BANCO CENTRAL DE RESERVA DEL PERÚ

Nowcasting Peruvian GDP using Leading Indicators and Bayesian Variable Selection

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DT. N°. 2018-010
Serie de Documentos de Trabajo
Working Paper series
Diciembre 2018

Nowcasting Peruvian GDP using Leading Indicators and Bayesian Variable Selection*

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December 13, 2018

Abstract

There exists a large set of leading indicators that are directly related with GDP growth. However, it is often very difficult to select which of these indicators can be used in order to choose the best short-term forecasting (*nowcasting*) model. In addition, it may be the case that more than one model can do this job accurately. Therefore, it would be convenient to average these potentially non-nested models. Following Scott and Varian (2015), we estimate a Structural State Space model through Gibbs Sampling and a spike-slab prior in order to perform the Stochastic Search Variable Selection (SSVS) method. Posterior simulations can be used to then compute the inclusion probability of each variable for the whole set of models considered. In-sample GDP estimates are very precise, taking into account the large set of regressors considered for the estimation. Data comes from the BCRPs database plus other additional sources.

Resumen

Existe un conjunto grande de indicadores adelantados que están directamente relacionados con el crecimiento del PBI. Sin embargo, a menudo nos cuesta mucho trabajo seleccionar cuáles de estos indicadores conforman el mejor modelo de regresión y predicción de corto plazo (*nowcasting*). Es más, es posible que exista más de un modelo que pueda realizar esta tarea de manera satisfactoria, por lo que sería conveniente tomar el promedio de estos mismos, los cuales son potencialmente no anidados. Siguiendo a Scott and Varian (2015), se estima un modelo de espacio de estados a través del muestreo de Gibbs y un prior spike-and-slab para la selección estocástica de variables (SSVS). Con ello, se obtiene la probabilidad de inclusión de cada variable dentro del conjunto de modelos posible. Los resultados muestran un ajuste bastante preciso para el PBI, teniendo en cuenta el gran número de variables utilizadas, las cuales provienen de la base de datos macroeconómicos del BCRP y de otras fuentes adicionales.

JEL Classification: E43, E51, E52, E52, E58

Key words: Nowcasting, Gibbs Sampling, Variable Selection, Model Averaging

*I would like to thank Diego Winkelried, the participants of the XXXVI Encuentro de Economistas of the BCRP, seminar participants at the BCRP and two anonymous referees for their helpful comments and suggestions. The views expressed are those of the author and do not necessarily reflect those of the Central Reserve Bank of Peru. All remaining errors are mine.

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1 Introduction

Information is a valuable item for decision makers. In particular, policy makers and private economic agents such as investors need all the time new information related with the aggregate economy in order to take proper decisions for the future. A well known issue is the fact that GDP growth data is only available with a lag. The length of this lag is variable across countries, but it is usually the case that the new GDP data is released with more than one month of lag. Therefore, given that current GDP is non-observable, economic agents need to perform an exercise of forecasting the present, i.e. *nowcasting*.

The latter is possible since there exists a large set of leading indicators and economic variables that i) are related with the GDP and ii) are released almost in real time, i.e. in advance of the GDP. As a result, we as econometricians can think on a linear regression model of the GDP onto a subset of these leading indicators in order to forecast the current value of GDP. In particular, previous nowcasting exercises for GDP growth with Peruvian data can be found in Pérez-Forero *et al.* (2017)[1]. However, it turns out that this task of nowcasting macroeconomic time series is not straightforward, since tons of potential regressors and model specifications can be spotted by different experts and professional forecasters at any point in time. Then the question is, which is the best linear regression model? How can we select the best regressors among a very large set of variables? Can we use different models? It is likely that more than one model is popular at any point in time, given the heterogeneity of views across the different experts. As a matter of fact, most of these experts can claim that they have 'the model', and when we take a look to the set of regressors, it turns out that these models are non-nested. Then, suppose that we want to take stock of the views of the different experts, since we want to construct an eclectic approach. Then a more elaborated question is, can we average these non-nested models with different sets of regressors? In this paper we implement an econometric approach that allows us give a positive answer to the latter question.

That is, in this paper we specify a Structural Time Series model, which will be estimated through

[1] In particular, this reference covers the early Peruvian literature related with leading indicators (see e.g. Escobal and Torres (2002), Ochoa and Lladó (2003), Kapsoli and Bencich (2004), among others).

Bayesian techniques following the lead of Scott and Varian (2015)[2]. The latter model has been used for nowcasting time series using a large set of variables, such as Google Trends data. Then, in order to select among different models and regressors, we implement the spike-and-slab approach developed by Madigan and Raftery (1994) and George and McCulloch (1997), and we use this machinery for finding the best predictors for the Peruvian GDP growth. After that, given the posterior distribution estimated for this model, we perform the nowcasting exercise, and we present the forecast density derived from our analysis.

The results indicate that the best predictors for the Peruvian GDP growth are i) electricity production, ii) the volume of imported inputs, iii) internal consumption of cement and some financial variables. For those readers who are familiar with the mentioned variables, this exercise is just a corroboration of their prior. As it was mentioned above, we present the full forecast density, rather than point estimates. The latter allows us to quantify the support of the forecast and also the probability of any particular forecast point, which could potentially be turned into a fanchart. Our result is inherently robust, since we depart from a very large set of economic indicators, including both contemporaneous values and lags, and we let the algorithm to select the main regressors conditional on the observed data and using standard conjugated priors. We expect to use this algorithm routinely as one of the satellite models for short run forecasting at the BCRP.

The document is organized as follows: section 2 describes the structural time series model, section 3 describes the estimation procedure, section 4 discusses the main results, and section 5 concludes.

[2]The literature of nowcasting GDP is large and it is still growing. The main references in this topic that are worth to mention are Evans (2005) and Giannone *et al.* (2008), Banbura *et al.* (2013) among others. For the specific case of Small Open Economies, we can mention the case of Brazil, India and Japan by Bragoli *et al.* (2015), and Bragoli and Fosten (2016) and Bragoli (2017), respectively.

2 A Structural time series model

2.1 The setup

Consider the stochastic generalization of the classic constant-trend regression model (Scott and Varian, 2015). In particular, the dependent variable y_t, which is in this case the GDP growth, is determined through the relationship:

$$y_t = \mu_t + \gamma_{t,1} + z_t + v_t, \qquad v_t \sim N(0, V) \tag{1}$$

$$\mu_t = \mu_{t-1} + b_{t-1} + w_{1,t}, \qquad w_{1,t} \sim N(0, W_1) \tag{2}$$

$$b_t = b_{t-1} + w_{2,t}, \qquad w_{2,t} \sim N(0, W_2) \tag{3}$$

$$\gamma_{t,1} = -\sum_{i=1}^{S-1} \gamma_{t-1,i} + w_{3,t}, \qquad w_{3,t} \sim N(0, W_3) \tag{4}$$

$$\gamma_{t,i} = \gamma_{t-1,i}, \quad i = 1, \dots, S-1 \tag{5}$$

$$z_t = \sum_{i=1}^{K} \beta_i x_{i,t} \tag{6}$$

where μ_t is the trend term, which follows a random walk, b_t is an auxiliar random walk term, $\gamma_{t,1}$ is the seasonal component, being S the data frequency [3] and z_t the exogenous component. As we pointed out above, the latter model is a generalization of a linear regression model where $W_1 = W_2 = W_3 = 0$. As a result, our model is sufficiently capable of capturing the time variation in trend and seasonal components. The latter is desirable, since we want to increase the precision of our forecasts.

Moreover, the set of regressors x_t can be potentially very large, where we will consider leading indicators both in the contemporaneous period t as well as lagged values $t - j$. In this case, we denote $K = dim(x_t) = dim(\beta)$. As a result, we have huge amount of candidate models, each one considering only a subset of these regressors. In the next subsection we explain how we determine each of these models and how we can adapt this approach in the bayesian estimation of the presented state space model.

[3] $S = 4$ when using quarterly data and $S = 12$ when using monthly data.

2.2 Spike and slab variable selection

Given the previous setup, we now need to explain how we implement the Stochastic Search Variable Selection (SSVS) procedure. First, let γ denote a vector the same length as the list of possible regressors x_t that indicates whether or not a particular variable $x_{i,t}$ is included in the model. That is, γ is a vector that has the same length as β, i.e $K = dim\,(\gamma)$, where $\gamma_i = 1$ means that $\beta_i \neq 0$ and $\gamma_i = 0$ means that $\beta_i = 0$, where β_i is the coefficient associated with $x_{i,t}$. In other words, each possible value of the binary vector γ is a regression model.

Furthermore, given the value of γ, let β_γ be the subset of entries from β for which $\gamma_i = 1$, and let σ^2 be the residual variance from the regression model γ. In this context, a spike and slab prior for the joint distribution of $\left(\beta, \gamma, \sigma^{-2}\right)$ can be re-expressed as:

$$p\left(\beta, \gamma, \sigma^{-2}\right) = p\left(\beta_\gamma \mid \gamma, \sigma^{-2}\right) p\left(\sigma^{-2} \mid \gamma\right) p\left(\gamma\right)$$

In particular, since we are going to consider a significant amount of zeros in each model γ, the *spike* part of a *spike-and-slab* prior refers to the point mass at zero, for which we assume an independent Bernoulli distribution for each entry γ_i with a probability of success equal to π_i. As a consequence, the joint prior for γ is a product of Bernoulli random variables:

$$\gamma \sim \prod_i \pi_i^{\gamma_i} \left(1 - \pi_i\right)^{1-\gamma_i} \tag{7}$$

It is then important to remark that, when detailed prior information is unavailable, it is convenient to set all π_i equal to the same number π, i.e. a flat prior. In fact, the common prior inclusion probability can easily be elicited from the expected number of nonzero coefficients for the *average* model. That is, if k out of K coefficients are expected to be nonzero, then we will set $\pi = k/K$ as our prior mean.

On the other hand, the *slab* component is a prior for the values of the nonzero coefficients, conditional on the knowledge of which coefficients are nonzero, i.e. conditional on γ. Let b be a vector that represents the prior mean for regression coefficients, let Ω^{-1} be a prior precision matrix, and let Ω_γ^{-1} denote rows and columns of Ω^{-1} for which $\gamma_i = 1$. As a result, a conditionally conjugate "slab" prior is a follows a typical Bayesian linear regression model as in Zellner (1971) and Koop (2003), where we have a normal distribution for coefficients:

$$\beta_\gamma \mid \gamma, \sigma^{-2} \sim N\left(b_\gamma, \sigma^2 \left(\Omega_\gamma^{-1}\right)^{-1}\right)$$

and an inverse-gamma distribution for the variance:

$$\frac{1}{\sigma^2} \sim \Gamma\left(\frac{df}{2}, \frac{ss}{2}\right)$$

Moreover, following the classical linear regression theory, $X'X/\sigma^2$ is the total Fisher information in the full data, which can be reasonable to parametrize as $\Omega^{-1} = \kappa X'X/T$. However, since $X'X$ is potentially rank deficient, we assume that

$$\Omega^{-1} = \frac{\kappa}{T}\left(wX'X + (1-w)\, diag\left(X'X\right)\right) \tag{8}$$

where $0 \leq w \leq 1$. With that assumption, it is possible to always have a positive definite matrix Ω^{-1}. It is important to remark that the actual value of w is very close to 1, so that we try to do not distort the sample properties of the data, and we just use this shortcut in order to get a stable numerical simulation. The complete information related with priors is shown in table 1[4].

Parameter	Distribution	Hyper-parameters
α_0	Normal	$N\left(0_{\dim\alpha\times 1}, I_{\dim\alpha}\right)$
V	Inverse-Gamma	$IG\left(\frac{1}{2}, \frac{0.01}{2}\right)$
$W_{i=1,2,3}$	Inverse-Gamma	$IG\left(\frac{1}{2}, \frac{0.01}{2}\right)$
β_γ	Normal	$N\left(0_{\dim\beta_\gamma\times 1}, \sigma^2\left(\Omega_\gamma^{-1}\right)^{-1}\right)$
σ^2	Inverse-Gamma	$IG\left(\frac{1}{2}, \frac{0.01}{2}\right)$
γ	Spike-slab	$\pi_i = 5/K$

Table 1: Priors for state-space parameters

[4] Where $\kappa = 0.25, w = 0.9925$ in $\Omega^{-1} = \frac{\kappa}{T}\left(wX'X + (1-w)\, diag\left(X'X\right)\right)$

2.3 Bayesian model averaging

As we have mentioned in a previous subsection, bayesian inference with spike-and-slab priors is an effective way to implement Bayesian model averaging, since it allows us to explore the entire space of time series regression models. As a result, using efficient Markov-Chain Monte Carlo (MCMC) methods, we will get the posterior simulation of the whole set of model parameters. Furthermore, having simulated the posterior distribution for the parameter space via MCMC methods, then each draw of parameters from the posterior distribution can be combined with the available data to produce a forecast of y_{t+1} for that particular draw. Moreover, repeating these draws many times gives us an estimate of the posterior density of the forecast y_{t+1}. As it is pointed out by Scott and Varian (2015), the latter approach is motivated by the Madigan and Raftery (1994)'s proof that averaging over an ensemble of models does no worse than using the best single model in the ensemble[5]. As a consequence, we can simulate the full forecast density and then take the corresponding percentiles in order to get an *average* forecast.

3 Bayesian Estimation

The statistical model presented above has to be estimated as a previous step for obtaining the nowcasting of GDP. In this section we will use Markov Chain Monte Carlo (MCMC) methods in order to perform this task. First, we need to re-write the model correctly as a state-space system, and then we need to explain the simulation routine that is going to be used for the bayesian estimation.

3.1 State-Space form

The model (1)-(2)-(3)-(4)-(5)-(6) can be re-written as a state-space system with an exogenous component and time varying matrices, so that:

$$y_t = D_t\alpha_t + Z_tX_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, H_t) \tag{9}$$

[5]Regarding Bayesian Model Averaging see also Fragoso *et al.* (2018), Hoeting *et al.* (1999) and Raftery *et al.* (1997).

$$\alpha_t = A_t\alpha_{t-1} + R_t\eta_t, \qquad \eta_t \sim N(0, Q_t) \tag{10}$$

Denote $\psi = \left(\theta, \alpha^T\right)$ as the parameter set of the model. Then, the complete posterior distribution for the parameter set ψ is:

$$p\left(\psi \mid y^T\right) = p\left(\theta, \alpha^T \mid y^T\right) \propto p(\theta)\, p(\alpha_0) \prod_{t=1}^{T} p(y_t \mid \alpha_t, \theta)\, p(\alpha_t \mid \alpha_{t-1}, \theta)$$

Notice that in this case the model is linear and normally distributed conditional on a value of γ. In line with that, the analytical computation of the posterior distribution is possible conditional on γ. In the next subsection we describe the main estimation algorithm.

3.2 A Gibbs Sampling routine

Bayesian estimation and posterior simulation is typically implemented through Markov Chain Monte Carlo (MCMC) methods. In this section we split the parameter set into many different blocks such that simulation is feasible, i.e. e implement a Gibbs Sampling routine as in Scott and Varian (2015). The algorithm sequence is as follows:

Algorithm 1

1. Simulate $\{\alpha_t\}_{t=1}^{T}$ from $p\left(\alpha_t \mid y^T, \psi_{-\alpha_t}\right)$: Carter and Kohn (1994)

$$\alpha_t \mid y^T, \psi_{-\alpha_t} \sim N\left(\overline{\alpha}_{t|T}, \overline{P}_{t|T}\right), \ t \leq T \tag{11}$$

2. Simulate V from $p\left(V \mid Y^T, \psi_{-V}\right)$: Inverse-Gamma

3. Simulate W_1 from $p\left(W_1 \mid y^T, \psi_{-W_1}\right)$: Inverse-Gamma

4. Simulate W_2 from $p\left(W_2 \mid y^T, \psi_{-W_2}\right)$: Inverse-Gamma

5. Simulate W_3 from $p\left(W_3 \mid y^T, \psi_{-W_3}\right)$: Inverse-Gamma

6. Simulate β from $p\left(\beta \mid y^T, \psi_{-\beta}\right)$: Normal

7. Simulate σ^2 from $p\left(\sigma^2 \mid y^T, \psi_{-\sigma^2}\right)$: Inverse-Gamma

8. Simulate γ from $p\left(\gamma \mid y^T, \psi_{-\gamma}\right)$: Metropolis step as in George and McCulloch (1997)

Notice that since γ is a binary vector where each component follows a discrete distribution, its posterior is non-standard in this context. Therefore, in order to sample from $p\left(\gamma \mid y^T, \psi_{-\gamma}\right)$ as in George and McCulloch (1997), we implement a Metropolis-Hastings step. The algorithm step for this part is as follows:

Algorithm 2

1. Generate a candidate value γ^* with probability distribution $q\left(\gamma^{(j)}, \gamma^*\right)$.

2. Set $\gamma^{(j+1)} = \gamma^*$ with probability:

$$\alpha^{MH}\left(\gamma^{(j)}, \gamma^*\right) = \min\left\{\frac{q\left(\gamma^*, \gamma^{(j)}\right)}{q\left(\gamma^{(j)}, \gamma^*\right)} \frac{g\left(\gamma^*\right)}{g\left(\gamma^{(j)}\right)}, 1\right\}$$

   Otherwise $\gamma^{(j+1)} = \gamma^{(j)}$.

In particular, $q\left(\gamma^{(j)}, \gamma^*\right)$ is such that γ^* is generated by randomly changing one component of $\gamma^{(j)}$. As a consequence, $q(.)$ is a symmetric proposal. The use of symmetric proposal distributions in fairly standard in the literature, and it gives us the possibility to simplify the kernel transition associated with the Metropolis-Hastings.

3.3 Estimation setup

We run the Gibbs sampler for $K = 500,000$ and discard the first $100,000$ draws in order to minimize the effect of initial values. In order to reduce the serial correlation across draws, we set a thinning factor of 100. As a result, we have $4,000$ draws for conducting inference. The acceptance rate of the metropolis-step associated with γ is around 0.29.

4 Results

After simulating the posterior distribution of different block parameters, we analyze the frequencies and capture the best predictors ranking, which are depicted in figure 1. We can observe that among the main regressors we have detected the following variables: electricity production, consumption of cement and the volume of imported input goods, all of them in contemporaneous form (t). The good fit of the model is shown in figure 2, where the suffix after each label represents the lag order of the regressor starting in 0.

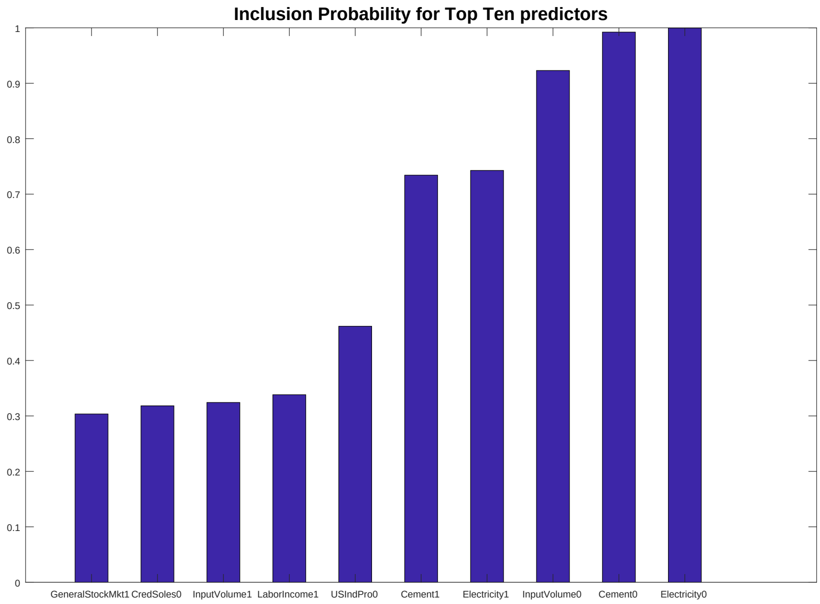

Figure 1: Top Ten Predictors for GDP

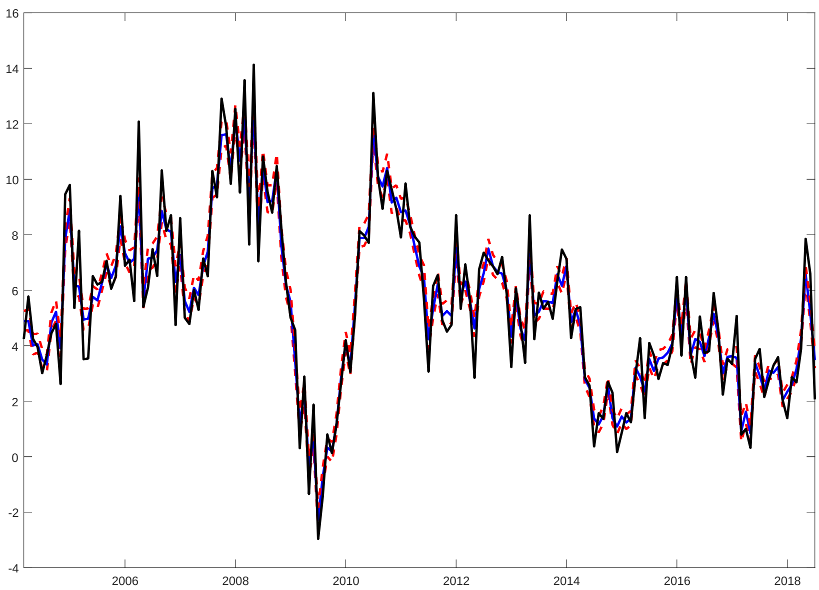

Figure 2: Predicted GDP growth

Given the posterior estimates of the parameter set $\psi = \left(\theta, \alpha^T, \gamma\right)$, then for each draw $i =$

$1, \ldots, S$ of ψ we can forecast the latent variable such that:

$$\alpha^{(i)}_{T+h|T} = \left[A^{(i)}_T\right]^h \alpha^{(i)}_{T|T} + \eta_{T+h}$$

where $\eta_{T+h} \sim N(0, Q_T)$. The latter, together with the data available of exogenous regressors up to a horizon h, is useful in order to forecast the dependent variable using the measurement equation:

$$y^{(i)}_{T+h|T} = D^{(i)}_{T+h} \alpha^{(i)}_{T+h|T} + (\beta \mid \gamma)^{(i)} x_{T+h} + \upsilon_{T+h}$$

where $\upsilon_{T+h} \sim N(0, V)$. That is, as long as we have out of sample data available of the vector x, then it is possible to compute the conditional forecast.

5 Concluding Remarks

Peruvian GDP short term forecasting and Nowcasting is not straightforward. We have selected and ranked regressors among a large set of variables using Bayesian techniques. Among the main regressors we have detected the following variables: electricity production, consumption of cement and the volume of imported input goods, all of them in contemporaneous form (t), among others. The method suggested by Scott and Varian (2015) is very powerful and promising. Model averaging using the method suggested by Scott and Varian (2015) allows us to produce density forecasts and quantify the uncertainty associated with the estimation, i.e. the outcome is not only a point forecast of GDP growth. This seems to be very powerful and promising for policymakers interested in producing risk scenarios. More work is needed related with the ex-ante selection of variables and with the sensitivity analysis of the results with different priors. Finally, our goal is also to use a wider set of indicators and apply big data techniques such as Bok *et al.* (2017). The latter is part of the research agenda.

A Data Description

We include monthly data from January 2003 until July 2018 of more than 30 regressors related with economic activity indicators, money aggregates, stock markets, labor market and also external variables, with both current values and lags. Details are depicted in Table 2.

Table 2: List of regressors included in the model

No.	Variable	Original Units of Measure	Transformation	Label	Source
1	Credit in Soles	Millions of Soles	Year-to-Year change (in %)	CredMN	BCRP
2	Credit in Dollars	Millions of Dollars	Year-to-Year change (in %)	CredME	BCRP
3	Total Credit	Millions of Soles	Year-to-Year change (in %)	CredTT	BCRP
4	Mortgage Credit	Millions of Soles	Year-to-Year change (in %)	CredHip	BCRP
5	Consumption Credit	Millions of Soles	Year-to-Year change (in %)	CredCons	BCRP
6	Deposits in Soles	Millions of Soles	Year-to-Year change (in %)	LiquMN	BCRP
7	Deposits in Dollars	Millions of Dollars	Year-to-Year change (in %)	LiquME	BCRP
8	Monetary Base	Millions of Soles	Year-to-Year change (in %)	Emis	BCRP
9	Cash	Millions of Soles	Year-to-Year change (in %)	Circ	BCRP
10	Electricity Production	GWh	Year-to-Year change (in %)	PELEC	COES
11	Consumption of Cement	Metric Tons	Year-to-Year change (in %)	CINTC	UNACEM
12	Indirect Taxes	Millions of Soles	Year-to-Year change (in %)	IGVInt	SUNAT
13	Chicken Sales	Average Daily Metric Tons	Year-to-Year change (in %)	VPOLLOS	BCRP
14	Labor Force	Units	Year-to-Year change (in %)	PEAO	BCRP
15	Monthly labor income	Millions of Soles	Year-to-Year change (in %)	Ingreso	BCRP
16	Unemployment rate	Percentages	Levels	Desempleo	BCRP
17	Non-Financial Government Expenditures	Millions of Soles	Year-to-Year change (in %)	GNF	BCRP
18	Volume of Imported Inputs	Units	Year-to-Year change (in %)	VOL_M_INPUT	BCRP
19	General Stock Market Index of Lima	(31/12/91 = 100)	Year-to-Year change (in %)	IGBVL	BCRP
20	Selective Stock Market Index of Lima	(31/12/91 = 100)	Year-to-Year change (in %)	ISBVL	BCRP
21	Consumer Price Index	(2009=100)	Year-to-Year change (in %)	IPC	BCRP
22	Non Food and Energy Price Index	(2009=100)	Year-to-Year change (in %)	IPCae	BCRP
23	Wholesale price Index	(2009=100)	Year-to-Year change (in %)	IPM	BCRP
24	Terms of Trade	(2007=100)	Year-to-Year change (in %)	TI	BCRP
25	LIBOR 3-Month rate	Percentages	Levels	Libor3M	FRED
26	Peruvian EMBI Spread	Basis points	Levels	EMBI	BCRP
27	Oil Prices (WTI)	Dollars per Barrel	Year-to-Year change (in %)	WTI	FRED
28	Real Exchange Rate	(2009=100)	Year-to-Year change (in %)	TCRB	BCRP
29	United States Consumer Price Index	(1982-1984=100)	Year-to-Year change (in %)	IPCUS	FRED
30	Industrial Production Index	(2012=100)	Year-to-Year change (in %)	INDPRO	FRED
31	Producer Price Index for All Commodities	(1982=100)	Year-to-Year change (in %)	PPIACO	FRED
32	CBOE Volatility Index: VIX	Units	Levels	VIXCLS	FRED

B The posterior distribution of hyper-parameters

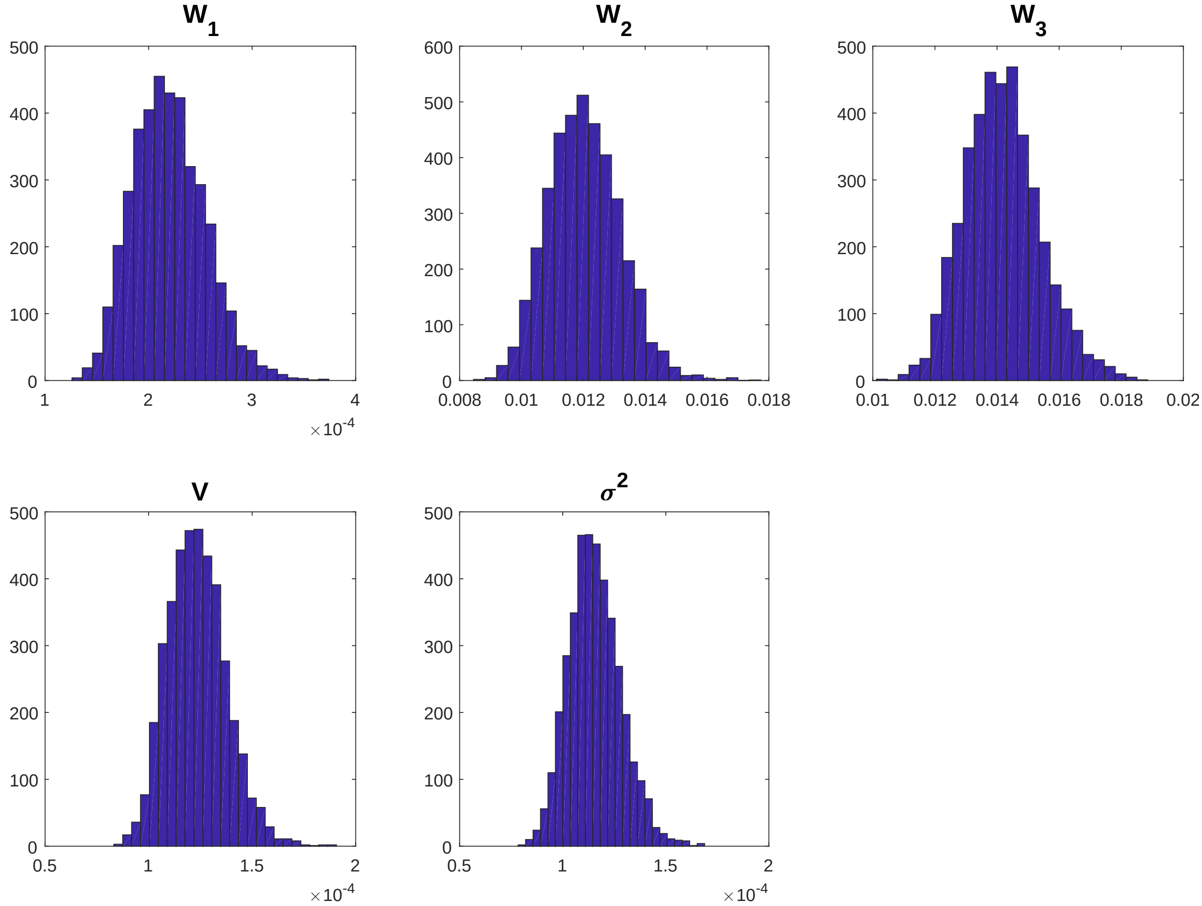

Figure 3: Posterior Distribution of hyper-parameters (GDP Model)

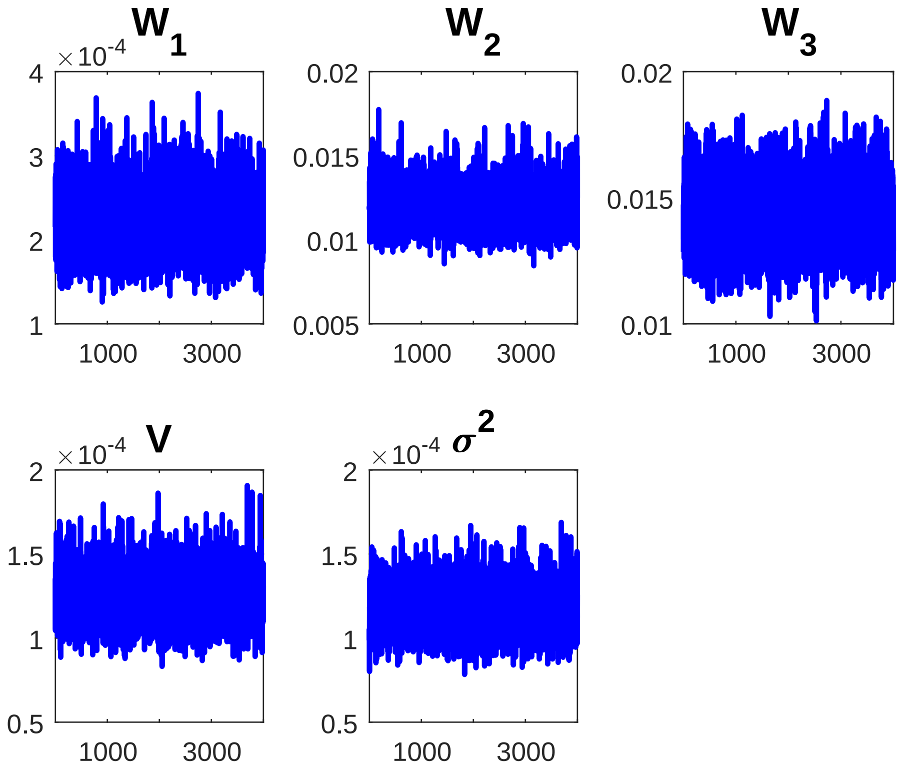

Figure 4: Posterior Draws of hyper-parameters (GDP Model)

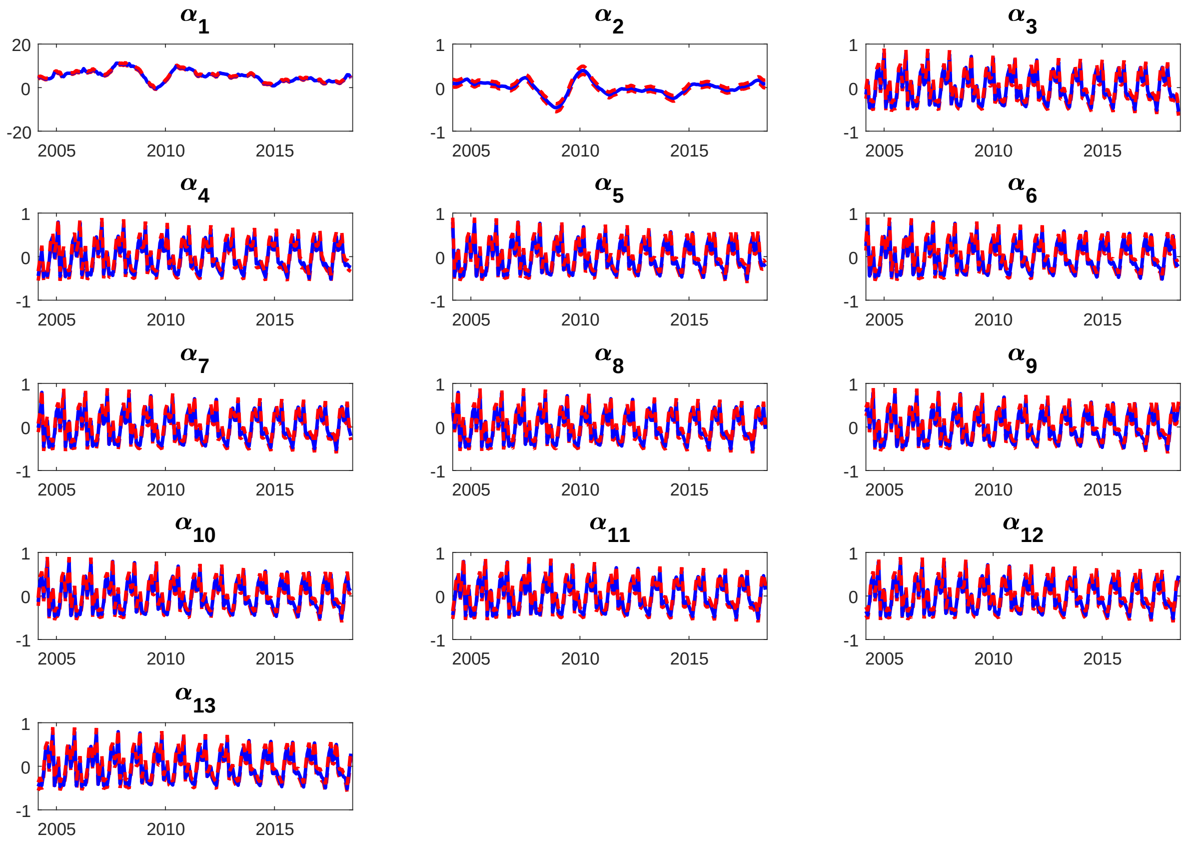

Figure 5: Posterior Distribution of latent factors (GDP Model)

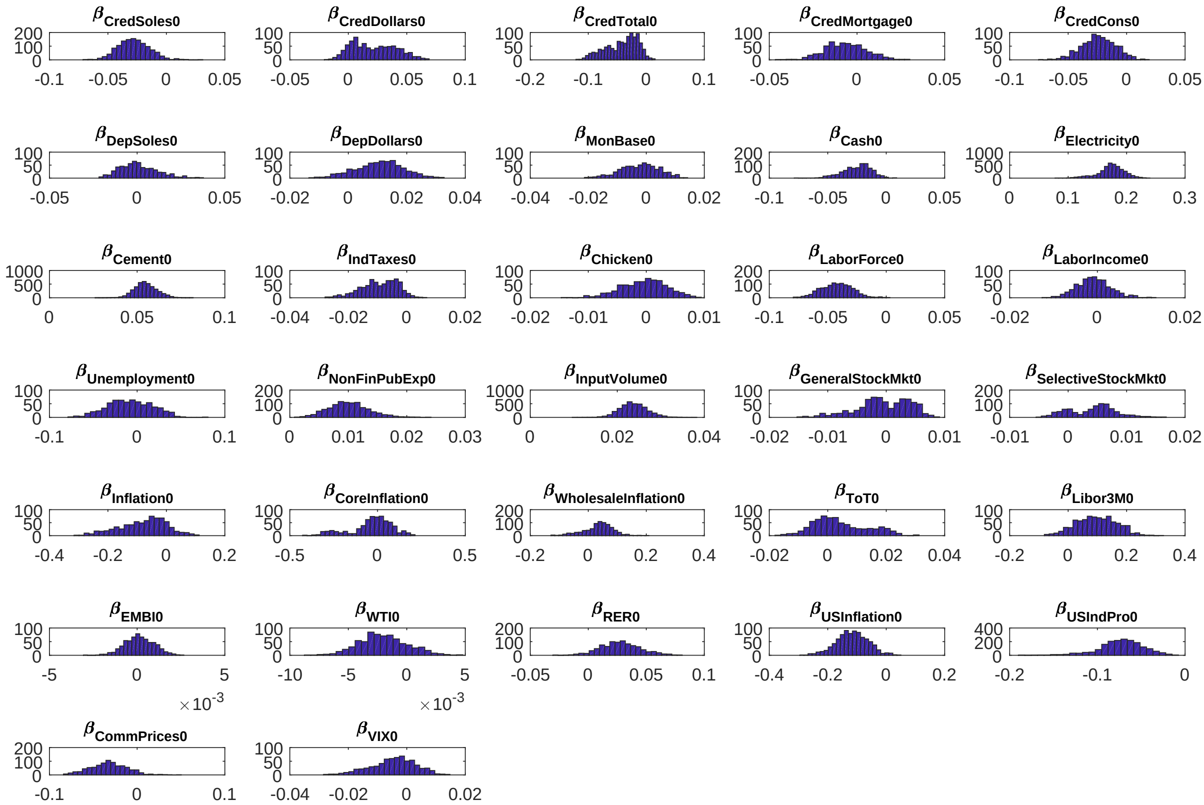

Figure 6: Posterior Distribution of coefficients (GDP Model) (1)

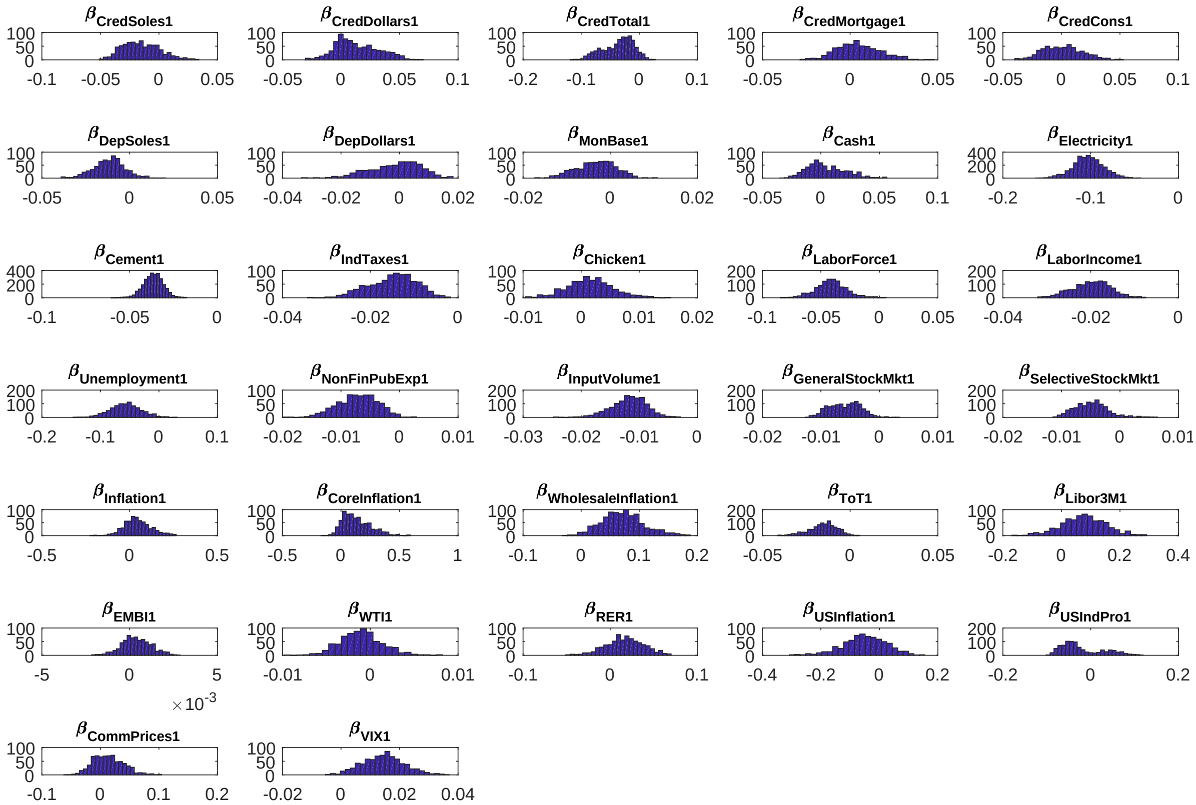

Figure 7: Posterior Distribution of coefficients (GDP Model) (2)

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