Analyzing and Forecasting Movements of the Philippine Economy using the Dynamic Factor Models (DFM)

Mapa, Dennis S. and Simbulan, Maria Christina

School of Statistics, University of the Philippines Diliman, School of Economics, University of the Philippines Diliman

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ABSTRACT

The country's small and open economy is vulnerable to both internal and external shocks. Is it therefore important for policy makers to have timely forecasts on the movement of the country's Gross Domestic Product (GDP), whether it will increase or decrease in the current quarter, to be able to guide them in coming up with appropriate policies to mitigate say, the impact of a shock. The current method used to forecast the movements of the GDP is the composite Leading Economic Indicators System (LEIS) developed by the National Economic Development Authority (NEDA) and the National Statistical Coordination Board (NSCB). The LEIS, using 11 economic indicators, provides one-quarter forecast of the movement of the GDP. This paper presents an alternative, and perhaps better, procedure to the LEIS in *nowcasting* the movements of the GDP using the Dynamic Factor Model (DFM). The idea behind the DFM 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 DFM is a commonly used data reduction procedure that assumes economic shocks driving economic activity arise from unobserved components or factors. The DFM aims to parsimoniously summarize information from a large number of economic series to a small number of unobserved factors. The DFM assumes that co-movements of economic series can be captured using these unobserved common factors. This paper used 31 monthly economic indicators in capturing a common factor to *nowcast* movements of GDP via the DFM. The results show that the common factor produced by the DFM performed better in capturing the movements of the GDP when compared with the LEIS. The DFM is a promising and useful methodology in extracting indicators of the country's economic activity.

Key Phrases: Dynamic Factor Model, Leading Economic Indicators System, Common Factor

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[1] Associate Professor and Director for Research, School of Statistics; Affiliate Associate Professor, School of Economics, University of the Philippines Diliman; email address: csmapa@upd.edu.ph, cdsmapa@yahoo.com. The authors would like to thank Drs. Joselito Magadia and Lisa Grace Bersales for their comments and suggestions on the earlier draft of this paper and the participants of the Econometrics Session at the 12th National Convention in Statistics held last October 1-2, 2013 at the EDSA Shang-rila, Mandaluyong City.

[2] Bank Officer, Bangko Sentral ng Pilipinas (BSP), Malate, Manila. Email address: chrissimbulan@gmail.com

I. Introduction

The Philippine economy, being a small and open economy, is vulnerable to domestic (internal) as well as international (external) shocks. Understanding the state of the country's economic activity is deemed crucial for policy decision making process. The Gross Domestic Product (GDP), published by the National Statistical Coordination Board (NSCB), is the broadest measure of the overall economic activity and the analysis of the movement of the GDP along the business cycle as well as the impact of internal and external shocks are important for policy makers, analysts, researchers and other stakeholders. A major issue with the GDP is the relatively long lag in the release of the official numbers, as well as the revisions associated with the previous releases.[3] The problem with the delay in the release of the official GDP numbers is the reason why researchers at the 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 that are available at a higher frequency (e.g. monthly, weekly, daily) than the quarterly GDP. These economic indicators are variables that are highly correlated with the GDP and are available at a higher frequency. Is it important to provide a timely assessment on the movements of the GDP (will it increase/decrease this quarter?) to be able to guide policy makers to come up with 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. The LEI seeks to answer the question whether the GDP is expected to go up or go down in the succeeding quarter. The LEI (as an index) is not concerned with forecasting the actual level or growth rate of the GDP, but is more interested with the direction of the GDP. The Leading Economic Indicator System (LEIS) was developed jointly by the National Statistical Coordination Board (NSCB) and the National Economic and Development Authority (NEDA) to serve as basis for short-term forecasting of the macroeconomic activity in the country. The NSCB has since been compiling data for the 11 identified leading economic indicators and generating the Composite Leading Economic Indicator on a quarterly basis. The LEIS involves the study of the behavior of indicators that consistently move upward or downward before the actual expansion or contraction of 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 to provide advance information on the direction of the country's economic activity or performance in the short run (NSCB, 2013).

A more popular method of studying movements in the GDP among researchers in other countries is the Dynamic Factor Model (DFM). The main idea behind the DFM is the stylized fact that overall economic movement, say the GDP, evolves in cycle which involves co-movements in large number of economic variables. The DFM is a commonly used data reduction procedure, from a large number of economic series, whose main assumption is that macroeconomic fluctuations are driven by common shocks and an idiosyncratic shock. The study of the DFM originates from the classical work of Burns and Mitchel (1946) in deriving lagging, coincident and leading economic indicators and later developed into a more formal models used by Stock and Watson (1991; 2001) – leading to the birth of Dynamic Factor Model.

[3] The GDP numbers are released by the NSCB about 60 days after the reference quarter for the 1st, 2nd and 3rd Quarters and 30 days after for the 4th Quarter. The GDP for the reference year is also released 30 days after the end of the reference year.

There are a number of country specific studies concerned with the construction of leading economic indicators using the DFM. Chow and Choy (2009) used the DFM to analyze and forecast movement in the business cycle in Singapore. The authors found four dynamic factors that explain more than half of the macroeconomic fluctuations in Singapore. The dynamic factors represent the international macroeconomic movement, regional dynamics, global demand for electronics, and domestic construction industry. Tsouma (2009) developed a composite coincident economic indicator for Greece applying Dynamic Factor Model with regime switching while Schulz (2007) used two different unobserved factor models following the strategy of Stock and Watson (1991; 2001) to forecast economic growth for Estonia; Mongardini and Saadi-Sedik (2003) presented a DFM in deriving coincident and leading economic indicator for open economy like Jordan; Gerlach and Yiu (2001) applied Dynamic Factor Model in constructing current-quarter estimates of economic activity in Hong Kong; Fukada and Onodera (2001) constructed composite index of coincident economic indicators in Japan to forecast recent short-run economic fluctuations using DFM; Bandholz and Funke (2001) presented two new composite leading indicators of economic activity in Germany estimated using DFM with and without Regime Switching. While the DFM is commonly used to a construct composite index of economic activity, it can also be used to identify external (foreign) and internal (domestic) disturbances that affect the GDP (Chow and Choy; 2009). The two authors used 177 quarterly economic time series in Singapore and were able to extract four common shocks defined as: (1) world shock; (2) regional shock; (3) electronics shock; and (4) domestic economic shocks that influence the movements of the GDP of Singapore.

II. Research Objectives

The major objective of this paper is to develop a *one-factor* Dynamic Factor Model (DFM) using monthly economic time series to arrive at an economic index that will be used to *"nowcast"* the movements of the country's current-quarter GDP. This timely index of economic indicators for the movement of the current quarter GDP can serve as a better alternative to the current leading economic indicator (LEI) of the NSCB.

III. The Leading Economic indicators System (LEIS)[4]

The Leading Economic Indicator System (LEIS) was developed jointly by the National Statistical Coordination Board (NSCB) and the National Economic and Development Authority (NEDA) to serve as basis for short-term forecasting of the macroeconomic activity in the country. The NSCB has since been compiling data for the 11 identified leading economic indicators and generating the Composite Leading Economic Indicator on a quarterly basis. The LEIS involves the study of the behavior of indicators that consistently move upward or downward before the actual expansion or contraction of 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 to provide advance information on the direction of the country's economic activity/ performance in the short run.

The computation of the composite leading economic indicator (LEI) involves the use of a reference series and eleven leading economic indicators, namely: (1) consumer price index, (2) electric energy consumption; (3) exchange rate, 4) hotel occupancy rate, 5) money supply; 6) number of new business incorporations, 7) stock price index, 8) terms of trade index, 9) total merchandise imports, 10) visitor arrivals, and 11) wholesale price index.

[4] The discussion on the LEIS is taken from the technical notes of the NSCB's LEIS (NSCB; 2013).

The LEIS methodology includes the decomposition of the reference series and each of the eleven indicators by doing the following steps:

1. Seasonally adjust and smoothen using X11ARIMA to obtain the cycle-trend component for each of the eleven leading indicators and the reference series (non-agriculture component of the GDP). Remove the trend component from the seasonally adjusted and smoothened series to obtain the cycle component of each of the indicators by using the Hodrick-Prescott (HP) Filter Method. Starting with the Q1 2004 LEI estimate released on 12 February 2004, the computation of the LEI adopts a new *de-trending* procedure called the *Hodrick-Prescott (HP) Filter Method,* which has effectively addressed observed limitations in the method used for the estimation of the LEI prior to 2004.

2. Correlate the cycle of each indicator with the cycle of the non-agriculture GDP (reference series) to obtain the lead period. The lead period determines the number of quarters the cycle series for each indicator is moved forward.

3. The index is computed as the linear combination of the indicators using the correlation coefficients of the indicators with the non-agriculture GDP as weights. In determining the relationship between the Non-agriculture GVA and the composite indicator, the following simple linear regression model is used:

$$\text{Non Agri GVA}_t = b_t \, LEI_t + e_t \qquad (1)$$

where, Non agri GVA_t is the Cycle component of the Non-Agriculture GDP; b_t is the amount of increase in the cycle component of the Non-Agriculture GDP per unit increase in the composite LEI; LEI_t is the Composite Leading Economic Indicator and e_t is the error term.

As the composite indicator, the LEI provides advance information on the direction of the country's economic activity/performance in the short run, the composite indicator is released ahead of the reference quarter. The main limitation of the LEIS is the use of forecast data for some of the indicators that are not yet available at the time of the LEI compilation/computation. Forecasting of unavailable data is done to accommodate the timely release of the composite indicator. The LEIS currently uses the X11 ARIMA program to forecast data.[5]

IV. Dynamic Factor Model (DFM)

The Dynamic Factor Model (DFM) is a data reduction procedure which summarizes the main sources of variation and co-variation of large number of economic variables. The DFM assumes that small number of unobserved factors can account for much of the observed economic aggregates and "if these factors were forecasted accurately and precisely, then forecasting with many predictors can be simplified substantially using these factors instead of using the entire set of series" (Stock and Watson, 2006).

[5] For the third quarter of 2013, the LEI used either forecasted or partially imputed data for eight (8) indicators: (1) electric energy consumption, (2) hotel occupancy rate, (3) total merchandise imports, (4) money supply, (5) visitor arrivals, (6) terms of trade index, (7) stock price index and (8) wholesale price index (NSCB; 2013)

The DFM expresses the observed time series (Y_{it}) as a distributed lag of a small number of unobserved common factors (f_t) and an idiosyncratic disturbance (u_t),

$$Y_{it} = \lambda_i(L) f_t + u_{it} \qquad i = 1,2...,n \qquad (2)$$

where f_t is an (r x 1) vector of unobserved factors, $\lambda_i(L)$ is an (r x 1) vector lag polynomial called the dynamic factor loadings (or weigths) and u_{it} is the idiosyncratic disturbance. The factors f_t and u_{it} are assumed to be uncorrelated at all leads and lags (i.e. $E[f_t u_{is}] = 0$) for all s. The unobserved factors are expressed following a linear dynamic process,

$$\Gamma(L) f_t = \eta_t \qquad (3)$$

where $\Gamma(L)$ matrix is a lag polynomial and η_t is an (r x1) disturbance vector.

The model in (2) expresses the economic series (Y_{it}) as the sum of two stochastic components: unobservable common components (f_t) and idiosyncratic component, $u_{it.}$ The two components are characterized using the Auto Regressive (AR) process. Assuming a single factor model, where both f_t and u_{it} follow an AR (1) process, we have,

$$\begin{aligned}
&(4)\ Y_{it} = \lambda_i + \gamma_i f_t + u_{it} && i = 1,2,...,n \\
&(5)\ f_t = \phi_o + \phi_1 f_{t-1} + \eta_t && \eta_t \sim i.i.d.N(0,\sigma_\eta^2) \\
&(6)\ u_{it} = d_{it} u_{it-1} + v_{it} && v_{it} \sim i.i.d.N(0,\sigma_v^2)
\end{aligned}$$

The main idea behind the models in equations (4) to (6) is that co-movement in economic indicators Y_{it} is explained by a single source, the common factor, f_t. This common factor enters into each Y_{it} with different weights, given by γ_i, i=1,2…,n.

The equations (4) to (6) are expressed in state-space representation and the parameters are estimated using the Kalman Filter.

V. State-Space Model and Kalman Filter

State-space and the Kalman Filter are very useful tools for expressing dynamic system that involved unobserved state variables and estimating the parameters of the system (Kim and Nelson, 1999). It was originally used in the field of control engineering. Before Kalman filter estimation can be used in estimating parameters, the DFM should be first transformed to its State-Space Model form.

5.1. State-Space Model

A state-space model consists of two equations, the transition (state equation) and the measurement equation. The measurement equation describes the relation between the observed variables (the data) and the unobserved state variables, while the transition equation describes the dynamics of the state variables. The transition equation has the form of a first order difference equation in the state vector. Following the discussion of Kim and Nelson (1999), we consider the following representative state space model:

Measurement equation:

$$Y_t = H_t f_t + A z_t + u_t \qquad (7)$$

Transition equation:

$$f_t = \tilde{\mu} + B f_{t-1} + \eta_t \qquad (8)$$

$u_t \sim iid\ N(0, R)$, $\eta_t \sim iid\ N(0, Q)$, $E[u_t \eta_s{}'] = 0$

where Y_t is an (n x 1) vector of variables observed at time t
f_t is a (r x 1) vector of unobserved state variables
H_t is an (n x r) matrix that links the observed Y_t vector and the unobserved f_t
Z_t is an (m x 1) vector of exogenous predetermined observed variables

5.2. Kalman Filter

The Kalman Filter is a recursive procedure used for computing the optimal estimates of the unobserved vector $f_t,\ t = 1,2,\dots,T$. It provides a minimum mean squared error estimate of f_t based on appropriate information set (Kim and Nelson, 1999). Depending on the information set available, there are two ways of estimating f_t – using the basic filter and smoothing. The basic filter refers to an estimate of f_t based on information available up to time *t* while smoothing gives an estimate of f_t based on all the available information in the sample through *T*.

Kalman filter consists of two steps: prediction and updating. Prediction is the optimal forecasting of y_t given available information up to *t-1*. In this step we estimate $f_{t|t-1}$, while updating is the reassessment of this estimate since at time *t*, $y_t$has been realized and prediction error can now be computed (i.e. $\eta_{t|t-1} = y_t - y_{t|t-1}$) which will give us new information about the unobserved variable f_t An inference on f_t using information until time *t* can be represented as $f_{t|t} = f_{t|t-1} + K_t \eta_{t|t-1}$, where K is the weights assigned to new information about f_t contained in the prediction error. To formally illustrate the process, we introduce the following equations:

Prediction Stage

$$f_{t|t-1} = \tilde{\mu} + F f_{t|t-1} \qquad (9)$$
$$P_{t|t-1} = F P_{t-1|t-1} F' + Q \qquad (10)$$
$$\eta_{t|t-1} = y_t - y_{t|t-1} = y_t - x_t f_{t|t-1} \qquad (11)$$
$$g_{t|t-1} = x_t P_{t|t-1} x' + R \qquad (12)$$

Updating Stage

$$f_{t|t} = f_{t|t-1} + K_t \eta_{t|t-1} \qquad (13)$$
$$P_{t|t} = P_{t|t-1} - K_t x_t P_{t|t-1} \qquad (14)$$

where $K_t = P_{t|t-1} x_t{}' f_{t|t-1}^{-1}$ (15)

$f_{t\|t-1} = E[f_t\|\psi_{t-1}]$	Expectation (estimate) of f_t conditional on information up to *t-1*
$P_{t\|t-1} = E[(f_t - f_{t\|t-1})(f_t - f_{t\|t-1})']$	Covariance matrix of f_t conditional on information up to *t-1*
$f_t = E[f_t\|\psi_t]$	Expectation (estimate) of f_t conditional on information up to *t*
$P_t = E[(f_t - f_{t\|t})(f_t - f_{t\|t})']$	Covariance matrix of f_t conditional on information up to *t*
$y_{t\|t-1} = E[(y_t\|\psi_{t-1})] = x_t f_{t\|t-1}$	Forecast of y_t given information up to time *t-1*
$\eta_{t\|t-1} = y_t - y_{t\|t-1}$	Prediction error
$g_{t\|t-1} = E[\eta_{t\|t-1}^2]$	Conditional variance of the prediction error
$f_{t\|T} = E[f_t\|\psi_T]$	Expectation (estimate) of f_t conditional on the information up to T (the whole sample)
$P_{t\|T} = E[(f_t - f_{t\|T})(f_t - f_{t\|T})']$	Covariance matrix of f_t conditional on information up to T (the whole sample)

VI. Empirical Results

6.1. Monthly Economic Indicators

A large number of monthly financial, economic and industry indicators were collected from various sources (BSP, NSCB, BAS, IMF, BLOOMBERG) for the period January 2000 to December 2009 (total of 120 months). Originally, there were 46 series collected for the study, the selection process was guided by the current LEIS and some economic theories suggesting underlying relationship among the series to the economic activity in the Philippines. From 46 economic series, the number was reduced to 31 due to the several problems, such as large number of missing observations. The 31 selected indicators are:

1. Gross international Reserves (GIR), Foreign assets that are readily available to and controlled by the BSP for direct financing of payments imbalances and for managing the

magnitude of such imbalances; consists of gold, special drawing rights (SDR), foreign investments and foreign exchange

2. OFW Remittances (REMITTANCES), Cash remittances coursed through commercial banks of sea-based and land-based Overseas Filipino Workers (OFWs)

3. PESO/USD rate (FX_RATE), Guiding rate for the exchange of one US Dollar for Peso; computed as the weighted average of all foreign exchange transactions done through the Philippine Dealing System

4. PESO/EUR rate (PESO_EURO), Guiding rate for the exchange of one US Euro for Peso; weighted average

5. PESO/SGD rate (PESO_SGD), Guiding rate for the exchange of one Singapore Dollar for Peso; weighted average

6. PESO/YEN rate (PESO_YEN), Guiding rate for the exchange of one Japanese Yen for Peso; weighted average

7. LIBOR 3MONTHS (LIBOR_3M), London Inter-bank Offered Rate; rate at which banks in London offer Eurodollars in the placement market

8. SIBOR 3 MONTHS (SIBOR_3M), Singapore Inter-bank Offered Rate; rate at which banks in Singapore offer Eurodollars in the placement market

9. Treasury Bill Rates (91-day) TBILL91_1, Rate on short-term debt instrument issued by the National Government for the purpose of generating funds needed to finance outstanding obligations; come in maturities of 91,182 and 364. For the purpose we chose the 91 and 364-day maturity Treasury bill rates.

10. Treasury Bill Rates (364-dayTbill rates), TBILL364_1

11. Time Deposit Rates (Short-term rates) TDRATE_ST_SA, Weighted average interest rate charged on interest-bearing deposits with fixed-maturity dates and evidenced by certificates issued by banks; can be short-term or long-term

12. Savings Deposit Rate (DEPORATE_SAVINGS_SA), Rate charged on all interest-bearing deposits of banks, which can be withdrawn anytime; derived as the ratio of the interest expense on peso deposit of reporting commercial banks to the total outstanding level of these deposits

13. Total Revenues (REVENUES_SA),

14. Total Expenditures (EXPENDITURES_SA), Consists of expenditures in the form of interest expense on domestic and foreign borrowings; current operating expenditures, e.g., salaries and wages, bonuses, hospitalization expenses etc.

15. Consumer Price Index (CPI), General measure of the average monthly and annual changes in the retail prices of commodities commonly purchased by households reckoned from a base year and weighted by the consumption pattern or basket of the household

16. Wholesale Price Index (WPI), Indicator designed to measure monthly changes in the general price level of commodities that flow into the wholesale trade intermediaries in the Philippines; measures price changes during trade turnover

17. Manufacturing Sector (Volume of Production Index -VOPI)MAN_VOPI_SA, Derived by dividing the VAPI by the Producer's Price Index (PPI) with 1992 as the base year; change in the volume of manufacturing production

18. Philippine Stock Exchange Index (PSEI), Serves as a measure of the changes in, and the movements of, the average prices of company shares of stock traded in the Philippine Stock Exchange (PSE)

19. Import (IMPORTS_SA), Import covers all goods in which ownership has been transferred from non-residents to Philippine resident through purchase, grants, gifts and donations

20. Export (EXPORTS_SA), Export covers all goods in which ownership has been transferred from Philippine residents to nonresidents through sales, grants, gifts and donation

21. Visitor Arrival (V_ARRIVAL), Visitor - Any person traveling to a place other than that of his/her usual environment for less than 12 months and whose main purpose of trip is other than the exercise of an activity remunerated from within the place visited. (NSCB Resolution No. 11 Series of 2003)

22. Sale of Major Appliances (SALE_APPLIANCE)

23. Hotel Occupancy Rate (HOTEL_OCCUPANCY), Number of rooms occupied for the month over the number of rooms available for sale for the month. Hotel occupancy rate as used in the LEI covers that of Metro Manila hotels only. The monthly hotel occupancy rate is computed as the overall average of the hotel occupancy rates of the four classes of hotels, namely, De Luxe Class, First Class, Standard Class and Economy Class.

24. Number of OFW deployed (OFW_DEPLOYED)

25. US Interest Rate (RATE_USA)

26. Singapore Interest Rate (RATE_SING)

27. Hong Kong Interest Rate (RATE_HK)

28. Average Retail Price of Rice (RS_RICE)

29. Volume of Palay (VOLUME_PALAY_SA)

30. Dubai Crude (DUBAICRUDE_SA)

31. Money Supply (M2) M2_IMF_SA

6.2. Tests for Presence of Unit Root(s) and Seasonality

Tests for presence of unit root and seasonality are performed on the 31 economic indicators. For the unit root test, the Augmented Dickey-Fuller (ADF) test is employed. The Dickey Fuller test statistic is derived from the estimation of the 1st order Auto Regressive model,

$$y_t = \rho y_{t-1} + \varepsilon_t,\ \ \varepsilon_t \sim WN(0, \sigma_\varepsilon^2) \qquad (16)$$

Note that if ρ = 1, then y_t is a random walk (unit root process), while if |ρ| < 1, the process is a stationary AR(1). Subtracting y_{t-1} to both sides of the equation (16),

$$\begin{aligned} y_t - y_{t-1} &= \rho y_{t-1} - y_{t-1} + \varepsilon_t \qquad (17) \\ \Delta y_t &= (\rho - 1) y_{t-1} + \varepsilon_t \end{aligned}$$

Thus, the hypotheses are, $H_0 = \rho - 1 = 0$ *vs.* $H_a : \rho - 1 < 0$

H_0: unit root (non-stationary) vs. H_a: 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,

$$\Delta y_t = \alpha^* + \delta^* t + (\rho - 1) y_{t-1} + \phi_1 \Delta y_{t-1} + \ldots + \phi_p \Delta y_{t-p} + \varepsilon_t \qquad (18)$$

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 maybe) is then applied. Test for presence of seasonality is done using regression based test with indicator variables for the months. If there is seasonality, the seasonal adjustment using CENSUS-X12 is then performed. The summary of the results of the tests for unit root and seasonality are presented in tables 1 and 2 below.

Table 1. Results from the ADF test for Unit Root(s)

	Series	ADF Test Stat	P-value	Remark
1	CPI	-2.415	0.370	I(1)
2	FX RATE	-2.716	0.232	I(1)
3	PSEi	-1.997	0.597	I(1)
4	RATE_USA	-1.693	0.748	I(1)
5	RATE_HK	-2.708	0.236	I(2)
6	RATE_SING	-1.799	0.699	I(1)
7	LIBOR_3MONTHS	-1.171	0.911	I(1)
8	SIBOR_3MONTHS	-1.190	0.907	I(1)
9	TDRATE_ST	-3.030	0.129	I(1)
10	DEPORATE_SAVINGS	-2.811	0.197	I(1)
11	PESO_YEN	-1.761	0.717	I(1)
12	PESO_EURO	-1.700	0.746	I(1)
13	PESO_SGD	-2.550	0.304	I(1)
14	EXPORTS	-3.086	0.114	I(1)
15	IMPORTS	-3.232	0.083	I(1)
16	DUBAICRUDE	-4.754	0.001	I(0)
17	M2_IMF	-1.895	0.651	I(1)
18	V_ARRIVAL	-2.602	0.281	I(2)
19	WPI	-3.940	0.013	I(0)
20	GIR	1.687	1.000	I(1)
21	TBILL_91	-3.105	0.110	I(1)
22	TBILL_364	-3.187	0.092	I(1)
23	REVENUES	-1.191	0.907	I(1)

24	EXPENDITURES	0.399	0.999	I(1)
25	SALE_APPLIANCE	-2.075	0.554	I(2)
26	OFW_DEPLOYED	-1.490	0.827	I(1)
27	REMITTANCES	-2.818	0.194	I(1)
28	HOTEL_OCCUPANCY	-0.564	0.979	I(1)
29	MAN_VOPI	-3.551	0.039	I(0)
30	RS_RICE	-3.440	0.051	I(1)
31	VOLUME_PALAY	-2.379	0.388	I(1)

Table 2. Summary of the Test for Seasonality

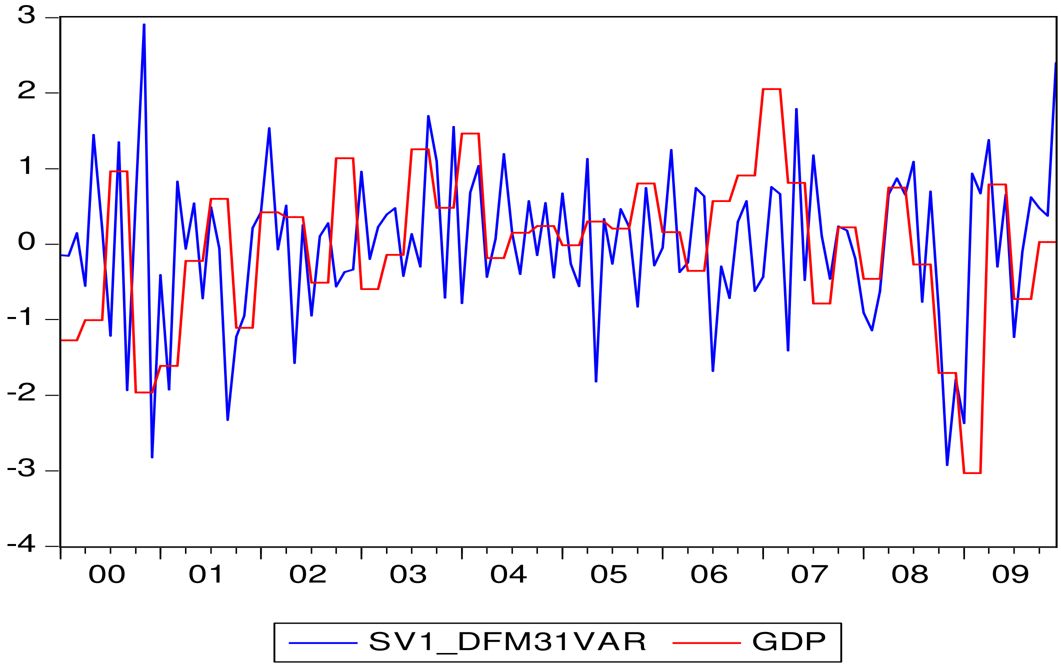
	Series with no seasonality		Series adjusted for seasonality
1	PSEI	11	CPI
2	RATE_USA	12	P/$ EXCHANGE RATE
3	RATE_HK	13	TDRATE_ST
4	RATE_SING	14	DEPORATE_SAVINGS
5	LIBOR_3M	15	PESO_YEN
6	SIBOR_3M	16	EXPORTS
7	PESO_EURO	17	IMPORTS
8	PESO_SGD	18	DUBAICRUDE
9	TBILL_91	19	M2_IMF
10	TBILL_364	20	V_ARRIVAL
		21	WPI
		22	GIR
		23	REVENUES
		24	EXPENDITURES

		25	SALE_APPLIANCE
		26	OFW_DEPLOYED
		27	REMITTANCES
		28	HOTEL_OCCUPANCY
		29	RS_RICE
		30	VOLUME_PALAY
		31	MAN_VOPI

6.3. Extracting the Common Component : Economic Index

In the process of extracting the common component associated with the economic index, three scenarios emerged in this study (1) A Dynamic Factor Model (DFM) applied to the entire 31 variables, denoted by DFM31VAR (2) A DFM applied to the nine series used in the LEIS (DFM9VAR) and (3) A DFM applied to set of variables selected through Principal Component Analysis (DFMPCA). Recall that the economic index from the LEIS has 11 series. Due to the limitations on the availability of the data, two of these series were not included in the DFM – (a) the total energy consumption and (b) number of new business incorporated. The specification of the DFM in the three scenarios, defined in equations (4) to (6), is AR(1) for both the unobservable common components (f_t) and idiosyncratic component, u_{it}.

The plots of the Common Components extracted from each DFM are given below, together with the quarterly change in GDP. In the plots, GDP quarterly change is mapped with the monthly change of the common components (SV1s).


3
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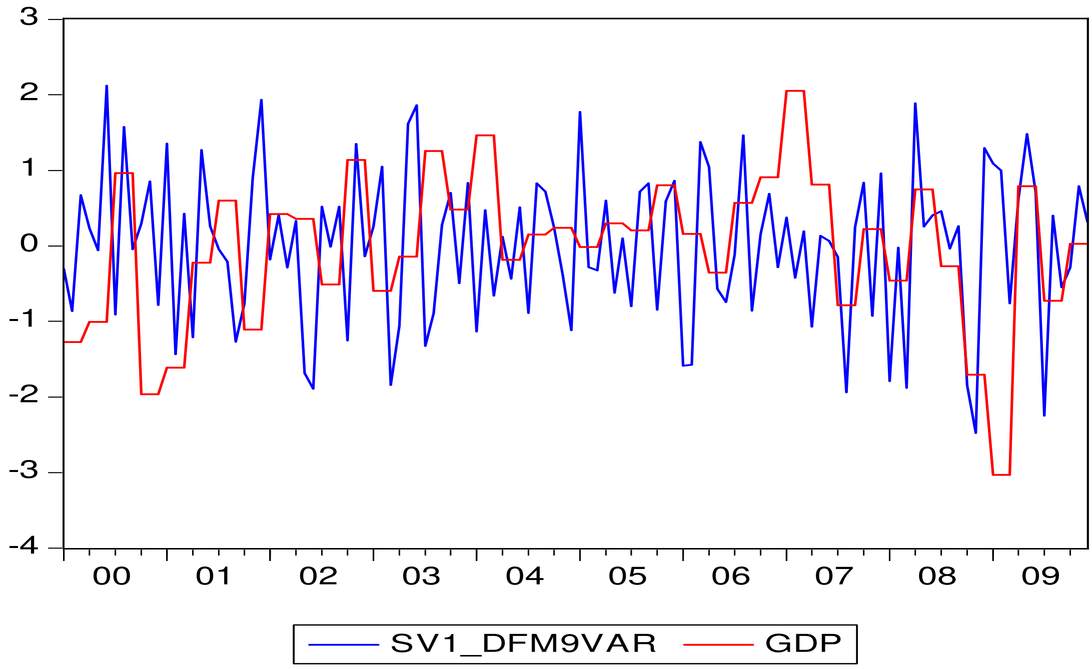
SV1_DFM31VAR
GDP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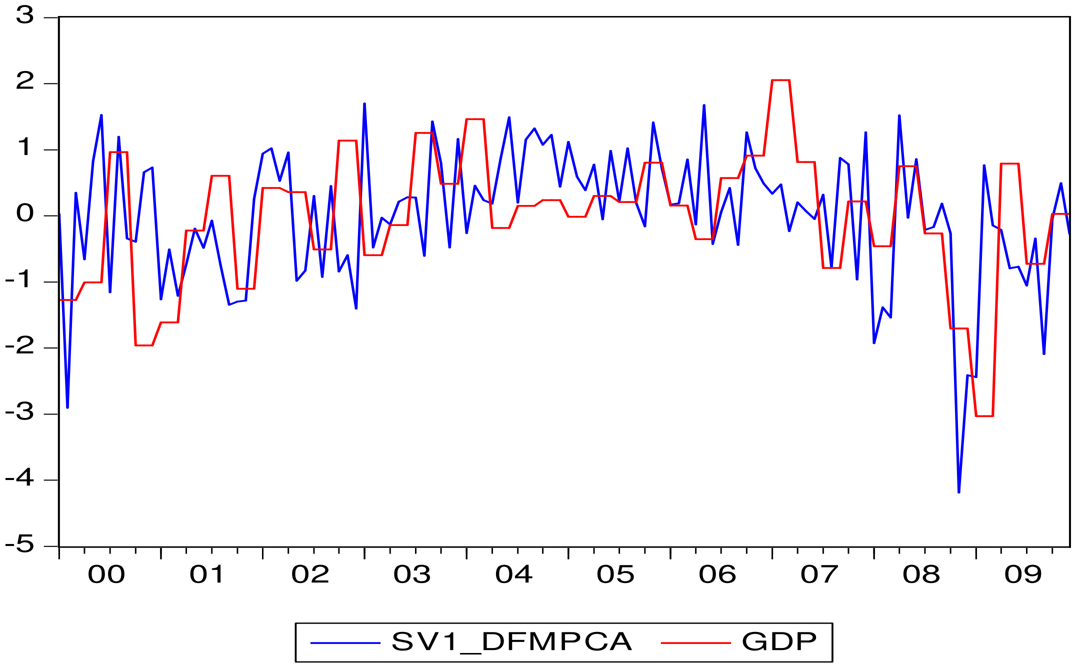
SV1_DFM9VAR
GDP



An in-sample evaluation of the forecasting performance of the three models is done using the models' prediction power. A correct prediction occurs when the common component is able to correctly predict the movement of the current quarter GDP otherwise, we have an incorrect prediction. Note that the extracted economic index extracted from DFM predicts the movement of the GDP and not its actual level. The evaluation is made using the entire data from January 2000 to December 2009 and years considered as *crisis periods* – 2000 to 2001 and 2008 to 2009. The results of the comparison are given in tables 3 and 4.

Table 3. In-Sample Evaluation of Models Performance (January 2000 to December 2009)

2000-2009	DFM31VAR	DFM9VAR	DFMPCA	NSCB LEIS
Correct Prediction	80%	74%	69%	69%
Incorrect Prediction	20%	26%	31%	31%

Table 4. In-Sample Evaluation of Models Performance (January 2000 to December 2009)

2000-2001 & 2008-2009	DFM31VAR	DFM9VAR	DFMPCA	NSCB LEIS
Correct Prediction	67%	67%	40%	45%
Incorrect Prediction	33%	33%	60%	55%

The DFM31VAR has the highest percentage of quarters in the sample correctly predicted, at about 80%, followed by DFM9VAR at 74%, the PCA-DFM model and the NSCB-LEIS both have about 69% correct prediction. During the crisis periods (2000 to 2001 and 2008 to 2009), the DFM performed better in predicting the actual movement of the GDP with the DFM31VAR and DFM9VAR as the leading models with about 67% correct prediction. The NSCB LEIS comparable figure is about 45%.

VII. Conclusions

This paper looks at an alternative model for extracting an index of economic activity that can be used to capture the movements of the Gross Domestic Product (GDP). The Dynamic Factor Model is a promising tool in extracting an index of overall economic activity. The results, using 31 monthly economic series, showed that an economic index extracted using the DFM, captures the movement relatively better when compared with the current economic index (LEI) computed by the NSCB. Given that the DFM is using high frequency data, the common component extracted using the DFM can be used to *nowcast* movements in the current-quarter GDP. The DFM is a useful tool that should be considered by the researchers who are interested in studying movements in the overall economic activity.

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