UPSS

Working Paper Series

Constructing Leading Economic Indicators for the Philippine Economy

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NO. 2016 – 11

October 2016

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ABSTRACT

This paper proposes three models, Dynamic Factor model, Hybrid Dynamic Factor-Vector AutoRegressive (DF-VAR) model and the Dynamic Factor-Mixed Frequency (DF-MF) model in *nowcasting* the movements and growth rates of the country's quarterly Gross Domestic Product (GDP) using monthly indicator variables. The DF, DF-VAR and DF-MF are alternative models to the usual time series econometric models used in forecasting GDP growth rates utilizing temporal aggregation. The idea behind the DF model is the stylized fact that economic movements evolve in a cycle and are correlated with co-movements in a large number of economic series. The DF model is a commonly used data reduction procedure that assumes economic shocks driving economic activity arise from unobserved components or factors. The DF model aims to parsimoniously summarize information from a large number of economic series to a small number of unobserved factors. The DF model assumes that co-movements of economic series can be captured using these unobserved common factors. While the DF model captures the movements in the GDP growth, combining the DF with the Vector AutoRegressive (VAR) model (or with the Mixed Frequency model) will be useful is also *nowcasting* the GDP growth rates and not just the movements. The DF-VAR and DF-MF models will serve as alternatives models to the current Leading Economic Indicators System (LEIS) developed by the National Economic Development Authority (NEDA) and the Philippine Statistics Authority (PSA) used in providing a one-quarter forecast of the movement of the GDP. The DF-VAR and DF-MF models used 32 monthly and 4 quarterly economic indicators in *nowcasting* the GDP.

Key Phrases: Dynamic Factor-Vector AutoRegressive Model, Mixed-Frequency (MF) Model, Principal Components

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1. Introduction

Understanding the movement of the country's economic activity is crucial for policy decision-making process. The Gross Domestic Product (GDP), published by the Philippine Statistics Authority (PSA), is the broadest measure of the overall economic activity. The analysis of its movement along the business cycle, as well as the impact of internal and external shocks, are critical for policymakers, analysts, researchers and other stakeholders. The PSA releases the GDP figures about 60 days after the reference quarter for the 1st, 2nd and 3rd Quarters and 30 days after for the 4th Quarter, and the GDP for the reference year is released 30 days after the end of the reference year. Because of the relatively long time difference between the reference quarter and the release of the official GDP numbers, National Economic and Development Authority (NEDA) and the Bangko Sentral ng Pilipinas (central bank) are interested in alternative methodologies to provide insights on the "real-time economic activity" using economic indicators. These economic indicators are variables that are highly correlated with the quarterly GDP and are available at a higher frequency (e.g. monthly, weekly, daily). It is important to provide a timely assessment of the movements of the GDP to be able to guide policy makers in formulating appropriate policies to mitigate, say the impact of a shock.

The Philippines has the Composite Leading Economic Indicators (LEI) that provides a one-quarter-ahead forecast of the movement of the GDP. It seeks to answer the question whether the GDP is expected to go up or go down in the following quarter. Moreover (as an index) it is not concerned with forecasting the actual level or growth rate of the GDP but is more interested in the direction of the GDP. The Leading Economic Indicator System (LEIS) was jointly developed by the Philippine Statistics Authority (PSA) and the National Economic and Development Authority (NEDA) to serve as a basis for short-term forecasting of the macroeconomic activity in the country. The PSA has since been compiling data for the 11 identified leading economic indicators and generating the

Composite LEI on a quarterly basis.[1] The LEIS involves the study of the behavior of indicators that consistently move upward or downward before the actual expansion or contraction of the overall economic activity. The system is based on an empirical observation that the cycles of many economic data series are related to the cycles of total business activity, i.e., they expand in general when business is growing and contract when business is shrinking. The LEIS was institutionalized by PSA to provide advance information on the direction of the country's economic activity or performance in the short run.

This study aims to model deseasonalized (quarter-on-quarter) GDP growth rates as a monthly series with missing observations. A one-step-ahead predicted GDP growth rates was then generated from state space models with monthly leading economic indicators as independent variables. Forecasting capabilities of competing models were then evaluated using different criteria.

This paper proposes three models: (a) the Dynamic Factor model, (b) Hybrid Dynamic Factor-Vector AutoRegressive (DF-VAR) model and (c) the Dynamic Factor-Mixed Frequency (DF-MF) model in nowcasting the movements and growth rates of the country's quarterly Gross Domestic Product (GDP) using monthly indicator variables. The paper benefitted from the earlier study of Mapa and Simbulan (2012) that utilized the Dynamic Factor Model (DFM) in studying the movements of GDP in the Philippines. In addition to studying just the movements of GDP, the paper extends the original study by also nowcasting the GDP growth rates. The data used in the analysis includes the 32 monthly economic series and four quarterly economic series (of which one is included in the final models).

The structure of the paper is as follows. Chapter 2 provides a comprehensive review of the DFM, MIDAS and other popular models in analyzing mixed-frequency data. Chapter

[1] The 11 indicator series were (1) consumer price index, (2) wholesale price index, (3) electricity energy consumption, (4) peso-dollar exchange rate, (5) hotel occupancy rate, (6) money supply, (7) number of new business corporations, (8) stock price index, (9) terms of trade index, (10) total imports, and (11) tourist or visitors arrivals.

3 provides the methodology and estimation results of the proposed models along with a short description of the preliminary tests performed on the data. Chapter 4 discusses the performance of the models, while Chapter 5 concludes.

2. Review of Mixed Frequency Models

Even before the problem of mismatched frequencies of data, econometricians have already been challenged with the peculiarities of macroeconomic data. Practitioners have hundreds of series at their disposal, although most of them are not desirably long enough, e.g. only 20 to 40 years of quarterly data.

2.1 Dynamic Factor Models

Dynamic factor models (DFM) can be estimated for datasets having more series than the number of time observations. Stock and Watson (2010) discussed in detail the DFM and enumerated several related studies. The DFM, which was based on the theory that there are latent dynamic factors that affect the co-movement of a collection time-series variables was first applied Geweke (1977) as an extension of the cross-sectional-factor-model in a time-series analysis. Sargent and Sims (1977) showed that two latent factors were able to explain a significant portion of the variability of different macroeconomic variables in the United States. The technique, moreover, has now been used in different applications such as in two-stage regression as instruments, and in forecasting (Stock and Watson, 2010).

Giannone, Reichlin, and Small (2008), for instance, developed a procedure that updates current-quarter GDP forecast every time a monthly data within that quarter are released. With an extensive collection of monthly data with different release dates, factors were computed using principal component analysis and then Kalman Smoothing. The marginal impact of each data released was able to be analyzed since the model was updated every time new information becomes available. Their results showed that current-quarter GDP forecast's precision increases as new monthly data comes in. Moreover, empirical evaluation of their proposed model showed fair performance compared to benchmarks they used.

Aruoba, Deibold and Scotti (2008) also used DFM to measure economic activity at a high frequency. They used it to extract latent factors from a variety of stock and flow data sampled at different frequencies as a measure of the macroeconomic state. They further suggested using higher frequency data in empirical macroeconomic studies instead of the usual monthly or quarterly data. One of the empirical examples shown in their study revealed that the model incorporating weekly initial jobless claims to a GDP-unemployment model performs better compared to a GDP-unemployment model without weekly initial jobless claims. Similarly, Camacho and Perez-Quiros (2008) proposed the DFM approach in forecasting the real-time euro-area quarterly GDP. They also looked at the impact of each release of new data to their projections. Their work primarily dealt with problems such as asynchronous macroeconomic data release and using aggregated euro-area data with short time spans.

2.2 Mixed Data Sampling

Another popular approach in dealing with a multi-frequency model is Mixed Data Sampling (MIDAS) regression models. The unrestricted MIDAS model (U-MIDAS) for an annual dependent variable Y_t^A and a quarterly explanatory variable X_t^Q, is given by:

$$Y_{t+1}^A = \beta_0 + \sum_{i=0}^{N_Q-1} \beta_j X_{N_Q-i,t}^Q + u_{t+1} \tag{1}$$

where N_Q is the number of high-frequency periods within the low-frequency period t. The U-MIDAS can be estimated by OLS. The model regresses all quarterly lags of X_t on $Y_{\mathrm{t+1}}^{\mathrm{A}}$; thus, each quarter will have an effect on the low-frequency period being estimated. The disadvantage of this approach is parameter proliferation if the explanatory variable is sampled at a much higher frequency, for example, monthly data regressed on a daily times series

Ghysels, Santa-Clara, and Valkanov (2006) introduced DL-MIDAS to deal with models with varied frequencies of dependent and explanatory variables. These models use distributed lags of regressors, which are sampled at a higher frequency compared to dependent variables sampled at a lower frequency. The solution of Ghysels et al. to parameter proliferation is to compute the weighted average of the quarterly data using a distributed lag polynomial function weights, called the DL-MIDAS:

$$Y_{t+1}^{A} = \beta_0 + \beta \sum_{i=0}^{N_Q - 1} W(L^{N_Q}; \theta_1, \theta_2) X_{N_Q - i,t}^{Q} + u_{t+1} \qquad (2)$$

where $W(L^{N_Q}; \theta_1, \theta_2)$ is the weighting function. Note that the effect of X^Q on Y^A is explained by only one parameter β. The exponential Almon lag polynomial function was recommended due to its flexibility in adapting to several shapes. The exponential Almon distributed lag polynomial function is given by:

$$W_i(\theta_1, \theta_2) = \frac{\exp\{\theta_1 i + \theta_2 i^2\}}{\sum_{i=1}^{m} \exp\{\theta_1 i + \theta_2 i^2\}} \qquad (3)$$

where θ_1 and θ_2 are parameters determined through data calibration

One of their example models involved stock market volatility. The quadratic variation over a long future horizon, which was sampled at low frequency, was modeled using intra-day market information. Another example in their 2004 paper involved GDP and other macroeconomic variables sampled at a higher frequency such as inflation. They suggested that instead of aggregating monthly inflation data to match the quarterly GDP estimates, one can implement a MIDAS regression to combine the two series. One of their key findings showed that MIDAS regression produced a more efficient estimation compared to the conventional regression used for time-aggregated data.

Armesto, Engemann, and Owyang (2010) surveyed different procedures to circumvent the dilemma of mixed frequency data. Their problem was that most of the macroeconomic variables are sampled monthly or quarterly, whereas financial data which were found to be related to the macro economy are sampled at higher frequencies. Their paper showed that in some cases, aggregating the higher frequency data (e.g. averaging) did not have any disadvantage. Although in some cases, the MIDAS technique introduced by Ghysels, Santa-Clara and Valkanov showed to be more advantageous especially in intra-period analysis. Faced with a similar problem, Clements and Galvão (2008) used monthly and weekly data to generate short-term forecasts of US output growth. Since GDP is sampled on a quarterly basis, an AR process was a reasonable candidate model. Consequently, they extended the distributed lag MIDAS specification of Ghysels, et. al., and introduced an AR component, resulting to a MIDAS-AR specification which was shown to have better short-term forecast compared to a benchmark AR model or and AR distributed lag model.

Similarly, Tay (2006) compared an AR(1) GDP growth model following a MIDAS framework and a usual quarterly AR(1) model of GDP growth with the most recent stock price index for each quarter as an additional explanatory variable. The result of his paper showed that particularly in recent years, stock returns were useful in predicting GDP growth. His results also showed that his MIDAS model was superior to his benchmark model. Furthermore, his study suggests that mixing frequencies can lead to better forecasts.

MIDAS was also used in Asimakopoulos, Paredes and Warmedinger's (2013) study of forecasting fiscal time series of different euro area countries. Using mixed frequency fiscal variables, MIDAS was employed to analyze annual or year-end fiscal variables. Their empirical work was able to show that quarterly information within the year was able to improve the year-end forecast.

2.3 VAR-Based Multi-Frequency Models

Another approach in multi-frequency modeling is Mixed-Frequency VAR (MF-VAR) models. MF-VARs are Vector Autoregressive (VAR) models containing component variables with different frequency. Götz and Hecq (2013) expressed a low frequency (aggregated) data (e.g. quarterly data) as a function of its lagged value and distributed lagged values of the independent variable with higher frequency (disaggregated data, e.g. monthly data within the same quarter); and disaggregated data as a function of the aggregated data and its lagged values. In the same study, they introduced nowcasting causality for mixed-frequency VAR models. Nowcasting is a process of predicting the value of a certain variable observed at a lower frequency using variables observed at a higher frequency, and are available in the current period. Meanwhile, nowcasting causality is analogous to Granger causality but is restricted to a definite period, say, months within each quarter. Both nowcasting and Granger causalities were then tested using selected US economic data. As an example, they showed that the weekly growth rate of the stock of money (M2) in the US does not Granger causes the monthly growth rate of industrial production index. Nonetheless, nowcasting causality was detected between the two series. They also showed that weekly growth of M2 does not Granger causes, nor nowcasting causes monthly variation in the civilian unemployment rate.

Qian (2010) used Varied Data Sampling (VARDAS), a variation of MF-VAR in Bayesian context. A key feature of the procedure was that it only requires users to provide the data and the aggregation structure of each series, while the estimation of VAR is handled similarly to the ordinary VAR model. As an example, a previous study involving demand and supply component of GNP and unemployment (both quarterly series) was replicated using monthly unemployment data. The results showed, using an impulse-response function that the dynamics between unemployment and GNP components was more evident than general models.

Mittnik and Zadrozny (2004) used Kalman filtering method to forecast monthly German real GDP. They argued that when quarterly GDP is regressed to monthly indicators, it may not address reverse causality. Instead, they proposed a quarterly and monthly VAR(2) models of quarterly GDP, monthly industrial production, and monthly current business condition. Their empirical work showed that the monthly VAR model produced better short-term (1 to 3 months) GDP forecast while the quarterly model produced a better long-term forecast (1 up to 24 months ahead).

2.4 Model Comparison and Other Applications

A paper by Kuzin, Marcellino and Schumacher (2009) compared the performance of the two popular approaches, MIDAS and MF-VAR, regarding forecasting and nowcasting of

GDP growth of euro area using 20 monthly indicators as explanatory variables. Results revealed that the two competing models tend to complement each other. MF-VAR was found to perform better for longer horizons while the other approach performs better for shorter horizons.

Aside from using the MIDAS approach, some papers treated low-frequency data as high-frequency data with missing observations. Those missing observations are then forecasted to proceed with the model building at a high sampling frequency. Fernández (1981) suggested interpolation by estimating missing data points using relevant series. This can be applied to stock data such as demand deposits which are usually available at year end to produce quarterly or monthly series. Aside from macroeconomics, mixed-frequency models were also used in signal processing. The Kalman Filter algorithm was also used by Fulton, Bitmead and Williamson (2001) to reproduce missing elements in an array processing. Using a state-space model, a signal model was used to reconstruct missing data streams. Kalman smoothing was implemented and showed a better performance than an existing process to reconstruct missing data streams.

3. Multi-Frequency Models for Philippine RGDP

The Dynamic Factor model, Hybrid Dynamic Factor-Vector AutoRegressive (DF-VAR) model and the Dynamic Factor-Mixed Frequency (DF-MF) model are constructed using the monthly and quarterly data from January 2000 to December 2013. The target variable is the Growth Rate Official Seasonally Adjusted Real Gross Domestic Product (RGDP) that is being reported quarterly. The economic indicators that will be used to nowcast the growth rate of the RGDP consist of 32 monthly indicators and four quarterly variables. The economic indicators are conveniently grouped into Fiscal variables (4 indicators), International variables (9 indicators) and Macro variables (23 indicators; 19 monthly indicators and four quarterly indicators). The variables are defined in Table 1 below.

Before further analysis is made, the indicators are first tested for the presence of unit root(s) using the Augmented Dickey-Fuller (ADF) test and the F-test for presence seasonality, before building the models. The Dickey-Fuller (DF) test statistic is derived from the estimation of the 1st order Auto Regressive model:

$$y_t = \rho y_{t-1} + \epsilon_t, \quad \epsilon_t \sim White\ Noise(0, \sigma_\epsilon^2) \tag{4}$$

Note that if $\rho = 1$, then y_t is a random walk (unit root process), while if $|\rho| < 1$, the process is a stationary AR(1). Subtracting y_{t-1} to both sides of the equation above,

$$\rightarrow y_t - y_{t-1} = \rho y_{t-1} - y_{t-1} + \epsilon_t$$

$$\rightarrow \Delta y_t = (\rho - 1) y_{t-1} + \epsilon_t$$

Thus, the hypotheses are, H0: ρ-1=0 (unit root or non-stationary) vs. Ha: $|\rho|$-1<0 (stationary)

The ADF test is an improvement over the original DF test. The test controls for serial correlations by adding lagged terms of 1st differences to the autoregressive equation:

$$\Delta y_t = \alpha^* + \delta^* t + (\rho - 1) y_{t-1} + \phi_1 \Delta y_{t-1} + \cdots + \phi_p \Delta y_{t-p} + \epsilon_t \tag{5}$$

where the number of lags, p, is determined by the Schwarz Criterion (SC) or the Akaike Information Criterion (AIC) with a maximum value for p of $p_{max} = [12(T/100)^{1/4}]$

In the ADF test, we are testing the null hypothesis that the series has unit root (series is not stationary). If the null hypothesis is not rejected, the series is not stationary. Transformation, using the first difference (or the second difference as the case may be) is then applied. For series with seasonality, the corresponding seasonally adjusted values are generated using the X-12 procedure in EVIEWS. The results are presented in Tables 1 and 2.

Table 1. Results of the Augmented Dickey Fuller (ADF) Tests for Presence of Unit Root

Group	Series Type	Variable		ADF		
				t- stat	p-value	Remark
Outcome	LOG	r_gdp	Gross Domestic Product (real)	-3.17651	0.1004	I(1)
Fiscal	LOG	ng_exp	National Government Expenditures	-2.4434	0.3559	I(1)
	LOG	ng_rev	National Government Revenues	5.4845	1.0000	I(1)

Group	Series Type	Variable		ADF		
				t- stat	p-value	Remark
	LOG	govspen	Government Spending under GFCE (COE less Interest Payments less Subsidy)	-1.7037	0.7453	I(1)
	LOG	pubconspen	Public Construction Spending (Infrastructure & other capital outlays + Capital transfers to LGUs)	-12.0143	0.0000	I(0)+TREND
International	LOG	exports	Exports	-3.7396	0.0223	I(0)+TREND
	LOG	er_usd	Exchange Rate	-3.5844	0.0341	I(0)+TREND
	LOG	gir	Gross International Reserves	-2.7544	0.2165	I(1)
	LOG	imports	Imports	-3.8270	0.0174	I(0)+TREND
	LEVEL	tot	Terms of Trade	-7.9059	0.0000	I(0)+TREND
	LOG	er_euro	Peso/Euro exchange rate	-2.2131	0.2025	I(1)
	LOG	er_sgd	Peso/SGD exchange rate	-3.6849	0.0260	I(0)+TREND
	LOG	er_yen	Peso/yen exchange rate	-2.4985	0.1176	I(1)
	LOG	remit	Remittances (Cash)	-2.1052	0.2430	I(1)
Macro	LOG	psei	PSEI	-3.2525	0.0779	I(1)
	LOG	cpi	Consumer Price Index	-1.9628	0.6170	I(1)
	LEVEL	deposit_rate	Deposit rate: Savings	-2.5094	0.3233	I(1)
	LOG	dubai	Dubai Crude	-3.2535	0.0778	
	LEVEL	libor	Libor 3m	-2.0425	0.0397	I(0)+TREND
	LOG	m2	M2: Money Supply	-2.3029	0.4293	I(1)
	LOG	mvpi	Manufacturing: Value of Production Index	-4.1512	0.0072	I(0)+TREND
	LOG	rice	Retail Sale: Price of Rice (Regular-milled)	-2.3130	0.4242	I(1)
	LEVEL	sibor	Sibor 3M	-2.0318	0.0407	I(0)+TREND
	LEVEL	tbill_364	Tbill rate:364	-3.9982	0.0110	I(0)+TREND
	LEVEL	tbill_91	Tbill rate: 91	-3.4504	0.0493	I(0)+TREND
	LEVEL	td_lt	Time deposit rate (Long-term)	-2.7509	0.2178	I(1)
	LEVEL	td_st	Time deposit rate(Short-term)	-3.4692	0.0460	I(0)+TREND
	LOG	visitor	Visitor arrival	-2.9124	0.1615	I(1)
	LOG	wpi	Wholesale Price Index	-2.4610	0.3472	I(1)
	LOG	meralco	Meralco Sales	-1.5187	0.8194	I(1)
	LEVEL	balr	Bank Average Lending Rate	-3.4615	0.0470	I(0)+TREND
	LOG	ukb_loans	UKB Loans Outstanding	-1.0891	0.9266	I(1)
	LOG	sec	Registered Stock Corporations and Partnership	-5.5477	0.0000	I(0)+TREND
	LEVEL	bes_curr	Business Expectation Survey (Current Quarter)	-3.3777	0.0656	I(1)
	LEVEL	bes_next	Business Expectation Survey (Next Quarter)	-4.2307	0.0083	I(0)+TREND

Group	Series Type	Variable		ADF		
				t- stat	p-value	Remark
	LEVEL	ces_curr	Consumer Expectation Survey (Current Quarter)	-3.4317	0.0621	I(1)
	LEVEL	ces_next	Consumer Expectation Survey (Next Quarter)	-3.8157	0.0265	I(0)+TREND

Table 2. F-test for Testing the Presence of Seasonality

Group	Variable		F-Test for Seasonality		
			F-stat	p-value	Remark
Outcome	r_gdp	Gross Domestic Product (real)	264.3150	0.0000	Seasonal
Fiscal	ng_exp	National Government Expenditures	10.8240	0.0000	Seasonal
	ng_rev	National Government Revenues	21.5280	0.0000	Seasonal
	govspen	Government Spending under GFCE (COE less Interest Payments less Subsidy)	24.6130	0.0000	Seasonal
	pubconspen	Public Construction Spending (Infrastructure & other capital outlays + Capital transfers to LGUs)	10.2890	0.0000	Seasonal
International	exports	Exports	7.6490	0.0000	Seasonal
	er_usd	Exchange Rate	2.7940	0.0025	Seasonal
	gir	Gross International Reserves	1.0320	0.4215	Not Seasonal
	imports	Imports	6.6990	0.0000	Seasonal
	tot	Terms of Trade	1.6130	0.1040	Not Seasonal
	er_euro	Peso/Euro exchange rate	0.7700	0.6696	Not Seasonal
	er_sgd	Peso/SGD exchange rate	1.7410	0.0698	Seasonal
	er_yen	Peso/yen exchange rate	4.1560	0.0000	Seasonal
	remit	Remittances (Cash)	10.3080	0.0000	Seasonal
Macro	psei	PSEI	0.5090	0.8953	Not Seasonal
	cpi	Consumer Price Index	2.1350	0.0211	Seasonal
	deposit_rate	Deposit rate: Savings	4.6610	0.0000	Seasonal
	dubai	Dubai Crude	2.6430	0.0041	Seasonal
	libor	Libor 3m	0.4280	0.9414	Not Seasonal
	m2	M2: Money Supply	9.0860	0.0000	Seasonal
	mvpi	Manufacturing: Value of Production Index	10.0010	0.0000	Seasonal
	rice	Retail Sale: Price of Rice (Regular-milled)	4.4310	0.0000	Seasonal
	sibor	Sibor 3M	0.4610	0.9242	Not Seasonal

Group	Variable		F-Test for Seasonality		
			F-stat	p-value	Remark
	tbill_364	Tbill rate:364	1.6270	0.0964	Seasonal
	tbill_91	Tbill rate: 91	1.4560	0.1541	Not Seasonal
	td_lt	Time deposit rate (Long-term)	2.3570	0.0104	Seasonal
	td_st	Time deposit rate(Short-term)	5.7170	0.0000	Seasonal
	visitor	Visitor arrival	49.6690	0.0000	Seasonal
	wpi	Wholesale Price Index	1.3150	0.2214	Not Seasonal
	meralco	Meralco Sales	63.0190	0.0000	Seasonal
	balr	Bank Average Lending Rate	3.2320	0.0006	Seasonal
	ukb_loans	UKB Loans Outstanding	5.3160	0.0000	Seasonal
	sec	Registered Stock Corporations and Partnership	6.0090	0.0000	Seasonal
	bes_curr	Business Expectation Survey (Current Quarter)	2.2530	0.0951	Seasonal
	bes_next	Business Expectation Survey (Next Quarter)	13.3130	0.0000	Seasonal
	ces_curr	Consumer Expectation Survey (Current Quarter)	0.6100	0.6139	Not Seasonal
	ces_next	Consumer Expectation Survey (Next Quarter)	2.3990	0.0868	Seasonal

3.1 Dynamic Factor (DF) Model

For the first model, the Dynamic Factor Model, only the 32 monthly indicators are included in extracting a common factor or several factors to nowcast the movement of the growth rate of the RGDP. None of the four (4) quarterly indicators are included in the model since only high-frequency (in this case monthly) data can be used to extract the factor(s). Assuming a single factor model for the 32 response (monthly) variables, and assuming an AR(1) process for the common component f_t and the idiosyncratic disturbance ε_t, the DF model is represented by its measurement and state equations. For a one factor model, the measurement equation is given by:

$$y_{it} = \gamma_i f_t + \varepsilon_{it}, \tag{6}$$

while the state equation is given by:

$$f_t = \phi_t f_{t-1} + \eta_t \tag{7}$$

where $\varepsilon_{it} = \theta_i \varepsilon_{i,t-1} + v_{it}$, for $i = 1,2,\ldots,32$, with $\eta_t \sim N(0,\sigma_\eta^2)$, $v_{it} \sim iid\ N(0,\sigma_v^2)$.

For a two-factor dynamic factor model where both the factors and the idiosyncratic disturbances follow an AR(1) process, we have the following:

Measurement equation:

$$\boldsymbol{Y}_t = \boldsymbol{Z}_t \boldsymbol{f}_t + \boldsymbol{\varepsilon}_t \tag{8}$$

$\boldsymbol{Z}_t$: $(q \times 2)$ matrix associated with $\boldsymbol{f}_t$ (i.e., state effect)

State transition equation:

$$\boldsymbol{f}_t = \begin{bmatrix} \emptyset_{1,1} & 0 \\ 0 & \emptyset_{2,2} \end{bmatrix} \begin{bmatrix} f_{1,t-1} \\ f_{2,t-1} \end{bmatrix} + \begin{bmatrix} \eta_{1,t} \\ \eta_{2,t} \end{bmatrix} \tag{9}$$

$$\boldsymbol{\varepsilon}_t = \begin{bmatrix} \theta_{1,1} & 0 \ldots & 0 \\ \vdots & \theta_{2,2} \ldots & 0 \\ 0 & 0 \ldots & \theta_{q,q} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1} \\ \vdots \\ \varepsilon_{q,t-1} \end{bmatrix} + \begin{bmatrix} v_{1,t} \\ \vdots \\ v_{q,t} \end{bmatrix} \tag{10}$$

where $\boldsymbol{\eta}_t \sim N(0,\sigma_\eta^2)$, and such that the covariance σ_η^2 is not necessarily diagonal. The parameters of the Dynamic Factor (DF) models are estimated using the Kalman Filter procedure.

All input series in the models are stationary series. The paper used two versions of the DF model, a one-factor DF model, and a two-factor DF model. The estimated coefficients (weights) associated with the one-factor and two-factor models are provided in Tables 3 and 4 below.

Table 3. Weights Associated with the Single DF Model

Variable	Weight Factor 1	SE (Factor 1)
dl_cpi_sa	0.03557	0.0548
dl_dubai_sa	-0.11264	0.085
dl_er_euro	-0.2089	0.119
dl_er_sgd_sa	-0.18467	0.1388
dl_er_usd_sa	-0.14558	0.0926
dl_er_yen_sa	-0.14136	0.1231
dl_exports_sa	0.48464	0.0793
dl_gir	-0.01571	0.0723

Variable	Weight Factor 1	SE (Factor 1)
dl_govspen_sa	-0.05436	0.0762
dl_imports_sa	-0.49696	0.0864
dl_m2_sa	0.05148	0.1245
dl_meralco_sa	0.08011	0.0779
dl_mvpi_sa	0.04452	0.1099
dl_ng_exp_sa	-0.02132	0.0732
dl_ng_rev_sa	-0.10804	0.0855
dl_psei	0.13632	0.0715
dl_pubconspen_sa	0.04717	0.071
dl_remit_sa	-0.0803	0.0852
dl_rice_sa	0.00143	0.0569
dl_sec_sa	0.1342	0.0778
dl_ukb_loans_sa	0.03434	0.0892
dl_visitor_sa	-0.10971	0.09
dl_wpi	-0.14785	0.0518
d_balr_sa	0.04831	0.0815
d_deposit_rate_sa	0.19831	0.0749
d_libor	-0.0068	0.0599
d_sibor	-0.01225	0.0591

Note:
Prefix ‘dl’ is for the indicates that the first difference of the logarithm was applied to the series, while the prefix ‘d’ indicates that the first difference was applied to the series. The suffix ‘sa’ indicates that seasonal adjustment was applied to the series.

Table 4. Weights Associated with the Two DF Model

Variable	Weight Factor 1	SE (Factor1)	Weight Factor 2	SE (Factor 2)
dl_cpi_sa	0.10912	1.069	-0.19184	4.2459
dl_dubai_sa	0.08474	0.8277	-0.07335	1.6247
dl_er_euro	0.20787	2.0237	0.01049	0.4018
dl_er_sgd_sa	0.40027	3.8961	-0.05869	1.3808
dl_er_usd_sa	0.27425	2.6699	-0.07127	1.5999
dl_er_yen_sa	0.25036	2.4373	-0.05706	1.2901
dl_exports_sa	0.03738	0.3688	-0.0696	1.5424
dl_gir	-0.00119	0.0402	0.00307	0.0948
dl_govspen_sa	0.02802	0.2764	-0.02343	0.5235
dl_imports_sa	-0.02113	0.2228	0.12342	2.7362
dl_m2_sa	-0.0332	0.3348	0.06785	1.5077
dl_meralco_sa	-0.03477	0.3425	0.04985	1.1054
dl_mvpi_sa	0.19258	1.8834	-0.27082	5.9943
dl_ng_exp_sa	0.04777	0.4687	-0.07248	1.6053
dl_ng_rev_sa	0.02826	0.2775	0.01859	0.4218
dl_psei	-0.06914	0.676	0.05993	1.3278
dl_pubconspen_sa	0.02813	0.2789	-0.06591	1.4607
dl_remit_sa	-0.01987	0.2036	0.0907	2.0107
dl_rice_sa	0.02551	0.2538	0.02242	0.5074
dl_sec_sa	0.03754	0.368	-0.01162	0.2695
dl_ukb_loans_sa	0.08926	0.8737	-0.0949	2.1022
dl_visitor_sa	-0.05832	0.5756	0.1344	2.9766
dl_wpi	0.09943	0.9694	-0.06019	1.3333
d_balr_sa	0.15992	1.5662	-0.2944	6.5159
d_deposit_rate_sa	0.36431	3.5675	-0.6785	15.0169

Variable	Weight Factor 1	SE (Factor1)	Weight Factor 2	SE (Factor 2)
d_libor	0.0446	0.441	-0.09731	2.1557
d_sibor	0.04549	0.4494	-0.09536	2.1125
d_tbill_364_sa	0.45731	4.4749	-0.80018	17.7083
d_tbill_91	0.53487	5.2328	-0.91976	20.3546
d_td_lt_sa	0.10994	1.0804	-0.25072	5.5511
d_td_st_sa	0.36069	3.5318	-0.66806	14.7858
d_tot	0.0696	0.6872	-0.18577	4.1142

Note:
Prefix ‘dl’ is for the indicates that the first difference of the logarithm was applied to the series, while the prefix ‘d’ indicates that the first difference was applied to the series. The suffix ‘sa’ indicates that seasonal adjustment was applied to the series.

3.2 Hybrid Dynamic Factor-Vector AutoRegressive (DF-VAR) Model

The procedure closely follows the approach of Chow and Choy (2009) in analyzing business cycles in Singapore that used Principal Components Analysis in the extraction of the latent dynamic factors. The paper used a hybrid DF-VAR model by generating first the factors using Principal Components Analysis (PCA), basically reducing the dimension of the variables. After identifying the PCs, the model used the Vector AutoRegressive (VAR) Model using the six (6) factors augmented with “stand alone” variables.

3.2.1 Principal Components Analysis (PCA)

The results of the Principal Components Analysis (PCA) are provided in Table 5 below. Using the results of the PCA, the six factors are augmented with stand-alone variables. The final factors are stand-alone variables are the following:

Factor 1	dl_wpi, dl_dubai_sa, dl_cpi_sa, dl_rice_sa
Factor 2	dl_er_yen_sa, dl_er_euro, dl_er_usd_sa, dl_er_sgd_sa
Factor 3	d_libor, d_sibor
Factor 4	d_tbill_364_sa, d_tbill91_sa, d_td_st_sa, dl_sec_sa, dl_mvpi_sa, dl_meralco_sa
Factor 5	d_tot, dl_exports_sa, dl_m2_sa, dl_imports_sa, dl_psei
Factor 6	dl_ng_exp_sa, dl_pubconspen_sa, dl_govspen_sa
Stand Alone	dl_remit_sa, dl_visitors_sa, d_bes_curr_sa

Table 5. Six Factor Solution (Principal Factor Solution) - Varimax Rotation

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
dl_wpi	0.8292	.	.	.	.	.
dl_dubai_sa	0.6904	-0.4302	.	.	.	.
dl_er_euro	0.5766	.	.	.	.	-0.3281
dl_cpi_sa	0.5482	.	.	.	.	.
dl_rice_sa	0.5326	.	.	.	.	.
dl_ukb_loans_sa	.	.	.	.	.	.

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
dl_er_yen_sa	.	0.7881	.	.	.	.
dl_er_usd_sa	.	0.7571	.	.	.	.
dl_er_sgd_sa	0.5264	0.6051	.	.	.	.
d_balr_sa	.	.	.	.	.	.
d_deposit_rate_sa	.	.	.	.	.	.
d_td_lt_sa	.	.	.	.	.	.
dl_psei	.	-0.5509	.	.	0.3049	.
d_libor	.	.	0.9655	.	.	.
d_sibor	.	.	0.9632	.	.	.
d_tbill_364_sa	.	.	.	0.6499	.	.
d_tbill_91	.	.	.	0.6297	.	.
d_td_st_sa	.	.	.	0.5324	.	.
dl_sec_sa	.	.	.	0.4574	.	.
dl_mvpi_sa	.	.	0.4017	0.4350	.	.
dl_meralco_sa	.	.	.	0.4152	.	0.4052
dl_visitor_sa	.	.	.	-0.3156	.	.
d_tot	.	.	.	.	0.8594	.
dl_exports_sa	.	.	.	0.3456	0.5959	.
dl_m2_sa	.	.	.	.	0.3561	.
dl_ng_rev_sa	.	.	.	.	-0.3769	.
dl_imports_sa	0.3767	-0.3059	0.3003	.	-0.4894	.
dl_ng_exp_sa	.	.	.	.	.	0.6610
dl_pubconspen_sa	.	.	.	.	.	0.5826
dl_govspen_sa	.	.	.	.	-0.3088	0.4657
dl_remit_sa	.	.	.	.	.	0.3267
dl_gir	.	.	.	.	.	.
d_bes_curr_sa	.	.	.	.	.	.

Factor Loadings less than 0.3 are not printed.

3.2.2 The Vector AutoRegressive (VAR) Model

The vector autoregressive (VAR) model is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances (or shocks) on the system of variables. The main distinction of the VAR approach, compared to the other econometric models, is that it treats every endogenous variable in the system as a function of the lagged values of all endogenous variables in the system. When we are not confident that a variable is actually exogenous, we can treat each variable symmetrically. In the three-variable case order one VAR (or VAR (1)) model we have,

$$\begin{aligned} y_t &= \beta_{10} - \beta_{12} z_t - \beta_{13} w_t + \gamma_{11} y_{t-1} + \gamma_{12} z_{t-1} + \gamma_{13} w_{t-1} + \varepsilon_{yt} \\ z_t &= \beta_{20} - \beta_{21} y_t - \beta_{23} w_t + \gamma_{21} y_{t-1} + \gamma_{22} z_{t-1} + \gamma_{23} w_{t-1} + \varepsilon_{zt} \\ w_t &= \beta_{30} - \beta_{31} y_t - \beta_{32} z_t + \gamma_{31} y_{t-1} + \gamma_{32} z_{t-1} + \gamma_{33} w_{t-1} + \varepsilon_{wt} \end{aligned} \tag{11}$$

where y_t, z_t and w_t are all at quarter t. The ε_{yt},, ε_{zt} and ε_{wt} are white noise disturbance terms with means 0 and standard deviations σ_y, σ_z and σ_w, respectively. The equations above are called the structural equations of the VAR. The parameters, β_{12}, β_{13}, β_{21}, β_{23}, β_{31} and β_{32} measure the contemporaneous effects while the γ's measure the lag 1 effects. The equations are not in reduced form since, for example, y_t has contemporaneous effect on z_t and w_t. Isolating the time t variables on the left-hand side, we have,

$$\begin{aligned}
y_t + \beta_{12} z_t + \beta_{13} w_t &= \beta_{10} + \gamma_{11} y_{t-1} + \gamma_{12} z_{t-1} + \gamma_{13} w_{t-1} + \varepsilon_{yt} \\
\beta_{21} y_t + z_t + \beta_{23} w_t &= \beta_{20} + \gamma_{21} y_{t-1} + \gamma_{22} z_{t-1} + \gamma_{23} w_{t-1} + \varepsilon_{zt} \\
\beta_{31} y_t + \beta_{32} z + w_t &= \beta_{30t} + \gamma_{31} y_{t-1} + \gamma_{32} z_{t-1} + \gamma_{33} w_{t-1} + \varepsilon_{wt}
\end{aligned} \tag{12}$$

In matrix form,

$$\begin{bmatrix} 1 & \beta_{12} & \beta_{13} \\ \beta_{21} & 1 & \beta_{23} \\ \beta_{31} & \beta_{32} & 1 \end{bmatrix} \begin{bmatrix} y_t \\ z_t \\ w_t \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ z_{t-1} \\ w_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \\ \varepsilon_{wt} \end{bmatrix} \tag{13}$$

Simplifying, we have,

$$\begin{aligned}
B\underline{x}_t &= \Gamma_0 + \Gamma_1 \underline{x}_{t-1} + \underline{\varepsilon}_t \\
\underline{x}_t &= B^{-1}\Gamma_0 + B^{-1}\Gamma_1 \underline{x}_{t-1} + B^{-1}\underline{\varepsilon}_t \\
\underline{x}_t &= A_0 + A_1 \underline{x}_{t-1} + \underline{e}_t
\end{aligned} \tag{13}$$

where $\underline{x}_t = \begin{bmatrix} y_t \\ z_t \\ w_t \end{bmatrix}$, $B = \begin{bmatrix} 1 & \beta_{12} & \beta_{13} \\ \beta_{21} & 1 & \beta_{23} \\ \beta_{31} & \beta_{32} & 1 \end{bmatrix}$, $\Gamma_0 = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{bmatrix}$, $\Gamma_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{bmatrix}$, $\varepsilon_t = \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \\ \varepsilon_{wt} \end{bmatrix}$

The equations in (3) are called the reduced-form representation of a VAR (1) model. We can generalize the mathematical representation of the reduced-form VAR model as,

$$\underline{x}_t = A_0 + A_1 \underline{x}_{t-1} + A_2 \underline{x}_{t-2} + ... + A_p \underline{x}_{t-p} + \underline{e}_t \tag{13}$$

where $\underline{\mathbf{x}}_{\mathbf{t}}$ is a (k x 1) vector of endogenous variables, $\underline{\mathbf{A}}_1$, $\underline{\mathbf{A}}_2$,…, $\underline{\mathbf{A}}_p$ are matrices of coefficients to be estimated, and $\underline{e}_t$ is a (k x 1) vector of forecast errors that may be contemporaneously correlated but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables. The error vector $\underline{e}_t$ is assumed to be normally distributed with mean **0** and covariance matrix **Σ**. The order of the VAR model (p) is determined using the information criteria (Akaike, Schwarz, and the Hannan-Quinn).

After the factors and the stand-alone variables have been identified, a Vector Auto-Regressive Model is used to *nowcast* the growth rate the RGDP. A Vector Auto-Regressive (VAR) model order (1,4) is used in the model. The estimated equation of the VAR (1,4) model is provided in Table 6 below.

Table 6. VAR Model for the Growth Rate of the RGDP (VAR 1,4)

Variable	Estimate	Standard Error	t-stat	p-value
Cons	1.55861	0.26391	5.91	0.0001
fincrisis(t)	-2.88385	0.81059	-3.56	0.0012
dl_remit_sa(t-1)	0.50088	1.79204	0.28	0.7817
dl_visitor_sa(t-1)	2.96759	1.89667	1.56	0.1278
d_bes_curr_sa(t-1)	-0.00217	0.01044	-0.21	0.8365
Factor1(t-1)	0.10417	0.05763	1.81	0.0804
Factor2(t-1)	-0.19659	0.07066	-2.78	0.0091
Factor3(t-1)	-0.01926	0.06751	-0.29	0.7773
Factor4(t-1)	0.15139	0.08224	1.84	0.0752
Factor5(t-1)	0.17783	0.08958	1.99	0.0560
Factor6(t-1)	0.12117	0.10931	1.11	0.2762
gdp_osa(t-1)	-0.10883	0.17570	-0.62	0.5402
dl_remit_sa(t-4)	-0.27729	0.71871	-0.39	0.7023
dl_visitor_sa(t-4)	-4.97263	1.70854	-2.91	0.0066
d_bes_curr_sa(t-4)	0.01259	0.01155	1.09	0.2841
Factor1(t-4)	0.01195	0.07828	0.15	0.8796
Factor2(t-4)	0.04373	0.05391	0.81	0.4235
Factor3(t-4)	0.15751	0.07223	2.18	0.0369
Factor4(t-4)	-0.20322	0.06036	-3.37	0.0020
Factor5(t-4)	-0.03668	0.07968	-0.46	0.6485
Factor6(t-4)	-0.03191	0.08771	-0.36	0.7185
gdp_osa(t-4)	-0.00994	0.13861	-0.07	0.9433

3.3 DF-Mixed Frequency Model

The procedure closely follows the approach of Gerlach and Yiu (2004) in nowcasting the GDP of Hong Kong. The paper treats the quarter-on-quarter growth rate of the seasonally-adjusted GDP estimates as a monthly series to match the higher frequency of different macroeconomic variables used in the study. The quarterly observations were placed on months corresponding to the end of quarters (e.g. March, June, September, and December) and the rest of the months were treated as missing observations. A monthly GDP growth rate series is generated by estimating the state space model with actual GDP growth rate as the left hand side of the signal equation and leading monthly economic indicators (e.g. Stock price index (PSEi), Peso-Dollar exchange rate, consumer price index, money supply - M1, wholesale price index, total merchandise exports, total merchandise imports, terms of trade index for merchandise goods, Meralco sales, registered stock corporations and partnership, and tourist/visitor arrivals) as exogenous variables with time-varying parameters.

One of the methodologies adopted in this paper came from Fulton, Bitmead and Williamson (2001) study on signal processing which was discussed earlier. This paper departs from theirs mainly by using economic data. Specifically, quarter-on-quarter growth rates of deseasonalized GDP entered at a monthly frequency with observations placed at each month corresponding to quarter ends (e.g. March, June, September, and December) and the rest of the sample were treated as missing observations.

To illustrate the series, let $t=1, 2,\dots, 165$ corresponding to 165 months from January 2000 to December 2013. The second quarter of 2000 GDP growth rate at June 2000 – corresponding to the last month of Q2 2000, while the third quarter 2000 GDP growth rate is entered in September 2000 and so on. The observations in between quarter ends were treated as missing observations. The paper then takes advantage of the state space models' ability to handle missing observations. Thus, state space models were fitted to the monthly GDP data, and the Kalman Filter algorithm was used to generate monthly GDP growth rate series. Following the discussion of state space models in the previous section, let y_t or the signal equation be the monthly GDP data with missing observations and μ_t is the state equation or unobserved component. We then supposed that $\{\, y_t \,\}_{t=l+1}^{l+h}$ observations are missing, where $h\geq 1$ and $1\leq l\leq T$. For t ϵ {$l+1,\dots, l+h$}, μ_t is expressed as a linear combination of μ_{l+1} and $\{\eta_j\}_{j=l+1}^{t-1}$. Thus, for t ϵ {$l+1,\dots, l+h$},

$$E(\mu_t|F_{t-1}) = E(\mu_t|F_t) = \mu_{l+1|l} \tag{14}$$

$$Var(\mu_t|F_{t-1}) = Var(\mu_t|F_t) = \Sigma_{l+1|l} + (t-l-1)\sigma_\eta^2. \tag{15}$$

Consequently, $\mu_{t|t-1} = \mu_{t-1|t-2,}$ for t = *l+1,…, l+h*. In other words, the Kalman filter algorithm can still be used even with missing observations by equating the Kalman gain and prediction error (η_t, used in updating state estimates) to zero. Similarly, the study made use of this procedure, but instead of having a signal equation stated above, a set of exogenous variables with time-varying parameters were fitted. The time-varying parameters were considered as state variables and the corresponding state equations followed a driftless random walk process. Thus, on periods with no actual GDP growth rate is available, a one-step-ahead forecast is generated factoring in the indicators in the signal equation.

3.3.1 Extracting the Factors using the Dynamic Factor Model (DFM)

The first step is similar to the extraction of the PCA in the Hybrid DF-VAR model. However, instead of the Principal Component (PC) representing the factors, a dynamic factor model approach is used to extract a common factor for each of the groupings:

Factor 1	dl_wpi, dl_dubai_sa, dl_cpi_sa, dl_rice_sa
Factor 2	dl_er_yen_sa, dl_er_euro, dl_er_usd_sa, dl_er_sgd_sa
Factor 3	d_libor, d_sibor
Factor 4	d_tbill_364_sa, d_tbill91_sa, d_td_st_sa, dl_sec_sa, dl_mvpi_sa, dl_meralco_sa
Factor 5	d_tot, dl_exports_sa, dl_m2_sa, dl_imports_sa, dl_psei
Factor 6	dl_ng_exp_sa, dl_pubconspen_sa, dl_govspen_sa

3.3.2 Time-Varying Parameter Model for GDP Growth

The time-varying parameter model was used to model the official seasonally adjusted GDP growth. The signal equation was composed of the GDP growth rate on the left-hand side and growth rate of the economic indicators with time-varying parameters on the right-hand side. The measurement equation is given by:

$$GDP_t = \beta_{1t}F_{1t} + \beta_{2t}F_{2t} + \cdots + \beta_{kt}F_{kt} + e_t \tag{16}$$

with the given signal equation:

$$\beta_{it} = \phi_i \beta_{i,t-1} + v_{it} \quad (17)$$

where $e_t \sim iid\, N(0, \sigma^2)$, $v_{it} \sim iid\, N(0, \sigma_i^2)$, $i = 1,2,\dots,k$, $E(e_t v_{is}) = 0$, for all t and s, $i = 1,2,\dots,k$, given x_{it}, $i = 1,2,\dots,k$ are predetermined or exogenous variables

In matrix form, the measurement and state equations are given respectively:

$$GDP_t = [F_{1t} \quad F_{2t} \quad \dots \quad F_{kt}] \begin{bmatrix} \beta_{1t} \\ \beta_{2t} \\ \vdots \\ \beta_{kt} \end{bmatrix} + e_t,\ (y_t = x_t \beta_t + e_t) \quad (18)$$

$$\begin{bmatrix} \beta_{1t} \\ \beta_{2t} \\ \cdots \\ \beta_{kt} \end{bmatrix} = \begin{bmatrix} \phi_1 & 0 & \dots & 0 \\ 0 & \phi_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \phi_k \end{bmatrix} \begin{bmatrix} \beta_{1,t-1} \\ \beta_{2,t-1} \\ \vdots \\ \beta_{k,t-1} \end{bmatrix} + \begin{bmatrix} v_{1t} \\ v_{2t} \\ \vdots \\ v_{kt} \end{bmatrix}, (\beta_t = \bar{\mu} + F\beta_{t-1} + v_t) \quad (19)$$

In addition, stand-alone variables are included: Remittances, Visitors Arrival and Business Expectation Survey (Current Quarter) from the BSP. The summary statistics and results are provided below.

Table 7.1 Likelihood Computation Summary

Statistic	Value
Nonmissing Response Values Used	56
Estimated Parameters	20
Initialized Diffuse State Elements	1
Normalized Residual Sum of Squares	55.00
Diffuse Log Likelihood	-60.97
Profile Log Likelihood	-58.94

*Likelihood optimization algorithm convered in 48 iterations.

Table 7.2 Information Criteria

Statistic	Diffuse Likelihood Based	Profile Likelihood Based
AIC (lower is better)	161.9489	159.8859
BIC (lower is better)	202.0956	202.4183
AICC (lower is better)	186.6548	187.0624

HQIC (lower is better)	177.4739	176.3756
CAIC (lower is better)	222.0956	223.4183

Table 7.3 Transition Matrix for beta

	Col1	Col2	Col3	Col4	Col5	Col6	Col7	Col8	Col9	Col10
Row1	1.61E-12	0	0	0	0	0	0	0	0	0
Row2	0	9.90E-10	0	0	0	0	0	0	0	0
Row3	0	0	6.67E-09	0	0	0	0	0	0	0
Row4	0	0	0	-0.9999	0	0	0	0	0	0
Row5	0	0	0	0	-4.21E-08	0	0	0	0	0
Row6	0	0	0	0	0	-0.71272	0	0	0	0
Row7	0	0	0	0	0	0	-0.88921	0	0	0
Row8	0	0	0	0	0	0	0	-7.60E-09	0	0
Row9	0	0	0	0	0	0	0	0	0.000226	0
Row10	0	0	0	0	0	0	0	0	0	0.000055

Table 7.4 Disturbance Covariance for beta

	Col1	Col2	Col3	Col4	Col5	Col6	Col7	Col8	Col9	Col10
Row1	1.05E-08	0	0	0	0	0	0	0	0	0
Row2	0	1.05E-08	0	0	0	0	0	0	0	0
Row3	0	0	1.05E-08	0	0	0	0	0	0	0
Row4	0	0	0	0.000018	0	0	0	0	0	0
Row5	0	0	0	0	1.05E-08	0	0	0	0	0
Row6	0	0	0	0	0	0.312388	0	0	0	0
Row7	0	0	0	0	0	0	0.048343	0	0	0
Row8	0	0	0	0	0	0	0	1.05E-08	0	0
Row9	0	0	0	0	0	0	0	0	1.05E-08	0
Row10	0	0	0	0	0	0	0	0	0	0.818124

4. Assessing the Nowcasting Performance of the Models

The weights associated with the single-factor and two-factor version of the Dynamic Factor (DF) models are given in Tables 3 and 4 in the appendix, respectively. Assessing the results of the nowcasting within the sample, from the first quarter 2000 to the fourth quarter of 2013, the 1-factor model captures the movement of the GDP with 48 percent accuracy. The 2-factor model, using the average of the two factors, generated 56 percent accuracy in the nowcasting exercise. The hybrid DF-VAR model produced an accuracy rate of 77 percent in nowcasting the movement of the GDP within the sample. The hybrid DF-VAR was also used in nowcasting the GDP growth rates and produced a mean error of 0.38 percentage point. The hybrid DF-MF model produced an accuracy rate of 94 percent, within the sample, in nowcasting the movement of the GDP and seemed to be the most accurate of the three models in terms of correctly tracking the movement of the GDP. For the nowcasting exercise associated with the GDP growth rates, the hybrid DF-MF model has a mean error of about 0.59 percentage point. The detailed nowcast results are provided in Appendix B.

5. Conclusions

This paper proposes Hybrid Dynamic Factor-Vector AutoRegressive (DF-VAR) model and the Dynamic Factor-Mixed Frequency (DF-MF) model in nowcasting the movement and growth rates of the country’s quarterly Gross Domestic Product (GDP) using 32 monthly variables and one quarterly indicator, in addition to the one- and two-factor DF model. The DF-VAR and DF-MF are alternative models to the usual time series econometric models used in forecasting GDP growth rates utilizing temporal aggregation. The assessment of the models, in terms of the percentage of correctly tracking the movement of the GDP, suggests that hybrid models are promising as nowcasting tools and can serve as alternative (and better) models to the current LEIS used by the NEDA and PSA.

6. References

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APPENDIX A. VAR Model Parameters (Complete)

VAR Model Parameters

DL_REMIT_SA Equation

Variable	Estimate	Standard Error	t Value	Pr > |t|
Cons	0.04050	0.02361	1.72	0.0962
fincrisis(t)	-0.00053	0.07251	-0.01	0.9943
dl_remit_sa(t-1)	-0.02519	0.16030	-0.16	0.8762
dl_visitor_sa(t-1)	0.09901	0.16966	0.58	0.5637
d_bes_curr_sa(t-1)	0.00026	0.00093	0.28	0.7800
Factor1(t-1)	-0.00906	0.00516	-1.76	0.0886

Factor2(t-1)	-0.00079	0.00632	-0.13	0.9011
Factor3(t-1)	-0.00736	0.00604	-1.22	0.2323
Factor4(t-1)	0.00892	0.00736	1.21	0.2346
Factor5(t-1)	0.00671	0.00801	0.84	0.4085
Factor6(t-1)	0.00516	0.00978	0.53	0.6016
gdp_osa(t-1)	-0.01012	0.01572	-0.64	0.5244
dl_remit_sa(t-4)	-0.03453	0.06429	-0.54	0.5950
dl_visitor_sa(t-4)	0.15775	0.15283	1.03	0.3100
d_bes_curr_sa(t-4)	-0.00066	0.00103	-0.64	0.5294
Factor1(t-4)	-0.00687	0.00700	-0.98	0.3343
Factor2(t-4)	-0.00261	0.00482	-0.54	0.5923
Factor3(t-4)	0.01140	0.00646	1.76	0.0875
Factor4(t-4)	0.00312	0.00540	0.58	0.5677
Factor5(t-4)	-0.00837	0.00713	-1.17	0.2493
Factor6(t-4)	0.02479	0.00785	3.16	0.0035
gdp_osa(t-4)	-0.00451	0.01240	-0.36	0.7186

DL_Visitor_SA Equation

Variable	Estimate	Standard Error	t Value	Pr > |t|
Cons	0.02093	0.02396	0.87	0.3892
fincrisis(t)	-0.10316	0.07360	-1.4	0.1710
dl_remit_sa(t-1)	0.50407	0.16272	3.1	0.0041
dl_visitor_sa(t-1)	-0.12360	0.17222	-0.72	0.4783
d_bes_curr_sa(t-1)	-0.00070	0.00095	-0.74	0.4674
Factor1(t-1)	-0.00497	0.00523	-0.95	0.3493
Factor2(t-1)	-0.01370	0.00642	-2.14	0.0407
Factor3(t-1)	0.00552	0.00613	0.9	0.3748
Factor4(t-1)	-0.00016	0.00747	-0.02	0.9831
Factor5(t-1)	0.01137	0.00813	1.4	0.1723
Factor6(t-1)	-0.01016	0.00993	-1.02	0.3138
gdp_osa(t-1)	-0.00096	0.01595	-0.06	0.9524
dl_remit_sa(t-4)	-0.08628	0.06526	-1.32	0.1958
dl_visitor_sa(t-4)	-0.19973	0.15514	-1.29	0.2075
d_bes_curr_sa(t-4)	-0.00151	0.00105	-1.44	0.1608
Factor1(t-4)	-0.00225	0.00711	-0.32	0.7540
Factor2(t-4)	-0.00408	0.00490	-0.83	0.4111
Factor3(t-4)	-0.00563	0.00656	-0.86	0.3969
Factor4(t-4)	-0.00124	0.00548	-0.23	0.8224
Factor5(t-4)	0.00209	0.00723	0.29	0.7745
Factor6(t-4)	-0.01036	0.00796	-1.3	0.2030
gdp_osa(t-4)	-0.00293	0.01259	-0.23	0.8173

D_BES_Current_SA Equation

Variable	Estimate	Standard Error	t Value	Pr > |t|
Cons	-0.52359	3.36598	-0.16	0.8774
fincrisis(t)	-19.81086	10.33847	-1.92	0.0646
dl_remit_sa(t-1)	-6.26834	22.85611	-0.27	0.7857
dl_visitor_sa(t-1)	33.39337	24.19055	1.38	0.1773
d_bes_curr_sa(t-1)	-0.46790	0.13313	-3.51	0.0014
Factor1(t-1)	-1.68856	0.73508	-2.3	0.0285

D_BES_Current_SA Equation

Variable	Estimate	Standard Error	t Value	Pr > |t|
Factor2(t-1)	-0.86350	0.90119	-0.96	0.3454
Factor3(t-1)	-0.31972	0.86101	-0.37	0.7129
Factor4(t-1)	0.63977	1.04890	0.61	0.5463
Factor5(t-1)	1.62215	1.14252	1.42	0.1656
Factor6(t-1)	0.10146	1.39418	0.07	0.9425
gdp_osa(t-1)	3.36412	2.24088	1.5	0.1434
dl_remit_sa(t-4)	-28.69888	9.16663	-3.13	0.0038
dl_visitor_sa(t-4)	-33.20614	21.79115	-1.52	0.1377
d_bes_curr_sa(t-4)	0.24963	0.14729	1.69	0.1001
Factor1(t-4)	1.90248	0.99842	1.91	0.0660
Factor2(t-4)	1.78482	0.68760	2.6	0.0143
Factor3(t-4)	0.74555	0.92122	0.81	0.4245
Factor4(t-4)	0.32850	0.76988	0.43	0.6726
Factor5(t-4)	1.07787	1.01622	1.06	0.2970
Factor6(t-4)	2.70124	1.11873	2.41	0.0218
gdp_osa(t-4)	-1.53378	1.76784	-0.87	0.3923

Factor 1 Equation

Variable	Estimate	Standard Error	t Value	Pr > |t|
Cons	1.36104	0.73837	1.84	0.0749
fincrisis(t)	2.04186	2.26788	0.9	0.3749
dl_remit_sa(t-1)	3.96925	5.01379	0.79	0.4346
dl_visitor_sa(t-1)	6.41951	5.30652	1.21	0.2355
d_bes_curr_sa(t-1)	0.01377	0.02920	0.47	0.6405
Factor1(t-1)	0.01985	0.16125	0.12	0.9028
Factor2(t-1)	-0.13545	0.19769	-0.69	0.4983
Factor3(t-1)	-0.19481	0.18887	-1.03	0.3103
Factor4(t-1)	0.01315	0.23009	0.06	0.9548
Factor5(t-1)	-0.04811	0.25063	-0.19	0.8490
Factor6(t-1)	0.00891	0.30583	0.03	0.9769
gdp_osa(t-1)	-1.45467	0.49157	-2.96	0.0059
dl_remit_sa(t-4)	0.25464	2.01082	0.13	0.9000
dl_visitor_sa(t-4)	-4.88407	4.78018	-1.02	0.3148
d_bes_curr_sa(t-4)	-0.02348	0.03231	-0.73	0.4729
Factor1(t-4)	-0.40766	0.21902	-1.86	0.0722
Factor2(t-4)	-0.07997	0.15083	-0.53	0.5998
Factor3(t-4)	0.16706	0.20208	0.83	0.4147
Factor4(t-4)	-0.05491	0.16888	-0.33	0.7473
Factor5(t-4)	-0.39763	0.22292	-1.78	0.0843
Factor6(t-4)	-0.09983	0.24541	-0.41	0.6870
gdp_osa(t-4)	0.39575	0.38780	1.02	0.3154

Factor 2 Equation

Variable	Estimate	Standard Error	t Value	Pr > |t|
Cons	0.46062	0.71367	0.65	0.5234
fincrisis(t)	2.39465	2.19200	1.09	0.2831
dl_remit_sa(t-1)	-2.57519	4.84603	-0.53	0.5989

Factor 2 Equation

Variable	Estimate	Standard Error	t Value	Pr > |t|
dl_visitor_sa(t-1)	0.51494	5.12897	0.1	0.9207
d_bes_curr_sa(t-1)	0.00478	0.02823	0.17	0.8666
Factor1(t-1)	0.12390	0.15585	0.79	0.4327
Factor2(t-1)	0.27944	0.19107	1.46	0.1537
Factor3(t-1)	0.00633	0.18256	0.03	0.9725
Factor4(t-1)	0.01256	0.22239	0.06	0.9553
Factor5(t-1)	-0.07164	0.24224	-0.3	0.7694
Factor6(t-1)	0.60829	0.29560	2.06	0.0481
gdp_osa(t-1)	-0.25965	0.47512	-0.55	0.5886
dl_remit_sa(t-4)	0.98563	1.94354	0.51	0.6157
dl_visitor_sa(t-4)	3.63275	4.62024	0.79	0.4377
d_bes_curr_sa(t-4)	-0.07708	0.03123	-2.47	0.0193
Factor1(t-4)	-0.44968	0.21169	-2.12	0.0417
Factor2(t-4)	-0.58591	0.14579	-4.02	0.0003
Factor3(t-4)	-0.14124	0.19532	-0.72	0.4750
Factor4(t-4)	0.16713	0.16323	1.02	0.3138
Factor5(t-4)	-0.03171	0.21546	-0.15	0.8839
Factor6(t-4)	0.26863	0.23720	1.13	0.2661
gdp_osa(t-4)	0.06596	0.37482	0.18	0.8615

Factor 3 Equation

Variable	Estimate	Standard Error	t Value	Pr > |t|
Cons	0.73474	0.49566	1.48	0.1483
fincrisis(t)	-8.29162	1.52241	-5.45	0.0001
dl_remit_sa(t-1)	6.71589	3.36572	2	0.0549
dl_visitor_sa(t-1)	2.35522	3.56222	0.66	0.5134
d_bes_curr_sa(t-1)	-0.00526	0.01960	-0.27	0.7904
Factor1(t-1)	0.14932	0.10825	1.38	0.1776
Factor2(t-1)	-0.22903	0.13271	-1.73	0.0943
Factor3(t-1)	0.39458	0.12679	3.11	0.0040
Factor4(t-1)	0.06808	0.15446	0.44	0.6624
Factor5(t-1)	0.11873	0.16824	0.71	0.4856
Factor6(t-1)	0.08496	0.20530	0.41	0.6819
gdp_osa(t-1)	-0.44427	0.32999	-1.35	0.1880
dl_remit_sa(t-4)	3.60591	1.34985	2.67	0.0119
dl_visitor_sa(t-4)	1.75017	3.20889	0.55	0.5894
d_bes_curr_sa(t-4)	-0.03484	0.02169	-1.61	0.1183
Factor1(t-4)	-0.16920	0.14702	-1.15	0.2586
Factor2(t-4)	-0.14038	0.10125	-1.39	0.1755
Factor3(t-4)	-0.01835	0.13566	-0.14	0.8933
Factor4(t-4)	-0.04146	0.11337	-0.37	0.7170
Factor5(t-4)	-0.42830	0.14965	-2.86	0.0075
Factor6(t-4)	-0.24695	0.16474	-1.5	0.1440
gdp_osa(t-4)	-0.20282	0.26033	-0.78	0.4418

Factor 4 Equation

Variable	Estimate	Standard Error	t Value	Pr > |t|
Cons	1.10165	0.61381	1.79	0.0824
fincrisis(t)	-0.43166	1.88530	-0.23	0.8204
dl_remit_sa(t-1)	-11.75672	4.16798	-2.82	0.0083
dl_visitor_sa(t-1)	2.41553	4.41132	0.55	0.5879
d_bes_curr_sa(t-1)	0.03281	0.02428	1.35	0.1864
Factor1(t-1)	0.31107	0.13405	2.32	0.0271
Factor2(t-1)	-0.06710	0.16434	-0.41	0.6859
Factor3(t-1)	0.02131	0.15701	0.14	0.8929
Factor4(t-1)	0.63672	0.19127	3.33	0.0023
Factor5(t-1)	-0.06133	0.20835	-0.29	0.7704
Factor6(t-1)	0.55720	0.25424	2.19	0.0360
gdp_osa(t-1)	-0.46642	0.40864	-1.14	0.2624
dl_remit_sa(t-4)	2.77646	1.67160	1.66	0.1068
dl_visitor_sa(t-4)	-3.47477	3.97377	-0.87	0.3886
d_bes_curr_sa(t-4)	0.00511	0.02686	0.19	0.8504
Factor1(t-4)	-0.10406	0.18207	-0.57	0.5717
Factor2(t-4)	0.21774	0.12539	1.74	0.0924
Factor3(t-4)	0.20753	0.16799	1.24	0.2260
Factor4(t-4)	-0.10447	0.14039	-0.74	0.4624
Factor5(t-4)	-0.20324	0.18531	-1.1	0.2812
Factor6(t-4)	0.06027	0.20401	0.3	0.7697
gdp_osa(t-4)	-0.00716	0.32238	-0.02	0.9824

Factor 5 Equation

Variable	Estimate	Standard Error	t Value	Pr > |t|
Cons	-0.23045	0.50437	-0.46	0.6509
fincrisis(t)	-3.03628	1.54915	-1.96	0.0590
dl_remit_sa(t-1)	3.78983	3.42483	1.11	0.2770
dl_visitor_sa(t-1)	-5.35712	3.62478	-1.48	0.1495
d_bes_curr_sa(t-1)	0.01685	0.01995	0.84	0.4048
Factor1(t-1)	-0.06078	0.11015	-0.55	0.5850
Factor2(t-1)	0.08144	0.13504	0.6	0.5509
Factor3(t-1)	-0.05756	0.12902	-0.45	0.6586
Factor4(t-1)	-0.15471	0.15717	-0.98	0.3326
Factor5(t-1)	-0.26198	0.17120	-1.53	0.1361
Factor6(t-1)	0.09586	0.20891	0.46	0.6495
gdp_osa(t-1)	0.21781	0.33578	0.65	0.5213
dl_remit_sa(t-4)	1.08450	1.37356	0.79	0.4358
dl_visitor_sa(t-4)	-0.59610	3.26525	-0.18	0.8563
d_bes_curr_sa(t-4)	0.01308	0.02207	0.59	0.5576
Factor1(t-4)	-0.12082	0.14961	-0.81	0.4255
Factor2(t-4)	-0.02990	0.10303	-0.29	0.7736
Factor3(t-4)	-0.02119	0.13804	-0.15	0.8790
Factor4(t-4)	0.03237	0.11536	0.28	0.7809
Factor5(t-4)	0.25658	0.15227	1.69	0.1020

Factor6(t-4)	-0.12567	0.16763	-0.75	0.4591
gdp_osa(t-4)	0.10911	0.26490	0.41	0.6833

Factor 6 Equation

Variable	Estimate	Standard Error	t Value	Pr > |t|
Cons	0.54285	0.45782	1.19	0.2447
fincrisis(t)	0.26050	1.40618	0.19	0.8542
dl_remit_sa(t-1)	3.55655	3.10875	1.14	0.2614
dl_visitor_sa(t-1)	4.35187	3.29026	1.32	0.1956
d_bes_curr_sa(t-1)	-0.00477	0.01811	-0.26	0.7940
Factor1(t-1)	0.05564	0.09998	0.56	0.5819
Factor2(t-1)	0.05414	0.12257	0.44	0.6618
Factor3(t-1)	-0.14496	0.11711	-1.24	0.2251
Factor4(t-1)	-0.09623	0.14266	-0.67	0.5050
Factor5(t-1)	-0.07950	0.15540	-0.51	0.6126
Factor6(t-1)	-0.12865	0.18963	-0.68	0.5025
gdp_osa(t-1)	-0.17688	0.30479	-0.58	0.5659
dl_remit_sa(t-4)	0.51499	1.24679	0.41	0.6824
dl_visitor_sa(t-4)	4.94245	2.96390	1.67	0.1055
d_bes_curr_sa(t-4)	-0.00846	0.02003	-0.42	0.6758
Factor1(t-4)	0.01397	0.13580	0.1	0.9188
Factor2(t-4)	-0.13193	0.09352	-1.41	0.1683
Factor3(t-4)	0.04628	0.12530	0.37	0.7143
Factor4(t-4)	0.01061	0.10471	0.1	0.9199
Factor5(t-4)	-0.08119	0.13822	-0.59	0.5612
Factor6(t-4)	0.02577	0.15216	0.17	0.8666
gdp_osa(t-4)	-0.61469	0.24045	-2.56	0.0157

GDP_OSA Equation

Variable	Estimate	Standard Error	t Value	Pr > |t|
Cons	1.55861	0.26391	5.91	0.0001
fincrisis(t)	-2.88385	0.81059	-3.56	0.0012
dl_remit_sa(t-1)	0.50088	1.79204	0.28	0.7817
dl_visitor_sa(t-1)	2.96759	1.89667	1.56	0.1278
d_bes_curr_sa(t-1)	-0.00217	0.01044	-0.21	0.8365
Factor1(t-1)	0.10417	0.05763	1.81	0.0804
Factor2(t-1)	-0.19659	0.07066	-2.78	0.0091
Factor3(t-1)	-0.01926	0.06751	-0.29	0.7773
Factor4(t-1)	0.15139	0.08224	1.84	0.0752
Factor5(t-1)	0.17783	0.08958	1.99	0.0560
Factor6(t-1)	0.12117	0.10931	1.11	0.2762
gdp_osa(t-1)	-0.10883	0.17570	-0.62	0.5402
dl_remit_sa(t-4)	-0.27729	0.71871	-0.39	0.7023
dl_visitor_sa(t-4)	-4.97263	1.70854	-2.91	0.0066
d_bes_curr_sa(t-4)	0.01259	0.01155	1.09	0.2841
Factor1(t-4)	0.01195	0.07828	0.15	0.8796
Factor2(t-4)	0.04373	0.05391	0.81	0.4235
Factor3(t-4)	0.15751	0.07223	2.18	0.0369
Factor4(t-4)	-0.20322	0.06036	-3.37	0.0020
Factor5(t-4)	-0.03668	0.07968	-0.46	0.6485

Factor6(t-4)	-0.03191	0.08771	-0.36	0.7185
gdp_osa(t-4)	-0.00994	0.13861	-0.07	0.9433

Covariances of Innovations

Variable	dl_remit_sa	dl_visitor_sa	d_bes_curr_sa
dl_remit_sa	0.00316	0.00052	0.01414
dl_visitor_sa	0.00052	0.00326	-0.01140
d_bes_curr_sa	0.01414	-0.01140	64.26722
Factor1	0.03262	0.00894	-2.62700
Factor2	-0.00478	-0.01579	3.44787
Factor3	0.02265	0.02634	-0.88616
Factor4	-0.00071	-0.01602	-1.12362
Factor5	0.00702	-0.00554	2.55693
Factor6	0.01231	0.02277	1.67118
gdp_osa	-0.00137	0.00790	0.79209

Covariances of Innovations

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	gdp_osa
dl_remit_sa	0.03262	-0.00478	0.02265	-0.00071	0.00702	0.01231	-0.00137
dl_visitor_sa	0.00894	-0.01579	0.02634	-0.01602	-0.00554	0.02277	0.00790
d_bes_curr_sa	-2.62700	3.44787	-0.88616	-1.12362	2.55693	1.67118	0.79209
Factor1	3.09256	-0.38584	1.19925	0.76329	0.15475	-0.60474	0.01169
Factor2	-0.38584	2.88907	-0.69379	0.83114	-0.46274	-0.58430	0.04201
Factor3	1.19925	-0.69379	1.39360	-0.11056	0.21270	0.20713	0.00781
Factor4	0.76329	0.83114	-0.11056	2.13715	-0.71655	-0.68246	0.13245
Factor5	0.15475	-0.46274	0.21270	-0.71655	1.44299	0.20877	0.20265
Factor6	-0.60474	-0.58430	0.20713	-0.68246	0.20877	1.18893	0.09644
gdp_osa	0.01169	0.04201	0.00781	0.13245	0.20265	0.09644	0.39508

APPENDIX B. Nowcast for the Models

Hybrid DF-VAR Model

Date	gdp_osa	Forecasts for gdp_osa
2000:01:00	1.6	.
2000:02:00	0.6	.
2000:03:00	1.7	.
2000:04:00	0	.
2001:01:00	0.3	0.25862
2001:02:00	1.2	1.36396
2001:03:00	1.2	1.69678
2001:04:00	0.3	0.31107
2002:01:00	0.9	1.37279
2002:02:00	1.1	1.5725
2002:03:00	0.7	1.06633
2002:04:00	1.5	1.33327
2003:01:00	0.9	0.81073

Date	gdp_osa	Forecasts for gdp_osa
2003:02:00	0.7	1.57842
2003:03:00	2.9	1.53097
2003:04:00	1.2	1.62236
2004:01:00	2.2	1.54955
2004:02:00	0.9	1.12704
2004:03:00	1.8	1.22374
2004:04:00	0.9	1.00783
2005:01:00	1.4	1.03203
2005:02:00	0.8	0.9318
2005:03:00	1.4	1.94677
2005:04:00	0.9	1.48164
2006:01:00	1.6	2.50109
2006:02:00	1.5	1.39829
2006:03:00	0.7	1.19728
2006:04:00	2.1	1.8301
2007:01:00	2.3	1.94401
2007:02:00	1.2	1.47545
2007:03:00	1.1	1.64366
2007:04:00	1.9	1.81184
2008:01:00	-0.1	-0.1
2008:02:00	1.2	0.84382
2008:03:00	2.2	2.0248
2008:04:00	0	0.21634
2009:01:00	-2.4	-2.09287
2009:02:00	1.4	1.2163
2009:03:00	1.7	1.90305
2009:04:00	1.3	1.16683
2010:01:00	3.3	2.66469
2010:02:00	2	1.42772
2010:03:00	0.6	0.93245
2010:04:00	0.8	1.32685
2011:01:00	0.7	0.84199
2011:02:00	1	1.01745
2011:03:00	0.8	1.47024
2011:04:00	1.7	1.04916
2012:01:00	2.4	2.10166
2012:02:00	1.1	0.95711
2012:03:00	2.1	1.6272
2012:04:00	1.7	1.49894
2013:01:00	2.3	0.89253
2013:02:00	1.3	1.64246
2013:03:00	1.6	1.15515
2013:04:00	1	1.26052
2014:01:00	1.7	1.33567
2014:02:00	.	1.27741
2014:03:00	.	1.26911
2014:04:00	.	2.01824
2015:01:00	.	1.68249
2015:02:00	.	1.71131
2015:03:00	.	1.09466
2015:04:00	.	0.89241

Date	gdp_osa	Forecasts for gdp_osa
2016:01:00	.	0.58544
2016:02:00	.	0.94089
2016:03:00	.	1.07622
2016:04:00	.	1.55516
2017:01:00	.	1.68666

Hybrid DF-MF Model

Date	gdp_osa	Forecast for gdp_osa
2000:01:00	1.6	.
2000:02:00	0.6	1.6
2000:03:00	1.7	0.88547
2000:04:00	0	1.32378
2001:01:00	0.3	0.68644
2001:02:00	1.2	1.40471
2001:03:00	1.2	1.26928
2001:04:00	0.3	1.20246
2002:01:00	0.9	1.42724
2002:02:00	1.1	1.24322
2002:03:00	0.7	1.13825
2002:04:00	1.5	1.19944
2003:01:00	0.9	1.27655
2003:02:00	0.7	1.12265
2003:03:00	2.9	1.03552
2003:04:00	1.2	1.11842
2004:01:00	2.2	1.1914
2004:02:00	0.9	0.56129
2004:03:00	1.8	1.71086
2004:04:00	0.9	1.311
2005:01:00	1.4	1.53099
2005:02:00	0.8	1.2092
2005:03:00	1.4	1.14
2005:04:00	0.9	1.21049
2006:01:00	1.6	1.37356
2006:02:00	1.5	1.33199
2006:03:00	0.7	1.49271
2006:04:00	2.1	1.37156
2007:01:00	2.3	1.14315
2007:02:00	1.2	1.6979
2007:03:00	1.1	1.33237
2007:04:00	1.9	1.43963
2008:01:00	-0.1	1.25386
2008:02:00	1.2	0.944
2008:03:00	2.2	1.51119
2008:04:00	0	0.79908
2009:01:00	-2.4	1.0127
2009:02:00	1.4	0.80302
2009:03:00	1.7	1.47561
2009:04:00	1.3	1.13636
2010:01:00	3.3	1.43468
2010:02:00	2	1.38592

Date	gdp_osa	Forecast for gdp_osa
2010:03:00	0.6	1.52211
2010:04:00	0.8	0.98813
2011:01:00	0.7	1.31023
2011:02:00	1	1.23234
2011:03:00	0.8	1.42618
2011:04:00	1.7	0.88393
2012:01:00	2.4	1.69192
2012:02:00	1.1	1.89544
2012:03:00	2.1	1.19822
2012:04:00	1.7	1.33153
2013:01:00	2.3	0.74821
2013:02:00	1.3	1.86074
2013:03:00	1.6	1.40133
2013:04:00	1	1.00908
2014:01:00	1.7	1.29209
2014:02:00	.	1.52271

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