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An Application of Large Bayesian Vector Autoregressive (BVAR) Model in Nowcasting the Philippine Economy

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Abstract

Nowcasting predicts the current situation, the very near future, and even the most recent past. Such models exploit information published earlier than the target variable. In macroeconometrics, nowcasting models are useful tools in the timely assessment of key macroeconomic variables due to publication lags of official statistics in most countries. These models are also used in structural and policy analysis in capturing short-run relationships in the system. In this paper, we formulate a vector autoregressive (VAR) model with mixed frequency data in nowcasting the Philippine economy. We also present a Bayesian estimation approach in addressing over-parametrization on most vector autoregressive models to include larger amounts of variables in the system through different prior specifications. These prior specifications are implemented to cater to violations of certain model assumptions in the VAR modeling framework. We deal with the ragged-edge problem on the data caused by publication lags of official statistics by aggregating the monthly indicators and taking the most recent observation for each series to fill-out gaps from the structure of the database. Forecast evaluation exercise shows better performance of the model in terms of the mean squared forecasting errors and mean absolute errors over benchmark models in the shorter horizon.

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1. Introduction

Official statistics in most countries are published with significant lags and are even subject to revisions after their initial release. In the Philippines, the official GDP statistics are released with a six-week lag from the end of the reference quarter. Policymakers rely on real-time information in setting the initial conditions and determining the relevant policy actions over the forecasting horizon. This implies that central banks and other government agencies will have to assess the current economic condition with high-frequency information subject to noise and uncertainty on the true path of the economy. In an inflation-targeting country like the Philippines where the BSP considers forward-looking indicators in the setting of monetary policy, nowcasts set the initial tone of the near-term path of the economy.

Nowcasting is defined as predicting the present, the near future, and the recent past. The primary objective of almost all nowcasting models is to exploit information published earlier than the target variable with the possibility of incorporating higher frequency indicators (Bańbura et al., 2013).

Central banks utilize a large number of indicators to "nowcast" the current condition and provide at least an approximate direction of where the economy is heading. Nowadays, real-time data from multiple sources gathered in different sectors apart from the official statistics is an asset in predicting macroeconomic variables in a timely manner. The Philippine Statistics Authority (PSA), the central statistical authority of the Philippine government, provides high-frequency indicators that may be used in nowcasting models. In addition, high-frequency indicators from the BSP and private institutions provide timely and relevant statistics to evaluate the current state of the economy.

We look at the plausibility of applying Vector Autoregressive (VAR) models, particularly the large Bayesian VAR (BVAR) model, to nowcast the quarterly GDP growth rate of the Philippine economy with mixed-frequency indicators from multiple sources. The advantages of a BVAR model are: (1) it can be specified in levels and (2) remedy the curse of dimensionality imposed by the unrestricted large VAR model. As in the former, making the data stationary by taking the first differences of variables is implemented in most Dynamic Factor Models (DFMs), which amplify the noise already present in a small open economy (Itkonen & Juvonen, 2017). On the latter, the curse of dimensionality is present on many indicators with long lag specifications in a VAR system which imposes many parameters to be estimated. This results

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in overparameterization since most macroeconomic data have limited sample sizes compared to the number of parameters the model needs to estimate (Bańbura et al., 2010).

As seen in most nowcasting and forecasting models, using many indicators typically violates established model assumptions. For example, the information set that tends to predict economic growth is large, which, in effect, poses high correlation with each other. In addition, the ragged edge problem (Table 1) due to different publication lags in the official statistics poses another issue when nowcasting (Itkonen & Juvonen, 2017). For example, the data on the volume of production generated from the Monthly Integrated Survey of Selected Industries (MISSI) in the Philippines roughly has a 2-month interval from its official release, while the consumer price index with only a 5 to 7-day lag from its reference period. Finally, forecasting a low-frequency variable like GDP growth using high-frequency indicators could result in some time aggregation issues.

Table 1. Data Availability of Select Indicators

Data Availability		1. M3 2. REMIT 3. ENERGY	1. CPI 2. WPI 3. VOPI 4. NG-REV 5. NG-EXP 6. MXG 7. MMG	1. FX 2. 91-TBILL 3. RRP 4. FED 5. DUBAI 6. AMRRP 7. GIR
End of Quarter	Month-1	x	x	x
	Month-2		x	x
	Month-3			x

Early BVAR models that were developed focused on a limited set of variables such as GDP, inflation, policy rate, and the exchange rate. However, with the greater amount of information, the advancement of computing power, and the ease of data collection are factors that could allow us to generate more accurate forecasts of the economy. Although we are also interested in the structure and the effects of sudden changes in each variable in the system, we only consider the forecasting performance of these models. Moreover, extensions of this research to structural analysis, policy analysis, and simulation can also be implemented on these types of models.

In this paper, we assess the forecasting performance of the BVAR on GDP and compare it to a relatively loose prior specification. In what follows, we present the large Bayesian VAR framework. Section 3 discusses forecasting performances in different forecasting horizons and Section 4 concludes.

2. Nowcasting Studies

Several nowcasting models have been explored for the Philippines. Rufino C. (2019) utilized Mixed Data Sampling (MIDAS) regression in solving the mixed-frequency problem when nowcasting Philippine economic growth. Several indicators were also included for variants of the MIDAS model. In particular, the differing frequency of the target variable (i.e., GDP growth) with the indicators (e.g., monthly inflation, industrial production, and Philippine

Stock Exchange index) indicated the superiority of the MIDAS framework over traditional models (Rufino C., 2019). More recently, a chapter in the Handbook of Statistics by Mariano and Ozmucur (2020) explored data-parsimonious to data-intensive nowcasting models. Models such as mixed-frequency dynamic factor latent model (MF-DFLM), current quarterly model (CQM), and MIDAS regressions were implemented using Philippine data. Empirical exercises pointed to the potentially superior performance of MF-DFLM for forecasting GDP growth, while MIDAS regression performed slightly better when forecasting inflation.

Practices of central banks also involve utilizing near-term forecasting models. Such is the case for the European Central Bank (ECB), which uses factor models in a state-space representation with the real-time data flow (Bańbura et al., 2013). Meanwhile, the Federal Reserve Bank of Cleveland implemented Bayesian mixed-frequency vector autoregressions in producing historical "true" quarterly estimates of GDP. Their recent work illustrated how new monthly data contribute to the historical understanding of business cycles and provide real-time nowcasting of monthly GDP over the pandemic recession (Koop et al., 2022).

The BSP is no different in using near-term forecasting models. Nowcasts play a vital role in the suite of macroeconomic models of the bank, particularly as an added assumption to the path of economic growth and inflation dynamics. The BSP's Forecasting and Policy Analysis System (FPAS) framework subscribes to a suite of models to generate the macroeconomic outlook (Abenoja et al., 2022). Under this approach, the nowcast of GDP growth serves as the initial condition and feeds into the medium-term forecasting models. At present, autoregressive integrated moving average (ARIMA) models on the different components of GDP on the expenditure- and production-sides are estimated and complemented with the judgment of sector specialists to generate nowcasts of GDP. Expanding the set of nowcasting models for GDP using a BVAR approach provides greater flexibility and options in understanding the current state of the economy.

3. Bayesian Vector Autoregressive (BVAR) Model

Typical to vector autoregressive models, these may be represented as a VAR(p):

$$y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \Sigma) \tag{1}$$

where y_t is a n-dimensional vector of observed variables at time t, c is a vector of constants, $A_1, A_2, \dots, A_p$ are the coefficient matrices and ε_t is a vector of errors which is normally distributed with a variance-covariance matrix Σ. The VAR(p) representation in equation 1 is simply a multiple-equation regression where the regressors are the lagged dependent variables such that there are n equations (representing the number of variables), and each equation has $k = np + 1$ regressors totaling to nk coefficients in the system. In this type of set-up, typical sample sizes generated from a low frequency variable as in the case of quarterly GDP growth can be smaller than the number of VAR coefficients. This is a problem imposed in most unrestricted VARs that considers large amount of indicators and relatively high specification of lag structure resulting to over-parameterization. Moreover, limiting the range of variables to include potentially creates an omitted variable bias, which has great effects on structural analysis and forecasting (Bańbura et al., 2010). In addition, using large number of indicators in a VAR framework tends to provide good performance in-sample-fit, but suffers in out-of-sample forecasting. Thus, a solution to this problem as seen on most application is through Bayesian inference with informative priors (Giannone et al., 2019).

Some key advantages of using Bayesian approach to VAR estimation as explicitly stated by Litterman (1986) is first, increasing the number of variables in VAR is not a problem even if the sample size is small. Adding "prior information" that reflects what is known about the likely value of the coefficients solves the curse of dimensionality. In particular, the tradeoff between decreased bias and increased variance[2] in a Bayesian specification framework disappears in a sense that the mean squared error loss function is minimized by including all relevant variables together with prior information which reflects what is known about the likely values of the coefficients (Litterman, 1986). Second, the Bayesian approach usually improves forecasts by combining useful information from the large amount of data at hand, which is weighted and utilized together with the prior and actual data. Lastly, we can specify a large order of lag then choose a prior distribution on the coefficients rather than choosing this autoregressive order.

Before we introduce some useful priors implemented on this paper, we emphasize that VARs are not parsimonious models. The number of parameters that these models estimate for a large set of indicators are usually larger than the sample data. As a result, it is often difficult to obtain precise estimates of so many coefficients which leads to imprecise forecast and impulse responses without prior information (Koop & Korobilis, 2010).

3.1 The Litterman/Minnesota Prior

Original works of "shrinkage" priors were done by researchers at the University of Minnesota or the Federal Reserve Bank of Minneapolis that resulted in the family of priors commonly called Minnesota priors (see Doan et al., 1984; Litterman, 1986). We follow closely the discussion of Koop and Korobilis (2010) where Minnesota priors are based on an approximation which leads to great simplifications in prior elicitation and computation by replacing Σ with an estimate, $\hat{\Sigma}$. Furthermore, this prior is even simplified by the assumption that the variance-covariance matrix is diagonal. With this specification, each equation in the VAR system can be estimated one at a time by setting $\hat{\sigma}_{ii} = s_i^2$ such that s_i^2 is the standard OLS estimate of the error variance in the i^{th} equation and $\hat{\sigma}_{ii}$ is the ii^{th} element of $\hat{\Sigma}$ which is analytically tractable (Koop & Korobilis, 2010). However, it is explicitly stated in their work that the full Bayesian approach to this type of set-up is neglected since we are replacing an unknown matrix of parameters by an estimate and fully neglecting the possibility of treating this variance-covariance structure as random with a corresponding probability distribution. Although a solution to this problem and a common practice in recent Bayesian econometrics is to involve Markov Chain Monte Carlo (MCMC) methods.

By replacing Σ with its estimate, the only parameters in the VAR(p) system to be estimated are the coefficients α such that:

$$\underline{\alpha} \sim N\left(\underline{\alpha}_{Mn}, \underline{V}_{Mn}\right) \tag{2}$$

[2] The tradeoff between decreased bias and increased variance in the forecasts can be seen on every additional coefficient by adding explanatory variables in the model which generally improves the in-sample fit (Litterman, 1986, p.8)

and this prior sets sensible values for $\underline{\alpha}_{Mn}$ and $\underline{V}_{Mn}$ in a systematic manner (Chan, 2019). The prior mean, $\underline{\alpha}_{Mn}$, sets most or all its elements to zero ensuring the shrinkage of VAR coefficients toward zero and reducing risk of over-fitting.

A major advantage of using Minnesota priors is that posterior inference involves only the Normal distribution such that the posterior for takes the form:

$$\alpha | y \sim N(\bar{\alpha}_{Mn}, \bar{V}_{Mn}) \tag{3}$$

where

$$\bar{V}_{Mn} = \left[\underline{V}_{Mn}^{-1} + \left(\hat{\Sigma}^{-1} \otimes (X'X)\right)\right]^{-1}$$

and

$$\bar{\alpha}_{Mn} = \bar{V}_{Mn}\left[\underline{V}_{Mn}^{-1}\bar{\alpha}_{Mn} + \left(\hat{\Sigma}^{-1} \otimes X\right)' y\right]$$

As an example, note that the explanatory variables in the VAR in any of its equation can be divided into own lags of the dependent variable, lags of other dependent variables, some exogenous variables, and the constant term. The elements of this variance-covariance structure, $\underline{V}_{Mn}$ with regards to the exogenous variables are set to infinity with an argument that no information about the exogenous variable is contained within the prior. In addition, the remaining elements is then a diagonal matrix with the diagonal elements denoted as v_{ij}^{l} for $l = 1, \dots, p$

$$v_{ij}^{l} = \begin{cases} \left(\dfrac{\lambda_1}{l^{\lambda_3}}\right)^2, & i = j \\ \left(\dfrac{\lambda_1 \lambda_2 \sigma_i}{l^{\lambda_3} \sigma_j}\right), & i \neq j \end{cases}$$

where σ_i^2 is the i^{th} diagonal element of Σ. Recent works such as with Banbura et al. (2010) utilized this prior with some minor modification on a large VAR with over 100 dependent variables. The comparative analysis with factor methods lead to this type of prior performing better in terms of forecasting exercises.

3.2 The Natural Conjugate Prior

The conjugate normal-Wishart prior for the coefficients A_i's and for the variance-covariance matrix, Σ in eq. 1 follows closely the formulation of Itkonen and Juvonen (2017). In this large Bayesian VAR context, we can specify the natural conjugate prior as:

$$\alpha | \Sigma \sim N\left(\underline{\alpha}, \Sigma \otimes \underline{V}\right) \tag{4}$$

and

$$\Sigma^{-1} \sim W\left(\underline{S}^{-1}, \underline{\nu}\right)$$

where $\alpha, \underline{V}, \underline{\nu}$ and $\underline{S}$ are the prior hyperparameters that the researcher can specify. Also, our specification assumes that each variable in the VAR follows an independent unit root process. Furthermore, in each equation of the VAR, the coefficient for the first lag of the same variable is assumed to equal unity, whereas all the other coefficients are assumed to equal zero. In this framework, the more the distant the lag, the smaller is the prior variance and hence a tighter prior (Itkonen & Juvonen, 2017).

Given the natural conjugate prior, analytical results exist on the posterior distribution for the coefficients and the variance-covariance matrix provided by:

$$\alpha|\Sigma, \mathrm{y} \sim N(\bar{\alpha}, \Sigma \otimes \bar{V}) \tag{5}$$

and

$$\Sigma^{-1}|y \sim W(\bar{S}^{-1}, \bar{v})$$

which has more desirable properties than the prior previously mentioned since this formulation allows for derivation of analytical results without the need of fixing the diagonal error variance-covariance matrix. However, a drawback to using natural conjugate priors as mentioned by Koop and Korobilis (2010) is that departures from the unrestricted VAR such as inclusion of different explanatory variables on each equation, VAR coefficients that change over time, heteroskedastic structures of the variance-covariance error and the like are not necessarily addressed in this specification. As a result, time-varying parameter factor augmented VARs (TVP-FAVARs) and some other nonlinear model specification of VARs such as Markov switching VARs, threshold VARs, smooth transition VARs, etc. were developed to address this issue. Nevertheless, performance of BVARs is still comparable to these more complex models in recent studies.

3.3 The GLP Prior

The main prior specification used in this paper is the GLP prior proposed by Giannone, Lenza and Primiceri in 2015. The GLP, which is a type of conjugate priors, revolves around the Normal-inverse-Wishart family of distribution. This prior uniquely identifies the hyper-parameters of the Minnesota and normal-inverse-Wishart distribution by maximizing the marginal data density for every estimation sample, i.e., specification vis-à-vis estimation. The proposed outline for this prior by Giannone et al. (2015) is such that prior parameters are treated to be additional parameters to be estimated, where these are assigned with their own hyperpriors. With the advancement of technology and the increase in computing power of modern computers, the GLP procedure is able to simulate the posterior distribution of the overall shrinkage parameter based on a standard Metropolis algorithm. According to empirical exercises, the use of this prior improved model performance but at the expense of computational power.

3.4 Other Prior Specifications

In addition to the priors set, we implemented two more priors namely the "sum of coefficients" and "dummy-initial-observation" – priors. The former addresses placing prior weights on unit root processes of higher order while the latter supports the belief that variables in the VAR system share some common stochastic trends. The dummy observation approach, originally proposed by Doan et al., (1984), and Sims and Zha (1998), was used to elicit the priors for structural VAR models. Moreover, the former can be specified following closely the formulation of Giannone, et al., (2015) as:

$$\underset{nxn}{y^{+}} = diag\left(\frac{\overline{y}_0}{\mu}\right) \tag{6}$$

and

$$\underset{nx(1+np)}{x^{+}} = \left[\underset{nx1}{0}, y^{+}, \dots, y^{+}\right] \tag{6.1}$$

where $\overline{y}_0$ is an $n \times 1$ vector containing the average of the first p observations for each variable, and eq. 6 denotes the diagonal matrix with its vector, $\frac{\overline{y}_0}{\mu}$ on the main diagonal. This specification introduces correlation among coefficients on each variable in each equation by centering these dummy observations at 1 for the sum of coefficients on own lags for each variable while the sum of coefficients on other variables' lags at 0. The hyperparameter, μ, controls the variance of prior beliefs such that setting $\mu \to \infty$ makes priors uninformative while $\mu \to 0$ implies the presence of unit root in each equation, ruling out cointegration (Giannone, Lenza & Primiceri, 2015).

The latter prior introduced by Sims (1993) was implemented using the following dummy observation:

$$\underset{1xn}{y^{++}} = \frac{\overline{y}_0'}{\delta} \tag{7}$$

and

$$\underset{1x(1+np)}{x^{++}} = \left[\frac{1}{\delta}, y^{++}, \dots, y^{++}\right] \tag{7.1}$$

where the hyperparameter, δ controls the tightness of the prior by setting $\delta \to 0$, implying that all variables in the VAR system are characterized by the presence of an unspecified number of unit roots without drift verifying consistency of cointegration among the set of variables. In this paper, we follow specifications set by Sims and Zha (1998) on λ, μ and δ to $0.2, 1$ and 1 respectively.

4. Forecasting Performance

In this section, we have applied a large Bayesian VAR to 4 quarterly macroeconomic indicators and 17 time-aggregated monthly indicators. The quarterly macroeconomic indicators (except for the unemployment rate) are transformed by getting the year-on-year growth rates, while every monthly aggregated variable was transformed to its corresponding log differences (excluding rates) to achieve stationarity. The general BVAR model removed the estimation of the constant term in each of its equation in the system to account for the data transformation used.

The strategy used to assess the forecasting performance of the BVAR model to GDP growth is by comparing different forecasting horizons with benchmark models. Specifically, the nowcast, wherein actual data up to the most recent observation is taken into account ($H = 1$), and a nowcast with one-step-ahead forecast ($H = 2$) with estimation period covering different data vintages. Overall, there were 21 variables included in the time aggregated quarterly model including real GDP (See annex for list of variables). The reported results are based on 200,000 draws with 20 percent burn-in. Hyperpriors were treated hierarchically as discussed in the previous sections. We compared the out-of-sample forecasts from all model specifications and generated forecasting performance using the root mean squared errors (RMSE) and mean absolute errors (MAE).

4.1 Data Vintages

This section presents the ratio of mean squared forecasting errors and mean absolute errors between the BVAR specification and the benchmark models. We used an autoregressive model and a random walk to compare the forecasting performance of the BVAR against the two. We specified an $AR(2)$ model and a random walk model which has a sample period covering multiple data vintages as the standard practice when benchmarking forecast performance (i.e., the best fitting model and the random walk). We identified a structural break as a consideration for the estimation period: (1) pre- COVID-19, and (2) during pandemic to assess the model performance in the presence of breaks. Further to the pandemic situation, rolling estimation were implemented to assess the model performance upon release of actual data and updates.

On both benchmark models, we estimated the parameters using data from 2005Q2 up to the different data vintages and generated nowcasts and forecasts for the one- and three-steps ahead in Table 2 and Table 3. The start of the estimation sample across different vintages evidently showed the viability of Bayesian estimation in a high-dimensional set-up, i.e., a small sample relative to the number of parameters to estimate. Results were broken down into two cases: (1) Data vintage prior to COVID-19, and (2) the performance during the pandemic. In Table 2, the Bayesian VAR outperformed the $AR(2)$ model for the nowcast and the short-term forecasting exercise in both RMSE and MAE measures. Note that in this case, despite a high lag specification for the BVAR ($p = 5$), small sample was not an issue in estimating the $n^2p = 2205$ parameters as compared to using a standard VAR using OLS. However, this is not the case for the nowcast and one-step-ahead forecast ($H = 2$).

In Table 3, we also find that there were multiple lag specifications in the BVAR relative to the data vintage. The outlying values present towards the latter part of almost all economic indicators imposed an issue in the estimation of high lag specifications, particularly on the variance-covariance structure. Prior to the pandemic, a one-year lag specification was induced and the BVAR model was able to include a large p. This is not the case upon realization of the pandemic effects for 2005Q2-2020Q2 from implementation of strict lockdowns, reducing the allowed lag structure to three (formerly from five). This, however, is still able to outperform the autoregressive model in most data vintages up to the most recent rolling forecast.

Table 2. Ratio of RMSE and MAE between BVAR and AR(2)

	Ratio to AR(2)					
	RMSE			**MAE**		
Data Vintages	H=1	H=2	H=4	H=1	H=2	H=4
2005Q2-2018Q4 *(p=5)*	0.6	1.3	0.8	0.6	1.1	0.6
2005Q2-2020Q1 *(p=5)*	1.2	1.3	-	1.2	1.3	-
2005Q2-2020Q2 *(p=3)*	0.7	0.7	-	0.7	0.7	-
2005Q2-2020Q3 *(p=3)*	1.3	0.4	-	1.3	0.3	-
2005Q2-2020Q4 *(p=3)*	0.6	0.8	-	0.6	0.7	-
2005Q2-2021Q1 *(p=3)*	0.9	0.8	-	0.9	0.8	-
2005Q2-2021Q2 *(p=3)*	1.4	1.5	-	1.4	1.5	-
2005Q2-2021Q3 *(p=4)*	0.8	-	-	0.8	-	-

Table 3. Ratio of RMSE and MAE between BVAR and Random Walk

	Ratio to Random Walk					
	RMSE			**MAE**		
Data Vintages	H=1	H=2	H=4	H=1	H=2	H=4
2005Q2-2018Q4 *(p=5)*	0.5	0.7	0.8	0.5	0.6	0.8
2005Q2-2020Q1 *(p=5)*	1.2	1.3	-	1.2	1.3	-
2005Q2-2020Q2 *(p=3)*	2.1	2.1	-	2.1	2.1	-
2005Q2-2020Q3 *(p=3)*	0.5	0.2	-	0.5	0.2	-
2005Q2-2020Q4 *(p=3)*	0.4	0.7	-	0.4	0.6	-
2005Q2-2021Q1 *(p=3)*	0.8	0.7	-	0.8	0.7	-
2005Q2-2021Q2 *(p=3)*	2.3	2.4	-	2.3	2.4	-
2005Q2-2021Q3 *(p=4)*	2.9	-	-	2.9	-	-

Note: This table provides the ratio of RMSE and MAE between benchmark models for the different horizons with the BVAR specification. A value below 1 would imply that BVAR has outperformed the benchmark model.

Table 4. Diebold-Mariano Test

	vs. AR(2)		vs. RW	
Data Vintages	H = 2	H = 4	H = 2	H = 4
2005Q2-2018Q4 *(p=5)*	0.67	0.28	0.14	0.05*
2005Q2-2020Q1 *(p=5)*	0.95	-	0.97	-
2005Q2-2020Q2 *(p=3)*	0.18	-	0.86	-
2005Q2-2020Q3 *(p=3)*	0.14	-	0.21	-
2005Q2-2020Q4 *(p=3)*	0.77	-	0.23	-
2005Q2-2021Q1 *(p=3)*	0.86	-	0.01*	-
2005Q2-2021Q2 *(p=3)*	0.90	-	0.99	-

**p-value is less than* $\alpha = 0.05$

In Table 3, the same story may be observed prior to the pandemic. The BVAR was able to outperform the random walk model across all possible nowcasting and forecasting horizon. The reduction of the lag structure also outperformed the benchmark as in the autoregressive model upon learning realized values from 2020Q1 and 2020Q2. However, the random walk model outperformed the BVAR model in the latter data vintages. This may be attributed to the increase in measurement errors when using large information set within the system. The advantage is that forecasts of these variables in the VAR system can also be produced to determine which indicators were driving the GDP forecasts produced, as opposed to a univariate approach. Table 4 shows the Diebold-Mariano test p-values for the specified forecast horizon on each data vintages. Results verified that the forecasting performance of BVAR is superior over the random walk model for the first data vintage (pre-pandemic) and for 2005Q2 to 2021Q1 estimation period with two forecasting horizons. Overall, the results manifested the plausibility of using the BVAR model for operational use as an addition and to complement the models used in coming up with an initial value of GDP, while an assessment of its model improvement with the presence of structural breaks may be an area of further research.

5. Conclusion

We introduced a nowcasting model using mixed-frequency indicators as an additional tool in assessing the real-time growth of the Philippine economy. We applied a Bayesian estimation approach by setting prior information hierarchically to address the problem of overparameterization evident on most applications of vector autoregressions with a restriction of including large number of variables in the system.

We also addressed the issue of including higher frequency variables in a low frequency system by time aggregation. In particular, we aggregated the monthly only variables to quarterly and take the most recent actual data for each variable to solve the ragged-edge data issue caused by publication lags and minor revisions of official statistics. With this approach, we were able to include 17 monthly variables to form a total of 21 variables in the system of nowcasting GDP.

Results of the forecast exercise showed that the BVAR outperformed our benchmark models on the shorter horizon. Moreover, based on forecast evaluation, the nowcasting model also performs better on a shorter horizon even with a large specification in the lag order and a relatively small sample, which verifies results from various related literatures that data-driven approach and inclusion of large information set to capture key macroeconomic variables are useful to short- to near-term forecasting. Finally, timely assessment of the model forecast performance may be implemented by producing forecasts and nowcasts of other indicators included in the VAR system.

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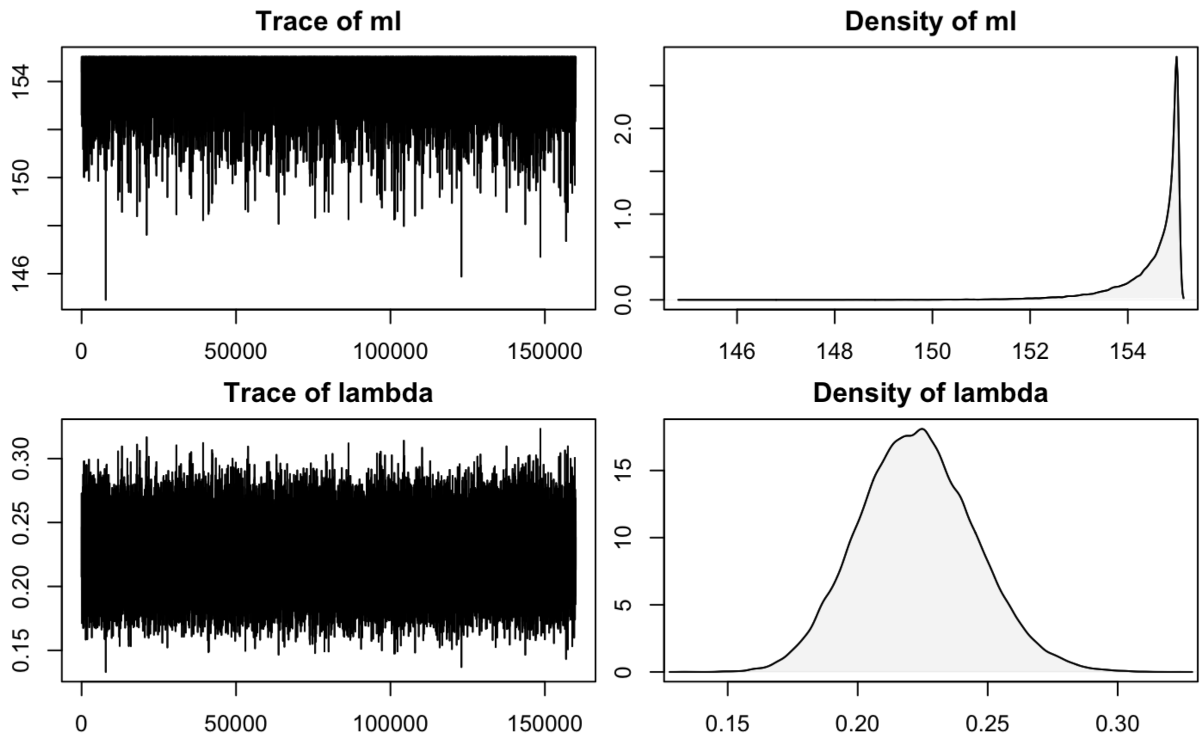
Annex

Table 5. List of variables

Variable Name	Variable Mnemonic	Frequency	Remarks
Real GDP	RGDP	Quarterly	In million pesos at constant 2018 prices
Real Household Final Consumption Expenditure	RHFCE	Quarterly	In million pesos at constant 2018 prices
Real Government Final Consumption Expenditure	RGFCE	Quarterly	In million pesos at constant 2018 prices
Rate of Unemployment	UNEMP	Quarterly	Unemployment Rate - Note: 2014 to 1st half of 2015 did not include entire Leyte in the survey due to Yolanda tragedy
Money Supply	M3	Monthly	In million pesos
OF Cash Remittances	REMIT	Monthly	In million US Dollars
Php/USD	FX	Monthly	Average
Consumer Price Index (2018=100)	CPI	Monthly	Index
91-day Treasury Bills Rate	91TBILL	Monthly	Rate
WAIR of BSP	RRP	Monthly	Rate
US Fed Funds	FED	Monthly	Average
General Wholesale Price Index (2012=100)	WPI	Monthly	Index
Volume of Production Index	VOPI	Monthly	Index
National Government Revenues	NG_REV	Monthly	In million pesos
National Government Expenditures	NG_EXP	Monthly	In million pesos
Average Dubai Crude Oil	DUBAI	Monthly	USD per barrel
Total electricity sales from residential, consumer, industry and others	ENERGY	Monthly	Volume (in million kilowatt hour)
Average of RMR and WMR Retail Price	AMRRP	Monthly	Retail Price
Gross International Reserve: End-period	GIR	Monthly	in million US Dollars
Merchandise Exports	MXG	Monthly	Merchandise Exports (PSA)
Merchandise Imports	MMG	Monthly	Merchandise Imports (PSA)

Figure 1. Trace and Density estimates - Likelihood and Overall Shrinkage Parameter, λ



Iterations = 200,000; 20% burn-in

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