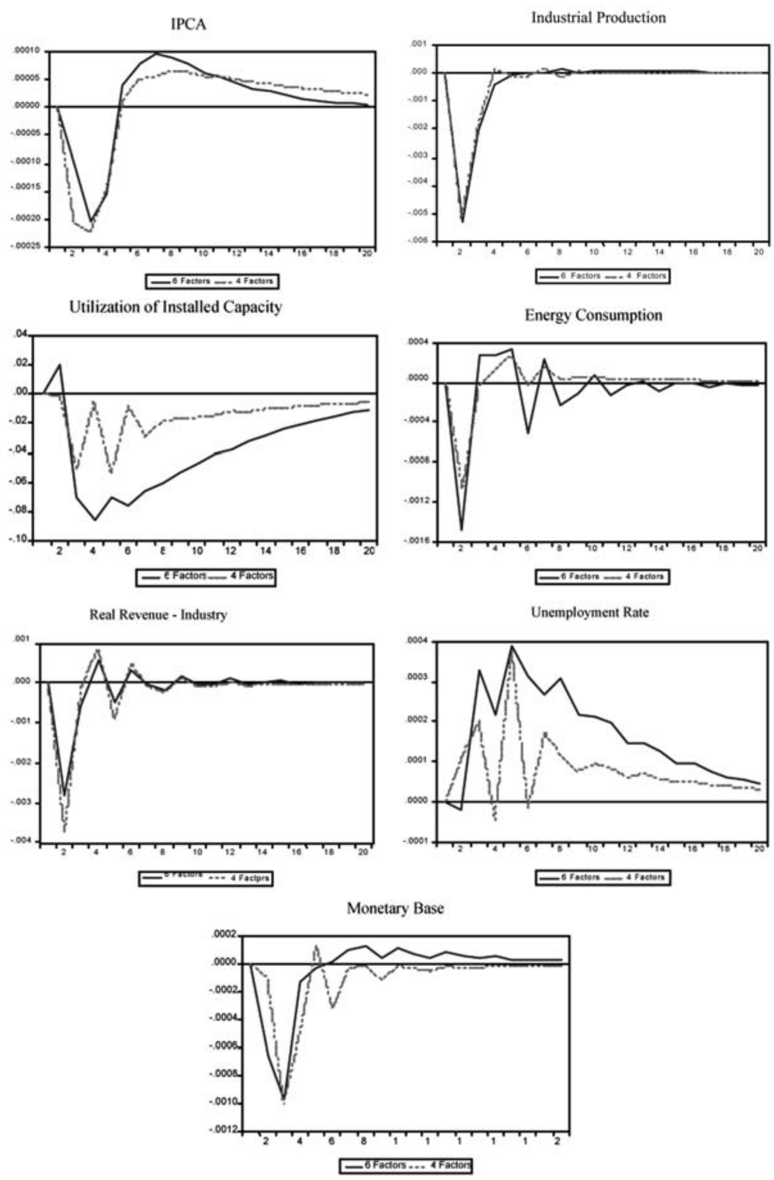

Figure 3
Comparison of FAVARs

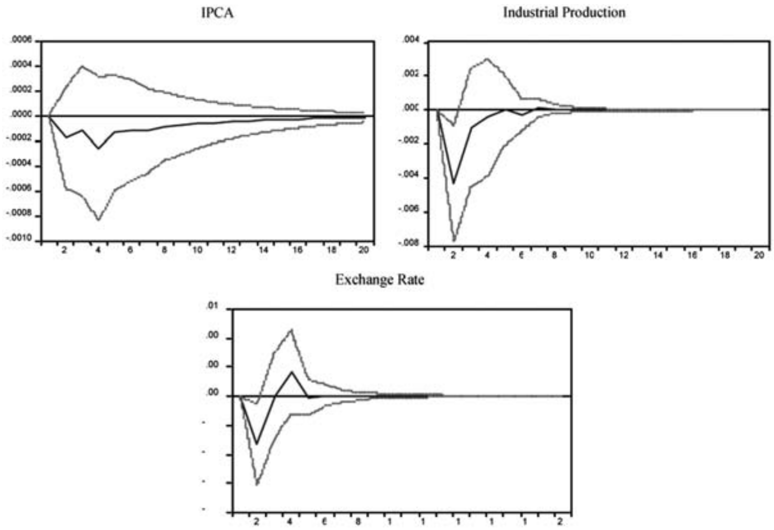

Figure 4
VAR without factors

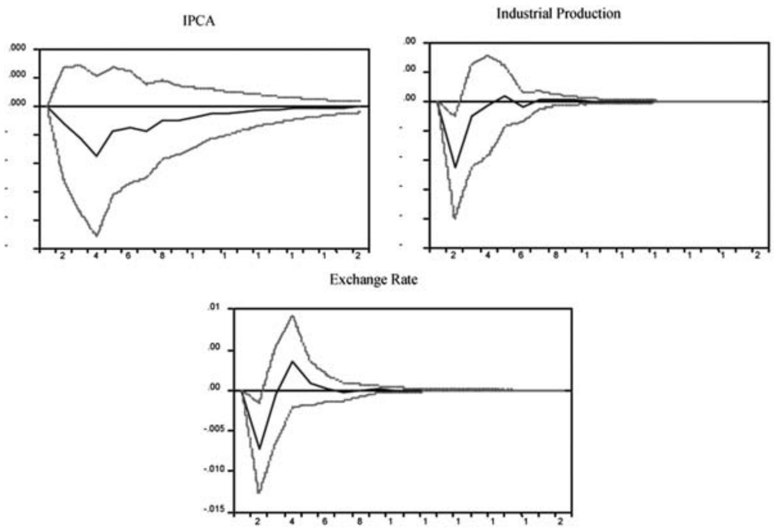

Figure 5
VAR with one factor

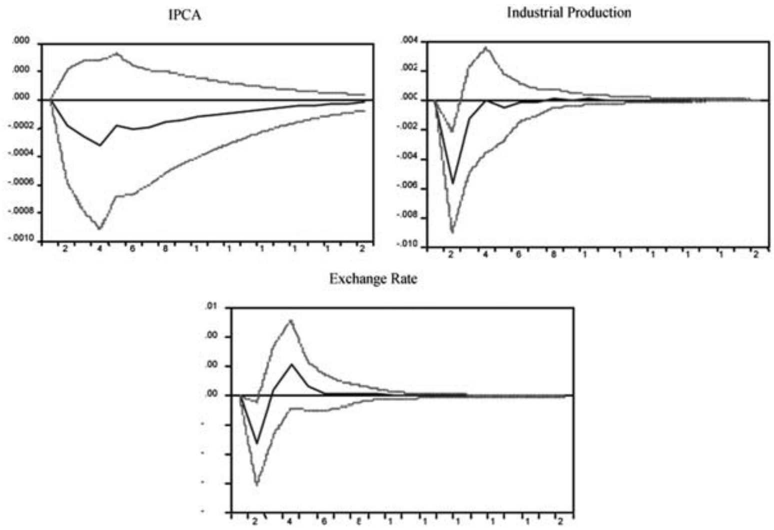

Figure 6
VAR with two factors

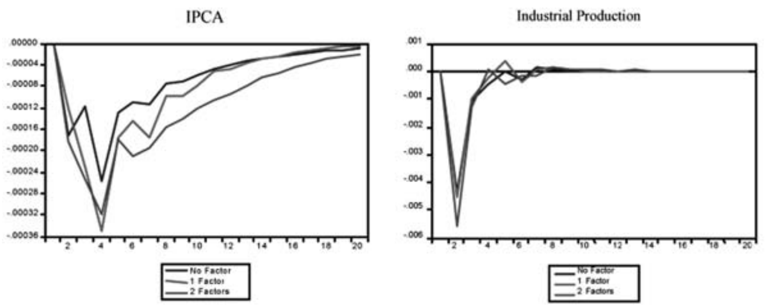

Figure 7
Comparison of VARs

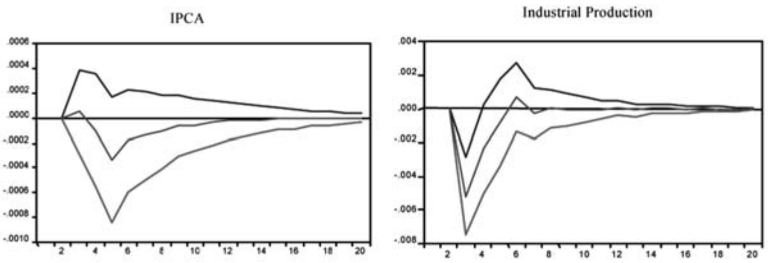

Figure 8
FAVAR price/Production with 2 factors

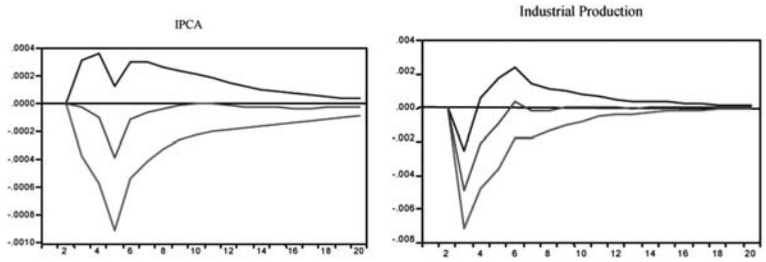

Figure 9
FAVAR price/Production with 3 factors

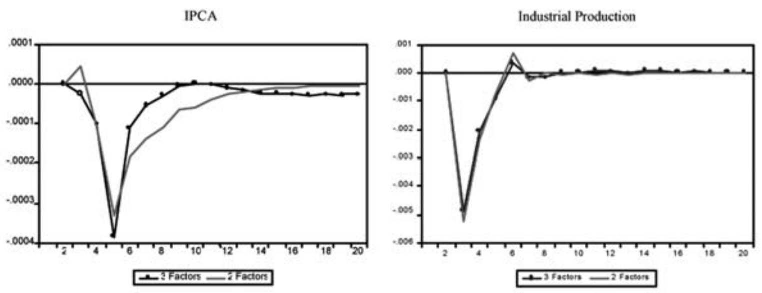

Figure 10
FAVAR price/Production comparison