TEXTO PARA DISCUSSÃO N° 1128

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TEXTO PARA DISCUSSÃO

Uma publicação que tem o objetivo de divulgar resultados de estudos desenvolvidos, direta ou indiretamente, pelo IPEA e trabalhos que, por sua relevância, levam informações para profissionais especializados e estabelecem um espaço para sugestões.

SUMÁRIO

SINOPSE

Neste artigo utiliza-se a teoria das previsões condicionais para o desenvolvimento de um novo Índice de Condições Monetárias [Monetary Conditions Index (MCI)] para o Brasil, comparando-o com os índices obtidos seguindo as metodologias sugeridas por Bernanke e Mihov (1998) e Batini e Turnbull (2002). Adicionalmente, desenvolvem-se e calculam-se intervalos de confiança bayesianos para os MCIs, empregando-se a abordagem proposta por Sims e Zha (1999) e Waggoner e Zha (1999).

O novo indicador desenvolvido é chamado de Índice de Condições Monetárias Condicional [Conditional Monetary Conditionals Index (CMCI)], e é construído utilizando-se alternativamente os modelos de Auto-regressão Vetorial Estrutural [Structural Vector Autoregressions (SVARs) e Antecipativo [Forward-Looking (FL). O CMCI é a previsão do hiato do produto, condicionada aos valores observados da taxa de juros nominal (taxa Selic) e da taxa de câmbio real. Mostra-se que o CMCI, comparado ao MCI desenvolvido por Batini e Turnbull (2002), é um melhor indicador do estado da política monetária porque leva em consideração a endogeneidade das variáveis envolvidas na análise.

O CMCI e o MCI Bernanke-Mihov (BMCI), apesar das diferenças conceituais, estabelecem uma cronologia semelhante para o estado da política monetária no Brasil. O CMCI é uma versão suavizada do BMCI, provavelmente porque o impacto de mudanças nos valores observados da taxa Selic é parcialmente compensado por mudanças no valor da taxa de câmbio real. De acordo com o CMCI e o BMCI, no período entre setembro de 2000 e abril de 2005, a política monetária brasileira tem sido expansionista nos meses próximos às eleições.

ABSTRACT

In this article we use the theory of conditional forecasts to develop a new Monetary Conditions Index (MCI) for Brazil and compare it to the ones constructed using the methodologies suggested by Bernanke and Mihov (1998) and Batini and Turnbull (2002). We use Sims and Zha (1999) and Waggoner and Zha (1999) approaches to develop and compute Bayesian error bands for the MCIs.

The new indicator we develop is called the Conditional Monetary Conditions Index (CMCI) and is constructed using, alternatively, Structural Vector Autoregressions (SVARs) and Forward-Looking (FL) models. The CMCI is the forecasted output gap, conditioned on observed values of the nominal interest rate (the Selic rate) and of the real exchange rate. We show that the CMCI, when compared to the MCI developed by Batini and Turnbull (2002), is a better measure of monetary policy stance because it takes into account the endogeneity of variables involved in the analysis.

The CMCI and the Bernanke and Mihov MCI (BMCI), despite conceptual differences, show similarities in their chronology of the stance of monetary policy in Brazil. The CMCI is a smoother version of the BMCI, possibly because the impact of changes in the observed values of the Selic rate is partially compensated by changes in the value of the real exchange rate. The Brazilian monetary policy, in the 2000:9-2005:4 period and according to the last two indicators, has been expansionary near election months.

1 INTRODUCTION

Annual interest rates in Brazil have been high—when compared to other emerging market economies—for a long time now. The rates have been high even after the inflation stabilization achieved by the Real Plan in 1994, implying that (ex post) real interest rates have been also high. Despite high nominal and real interest rates, there is not much agreement about whether the Brazilian monetary policy has been tight since 1994. This disagreement means that people have different assessments about monetary policy. As a matter of fact, how does one make judgments about the stance of monetary policy and what does "high interest rates" or "tight monetary policy" mean? These questions motivate this article and in order to answer them we discuss different approaches taken in the literature to evaluate the stance of monetary policy.

A quantitative measure of policy stance is useful and important for at least two reasons. First, knowing how tight or how loose its current stance is, helps the Central Bank determine the course of monetary policy needed to keep inflation within the target range. Second, a quantitative measure of stance is important for the empirical study of the past behavior of the Central Bank indicating periods where monetary policy was more accommodating or not. The quantitative measure of stance is usually called the Monetary Conditions Index (MCI). The MCI is a measure of the ease or tightness of monetary conditions relative to a base period.

In this article we use the theory of conditional forecasts to develop a new indicator of monetary policy stance for Brazil and compare it to the ones constructed using the methodologies suggested by Batini and Turnbull (2002) and Bernanke and Mihov (1998). We call the new indicator the Conditional Monetary Conditions Index (CMCI) and use, alternatively, Structural Vector Autoregressions (SVARs) and Forward-Looking (FL) models in its construction. The CMCI is the forecast of the (log of) output gap, conditioned on given interest rate and exchange rate paths, relative to a base period. We show that the CMCI, when compared to the Partial Monetary Conditions Index (PMCI) developed by Batini and Turnbull (2002), is a better measure of monetary policy stance because it takes into account the endogeneity of variables involved in the analysis. We also compare our CMCI with the Bernanke and Mihov (1998) indicator and explore their similarities or differences. We use Sims and Zha (1999) and Waggoner and Zha (1999) approaches to develop and compute Bayesian error bands for all MCIs based on SVAR models and present the methodology in Appendix B.

The paper is organized as follows. Section 2 reviews the approaches used in the literature to measure monetary policy stance. Section 3 contains the SVARs models, which are less restrictive versions of our FL models. The FL models are presented in Section 4, and some of their parameters are calibrated based on some SVARs estimates. Section 5 explains in details how we constructed alternative indicators of monetary policy stance for Brazil. Finally, the Section 6 provides some concluding remarks.

2 ALTERNATIVE APPROACHES TO THE MEASUREMENT OF MONETARY POLICY STANCE

The identification and measurement of the effect of monetary policy on the economy is difficult and in empirical work it is important to distinguish between the endogenous and exogenous components of policy change. Only the effect of the latter one is, in general,[1] possible to identify econometrically. Most recent empirical studies have employed the sSVAR methodology to identify exogenous shifts in policy [see for example Leeper, Sims and Zha (1996) and Christiano, Eichenbaum and Evans (1999)]. The literature associated with the measurement of monetary policy stance is less concerned with econometrically measuring the effects of monetary policy and more directed at finding an overall indicator of monetary policy irrespectively if it is anticipated or not by economic agents. Hence, changes in this indicator should not be confused with exogenous change in monetary policy and the forecasted value of variables given these changes are not necessarily what one would expect of exogenous changes to monetary policy. This indicator, nonetheless, is useful in characterizing the behavior of the Central Bank providing the degree to which it accommodates various types of shocks and measuring the general monetary condition.

Generally speaking, there are two main approaches taken in the literature for measuring monetary policy stance.

The first approach associates the stance of monetary policy with the level (or the rate of change) of the instrument(s) used by the Central Bank to implement changes in policy. Instruments are variables that are under direct control of the Central Bank, like the reserve requirement ratios or the discount rate. The instruments of policy are manipulated to achieve a prespecified value of an operational target, like the overnight interbank rate, nonborrowed reserves, or a MCI that combines an interest rate and the exchange rate.[2] Despite the conceptual difference, it is common to treat an operational target variable, such as overnight interbank rate or a reserve aggregate, as the policy instrument, given that these variables can be closely controlled.[3] Bernanke and Mihov (1998) [BM] developed a VAR-based methodology in which the measure of policy stance is not assumed but rather derived from an estimated model of the central bank's operational procedure. BM employed a specification of the bank reserves market that can accommodate a variety of alternative operational procedures, nesting the best known quantitative measures of monetary policy used in VAR modeling. BM constructed a measure of the overall stance of monetary policy for the U.S.,[4] which is a linear combination of policy variables.[5] This linear combination is composed of the anticipated or endogenous part of policy (the "policy rule") and of the monetary policy shocks. One problem in interpreting the monetary policy instrument as a measure of policy stance is that it is not clear what should be the neutral stance. To overcome this problem, BM

1. As pointed out by Bernanke and Mihov (1998): "the effects of different monetary policy rules on the economy is much more difficult; such an analysis requires either observations on a large number of monetary regimes, or else a structural model identified by strong prior restrictions."

2. The use of the MCI as an operational target for monetary policy was introduced in the 90's by the Bank of Canada.

3. Treating, for example, a short-term interest rate as the instrument of monetary policy should be interpreted to mean that the central bank, by engaging in open-market operations (its actual instrument), can control the interest rate, so that for many purposes, we can ignore the reserve market and treat the short-term interest rate as if it were set directly by the Central Bank.

4. BM methodology have been applied to Germany by Bernanke and Mihov (1997), to Italy by De Arcangelis and Di Giorgio (1998), and to Canada by Fung and Yuan (1999).

5. Policy variables are variables that contain information about the stance of policy but are affected by other forces as well. The Central Bank might not have complete control over the policy variables but it might have a significant influence on these variables within the current period.

suggests normalizing the stance at each date by subtracting from it a 36-month moving average of its own past values. Smets (1999) made two remarks about this kind of measure of policy stance. First, the choice of 36 months is arbitrary. Second, it is not clear how this measure should be related to future output or inflation, the ultimate policy goals.[6]

The second approach measures the stance of monetary policy according to the intended impact of changes in monetary policy instruments on policy goals, such as output or inflation. There are two main methodologies for constructing such indicators: the narrative-based and the econometric-based methodologies. The narrative-based methodology uses historical record, such as proceedings of the meetings of the Monetary Policy Committee to determine the stance of monetary policy over a given time period. An example of such approach is Boschen and Mills (1995) who develop a monthly index of monetary policy stance for the U.S. based on their reading of the Federal Open Market Committee (FOMC) policy directives and records contained in the *Annual Report* volumes of the Federal Reserve (FED). Their index is constructed according to the importance that policymakers assigned to reducing inflation relative to promoting real growth. The index takes integer values between –2 and 2, with –2 indicating a strong policy emphasis on inflation reduction and a value of 2 indicating a strong emphasis on promoting real growth. The narrative approach provides a measure of policy stance but it has difficulties in distinguishing between exogenous shifts in policy and the endogenous response of policy to economic developments.[7] In contrast with the narrative-based methodology, the econometric-based approach uses statistical evidence to determine the stance of monetary policy. In general this approach involves the development of some kind of index or indicator that summarizes monetary policy, known as MCI. The MCI at time t is constructed as a weighted sum of changes in the short-run interest rate (r) and the exchange rate (q) from a chosen base year (t = 0):[8]

$$MCI_{v,t} = \theta_{v,q}(q_t - q_0) + \theta_{v,r}(r_t - r_0) \tag{1}$$

The weights $\theta_{v,q}$ and $\theta_{v,r}$ are the parameters of interest in the construction of the MCI and they reflect the effects that the interest rate and the exchange rate have on some target variable v (usually output or inflation) as the result of changes in the monetary policy instrument(s).[9] MCI weights cannot be observed directly, so they are estimated using econometric techniques based on some model of the economy, like the simulation of large-scale macroeconometric models or estimation of reduced form aggregate demand equations.

The MCI have been used as an operational target for monetary policy and as a measure of monetary policy stance. When the MCI is used as an operational target,

6. More details of the BM measure of policy stance will be given in Subsection 5.3, when we calculate such indicator for Brazil.

7. For a critical evaluation of the narrative approach to monetary policy, see Hoover and Perez (1994) and Leeper (1997).

8. The MCI can be defined in either real or nominal terms.

9. More recently, some researchers (e.g., Goodhart and Hofmann (2001)) have advocated the inclusion of asset prices in the measurement of monetary policy stance in order to capture also the credit channel. The indexes that include asset prices are known as Financial Condition Indexes (FCI).

the Central Bank chooses a target level for the MCI that is consistent with the long run objectives of policy, and then uses its monetary policy instruments so as to bring the actual MCI to the target MCI.[10] When the MCI is used as a measure of monetary policy stance, it is interpreted as an indicator of the degree of ease or tightness in monetary conditions relative to a base period. However there are several drawbacks in the use of the MCI as a measure of monetary policy stance. First, the construction of the MCI assumes that both the interest rate and the exchange rate are policy instruments. In practice they can be operational targets, but that depends on the monetary policy operational procedure followed by the Central Bank, and this is likely to differ between countries and across time. Second, even in cases where the MCI is employed as an operational target, it should not be interpreted as a fundamental measure of policy stance or monetary conditions, as non-policy variables may play an important role in determining changes in the interest rate and the exchange rate. Therefore, movements in the MCI cannot be tied unequivocally to changes in monetary policy stance.[11]

Recently, Batini and Turnbull (2002) [BT] trying to overcome some of the major criticisms to MCIs, developed a dynamic MCI for the U.K. given by

$$DMCI_{v,t} = \sum_{j=1}^{k_q} \theta_{v,q,t-j}(q_t - q_0) + \sum_{j=1}^{k_r} \theta_{v,r,t-j}(r_t - r_0), \tag{2}$$

where the weights are given by the coefficients of the individual lags of q_t and r_t in the final form regression of the target variable v.

In Subsection 5.1 we discuss in detail the BT methodology when we calculate their MCI for Brazil and show why the CMCI we develop is a better measure of monetary policy stance.

3 THE STRUCTURAL VAR

The VAR is our background model because some of its equations appear also in the forward-looking model (FL model). Moreover, the FL model was calibrated to have the same steady-state values of the VAR and an impulse response function as close as possible to that of the VAR.

The Structural VAR (SVAR) can be represented by

$$A_0 Y_t = a + \sum_{i=1}^{p} A_i Y_{t-i} + e_t \tag{3}$$

If we assume that A_0 is invertible then (3) has a reduced form given by

$$Y_t = \beta + \sum_{i=1}^{p} B_i Y_{t-i} + u_t \tag{4}$$

10. In addition to the Bank of Canada, the Reserve Bank of New Zealand also adopted the MCI as an operational target. However, according to Batini and Turnbull (2002), the role of the MCI as an operational target has been de-emphasized in both countries.

11. For a critical evaluation of MCIs, see Eika, Ericsson, and Nymoen (1996).

with $u_t \sim N(0,\Sigma)$ and $E(u_t u_s) = 0, \forall t \neq s$, where u_t is the reduced form residuals and β is a vector of constants. It is assumed that $\varepsilon_t \sim N(0,\Omega)$, Ω diagonal. The relation between models (3) and (4) is based on the following identities:

$$\beta = A_0^{-1}\alpha, B_i = A_0^{-1}A_i, \ u_t = A_0^{-1}\varepsilon_t \text{ and } \Sigma = A_0^{-1}E(\varepsilon_t \varepsilon_t')(A_0^{-1})' = A_0^{-1}\Omega(A_0^{-1})'.$$

The estimated VAR has five variables represented by the vector Y_t = [$y_t, \pi_t, R_t, q_t, rl_t$], where:

y_t: the Brazilian Institute of Geography and Statistic [Instituto Brasileiro de Geografia e Estatística (IBGE)] seasonally adjusted industrial production gap (the log of the index was seasonally adjusted and detrended by the Hodrick-Prescott filter);

π_t: the annualized monthly inflation rate defined by $\log(IPCA_t / IPCA_{t-1})$, where IPCA (Índice de Preços ao Consumidor Amplo) is the Brazilian consumer price index;

R_t: the short-run annualized monthly nominal Selic interest rate;

q_t: the real exchange rate, computed as the nominal exchange rate deflated by the ratio between the American consumer price index (all urban consumers) and the Brazilian IPCA; and

rl_t: the 180 days annualized Swap rate (Di x Pre).

The VAR was estimated with monthly data from March 1999 to March 2005 with one lag (SVAR1), following the SC (Schwarz) information criterion, or two lags (SVAR2) following FPE (final prediction error) and HQ (Hannan-Quinn) information criteria (the lag selection tests are presented in Table 1). According to Céspedes, Lima and Maka (2005) there are significant differences in the impulse response functions when the model is estimated for two different sub-periods, 1995-1998 and 1999-2005. The second sub-period is characterized by a significant change in the exchange rate policy: the exchange rate became flexible. Since all variables are stationary we can obtain their steady-state values (and error bands), shown in Table 2.[12]

Without additional restrictions on A_0 we cannot recover the structural form from the reduced form because Σ does not have enough estimated coefficients to recover an unrestricted A_0 matrix. Therefore, we need to impose a certain number of restrictions that will allow us to identify and estimate A_0.[13] In order to identify matrix A_0 we adopt a data oriented procedure to select over-identifying restrictions and estimate our SVARs. These restrictions can be read off directed acyclic graphs (DAGs) estimated by the PC algorithm, developed by Spirtes, Glymour, and Scheines (1993 and 2000), which intends to uncover the causal contemporaneous relations between variables, using as input the covariance matrix of reduced form VAR disturbances. Applying TETRAD at the 20% significance level and assuming that the set of variables is causally sufficient,[14] we

12. The steady-state values for nominal interest rate and real exchange rate are necessary to evaluate the MCI.

13. Good descriptions of structural VAR can be found in Sims (1986), Fackler (1988), Hamilton (1993) and Enders (1995).

14. A set of variables *V* is said to be causally sufficient if every common cause of any two or more variables in *V* is in *V*.

obtain what is known as a *pattern*,[15] shown in Figure 1. The pattern is a graphical representation of the set of observationally equivalent DAGs containing the contemporaneous causal ordering of the variables.

TABLE 1
VAR LAG ORDER SELECTION CRITERIA
[Included observations: 63 sample: 1999:03 2005:03]

Lag	LogL	LR	FPE	AIC	SC	HQ
0	625.1121	NA	1.94E–15	–19.68610	–19.51601	–19.61920
1	864.5317	433.2355	2.15E–18	–26.49307	–25.47253[a]	–26.09169
2	915.1444	83.55114	9.70E–19[a]	–27.30617	–25.43518	–26.57030*
3	940.4683	37.78488[a]	9.98E–19	–27.31645	–24.59501	–26.24610
4	967.0677	35.46581	1.02E–18	–27.36723	–23.79534	–25.96239
5	984.6075	20.60239	1.47E–18	–27.13040	–22.70806	–25.39107
6	1006.678	22.42048	1.99E–18	–27.03739	–21.76460	–24.96357
7	1031.759	21.49844	2.72E–18	–27.03998	–20.91673	–24.63167
8	1062.689	21.60160	3.62E–18	–27.22822	–20.25452	–24.48543
9	1117.202	29.41984	2.95E–18	–28.16514	–20.34100	–25.08787
10	1171.482	20.67793	3.76E–18	–29.09465*	–20.42006	–25.68289

[a] indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error.
AIC: Akaike information criterion.
SC: Schwarz information criterion.
HQ: Hannan-Quinn information criterion.

TABLE 2
VAR MODEL — STEADY-STATE (68% PROBABILITY BANDS)

	Lag =1		Lag = 2	
	Bands	Mean Value	Bands	Mean Value
Output gap	0.99 - 1.01	1.0	0.99 - 1.01	1.00
Inflation rate (%)	7.4 - 10.8	9.2	6.3 - 11.6	8.8
Nominal Selic rate (%)	17.6 - 20.1	18.8	17.2 - 20.5	18.9
Real exchange rate (R$/US$)a	2.8 - 3.3	3.0	2.7 - 3.4	3.0
Nominal swap rate (%)	18.9 - 21.8	20.3	18.1 - 22.1	20.0

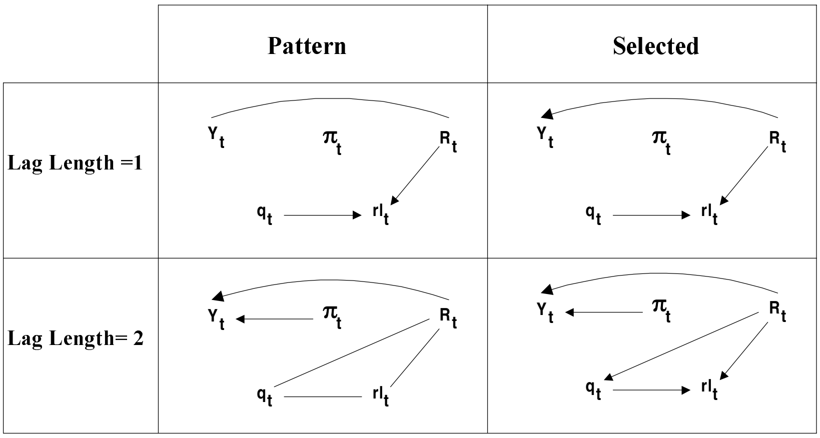
Note: All rates are yearly rates.
[a] At April 2005 prices.

The pattern for SVAR1, in Figure 1, allows two different specifications of the causal ordering: the Selic affecting contemporaneously the output gap or vice-versa. Following Sims and Zha (1996) we assume that the former is true and arrive at a unique contemporaneous causal ordering. The pattern for SVAR2 allows several different specifications of the causal order. Nevertheless, if we select the causal ordering which is the closest to that of lag length = 1 and does not exhibit the "price puzzle" we arrive at just one causal ordering, the adopted one.

15. A pattern is a partially oriented DAG, where the directed edges represent arrows that are common to every member in the equivalent class, while the undirected edges are directed one way in some DAGs and another way in others. Undirected edges mean that there is causality in one of the two directions but not on both, while double oriented edges (↔) mean causality on both directions.

Figure 1 shows the selected contemporaneous causal ordering for SVAR1 and SVAR2.

FIGURE 1
CONTEMPORANEOUS CAUSAL ORDERING (VAR)



Note: For lag length = 2 we present only the pattern we arrived at after imposing that Y_t does not affect R_t contemporaneously. Selecting, for lag length = 2, the causal ordering which is the closest to that of lag length = 1 and does not show the "price puzzle" we arrived at just one causal ordering, the adopted one.

Using the selected contemporaneous causal orderings, displayed in Figure 1, to identify the SVAR models (with one or two lags), we obtained the impulse response functions (IRF) shown on Figure 2 (lag length = 1) and Figure 3 (lag length= 2).

As can be seen in Figures 2 and 3, responses to positive Selic innovations are in line with the results that one would expect from a monetary policy shock: inflation decreases, output decreases, and the real exchange-rate appreciates (at least for SVAR2). Positive real exchange rate shocks induce an immediate increase in the Swap rate and a slower increase in inflation and in the Selic rate. The output gap decreases slowly (SVAR1), or decreases after an initial increase (SVAR2), in response to a positive real exchange rate shock.

FIGURE 2
IMPULSE RESPONSE FUNCTION OF THE VAR MODEL
(Lag Length=1)

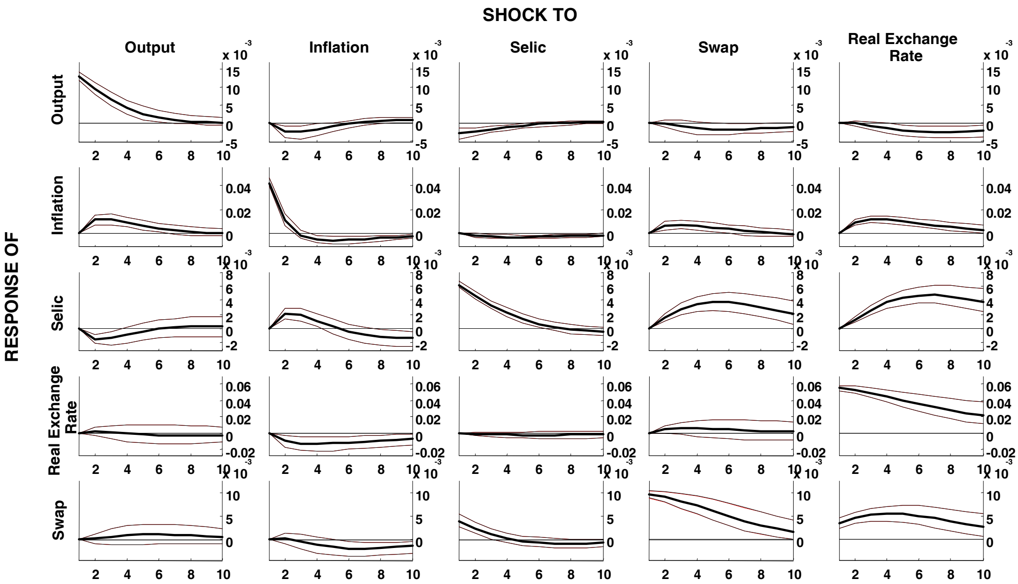
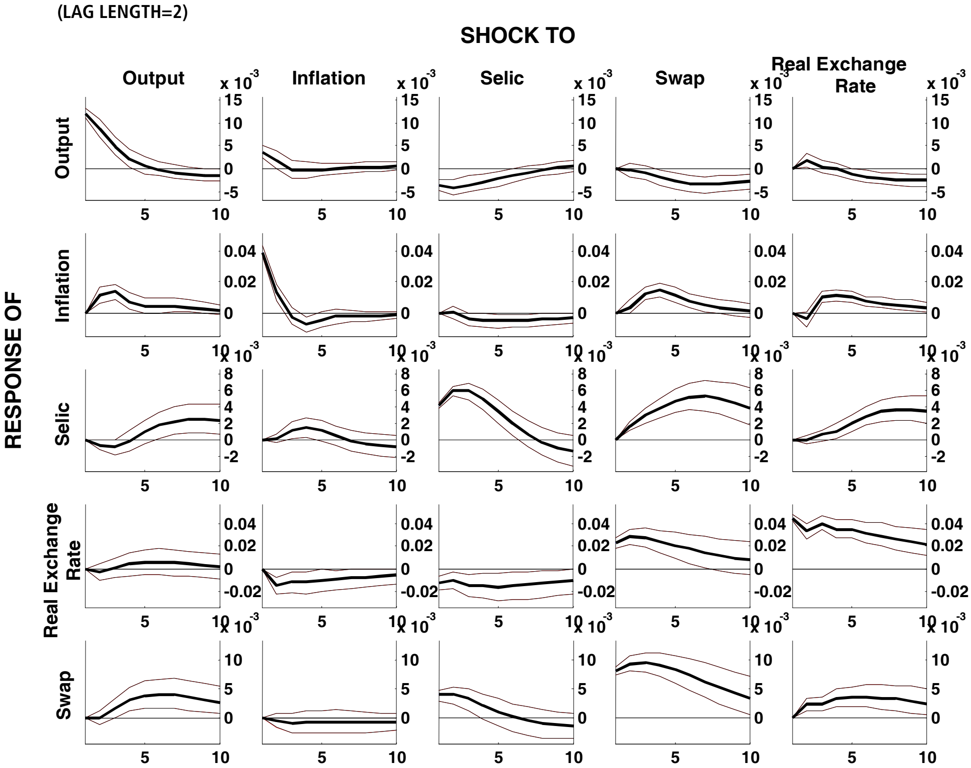


FIGURE 3

IMPULSE RESPONSE FUNCTION OF THE VAR MODEL
(LAG LENGTH=2)



4 THE FORWARD-LOOKING MODEL

We built the FL model by imposing a set of restrictions, consistent with economic agents' FL behavior, to the original SVAR model [equation (3)].

4.1 SPECIFICATION, CALIBRATION AND IMPULSE RESPONSE OF THE FORWARD-LOOKING MODEL

The SVAR model is a good forecasting model for almost all variables of the model with the exception of the real exchange rate and of the Swap rate. This is one of the reasons why the FL model is composed of only three equations taken from the estimated SVAR model—the ones for the industrial production gap, inflation and the short-run nominal interest rate (Selic)—plus three new equations: the covered real interest rate parity condition plus a risk premium, the expectational hypothesis of the term structure of interest rates, and the Fischer equation.[16] The first two new equations replace the real exchange rate and the swap rate equations of the SVAR model and the last equation adds a new variable to the analysis, the ex ante short-run real interest rate. The FL model, as the SVAR model, has two versions: one partially taken from the SVAR with lag length equal to one (FL1) and another partially taken from the SVAR with lag length equal to 2 (FL2). The additional equations of the FL mod el are:

16. This is similar to how BT built their model with the difference that they add the restrictions to a reduced form macroeconometric model.

$$q_t = E_t q_{t+1} - \frac{r_t}{12} + \frac{rf_t}{12} + k_t \tag{5}$$

$$rl_t = pr + \frac{1}{6} \cdot E_t \sum_{j=0}^{5} R_{t+j} + u_t \tag{6}$$

$$r_t = R_t - E_t \pi_{t+1} \tag{7}$$

where: r_t is the (short-term) ex ante real interest rate; $pr + u_t$ is a stochastic risk premium, $\frac{rf_t}{12} + k_t$ is a combination of risk premium (country risk and currency risk) plus the short-term ex ante foreign real interest rate;[17] E_t is the expectation operator given information up to period *t*; k_t and u_t are i. i. d. and normally distributed disturbances with zero mean and variances that are calibrated so that the impulse response of the FL model matches, at least in the first step ahead, that of the SVAR model. We also choose a constant value for rf_t and pr so that the steady-state of the FL model matches that of the SVAR model.

The FL model is a structural model in the sense that it has five, contemporaneously uncorrelated, exogenous structural shocks: μ_y (output gap equation disturbance), μ_π (inflation equation disturbance), μ_R (short-run nominal interest rate (Selic) equation disturbance), k_t (covered real interest rate parity equation disturbance) and u_t (expectational hypothesis equation disturbance). Since the FL model involves expectations we adopt the hypothesis of rational expectations and use the algorithm developed by Sims (2001) to solve the model. Sims methodology for solving linear models with rational expectations is similar to that of Blanchard and Kahn (1980) with important advantages.[18]

To use the algorithm developed by Sims (2001) the FL model was cast in the following form:

$$\Gamma_0 x_t = c + \Gamma_1 x_{t-1} + \Psi \varepsilon_t + \Pi \eta_t \tag{8}$$

where:

c is a vector of constants;

17. The $\frac{\mathrm{rf}_t}{12} + k_t$ term is not observable and can be decomposed into three different terms: $\frac{rf_t}{12} + \mathrm{k}_t = \frac{r_t^*}{12} + crp_t + cup_t$, where r_t^* is the ex ante foreign short-run real interest rate at period *t*, crp_t is the country real risk premium at period *t* and cup_t is the currency real risk premium at period *t*. An analysis of the Brazilian country risk and currency risk can be found in Garcia and Brandão (2003).

18. For instance, there is no need to specify whose elements of the system are predetermined which is consistent with the VAR methodology. Additionally, each conditional expectation and the associated expectation error are treated as additional endogenous variables and an equation is added to the model defining the expectation error. Finally, Blanchard and Kahn (1980) method assume transversality conditions associated to a maximal rate of growth for any element of the system. Sims`s algorithm recognizes that in general only certain linear combinations of variables are required to grow at bounded rates.

$\varepsilon_t = (\mu_y, \mu_\pi, \mu_R, k_t, u_t)'$ = vector of exogenous structural disturbances;

$\eta_t = (\eta_{t\pi}, \eta_{t0}, \eta_{t1}, \eta_{t2}, \eta_{t3}, \eta_{t4}, \eta_{tq})'$ = vector of expectational errors satisfying $E_t \eta_{t+i} = 0, i > 0$;

$\eta_{t\pi} = \pi_t - E_{t-1}\pi_t$; $\eta_{ti} = E_t R_{t+i} - E_{t-1} R_{t+i}$, $i = 0,1,...4$; $\eta_{tq} = q_t - E_{t-1} q_t$;

Γ_0, Γ_1, Ψ and Π are matrices of equations' parameters.[19]

The solution of (8) applying Sims' algorithm is given by

$$x_t = \Theta_1 c + \Theta_2 x_{t-1} + \Theta_3 \varepsilon_t \tag{9}$$

where: Θ_1, Θ_2 and Θ_3 are matrices of coefficients supplied by the algorithm.

Equation (9) is an autoregression of order one and is used in the construction of both the PMCI and the CMCI of the SVAR and FL models. Adequately defining x_t, in terms of contemporaneous and lagged elements of y_t, the SVAR model [equation (3)] can also be represented by equation (9), independently of its lag length.

Given equation (9) and data up to time $T+h$, the value of x at time $T+h$ is given by:

$$x_{T+h} = K_h \,.\, c + \Theta_2^h x_T + \sum_{\upsilon=0}^{h-1} M_\upsilon \varepsilon_{T+h-\upsilon} \tag{10}$$

where:

$$K_h = (I - \Theta_2^{h+1})(I - \Theta_2)^{-1}\Theta_1 \quad \text{and} \quad M_\upsilon = \Theta_2^\upsilon \Theta_3$$

The M_υ parameters give the response of x_{T+h} to the impulse given by $\varepsilon_{T+h-\upsilon}$

Figures 4 and 5 display, respectively, the impulse response function of the FL model with lag length equal to one (FL1) and two (FL2). We calibrate the variance of the ε_t disturbances in such a way as to make the IRF of the FL model look as close as possible to that of the corresponding SVAR model. As can be seen in Figures 4 and 5, responses to Selic innovations for both FL models (FL1 and FL2) are in line with those of the SVAR models and those one would expect from a monetary policy shock: inflation goes down, output decreases, and the real exchange rate appreciates (at least for the FL2 model). Positive real exchange rate shocks induce a delayed response of inflation and the Selic rate and an effect on output which is null (FL1) or is initially positive becoming negative.

19. The vector x_t is composed of observed and non-observed variables. When the model has lag length equal to 1 it can be written as:

$x_t = (y_t, R_t, \pi_t, q_t, rl_t, r_t, E_t\pi_{t+1}, E_t R_{t+1}, E_t R_{t+2}, E_t R_{t+3}, E_t R_{t+4}, E_t R_{t+5}, E_t q_{t+1})$.

FIGURE 4

IMPULSE RESPONSE FUNCTION OF THE FORWARD LOOKING MODEL

(Lag Length=1)

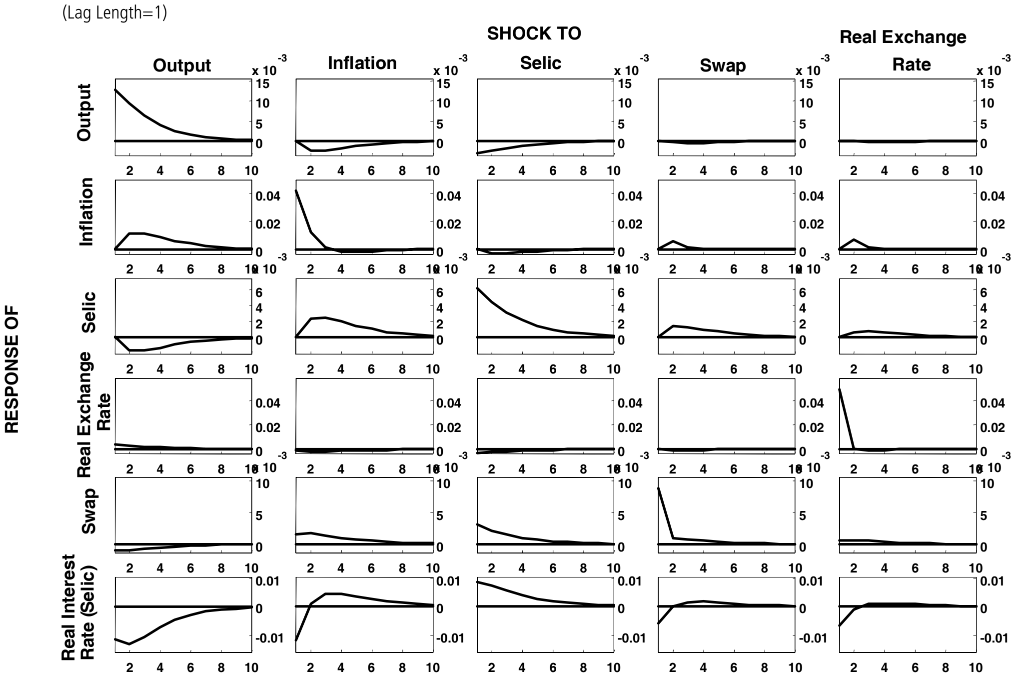
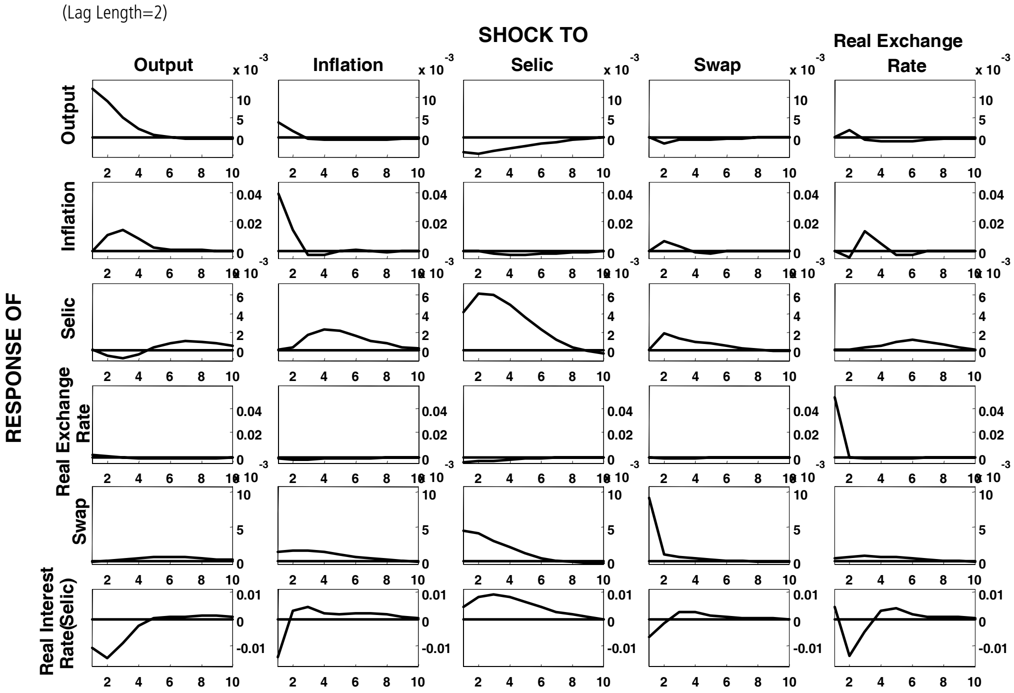


FIGURE 5

IMPULSE RESPONSE FUNCTION OF THE FORWARD LOOKING MODEL

(Lag Length=2)



4.2 SENSITIVITY TO CHANGES IN THE CALIBRATED VALUE OF THE STEADY-STATE REAL SHORT-RUN INTEREST RATE

In this Subsection we investigate how changing the calibrated value of the non-stochastic part (rf) of the ex ante foreign short-run real interest rate ($\frac{rf}{12}+k_t$) faced by the domestic economy affects the steady-state values of all FL model variables.

The ex ante foreign short-run real interest rate faced by the domestic economy is the ex ante foreign short-run real interest rate plus the country risk and plus the currency risk.[20] As pointed out by various authors, in the case of Brazil the foreign rate it faces is, in its major part composed of the country risk and the currency risk. Hence, it is not totally exogenous with respect to domestic variables even though its short-run movements may be mostly caused by factors external to the domestic economy. Consequently, a unidirectional causal interpretation of equation (5) above is not granted. Furthermore, our FL model does not explicitly model the impact of external factors on domestic variables or rf.

As indicated before, one of the possible shortcomings of our FL model[21] is the hypothesis that the ex ante foreign short-run real interest rate faced by the country is exogenous and normally distributed around a constant term. Even assuming that the specification of equation (5) is correct we still do not know the true value of rf. We have calibrated it to be equal to the estimated steady-state value of the ex post domestic short-run real interest rate (given by SVAR1 or SVAR2). In this subsection we show how changing the value of this parameter—, which is equal by a non-arbitrage condition to the ex ante domestic short-run real interest rate (r_{ss})—affects the steady-state values of other variables of the model.

In our sensitivity analysis the calibrated values of rf change according to a grid and, keeping all the other parameters constant, for each value of rf we compute the steady-state value of the other variables. Therefore, we are constructing intervals for the steady-state value of the other variables, conditioned on the true value of rf belonging to the chosen grid and on the estimated value of the other parameters. This is not the same as saying that the analysis is giving us steady-state values of variables for samples generated by the different calibrated values of rf—different from the one which have generated our sample data—which are different from its true value during our sample period. Consequently, the correct question we are trying to answer with the sensitivity analysis of this section is: what are the different steady-state values of the domestic variables, if their observed past values were generated by different values of rf (or r_{ss}) from the one assumed?

20. The country risk plus the currency risk is usually denominated the covered real interest rate parity differential.

21. Another possible shortcoming of the FL model is the implicit hypothesis that the potential output (the trend extract by the Hodrick-Prescott filter) is an exogenous variable. Any comparative static analysis of the model—changing rf or any other parameter of the model—is not going to affect potential output but only the output gap. The model may predict adequately movements of variables as long as the changes have not affected substantially the long-run growth potential of the economy. It is not able to predict correctly what is going to occur when for instance the country risk decreases and this change alters the growth potential of the economy and the supply of foreign goods to the domestic economy. The FL model can be roughly interpreted as a model of the deviations of the economy from its trends, given the average observed state of the world economy, during the covered period.

Or putting it differently, what are the changes in the steady-state values of the variables if the domestic economy is moving to a different r_{ss} from the one that was assumed.

Table 3 shows the impact of changes, in the calibrated steady-state values of the ex ante real short-run interest rate (foreign or domestic), on the steady-state value of other variables of the model. There is a negative relation between *rf* (or r_{ss}) and the steady-state inflation rate. A decrease of half percent point in r_{ss} (or *rf*) increases steady-state inflation rate by, approximately, 1.4 (SVAR1) or 1.2 (SVAR2) percent points. That is, the smaller the true value of *rf* during the period covered by our analysis the higher is the steady-state inflation rate. There is also a positive relation between r_{ss} and the output gap. Hence, a lower than assumed r_{ss} is associated with a higher inflation and a smaller observed output when compared to potential output. In line with all these results, there is a negative relation between r_{ss} and the steady-state real exchange rate.

TABLE 3
FORWARD-LOOKING MODEL STEADY-STATE VALUES
[Lag Length = 1]

Real Interest Rate (%) / Variables	rf = 11.6	rf = 11.1	rf = 10.6	rf = 10.1	SVAR1 Steady-state values	rf = 9.1	rf = 8.6	rf = 8.1	rf = 7.6
Output gap	1.02	1.02	1.01	1.01	1.00	1.00	1.00	0.99	0.99
Rate of inflation	3.68	5.01	6.39	7.79	9.19	9.21	10.65	12.11	13.62
Nominal Selic rate	14.69	15.69	16.72	17.76	18.79	18.81	19.87	20.94	22.05
Real exchange rate (US$/R$)[a]	2.23	2.41	2.59	2.81	3.03	3.03	3.28	3.53	3.83
Nominal swap rate	16.15	17.16	18.20	19.26	20.30	20.32	21.39	22.48	23.60
Ex-ante Real Selic Rate (r_{ss})	11.60	11.10	10.60	10.10	9.60	9.10	8.60	8.10	7.60

(Lag Length = 2)

Real Interest Rate (%) / Variables	rf =12.05	rf = 11.55	rf = 11.05	rf = 10.55	SVAR2 Steady-state values	rf = 9.55	rf = 9.05	rf = 8.55	rf = 8.05
Output Gap	1.02	1.02	1.01	1.01	1.00	1.00	1.00	0.99	0.99
Rate of Inflation	4.03	5.18	6.38	7.59	8.80	8.81	10.05	11.30	12.56
Nominal Selic Rate	15.55	16.35	17.18	18.02	18.90	18.86	19.70	20.56	21.42
Real Exchange Rate (US$/R$)*	2.28	2.44	2.61	2.80	2.97	3.00	3.22	3.45	3.70
Nominal Swap Rate	16.69	17.50	18.33	19.18	20.00	20.03	20.88	21.75	22.61
Ex-ante Real Selic Rate (r_{ss})	12.05	11.55	11.05	10.55	10.10	9.55	9.05	8.55	8.05

Note: All rates are yearly rates. [a]At April 2005 prices.

5 MEASURING MONETARY POLICY STANCE

In this section we explain how we constructed our measures of monetary policy stance. We have three indicators: the PMCI, the CMCI, and the Bernanke-Mihov Monetary Conditions Index (BMCI).

5.1 THE PARTIAL CONDITIONAL MONETARY CONDITIONS INDEX

What we call PMCI is in fact the Dynamic MCI (DMCI) developed by Batini and Turnbull (2002) (BT). However, we show that this indicator is inaccurate and can be improved. The improved indicator (the CMCI) will be presented in the next subsection.

In order to calculate the MCIs we manipulate algebraically equation (9) (which can represent both the FL model and the SVAR model) by partitioning vector x_t, such that $x_t = (Z_{1t}, Z_{2t})$ and Z_{2t} contains only contemporaneous and lagged values of the short-run nominal interest rate and the real exchange rate.[22]

After processing the above mentioned manipulation, Z_1 is given by:

$$Z_{1t} = C_1 + \Lambda_{11} Z_{1t-1} + \Lambda_{12} Z_{2t-1} + \Lambda_2 \varepsilon_t \tag{11}$$

where: C_1 is a column vector whose elements are taken, according to the partition, from $\Theta_1 c$ [parameters of equation (9) above]; Λ_{11} and Λ_{12} are matrices whose elements are taken, according to the partition, from Θ_2 and Λ_2 is a matrix of coefficients taken from Θ_3 [parameters of equation (9) above].

By recursive substitution of lagged values of Z_1, we arrive at:

$$Z_{1t} = (I - \Lambda_{11}^t)(I - \Lambda_{11})^{-1} C_1 + \Lambda_{11}^t Z_{10} + \sum_{s=1}^{t} \Lambda_{11}^{s-1} \Lambda_{12} Z_{2t-s} + \sum_{s=1}^{t} \Lambda_{11}^{s-1} \Lambda_2 \varepsilon_{t-s+1} \tag{12}$$

or, alternatively,

$$Z_{1T+h} = (I - \Lambda_{11}^{T+h})(I - \Lambda_{11})^{-1} C_1 + \Lambda_{11}^{T+h} Z_{10} + \sum_{s=1}^{T+h} \Lambda_{11}^{s-1} \Lambda_{12} Z_{2,T+h-s} + \sum_{s=1}^{T+h} \Lambda_{11}^{s-1} \Lambda_2 \varepsilon_{T+h-s+1}$$

where: Z_{10} is the initial value of Z_1 before the sample starts.

All variables in the SVAR and FL models are stationary and, therefore, $\lim_{T\to\infty} \Lambda_{11}^T = 0$. For large enough T, the last equation collapses to

$$Z_{1T+h} = (I - \Lambda_{11})^{-1} C_1 + \sum_{s=1}^{T} \Lambda_{11}^{s-1} \Lambda_{12} Z_{2,T+h-s} + \sum_{s=1}^{T} \Lambda_{11}^{s-1} \Lambda_2 \varepsilon_{T+h-s+1} \tag{13}$$

Based on equation (13) we conclude that, for large enough T, the value of $Z_{1,T+h}$ does not depend on the pre-sample or any value of Z_1 and depends only on the last T lags of Z_2 and ε.

Let us extract, from the set of equations (13), the equation corresponding to the industrial production output gap (*xg*) and express it in terms of elements of Z_2 (i.e., lags of the short-run interest rate and of the real exchange rate):

$$xg_{T+h} = \sum_{s=1}^{T} \lambda_s^1 q_{T+h-s} + \sum_{s=1}^{T} \lambda_s^2 R_{T+h-s} + \sum_{s=1}^{T} \lambda_s^3 \varepsilon_{T+h-s+1} \tag{14}$$

22. When the model has lag length equal to one, $Z_{1t} = (y_t, \pi_t, rl_t, r_t, E_t\pi_{t+1}, E_tR_{t+1}, E_tR_{t+2}, E_tR_{t+3}, E_tR_{t+4}, E_tR_{t+5}, E_tq_{t+1})$.

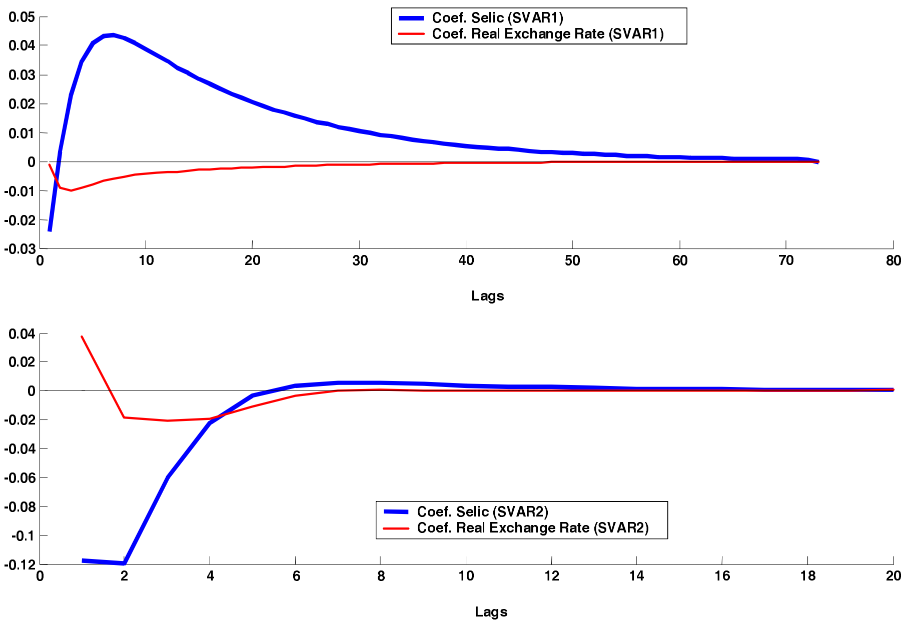
where λ_s^1 and λ_s^2 are extracted from the coefficients of Z_2 and λ_s^3 from the coefficients of ε_{T+h-s} of equation (13).

The values of λ_s^1 and λ_s^2 (for s = 1,2,...) are presented in Figure 6 (SVAR1 and SVAR2) and Figure 7 (FL1 and FL2). As can be observed in both tables the direct effect of the real exchange rate on the output gap is considerable less important than that of the nominal short-run rate. Different lag lengths alter considerably the magnitude and sign of coefficients, more notably for those of the short-run Selic rate. Nevertheless, it is difficult to attribute any expected theoretical sign to the coefficients of equation (13), since they are not structural equation's coefficients. The sensibility of coefficients to lag length choice is critical for the PMCI but not, as we will show, for the CMCI.

Our PMCI measures the forecasted impact on *xg*, the element of the column vector Z_1 corresponding to the industrial production gap, of the observed sample path of Z_2 (lagged values of the nominal interest rate and of the real exchange rate) minus the same impact when Z_2 is fixed at its steady-state value. The PMCI is calculated for observations T+1,…,T+K, where T+K is equal to the sample size. Our sample size is equal to 72 and we fix T = 18 (therefore, K = 56). More explicitly, the PMCI is constructed as if the distributions, of the random disturbances ε, are not affected by different paths of the interest rate and of the exchange rate. The PMCI is calculated as follows:[23]

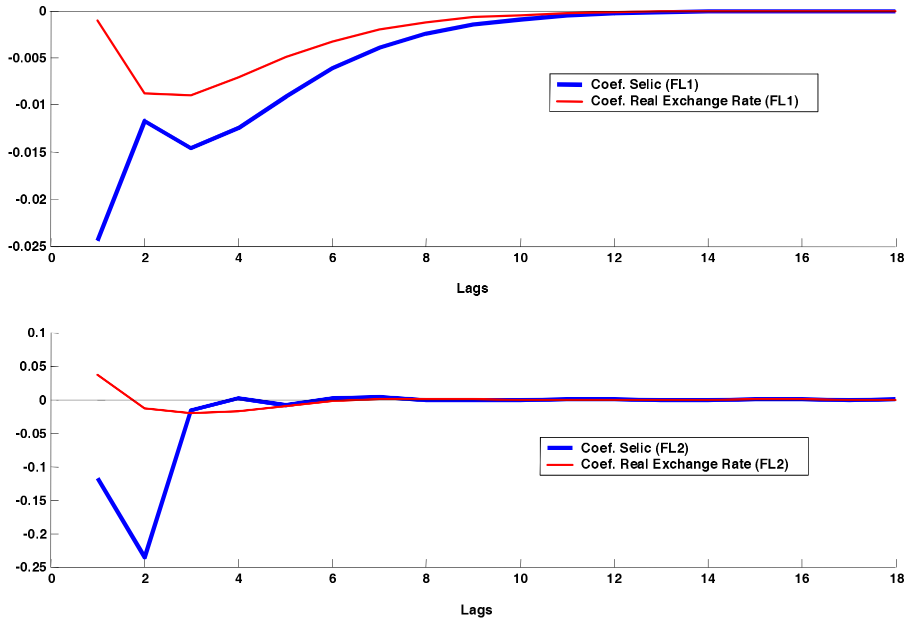
$$PMCI_{T+h} = \sum_{s=1}^{T} \lambda_s^1 (q_{T+h-s} - q_{ss}) + \sum_{s=1}^{T} \lambda_s^2 (R_{T+h-s} - R_{ss}),\ \ h = 1,\ldots,K \qquad (15)$$

FIGURE 6
STRUCTURAL VAR MODEL COEFFICIENTS



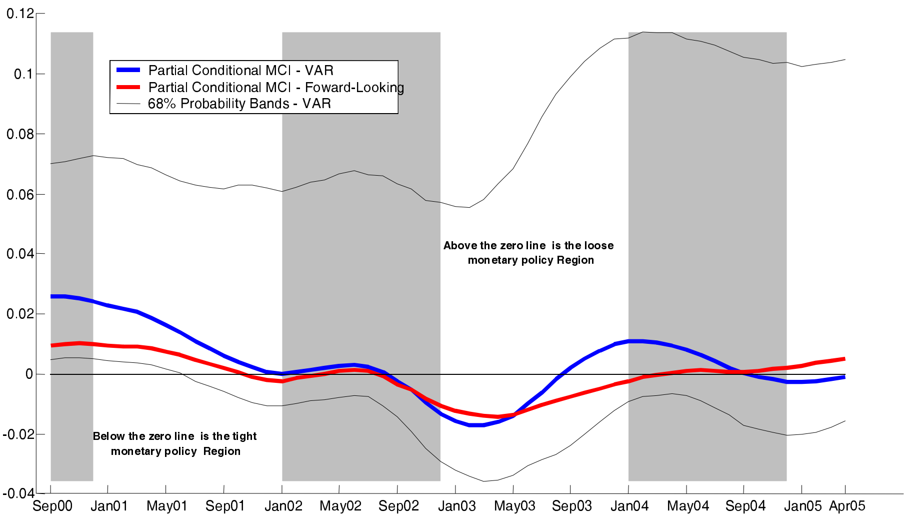
23. Batini and Turnbull (2002) use a different route and, instead of algebraic calculations, estimate the parameters of (14) applying OLS to the model's simulated data. We consider this process flawed due to the presence of perfect multicolinearity between sets of explanatory variables (the disturbance terms $\varepsilon_{T+h-s+1}$ are part of the set of explanatory variables).

FIGURE 7
FORWARD-LOOKING MODEL COEFFICIENTS



A positive (negative) value of the PMCI indicates loose (tight) monetary policy, as the log of the output gap will be above (below) its zero[24] steady-state level as a result of the deviation of the observed path of the short-run nominal interest rate (Selic) and of the real exchange rate from their steady-state levels. Figures 8 and 9 show the PMCI for Brazil from september 2000 to april 2005 calculated for both the SVAR and FL models and their respective lag structure versions. As can be observed in Figures 8 and 9, the PMCI is sensible to the assumed lag length of both SVAR and FL models but there is not much difference between the SVAR and FL's PMCIs for lag length equal 2. We will discuss next why the PMCI fails to capture the stance of monetary policy and we introduce a better indicator, the CMCI.

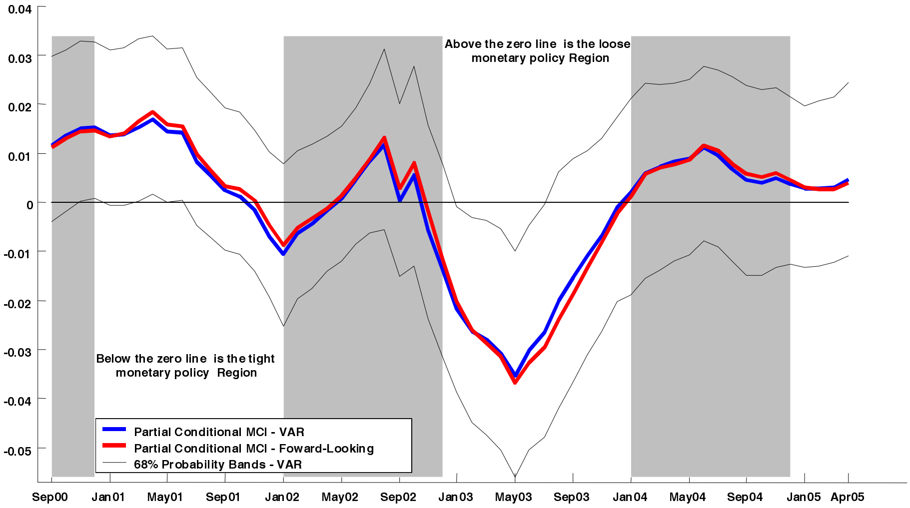
FIGURE 8
MONETARY POLICY STANCE IN BRAZIL — STRUCTURAL VAR MODEL X FOWARD-LOOKING MODEL (LAG=1)



Note: The shaded areas represent election years.

24. The output gap is defined as "observed industrial production index/potential industrial production index" and when the numerator is equal to the denominator the log of the ratio is equal to zero.

FIGURE 9
MONETARY POLICY STANCE IN BRAZIL — STRUCTURAL VAR MODEL X FOWARD-LOOKING MODEL (LAG=2)



Note: The shaded areas represent election years.

5.2 THE CONDITIONAL MONETARY CONDITIONS INDEX

One caveat of the PMCI, defined above, is that in its calculation it was assumed that the distribution of equations' disturbances, conditional on trajectories of endogenous variables [the nominal interest rate (Selic) and the real exchange rate], is equal to its unconditional distribution.[25] This is only true if the interest rate and the exchange rate were exogenous. BT implicitly assumes that these conditional distributions have zero mean and are unaffected by the trajectories of the interest rate and of the exchange rate. According to Doan, Litterman, and Sims (1984) and Waggoner and Zha (1999), when the future path of a set of endogenous variables is fixed, the future values of shocks depend on the path of these endogenous variables. This implies that the mean of the distribution of shocks is different from zero. Therefore, the PMCI does not measure accurately the monetary conditions because the values that come from equation (14) do not represent the most likely value of output given the paths of the short-run interest rate and exchange rate.

According to Waggoner and Zha (1999) "when one imposes conditions on the future values of an endogenous variable, the variable should continue to be treated as endogenous over the future periods". Predictions under such conditions are called conditional forecasts.[26] The theory associated with conditional forecasting first appeared in Doan, Litterman, and Sims (1984). They showed how to calculate point conditional forecasts in the VAR framework. More recently, Waggoner and Zha (1999) developed a method for computing probability distributions or error bands around conditional forecasts in VAR models. The conditions associated with the requirement that a group of variables assume a specific value have been often

25. It is important to stress that this criticism applies to most MCIs, not only the DMCI.

26. The methods that can be applied only to forecasts with no conditions on future variables or future structural shocks are often called unconditional forecasts in the forecasting literature.

considered in the forecasting literature and are called hard conditions.[27] The next paragraphs, partially taken from Waggoner and Zha (1999) and adapted to our notation, present how the distribution of disturbances is affected by the imposition of future values for endogenous variables.

Suppose the value of the *jth* variable is constrained to be equal to $\bar{x}_{T+h}(j,1)$, from (10) this constraint implies the following condition:

$$\sum_{\upsilon=0}^{h-1} M_{\upsilon}(j,.)\omega_{T+h-\upsilon} = \bar{x}_{T+h}(j,1) - K_h(j,.).c - \Theta_2^h(j,.)x_T \tag{16}$$

where the notation (*j*,.) denotes the *jth* row of the matrix and the *r.h.s.* of equation (15) is a forecast error.

If we have multiple conditions, for different variables and different steps-ahead, they can be generalized and presented in the following compact form:

$$R_{qxk}\varepsilon_{kx1} = r, \tag{17}$$

where q is the number of constraints, k is the total number of future shocks, R is a stacked matrix from impulse responses $M_{\nu}(j,.)$ (conditional on the parameters of the model), ε is a vector correspondingly stacked from $\varepsilon_{T+h-\upsilon}$ and r (conditional on the parameters of the model) is the correspondingly stacked forecast errors constructed from the predetermined values of the endogenous variables (the future paths of the interest rate and of the exchange rate).

Waggoner and Zha (1999) show that conditional on equation (17), and on the parameters of the model, the distribution of disturbances ε is given by

$$p(\varepsilon \mid parameters \quad and \quad R\varepsilon = r) = N[R'(RR')^{-1}r, I - R'(RR')^{-1}R'] \tag{18}$$

The most likely path of ε is given by the mean of (18).[28] From this expression we can see why the PMCI is imprecise. The "conditional" forecasts based on equation (15) do not take into account the restrictions imposed by the path of forecast errors that follows from the fact that the path of endogenous variables have been fixed. In other words, the constraint on $\{q_{T+h}\}_{h=1}^{K}$ and $\{R_{T+h}\}_{h=1}^{K}$ can be transformed on equivalent constraint on the most likely value of $\{\varepsilon_{T+h}\}_{h=1}^{K}$ [Doan, Litterman and Sims (1984)].

Based on the idea of conditional forecasts we propose a new measure of monetary policy stance that we called CMCI. Conditional forecasts allows us to predict the most likely path for the industrial production output gap given trajectories for the short-run interest rate and the real exchange rate treating both as

27. Waggoner and Zha (1999) developed another method that deals with conditions that only restrict the future values within a certain range. The future values pertain to either variables or structural shocks. These types of conditions are called soft conditions. Examples of such conditions are a certain range for the Selic path, a target range for the M2 growth rate.

28. In previous work, Doan, Litterman, and Sims (1984) derive a single path of forecasts by minimizing the objective function $\omega'\omega$ constrained by (12) and show that the prediction error of the most efficient path is given by $\varepsilon^* = R'(RR')^{-1}r$. In Appendix A we give a simple example where we construct matrices r and R.

endogenous. The CMCI measures the stance of policy by the difference between the most likely value of the output gap conditioned on the observed values of nominal interest rate and real exchange rate minus the most likely value conditioned on a path where this same variables were fixed at their steady-state values. The CMCI is given by:

$$CMCI_{T+h} = \sum_{s=1}^{T} \lambda_s^1 (q_{T+h-s} - q_{ss}) + \sum_{s=1}^{T} \lambda_s^2 (R_{T+h-s} - R_{ss}) + \sum_{s=1}^{T} \lambda_s^3 [E(\varepsilon_{T+h-s+1} / Iobs) - E(\varepsilon_{T+h-s+1} / Iss)], \quad \mathrm{h} = 1, \ldots, \mathrm{K} \qquad (19)$$

where: Iobs—is the information set given by pre-sample observations, the estimated (or calibrated) parameters of the model (using data from t = 1 until t = T+K), the observations of all observable variables from t = *1* until T and the observed trajectories of the interest rate and the real exchange rate from T+1 to T+K;

Iss—is the information set composed of pre-sample observations, the estimated (or calibrated) parameters of the model (using data from t = 1 until t = T+K), of all variables at their steady-state values, at and before T, and the values of interest rate and the real exchange rate fixed at their steady-state values from T+1 to T+K;

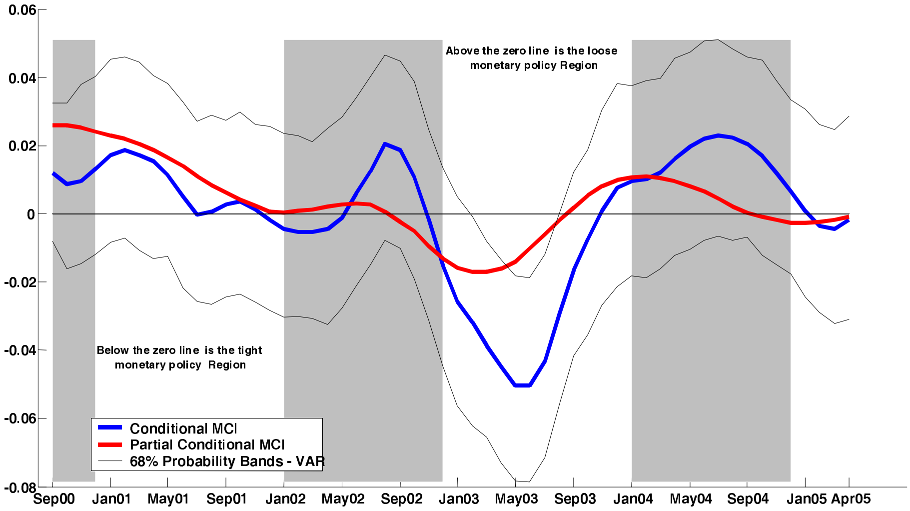
$E(\varepsilon_{T+h-s+1}$ / I)—is the mean of the conditional distribution of $\varepsilon_{T+h-s+1}$, taken from the mean of ε given by the conditional distribution (18), (I = *Iobs*, *Iss*). In the case of the FL model, the unconditional forecast, from t = 1 until de end of the sample at t = T+K, always takes all variables (observed and non-observed) at their steady-state values at pre-sample observations (t= –*nlag*+1, … , 0; 0 < *nlag* = number of lags of the model). The MCIs of the FL model are not significantly affected by this initialization since their calculations start for $t > T$. For the SVAR model the unconditional forecast, from t = 1 until the end of the sample at t = T+K, sets the pre-sample values equal to pre-sample observations if I = *Iobs* or at their steady-state values if I = *Iss*.

Compared to the PMCI, the CMCI shows less sensibility to the assumed lag structure of the SVAR and FL models. Figures 10, 11, 12 and 13 compare the results of the CMCI and the PMCI from september 2000 to april 2005 for both the SVAR and the FL model. The difference between them is particularly pronounced for models with lag length 1. Notice that at some points the CMCI and the PMCI indicate opposite stances of monetary policy. As we discussed above, the CMCI is a more accurate indicator of monetary policy stance. The CMCIs presented in Figures 10, 11, 12 and 13 suggest that monetary policy is looser in election years and tighter in non-election years. The most recent values plotted (April 2005) suggest a neutral monetary policy.

We also tested the impact of changes in the calibrated value of the real steady-state interest rate on the CMCIs of the FL model. Figures 14 (FL1) and 15 (FL2) show that a different real interest rate results in a parallel shift in the CMCIs.

FIGURE 10

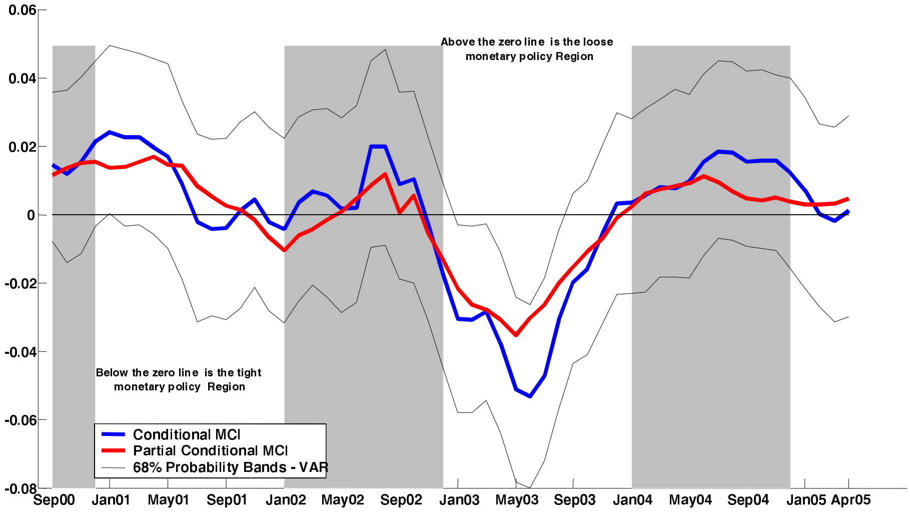
MONETARY POLICY STANCE IN BRAZIL — STRUCTURAL VAR MODEL (LAG=1)



Note: The shaded areas represent election years.

FIGURE 11

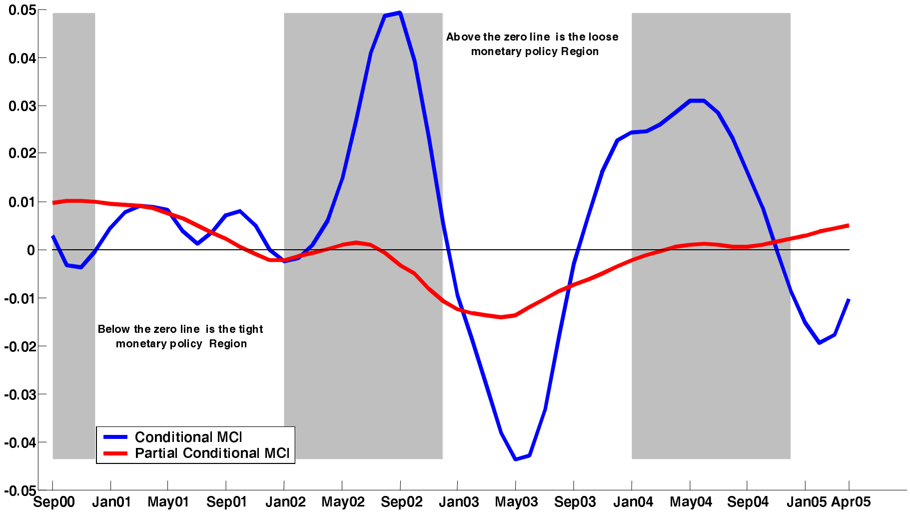
MONETARY POLICY STANCE IN BRAZIL — STRUCTURAL VAR MODEL (LAG=2)



Note: The shaded areas represent election years.

FIGURE 12

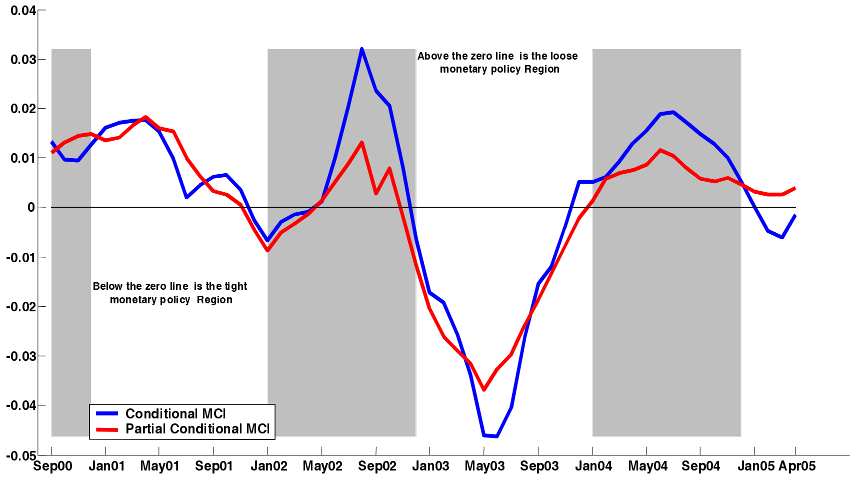
MONETARY POLICY STANCE IN BRAZIL — FOWARD-LOOKING MODEL (LAG=1)



Note: The shaded areas represent election years.

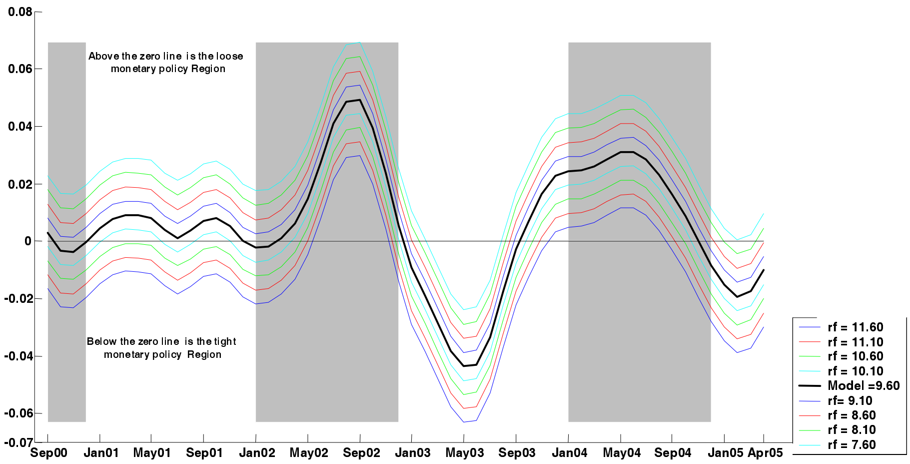
FIGURE 13

MONETARY POLICY STANCE IN BRAZIL — FOWARD-LOOKING MODEL (LAG=2)



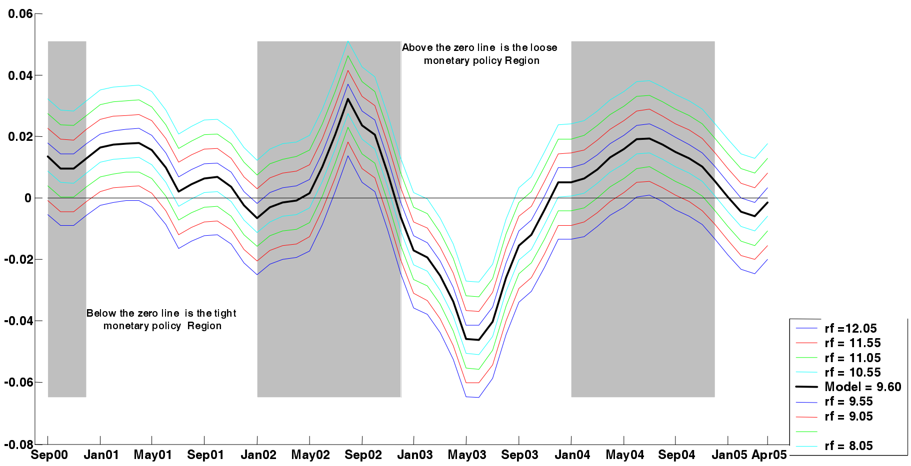
Note: The shaded areas represent election years.

FIGURE 14
MONETARY POLICY STANCE IN BRAZIL: CONDITIONAL MCI — FORWARD-LOOKING MODEL (LAG=1)



Note: The shaded areas represent election years.

FIGURE 15
MONETARY POLICY STANCE IN BRAZIL: CONDITIONAL MCI — FORWARD-LOOKING MODEL (LAG=2)



Note: The shaded areas represent election years.

5.3 THE BERNANKE-MIHOV MONETARY CONDITIONS IINDEX

Bernanke and Mihov (1998) [BM] developed an "overall measure of policy stance" for the U.S., identifying the Central Bank's policy rule in a SVAR carefully built to reproduce the Central Bank's operational procedures. The BM indicator is the linear combination, of contemporaneous policy variables (in the same period of time, without lags), that can be extracted from the Central Bank's estimated policy rule. The weights of policy variables, in the linear combination, are given by their coefficients in the row of matrix A_0, defined in Section 3, corresponding to the policy rule. The innovations of the policy rule equation are monetary policy innovations. The coefficients of contemporaneous non-policy variables, in the linear combination, are restricted to be equal to zero (the coefficients of A_0, corresponding to the policy rule equation and to non-policy variables, are not restricted to be equal to zero). The selected policy variables contain information about the stance of monetary policy and are affected by the contemporaneous values of other variables of the model (non-policy variables) nevertheless policy variables do not affect non-policy variables contemporaneously. The Central Bank might not have complete control over all the relevant policy variables but it has control over their linear combination if it controls at least one of them.

To obtain the BMCI measure of policy stance, a key decision is determining what policy variables should be included contemporaneously in the policy rule and, therefore, included in the linear combination that measures policy stance. In an open economy the exchange rate is a potential candidate. In the case of Brazil, however, the Selic rate is not only the main instrument of monetary policy but it is also its operational target, and the contemporaneous causal ordering obtained for the SVAR models (see Figure 1) does not indicate any contemporaneous causality from other variables, including the exchange rate, to the Selic rate. Therefore, following the BM methodology,[29] a MCI that considers only the Selic rate measures the monetary policy stance in Brazil. We add a new feature to the BM indicator considering the departure of the actual Selic rate from its steady-state value. Therefore, our BMCI is given by

$$\mathrm{BMCI}_t = R_{ss} - R_t, \qquad (20)$$

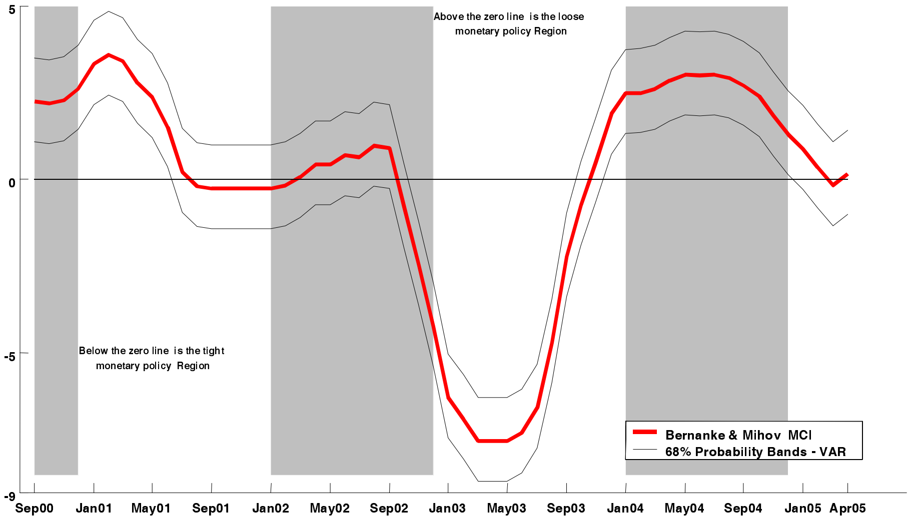
were R_{ss} is the steady-state Selic rate (given by SVAR1 or SVAR2) and R_t is the observed Selic rate.

The BMCIs for SVAR1 and SVAR2 are displayed in Figures 16 and 17. The BMCI and the CMCI are similar for two reasons: the effect of the Selic rate on the output gap is much larger than the effect of the real exchange rate and there is not a significant lag between a change in the Selic rate and the response of the output gap (both facts can be extracted from Figures 6 and 7). Nevertheless, there are differences between these two indicators and they are actually measuring different things. The BMCI is more adequately related to the stance of monetary policy, if the level of monetary policy instruments measures the stance. The CMCI, more than the instruments or their linear combination, is inferring the impact, of the observed values of the main potential instruments of monetary policy (the Selic rate and the real exchange rate), on the output gap.

29. Contrary to Bernanke and Mihov (1998) our policy variable, the Selic rate, affects contemporaneously some of the non-policy variables of the model. This does not constitute a problem because the variables that are affected contemporaneously by the Selic do not affect the Selic contemporaneously.

FIGURE 16

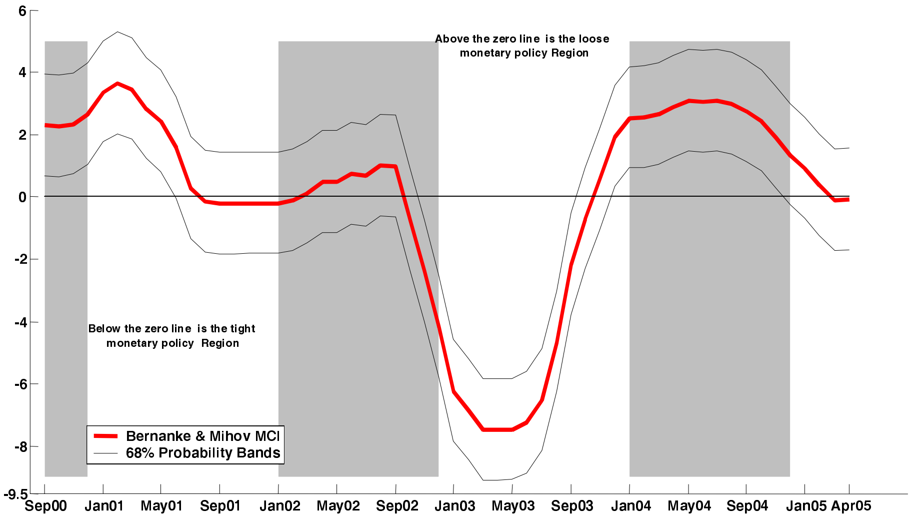
MONETARY POLICY STANCE IN BRAZIL — BERNANKE & MIHOV MCI (LAG=1)



Note: The shaded areas represent election years.

FIGURE 17

MONETARY POLICY STANCE IN BRAZIL — BERNANKE & MIHOV MCI (LAG=2)



Note: The shaded areas represent election years.

6 CONCLUDING REMARKS

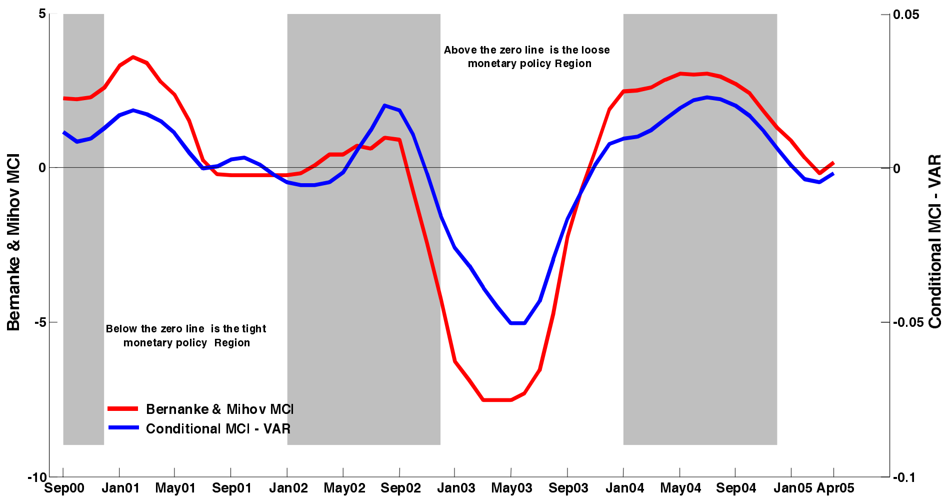
In this article we have used the theory of conditional forecasts to develop a new indicator of monetary policy stance called CMCI, based on SVARs and Forward-Looking models. We showed that the CMCI, when compared to the PMCI developed by Batini and Turnbull (2002), is a better measure of monetary policy stance because it takes into account the endogeneity of variables involved in the analysis.

We also constructed two basic monetary conditions indexes for Brazil: the BMCI and the CMCI. The latter one is based on the new developed approach. The MCI's Bayesian error bands of our overidentified SVAR models were computed following the procedures suggested by Sims and Zha (1999) and are presented in Appendix B.

It is important to emphasize that each of the two MCI indexes constructed measures different things. The BMCI measures the stance by a linear combination of contemporaneous values of policy variables with weights give by a SVAR. Given the specification of our SVARs, the Brazilian BMCI is simply the observed Selic rate. We use a slightly altered version of the BMCI and define it as the steady-state value of the Selic rate minus its observed value. The CMCI defines the stance of monetary policy as the log of the output gap conditional forecast given observed paths of the main potential instruments of monetary policy (the Selic rate and real exchange rate). For this latter MCI, the stance of monetary policy is measured by the discomfort the observed value of those main potential instruments are associated with, as indicated by the log of the output gap conditional forecast.

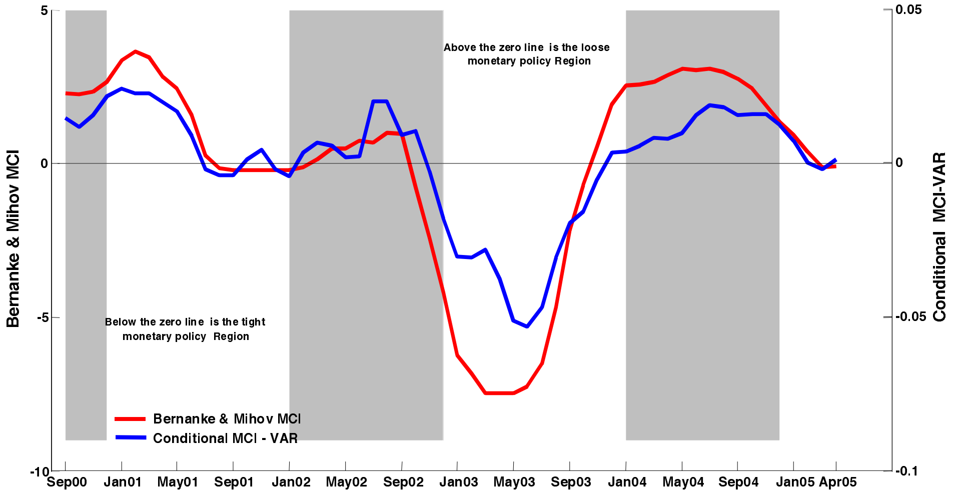
The two MCIs are compared in Figures 18 and 19. They show, despite conceptual differences, some similarity in their chronology of the stance of monetary policy. The CMCI is a smoother version of the BMCI, possibly because the impact of changes in the observed values of the Selic rate is partially compensated by changes in the value of the real exchange rate. The BMCI and the CMCI show similarities for two reasons: the output gap conditional forecast is much more affected by the observed values of the Selic ra te than by those of the real exchange rate and there is not a significant lag between an observed change in the Selic rate and the response of the conditional forecast of the output gap (both facts can be partially extracted from Figures 6 and 7). Although we have very few observations, Figures 16, 17, 20, and 21 show that monetary policy is expansionary in election years and they tend to be even more though closer to election months. Both MCIs do not change much when we change the lag length of the models.

FIGURE 18
MONETARY POLICY STANCE IN BRAZIL — CONDITIONAL MCI (STRUCTURAL VAR) AND BERNANKE & MIHOV METHOD (LAG=1)



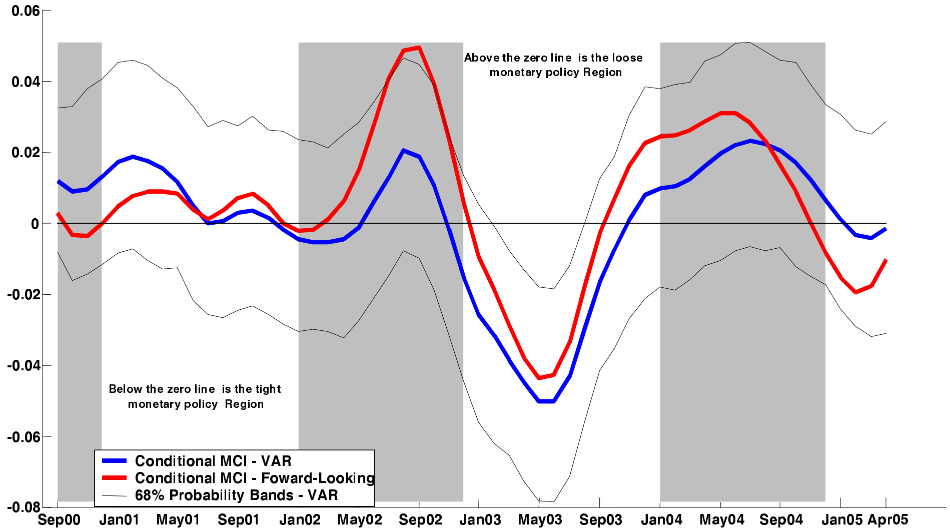
Note: The shaded areas represent election years.

FIGURE 19
MONETARY POLICY STANCE IN BRAZIL — CONDITIONAL MCI (STRUCTURAL VAR) AND BERNANKE & MIHOV METHOD (LAG=2)



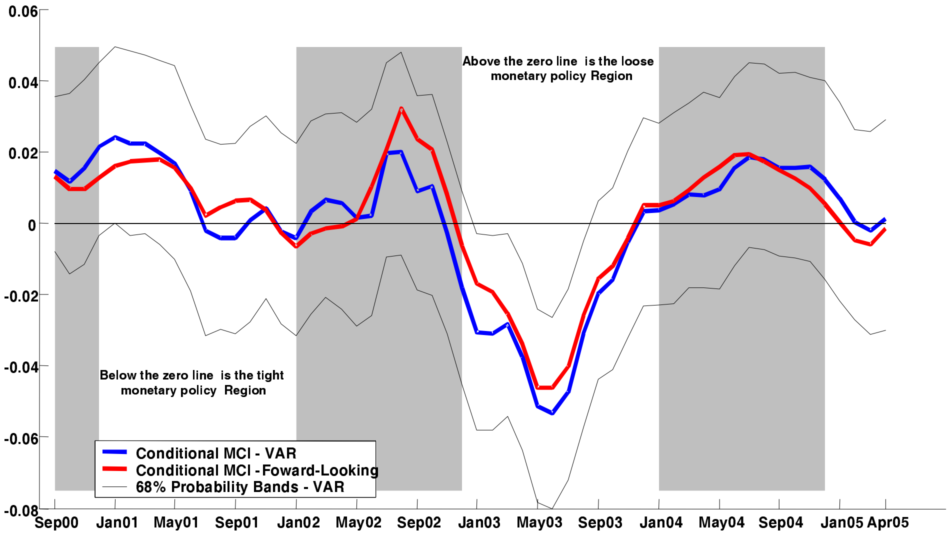
Note: The shaded areas represent election years.

FIGURE 20
MONETARY POLICY STANCE IN BRAZIL — STRUCTURAL VAR MODEL X FOWARD-LOOKING MODEL (LAG=1)



Note: The shaded areas represent election years.

FIGURE 21
MONETARY POLICY STANCE IN BRAZIL — STRUCTURAL VAR MODEL X FOWARD-LOOKING MODEL (LAG=2)



Note: The shaded areas represent election years.

Our FL models could, potentially, be used to forecast the impacts of exogenous changes in the foreign real interest rate faced by Brazil (which includes the country risk and the currency risk). However, this rate is not exogenous with respect to domestic variables and affects the economy through channels other than the real exchange rate or the domestic real interest rate. Therefore, our model is not appropriate to conduct this analysis. Nevertheless, a comparative analysis carried out (Subsection 4.2) indicates that steady-state value of the domestic (foreign) real interest rate affects substantially the steady-state value of other variables of the model.

APPENDIX A:

AN EXAMPLE OF HOW TO EVALUATE CONDITIONAL FORECASTS

Now we use a simple example to show to evaluate a conditional forecast. Suppose that there is a reduced first order VAR with two variables such that,

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0.5 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{A.1}$$

ow suppose we want to forecast two periods ahead from t based on the fact that we impose that both in periods $t+1$ and $t+2$, a variable y_2 assume the same value $\bar{y}_2$. Then our problem reduce to predict y_{1t+1} and y_{1t+2}. If we are in t the values for these two periods are determined according to:

$$\begin{bmatrix} y_{1t+1} \\ \bar{y}_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0.5 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t+1} \\ \varepsilon_{2t+1} \end{bmatrix} \tag{A.2}$$

and

$$\begin{bmatrix} y_{1t+2} \\ \bar{y}_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 1.5 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t+1} \\ \varepsilon_{2t+1} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0.5 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t+2} \\ \varepsilon_{2t+2} \end{bmatrix} \tag{A.3}$$

Taking the second equation of (A.2) and (A.3) we have:

$$r = \begin{bmatrix} r_1 \\ r_2 \end{bmatrix} = \begin{bmatrix} \bar{y}_2 - y_{1t} - y_{2t} \\ \bar{y}_2 - 2y_{1t} - y_{2t} \end{bmatrix} = \begin{bmatrix} 0.5\varepsilon_{1t+1} + \varepsilon_{2t+1} \\ 1.5\varepsilon_{1t+1} + \varepsilon_{2t+1} + 0.5\varepsilon_{1t+1} + \varepsilon_{2t+1} \end{bmatrix} \tag{A.4}$$

Note that (A.4) can be cast as $r = R(a)\varepsilon$, where:

$$R(a) = \begin{bmatrix} 0.5 & 1 & 0 & 0 \\ 1.5 & 1 & 0.5 & 1 \end{bmatrix} \text{ and } \varepsilon = \begin{bmatrix} \varepsilon_{1t+1} \\ \varepsilon_{2t+1} \\ \varepsilon_{1t+2} \\ \varepsilon_{2t+2} \end{bmatrix}$$

Now our task in order to finding the most likely path for y_{1t+1} and y_{1t+2} is minimizing the function $\varepsilon'\varepsilon$ subject to $r = R(a)\varepsilon$. To do this we set the function:

$$\phi = \varepsilon'\varepsilon + 2\lambda'(r - R\varepsilon)$$

where λ is q-vector of Lagrange multipliers. The first-order conditions (assuming interior solution — Doan, Litterman, and Sims (1984) give a more general proof) are:

$$-2\varepsilon' + 2\lambda' R = 0 \quad \text{(FOC1)}$$

$$2(r - R\varepsilon) = 0 \qquad \text{(FOC2)}$$

Based in (FOC1) and (FOC2) we have that $r = R\varepsilon$ and $\varepsilon = R'\lambda$. Combining these two expressions we show that $\lambda = (RR')^{-1} r$. Using this last expression in $\varepsilon = R'\lambda$, we can show that $\varepsilon^* = R'(RR')^{-1} r$. Now using the fact that $\varepsilon^* = R'(RR')^{-1} r$ derived below to evaluate ε^* and having in mind that the values for y_{1t}, y_{2t} and $\bar{y}_2$ are known, the solution for this example yields that:

$$\varepsilon^* = \begin{bmatrix} \varepsilon^*_{1t+1} \\ \varepsilon^*_{2t+1} \\ \varepsilon^*_{1t+2} \\ \varepsilon^*_{2t+2} \end{bmatrix} = R'(RR')^{-1} r = \begin{bmatrix} -0.146r_1 + 0.390r_2 \\ 1.073r_1 - 0.195r_2 \\ -0.342r_1 + 0.244r_2 \\ -0.683r_1 + 0.488r_2 \end{bmatrix} \tag{A.5}$$

Finally, in order to evaluate the most likely values for y_{1t+1} and y_{1t+2}, we just have to take the first equations in (A.2) and (A.3) and using ε^* put in (A.5).

APPENDIX B:

COMPUTING BAYESIAN ERROR BANDS FOR MCIs OF AN OVERIDENTIFIED STRUCTURAL VAR

Waggoner and Zha (1999) and Sims and Zha (1999) show how to generate a Monte Carlo sample from the non standard p.d.f. of SVAR coefficients, equation (3), when the SVAR is overidentified and the priors in coefficients are flat. We present below a brief reproduction of the procedure developed by them.

Let $A(L) \equiv A_0 - A_1 L - .... - A_p L^p$ and $B(L) \equiv I - B_1 L - .... - B_p L^p$. Then equation (3) and (4) can be rewritten as:

$$A(L)Y_t = \alpha + \varepsilon_t \tag{3}$$

$\mathrm{var}(\varepsilon_t) = \Omega$, and Ω is a diagonal matrix.

$$B(L)Y_t = \beta + u_t\,,\ \mathrm{var}(u_t) = \Sigma. \tag{4}$$

The SVAR, equation (3), can be reparameterized as:

$$\Gamma(L)Y(t) = \delta + \eta(t), \tag{3'}$$

where $\Gamma_i = \Omega^{-1/2}A_i$ $(i = 0,\ldots,p)$,$\delta = \Omega^{-1/2}\alpha$; $\eta(t) = \Omega^{-1/2}\varepsilon_t$ so that $\mathrm{var}(\eta(t)) = I$

Let A be the set of all coefficients of $A(L)$ plus α and B be the set of all coefficients of $B(L)$ plus β. Taking a flat prior in B (reduced form coefficients) and Γ_0, we can integrate over B to obtain the marginal posterior on Γ_0 ,

$$p(\Gamma_0)\ \alpha\ |\Gamma_0|^{T+K-\nu} \exp[(-\frac{1}{2}\mathrm{trace}\ (\Gamma_0 S(\hat{B})\Gamma'_0)]$$

were:

$$S(\hat{B}) = \sum_{t=1}^{T+K} \hat{u}(t,B)\hat{u}(t,B)'\,,\ \hat{u}(t,B) = Y_t - \hat{b} - \sum_{i=1}^{p} \hat{B}_i Y_{t-i}$$

the ‘degrees of freedom correction $-\nu$’ is usually dropped as in effect using $|\Gamma_0|^{-\nu}$ as an improper prior or as the consequence of starting with a flat prior on the coefficients of $\Gamma(L)$ and δ, then converting to a parameterization in terms of Γ_0 and B. As pointed out by Sims and Zha (1999), this drop “has the effect of making the marginal posterior on Γ_0 proportional to the concentrated likelihood and thereby eliminating possible discrepancies between posterior modes and maximum likelihood estimates.”

The distribution described above is not a standard p.d.f. and to generate a Monte Carlo sample from it we used a version of the random walk Metropolis algorithm for Markov chain Monte Carlo (MMCMC) developed by Waggoner and Zha (1999).

A Monte Carlo sample can be extracted, from the p.d.f. of SVAR coefficients in an overidentified SVAR with flat priors, by the following steps:

a) Take draws (Γ_0^i, i = 1,…,N) from the Monte Carlo sample of Γ_0, generated as described before.

b) For each draw Γ_0^i computes $\Sigma_R^i = (\Gamma_0^i)^{-1}\Gamma_0^i$, the restricted covariance matrix of reduced form VAR residuals, and draw B^i from the multivariate normal $N(\hat{B}$, Var($\hat{B}$)), where Var($\hat{B}$) is computed using Σ_R^i instead of $\hat{\Sigma}$.

c) For each pair (B^i,Γ_0^i) compute A^i, i =1,...,N.

Given $\{A^i\}_{i=1}^{N}$ we generate the error bands for the PMCI, the CMCI and the Bernanke MCI (BMCI) as follows:

a) For each A^i compute q_{ss}^i and R_{ss}^i (the steady-state values of the real exchange rate and the nominal short-run interest rate);

b) For each i, given R_{ss}^i compute $\{BMCI_{T+h}^i\}_{h=1}^{K}$ as follows:

$BMCI_{T+h}^i = R_{ss}^i - R_{T+h}$

c) Given q_{ss}^i, R_{ss}^i, A^i (i.e, λ_s^{i1} and λ_s^{i2}) and equation (15) compute, for each i, $\{PMCI_{T+h}^i\}_{h=1}^{K}$ as follows:

$$PMCI_{T+h}^i = \sum_{s=1}^{T} l_s^{i1}(q_{T+h-s} - q_{ss}^i) + \sum_{h=1}^{T} l_s^{i2}(R_{T+h-s} - R_{ss}^i)$$

d) For each A^i draw $\{\varepsilon_{T+h}^i / I\}_{h=1}^{K}$ (I = Iobs, Iss—as described in the last section) from distribution (18);[30]

e) For each i, given $\{\varepsilon_{T+h}^i/I\}_{h=1}^{K}$, q_{ss}^i , R_{ss}^i , A^i (i.e, λ_s^{i1}, λ_s^{i2} and λ_s^{i3}) and equation (14), compute $\{CMCI_{T+h}^i\}_{h=1}^{K}$ as follows:

$$CMCI_{T+h}^i = \sum_{s=1}^{T} l_s^{i1}(q_{T+h-s} - q_{ss}^i) + \sum_{s=1}^{T} l_s^{i2}(R_{T+h-s} - R_{ss}^i) +$$
$$+ \sum_{s=1}^{T} \lambda_s^{i3}[\varepsilon(_{T+h-s+1} / Iobs) - (\varepsilon_{T+h-s+1} / Iss)], h = 1,...,K$$

The sequence $\{\varepsilon_t / I\}_{t=1}^{\cdot}$ is easily computed given I, the relation $\varepsilon = R'(RR')^{-1} r$ (defined last section) and the estimated coefficients of the SVAR (estimated with data from t = 1 to T+K). We explained in the previous section how to get, from A, the coefficients of the above equation.

30. Waggoner and Zha (1999) use Gibbs sampling to generate error bands for out-of-sample conditional projections. Here we can use a simpler procedure because our conditional projections are in-sample and are conditioned on sample values of variables (the nominal interest rate and the real exchange rate) or their estimated steady-state values. Notice that the Monte Carlo sample of the p.d.f. of SVAR coefficients was extracted conditioned on all observations of variables, for the entire sample (i.e, t = 1,…,T+K). Therefore, insample we can draw parameters of the model from its distribution and then condition on these draws generate draws of ε from (18).

f) Given $\{\text{BMCI}_{T+h}^{i}\}_{h=1}^{K}$, $\{\text{PMCI}_{T+h}^{i}\}_{h=1}^{K}$ and $\{\text{CMCI}_{T+h}^{i}\}_{h=1}^{K}$ ($i = 1,\ldots,N$) compute the error bands for the MCIs.

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