

Use of Dynamic Factor Model to Analyze Annual Inflation Data from Twelve Asian Countries

V. Pathmanathan and S. Samita¹

Postgraduate Institute of Agriculture
University of Peradeniya
Peradeniya, Sri Lanka.

ABSTRACT. *In general, time series analysis requires the series to be stationary and with no missing values. The univariate structural time series provides reasonable solutions to the above problems. However, univariate structural time series cannot provide a basis to detect common patterns among multivariate time series. The Dynamic Factor Model (DFM) provides solutions to the above problems. In addition, effects of some explanatory variables on multivariate time series can also be investigated using DFM. Inflation data from twelve Asian countries from 1975 to 2001 was used in this paper to illustrate the use of DFM to identify common trends in the above twelve time series. The analysis showed that there was one common trend (pattern) in all series and inflation was affected by either or both money supply and exchange rate in certain countries.*

INTRODUCTION

Time series analysis is often used to identify patterns, such as cyclic and seasonal, for forecasting. Spectral analysis (Priestley, 1981) and wavelet analysis (Shumway and Stoffer, 2000) are commonly used to identify patterns. The techniques, Auto Regressive Integrated Moving Average (ARIMA) (Chatfield, 1989) and Box-Jenkins models (Ljung, 1987) are designed merely for prediction. All these techniques require time series to be stationary with no missing values. In time series analysis the non-stationarity is removed using smoothing techniques. However the removal of this non-stationarity hides the correct behavior of the data.

In actual time series analysis we often deal with several time series simultaneously. In such situations one might want to study whether all time series are behaving similarly. The standard time series analysis as well as univariate structural time series do not provide solutions to this problem, due to the fact that in all these methods, each time series is modeled separately. One other limitation with a separate model for each time series is that model validation has to be carried out separately.

The univariate structural time series, suggested by Harvey (1989) introduced a new approach to time series analysis. This method provides a basis of incorporate explanatory variables into time series models. In addition, this method does not have stationarity requirement and it can also handle missing values. The Dynamic Factor Model (DFM) suggested by Harvey (1989), Molenaar et.al (1992) Pena and Poncela (1999) can rectify the above two limitations. This paper illustrates how DFM can effectively be used in multivariate time series analysis using inflation data from twelve Asian countries.

¹ Department of Crop Science, Faculty of Agriculture, University of Peradeniya, Peradeniya, Sri Lanka

MATERIALS AND METHODS

Secondary Data

Annual Consumer price index (a measure of inflation), exchange rate and money supply extracted from the reports of International Financial Statistics (IFS, 1999- 2002) for the twelve countries, *VIZ*, Bangladesh, Fiji, India, Indonesia, Korea, Malaysia, Nepal, Pakistan, Philippines, Sri Lanka, Singapore, and Thailand, for the period 1975 to 2001 were used for the study. The consumer price indices from twelve countries were considered as the multivariate time series (multivariate response) and, the money supply and exchange rate were considered as explanatory variables.

Dynamic Factor Model (DFM)

In general DFM is of the form (Harvey, 1989; Zuur, 2003),

$$y_t = \Gamma\alpha_t + \mu + \beta x_t + e_t \quad (1)$$

where y_t is a $N \times 1$ vector containing the values of N time series at time t , μ is a $N \times 1$ vector containing level parameters, α_t is a $M \times 1$ vector representing the values of M common trends (factors from response time series variables) at time t , Γ is a $N \times M$ matrix containing the factor loading from M common trends, β is a $N \times k$ matrix containing regression coefficients, x_t is $k \times 1$ vector containing factor scores from explanatory variables and e_t is a $N \times 1$ noise component [$e_t \sim N(0, R)$]. The covariance matrix of the residuals, R could be diagonal, positive - definite, symmetric or non - diagonal. Off diagonal elements of R represent the joint information (covariance) of time series variables, which cannot be explained with the other terms (explanatory variables and common trends).

The Γ matrix describes each time series variable (response variables) by means of a linear combination of the common trends. The magnitude of factor loading infer which common trends are important to describe a particular response variable, and which group of response variables are related to the same common trend. The trends here represent the underlying common patterns over time and can be formulated as,

$$\alpha_t = \alpha_{t-1} + f_t \quad (2)$$

where $f_t \sim N(0, Q)$ and f_t is independent of e_t . If the corresponding diagonal element of Q is relatively small the contribution of the error component is likely to be small for all t , and the trend will be a smooth curve. If diagonal elements are relatively large, the trend will show more variation. Hence, the trends are smoothing functions over time and are independent of each other. The effects of k explanatory variables are included as in the standard linear regression form.

The possible four types of DFM are;

Model Type	Model	R
I	$y_{it} = M$ common trend + level + noise	Diagonal
II	$y_{it} = M$ common trends + level + explanatory +noise	Diagonal
III	$y_{it} = M$ common trend + level + noise	Non Diagonal
IV	$y_{it} = M$ common trends + level + explanatory +noise	Non Diagonal
	$i=1,2,\dots,N$ $t=1,2,\dots,T$	

Estimation of parameters is carried out with the EM algorithm using the Kalman Filter Smoothing techniques (Harvey, 1989), implemented by using BRODGAR software package.(BRODGAR, 2000).

The model selection can be done based on the statistics by Akaike information criterion (AIC)(Akaike, 1976)). The AIC values for different models can also be obtained using BRODGAR. The software is particularly written for multivariate and multivariate time series analysis.

RESULTS AND DISCUSSION

Different DFMs fitted under the four possible types are given in Table 1. The AIC values for the models containing non diagonal matrix R were smaller. This indicates that there is certain amount of information in the inflation series that cannot be explained by common trends and explanatory variables. However the best-fitted model was judged using stepwise model fitting approach, type I to type IV, in order to identify the best model for each type. For instance AIC value of model 1 to 3 reveals that model 2 as the best fitting model for type I (Table 1). Similarly AIC values of models 4 to 13 reveals model 5 to be the best for type II. Also model 14 is the best for type III and model 21 is the best for type IV. Among the best models for each type, the

Table 1: AIC values for all models applied on the inflation series.

Model Number	M Number of Common Trends	AIC	Explanatory Variables	Error Matrix
1	1	848.728	No	Diagonal
2	2	802.950	No	do
3	3	803.297	No	do
4	1	842.349	Money supply	do
5	2	803.258	do	do
6	3	809.231	do	do
7	1	831.015	Exchange rate	do
8	2	810.633	do	do
9	3	810.390	do	do
10	4	812.268	do	do
11	1	817.578	Money supply & Exchange rate	do
12	2	803.442	do	do
13	3	809.071	do	do
14	1	799.026	No	Non diagonal
15	2	783.840	No	do
16	1	787.018	Money supply	do
17	2	783.470	do	do
18	3	791.484	do	do
19	1	779.009	Exchange rate	do
20	2	783.975	do	do
21	1	777.484	Money supply & Exchange rate	do
22	2	785.085	do	do

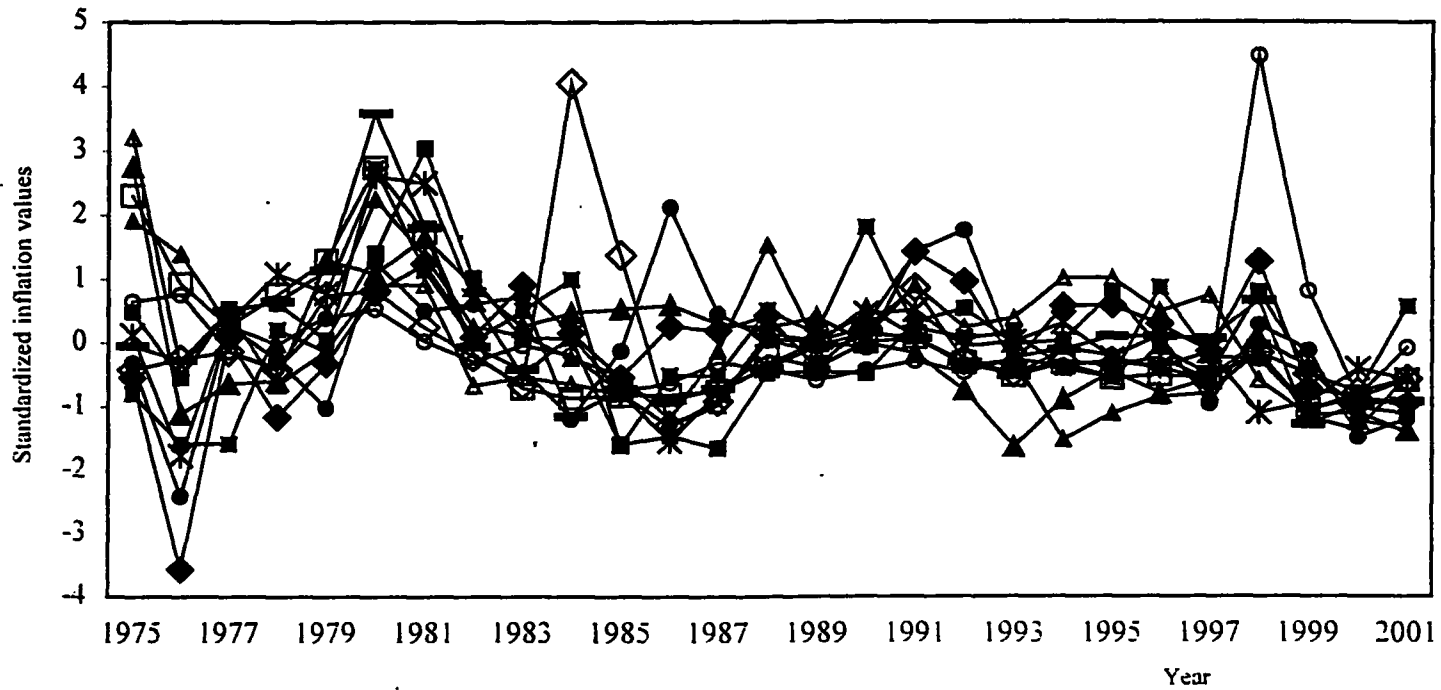


Fig.1. Standardized Inflation time series for twelve asian countries.

◆ India	■ Sri Lanka	▲ Fiji	○ Indonesia
□ Korea	● Nepal	▲ Pakistan	◇ Philippines
* Singapore	— Thailand	■ Malaysia	▲ Bangladesh

best model for the whole data was selected based on minimum AIC. Hence the best fitting model is the model containing one common trend, the money supply and exchange rate as explanatory variables and positive-definite non-diagonal covariance matrix R (Model 21). The graphical presentation of individual inflation series and common trend are given in Figure 1 and Figure 3 respectively.

Parameter estimates for explanatory variables from the best-fitting model are given in table 2. Accordingly, for Korea, Nepal, Malaysia, Singapore, and Thailand, both money supply and exchange rate are moderately related to inflation. Similarly, for Fiji only the exchange rate is related (moderately) to inflation.

Table 2. Estimated regression parameters for money supply and Exchange rate, and level of significance P.

Countries	Money Supply		Exchange rate	
	Co efficient	P	Co efficient	P
Ind	-0.33 (0.41)	0.29	0.60 (0.41)	0.13
Sri	0.31 (0.46)	0.32	0.16 (0.46)	0.38
Fiji	-0.18 (0.31)	0.34	0.53 (0.31)	0.09
Indo	0.62 (0.43)	0.14	0.56 (0.43)	0.17
Kore	0.71 (0.26)	0.01	1.37 (0.26)	0.00
Nepa	-0.72 (0.41)	0.08	-0.70 (0.41)	0.09
Paki	-0.06 (0.44)	0.40	0.34 (0.45)	0.30
Phil	-0.53 (0.42)	0.18	-0.34 (0.42)	0.29
Sing	0.73 (0.41)	0.08	0.98 (0.41)	0.02
Thai	0.99 (0.37)	0.01	1.30 (0.38)	0.00
Mala	0.89 (0.38)	0.03	1.14 (0.38)	0.00
Bang	-0.39 (0.36)	0.25	0.17 (0.36)	0.36

Note: Values in parenthesis are the corresponding standard error of estimates

Ind - India	Kore - Korea	Sing - Singapore
Sri - Sri Lanka	Nepa - Nepal	Thai - Thailand
Fiji - Fiji	Paki - Pakist	Mala - Malaysia
Indo - Indonesia	Phil - Philippine	Bang - Bangladesh

For Fiji, Indonesia, and Korea, factor loadings (Figure 2) from the common trend were smaller than 0.1, the value usually used as the cutoff point in Multivariate time series analysis (Zuur *et al.*, 2003). Thus it can be interpreted, that the inflation in these countries cannot be explained by the common trend.

Therefore it can be interpreted that for countries Malaysia, Thailand, Singapore, inflation series are related to money supply, exchange rate and common trend. Whereas, Inflation series of Korea is related to money supply and exchange rate only. Similarly in Sri Lanka, India, Bangladesh, & Philippines inflation series are not related to both money supply and exchange rate but to the positive common trend only. In Pakistan inflation series is related only to the negative the common trend.

The estimated common trend is presented in Figure 3. The common trend is characterized by a sharp increase from 1975 to 1981. After that it has decreased until 1993. From 1993 to 1994 it has been fairly static. Then from 1994 to 2001 it has increased sharply (Fig. 3).

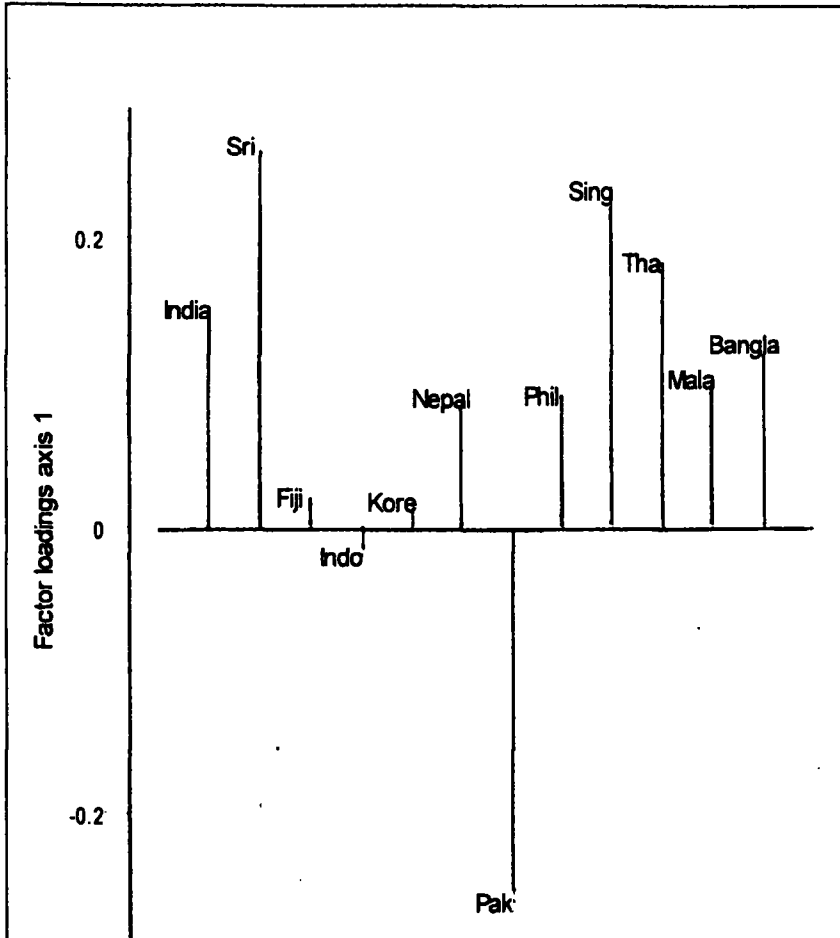


Fig. 2. Factor loadings from the common trend.

India- India	Sri- Sri Lanka	Fiji - Fiji	Indo - Indonesia
Kore- Korea	Nepal -Nepal	Pak - Pakistan	Phil - Philippines
Sing - Singapore	Tha - Thailand	Mala - Malaysia	
Bangla-Bangladesh			

The Middle East war in 1973 which hiked oil prices in Asian Countries could have been the reason for the high inflation during 1975 to 1981. The liberalization of the economy and the hospitable climate in Asian countries have been identified as reasons for the decrease in inflation during 1981 to 1983. Similarly, mismanagement of economies in Asian countries could have been the reason for increase of inflation during 1994 to 2001. (Pablo Bustelo 1998).

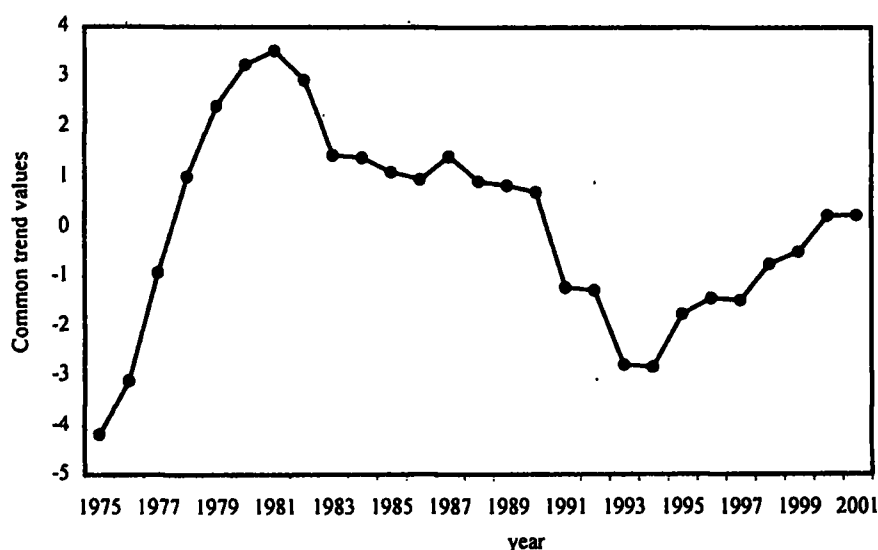


Fig. 3. Common trends from the best fitted model.

The factor loadings of the common trend for the countries India, Sri Lanka Nepal, Philippines, Singapore, Thailand, Malaysia and Bangladesh are more or less same (0.1 to 0.267). This can be due to these countries having a common inflation pattern. Indonesia and Pakistan factor loadings are -0.023 and -0.260 respectively, and thus the inflation patterns in these two countries are different from others.

CONCLUSIONS

The conditions needed to be satisfied in univariate time series are not easy to meet usually. Thus, in reality, univariate time series analysis has limited use. The DFM, as this analysis has shown is an attractive alternative to univariate time series. Dynamic factor analysis applied on the 12 inflation series (in Asian countries) indicated that there is only one underlying common trend. In most Asian countries inflation patterns are similar. In addition the money supply and exchange rate have been found to be related to inflation.

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