Conference Proceeding Issue Published in International Journal of Trend in Research and Development (IJTRD), ISSN: 2394-9333, www.ijtrd.com

Tracking the Business Cycle of Thailand using the Stacking Approach

Masaru CHIBA[a],
[a]Faculty of Environmental and Information Sciences, Fukui University of Technology, Fukui, Japan

Abstract: This paper proposes a multivariate bandpass filter based on the trend, cycle, and seasonality decomposition model. Cycle shifts for individual time series are incorporated as part of the multivariate model. The inclusion of leading, coincident, and lagging variables for the measurement of the business cycle is therefore possible without prior analysis of lead-lag relationships between economic variables. In addition, we explore a stacking approach that is specified by means of a low-frequency time index. In this approach, no artificial missing values are needed and also no information is lost about the high-frequency series and their dynamic features. Our approach is illustrated in detail for business cycle tracking of Thailand.

Keywords: *Business Cycle; Bandpass Filter; State-Space Model;*

I. INTRODUCTION

Designing fiscal and monetary policies requires a clear economic picture of the state of the economy. To avoid a solely judgment-based procedure, one should be able to extract the relevant information through a statistically rigorous method. A business cycle indicator aims to present deviations from a long-term trend in economic activity. When considering trends, cycles, and seasonalities in multivariate time series, we need to focus on possible lead-lag relationships between variables and the business cycle. Therefore, we incorporate the phase-shift mechanism of Rünstler [1] for individual cycles with respect to the base cycle modelled as the generalized cycle component of Harvey and Trimbur [2].

In addition, policy decision makers need a business cycle indicator despite the fact that time series information is usually not available at the desired frequency. But information recorded at a lower frequency must not be discarded. Therefore, we consider a new approach based on ideas developed for periodic systems in the control engineering literature; see Bittanti and Colaneri [3]. The main idea is to formulate the model with a lower frequency time index and collect the observations for a higher frequency variable in a vector. Then, different frequency series can be formulated with a lower time index simultaneously.

Furthermore, we implement the proposed multivariate model-based bandpass filter for business cycle tracking of Thailand. By pooling information from seven key economic variables (including GDP, manufacturing production, retail sales, confidence indicators, and others), it obtains a business cycle indicator in line with common wisdom regarding Thailand's developments.

II. THE MODEL

In this paper, assume that a panel of N economic time series in the $N \times 1$ vector y_t and that we observe T data points over time, that is, $t = 1, 2, \ldots, T$. The nth element of the observation vector at time t is denoted by y_{nt}.

A. Trend, cycle, and seasonality

The basic unobserved components time series model for measuring the business cycle from a panel of economic time series is based on the decomposition model

$$y_{nt} = \mu_{nt} + \delta_n c_t + s_t + u_{nt}, \quad (1)$$

$$u_{nt} \sim \text{i.i.d.} N(0, \sigma_n^2), \qquad n = 1, \ldots, N.$$

where μ_{nt} is the individual trend component for the nth time series. In addition, c_t, s_t denotes the cycle, seasonal component (common to all time series), respectively. For each series, the contribution of the cycle is measured by the coefficient δ_n. The idiosyncratic disturbance u_{nt} is assumed normal and independent from u_{mt} for $n \neq m$ and/or $t \neq t$. The variance of the irregular disturbance varies for the different individual series.

Each trend component is specified as the local linear trend component, that is,

$$\mu_{nt} = \mu_{n,t-1} + \nu_{n,t-1}, \quad \nu_{nt} = \nu_{n,t-1} + \varepsilon_{nt}, \quad (2)$$

$$\varepsilon_{nt} \sim \text{i.i.d.} N(0, \omega_n^2),$$

where ν_{nt} is the slope of nth trend μ_{nt}. The cycle component can be specified as an autoregressive model with polynomial coefficients that have complex roots, that is,

$$\begin{bmatrix} c_t \\ c_t^* \end{bmatrix} = \phi \begin{bmatrix} \cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda \end{bmatrix} \begin{bmatrix} c_{t-1} \\ c_{t-1}^* \end{bmatrix} + \begin{bmatrix} \omega_t \\ \omega_t^* \end{bmatrix} \quad (3)$$

$$\begin{bmatrix} \omega_t \\ \omega_t^* \end{bmatrix} \sim \text{i.i.d.} N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \varpi^2 & 0 \\ 0 & \varpi^2 \end{bmatrix} \right)$$

The damping term $0 < \phi \leq 1$ ensures that the cycle series is stationary process. The period of the cycle is defined as $2\pi / \lambda$, where $0 \leq \lambda \leq \pi$ is approximately the frequency at which the spectrum of the cycle has the largest mass.

To model the seasonal component, suppose there are S "month"per "year". Thus for monthly data $S = 12$, for quarterly data $S = 4$. If the seasonal pattern is constant over time, the seasonal values for 1to S can be modeled by the constants $s_1, s_2, \ldots, s_S$ where $\Sigma s_p = 0$. From this relation, the seasonal component can be specified as a restricted autoregressive model of order $S - 1$, that is,

$$s_t = -\sum_{p=1}^{S-1} s_{t-p} + e_t, \qquad e_t \sim \text{i.i.d.}N(0, \varphi^2). \quad (4)$$

B. Phase shifts of the cycle

In the model (1), (2), (3), and (4), only economic time series with coincident cycles are viable candidates for inclusion into the model. Prior analysis may determine whether including leads or lags of economic variables is appropriate.

To avoid such a prior analysis, we adopt the phase-shift mechanism for a multivariate cycle specification as proposed byRünstler [1]. For a cycle component (3), it follows from a standard trigonometric identity that the cycle is shifted ξ to the right (when $\xi > 0$) or to the left (when $\xi < 0$) by considering $\cos(\lambda \xi) c_t + \sin(\lambda \xi) \tilde{c}_t$.

The shift term ξ is measured in real time, so that ξ is measured in radians, and due to the periodicity of trigonometric functions, the parameter space of ξ is restricted within the range $-\pi / 2 < \lambda \xi < \pi / 2$. This treatment allows the exploitation of information contained in both lags and leads of variables for computing the cycle indicator, and it overcomes the restriction of using only coincident variables. The shifted cycle is introduced in the model by replacing (1) with

$$y_{nt} = \mu_{nt} + a_n c_t + b_n \tilde{c}_t + s_t + u_{nt}, \quad (5)$$

$$a_n = \delta_n \cos(\lambda \xi_n), \qquad b_n = \delta_n \sin(\lambda \xi_n),$$

Further, we assumed that the first equation of (5) identifies the base cycle and thus $\delta_1 = 1$ and $\xi_1 = 0$, so that

$$y_{1t} = \mu_{1t} + c_t + s_t + u_{1t}.$$

Then, c_t coincides contemporaneously with y_{1t}. The restriction $\xi_1 = 0$ allows the cycles of other variables to shift with respect to the cycle of y_{1t}.

C. The mixed-frequency model

Finally, we show how the stacking approach can be used to simultaneously model variables with different frequencies. Here, for the sake of simplicity, we assume that the quarterly observed series y_1 and monthly observed series y_2 are decomposed by the trend, cycle, and irregular components. Then, the simultaneous process for y_{1t} and y_{2t} can be described as follows:

$$\begin{bmatrix} y_{1t} \\ y_{2t}^{(1)} \\ y_{2t}^{(2)} \\ y_{2t}^{(3)} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & a_2 & b_2 \\ 0 & 1 & 0 & 0 & a_2 & b_2 \\ 0 & 1 & 0 & 0 & a_2 & b_2 \end{bmatrix} \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \\ \nu_{1t} \\ \nu_{2t} \\ c_t \\ \tilde{c}_t \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t}^{(1)} \\ u_{2t}^{(2)} \\ u_{2t}^{(3)} \end{bmatrix} \quad (6)$$

$$\begin{bmatrix} u_{1t} \\ u_{2t}^{(1)} \\ u_{2t}^{(2)} \\ u_{2t}^{(3)} \end{bmatrix} \sim \text{i.i.d.}N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 \\ 0 & 0 & \sigma_2^2 & 0 \\ 0 & 0 & 0 & \sigma_2^2 \end{bmatrix} \right).$$

Similarly, the dynamics of trend and cycle components employed here are defined as

$$\begin{bmatrix} \mu_{1t} \\ \mu_{2t} \\ \nu_{1t} \\ \nu_{2t} \\ c_t \\ \tilde{c}_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & a & b \\ 0 & 0 & 0 & 0 & -b & a \end{bmatrix} \begin{bmatrix} \mu_{1,t-1} \\ \mu_{2,t-1} \\ \nu_{1,t-1} \\ \nu_{2,t-1} \\ c_{t-1} \\ \tilde{c}_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \omega_t \\ \tilde{\omega}_t \end{bmatrix} \quad (7)$$

$$\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \omega_t \\ \tilde{\omega}_t \end{bmatrix} \sim \text{i.i.d.}N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \omega_1^2 & 0 & 0 & 0 \\ 0 & \omega_2^2 & 0 & 0 \\ 0 & 0 & \omega_2^2 & 0 \\ 0 & 0 & 0 & \omega_2^2 \end{bmatrix} \right).$$

In this approach, the monthly series y_2 and its irregular component u_2 are transformed into three quarter time series, each containing observations for, respectively, the first, second or third month of the quarter, that is $y_{2t}^{(i)}, u_{2t}^{(i)}$, with index t indicating the number of quarter and index i indicating the number of month within the quarter t.

The mixed-frequency model discussed above falls within the class of multivariate structural time series models that can be cast in *state-space system*. In this system, (6), (7) is called *a observation equation*, *a transition equation*, respectively. Then, the signal extraction of unobserved components is carried out by the Kalman filter and associated smoothing methods. For a detailed discussion of the algorithms, seeDurbin and Koopman [4].

III. EMPIRICAL ANALYSIS

A. Description of data

Along with remarkable economic developments in Southeast Asia, capturing the cycle and growth dynamics is becoming more important for policy decision makers. Hence, we apply the proposed model to the Thailand's economic data. We use quarterly and monthly data of seven key variables during 2001/01~2016/03 (2001Q1~2016Q1). Table 1 gives a complete list of their labels, units, and other definitions.

Table1: The labels and definitions of the economic variables in Thailand

Variable	Description	[1]Unit
GDP	Real Gross Domestic Product	THB (Million)
INC	Personal income less transfer payments	THB
CCI	Consumer confidence index	Index (2003=100)
MP	Manufacturing production index	Index (2011=100)
UER	Unemployment rate	%
RS	Retail sales	Index (2002=100)
IRS	Interest rate spread	% (AR)

[1]The third column means the unit of variables: THB, AR means Thai Baht, Annual Rate, respectively.

Variable	Frequency	[2]SA	Source
GDP	Quarterly	No	Bank OfThailand
INC	Quarterly	No	tradingeconomics.com
CCI	Monthly	No	University of the Thai Chamber of Commerce
MP	Monthly	No	Bank OfThailand
UER	Monthly	No	Bank OfThailand
RS	Monthly	No	Bank OfThailand
IRS	Monthly	—	International Monetary Fund

[2]SAmeans whether each variable is seasonally adjusted (SA) or not.

B. Estimation results

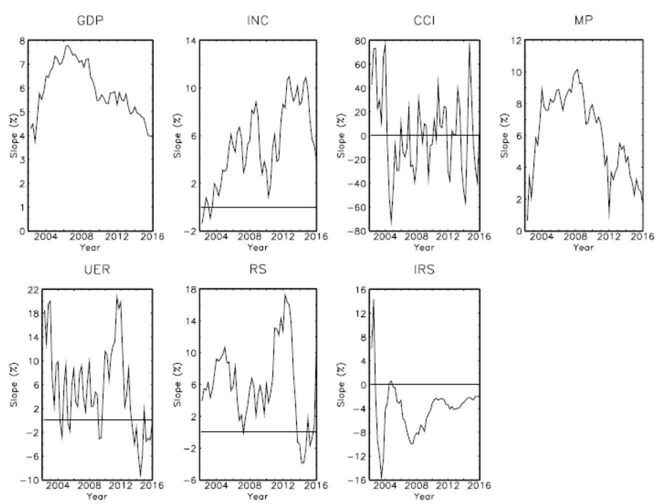

Fig.1: Slope of the each trend component

From Fig. 1, we find that the slope of GDP picked up from 2003 to 2006; The value of slope in this period is between 4% and 8%. This result is owing to a relatively weak baht encouraging exports, increased domestic spending as a result of several mega projects, and incentives of Prime Minister Thaksin Shinawatra, known as Thaksinomics. However, with the instability surrounding major 2010 protests, the slope of GDP settled at around 5%. After that, the economy rebound to around 6% in 2012. This due to the monetary policy of BOT, as well as a package of fiscal stimulus measures introduced by the former Yingluck Shinawatra government. However, following the Thai military coup of 22 May 2014, the slope of GDP tends to decrease to 4%.

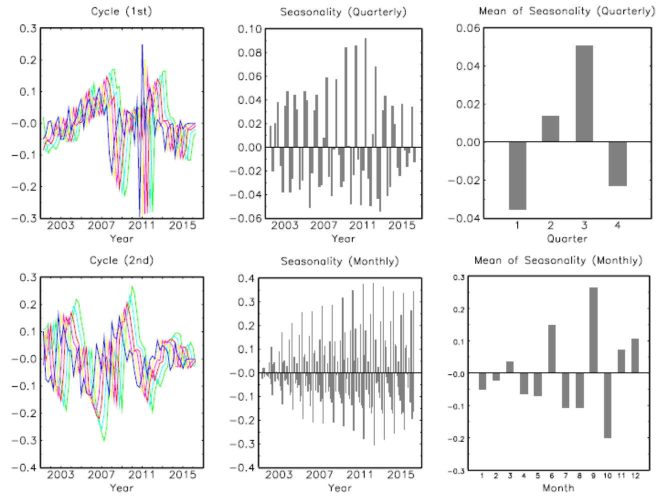

Fig.2: Cycle and seasonal components

Thailand is divided into three seasons. The first is the rainy season which prevails over most of the country. This season is characterized by abundant rain with August and September being the wettest period of the year. Winter starts from October until February. Summer season runs from February until May and is characterized by warmer weather. Such climates have a significant effect on the cycle and seasonal components.

For example, in 2011, Thailand encountered the worst floods crisis in 70 years. The economy was broadly affected, experiencing a temporary halt in some production sectors. As a result, the cycle in 2011Q4 was significantly downturned.Shift parameter x in Table 2 suggests that IRS, CCI, MP and RS are leading variables and that UER and INC are lagging variables. From volatile parameter w, we find that the trend of CCI has the highest volatility. In addition, from Table 3, we find that GDP, MP, RS and IRS are mainly affected by the cycle component.

Table2:[1]Estimation results

Variable	d	x	s (%)	w (%)
GDP	1	0	*3.58* (0.31)	*0.31* (0.03)
INC	*0.26* (0.09)	*-2.83* (0.60)	*11.13* (0.95)	*1.48* (0.13)
CCI	*2.45* (0.09)	*2.68* (0.61)	*21.22* (1.82)	*34.78* (2.98)
MP	*3.34* (0.09)	*0.72* (0.68)	*18.80* (1.61)	*0.79* (0.07)
UER	*0.98* (0.09)	*-2.08* (0.64)	*43.90* (3.76)	*3.75* (0.32)
RS	*2.15* (0.09)	0.54 (0.68)	*11.58* (0.99)	3.02 (0.26)
IRS	*5.76* (0.09)	*8.00* (0.00)	*26.10* (2.23)	0.53 (0.05)

[1]The corresponding standard errors are in parentheses.Values in italic represent not significant at the 5% level.

Table3:[1]Relative importance of trend, cycle, and irregular components (%)

Variable	Trend	Cycle	Irregular
GDP	2.65	*67.11*	30.24
INC	10.08	13.91	*76.01*
CCI	*46.07*	25.83	28.10
MP	1.72	*57.54*	40.74

UER	6.76	14.06	*79.17*
RS	9.51	*53.99*	36.50
IRS	0.73	*63.25*	36.02

[1]Values in italic represent represent the most impotant component.

CONCLUSIONS

In this paper, we propose a multivariate approximate bandpass filter that incorporates three relevant contributions: (i) the inclusion of a particular cycle component that has properties similar to those of bandpass filtered series, (ii) the incorporation of phase shifts within the cycle, (iii) the stacking approach that permits the inclusion of mixed frequency data. The resulting filter is useful for extracting the essential features in Thailand.

References

[1] G, Rünstler, "Modelling Phase Shifts Among Stochastic Cycles,'' Econometrics Journal, Vol. 7, No. 1, pp.232-248, June 2004.

[2] A. C. Harvey and T. Trimbur, "Generalised Model-Based Filters for Extracting Trends and Cycles in Economic Time Series", Review of Economics and Statistics, Vol. 85, No. 2, pp.244-255, May 2003.

[3] S. Bittanti and P. Colaneri, Periodic Systems: Filtering and Control, Springer-Verlag, Oct 2009.

[4] J. Durbin and S. J. Koopman, Time Series Analysis by State Space Methods, 2nd ed, Oxford University Press, Aug 2012.