COINCIDENT AND LEADING INDICATORS OF THE BARBADIAN BUSINESS CYCLE

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Abstract

This paper constructs coincident and leading indicator indices for the Barbadian business cycle using the Stock and Watson (1989) method and a variant thereof. The results indicate that both procedures seem to provide indices that reflect the reference business cycle fairly well.

Key words: State Space model, Kalman Filter, Business Cycle, Coincident and Leading Indicators

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1. Introduction

An understanding of macroeconomic fluctuations provides an input into forecasting growth and recession phases of an economy, which are necessary ingredients for the formulation of macroeconomic policies. Important tools in this analysis are leading, coincident and lagging economic indicators[2]. These indices have been used in industrialized countries, such as the U.S. and Canada, to understand and forecast the business cycle (see Gaudreault, Lamy and Liu, 2003; Stock and Watson, 1989). For most developing countries, especially the Caribbean islands like Barbados, these indices have not yet been developed. In this paper, an attempt is made to fill this void by establishing coincident and leading indicator indices for Barbados. The approach employed is based on econometric techniques and is due to Stock and Watson (1989), hereafter SW.

The structure of the paper is as follows. Section 2 is a brief review about coincident and leading indicators. Section 3 deals with the economic performance of Barbados. Section 4 presents a chronology of the Barbadian real GDP series. Section 5 discusses the SW method. Section 6 constructs coincident and leading indicators with the SW methodology. Section 7 develops a simplified version of SW approach, and compares these results with those from the SW estimation and section 8 concludes.

2. A Brief Review of the Literature on Coincident and Leading Indicators

The approach to developing cyclical indices originated with the U.S. National Bureau of Economic Research (NBER), pioneered by the work of Burns and Mitchell (1946) in the 1920s and 1930s and extended by economists, notably Moore and Skriskin (1967), in the 1950s and 1960s. These researchers combined a number of economic time series, selected on the basis of various criteria - economic significance, cyclical behaviour, data quality, timeliness and

[2] A coincident indicator is a economic index that generally has the same trend as the business cycle, such as industrial production. Leading indicators are industrial and economic statistics that are considered to rise or fall before the changes in economic growth rates and total business activity. They generally predict the future performance of economy activity six month into the future. A lagging indicator is a statistical measure of a country's activity, which reflects the economic change with a delay of a defined period. For more details see the following website: http://www.aquanto.com/glossary/l.html.

availability - into coincident, leading and lagging economic indices using specific weighted schemes.

In the 1970s and 1980s, this approach spread to Europe and the Organisation for Economic Co-operation and Development (OECD) applied a modified version of the NBER method[3] to its member countries.

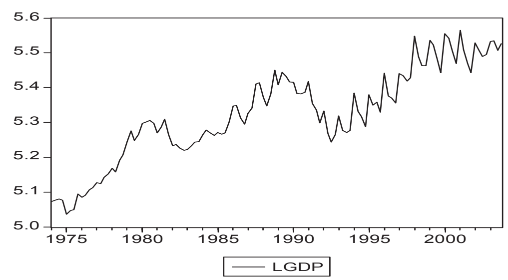
However, the selection and weighting processes of the NBER cyclical indicator procedure remained unchanged until Stock and Watson (1989) developed a new system of composite indices of coincident and leading indicators, as well as a recession index for the United States, using modern econometric techniques. The composite coincident economic index is based on econometric models that depict the state of the economy as an unobserved variable, which is common to several macroeconomic variables. Then, instead of utilising a weighted average of leading indicators as done in the NBER approach, the leading indicator index is derived from a vector autoregression (VAR) forecast of the change in the composite coincident index on past changes in the composite coincident economic index and other variables that have historically led the business cycle. If the coincident index truly reflects the state of the economy, then a good forecast of this coincident index should provide for a good leading index. This method, unlike the traditional approach, does not lack theoretical rigour, that is, it pays attention to economic theory in determining the relationship between the indicators and economic activity, as well as it does not rely heavily on subjective analysis, rather an econometric (scientific) approach is used (see Koopmans, 1947; Averbach, 1982; Leeuw, 1991 for further details).

The literature for developing countries is fairly scant, possibly because (i) the business cycle in developing countries are likely to be more dependent on weather patterns than cyclical fluctuations, as a result of the preponderance of agriculture in the production process (Mall, 1999); (ii) there are heavy restrictions on the quality and frequency of the data and; (iii) of difficulties in discerning any type of cycle or economic regularity because of the sudden crises and market gyrations typical of developing countries (Agenor, McDermott and Prasad, 2000). However, increasingly, examples for developing countries are appearing. Mall (1999) and Dua and Banerji (1999, 2001) developed coincident and leading indicators for India, Simone (2000) for Argentina and more recently, Mongardini and Saadi-Sedik (2003) for Jordan. All of these studies have performed relatively well but their methodologies, unlike in the developed world, have not been officially adopted or tested to predict future business cycles. Since the year 1990, the Conference Board (and before that the Bureau of Economic Analysis) has regularly published leading, lagging and coincident index for the U.S.[4]

3. The Economic Performance of Barbados

Despite its small size of 431 square kilometres, a population of less than 270,000 inhabitants and a meagre endowment of natural resources, Barbados' development experience has been a true success story. It has diversified from a monoculture based on the production and export of raw sugar, to an economy driven by tourism and financial services. Barbados remains among the most developed countries in Latin America and the Caribbean, with levels of health, education, communication and social services comparable to those of industrialised countries. In fact, in 2004, Barbados was ranked 29th among 177 countries in the United Nations Development Programme's Human Development Index.

Graph 1: The Real GDP of Barbados



[3] See http://cs3-hq.oecd.org/scripts/stats/mei_sd.asp?ctry=CAN&subj=LEADINC&lang=e for an explanation of the method.

[4] See http://www.conference-broad.org/economics/bci/bciproject.cfm for more details.

Graph 1 depicts the growth experience of Barbados, which can be summarised in terms of following sub-periods:

- The diversification and growth phase of the 1974-1980 period, when tourism and manufacturing were taking over from sugar as the dominant earners of revenue and generators of employment. In the first half of this decade, in the midst of a global recession with high inflation, stagnation in the principal markets for goods and services and increasing transportation costs there was declining sugar production and moderate growth in the industrial and tourism sectors, leading to a drop in real output between 1974 and 1975. However, by 1976 the Barbadian economy rebounded.

- The slower growth phase of the 1980-1990 period, associated with two oil shocks that had very negative effects on Barbados' trading relations. The second shock in 1979/1980 triggered a long and deep recession, as shown in a fall in production between 1981 and 1982, which was accompanied by an abnormally high inflation rate. From 1983 to 1986, there was increased optimism about economic prospects, thanks to international tourism. Nevertheless, the economy showed signs of slowing and the dynamism, which had long been a positive feature of the economy, disappeared. Investment declined sharply, manufacturing output shrank, and agriculture – mainly sugar – continued its downward trend and tourism suffered a decrease in arrivals from regional sources. Consequently, the Barbadian economy recorded contractions in real GDP of 3.1% in 1990, then 4.1% in 1991 and 6.2% in 1992. This real sector crisis was accompanied by a balance of payments crisis, which led to capital flight and debt accumulation.

- The recovery phase between 1993 and 2000, primarily occasioned by the application of austerity measures from the International Monetary Fund structural adjustment programme. In this period, Barbados resumed a positive growth path, with real GDP rising for eight consecutive years, boosted mainly by tourism and financial services.

- The September 11 period 2000 to 2001. A world recession and the September 11 terrorist attacks put a damper on real value added of major sectors like tourism and manufacturing. Government had to increase expenditure to keep its main engines of growth going.

- The post September 11 period. With government counter cyclical spending, tourism recovered and real output started to grow.

4. A Chronology of the Real GDP Series

Business cycles are recurrent sequences of alternating phases of expansions and contractions in the level of a time series, usually explained by the co-movements of other economic variables. This definition is based on the early work of Burns and Mitchell (1946) who wrote that:

"*Business Cycles are a type of fluctuation found in the aggregate activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many activities, followed by similarly general recessions, contractions and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own"(pp.3).*

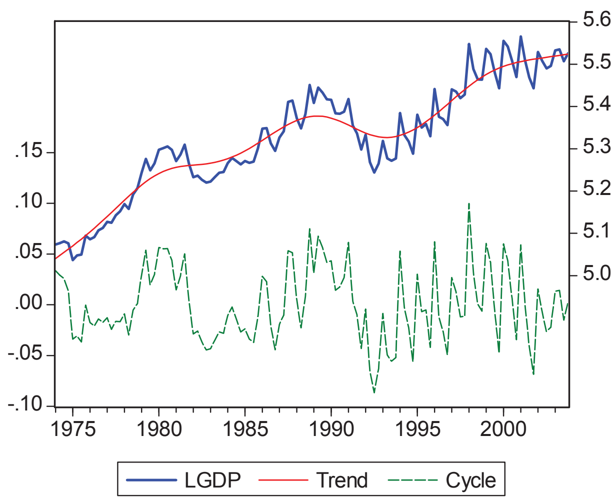
Business cycle fluctuations are often measured using the real gross domestic product of an economy, on the assumption that it represents the economic strength of a nation. In this section a chronology of the Barbadian business cycle is developed using quarterly real GDP, measured in millions of Barbadian dollars and covering the period 1974 to 2003, with base year = 1974. The data source is the Central Bank of Barbados and all estimations are done utilising the RATS and EVIEWS statistical software packages. This analysis is basically an update of Craigwell and Maurin (2002) and therefore, it will necessarily be brief.

From Graph 1 above, it appears that there is a growing trend, many seasonal cycles and three possible business cycles (namely, 1974 –1982, 1983-1992 and 1993-2003). However, because of the many perturbations in the series, the cycles are not well defined, and the latter should be separated from the trend and the irregular components. Several filters of trend-cycle decomposition are available but the Hodrick-Prescott (1980) filter is the one chosen here. This method consists of minimising the variance of the time series around the trend. The minimization schedule is as follow:

$$\underset{y_t^p}{Min}\left\{\sum_{t=1}^{T}(y_t-y_t^p)^2+\lambda\sum_{t=2}^{T-1}\left[\left(y_{t+1}^p-y_t^p\right)-\left(y_t^p-y_{t-1}^p\right)\right]^2\right\}$$

where y_t is real GDP, y_t^p is the permanent component of y_t and λ is the lagrange multiplier, which divides the total fluctuations into long-term and short-term movements, with its value determined by the observed fluctuations. Hodrick and Prescod (1980) established a value of λ = 1600 for quarterly U.S. data, and this same number and other values were tried in Craigwell and Maurin (2002,2004,2005a,b) with no appreciable difference in the underlying results. As a result, this paper utilises a value of 1600 for λ.

Graph 2: GDP decomposition using the Hodrick-Prescott Filter



Graph 2 depicts the trend-cycle GDP decomposition and shows the separate components. The trend can be interpreted as potential output and the cycle reveals impulse response of shocks on the economy and all the seasonal cycles. After identifying the cycle, the next step is to discern the cycle by determining its peaks and troughs. Formally, a turning point occurs in a series when the deviation from trend reached a local maximum (peak) or a local minimum (trough). Table 1 gives these expansion and recession phases for real GDP.

Table 1: Expansions and recessions of Barbados

Period	Phase of cycle	Year of peak and trough	Quarter time
		Trough = 1974 :1	
1974 :1-1981 :3	Expansion	Peak = 1981 :3	31
1981 :4-1982 :4	Recession	Trough = 1982 :4	8
1985 :1-1989 :2	Expansion	Peak = 1989 :2	18
1989 :3-1992 :3	Recession	Trough = 1992 :3	16
1992 :4-2003 :4	Expansion		44

Given that the cycle is defined by the distance of two troughs, then, the economy of Barbados shows two business cycles over the study's sample period, that, is 1974:1 – 1982:4 (approximately 9 years) and 1982:4 – 1992:3 (approximately 10 years), confirming the existence of business cycles in the economic fluctuations of Barbados (see also Craigwell and Maurin,2002; 2004;2005a,b). Indeed, they correspond to the stylised facts summarised in Section 3 above. The period 1974-1982 is an era of rapid growth and employment emanating from the diversification of sugarcane cultivation to manufacturing, tourism and financial services. 1983-1992 relates to a decline in real output because of the international recession that was associated with the stagnation of markets, the oil shocks and world - wide inflation. The period 1993 - 2003 is an era of expansion, driven mainly by the tourist industry and financial services, helped by the IMF austerity measures of the structural adjustment programme. Given these business cycles, indices of economic indicators can be built to forecast real economic activity.

5. The Stock and Watson Theoretical Approach to Economic Indicators

Many approaches have been used to compute a business cycle index using the Burns and Mitchell (1946) 's definition of the business cycle. The first and the most utilised is that provided by the NBER. Indeed, in 1937, Mitchell and Burns (1946) developed a list of 487 indicators that led, lagged or were coincident with the business cycle. The project embraced the concept that there is a business cycle or reference cycle that cannot be observed directly but can be measured by the consistent movement of many economic variables as the phases of growth change.

In the 1950s and 1960s, researchers from the NBER extended the concept by constructing indices from these indicators, weighting and adding together variables that consistently led, lagged or kept pace with the business cycle. This method estimates the index as a weighted average of individual indicators. Mathematically,

$$X = \sum_{i=1}^{n} w_i I_i,$$

where X is the composite index, I_i is the i^{th} indicator index and w_i is the weight allocated to I_i.

Due to the atheoretical and unscientific nature of the above procedure, a second approach was initiated by Stock and Watson (1989, 1992). The composite coincident economic index (CEI) is based on an econometric model in which the "state of the economy" is an unobserved variable, which is common to several macroeconomic variables. The model relies on the fact that the fluctuations in these variables share a common element, which can be estimated. If the coincident index truly reflects the state of the economy, then a good forecast of this coincident index should make a good leading index. The co-movements at all leads and lags among the coincident variables are modelled as arising from a single common source C_t, a scalar unobserved time series that can be thought of as the overall state of the economy. The structure of the model used here is:

$$Y_t = \beta + \Theta(L)C_t + u_t \tag{1}$$

$$D(L)u_t = \varepsilon_t \tag{2}$$

$$\Psi(L)C_t = \delta + \eta_t \tag{3}$$

where Y_t is a vector of the logarithm of observed coincident economic variables, β is the mean of Y_t , C_t represents the logarithm of the state of the economy at time t, L denotes the lag operator and $\Theta(L)$, $D(L)$, $\Psi(L)$ are respectively vector, matrix and scalar lag polynomials. The error term u_t is serially correlated and its dynamics are specified by an autoregressive process $D(L)u_t = \varepsilon_t$ where $D(L) = 1 - d_1 L - ... - d_k L^k$, while the error terms (ε_t, η_t) are assumed to be serially uncorrelated with a zero mean and a diagonal covariance matrix Σ.

The stochastic dynamic of C_t is described by $\Psi(L)C_t = \delta + \eta_t$ where $\Psi(L)$ is an autoregressive stationary operator of order p and δ is the mean of C_t. Y_t is a non-stationary series and it's possible that Y_t and C_t have common stochastic trends. Hence, consider the model in first difference form:

$$\Delta Y_t = \beta + \Theta(L)\Delta C_t + u_t \tag{4}$$

$$D(L)u_t = \varepsilon_t \tag{5}$$

$$\Psi(L)\Delta C_t = \delta + \eta_t \tag{6}$$

The coincident index is the estimated value of ΔC_t conditional on the information available at time *t*, and notice $\Delta C_{t/t}$. Then, the indicator is a linear combination of past and present values of ΔY_t variables, that is, $\Delta C_{t/t} = W(L)\Delta Y_t$ where $W(L)$ is a weighting vector.

Two further steps are necessary for the estimation of the coincident indicator: (i) rewrite Expression (4) and (6) in a state-space form and estimate the parameters of the model and the unobserved state of the economy using a Kalman filter (See Y. Liu (2001) and Appendix 1) and; (ii) in the procedure, each coincident economic variable in the vector *Y* is first difference and normalised by subtracting its mean difference and then dividing by the standard deviation of its difference. Hence, ΔC_t must be de-normalised and de-logged in order to find the final coincident index.

Finally, to estimate the leading indicator Stock and Watson (1989) used the Vector Autoregressive (VAR) methodology. Formally,

$$\Delta C_t = \mu_c + \lambda_{cc}(L)\Delta C_{t-1} + \lambda_{cx}(L)X_{t-1} + V_{ct} \tag{7}$$

$$X_t = \mu_x + \lambda_{xc}(L)\Delta C_{t-1} + \lambda_{xx}(L)X_{t-1} + V_{xt} \tag{8}$$

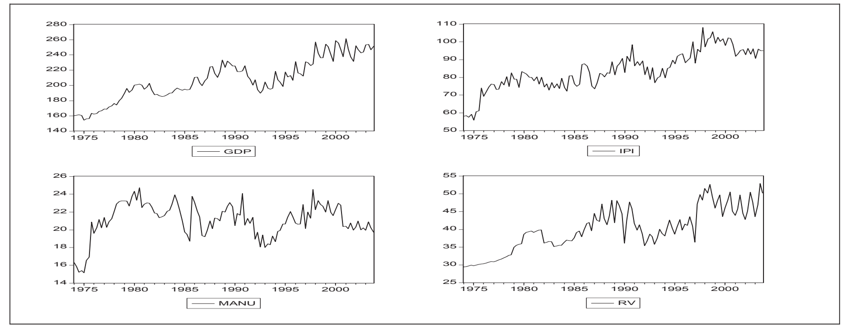
where X_t is a vector with stationary leading indicators and V_{ct} and V_{xt} are serially uncorrelated error terms. ΔC_t is the coincident index.

6. Construction of a Coincident and Leading Indicator with the Stock and Watson methodology

The Coincident Indicator

The first step in estimating a composite index of coincident economic indicators (CEI) is to determine a reference series for the state of the economy. Real GDP was chosen and its chronology developed in the fourth section of this paper. Next, chose indicators in order to determine the state of the economy: this paper uses the industrial production index (IPI), the retail value added (RV) and manufacture value added (manu) as indicators. Why these series? Not only are readily available and account for significant activities in the Barbadian economy, but these series are highly correlated and closely mimics the reference series (see Graphs 3 and 4 and Table 2).

Graph 3: Series evolutions



Graph 4: Series growth rate

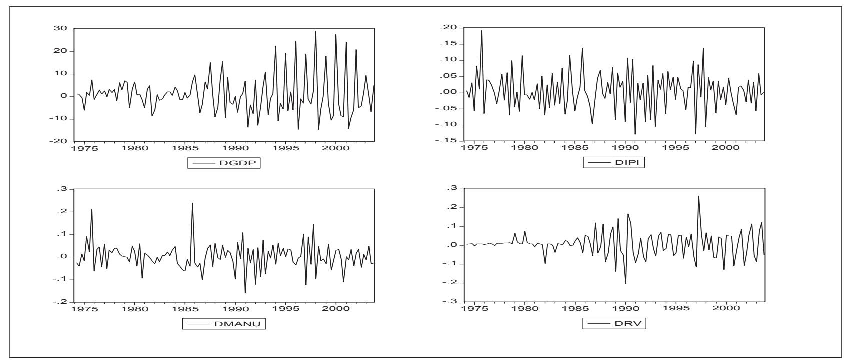
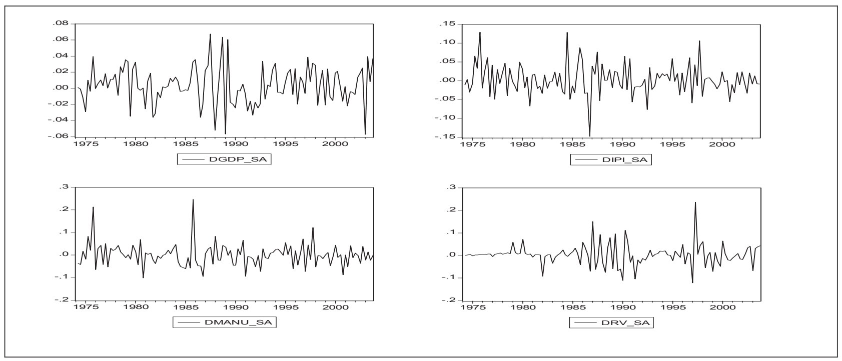


Table 2: Correlation of indicators with GDP for the Coincident Indicator

GDP	IPI	MANU	RV
1.000000	0.856852	0.611578	0.903366
0.856852	1.000000	0.498427	0.835497
0.611578	0.498427	1.000000	0.332688
0.903366	0.835497	0.332688	1.000000

The next step is to estimate Equations (4) to (6). To start, the series are tested for the presence of unit roots and cointegration. The results of the Augmented Dickey and Fuller's unit root test (see appendix 2) indicate that the log series need to be difference once to be stationary. Moreover, because of the seasonality in the series, the standard X12 procedure developed by the U.S. Census Bureau is used to seasonally adjust the series (see Graph 5). Furthermore, the Johansen's cointegration test indicates that the series are not co-integrated (rank equals 1) at the 5% level of significance (see Appendix 2).

Graph 5: Seasonally adjusted series



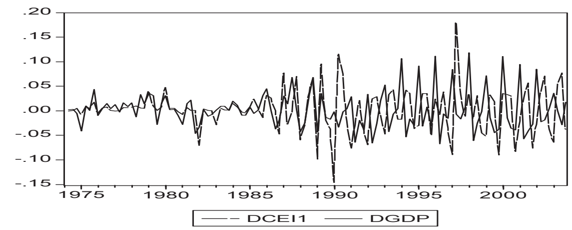
Now, the Kalman filter, which consists of a sequence of prediction and update steps, can be applied to Equations 4 to 6. Assuming that C_t follows an *AR(1)* and u_t an *AR(2),* we obtain the measurement and transition equation (see appendix 3)

The results indicate that a few of the coefficients are statistically significantly different from zero suggesting that the model is reasonably well specified.

The coincident indicator can be written as a function of its components in the following way: $\Delta C_{t/t} = W(L)\Delta Y_t$ where *W (L)* is a weighting vector that gives the contribution of each variable to the composition of the index. Doing this gives:

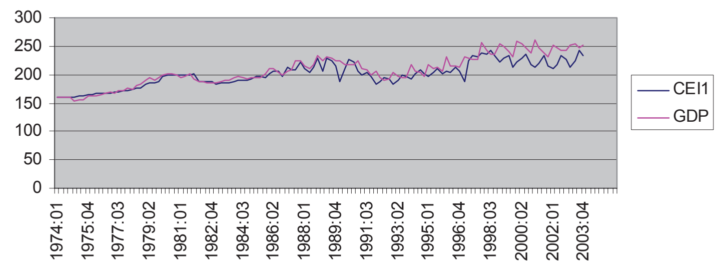
$$\Delta C_t = 2.50 * \Delta DMANU_t + 3.25 * \Delta DIPI_t - 0.67 * \Delta DRV_t$$

Graph 6: Comparison CEI1 and GDP growth



The dynamics of the estimated coincident growth rate index exhibits similar properties to the GDP growth rate (see graph 6). Hence, the fitted values of the equation can be interpreted as the growth rates of the composite index. A simple procedure is then used to derive the index: the initial value of the index is set equal to the equivalent observation for real GDP; subsequent observations are then derived by multiplying the previous observation by the fitted quarterly growth rate. The CEI1 so derived is shown in Graph 7.

Graph 7: Comparison CEI1 and GDP



From Graph 7, the coincident indicator index displays similar business cycle characteristics of the Barbadian economy as the reference series, real GDP.

The Leading indicator

The approach for estimating the leading indicator is similar to that for the coincident indicator. All possible available series from different sectors of the economy are considered but only four series are selected: the retail price index (RPI); the net foreign assets of commercial banks (FA); long stay visitors (LSV) and money supply (M2). Graph 8 and Table 3 show a relatively close association of these series with GDP.

Graph 8: Series evolution

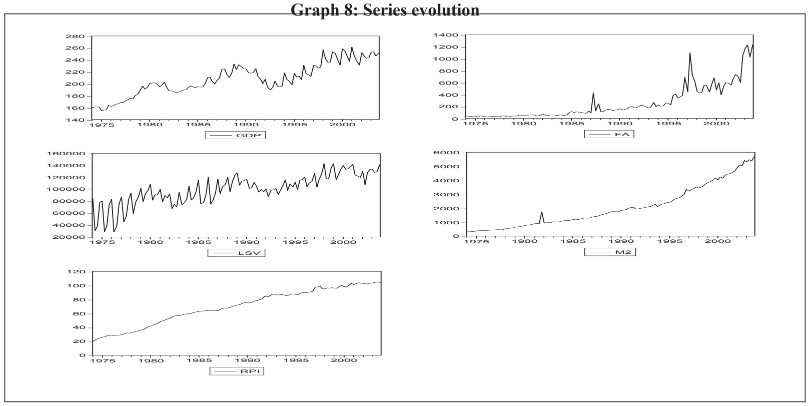


Table 3: Correlation of the variables

	GDP	FA	LSV	M2	RPI
GDP	**1.000000**	0.749765	0.869676	0.871812	0.876348
FA	**0.749765**	1.000000	0.657663	0.919608	0.768148
LSV	**0.869676**	0.657663	1.000000	0.773482	0.806961
M2	**0.871812**	0.919608	0.773482	1.000000	0.905126
RPI	**0.876348**	0.768148	0.806961	0.905126	1.000000

In order to construct the leading indicator index, a VAR is undertaken using Equations 7 and 8. As is customary, the variables are first checked for stationarity. The results in the Appendix 2 indicate that the variables are all stationary in first difference form. Also, the X12 procedure is utilised to seasonally adjust the data.

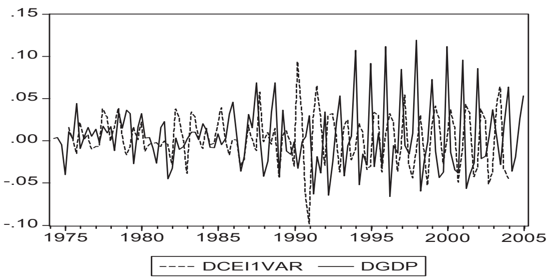
The components of the VAR are the leading indicators discussed above plus the coincident indicator, CEI1. Based on various model selection criteria (see Appendix 4), the optimal model of the VAR is with 4 lags. Also, the Johansen cointegration tests indicate no cointegration at conventional significance levels, justifying that a VAR in first differences is appropriate. The results of the VAR are given below

After estimating the VAR, the equation ΔC_t is considered and the leading indicator is obtained as follow:

$LEI1_{t+2}$ = - 0.38*DCEI1(-1) - 0.43*DCEI1(-2) - 0.232*DCEI1(-3) + 0.22*DCEI1(-4) - 0.003*DFA(-1) + 0.03*DFA(-2) + 0.03*DFA(-3) + 0.01*DFA(-4) + 0.10*DLSV(-1) + 0.09*DLSV(-2) + 0.09*DLSV(-3) + 0.10*DLSV(-4) - 0.03*DM2(-1) - 0.01*DM2(-2) - 0.01*DM2(-3) - 0.03*DM2(-4) - 0.25*DRPI(-1) - 0.07*DRPI(-2) - 0.02*DRPI(-3) + 0.51*DRPI(-4) - 0.0004

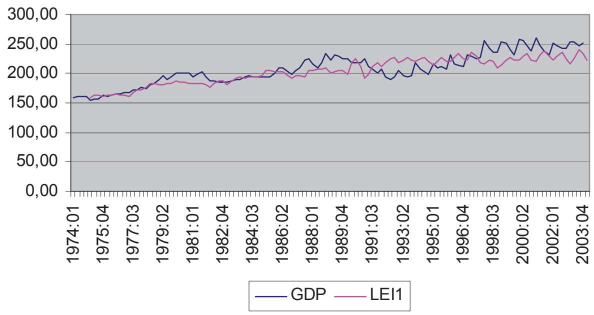
LEI1 is an estimation of the growth on two quarters of the coincident index. In addition, it's clear that the leading indictor is not the growth rate of GDP but only a way to know if the economy will be in recession or contraction. The graph 9 shows the lag between the growth of LEI1 and the growth of GDP.

Graph 9: Growth of the leading indicator and growth GDP



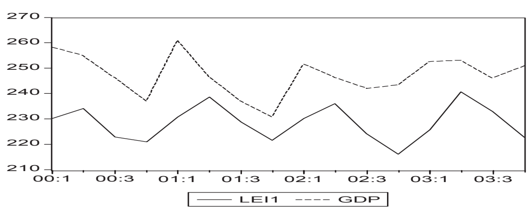
In order to obtain the evolution of LEI1, the same operation that was done for the CEI1 is repeated. Graph 10 shows the evolution.

Graph 10: Comparison LEI1 and GDP



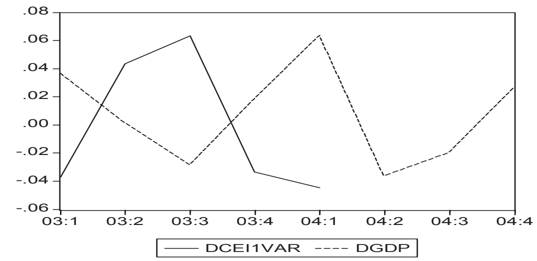
In conclusion, the leading indicator is shown as two quarters ahead forecast. It's not possible to see clearly if the leading indicator predicts the GDP well. An example using a small sample is depicted in Graph 11 and makes the picture clearer.

Graph 11: Prediction of LEI1



It can be seen that some peaks and troughs are predicted by the leading indicator. An evaluation for post sample period of 2004 is given in Graph 12. The results indicate that the LEI1 forecasts a peak in 2003:3 for GDP which actually peaks in 2004:1 we have a peak. Then LEI1 is realized two quarters before the change in GDP.

Graph 12: Forecast LEI1 two quarters ahead for 2004



7. A Comparison with Mongardini and Saadi-Sedek Method

The coincident index

Mongardini and Saadi-Sedik (2003), hereafter MS, provides a simplification of the SW method, and they argued that it could be y when there is a limited sample size. It assumes that the reference series are highly correlated with GDP and have a similar evolution. The same indicators in the SW method are utilised here but only industrial production has these features. Hence, a reduced form equation is estimated as follows:

$$\Delta IPI_t = \alpha + \beta \Delta LCI_t + u_t \qquad (9)$$
$$u_t = \varepsilon_t + \theta \varepsilon_{t-1}$$

It's a simple regression of the reference series on other indicators that represent the state of the economy. ΔIPI is the growth rate of the seasonally adjusted industrial production index, ΔLCI_t is a vector of the seasonally adjusted coincident indicators expressed in growth rates, u_t is an error term with a moving average component of order 1. As the error term is not normally distributed in the regression, the standard errors and covariance matrix are estimated using the Newey-West heteroskedastic-consistent procedure. The results of this estimation are given in Table 4 below

Table 4: Estimation of Coincident Economic Indicator

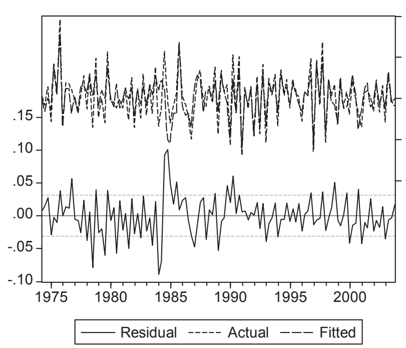
Dependent Variable: DIPI
Method: Least Squares
Date: 07/21/05 Time: 09:52
Sample(adjusted): 1974:2 2003:4
Included observations: 119 after adjusting endpoints
Convergence achieved after 6 iterations
Newey-West HAC Standard Errors & Covariance (lag truncation=4)
Backcast: 1974:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DMANU	0.683771	0.075074	9.108009	0.0000
DRV	0.077451	0.038957	1.988146	0.0492
C	0.002413	0.001023	2.358516	0.0200
MA(1)	-0.676025	0.070122	-9.640710	0.0000

R-squared	0.714818	Mean dependent var	0.004127
Adjusted R-squared	0.707378	S.D. dependent var	0.058525
S.E. of regression	0.031659	Akaike info criterion	-4.034581
Sum squared resid	0.115260	Schwarz criterion	-3.941165
Log likelihood	244.0576	F-statistic	96.08368
Durbin-Watson stat	2.060661	Prob(F-statistic)	0.000000
Inverted MA Roots	.68		

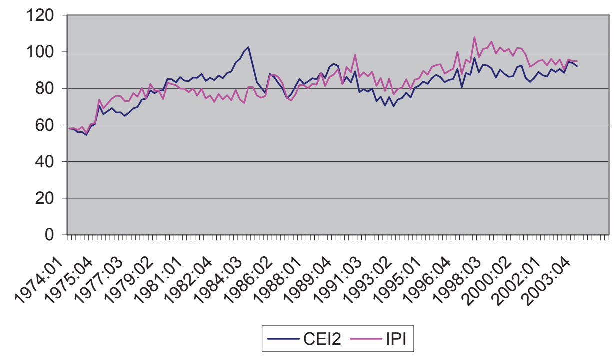
The coefficients are statistically significant and correctly signed, and therefore, can provide appropriate weights. Graph 13 shows that the fitted value closely tracks the actual data, which means that the fitted values of the regression can be interpreted as the growth rates of the composite index.

Graph 13: Estimation of CEI2: Actual, Fitted and Residual values



The final step is to derive the CEI2 from the regression results. As in the SW approach, a simple procedure is used to derive the index: the initial value of the index is set equal to the equivalent observation for industrial production; subsequent observations are then derived by multiplying the previous observation by the fitted quarterly growth rate. The Coincident Indicator Index so derived is shown in Graph 14:

Graph 14: Comparison of CEI and Index of Industrial Production



The index seems to represent the state of the economy relatively well. All the turning points in the cyclical GDP are predicted by the CEI2.

The Leading index

As in the estimation of CEI2, the economic activity variable is proxied by the IPI. The statistical relationship is then formulated in the form of the following reduced form equation:

$$\begin{aligned} \Delta IPI_{t+2} &= \alpha + \beta \Delta LLI_t + u_t \\ u_t &= \varepsilon_t + \theta \varepsilon_{t-1} \end{aligned} \qquad (10)$$

where ΔIPI_{t+2} is the growth rate of the seasonally adjusted IPI two quarters ahead, $\beta \Delta LLI_t$ is a vector of seasonally adjusted leading indicators and u_t is an error term with a moving average component of order 1. The procedure to estimate equation (10) is the same as that used to determine CEI2 and LEI1 above.

Table 5: Estimation of Leading Economic Indicators

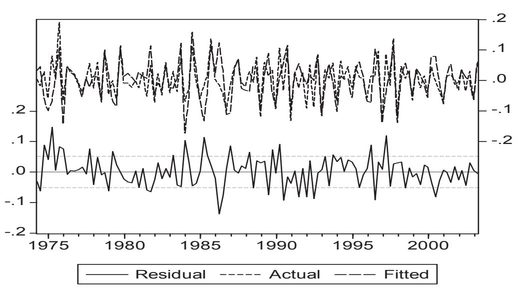
Dependent Variable: DIPI(2)
Method: Least Squares
Date: 07/22/05 Time: 06:15
Sample(adjusted): 1974:2 2003:2
Included observations: 117 after adjusting endpoints
Convergence achieved after 11 iterations
Newey-West HAC Standard Errors & Covariance (lag truncation=4)
Backcast: 1974:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLSV	-0.058389	0.022191	-2.631271	0.0097
DM2	0.082828	0.055830	1.483563	0.1407
DRPI	0.038370	0.145390	0.263912	0.7923
DFA	0.006224	0.017762	0.350408	0.7267
MA(1)	-0.442295	0.088161	-5.016916	0.0000

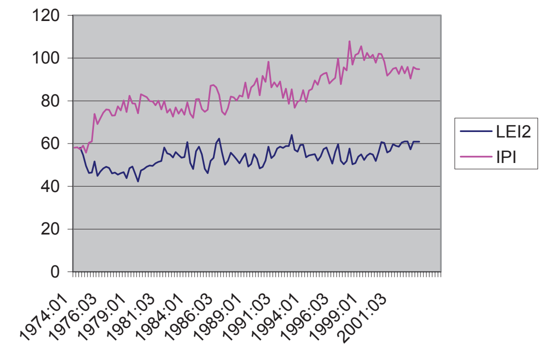
R-squared	0.281790	Mean dependent var	0.004303
Adjusted R-squared	0.256140	S.D. dependent var	0.058996
S.E. of regression	0.050883	Akaike info criterion	-3.076793
Sum squared resid	0.289973	Schwarz criterion	-2.958751
Log likelihood	184.9924	Durbin-Watson stat	2.079603
Inverted MA Roots	.44		

Unlike for CEI2, most of the variables in the estimation (see Table 5) are not statistically significant. However, the fitted value and the growth of IPI appear to be highly correlated (see Graph 15). Hence, it seems possible to construct the index with this simplified method as done above for the more sophisticated SW. The results are given in Graph 16.

Graph 15: Estimation of LEI2: Actual, fitted and residual values

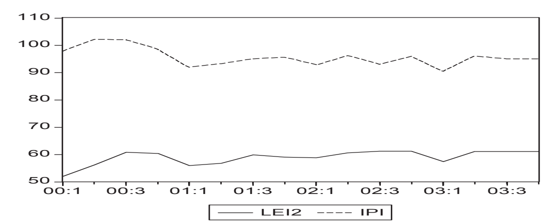


Graph 16: Industrial Production and Leading Indicator
(LEI2 lagged two quarters forward)



Again the two graphs don't have the same evolution since the leading index just shows the direction of possible changes in the economy. Graph 17 gives a better view. For the period 2000 to 2003, one can see that when the LEI2 predicts the increase in 2000:3, the same increase is true in 2000:2 for the leading index.

Graph 17: Prediction of the LEI2 from 2000 to 2003

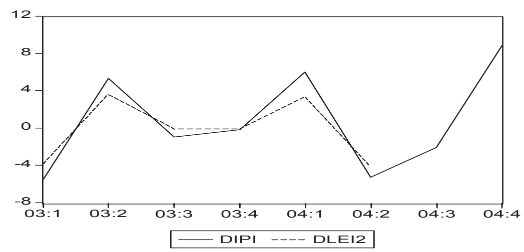


In conclusion, this method can provide a good estimation of the future evolution of the economy. It's simple and clear.

We can see that some peaks and troughs are predicted by the leading indicator.
An evaluation for 2004 is given in graph 18:

The results of forecasting: the LEI2 forecasts a peak in 2003:3 for GDP and we see that in 2004:1 we have a peak. Then the prediction two quarters before of the LEI1 is realized two quarters after.

Graph 18: Forecast LEI1 two quarters forward



8. Conclusion

This paper has attempted to provide a structured approach to analyzing business cycles in Barbados. The models developed are based on the single-index methodology of Stock and Watson and they gave coincident indices that dated and followed the Barbados business cycles closely . The model also established leading indicators which could be used to predict future movements in the coincident index. However, it's possible that there indices could be untamed with the availability of more highly correlated data and on a higher frequencies for example monthly.

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Appendix 1: State space model and Kalman filter[5]

Space State model

Many time-series models used in econometrics are special cases of the class of linear state space models developed by engineers to describe physical systems. The Kalman filter, an efficient recursive method for computing optimal linear forecasts in such models, can be exploited to compute the exact Gaussian likelihood function.

The linear state-space model postulates that an observed time series is a linear function of a (generally unobserved) state vector and the law of motion for the state vector is first-order vector autoregression. More precisely, let y_t be the observed variable at time t and let α_t denote the values taken at time t by a vector of p state variables. Let A and b be $p \times p$ and $p \times 1$ matrices of constants. We assume that $\{y_t\}$ is generated by

$$y_t = b'\alpha_t + u_t, \quad (1)$$

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

where the scalar u_t and the vector v_t are mean zero, white-noise processes, independent of each other and of the initial value α_0. We denote $\sigma^2 = E(u_t^2)$ and $\Sigma = E(v_t v_t')$. Equation (1) is sometimes called the "measurement" equation while (2) is called the "transition" equation. The assumption that the autoregression is first-order is not restricitve, since higher-order systems can be handled by adding additional state variables.

The Kalman Filter

Denote the vector $(y_1, ..., y_t)$ by Y_t .The Kalman filter is a recursive algorithm for producing optimal linear forecasts of y_{t+1} from the past history Y_t, assuming that A, b, σ^2, and Σ are known. Define

$$a_t = E(\alpha_t | Y_{t-1}) \quad \text{and} \quad V_t = var(\alpha_t | Y_{t-1}). \quad (3)$$

If the u's and v's are normally distributed, the minimum MSE forecast of y_{t+1} at time t is $b'a_{t+1}$. The key fact (which we shall derive below) is that, under normality, a_{t+1} can be calculated recursively by

$$a_{t+1} = Aa_t + AV_t b \frac{y_t - b'a_t}{b'V_t b + \sigma^2}, \qquad V_{t+1} = \Sigma + AV_t A' - \frac{AV_t bb'V_t A'}{b'V_t b + \sigma^2} \quad (4)$$

starting with the appropriate initial values (a_1, V_1). To forecast y_{t+1} at time t, one needs only the current y_t and the previous forecast of α_t and its variance. Previous values $y_1, ..., y_{t-1}$ enter only through a_t . Note that y_t enters linearly into the calculation of a_t and does not enter at all into the calculation of V_t . The forecast of y_t is a linear filter of previous y's. If the errors are not normal, the forecasts produced from iterating (4) are still of interest; they are best linear predictors.

[5] More information is available on http://emlab.berkeley.edu/~rothenbe/Fall2004/kalman.pdf

Appendix 2: Unit Root and Cointegration test results for the coincident and leading indicator variables

Table 6: Augmented Dickey-Fuller test statistic

Variables	Level	First difference
MANU	-3.286 (0.017)	-16.109 (0.000)
IPI	-2.922 (0.045)	-9.865 (0.000)
RV	*-1.643* *(0.458)*	*-5.837* *(0.000)*
RPI	-2.231 (0.196)	-10.239 (0.000)
FA	0.576 (0.988)	-17.693 (0.000)
LSV	-1.433 (0.563)	-5.036 (0.000)
M2	3.640 (1.000)	-16.82 (0.000)

Numbers in brackets are the probability of the p-value
The critical test at 5% is -2.887

Sample(adjusted): 1975:2 2003:4
Included observations: 115 after adjusting endpoints
Trend assumption: Linear deterministic trend
Series: MANU IPI RV
Lags interval (in first differences): 1 to 4
Unrestricted Cointegration Rank Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None	0.157821	29.33785	29.68	35.65
At most 1	0.075436	9.585172	15.41	20.04
At most 2	0.004904	0.565337	3.76	6.65

*(**) denotes rejection of the hypothesis at the 5%(1%) level
Trace test indicates no cointegration at both 5% and 1% levels

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5 Percent Critical Value	1 Percent Critical Value
None	0.157821	19.75268	20.97	25.52
At most 1	0.075436	9.019835	14.07	18.63
At most 2	0.004904	0.565337	3.76	6.65

*(**) denotes rejection of the hypothesis at the 5%(1%) level
Max-eigenvalue test indicates no cointegration at both 5% and 1% levels

Appendix 3: Kalman Filter Results

Measurement equation

$$\Delta\text{DMANU} = -3.52 - 1.15^{*}\Delta C_t + U_t$$
$$\qquad (1.00) \quad (0.95)$$

$$\Delta\text{DIPI} = -0.13 - 3.43^{*}\Delta C_t + U_t$$
$$\qquad (1.00) \quad (0.00)$$

$$\Delta\text{DRV} = -12.50 - 0.61^{*}\Delta C_t + U_t$$
$$\qquad (1.00) \quad (0.50)$$

State equations

$$U_t^{MANU} = -0.57^{*}U_{t-1}^{MANU} - 0.79^{*}U_{t-2}^{MANU} + \varepsilon_t^{MANU} \;;\; \sigma_{MANU} = -3.08$$
$$(0.00) \qquad (0.00) \qquad\qquad (0.00)$$

$$U_t^{IPI} = -0.08^{*}U_{t-1}^{IPI} - 15.04^{*}U_{t-2}^{IPI} + \varepsilon_t^{IPI} \;;\; \sigma_{IPI} = -5.23$$
$$(0.00) \qquad (0.13) \qquad\qquad (0.00)$$

$$U_t^{RV} = 0.52^{*}U_{t-1}^{RV} - 1.34^{*}U_{t-2}^{RV} + \varepsilon_t^{RV} \;;\; \sigma_{RV} = -2.45$$
$$(0.00) \qquad (0.01) \qquad\qquad (0.00)$$

$$\Delta C_t^{MANU} = 0.76^{*}\Delta C_{t-1}^{MANU} + \eta_t \;;\; \sigma_\eta = 1$$
$$(0.09)$$
$$\Delta C_t^{IPI} = 0.95^{*}\Delta C_{t-1}^{IPI} + \eta_t \;;\; \sigma_\eta = 1$$
$$(0.001)$$
$$\Delta C_t^{RV} = 0.36^{*}\Delta C_{t-1}^{RV} + \eta_t \;;\; \sigma_\eta = 1$$
$$(0.00)$$

*Numbers in brackets are standard errors

In order to find the expression of C_t, we de-normalize Y_t

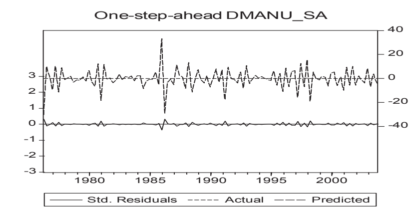
For the first equation we have:

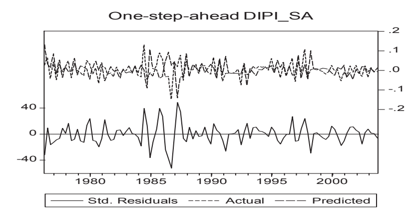
$$\left(\frac{\Delta\text{DMANU} + 3.52}{-3.08}\right) \times \frac{1}{-1.15} = \quad \Rightarrow \Delta C_t = 0.05 * \Delta\text{DMANU}$$

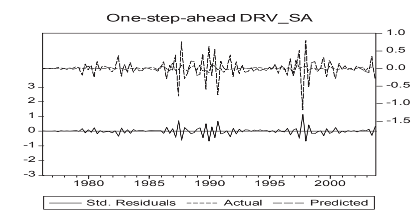
and

$$\Delta C_t = 0.025 * \Delta\text{DIPI}$$
$$\Delta C_t = 0.67 * \Delta\text{DRV}$$

Then: $\Delta C_t = 0.050 * \Delta\text{DMANU} + 0.025 * \Delta\text{DIPI} + 0.67 * \Delta\text{DRV}$







Appendix 4: Optimal VAR lag and VAR output

Sample(adjusted): 1975:2 2003:4
Included observations: 115 after adjusting endpoints
Trend assumption: Linear deterministic trend
Series: RPI M2 FA LSV
Lags interval (in first differences): 1 to 4

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5 Percent Critical Value	1 Percent Critical Value
None	0.195451	25.00941	27.07	32.24
At most 1	0.146509	18.21834	20.97	25.52
At most 2 *	0.138499	17.14413	14.07	18.63
At most 3	0.008235	0.950958	3.76	6.65

*(**) denotes rejection of the hypothesis at the 5%(1%) level
Max-eigenvalue test indicates no cointegration at both 5% and 1% levels

VAR Lag Order Selection Criteria
Endogenous variables: DCEI1 DFA DLSV DRPI
Exogenous variables: C
Date: 07/21/05 Time: 07:14
Sample: 1974:1 2003:4
Included observations: 111

Lag	LogL	LR	FPE	AIC	SC	HQ
0	184.8352	NA	4.52E-07	-3.258291	-3.160651	-3.218681
1	229.6268	85.54798	2.69E-07	-3.777059	-3.288856	-3.579010
2	278.5760	89.96060	1.49E-07	-4.370738	-3.491971	-4.014248
3	362.9570	148.9972	4.35E-08	-5.602829	-4.333500	-5.087900
4	407.0837	74.73718*	2.64E-08*	-6.109617*	-4.449725*	-5.436248*
5	413.8243	10.93068	3.14E-08	-5.942781	-3.892325	-5.110972
6	424.8634	17.10562	3.48E-08	-5.853395	-3.412377	-4.863146
7	434.5413	14.29890	3.97E-08	-5.739484	-2.907902	-4.590795
8	445.5754	15.50734	4.45E-08	-5.650007	-2.427863	-4.342879

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Vector Autoregression Estimates
Sample(adjusted): 1975:2 2003:4
Included observations: 115 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

	DCEI1	DFA	DLSV	DM2	DRPI
DCEI1(-1)	-0.389674	0.931321	0.479306	0.269424	0.048254
	(0.10027)	(0.68347)	(0.20907)	(0.21001)	(0.04179)
	[-3.88606]	[1.36263]	[2.29252]	[1.28291]	[1.15468]
DCEI1(-2)	-0.428534	-0.937600	0.364238	0.188291	-0.056415
	(0.10579)	(0.72109)	(0.22058)	(0.22157)	(0.04409)
	[-4.05063]	[-1.30025]	[1.65125]	[0.84980]	[-1.27952]
DCEI1(-3)	-0.232496	0.555301	0.221036	0.189952	-0.005798
	(0.10798)	(0.73597)	(0.22513)	(0.22614)	(0.04500)
	[-2.15320]	[0.75452]	[0.98180]	[0.83997]	[-0.12885]
DCEI1(-4)	0.229214	-0.656317	0.270607	0.018892	0.017042
	(0.10559)	(0.71969)	(0.22015)	(0.22114)	(0.04400)
	[2.17084]	[-0.91195]	[1.22918]	[0.08543]	[0.38728]
DFA(-1)	-0.003390	-0.616177	0.029285	-0.021234	0.002948
	(0.01470)	(0.10017)	(0.03064)	(0.03078)	(0.00612)
	[-0.23067]	[-6.15120]	[0.95569]	[-0.68986]	[0.48136]
DFA(-2)	0.038163	-0.204794	0.037092	-0.048329	-0.006148
	(0.01649)	(0.11240)	(0.03438)	(0.03454)	(0.00687)
	[2.31412]	[-1.82194]	[1.07875]	[-1.39928]	[-0.89450]
DFA(-3)	0.030251	-0.236340	-0.046885	-0.041592	-0.009863
	(0.01649)	(0.11242)	(0.03439)	(0.03454)	(0.00687)
	[1.83406]	[-2.10221]	[-1.36331]	[-1.20402]	[-1.43486]
DFA(-4)	0.011684	-0.112353	-0.040107	-0.017824	-0.003588
	(0.01431)	(0.09753)	(0.02983)	(0.02997)	(0.00596)
	[0.81656]	[-1.15197]	[-1.34431]	[-0.59475]	[-0.60165]
DLSV(-1)	0.105842	-0.254959	-0.397391	0.121057	0.003790
	(0.04147)	(0.28263)	(0.08646)	(0.08684)	(0.01728)
	[2.55256]	[-0.90211]	[-4.59650]	[1.39398]	[0.21931]
DLSV(-2)	0.087804	-0.520786	-0.351680	0.085423	0.025219
	(0.04110)	(0.28015)	(0.08570)	(0.08608)	(0.01713)
	[2.13626]	[-1.85896]	[-4.10372]	[0.99234]	[1.47228]
DLSV(-3)	0.087968	-0.219303	-0.321170	0.107989	0.021629
	(0.03956)	(0.26967)	(0.08249)	(0.08286)	(0.01649)
	[2.22345]	[-0.81324]	[-3.89338]	[1.30326]	[1.31177]
DLSV(-4)	0.097694	-0.205699	0.516743	0.064403	0.017710
	(0.03839)	(0.26165)	(0.08004)	(0.08040)	(0.01600)
	[2.54490]	[-0.78615]	[6.45605]	[0.80105]	[1.10698]
DM2(-1)	-0.027237	0.654165	0.012714	-0.694831	-0.002483
	(0.05108)	(0.34814)	(0.10649)	(0.10697)	(0.02129)
	[-0.53326]	[1.87905]	[0.11939]	[-6.49548]	[-0.11663]
DM2(-2)	-0.010926	0.617773	-0.139864	-0.443800	0.050927
	(0.06106)	(0.41617)	(0.12731)	(0.12788)	(0.02545)
	[-0.17895]	[1.48441]	[-1.09862]	[-3.47050]	[2.00134]
DM2(-3)	-0.011481	-0.122915	-0.186820	-0.241282	0.041855
	(0.06100)	(0.41575)	(0.12718)	(0.12775)	(0.02542)
	[-0.18823]	[-0.29565]	[-1.46897]	[-1.88876]	[1.64650]
DM2(-4)	-0.029309	0.104790	-0.241140	-0.099420	0.029541
	(0.05137)	(0.35013)	(0.10711)	(0.10759)	(0.02141)
	[-0.57055]	[0.29928]	[-2.25141]	[-0.92410]	[1.37986]

DRPI(-1)	-0.252709	2.090288	0.059323	0.073566	0.140507
	(0.24812)	(1.69121)	(0.51734)	(0.51966)	(0.10341)
	[-1.01848]	[1.23597]	[0.11467]	[0.14157]	[1.35877]
DRPI(-2)	-0.073941	0.826022	0.025329	0.223341	0.014559
	(0.23929)	(1.63098)	(0.49892)	(0.50115)	(0.09972)
	[-0.30901]	[0.50646]	[0.05077]	[0.44566]	[0.14600]
DRPI(-3)	-0.024208	-0.983826	-0.351346	0.849593	0.113720
	(0.23190)	(1.58064)	(0.48352)	(0.48568)	(0.09665)
	[-0.10439]	[-0.62242]	[-0.72665]	[1.74928]	[1.17666]
DRPI(-4)	0.513090	-4.432185	-0.321552	0.086485	0.129208
	(0.21685)	(1.47802)	(0.45213)	(0.45415)	(0.09037)
	[2.36615]	[-2.99873]	[-0.71120]	[0.19043]	[1.42974]
C	-0.000498	0.087395	0.031083	0.043025	0.003634
	(0.00587)	(0.04003)	(0.01225)	(0.01230)	(0.00245)
	[-0.08479]	[2.18323]	[2.53838]	[3.49794]	[1.48457]
R-squared	0.442209	0.494599	0.910251	0.371630	0.320256
Adj. R-squared	0.323529	0.387067	0.891155	0.237934	0.175630
Sum sq. resids	0.130125	6.045330	0.565692	0.570768	0.022601
S.E. equation	0.037206	0.253598	0.077576	0.077923	0.015506
F-statistic	3.726088	4.599555	47.66812	2.779664	2.214369
Log likelihood	226.9130	6.196718	142.4138	141.9001	327.5673
Akaike AIC	-3.581096	0.257448	-2.111544	-2.102610	-5.331606
Schwarz SC	-3.079848	0.758697	-1.610296	-1.601362	-4.830358
Mean dependent	0.003286	0.032121	0.004897	0.024101	0.012112
S.D. dependent	0.045237	0.323921	0.235138	0.089263	0.017078
Determinant Residual Covariance		5.98E-13			
Log Likelihood (d.f. adjusted)		802.4737			
Akaike Information Criteria		-12.12998			
Schwarz Criteria		-9.623736			