

CHAPTER IV
METHODOLOGY

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1 Introduction

This chapter describes the econometric framework and techniques of analysis applied to meeting the objectives of the study. In this study, model equations are formulated in line with the theoretical arguments.

The methodology used in this study includes an evaluation model and statistical tests, which assess the interrelation between the variables mentioned in the model and their influence on sectoral production in Malaysia. A necessary step prior to the core analysis was to assess the stationarity of the variables using the unit root test. The augmented Dickey-Fuller (ADF) and the Phillips Perron (PP) unit root test procedures were used in testing for stationarity of the variables.

The next step involves testing for cointegration between variable using the Johansen and Juselius (1990) test. Finally, the MWALD test for testing Granger non-causality (Toda and Yamamoto, 1995) was constructed using Seemingly Unrelated Regressions (SUR).

Scope of the Study

The data of each variable used for the period of 1991:q1 to 2001:q2. In the study, several statistical tests are used to provide consistent estimates of the parameters

This study employs quarterly data series over the period of 1990: q1 to 2001: q2. Three standard monetary aggregates namely, M1, M2 and M3^{4.1} are utilized in this study. The sectors studied are agricultural (AG), mining and quarrying (MN) , manufacturing (MF), construction (C), electric, gas and water (EW), transport, storage and communication (TR), wholesale and retail trade and hotel and restaurant (WR), finance and insurance and real estate and business services (FB), government services (GS) and other services (OS) in Malaysia. Two additional financial variable namely, commercial bank loans (CR) and stock prices (CI) are also utilized.

Sources of Data

Data on monetary aggregates, sectoral production, and commercial bank loans are extracted from various of issues of the Quarterly and Monthly Bulletin published by Bank Negara Malaysia (BNM). The stock price indices were obtained from the Kuala Lumpur Stock exchange (KLSE).

M1: Currency in circulation plus demand deposits.

M2: M1 plus fixed deposit, negotiable certificates (NCD) and saving and other deposits.

M3 M2 plus net deposit with non-bank financial institution by finance companies and post office saving.

Use of Software Packages

Econometric views (or Eviews) will be used to analyze and test the functional relationships for the above model such as the Augmented Dickey-Fuller (ADF) and the Phillips Perron (PP) unit root test, and the Johansen and Juselius (1990) test.

Other software will be used to analyze Granger-causality. The MWALD test using the R routine was implemented involving the programming of the corresponding matrices. To illustrate, we have programmed the steps using RATS software and the programs are presented in Appendix A.1. The attached appendix in this report is just one part of the three models presented and discussed.

Properties of Time Series

1.1 Trend

There is an important step in dealing with the time-series data, which is to identify the basic pattern or components inherent in the data. Once these components have been identified, the methods that best describe these patterns can be employed. The time-series data usually consist of four basic components, which are trend (T_t), seasonal variation (S_t), cycle (C_t) and irregularity fluctuation (I_t). With regard to the data used in this study, which is from the period of 1991-2001, we are dealing with the trend component.^{4,2}

Trend component is a persistent upward or downward movement of the data over the long period of time. It reflects the long-term growth or decline in the time series. In the case of this study, we are dealing with long-term movement of sectoral production and financial variables in Malaysia. If a time-series does not contain any trend component, the data is said to be stationary (see Nelson and Plosser, 1982).

^{4,2} Refer to the Correlogram by using Eviews and we have to determine if this trend is stochastic or deterministic.

1.2 Stationarity

A type of stochastic process that has received a great deal of attention and scrutiny by the series analysis is the so-called stationary stochastic process. Broadly speaking, a stochastic process is said to be stationary if its mean and variance are constant over time and the value of variance between two time periods depends only on the distance or lag between the two periods and not on the actual time at which the covariance is computed.

There are important differences between stationary and nonstationary time-series. In stationary time-series, shocks are considered as temporary; the effect of the shocks will disappear and the time series will be reverting to its long-run mean level. On the other hand, a nonstationary series has a permanent component. The mean and variance of a nonstationary series are time-dependent and there is no long-run mean to which the series returns.

Unit Root Tests

An alternative test of stationarity that has recently become popular is known as the unit root test. When the series indicates the presence of unit roots, it means that the time series of the observation indicates non-stationarity.

In econometrics, a time series that has a unit root is known as random walk (time series). We need to apply first differences to achieve stationarity. Therefore, the time series is said to be first-order integrated, denoted by $I(1)$. When a time series is stationary in level form it is denoted as $I(0)$. Similarly, when the original series is integrated of order 2, it is denoted by $I(2)$. In obtaining stationarity, a variable is understood that its mean, variance and co-variance are all invariant with respect to time period.

The analysis of cointegration starts with the determination of the univariate properties of time series. If the series do not follow the same order of integration, then there is no meaningful relationship between them. In the present context, if all the variables are integrated of the same order, we can proceed to the cointegration test. Two asymptotically equivalent procedures for detecting unit roots are employed here, namely the Augmented Dickey Fuller (ADF) (see Said and Dickey, 1984) and the Philips Perron (PP) (Philips and Perron, 1988) tests.

4.1 The Augmented Dickey Fuller (ADF) Unit Root Test

Dickey and Fuller (1979) introduced the Dickey-Fuller test to check the presence of unit root in economic time series. The Augmented Dickey Fuller (ADF) (Said and Dickey, 1984) test is an extension of the Dickey Fuller by allowing a higher order of autoregression process. ADF is induced from the OLS estimation of regression as shown below:

$$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} + \sum_{i=2}^p \beta_i X_{t-i+1} + \mu_t \quad (4.1)$$

$$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} + \alpha_2 t + \sum_{i=2}^p \beta_i X_{t-i+1} + \mu_t \quad (4.2)$$

Where

ΔX_t = $X_t - X_{t-1}$ (the first difference of the series)

α_0 = intercept

α_1, α_2 = constant parameters

μ_t = white noise error term

t = time or trend variables

p = the number of lagged variables

Equation (4.1) is with-constant, no trend variable regression and equation (4.2) is with-constant, with trend variable regression. The number of lagged variable, k is important to avoid problem of autocorrelation i.e. to ensure terms are uncorrelated.

In order to implement the ADF test, it is necessary to choose the order autoregression, k . In practice, k is unknown, so the researcher must choose k . In this case, we cannot arbitrarily choose k because, as contended by Batten and Thornton (1985), if k is chosen to be too small, the ensuing inference about the unit root is biased. Moreover, if k is chosen to be too large, it may cause the deterioration in the finite-sample properties of the ADF tests. The optimal lag length, k may be selected by using the Akaike's information Criterion (AIC) from Eviews. The lag length that produced that lowest AIC value for the equation was determined to be the appropriate lag length.

The null and alternative hypothesis under the ADF test; $H_0: \alpha_1 = 1$ against the $H_a: \alpha_1 = 0$, H_0 is rejected if the observed t statistic is sufficiently negative compared to the critical value at the accepted level of significance. It means the series is stationarity. If the observed t statistic is smaller than the reported critical value, H_0 is not rejected; it means the series is non-stationarity.

2 The Philips-Perron (PP) Unit Root Test

The distribution theory supporting the Dickey-Fuller test assumes that the errors are statistically independent and have a constant variance. By applying this methodology, care must be taken to ensure that the error terms are uncorrelated and have a constant variance. The PP test was introduced by Philips and Perron (1988) to develop a generalization of Dickey-Fuller procedure that allows for fairly mild assumptions concerning the distribution of the error.

The PP test accounts for possible relationship in the first-differences of the economics series using the non-parametric correction as an alternative to the inclusion of lag variables. The test also allows for the presence of a non-zero mean and a deterministic linear time trend.

The PP test is based on the Ordinary Least Square (OLS). The approach is to first test for unit roots from the regression equation with $k=0$. Then the statistics were converted to filter out the consequences of autocorrelation on the asymptotic distribution of the test statistic. The critical values are similar as those used for the Dickey-Fuller tests because the PP test is a modification of the DF t-statistic that takes into account the less restrictive nature of the error process. The PP test can be conducted using the following equations:

$$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} + \mu_t \quad (4.3)$$

$$\Delta X_t = \bar{\alpha}_0 + \bar{\alpha}_1 X_{t-1} + \bar{\alpha}_2 t + \mu_t \quad (4.4)$$

The t-statistic are calculated and then transformed to remove the effect of the serial correlation on the asymptotic distribution of the test statistic. In both equations the adjusted (transformed) t-statistics for both α_1^* and $\bar{\alpha}_1$ should be negative and significantly different from zero for X_t to be stationary. The null and alternative hypotheses in unit root test are:

Ho: X_t is non-stationarity/ a unit root process

Ha: X_t is stationarity

The critical for all tests are 5% significant level. The unit root test hypothesis of Dickey-Fuller and Philips-Perron can be rejected if t-test statistics from these tests are less than (more negative) the critical value tabulated. Critical values for both tests are tabulated in Osterwald-Lenum (1992).

2.7 Cointegration Tests

Cointegration tests provide the natural tool to investigate common trends between two time series over time. This analysis became invaluable when researchers realize that most of the time series are non-stationary in their levels, therefore, leading to spurious results. Two non-stationary series are said to be co-integrated if a stationary linear combination of two series exists. For example, by using standard OLS regression techniques to estimate the parameters of the cointegrating regression, the estimates of the residual errors, U_t , may be determined. Where:

$$Y_t = \alpha + \beta X_t + U_t \quad (4.5)$$

Suppose variable are first order integrated, $I(1)$, however, there exist values of α and β , such that $U_t = Y_t - \alpha - \beta X_t \sim I(0)$, $E(U_t) = 0$. Then we conclude that the variables are cointegrated.

1 Johansen-Juselius (1990) Cointegration Tests

In earlier studies, the Engle-Granger (1987) two-step estimation procedure is frequently used to test for cointegration. However, this procedure has been criticized for being static and giving rise to several econometric problems. First, Banerjee *et al.* (1986) noted that although the Engle-Granger procedure produces super consistent parameter estimates, for small samples the biases could be quite severe. Second, when cointegration relationships are not unique as in the present case, then the Engle-Granger procedure performs less satisfactorily. The estimates are not invariant to the choice of normalization. Finally, regressing integrated series by using OLS tends to invalidate statistical inferences (see Perman, 1991).

This study adopts the Johansen-Juselius (1990) maximum likelihood method in the context of the multivariate regression test, which is generally applied to $I(1)$ variables. This method is the extended work of Johansen (1988)^{4.3} and it provides a likelihood-ratio statistic to test for the maximum number of independent equilibrium vectors on the co-integrating matrix.^{4.4} Consider the following co-integrating vectors of the system,

$$\beta'X_t = Z_t \quad (4.6)$$

^{4.3} Johansen (1988) does not allow an intercept in the model.
^{4.4} The complete testing procedure is reported in Johansen (1988) and Johansen and Juselius (1990).

matrix β is called the co-integrating matrix. For N jointly determined variables, it will be of dimension $N \times N$, but of the rank $r \leq N - 1$, where r is the number of linearly independent co-integrating vectors. In specification form, the model be written as:

$$\Delta X_t = \delta + \sum_{i=1}^{k-1} \Pi_i \Delta X_{t-i} + \Pi X_{t-k} + \varepsilon_t \quad (4.7)$$

here X_t is a column vector of two variables. There are three possibilities to consider. If Π has full rank, no stationary linear combination can be identified. In other words, the variables in X_t are non-co-integrated. If the rank is r ($0 < r < n$), however, there will now exist r possible stationary linear combinations. From equation (4.7), the general hypothesis of the r co-integrating vector can be formulated as:

$$H_0: \Pi = \alpha\beta'; \quad (4.8)$$

where β' is the $r \times p$ matrix of cointegrating vectors, and α the $p \times r$ matrix of adjustment or error correction coefficient. This procedure provides two different likelihood ratio tests to determine the value of rank, r , of the matrix Π in (4.8). The first is known as the trace test. This test provides a test of the null hypothesis $H_0: r \leq r_0$ against $H_a: r > r_0$ where r refers to the number of co-integrating vectors.

second likelihood ratio test is the maximal eigenvalue test (λ -max) statistic of $H_0: r = r_0$ inst $H_a: r = r_0 + 1$;

$$\lambda_{\max} = T \ln (1 - \hat{\lambda}_{r+1})$$

where $\hat{\lambda}$'s are the estimated eigenvalues from Π ; and T is the number of observations. Hansen and Juselius (1990) indicate that the trace test may lack power relative to the maximal eigenvalue test. Based on the power of the test, the maximal eigenvalue test statistic is often preferred. Critical values for both tests are tabulated in Osterwald-Lunum (1992).

According to cointegration analysis, if two variables are cointegrated, the finding of non-causality in either direction is ruled out. In other words, two variables that possess a common trend, causality (in Granger sense) must exist in at least one direction, either unidirectional or bidirectional. However, although cointegration indicates presence or absence of Granger-causality, it does not indicate the direction of causality between variables.

8 Granger Non-Causality Test

Testing for Granger Non-causality in the context of stable VAR models involves testing whether some parameters of the model are jointly zero. In the past such testing has involved a standard F-test in a regression context. However, recent research (see Toda and Philips, 1993) has shown that when the variables are integrated, the F-test procedure is not valid, as the test statistic does not have a standard distribution.

8.1 The Baseline Model

The vector autoregression (VAR) model is one of the popular tools for empirical studies on the monetary transmission, since Sims' (1980) seminal work. A conventional or standard VAR is a reduced system, which can easily be estimated using Ordinary Least Squares (OLS) regression. A VAR consists of a set of variables and is regressed on lagged values of its exogenous variables and other exogenous variables in a system of equations. However, Sims, Stock and Watson (1990) argue that the conventional asymptotic is not applicable in testing the hypothesis in level VAR's if the variables are integrated or cointegrated. Further, Toda and Phillips (1993) has shown that the traditional F-test procedure is not valid. Unfortunately, several alternative methods for testing of non-causality such as error-correction model (ECM) (See Engle and Granger, 1987) and Vector autoregression error-correction model (VECM) (See Johansen and Juselius, 1990) are cumbersome and sensitive to the values of nuisance parameters in finite sample and therefore "virtues of simplicity and ease of application have been largely lost" (Rambaldi and Doran 1996).

2 Toda and Yamamoto (1995) Test

The more recent Granger no-causality test developed by Toda and Yamamoto (1995) offered simple procedures, which require researchers to estimate an augmented VAR model in a straightforward way. Moreover, in the context of integrated variable, conventional application of test (i.e. in standard VAR model) was recently criticized by Toda and Philips (1993) for spurious regression due to non-standard distribution of test statistic.

Toda and Yamamoto (1995) approach utilizes the Modified Wald (MWALD) test for testing linear restriction on the parameters. This test has an asymptotic χ^2 distribution when a VAR($k + d_{\max}$) is estimated, where d_{\max} is the maximum degree of integration suspected to occur in the system and k is the number of lag(s). Therefore, the Toda Yamamoto causality procedure has been labeled as the long-run causality test. Toda and Yamamoto (1995) point out that, for $d = 1$, the lag selection procedure is always valid since $k \geq 1 = d$. If $d = 2$, then the procedure is valid unless $k = 1$. Moreover, according to Toda and Yamamoto, the MWALD statistic is valid regardless whether a series is $I(0)$, $I(1)$ or $I(2)$, non-cointegrated or cointegrated of an arbitrary order. In addition, Zapata and Rambaldi (1997) provide evidence that MWALD test has a comparable performance in size and power to LR and WALD tests if the correct number of lags for estimating $k + d_{\max}$ is identified and no importance variable are omitted.

Rambaldi and Doran (1996) have demonstrated that the MWALD procedure for testing Granger non-causality can be easily constructed by using Seemingly Unrelated Regression (SUR).

Specification of Model

This section summarizes the theoretical model underlying the empirical analysis. Following Toda and Yamamoto (1995) Granger non-causality test for this study can be implemented SUR as follows:

$$\begin{bmatrix} Y_t^i \\ MS_t^i \\ CR_t \\ CI_t \end{bmatrix} = \alpha_0 + \alpha_1 \begin{bmatrix} Y_{t-1}^i \\ MS_{t-1}^i \\ CR_{t-1} \\ CI_{t-1} \end{bmatrix} + \alpha_2 \begin{bmatrix} Y_{t-2}^i \\ MS_{t-2}^i \\ CR_{t-2} \\ CI_{t-2} \end{bmatrix} + \alpha_3 \begin{bmatrix} Y_{t-3}^i \\ MS_{t-3}^i \\ CR_{t-3} \\ CI_{t-3} \end{bmatrix} + \alpha_4 \begin{bmatrix} \varepsilon_{Yit} \\ \varepsilon_{MSit} \\ \varepsilon_{CRt} \\ \varepsilon_{CIt} \end{bmatrix}$$

Where,

Y_t^i : Sectoral production with $i = AG, MN, MF, CS, EW, TR, WR, FB, GS$, and OS at time t ;

MS_t^i : Money supply with $i = M1$ or $M2$ or $M3$ at time t ;

CR_t : Total commercial bank loans at time t ;

CI_t : Total Stock prices at time t ;

ε_t : error terms.

For example to examine that MS_t^i does not Granger causes Y_t^i , the restriction test procedure is applied with null hypothesis $H_0: \alpha_{12}^1 = \alpha_{12}^2 = \alpha_{12}^3 = 0$, where α_{12}^i are the coefficients of MS_t^i in the first equation of the above system. If the MWALD statistic for the lagged

dependent variables (MS_t^i) are significant, a causality from MS_t^i to Y_t^i can be established by rejecting the null hypothesis. A similar testing procedure can be applied to test the null hypothesis that reverses causality running from Y_t^i to MS_t^i with $H_0: \alpha_{21}^1 = \alpha_{21}^2 = \alpha_{21}^3 = 0$, where α_{21}^i are the coefficients of Y_t^i in the second equation of the system. A similar procedure can be used to test the non-causality from CR_t to Y_t^i and from CI_t to Y_t^i and also for the reverse orders.

This study is based on the methods used by Azali and Habibullah (2000)^{4,7}. They analyzed the responses of sectoral output namely manufacturing, services and agricultural sectors to selected financial variables (i.e. money supply aggregates, credit and stock prices). A sectoral augmented VAR model based on Toda and Yamamoto's (1995) work was estimated. However, in this study we analyze the response of 10 sectoral production levels (refer to Table 1.2: A Sectoral Breakdown of GDP) to the same financial variables using quarterly data in Malaysia.

⁷ See Azali, M and M.S. Habibullah (2000). The journal paper of "Sectoral impact of monetary policy in Malaysia and Singapore." *University Putra Malaysia, Faculty of Economy and Management, Working paper no. 7626*.

10 Conclusion

This chapter states the methodology and data used in the study. It consists of a general description on the technique adopted in completing the study. The augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) unit root test procedures; Johansen and Juselius (1990) integration test; and Toda and Yamamoto's (1995) test are conducted to achieve the objectives of the study.