BANCO CENTRAL DE RESERVA DEL PERÚ

A BVAR FORECASTING MODEL
FOR PERUVIAN INFLATION

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Abstract

We build a simple non-structural BVAR forecasting framework to predict key Peruvian macroeconomic data, in particular, inflation and output. Unlike standard applications we build our Litterman prior specification based on the fact that the structure driving the dynamics of the economy might have shifted towards a state where a clear nominal anchor has become well grounded (Inflation Targeting). We compare different BVAR specifications with respect to a "naive" random walk and we find that they outperform the random walk in terms of inflation forecasts at all horizons. However, our PBI forecasts are not accurate enough to beat a "naive" random walk.

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1   Introduction

Explicit inflation targeting is being adopted by an increasing number of central banks and a substantial body of literature has emphasized the advantages of this approach for conducting monetary policy. Since 2002, the Central Bank of Peru has been implementing an explicit inflation targeting regime (IT) by announcing an inflation target of 2,5 percent and adopting the standard operational and policy procedures implied by IT[1]. Specially since 2002, the inflation forecast process has increased in significance to become one of the most important tasks in policy making.

   Together with the adoption of a fully-fledged IT regime, staff at the Central Bank of Peru and elsewhere developed semi-structural models to forecast inflation[2]. The current core forecasting model at the Central Bank is the so called MPT (*Modelo de Proyección Trimestral*) which in fact is a mixture of calibrated and estimated semi-structural equations such as a Phillips Curve, a demand driven output gap equation, a forward-looking monetary policy rule for the interbank interest rate and so on. A typical forecasting exercise with this model comprises the input of the various sectorial experts that either provide assumptions or forecasts about the exogenous variables in the model. Hence the framework allows itself to the intervention of judgemental information which might not necessarily be present within the data.

   Though, a criticism that is usually made about this process is the non-replicability of the forecasts by agents outside the forecasting process who might happen to have the same model[3]. Hence, this criticism calls for models that can in fact be independent of the forecaster, models parsimonious yet aggregate enough to have a rough understanding of the joint evolution of the relevant macroeconomic variables[4,5].

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[1]In particular, a central feature of the Peruvian monetary policy in the 90's has been the acquired autonomy of the Central Bank and the pre-announcement of the inflation rate since 1994. For a comprehensive view of the implementation of inflation targeting in Peru see Armas et.al (2001)

[2]See for example Luque and Vega (2003) and LLosa (2004).

[3]Precisely, Inflation Reports are deemed to explain to the public the forecasts and assumptions lying behind them.

[4]Models trying to understand the transmission mechanism of monetary policy have been published at various points during the 90's and this decade, key aspects of these models have been the measure of monetary policy using money aggregates - e.g. Bringas and Tuesta (1997), León (1999) and Quispe (2000). Only recently have VAR type of papers focused on interest rates as the monetary policy instrument - e.g. Winkelried (2004) and Grippa (2004).

[5]Winkelried (2003) and Barrera (2005) develop models for forecasting inflation using disaggregated

We propose a VAR methodology with the following features: a) it encompasses previous work on VAR modelling at the central bank of Peru, b) it is suited to forecast aggregate variables, c) it relies heavily on the data and priors about the data generating process.

Our purpose is achieved by estimating simple BVARs with Litterman assumptions for the priors about the parameters of the VAR. This allows us to input appropriate priors to the data generating process. As we see on the section about our data analysis, the economic time series have been the subject of possible breaks in regimen which have rendered standard VAR models to forecast failure. By considering alternative BVAR specifications that can perform fairly well in out-of-sample forecast exercises, we can set up a benchmark for the structural identification of the models.

We follow the approach in Doan et.al (1984) and Robertson and Tallman (1999) to evaluate forecast performance in our proposed models. We also discuss the forecast procedure in which we emphasize the complications that arise from the timing of data realizations. In particular, we perform the so-called conditional forecasting technique, as described in Doan et.al (1984). Up to four possible VAR models with increasing number of variables are considered. The smaller model (model 1) contains prices, real GDP, the real effective exchange rate, the nominal interbank rate and an index of commodity metals. The larger model contains the variables of model 1 plus the monetary base and a block of external variables comprising the Fed funds rate, US CPI and the US industrial production index.

Importantly, the choice of hyperparameters is crucial in any Bayesian specification. In order to elicit our priors we use a novel feature that consists in using a rule to choose the tightness and decay parameters based on the distance between long-run (seven years ahead) forecasts of nominal variables and the respective nominal anchor the central bank aims at.

Our results show that the use of BVAR models to forecast inflation and GDP growth can significantly improve the performance over models that do not use judgement-based forecasts, for example a naive random walk. All competing models perform quite well compared with a naive random walk. Overall, the simplest BVAR (which includes CPI,

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data. This approach is not suited for the task we pursue given that it does not have a clearly defined joint process for the key aggregate variables of interest as VAR models.

GDP, interest rate, effective real exchange rate and external prices) outperforms other specifications, being robust to changes in both the sample and the judgement criteria.

The rest of the paper is organized as follows, in section 2 we provide the description of the main features of the macroeconomic data we use in our models, in section 3 we set up the BVAR specifications and we describe the ideas behind our choice of priors, in section 4 we provide results about our out-of-sample diagnostics and section 5 concludes and suggests the research agenda.

2   Peruvian macroeconomic data

In this section, we briefly characterize the evolution of the main macroeconomic variables for the Peruvian economy during the period that spans from 1994 until late 2004. These variables belong to the set of main aggregate information the central bank uses in order to take monetary policy decisions.

We provide key facts, starting from some historical perspective about our main variables in order for readers to gather insight. Overall there is an important change in the cyclical behavior of the main macroeconomic variables which to some extent were influenced by changes in both the monetary policy operating procedures and the fully-fledged IT regime adopted in 2002[6].

Figure 1 depicts the evolution of monthly CPI inflation rates measured as year on year log differences for the period 1994 until 2004. It is clear from this figure that inflation has followed a downward trend from two-digit levels to even negative values at the end of 2001, period where the fully-fledged inflation targeting framework was adopted. From then on, there has been an upward movement towards an inflation rate between 2 and 4 percent. It is believed that inflation has achieved a stationary situation, whereby shocks of any kind will make inflation revert to the nominal anchor established by the central bank. No doubt, the unconditional mean considering the entire sample size might not be accurate enough within this stationary inflation rate environment because data from the early part of the sample lacks the intrinsic property of a well-defined long run anchor.

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[6]Before 2002 the Central Bank of Peru has used different monetary aggregates as guides for monetary policy. Importantly, academics agree upon the less relevant role of money aggregates when interest rates are used as the instrument for monetary policy.

On the other hand, throwing data from the early sample implies discarding important information about short run dynamics of inflation.

Figure 2 shows the growth rate of monthly deseasoned GDP[7]. There is an important decrease in the volatility of this series, coinciding with the period the inflation targeting period has been in place. From 2002 onwards GDP growth has been always positive and ranging up to about 8 per cent. In previous years this growth rate exhibited huge cyclical swings, ranging from -6 percent up to two digit levels.

Another key macroeconomic variable which has significantly changed its behavior across periods is the interbank interest rate[8]. Figure 3 shows the evolution of the interbank rate vis -a- vis the FED funds rate for the period of study. During the monetary targeting era the interbank rate exhibited a highly volatile pattern without any clear co-movement with the FED funds rate. Periods of high interbank rates coincided with episodes of financial distress, for example the adverse effects on capital flows resulting from the Asian crisis during 1998[9]. The recent period has witnessed a downward trend in the interbank rate volatility and its movements are more associated with those of the FED funds rate (see Table 1 for the relevant cross-correlations).

In Figure 4 the evolution of money growth and CPI inflation are jointly presented. Again the change in the co-movement between these two variables is striking. For the period spanning from 1994 until 2001, the sharp fall in CPI inflation was linked with a persistent decrease in the monetary base growth rate. Interestingly, this relationship breaks after 2001 where both, an upward trend in base money growth and a steady level of inflation are observed. The previous result suggests, somehow, a less relevant role for money to explain inflation dynamics after the adoption of the IT regime[10].

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[7]The official statistical authority in Peru (*Instituto Nacional de Estadística e Informática*) reports monthly estimates of Peruvian GDP obtained from sectorial production. Given the nature of this estimate, it is subject to constant revisions

[8]Previous studies about the transmission mechanism of monetary policy for the Peruvian economy were not able to incorporate this variable due to the short span these data have existed.

[9]It is an open question if these interest rate hikes induced by the central bank were an optimal response that helped mitigate the effects of the external shock. The answers to this ever important question go beyond the scope of this paper

[10]Remarkably, empirical work on monetary policy has reached the point in which it is more natural to add commodity prices rather than money in VARs to improve forecasts. However, Leeper and Roush (2003) have recently found out, for the U.S., that the way money is modelled matters at explaining inflation dynamics after a policy shock.

Figure 5 presents a panel of graphs showing the relationship between two commodity prices (Oil price and metal price indices) with the terms of trade[11] and the effective real exchange rate.

In general, we observe two clear periods, the first part of the sample has the real exchange rate grossly moving in opposite direction to the terms of trade. Periods of low terms of trade are equivalent to periods with low relative export prices and hence with less favorable external price impacts on external balances. In those periods, the real exchange rate moved upwards in an accommodating fashion. After 2003 we observe a sizeable increase in the terms of trade and thereby affecting external balances positively, however the real exchange rate does not fall. Even though there have been factors pushing the Dollar to historical low levels vis-a-vis the majority of the currencies, the fact that the nominal exchange rate is less volatile than our trading partners (whose currencies have been appreciating faster against the dollar than the Sol) has generated a relatively constant real exchange rate.

The evolution of metal and oil prices govern the dynamics of the terms of trade. Metal prices are a strong component of export prices while oil prices affect import prices the most. We observe that the terms of trade dynamics mimic closely metal prices, except for periods where oil price hikes are in place.

Oil prices on the other move somewhat closely to the effective real exchange rate series, capturing the fact that foreign prices are affected by oil price shocks.

This graphical inspection to the data allows us to configure a set of variables to use in the VAR specifications. In particular, we favor the use of the metal price index instead of the terms of trade, while the effective exchange rate has been moving along the oil price index and thus seems to be a good variable for inflation forecasts purposes, let alone its possible effects on output.

It seems that a switching regime is a feature of the data analyzed so far. Table 1 confirms our graphical analysis, we observe that the properties of the data sometimes change dramatically from one sample to another, the first sample goes from January 1994 to December 2000 while the second sample includes the IT period.

Overall, unconditional means and volatilities fall towards the IT period. Differences

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[11]Measures as the relative price of exports against the price of imports

in cross-correlations between the two periods are also important for some variables[12]. Interestingly, the cross-correlation between CPI inflation and the interbank interest rate has become less negative in the second sub-sample (shifting from -0.44 to -0.16). A second point to highlight is that the domestic interbank rate has become more correlated with foreign rates in the more recent period. During the first period the correlation between foreign rates and the interbank rate was 0.11 and the same correlation has become highly positive during the second period (0.81).

In conclusion, the seeming changes in regime observed in the data supports the idea of VAR modelling able to incorporate prior information. Classical linear VARS performed with these type of data may render in out-of-sample forecasts that are too poor to be of use. On the hand, a properly defined Bayesian VAR can perform better even in this environment.

3   Multivariate Analysis

First, we specify the variables and the alternative BVARs. The variables defined are the deseasoned GDP at 1994 prices (y_t), the consumer price index in Lima city (p), the deseasoned monetary base (m), the monthly average interbank rate (i_t), the effective real exchange rate[13] (q), the monthly Fed Funds rate (i_t^*), the monthly US industrial production index (y_t^*), the US core inflation rate (p_t^*) and the index of the price of a set of metal commodities as published by the IMF (p_t^{cm}). All variables but interest rates are expressed in logs and then multiplied by a 100. On the other hand, as discussed in the previous section, the presence of p_t^{cm} is justified by the fact that it is capturing that other bit that affects the terms of trade not impounded in the real exchange rate for this small open economy.

We run the VAR in levels given that non-stationarity of the variables are not a concern in Bayesian econometrics. It would be better to run with as many lags as possible but the sample size hinders this approach so we settle on $p = 6$ lags.

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[12]Cross-correlations were adjusted following Forbes and Rigobon (2002) in order to correct the business cycle moment using estimates of standard deviation in the two sub-samples.

[13]The effective real exchange rate is calculated using a nominal effective exchange rate that considers the 20 most important trading country partners and the respective official consumer price indices.

The alternative model representation is given by the following table

Table 1: **BVAR Specifications**

	y_t	p_t	m_t	q_t	i_t	i_t^*	y_t^*	p_t^*	p_t^{cm}
VAR 1	x	x		x	x				x
VAR 2	x	x	x	x	x				x
VAR 3	x	x	x	x	x	x			x
VAR 4	x	x	x	x	x	x	x	x	x

With this specifications in mind, the VAR models in general can be expressed as[14]

$$
\begin{pmatrix} y_1 \\ ... \\ y_T \end{pmatrix}_{T.k} = \begin{pmatrix} z_1 \\ ... \\ z_T \end{pmatrix}_{T.\kappa} \Gamma_{\kappa.k} + \begin{pmatrix} u_1 \\ ... \\ u_T \end{pmatrix}_{T.k} \tag{1}
$$

Where y_t is a row vector of endogenous variables of size k, z_t is a row vector of size $\kappa = kp$ containing the lags of y_t up to the p-th lag: $z_t = \begin{bmatrix} y_{t-1} & ... & y_{t-p} \end{bmatrix}$, u_t is a row vector containing reduced-form shocks with zero mean and covariance matrix Ψ and Γ is a matrix of parameters which contains κ rows and k columns $\Gamma = \begin{bmatrix} A_1 & ... & A_p \end{bmatrix}'$.

The left-hand side of Equation [1] is a matrix with T rows and k columns, if we pick the $i-th$ column of this matrix and its corresponding element on the right hand side we get the equation for the ith variable.

$$
y_i = Z\gamma_i + u_i \tag{2}
$$

Here Z stacks the T row vectors z_t, y_i is a column vector of size T, γ_i is the ith-column of Γ and u_i is the ith-column of the matrix of stacked error row vectors u_t. We pile this k equations for all the endogenous variables to get the standard set up

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[14]We have chosen no to model constants, seasonal dummies and time trends.

$$
\begin{pmatrix} y_1 \\ ... \\ y_k \end{pmatrix}_{Tk.1} = (I_k \otimes Z_{T.\kappa})_{(Tk).\kappa k} \begin{pmatrix} \gamma_1 \\ ... \\ \gamma_k \end{pmatrix}_{k\kappa.1} + U_{Tk.1} \tag{3}
$$

Which takes the form of a general linear model as defined in Kadiyala and Karlsson (1997).

$$
Y = \mathcal{Z}\gamma + U \tag{4}
$$

The parameter we are interest in finding is given by γ which is a collection of k column vectors containing all the parameters in each of the k equations in the system. The parameters γ can be solved using the standard least-square formulas or by MLE estimation. It is straightforward to show that the parameter estimate is

$$
\widehat{\gamma} = (\mathcal{Z}'\mathcal{Z})^{-1} \mathcal{Z}'Y \tag{5}
$$

With covariance matrix

$$
\widehat{\Psi} = Y'M_z Y \tag{6}
$$

Where M_z is the well known matrix $M_z = I - \mathcal{Z}(\mathcal{Z}'\mathcal{Z})^{-1}\mathcal{Z}'$.

3.1 The Litterman specification

The number of parameters in our system is quite large; it includes the length of the column vector γ which is given by $k^2 p$ namely, the number of equations multiplied by the number of regressands of their right hand side. The total number of variables also includes the $k(k+1)/2$ elements of the covariance matrix Ψ. Bayesian estimation requires us to have a prior distribution for all these variables. The standard approach to this too-many-parameters problem is the one advanced by Doan et.al (1984) which consists on using a small set of hyperparameters to characterize a suitable prior. We start characterizing the priors by means of proposing prior means and variances for the vector γ. The vector Ψ is assumed to be known:

Prior means of γ

The vector of parameters γ has k blocks, each block represents the parameters contained in each endogenous variable equation. There are kp parameters in each block, there one parameter counting the effect of the first own lag in each equation. The Litterman prior assumes that the variables are random walk, which means that only the parameters with own lags are equal to one and all the rest of the parameters are equal to zero. Here we consider non-zero constant parameters.

$$E(\gamma) = \begin{cases} 1 & \text{for params. on own lags} \\ 0 & \text{for params. on lags of other vars. and other than first lags of own variable} \end{cases}$$

In short, we are going to group this information as $E(\gamma) = \widetilde{\gamma}$

Prior variance of γ

First we assume that the prior covariances among parameters is zero (for simplicity), then we will only refer to the diagonal elements of $V(\gamma)$. Here we have to gauge on the importance of the first own lags, those regarding to the rest of the variables and the rest of the lags.

Our uncertainty about first-own-lag parameters will be measured by the hyperparameter θ, this is true for all equations alike and provides a measure of how strong we believe on our random walk prior hypothesis. For second and higher order own lags, our uncertainty will shrink at a rate given by h^λ, where h is the lag order.

For parameters on other variables, θ is appropriately shrunk or expanded by virtue of a general weighting parameter ω_{ij}.

$$V(\gamma) \equiv \widetilde{V}_\gamma = \begin{cases} \frac{\theta}{h^\lambda}\omega_{ii} & \text{for parameters on own lags} \\ \frac{\theta}{h^\lambda}\omega_{ij} & \text{for parameters on lags of variable } j \neq i \end{cases}$$

Given that θ controls all the endogenous parameter variances, it is called *overall tightness*, on the other hand λ is called the *decay parameter*. The weighting parameters ω_{ij} are yet to be defined. Following Doan et.al (1984), we take into account the fact that variables in each equations might be measured in different scales. Hence, we compute error variances from running univariate autorregressions for each variable and put them on a diagonal matrix $\Omega = [\widehat{\sigma}_{ii}^2]$.

We also construct the matrix $W = [W_{ij}]$ which captures how much we shrink or expand the overall tightness for each lag. The diagonal elements W_{ii} are set to one, if we have more certainty about the prior regarding the parameter of variable j in equation i, then we can assume a lower value W_{ij}. The matrix of final weights $[\omega_{ij}]$ is obtained by computing $[\omega_{ij}] = \Omega W \Omega^{-1}$, which leads to

$$
\begin{bmatrix}
\omega_{11} & \omega_{12} & ... & \omega_{1k} \\
\omega_{21} & \omega_{22} & ... & \omega_{2k} \\
... & ... & ... & ... \\
\omega_{k1} & \omega_{k2} & ... & \omega_{kk}
\end{bmatrix}
=
\begin{bmatrix}
1 & W_{12}\left(\frac{\widehat{\sigma}_1^2}{\widehat{\sigma}_2^2}\right) & ... & W_{1k}\left(\frac{\widehat{\sigma}_1^2}{\widehat{\sigma}_k^2}\right) \\
W_{21}\left(\frac{\widehat{\sigma}_2^2}{\widehat{\sigma}_1^2}\right) & 1 & ... & W_{2k}\left(\frac{\widehat{\sigma}_1^2}{\widehat{\sigma}_k^2}\right) \\
... & ... & ... & ... \\
W_{k1}\left(\frac{\widehat{\sigma}_k^2}{\widehat{\sigma}_1^2}\right) & W_{k2}\left(\frac{\widehat{\sigma}_k^2}{\widehat{\sigma}_2^2}\right) & ... & 1
\end{bmatrix}
$$

The prior information can be represented in terms of a set of stochastic restrictions:

$$
\widetilde{\gamma}_{k\kappa} = I_{k\kappa}\gamma_{k\kappa} + \varpi_{k\kappa} \tag{7}
$$

Where ϖ is an *iid* perturbation with zero mean and variance defined by $\widetilde{V}_\gamma$. And $I_{k\kappa}$ is an identity matrix. This restriction [7] can be combined with the VAR model in [4] to generate a mixed estimation as proposed in Theil and Goldberger (1961). The mixed model is

$$
\begin{bmatrix} Y \\ \widetilde{\gamma} \end{bmatrix} = \begin{bmatrix} \mathcal{Z} \\ I \end{bmatrix} \gamma + \begin{bmatrix} U \\ \varpi \end{bmatrix} \tag{8}
$$

Where the weighted OLS estimation results in

$$
\widehat{\gamma}_{TG} = \left(V_{\widehat{\gamma}}^{-1} + V_\varpi^{-1}\right)^{-1}\left[\left(\Psi_k^{-1} \otimes Z'_{T.\kappa}\right)Y + V_\varpi^{-1}\widetilde{\gamma}\right] \tag{9}
$$

Where $V_{\widehat{\gamma}}$ is the variance of the OLS estimator found in equation [4]. This formula for this variance is given by

$$
V_{\widehat{\gamma}} = \left(\Psi_k \otimes (Z'_{T.\kappa}Z_{T.\kappa})^{-1}\right)_{k\kappa.kk}
$$

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3.2 Deep priors

Equation [9] provides an estimator that weights both the OLS and the prior parameters according to their covariance matrices. What is the extent of our prior variance? do we have more information on the data generating process besides of what the data give us? how can we elicit values for the hyperparameters defining the overall tightness θ, the decay parameter λ, and the weighting matrix W based on out-of-model information?.

In fact we do have relevant information. First we know that in all the BVAR specifications there is an external block, variables whose dynamics are invariant to domestic conditions[15]. Second, we know that inflation targeting regime is the current monetary policy framework. We treat both pieces of information one by one.

Prior block exogeneity

The natural way of using the external block exogeneity is by assuming that the random walk prior for the external variables is stronger, namely the corresponding prior variance of our believe is smaller. Hence, we assume a specific form for the weighting matrix W, whose element will take three possible values:

$$W_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0.5 & \text{if } i \neq j \text{ and } i \rightarrow \text{domestic variable} \\ 0 & \text{if } i > j \text{ and } i \rightarrow \text{external variable} \end{cases}$$

The nominal anchor

Next, we choose θ and λ using a simple criteria: If there exists a nominal anchor, which under inflation targeting is clearly defined as a specific inflation rate attained in a long-enough horizon in the future - then long-run forecasts of nominal variables should be compatible with it.

If we assume the "neutral" interest rate during the last part of the sample period and expected to hold in the future is about $r_{ss} = 4$ per cent, then, given an inflation goal of $\pi_{ss} = 2.5$ per cent, the nominal interest rate ought to be $i_{ss} = 6.5$ percent. Alternatively if we assume a steady state nominal world interest rate of 4.5 percent and a steady state risk premium of 2 percent, then the implied domestic equilibrium interest rate would be also close to $i_{ss} = 6.5$.

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[15]See Cushman and Zha (1995)

So we try to choose the hyperparameters $\begin{bmatrix} \theta & \lambda \end{bmatrix}'$ in such a way to indirectly minimize a loss function of the form

$$d = a_\pi \left(\widehat{\pi}_{ss} - 2.5\right)^2 + a_i \left(\widehat{i}_{ss} - 6.5\right)^2$$

Where $\widehat{\pi}_{ss}$ and $\widehat{i}_{ss}$ are long-horizon forecasts (6 to 7 years ahead).

The procedure results in different sets of hyperparameters according to each possible criteria. If $a_\pi = 1$ and $a_i = 0$ we only care about long-run inflation rates (inflation criterion) and the results are summarized in Table 3, there we compute 24 out of sample long-run forecasts for each BVAR and OLS-VAR associated and present the median values corresponding to the tightness and decay parameters. We observe that both tightness and decay values are sizeable, suggesting a mixed effect on the variance of the Litterman prior; a large variance due to a high value of the tightness parameter and a low variance due to a stronger decay to zero.

4   Empirical Results

We use the median values for both tightness and decay parameters corresponding to each BVAR and possible criteria to perform the estimations and out-of-sample forecasts.

4.1   Procedure

To evaluate the out-of-sample forecast performance, we have to consider the timing of data releases. All variables are available at the end of the month being measured, however, domestic GDP is only available with two months delay [16].

To use current information for data that is quickly released we resort to a conditional forecasting technique. This framework allows all data series that are not yet available for a given month to be forecasted "conditional" upon all the variables for which observations are available. Conditional forecasting consists in the following steps. First, we estimate the different BVARs at the end of a particular month using the data just available at that moment. For example, since domestic GDP is released with two months lag, the

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[16]For example, January GDP is released in March

models are estimated without the last two observations of all variables. Second, data is completed with forecasts of domestic GDP for the last two months conditional on the observation of the rest of the variables within those two months.

The assessment of forecast accuracy of each BVAR specification is obtained by recursively estimating and forecasting. The first vintage of data for estimation spans from August 1995 to November 2001 and the selected out-of-sample period for forecast validation goes from December 2001 to August 2004. We start the recursion by estimating the BVARS with data available until September 2001, two months before the first month of the out-of-sample period. Next, GDP observations of the last two months (October and November 2001) are completed by the above conditional forecasting procedure. Then forecast of variables starting at December 2001 are recorded and transformed as year-on-year changes, i.e. year-on-year inflation and year-on-year GDP growth. Finally, forecasts of transformed variables are compared to realized values at different horizons: three, six, nine, twelve and twenty-four months ahead and forecasts errors are stored. After that, next month observations are added to the data set for estimation and the above-detailed procedure is applied again. These steps are repeated until the out-of-sample period is completed [17]

Pooling the results for each period yields a set of 33 three-months ahead forecasts, 30 six-months ahead forecasts, 27 nine-months ahead forecasts, 24 twelve-months ahead forecasts, and 12 twenty-four-months ahead forecasts. Given that, the forecasting performance for each model is measured by the difference between forecasts and actual outcomes over the out-of-sample period. The assessment of forecast accuracy is based on mean square error (MSE) and U-theil statistics.

During this exercise we note that overall forecast performance improves towards the end of the evaluation sample. To highlight this, we additionally calculate MSEs for a sample spanning from December 2002 to August 2004. This subsample is not large enough to track the forecasting performance of models for twenty-four-months ahead forecasts. However, we suspect that MSE and U-theil should have reduced for that

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[17]These steps describe the procedures taken in actual forecast exercises, using just the amount of data available at the time the forecasts are made. However, it is worth emphasizing that the BVAR estimation relies on fixed hyperparameters which we actually choose after the realization of data in our out-of-sample period, i.e. our objective choice of hyperparameters incorporates some notion of the evolution of the data thus far.

horizon as well.

4.2 Results

After performing the out-of-sample forecasts we construct the MSE and U-Theil values for each BVAR using the hyperparameters corresponding to the inflation only criterion (results for other criteria are shown in Tables 4 and 5).

Table 3 in the appendix reports MSE and U-Theil (in parenthesis) for different BVAR models in predicting CPI inflation and GDP growth, both measured on a year-on-year basis. The table also shows the hyperparameters (decay and overall tightness) and long-run forecasts (seven years ahead) for CPI inflation and domestic interest rate of each model. As shown, all models but the BVAR 4 perform quite well for the inflation forecast in the first out-of-sample period (spanning from December 2001 to August 2004). Thus, the U-Theil statistics corresponding to all horizons are consistently smaller than one for the three first models. Yet, the random walk model beats the BVAR 4 at the last two horizons. On average BVAR 1 has the most outstanding ability in forecasting inflation reporting the smallest U-theil statistics (0.16).

Regarding GDP growth, both BVAR 1 and BVAR 2 behave better than the random walk at all horizons. At the short horizon, within three-months and nine-months, MSE and U-Theil values reveal that the latter model outperforms the former. However, at medium run horizons, twelve-months and twenty-four-months, the comparison between first and second models seems to be not quite defined. Overall, the BVAR 2 is marginally more accurate on average than BVAR 1. These results might suggest that there is a little gain of information in money aggregates for the GDP growth forecasting. On the other hand, both BVAR 3 and BVAR 4 were less accurate than the simple random walk for most horizons. As in the case of inflation forecast, evaluation of accuracy indicates that the BVAR 4 generates the worst-performing forecast.

By shortening the period of forecast evaluation from December 2004 to August 2004 (second panel of Table 3) we get similar results with respect to the GDP growth forecasts. Though, the results change at evaluating inflation forecast performance. Remarkably, all models outperform the naive random walk, getting U-theils statistics smaller than one. These results are consistent at both short and medium run horizons. On average the

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BVAR 3 outperforms marginally the rest of the models and has the best forecast performance at twelve-months horizon. Overall it seems that by dropping the first observations of the out-of-sample period the forecast accuracy improves significantly.

4.2.1 Robustness Exercise: Changing the prior's criteria

A key issue in the estimation of Bayesian VARs is the choice of the hyperparameters. In order to factor the importance of the deep priors and the robustness of our results, we evaluate the forecast performance of the models under two alternative criteria regarding the choice of the hyperparameters. The first one is the *interest rate criterion* in which we minimize $d = \left(\widehat{i}_{ss} - 6.5\right)^2$ where $\widehat{i}_{ss}$ is the simulated forecast at long horizon. We have assumed a the steady state level of the nominal interest rate consistent with the inflation target in the order of 6.5% . The second is the *joint inflation and interest rate criterium* in which we minimize the following loss function $d = (\widehat{\pi}_{ss} - 2.5)^2 + \left(\widehat{i}_{ss} - 6.5\right)^2$. Tables 4 and 5 report the summary statistics for each criteria, respectively.

Interestingly, in terms of inflation forecast accuracy BVAR 1 outperforms the rest of the models across criteria within the first sample (December 2001 to August 2004). In the second sample (December 2002 to August 2004), BVAR3 displays the best accurate forecast under inflation criterion. Although, across criteria the improvement of BVAR 3 is slightly superior than that of BVAR 1.

Regarding GDP growth, the BVAR 2 (which includes money aggregates) performs the best in the first sample by using both the inflation criterion and the joint inflation and interest rate criterion. Moreover, averaging MSE and U-theil at all horizons, the BVAR 2 has the best forecast accuracy in terms of GDP growth in the first sample by using the inflation criterion and in the second sample, under joint inflation and interest rate criterion. From the previous result, we infer that money might be helping at predicting GDP growth.

By ranking the results across criteria, we note that the interest rate criterion performs the worst no matter which sample is analyzed. Additionally, joint inflation and interest rate criterion only improves slightly some results. This gives more support towards the inflation criterion considered as the benchmark. Finally, overall the forecast accuracy improves considerably for inflation and GPD growth for the second sample pe-

riod regardless the criteria and the model specification. This result might be associated with the significant change observed in the unconditional moments, in particular, sharp reduction in volatilities of the main macroeconomic variables which coincides with the adoption of the fully-fledged inflation targeting regime.

5 Concluding remarks

From the beginning of 2002, the Central Bank of Peru has been implementing an inflation targeting regime. Thus, constructing forecast of the main macroeconomic variables, in particular inflation, has become the core task of the policy makers. In this paper, we introduce a Bayesian forecast methodology suitable to evaluate forecast performance of inflation and GDP growth for the peruvian economy.

Unlike other contributions, in our paper we have presented a rule that can be used to elicit Minnesota-type of priors in a Bayesian VAR context that can be more accurate to describe the dynamics of key macroeconomic variables for a country like Peru. The rule is based on choosing decay and tightness parameters that would induce the nominal anchor brought about by inflation targeting.

Our results show that the out-of-sample forecasts performed with the BVARs favor small BVAR specifications under various possible criteria.

Our Bayesian procedure can be improved remarkably in two fronts, first we need to compute confidence bands for forecasts and test the out-of-sample forecast densities rather than point forecasts as presented in this paper. Second, we need to go beyond the simple non-structural VARs presented in this paper and perform Bayesian structural VAR estimation and forecasting. Only when that final step is done we will be able to make our BVAR forecasting framework for ample use.

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A Tables and figures

Table 2: **KEY UNCONDITIONAL MOMENTS**

	Sample		
	EARLY [a]	RECENT [b]	WHOLE [c]
Mean			
CPI Inflation	0.63	0.15	0.47
Interbank Interest Rate	13.32	4.72	10.43
Fed Funds Rate	5.35	2.06	4.25
Standard Deviation			
Output	1.90	1.04	1.66
CPI Inflation	0.41	0.33	0.45
Δ in Monetary Base	2.31	1.54	2.08
Real Effective Exchange Rate	3.14	2.11	2.86
Interbank Interest Rate	4.70	3.39	5.92
First order autocorrelation			
Output	0.84	0.73	0.83
CPI Inflation	0.53	0.35	0.62
Interbank Interest Rate	4.60	0.90	0.82
Cross correlation relative to output			
CPI Inflation	-0.16	0.19	-0.02
Δ in Monetary Base	0.06	-0.10	0.04
Interbank Interest Rate	0.01	-0.47	-0.00
Cross correlation relative to interbank rate			
Output	0.01	-0.45	-0.00
CPI Inflation	-0.44	-0.16	0.09
Δ in Monetary Base	-0.15	-0.18	-0.08
Real Effective Exchange Rate	0.09	0.05	0.18
Fed Funds Rate	0.11	0.81	0.73
Cross correlation relative to FED funds rate			
Output	0.25	-0.63	0.07
CPI Inflation	-0.19	-0.22	0.32
Interbank Interest Rate	0.07	0.84	0.73

[a] 1994:01 to 2000:12

[b] 2001:01 to 2004:06

[c] 1994:01 to 2004:06

TABLE 2b: RMSE of BVAR Forecasts – Inflation criterion

	BVAR 1	BVAR 2	BVAR 3	BVAR 4
Overall Tightness (θ)	2.82	3.68	3.78	2.03
Decay (λ)	2.30	5.09	7.16	2.59
Long−run CPI inflation	1.79	1.92	2.38	2.30
Long−run interest rate	7.99	8.09	8.41	−1.84

Sample: 2002.10 to 2004.10

CPI Inflation

	BVAR 1	BVAR 2	BVAR 3	BVAR 4
3 months	0.71 (0.11)	0.90 (0.15)	0.78 (0.13)	1.35 (0.22)
6 months	1.05 (0.16)	1.53 (0.23)	1.32 (0.20)	2.22 (0.33)
9 months	1.21 (0.16)	2.31 (0.31)	1.47 (0.20)	3.45 (0.46)
12 months	1.68 (0.20)	3.49 (0.42)	1.86 (0.22)	7.31 (0.88)
24 months	1.92 (0.16)	1.11 (0.09)	2.70 (0.23)	11.49 (0.97)
Average	1.32 (0.16)	1.87 (0.24)	1.63 (0.19)	5.17 (0.57)

GDP Growth

	BVAR 1	BVAR 2	BVAR 3	BVAR 4
3 months	3.83 (0.19)	1.77 (0.09)	6.56 (0.33)	8.11 (0.40)
6 months	5.09 (0.26)	2.86 (0.15)	18.75 (0.96)	20.56 (1.05)
9 months	6.31 (0.33)	3.38 (0.18)	23.71 (1.23)	36.23 (1.88)
12 months	9.91 (0.54)	5.32 (0.29)	45.28 (2.49)	55.92 (3.07)
24 months	2.87 (0.18)	4.74 (0.30)	47.60 (2.98)	11.46 (0.72)
Average	6.28 (0.33)	3.33 (0.18)	23.57 (1.25)	30.21 (1.60)

Sample: 2003.10 to 2004.10

CPI Inflation

	BVAR 1	BVAR 2	BVAR 3	BVAR 4
3 months	0.77 (0.09)	0.82 (0.09)	0.77 (0.09)	0.87 (0.10)
6 months	1.35 (0.15)	1.20 (0.13)	1.09 (0.12)	1.66 (0.18)
9 months	1.34 (0.13)	1.43 (0.14)	1.17 (0.12)	1.56 (0.16)
12 months	1.36 (0.12)	1.24 (0.10)	0.81 (0.07)	1.76 (0.15)
Average	1.21 (0.12)	1.17 (0.12)	0.96 (0.10)	1.46 (0.15)

GDP Growth

	BVAR 1	BVAR 2	BVAR 3	BVAR 4
3 months	3.73 (0.22)	1.52 (0.09)	4.68 (0.28)	9.75 (0.58)
6 months	4.13 (0.26)	2.09 (0.13)	10.15 (0.65)	24.47 (1.56)
9 months	4.74 (0.31)	3.02 (0.20)	10.16 (0.66)	32.78 (2.14)
12 months	6.15 (0.39)	4.08 (0.26)	18.03 (1.13)	40.98 (2.56)
Average	4.69 (0.29)	2.68 (0.17)	10.75 (0.68)	26.99 (1.71)

MSE (U–Theil) of BVAR Forecasts – Inflation and interest ra te joint criterion

	BVAR 1	BVAR 2	BVAR 3	BVAR 4
Overall Tightness (θ)	0.84	2.68	3.14	2.53
Decay (λ)	0.72	3.08	5.57	3.13
Long–run CPI inflation	1.54	1.39	2.24	2.62
Long–run interest rate	7.41	6.42	7.49	–2.92

Sample: December 2001 to August 2004

	CPI Inflation			
	BVAR 1	BVAR 2	BVAR 3	BVAR 4
3 months	0.73 (0.12)	0.93 (0.15)	0.86 (0.14)	1.44 (0.23)
6 months	1.08 (0.16)	1.96 (0.29)	1.70 (0.25)	2.31 (0.34)
9 months	1.22 (0.16)	2.88 (0.38)	2.25 (0.30)	3.65 (0.49)
12 months	1.69 (0.20)	4.37 (0.53)	3.31 (0.40)	7.84 (0.94)
24 months	1.94 (0.16)	0.74 (0.06)	1.11 (0.09)	13.28 (1.12)
Average	1.33 (0.16)	2.18 (0.28)	1.85 (0.24)	5.70 (0.63)

	GDP Growth			
3 months	3.75 (0.19)	1.65 (0.08)	4.49 (0.22)	8.05 (0.40)
6 months	4.95 (0.25)	2.60 (0.13)	11.43 (0.58)	20.92 (1.07)
9 months	5.86 (0.30)	3.71 (0.19)	14.06 (0.73)	35.27 (1.83)
12 months	9.07 (0.50)	6.14 (0.34)	25.96 (1.43)	54.49 (3.00)
24 months	2.42 (0.15)	6.64 (0.42)	27.77 (1.74)	17.05 (1.07)
Average	5.91 (0.31)	3.53 (0.19)	13.99 (0.74)	29.68 (1.57)

Sample: December 2002 to August 2004

	CPI Inflation			
3 months	0.79 (0.09)	0.81 (0.09)	0.81 (0.09)	0.84 (0.09)
6 months	1.37 (0.15)	1.34 (0.15)	1.31 (0.14)	1.58 (0.17)
9 months	1.33 (0.13)	1.48 (0.15)	1.54 (0.15)	1.50 (0.15)
12 months	1.36 (0.11)	1.35 (0.11)	1.36 (0.11)	1.87 (0.16)
Average	1.21 (0.12)	1.24 (0.12)	1.25 (0.13)	1.45 (0.14)

	GDP Growth			
3 months	3.68 (0.22)	1.22 (0.07)	4.39 (0.26)	9.71 (0.57)
6 months	4.09 (0.26)	0.75 (0.05)	8.58 (0.55)	25.25 (1.61)
9 months	4.55 (0.30)	0.91 (0.06)	6.78 (0.44)	32.63 (2.13)
12 months	5.79 (0.36)	1.31 (0.08)	9.27 (0.58)	39.21 (2.45)
Average	4.53 (0.28)	1.05 (0.07)	7.25 (0.46)	26.70 (1.69)

MSE (U–Theil) of BVAR Forecasts – Interest rate criterion

	BVAR 1	BVAR 2	BVAR 3	BVAR 4
Overall Tightness (θ)	0.71	0.06	0.71	2.76
Decay (λ)	1.23	2.27	4.85	3.32
Long–run CPI inflation	0.70	0.94	4.42	2.60
Long–run interest rate	7.31	6.50	4.91	–2.82

Sample: December 2001 to August 2004

	CPI Inflation			
3 months	0.72 (0.12)	1.27 (0.21)	0.85 (0.14)	1.48 (0.24)
6 months	1.08 (0.16)	2.15 (0.32)	1.53 (0.23)	2.35 (0.35)
9 months	1.24 (0.17)	3.24 (0.43)	1.88 (0.25)	3.72 (0.50)
12 months	1.71 (0.21)	3.69 (0.44)	2.40 (0.29)	8.08 (0.97)
24 months	1.95 (0.17)	6.23 (0.53)	2.78 (0.24)	14.05 (1.19)
Average	1.34 (0.16)	3.32 (0.39)	1.89 (0.23)	5.94 (0.65)

	GDP Growth			
3 months	3.63 (0.18)	7.40 (0.37)	3.45 (0.17)	8.03 (0.40)
6 months	4.68 (0.24)	22.59 (1.15)	5.50 (0.28)	21.04 (1.07)
9 months	5.48 (0.28)	42.47 (2.20)	5.06 (0.26)	34.73 (1.80)
12 months	8.54 (0.47)	67.29 (3.70)	9.08 (0.50)	53.58 (2.95)
24 months	2.36 (0.15)	29.89 (1.87)	5.98 (0.37)	18.68 (1.17)
Average	5.58 (0.29)	34.94 (1.86)	5.77 (0.30)	29.35 (1.55)

Sample: December 2002 to August 2004

	CPI Inflation			
3 months	0.79 (0.09)	0.93 (0.10)	0.77 (0.09)	0.83 (0.09)
6 months	1.38 (0.15)	1.29 (0.14)	1.25 (0.14)	1.55 (0.17)
9 months	1.37 (0.14)	1.73 (0.17)	1.41 (0.14)	1.48 (0.15)
12 months	1.37 (0.12)	1.26 (0.11)	1.11 (0.09)	1.93 (0.16)
Average	1.23 (0.12)	1.30 (0.13)	1.13 (0.11)	1.45 (0.14)

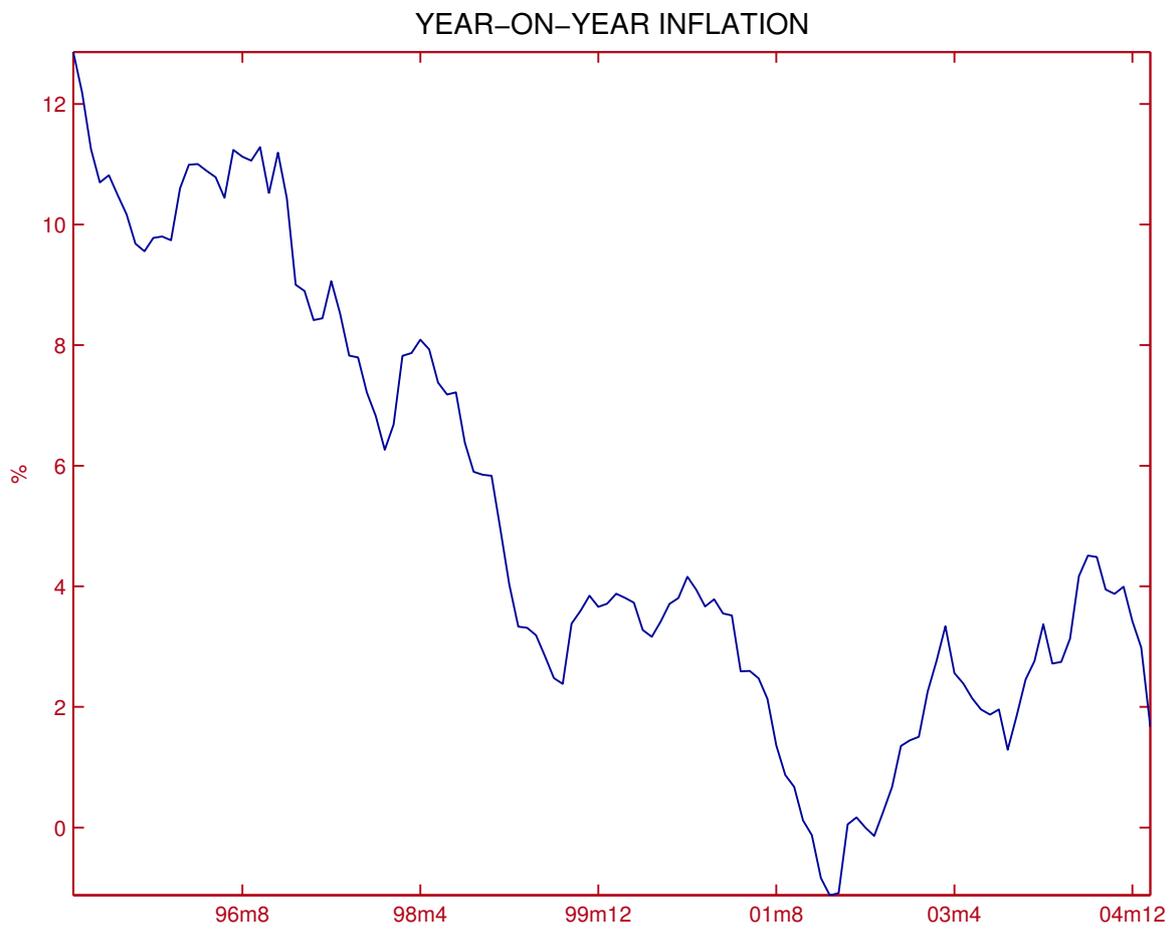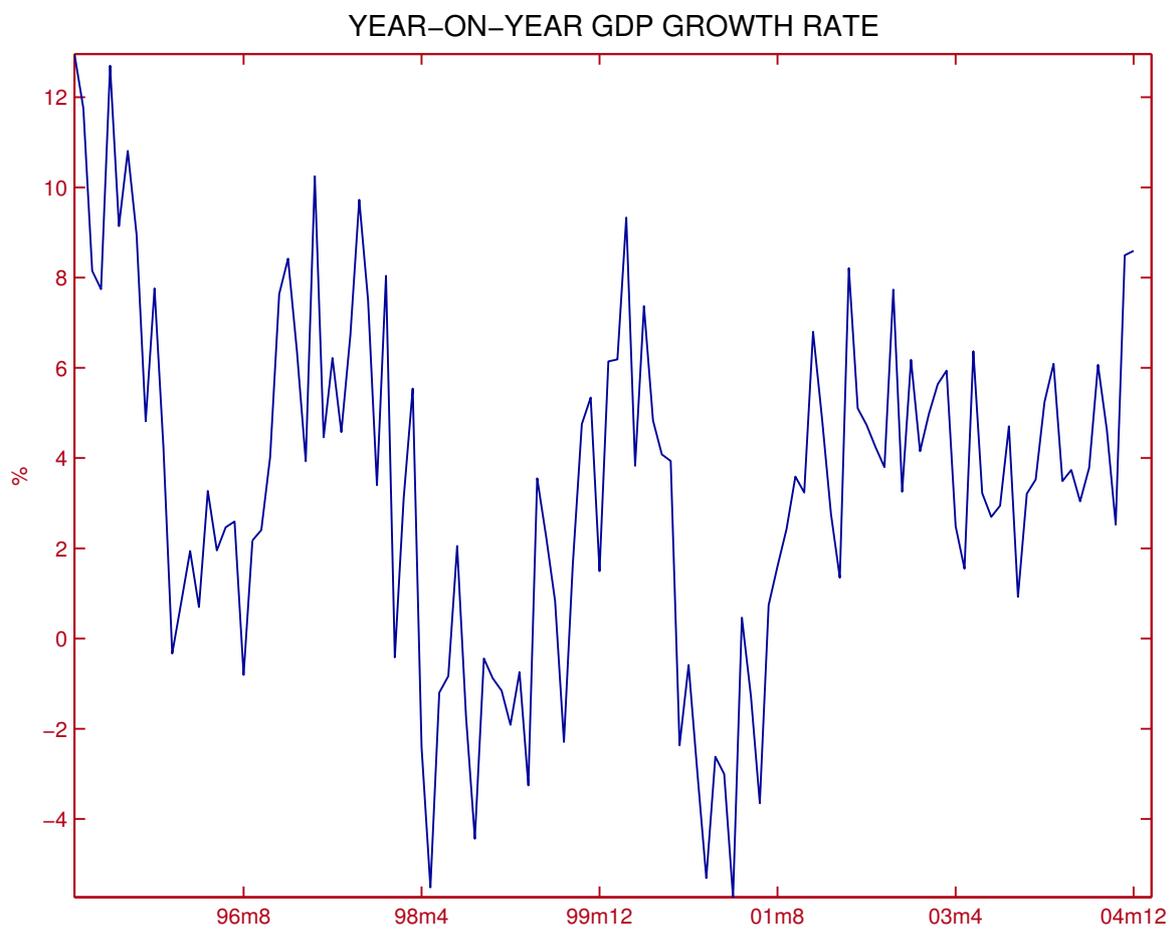|	GDP Growth			
3 months	3.59 (0.21)	1.65 (0.10)	4.07 (0.24)	9.69 (0.57)
6 months	3.89 (0.25)	3.63 (0.23)	4.54 (0.29)	25.53 (1.63)
9 months	4.32 (0.28)	9.75 (0.64)	3.05 (0.20)	32.49 (2.12)
12 months	5.48 (0.34)	19.31 (1.21)	3.81 (0.24)	38.43 (2.41)
Average	4.32 (0.27)	8.58 (0.54)	3.87 (0.24)	26.53 (1.68)

Figure 1: Year-on-year headline inflation

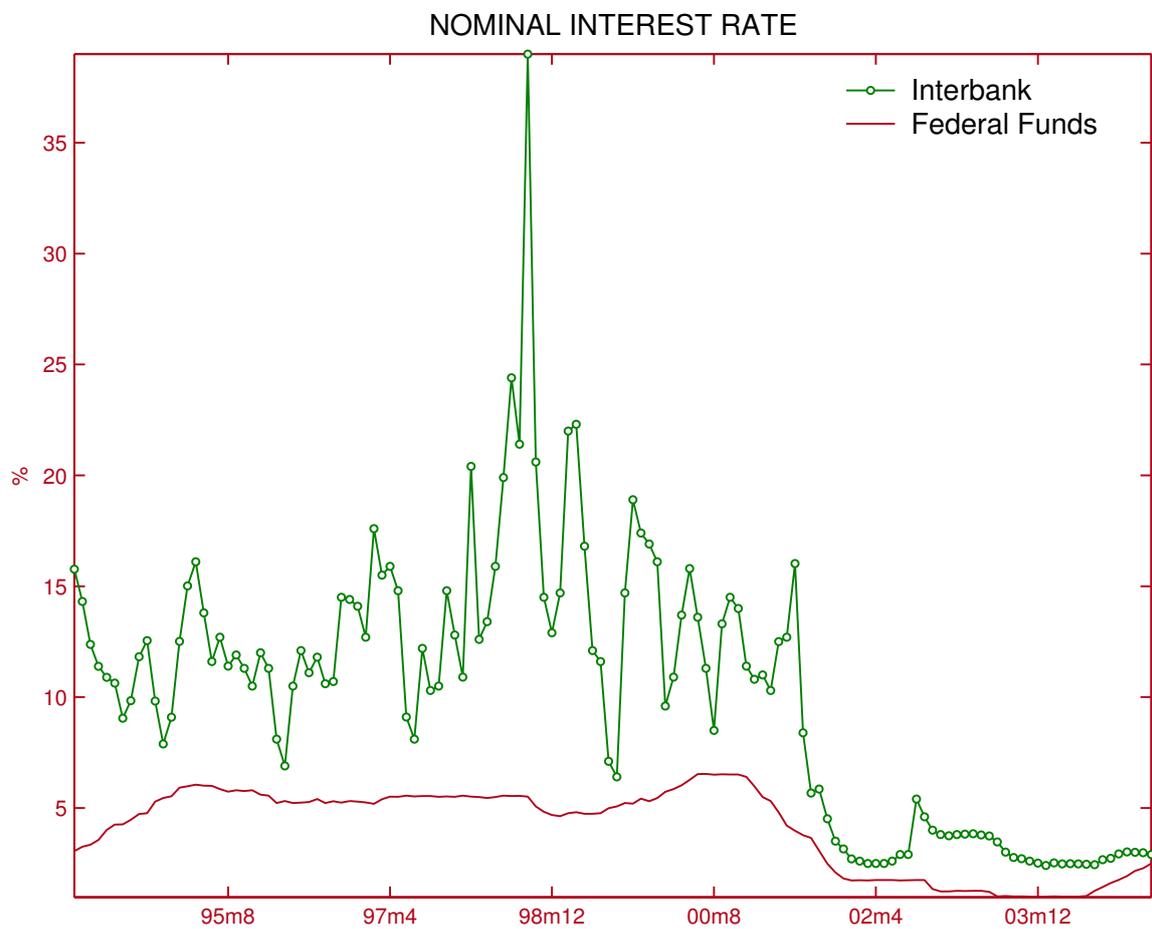Figure 2: Year-on-year GDP growth rate

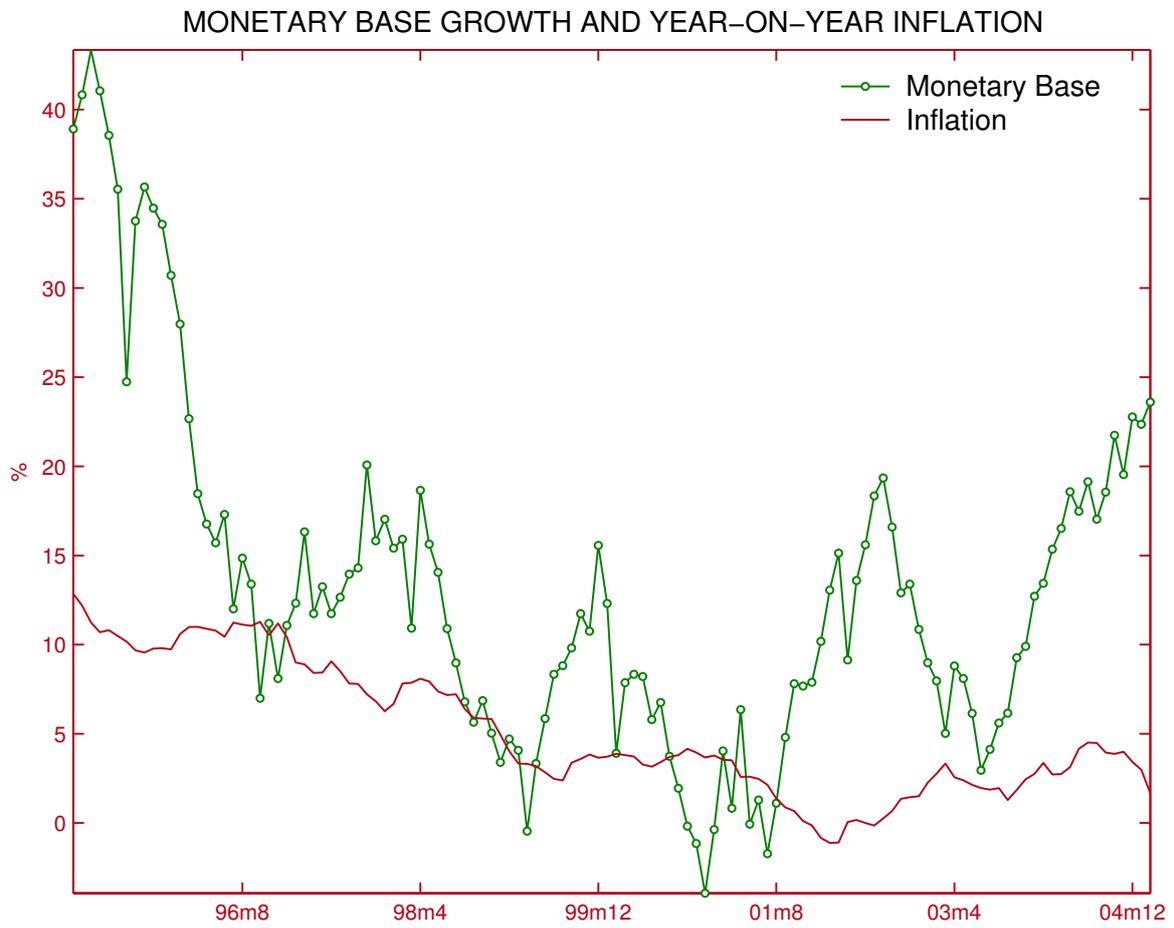Figure 3: Interbank rate and FED funds rate

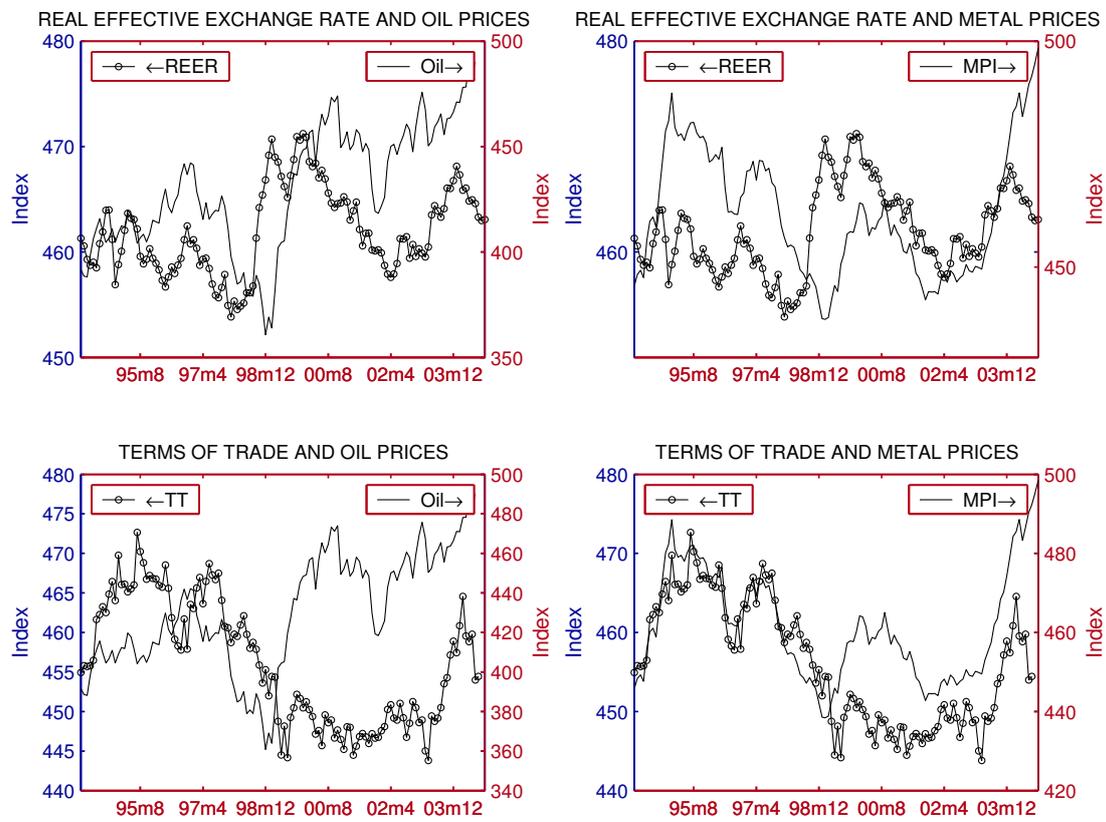Figure 4: Monetary base growth rate and year-on-year inflation

Figure 5: Real Effective Exchange Rates and Terms of Trade

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