Time Series Analyses of Inflation in New Zealand

A THESIS PRESENTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
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ABSTRACT

Modelling of the economy has become increasingly important over the years. It serves two main purposes. It enables forecasts and it can be used for the evaluation of various economic policies. Economic models come with various degrees of size and statistical complexity. Models can be of a qualitative or of a quantitative nature. The soundness of the statistical techniques that are used for quantitative models is critical. In recent years a number of such techniques have been developed. This thesis will evaluate some on existing economic New Zealand time series.

Inflation plays a main role in everyday life and it has been of major ongoing concern to the New Zealand governments in recent times. These governments have instructed the Reserve Bank of New Zealand (RBNZ) to set monetary policies to ensure certain targets are met. The RBNZ achieves this to a large degree by setting the Official Cash Rate which is the major determinant of the interest rates that are used by the banks.

This thesis will consider some theoretical aspects of time series analysis. In particular the Dickey-Fuller tests and cointegration analysis are considered. Also some theoretical aspects of inflation are considered. Examples are given of aspects of New Zealand life other than the interest rates that may also affect the current inflation rates.

The time series that were analysed could be categorised as inflation indices, monetary aggregates, interest rates and gross domestic product. The thesis attempted to evaluate the time series in such a manner that there was little room for an analyst's bias. This was mainly achieved by developing a standardised approach to the analysis of these series. A number of interactions between the time series were evaluated and some were identified as being suitable for further research with the ultimate aim of developing a small model of the New Zealand economy. Another aim was to evaluate some aspects of economic policy where possible given the small number of time series that were used. Granger

Causality tests seemed to show the effect of economic policy, where the interest rates affect the inflation rates. However, this was not further supported by cointegration analyses. There are various possible explanations for this. It was surmised that the standardised way of analysis may not have identified this relationship where it existed.

The analyses showed that at times the results of the statistical tests were inconsistent. This applied to the Dickey-Fuller tests as well as the cointegration analyses. In some cases unit root models with significant coefficients for the deterministic components were identified. Further analysis would show that the deterministic components were not significant after all. However, the resulting models without these components did not have a unit root. The cointegration analyses invariably showed a number of Vector Error Correction Models with significant cointegration equations. Since their economic implications would be quite different at times there was a reason for concern.

In conclusion there are some worrying problems when the methodology is used for existing short New Zealand data series. However, at times some plausible results were shown as well. Suggestions for further research were made.

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NOTATIONS

Abbreviations of statistical terms

* (**)	denotes rejection of the hypothesis at the 5% (1%) significance level
AIC	Akaike Information Criterion
ACF	Autocorrelation function
ADF	Augmented Dickey-Fuller test statistic
Adj. R^2	Adjusted R-squared value
CE	Cointegrating Equation
DF	Dickey-Fuller
GC	Granger Causality
IRF	Impulse Response Function
n	Sample size
k	number of parameters
p	P-value
RSS	Residual Sum of Squares
SC	Schwartz Criterion
SD	Standard Deviation
SE	Standard Error
T	Number of usable observations
VAR	Vector Autoregression
VD	Variance Decomposition
VECM	Vector Error Correction Model
γ	Coefficient of ADF test statitic
τ	Various τ statistics (See Chapter 2)
ϕ	Various ϕ statistics (See Chapter 2)

Abbreviations of economic terms

CD	Call Deposit Rate
CPI	Consumer Price Index
CPINT	CPI Non-Tradable Inflation
CPIT	CPI Tradable Inflation
CPIX	CPI excluding credit services
EGDP	Expenditure-based real Gross Domestic Product in 1995/96 million dollars
GDP	Gross Domestic Product
HE	Average Hourly Earnings
LC	Labour Cost Inputs
M1	Notes and coins held by the public plus chequeable deposits, minus inter-institutional chequeable deposits, and minus central government deposits.
M2	M1 plus all non-M1 funding (call funding includes overnight money and funding on terms that can of right be broken without break penalties) minus inter-institutional non-M1 call funding.

M3	Notes and coins held by the public plus NZ dollar funding minus inter-M3 institutional claims and minus central government deposits.
M3(R)	Same as M3, less funding from non-residents.
M2R	M2 – M1
M3RR	M3(R) – M2
NT	CPI Non-Tradable Inflation
OCR	Official Cash Rate
PGDP	Production-based real Gross Domestic Product in 1995/96 million dollars
RBNZ	Reserve Bank of New Zealand
SMD	Six Month Deposit Rate
T	CPI Tradable Inflation

Prefix or Suffix

Time series may have undergone some statistical manipulations. This is usually indicated by a prefix or suffix

A	Suffix for CPI adjustment
D	Prefix for differenced time series
LOG	Prefix for logarithmic transformation
SA	Suffix for seasonal adjusted
Δ	Prefix for differenced time series

Note that in some cases a transformed time series may be displayed in equations without its prefix or suffix. This was done to keep the equation concise and it will be explained when it occurs.

Typeface

Italics	Denotes time series
Bold in cointegration tables	Denotes optimal model according to SC and AIC
Bold in equations	Denotes significant coefficients based on availability of relevant statistics. Note that the standard error is not always available (see Table 2.5)

CHAPTER 1

GENERAL INTRODUCTION

1.1 The importance of inflation

"Inflation is the one form of taxation that can be imposed without legislation"
(Quote from Milton Friedman)

Inflation is the increase of price levels. It can be measured for a multitude of baskets of goods and services. Examples of inflation measures are the commonly used Consumer Price Index (CPI) and the Producers Price Index (PPI). Inflation means that the basket of goods and services becomes more expensive when expressed in nominal dollars as time goes by. Nominal dollars are dollars used currently, without any inflation adjustment.

There is a perception that inflation is bad. Since inflation will generally not be the same for all goods and services, the relative prices for the different goods and services may change. This may be a beneficial process from a resource allocation perspective. It is not surprising that people will regard inflation as negative if they pay more for their goods and services and they are on fixed incomes. From a rational perspective, this negative perception should not be the case if their income increases at a level that compensates for inflation, ie if their purchasing power is maintained. Successive New Zealand governments have arguably made considerable attempts to keep inflation within certain bounds but their objective has not been a zero rate of inflation.

Inflation can lead to a redistribution of income and wealth. Interest rates are of particular relevance. A lender will be worse off and a borrower will benefit if interest rates do not include sufficient compensation for inflation. The use of tax brackets where higher tax rates apply if income exceeds certain nominal levels are a clear reason why inflation is perceived as a negative event.

Even if there is compensation for inflation, there may still be a negative perception since inflation will create uncertainty regarding the purchasing power of incomes and investments or debt. This is especially the case for high levels of inflation and there can be little doubt that high inflation is undesirable. What precisely determines the optimal level of inflation is not a trivial question.

1.2 Current issues in New Zealand

In the 1980's New Zealand experienced high inflation rates. Since then various governments have been committed to reduce the inflation rates to lower levels and to keep it at these levels. The interest rates that currently (February 2004) exist seem to be considered low if one considers the flourishing market for houses and mortgages. Similarly they are beneficial for those who wish to borrow for investment in plant and equipment.

The Reserve Bank of New Zealand (RBNZ) sets the Official Cash Rate (OCR) which determines the interest rates charged by banks to their customers. The main criterion of the RBNZ is to ensure that the CPI remains within certain bounds as agreed to with government. If the RBNZ believes that the CPI will become too high it will increase the OCR thereby reducing demand. If, on the other hand, it believes the CPI will become too low it will lower the OCR. Currently (2004) the RBNZ believes the housing market is overheating and is putting too much pressure on the inflation rates. Consequently there is an incentive for the RBNZ to increase the OCR.

The combination of interest rates and expected inflation are important factors for establishing the exchange rates. An increase of the exchange rate will be detrimental to exporters and beneficial to importers. At the time of writing (2004) the US dollar has depreciated considerably in recent months in value against many currencies including the NZ dollar. Much of the international trade is carried out with US dollars and consequently many exporters would like to see a decrease in the OCR.

The two conflicting pressures described above results in the RBNZ's unenviable position. Whatever its decision, there is likely to be severe criticism. It raises the question whether the reliance on one tool only (the OCR) to deal with multiple objectives is too limited.

1.3 The use of statistical techniques to analyse inflation

The analysis of historic data seems a prerequisite for making rational decisions. In this case statistical techniques will be used to analyse inflation rates and other variables that may influence inflation. These variables include monetary aggregates, interest rates and the Gross Domestic Product. Without a doubt there are other factors that affect inflation as well. Examples are the exchange rate and unemployment. However a full analysis of all possible factors that affect inflation is beyond the scope of this thesis.

Time series analysis will be used to analyse the datasets. Initially analyses will be carried out at the univariate level and they will be followed by multivariate analyses to evaluate possible interactions.

An important aspect of time series analyses is whether they are stationary or not. A full explanation will follow in a later chapter but crudely speaking lack of stationarity means that the mean and variance of the series vary over time. In the late 1970's techniques were developed to evaluate this aspect. Since the late 1980's a number of techniques have been developed to analyse the interaction of time series that are not necessarily stationary.

The explanation in some publications of a number of the currently used time series techniques is not always clear and what appear to be mistakes may at times be detected. These mistakes may be 'typographical' but they may also be the result of a theory that sometimes appears confusing (at least to the author of this thesis). The time series that are commonly used in the area of econometrics are generally of short duration. This combined with the small power of some of the tests, results in difficulties when attempting to analyse these series. Like other statistical tests, the tests discussed in this thesis require assumptions of a statistical nature before they can be used. In addition diagnostic checking is required to ensure that the results are valid. Therefore there are a number of issues that need to be addressed before one can confidently draw conclusions regarding economic time series that are valid from a statistical perspective. This thesis attempts to describe in a clear and consistent way some of these issues and will analyse some time series taking these limitations into account. It does not claim to be able to give a definitive conclusion on what is wrong and what is right.

The findings of the analyses will depend heavily on the assumptions made. Where possible these assumptions will be explicit. An issue arises where the data are collected under certain policy regimes. If these regimes change, the findings of the analyses may no longer be applicable. In a sense the existing policies, where not clearly described as variables, are implicit assumptions. This means that one has to be careful when generalising results.

Once the analyses have been performed the results can be used for developing models. The two main purposes of these are policy analysis and forecasting. Policy analysis allows the evaluation of 'what-if' scenarios while forecasting attempts to predict what the future will bring. It has been claimed that generally a model can only be used for either of these two purposes but not for both at the same time.

1.4 The structure of this thesis

The key questions in relation to inflation are:

- What causes inflation?
- What is the appropriate level of inflation?
- How can the appropriate level of inflation be achieved on an ongoing basis?

In order to answer the last question one should, at least, attempt to answer the first question. The main purpose of this thesis is to find an answer to the first question. There are no guarantees that the approach taken will provide the answers, if only because other factors that might drive inflation are not analysed in this thesis. However, it is maintained that the approach taken is a minimum requirement to deal with questions relating to inflation.

The key research questions for this thesis fall in two categories: They are the statistical ones and the economic ones.
Various economic models exist. The key economical research questions are:

1. Can equations be found that could serve as a backbone for a small model of the New Zealand economy for the period in question?
2. Can economic and monetary policy be seen reflected in the data sets (eg do interest rates rise as inflation rises)? More importantly perhaps is the question whether economic or monetary policies are successful.

The statistical techniques discussed in this thesis are used widely. The key statistical research questions are:

1. How well do standard cointegration techniques work under practical conditions? Policy changes that may affect relationships and trends of time series occur relatively frequently in practice. Consequently it will often be more appropriate to evaluate short

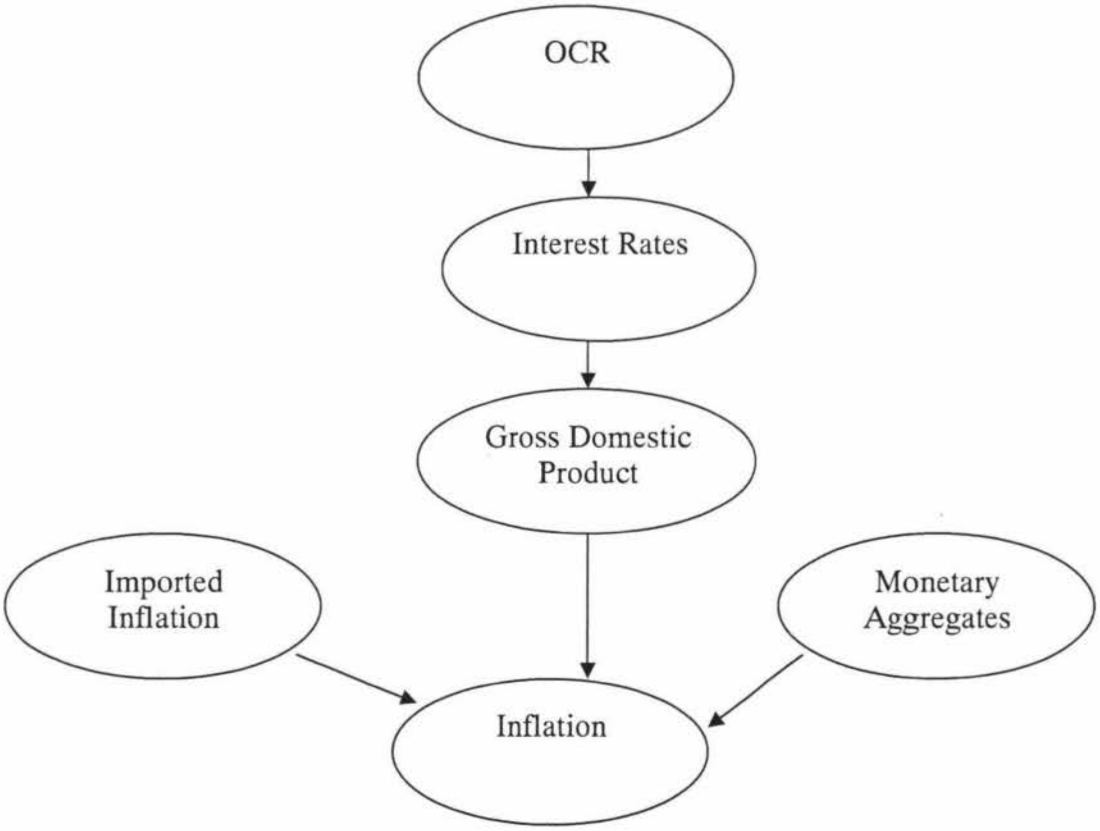
time series rather than long ones. New Zealand series of approximately ten years are used to evaluate this issue.

2 Can an automated approach involving the examination of a large number of possible models produce sensible results? Sensible can be interpreted as meaning that the results of the various models should not contradict each other. In addition the final result of a model, ie a group of equations, should preferably cover the area of interest in a coherent manner

Sometimes data analysis is performed and only a limited number of the possible models will be displayed. This thesis attempts to demonstrate the large number of options that might be possible at times. The drawback of the selective approach of only showing a limited number of models is that they may be heavily influenced by the analyst's economic views. Alternative equally plausible models may be ignored unintentionally; the analyst just did not test for it. Therefore different views of economic theory might lead to different admissible models according to some commonly used statistical techniques.

The analysis will be performed in the New Zealand context. The emphasis of the thesis will be on the use of certain statistical techniques when analysing economic time series. Although economic theory will be considered the focus will mainly be on the use and limitations of these statistical techniques. This is because it will provide insights into the validity of conclusions when statistical techniques are evaluated in-depth.

Figure 1.1 Schematic overview of factors affecting inflation that are evaluated in this thesis



The following two chapters will discuss theoretical aspects of time series analysis (Chapter 2) and of inflation (Chapter 3). Chapter 4 will analyse inflation time series. Chapter 5, 6 and 7 will evaluate monetary aggregates, interest rates and GDP respectively. This will first be at a univariate level followed by multivariate techniques. Figure 1.1 provides an overview of the interaction of these variables.

Currently the understanding of inflation in New Zealand relies heavily on this country having its own currency, the New Zealand dollar. International communications are continually improving and differences between countries are becoming increasingly smaller. If currency substitution (ie the use of other currencies for trade within New Zealand) became a commonly accepted practice, the dynamics of inflation might change. A final chapter is dedicated to currency substitution and various ramifications for the New Zealand economy.

CHAPTER 2

STATISTICAL METHODS OF TIME SERIES ANALYSIS

2.1 Introduction

Economic and financial time series are to a large degree a reflection of a multitude of events that occur prior to and during the time when the observations are made and anticipated events may affect them too. These series may have been influenced by some variables that did not change during the period in question but they may have been very important nevertheless (eg certain fiscal policies). If measurements are taken in later periods when these variables have changed, the resulting time series can be quite different from what would have been forecast. This is because the effect of these other variables would not have been accounted for. These changes are called structural breaks. Lack of knowledge of important variables (and their interaction) can make the generalisation of findings of econometric research problematic.

Another form of generalisation, extrapolation beyond the data range that was actually measured can also lead to incorrect conclusions.

Despite these issues, an analysis of currently available and apparently relevant data will still be useful since it may alert to economic aspects that should be considered when setting monetary and/or fiscal policy. The time series that will be used for investigating inflation in New Zealand will be relatively short. The longest ones started in March 1988 and the shortest ones in the first quarter of 1994. The datasets used in this thesis have been downloaded from the website of the Reserve Bank of New Zealand.

A number of aggregates that are described in this thesis are actually amalgams of other aggregates. For instance M3 contains M2 and some other variables. Consequently, virtually by definition, a relationship must exist between these variables unless one variable is much smaller than the other variable. In order to separate out such inclusions, at times the differences between the aggregates were used in this analysis. This has been denoted by "R" for "reduced" below. In the case of M3, M2 was subtracted from the M3 residents and not from non-residents since non-residents are not likely to have much money invested in M2 or M1.

The analyses of the time series will be performed with EViews 3.1 Student Version (Quantitative Micro Software, LLC, Irvine CA).

2.2 Linear stochastic models

A time series can be analysed in isolation (univariate analysis) or in relation to other time series (multivariate analysis). Univariate analyses are valuable for understanding the behaviour of a time series before progressing any further. Multivariate analyses serve to include aspects that are deemed to be important and should provide a better understanding of economic events.

The analyses below will make extensive use of difference equations. Instead of using the actual observation for the analysis, the increase or decrease in value since the previous observation will be used. The first difference is:

$$\Delta y_t = f(t) - f(t-1) = y_t - y_{t-1} \tag{2.1}$$

Similarly a second difference can be constructed as:

$$\Delta^2 y_t = \Delta(\Delta y_t) = \Delta y_t - \Delta y_{t-1} = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) = y_t - 2y_{t-1} + y_{t-1} \tag{2.2}$$

An important aspect of the analysis of any time series is to establish whether or not it is stationary. This means whether the mean and variance do not change over time. Viewing a graph is important for acquiring an appreciation of stationarity but formal tests are required to refute a hypothesis or not. These formal tests will be discussed at a later stage.

If the mean changes over time the time series is said to have a trend. It was commonly accepted in the past that it was desirable to remove trends for analysis purposes but it has recently been shown that this is not always required or desirable (see below). It is also possible that the variance changes over time. Transformation of the data set (eg logarithmic transformation, square root transformation) can be performed to make the series stationary.

The values of a time series may be correlated to previous values. In that case an autoregressive (AR) process may exist.

$$y_t = a_1 y_{t-1} + \varepsilon_t \tag{2.3}$$

where ε_t is the error term.

This is a AR(1) only. More generally the following equation applies:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_n y_{t-n} + \varepsilon_t \tag{2.4}$$

Another possibility is a time series that is a function of a number of error terms in the past. In that case a moving average (MA) process exists.

$$x_t = \sum_{i=0}^{q} \beta_i \varepsilon_{t-i} \tag{2.5}$$

where x_t are the observations, β_i are the coefficients of the errors at various lags and ε_t is the error term.

The two approaches above can be combined resulting in an autoregressive moving average model (ARMA model). This model would combine correlations with past values of observations and it would continue to have the error terms (up to i = q) of past observations.

Three distinctive components to a linear stochastic equation can be identified (Enders 1995, p. 166):

y_t = trend + seasonal component + irregular component

Frequently a sustained upward trend can be distinguished in time series (eg GNP). These trends have been modelled with a simple linear time trend:

$$y_t = a_0 + a_1 t + \varepsilon_t \qquad (2.6)$$

where a_0 is a constant, t is a trend and ε_t is the error term.
A deterministic trend indicates that the series changes in a constant and highly predictable fashion. The effect of any shocks on the series would disappear quickly. Another type of trend is a stochastic trend. There is a (stationary) irregular component. The effect of this component does not disappear over time.

An example of a model with a stochastic trend is the Random Walk model:

$$y_t = y_0 + \sum_{i=1}^{t} \varepsilon_i \qquad (2.7)$$

or equivalently

$$y_t = y_{t-1} + \varepsilon_t \qquad (2.8)$$

where y_t is the observation and ε_t is the error term.
The shock constituted by ε_i has a permanent effect on the time series y_t. The variance depends on the time:

$$Var(y_t) = t\sigma^2 \qquad (2.9)$$

where y_t is the observation, t is the number of periods and ε_t is the error term
The variance is increasing over time and therefore the time series is not stationary. As a result of all these factors the time series wanders and does not show any tendency to arrive at some long-run equilibrium position. A visual inspection of such a time series may give the impression of a deterministic trend (also depending on the length of the time series). The autocorrelation function (ACF) cannot be used to distinguish these time series from a unit root process. The ACF is a function that describes the linear correlation between the points of a data series with various lags (1, 2, ..., n).

The random walk model can be extended by including a drift component:

$$y_t = y_{t-1} + a_0 + \varepsilon_t \qquad (2.10)$$

where y_t is the observation, a_0 is a constant that forms the drift component and ε_t is the error term.

If the initial condition (y_0) is known, then the general solution becomes:

$$y_t = y_0 + a_0 t + \sum_{i=1}^{t} \varepsilon_i \tag{2.11}$$

where y_t is the observation, a_0 is a constant, t is the number of periods and ε_t is the error term.

This model now has two nonstationary components. They are the linear deterministic trend ($a_0 t$) and the stochastic trend created by ε_i .

The random walk model can be modified by including a noise model. The time series y_t has become the sum of a stochastic trend and a white-noise component. This model is shown as:

$$y_t = \mu_t + \eta_t \tag{2.12}$$

where $\mu_t = \mu_{t-1} + \varepsilon_t$, the observations with the error term ε_t that will remain in the time series and η_t is a second error term.

The essence of this model is that $\{\eta_t\}$ is a white noise process that only applies to time *t*, its effect is temporary only. This means that $E(\varepsilon_t \eta_t) = 0$

If the initial condition μ_0 is known, then y_t can be expressed as:

$$y_t = \mu_0 + \sum_{i=1}^{t} \varepsilon_i + \eta_t \tag{2.13}$$

Enders demonstrates how the above models can be combined into more detailed models (p. 173). He describes a general trend plus irregular model as:

$$y_t = \mu_0 + a_0 t + \sum_{i=1}^{t} \varepsilon_i + A(L)\eta_t \tag{2.14}$$

where y_t is the observation, a_0 is the coefficient of the trend, *t* is the trend term, ε_t and η_t are error terms and A(L) is a polynomial in the lag operator L.

The selection of A(L) is important and wil be addressed in later sections. The random walk plus drift process has now been augmented with the stationary noise process $A(L)\eta_t$.

The local linear trend model is defined by Enders (p. 174) as being based on three mutually uncorrelated white-noise processes $\{\varepsilon_t\}$, $\{\eta_t\}$ and $\{\delta_t\}$.

The model is:

$$\begin{aligned} y_t &= \mu_t + \eta_t \\ \mu_t &= \mu_{t-1} + a_t + \varepsilon_t \\ a_t &= a_{t-1} + \delta_t \end{aligned} \tag{2.15}$$

This model has a stochastic trend term μ_t. The other models discussed above are all special cases of this model.

2.3 Unit root processes

Many financial and economic time series are not (covariance) stationary. This is because their mean and variance vary over time. Regression analyses on such series are likely to lead to spurious results. There are various ways to make these time series stationary. They can be transformed by using the logarithm, square root or y^a Box-Cox family if the variance over time is not constant. There are two detrending techniques: differencing and removing the linear trend (called detrending). Which of these techniques should be used will depend on the actual time series, ie whether the series is difference stationary or trend stationary.

The evaluation of the existence of a unit root is done by viewing the graph and the ACF function. Formal test that are commonly used are the (Augmented) Dickey Fuller test and the Phillips-Perron unit root test. This thesis will use the Dickey-Fuller test extensively and the details are discussed in 2.4.

The test for stationarity is based on testing whether $a_1 = 1$ (unit root) in the equation

$$y_t = a_1 y_{t-1} + \varepsilon_t \tag{2.16}$$

Therefore the null hypothesis is that $a_1 = 1$ and that the equation is non-stationary. If the p-value $p < 0.1$, the series is deemed stationary. Because of the possible non-stationarity of the variables, the t-test cannot be applied to $a_1 = 1$ and the equation is re-written as:

$$y_t - y_{t-1} = (a_1 - 1) y_{t-1} + \varepsilon_t \text{, or}$$

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t \tag{2.17}$$

where $\gamma = a_1 - 1$

The equivalent hypothesis has now become:

$H_0 : \gamma = 0$ against $H_1 : \gamma \prec o$

This is a one-sided test and rejection of H_0 occurs when t-values are in the left hand tail of the Dickey-Fuller distribution. Rejection of the null hypothesis is interpreted to mean that the series is stationary and does not have a unit root. The critical percentage of 10% is commonly used. The standard t-distribution does not apply in this situation.

There may be a constant term and it is recommended to include a constant term in the DF test unless there are reasons to the contrary. The equation if the mean for the y_t series is not zero is

$$\Delta y_t = \gamma y_{t-1} + a_0 + \varepsilon_t \tag{2.18}$$

where a_0 is the constant term.

There is a random walk process if both $\gamma = 0$ and $a_0 = 0$. However, if $\gamma = 0$ and $a_0 \neq 0$, a random walk with drift exists. In essence this means that the new observation includes the value of the previous one and in addition the stochastic term (ε_t) is added. At each point in time the deterministic component a_0 is added. Since this term is added at each observation it is cumulative over time. The impression one acquires by viewing the graph is that the time series drifts in a certain direction, with decreases and increases to this drift as determined by the stochastic term.

A deterministic linear trend in Δy_t may exist in which case the equation becomes:

$$\Delta y_t = \gamma y_{t-1} + a_0 + a_2 t + \varepsilon_t \tag{2.19}$$

where $a_2 t$ is the deterministic linear trend.

In the situation where $\gamma = 0$ (unit root) but $a_0 \neq 0$ and $a_2 t \neq 0$ a random walk with drift of a_0, $a_2 t$ exists and this is a quadratic deterministic trend.

The whole meaning of the intercept and trend terms in the equations depends crucially on whether γ is zero (unit root) or not. If γ is zero (unit root), the intercept (a_0) represents a linear trend term in the series, and the 'linear' trend term (a_2) a quadratic trend. If not a unit root, the intercept (a_0) represents a non-zero mean and the trend term (a_2) a linear trend. In the case of unit root the differenced series will be stationary. Figures 2.1 – 2.12 are simulations that illustrate these points.

The proof of the above statement is as follows:

$\Delta y_t = \gamma y_{t-1} + a_0 + a_2 t + \varepsilon_t$

If $\gamma = 0$ and the stochastic component ε_t is ignored. So,

$\Delta y_t = a_0 + a_2 t$

$y_t - y_{t-1} = y_{t-1} + a_0 + a_2 t$

$y_t = y_{t-1} + a_0 + a_2 t$

If $a_2 = 0$, at each subsequent point in time a_0 is added. If y_0 is given:

$y_{t+p} = y_1 + p \times a_0$

and therefore a linear trend exists $p \times a_0$.

Now if the term a_2 is included in the equation:

$y_{t+1} = y_0 + (a_0) + (a_2)$

$y_{t+2} = y_0 + (2 \times a_0) + (a_2 + 2 \times a_2)$

$y_{t+p} = y_0 + (p \times a_0) + ((1 + 2 + ... + p) \times a_2)$

where the last term of the equation is quadratic.

Now if $\gamma \prec 0$, y_0 is given, $a_2 = 0$, and the term ε_t is ignored.

$y_{t+1} = (1 + \gamma) y_0 + (a_0)$

Make $\gamma = -0.5$ for ease of understanding without loss of generality

$$y_{t+1} = (0.5)y_0 + (a_0)$$

$$y_{t+p} = (0.5)^p y_0 + (a_0)$$

where the first term on the RHS approaches 0 as p increases in time.

Now if a_2 is included in the previous equation the following equation eventuates.

$$y_{t+p} = (0.5)^p y_0 + (a_0) + p \times a_2$$

which is a linear trend.

The graphs below have been simulated in @RISK 4.0.5 (Palisade Corporation, Newfield, NY) to illustrate the points made above.

The settings chosen in the various graphs were $a_0 = 2$, $a_1 = 0.6$ or $a_1 = 1$(unit root) and $a_2 = 5$. Figures 2.1 – 2.6 are models that do not have a unit root.

Figure 2.1 Time series with no drift ($a_0 = 0$) and no trend ($a_2 = 0$), $a_1 = 0.6$

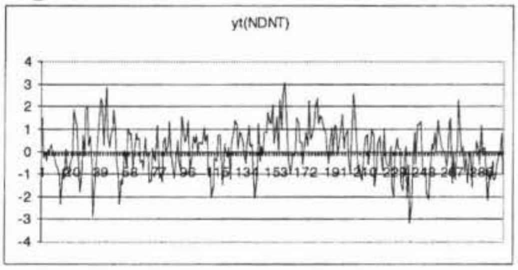


Figure 2.2 Differenced time series with no drift ($a_0 = 0$) and no trend ($a_2 = 0$), $a_1 = 0.6$

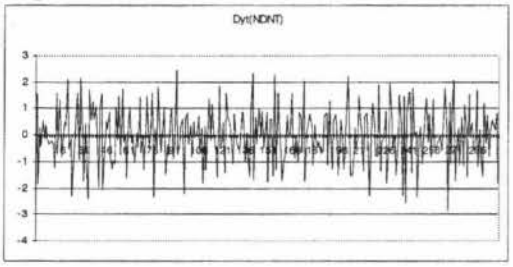


Figure 2.3 Time series with drift ($a_0 = 2$), no trend ($a_2 = 0$) and $a_1 = 0.6$

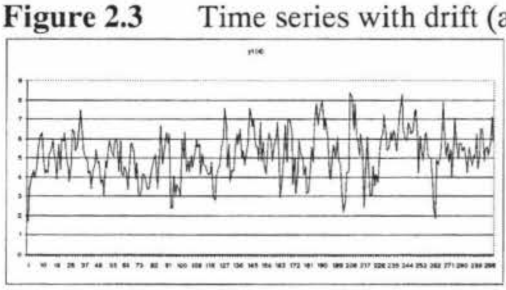


Figure 2.4 Differenced time series with drift ($a_0 = 2$), no trend ($a_2 = 0$) and $a_1 = 0.6$

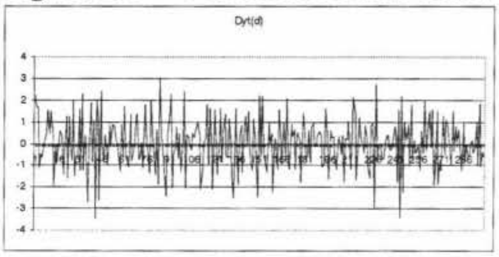


Figure 2.5 Time series with drift ($a_0 = 2$), trend ($a_2 = 5$) and $a_1 = 0.6$

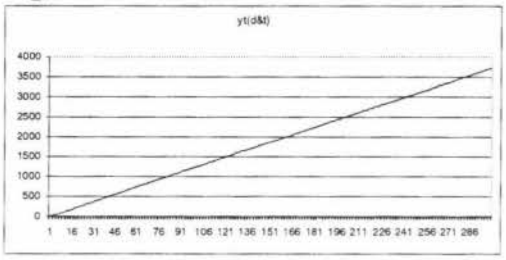
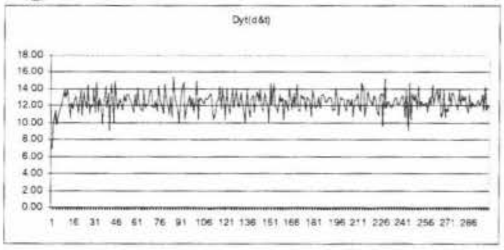


Figure 2.6 Differenced time series with drift ($a_0 = 2$), trend ($a_2 = 5$) and $a_1 = 0.6$



The unit root versions of the above models are displayed in Figures 2.7 – 2.12.

Figure 2.7 Time series with no drift ($a_0 = 0$) and no trend ($a_2 = 0$), $a_1 = 1$

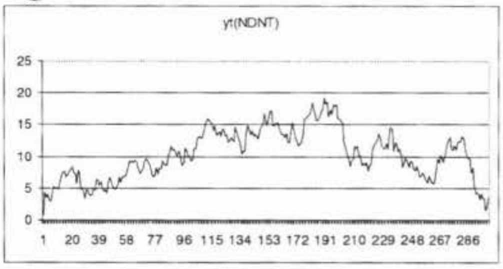


Figure 2.8 Differenced time series with no drift ($a_0 = 0$) and no trend ($a_2 = 0$) $a_1 = 1$

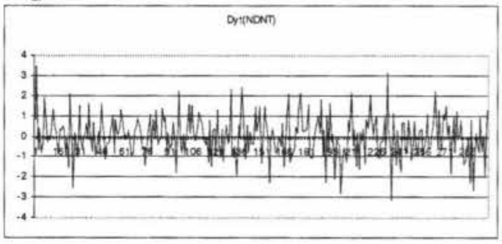


Figure 2.9 Time series with drift ($a_0 = 2$), no trend ($a_2 = 0$) and $a_1 = 1$

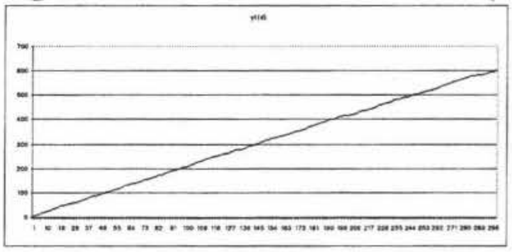


Figure 2.10 Differenced time series with drift ($a_0 = 2$), no trend ($a_2 = 0$) and $a_1 = 1$

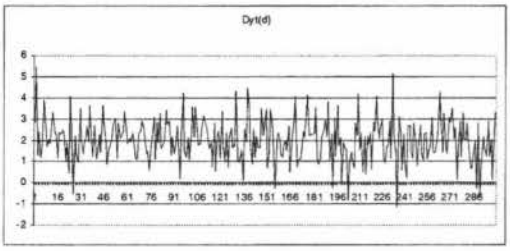


Figure 2.11 Time series with drift ($a_0 = 2$), trend ($a_2 = 5$) and $a_1 = 1$

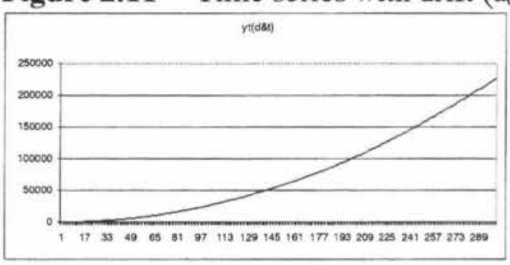
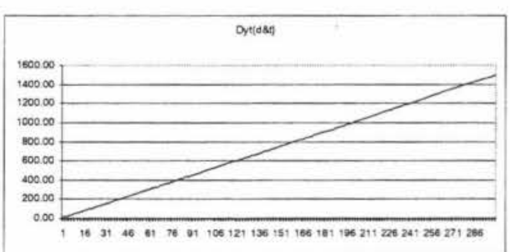


Figure 2.12 Time series with drift ($a_0 = 2$), trend ($a_2 = 5$) and $a_1 = 1$



The above figures show the difficulty of an "*a priori*" model selection followed by rejection of the null hypothesis or not. As an example if figure 2.5, 2.9 or 2.12 were assessed by viewing, which analyst would be able to select the appropriate model?

2.4 Univariate Model identification

Three models

The discussion in Section 2.3 and the simulations have demonstrated the difficulties of model selection that is based on viewing figures of time series. A structured approach is recommended because a number of decisions have to be made in sequence, with each decision affecting subsequent analysis. Chapters 4 to 7 will investigate whether any of the three models that are listed below are appropriate for the time series under investigation.

The three models that have been used are alternative formulations of the Dickey Fuller equations to test for a unit root. In addition, these models also test whether the deterministic components are significant or not. The first model (Model 1) is the most unrestricted model and it includes both a_0 and a_2 as well as γ. In the case of Model 2 a_2 has been deleted. The restricted form of Model 2 (Model 2R) also does not have γ included. Finally Model 3 lacks a_0 as well and its restricted form again does not include γ. The t-tests and F-tests that have been used are described in Dickey and Fuller (1981).

Model 1

$$\Delta y_t = a_0 + a_2 t + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i-1} + \varepsilon_t \tag{2.20}$$

Model 2

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i-1} + \varepsilon_t \tag{2.21}$$

Model 2R

$$\Delta y_t = a_0 + \sum_{i=2}^{p} \beta_i \Delta y_{t-i-1} + \varepsilon_t \tag{2.22}$$

Model 3

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i-1} + \varepsilon_t \tag{2.23}$$

Model 3R

$$\Delta y_t = \sum_{i=2}^{p} \beta_i \Delta y_{t-i-1} + \varepsilon_t \tag{2.24}$$

The restricted models are denoted by "R" where the restriction is that $\gamma = 0$.

The first step to investigate whether or not a model is appropriate is to inspect the graphs of the time series with the raw or transformed observations and in a differenced format. Figures 2.1 – 2.12 have shown simulations of the types of graphs that can be expected. A visual inspection of the graph to ascertain what model to choose can also be problematic for other reasons (it pre-judges the issue).

In all three models above $\gamma = 0$ is to be evaluated. However a_0 and a_2 have different interpretations which depend on the model chosen. This issue was discussed in the previous section.

In the case of Model 1 if $\gamma = 0$, then y_t will have a deterministic quadratic trend. Δy_t will show a linear trend. However, if $\gamma \prec 0$, then y_t will show a linear trend while Δy_t will be stationary with a non-zero mean.

In the case of Model 2 if $\gamma = 0$, then y_t will display a drift (ie a linear deterministic trend). At each subsequent point in time (y_t), the value of a_0 has been added to the value of the previous time point (y_{t-1}). Depending on the value of a_0, the drift may look like a linear trend in the graph. Δy_t will be a stationary series. However, if $\gamma \prec 0$, then both y_t and Δy_t will be stationary. The mean will be determined by a_0.

In the case of Model 3 if $\gamma = 0$, then y_t is a random walk without drift. Δy_t will be a stationary series. However, if $\gamma \prec 0$, then both y_t and Δy_t will be stationary with a zero mean. Table 2.1 summarises these impressions.

Table 2.1 Summary of impressions of the graphs relating to the three models

Equation	γ	y_t	Δy_t
Model 1	$\gamma = 0$	Quadratic trend	Linear trend
Model 1	$\gamma \prec 0$	Linear trend	Stationary series, Non-zero mean
Model 2	$\gamma = 0$	Drift (Can look like linear trend, depends on value of a_0)	Stationary series, non-zero mean
Model 2	$\gamma \prec 0$	Stationary series, non-zero mean	Stationary series, zero mean
Model 3	$\gamma = 0$	Random walk	Stationary series, zero mean
Model 3	$\gamma \prec 0$	Stationary series	Stationary series, zero mean

Statistical tests for univariate time series

As mentioned above, inspection of graphs may at times be inadequate and it is preferable to use formal tests in a structured manner to decide on the appropriate model for a time series, in particular whether they are trend and/or difference stationary. This becomes even more important where several time series are to be evaluated in relation to each other by using multivariate tests such as VAR or cointegration tests.

The tests that are used can be categorised as t-tests and F-tests. The t- and the F-statistics do not follow the respective standard distributions. Dickey and Fuller carried out a number of simulations to investigate the distributions and the results can be seen in Dickey and Fuller (1979, 1981).

The null hypothesis of unit root is rejected if the t-value for γ is less than the value in the appropriate DF table. This is interpreted as meaning that the series is stationary.

Instead of testing γ only for unit root, Dickey and Fuller extended their approach by providing F-statistics for testing joint hypotheses on coefficients of the differenced series. These simultaneous tests are intended to evaluate whether any of the explanatory variables is zero or not.

Table 2.2 Summary of the Dickey-Fuller tests (from Enders (1995, p. 223)

			Critical values for Confidence Intervals	
Model	Hypothesis	Test Statistic	95 %	99 %
1	$\gamma = 0$	τ_τ	- 3.45	- 4.04
	$a_0 = 0$ *given* $\gamma = 0$	$\tau_{\alpha\tau}$	3.11	3.78
	$a_2 = 0$ *given* $\gamma = 0$	$\tau_{\beta\tau}$	2.79	3.53
	$\gamma = a_2 = 0$	ϕ_3	6.49	8.73
	$a_0 = \gamma = a_2 = 0$	ϕ_2	4.88	6.50
2	$\gamma = 0$	τ_μ	-2.89	-3.51
	$a_0 = 0$ *given* $\gamma = 0$	$\tau_{\alpha\mu}$	2.54	3.22
	$a_0 = \gamma = 0$	ϕ_1	4.71	6.70
3	$\gamma = 0$	τ	-1.95	-2.60

ϕ_1 is provided to test whether or not both coefficients a_0 and γ in Model 2 are significant or not. This may seem a partial repeat of the conclusions reached by the test statistic τ_μ. If τ_μ is greater than the critical value (eg –2.89, 5% significance) then the conclusion is not significant and a unit root process is assumed.

If ϕ_1 is smaller than the critical value (eg 4.71, 5% significance), then the null hypothesis that both coefficients are zero is accepted. This would confirm the unit root part of the hypothesis. However, this would also reject the hypothesis that the drift term is significant. The results of this test could be difficult to interpret if the result is significant. While it might suggest the drift is significant it also suggest the process is not unit root. (Note again that the meaning of a_0 depends on whether γ is zero).

The $\tau_{\alpha\mu}$ statistic is designed to overcome the ambivalence that may result from the ϕ_1 statistic. Now the unit root process is taken as given. Although the null hypothesis is that $a_0 = 0$ (ie the drift is not significant), the equation is such that drift is expected in the unit root process and consequently there is an expectation that the null hypothesis will be rejected.

Two F-statistics, ϕ_2 and ϕ_3 can be used for Model 1. One can test whether any of all coefficients is zero or whether any of two variables (γ or a_2) are zero.

The ϕ_i statistics are calculated as follows (Enders, 1995, p.222):

$$\phi_i = \frac{[RSS\,(restricted) - RSS(unrestricted)]/\,r}{RSS\,(unrestricted)/(T-k)}$$

where r = number of restrictions
T = number of usable observations
k = number of parameters estimated in the unrestricted model

The criterion for rejecting the τ (other than τ_t) and ϕ statistics is $p < 0.05$. The criterion for rejecting a unit root is $p < 0.1$, although lower values are considered too. The rationale for this is based on (Gujarati, p. 819). He comments that "most tests of the DF type have a low power; they tend to accept the null of unit root more frequently than is warranted." Given this problem it seemed reasonable to reject the unit root more frequently by making the cut-off 0.1 rather than 0.05. However, the result $0.1 > p > 0.05$ would at times be considered weak support for unit root.

Lags in DF Models

The various equations may have errors that are autocorrelated. This has already been addressed above by the inclusion of lags ($\sum_{i=2}^{p} \beta_i \Delta y_{t-i+1}$) and it will be discussed here. The critical values of the Dickey-Fuller tests are only affected slightly by this approach since it reduces the length of the series.

The approach that has been taken in this thesis for identifying the correct number of lags in the model is as follows. As a first step two lagged differences are included and the t-statistics are evaluated. If the t-value is not significant the model will be re-run with 1 lagged difference only. If this value is not significant the model will be re-run without this lagged difference. As previously discussed, such models make the calculation of ϕ_i statistics impossible.

Once a model has been preliminarily selected, the ACF of the resulting error series will be evaluated and its Ljung-Box Q statistics. Ideally autocorrelation should no longer be evident.

If the model with the second lagged difference was significant and autocorrelation in the error terms was still evident, then the model was re-run with three lagged differences.

From an analysis perspective the number of lagged values of Δy_t has several important aspects. It is necessary for the F-tests, which need nested models, to have the same number of lags in each model. Various strategies can be considered. All five models are checked and the maximum number of lags across all five is used. An alternative approach is to determine the number of lags of one model (eg Model 1 or Model 3R) and use this for the other models as well.

In some instances a situation may arise where the second or third autocorrelated term is significant but not the first or second terms. In such situations the non-significant terms are left in the model.

During the multivariate analysis the number of autocorrelated terms will become relevant too. Again their numbers should be similar for all equations that are used.

Since it is important to avoid autocorrelation in the error terms, the thesis will usually use the highest number of differenced lags as required to minimise autocorrelation.

Log transformation

The time series that are analysed in this thesis are usually the natural logarithm of the original data series. When evaluating inflation, it is not the actual price level that usually matters but rather the change in price level. A log transform means that the first difference is measuring proportional changes in CPI, rather than absolute changes. Consequently the use of natural logarithms seems more appropriate when comparing the observations at different points in time than comparing the raw data. However in one instance (CPI) the raw data series was analysed in addition to the log transformed series to evaluate how the log transformation affected the analysis. Also in the case of the interest rates, the original time series will not be log transformed.

Seasonal adjustment

Some time series of the monetary aggregates displayed seasonality. Various techniques are available to deal with this issue. Two classes of seasonal adjustment are possible in EViews: multiplicative and additive. Since the time series that are analysed have been generally been log transformed, additive seasonal adjustment will be used in this thesis.

EViews uses the difference from moving average approach. The moving average of the quarterly series to be filtered (y_t) are calculated as:

$$x_t = (0.5\, y_{t+2} + y_{t+1} + y_t + y_{t-1} + 0.5\, y_{t-2}) / 4$$

The difference $d_t = y_t - x_t$ is calculated. The quarterly seasonal index i_q for quarter q is the average of d_t using observations for quarter q only. The seasonal indices are then adjusted so they add up to zero. This is brought about by setting $s_j = i_j - \bar{i}$, where $\bar{i}$ is the average of all seasonal indices. EViews then computes the seasonally adjusted series by subtracting the seasonal factors s_j from y_t.

CPI Adjustment

As the price level (eg CPI) increases, the value of the monetary aggregates per unit will decrease. This thesis has considered the use of monetary aggregates that have been adjusted or not for inflation. The adjustment was performed by multiplying the value of the monetary aggregate by 1000/CPI current at the time. Next the value was log transformed. Adjusted monetary aggregates are denoted by “A”. The adjustment consisted of multiplying by 1000/CPI, in which case *LOGM1A* = *LOGM1* – *LOGCPI* + log(1000). This should mean that any cointegration (see below) involving LOGM1 can be turned into one involving LOGM1A algebraically. It was expected that the analyses were going to be very similar.

2.5 Structural breaks

Structural breaks can affect unit root tests. Examples are changes in government policies that were discussed in the general introduction. During the various periods the variable in question may be stationary at each side of the structural break. Over the entire period the equations will be such that a bias of the Dickey-Fuller test towards non-rejection of the unit root exists. Another situation that can also exist is a unit root process with one or several structural breaks.

Chapter 4 will use the Chow test to evaluate the existence of structural breaks.

$$F = \frac{\left(\sum_{t=1}^{T} u_{0t}^2 - (\sum_{t=1}^{TB-1} u_{1t}^2 + \sum_{t=TB}^{T} u_{2t}^2)\right) / k}{(\sum_{t=1}^{TB-1} u_{1t}^2 + \sum_{t=TB}^{T} u_{2t}^2)/(T-k)}$$

This test assumes previous knowledge of the breakpoints. This would usually be acquired from inspecting graphs or from previous knowledge for instance policy changes. The selection of the largest change in a graph (eg of Δy_t) would to a certain extent compromise the validity of the test. This issue is similar to the selection of the most appropriate model that was discussed in one of the previous sections. In that instance it was decided to compute a number of models and select the most appropriate one. In this case it is decided to use the more subjective approach of assessing a graph, but keeping the reservations that are outlined above in mind.

Enders (p. 246) describes another approach that has been proposed by Perron. This approach is briefly described below but will not be pursued here.

$$H_1 : y_t = a_0 + y_{t-1} + \mu_1 D_P + \varepsilon_t$$

$$A_1 : y_t = a_0 + a_2 t + \mu_2 D_L + \varepsilon_t$$

where D_P is the pulse dummy variable such that $D_P = 1$ if $t = \tau + 1$ and 0 otherwise
D_L is the dummy variable such that $D_L = 1$ if $t < \tau$ and 0 otherwise

2.6 Vector Autoregression (VAR) models

Interpretation of the various time series can be carried out in isolation, for instance by viewing their graphs and performing ARIMA analysis without considering the impact on these time series of other variables. Although viewing graphs is crucial to provide some insights in developments over time, it will only have limited explanatory power especially with regard to other economic factors.

In any case, variables will influence each other. The VAR methodology is of particular value to deal with such situations especially because it allows the concurrent evaluation of multiple outputs.

The fundamental equation on which this approach is based is:

$$\mathbf{y}_t = \boldsymbol{\mu} + \boldsymbol{\Phi}\mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t \qquad (2.25)$$

where $\mathbf{y}_t$ are the current observations, $\boldsymbol{\mu}$ is a vector of fixed means, $\boldsymbol{\Phi}$ is a matrix with weighting coefficients and $\boldsymbol{\varepsilon}_t$ are the error terms (also called shocks or innovations).

The errors have a covariance matrix:

$$\boldsymbol{\Sigma} = \mathbf{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t')$$

Exogenous variables can be added to this equation in which case it becomes

$$\mathbf{y}_t = \boldsymbol{\mu} + \boldsymbol{\Phi}\mathbf{y}_{t-1} + \mathbf{B}\mathbf{x}_t + \boldsymbol{\varepsilon}_t \qquad (2.26)$$

An advantage of these VARs is that restrictions of economic models can be incorporated resulting in structural VARs (Enders, pp. 270 and 320).

The above equation is written out below as for a bivariate system in order to facilitate the explanations of innovation accounting. They are based on Enders pp 294-295.

$$y_t = b_{10} - b_{12}z_t + \gamma_{11}y_{t-1} + \gamma_{12}z_{t-1} + \varepsilon_{y,t} \qquad (2.27)$$

$$z_t = b_{20} - b_{21}y_t + \gamma_{21}y_{t-1} + \gamma_{22}z_{t-1} + \varepsilon_{z,t} \qquad (2.28)$$

The assumptions are that y_t and z_t are stationary, the innovations are white-noise disturbances with standard deviations σ_y and σ_z and that the disturbances are uncorrelated to each other.

In the above equations $\varepsilon_{y,t}$ and $\varepsilon_{z,t}$ are pure ***innovations*** in y_t and z_t respectively. However $\varepsilon_{y,t}$ can have an indirect contemporaneous effect on y_t through b_{21} and a lagged effect through γ_{21}.

Equations (2.27) and (2.28) which are not reduced equations can be transformed as follows

$$\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}\begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{z,t} \end{bmatrix} \quad (2.29)$$

Premultiplication by $\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}^{-1}$ results in the following equations

$$y_t = a_{10} + a_{11}y_{t-1} + a_{12}z_{t-1} + e_{1t} \quad (2.30)$$
$$z_t = a_{20} + a_{21}y_{t-1} + a_{22}z_{t-1} + e_{2t} \quad (2.31)$$

These latter two equations are the VAR in the standard form.

The sections on innovation accounting will further discuss the latest error terms. It should be understood that e_{1t} and e_{2t} are composites of the pure innovations $\varepsilon_{y,t}$ and $\varepsilon_{z,t}$.

$$e_{1t} = \left(\varepsilon_{y,t} - b_{12}\varepsilon_{z,t}\right)/\left(1 - b_{12}b_{21}\right) \quad (2.32)$$
$$e_{2t} = \left(\varepsilon_{z,t} - b_{12}\varepsilon_{y,t}\right)/\left(1 - b_{12}b_{21}\right) \quad (2.33)$$

It follows from the above that $e_{1,t}$ and $e_{2,t}$ may well be correlated.

The VAR in standard form has fewer parameters than the structural VAR. As a consequence when the VAR is estimated it is not possible to estimate both *b12* and *b21*. This means that the innovation series cannot be recovered from the VAR errors, unless some extra assumption is made, eg *b12* = 0 or *b21* = 0.Both of these correspond to assuming that one innovation does not affect the other series contemporaneously. More generally, for any number of series, a Choleski decomposition can be used to diagonalise the covariance matrix of the VAR errors and recover the innovation series. This corresponds to an ordering of the variables such that the innovation in one variable is assumed to have no contemporaneous effect on variables higher in the order. Different orderings will lead to different interpretations of the effect of further innovations. See the section on Impulse Response Functions below.

Several ***information criteria*** can be used to establish the 'best' VAR model. This thesis will use the criteria described in EViews. These criteria consider the goodness-of-fit and attempt to maintain a parsimonious model. The information criteria are:

Akaike Info Criterion (AIC)	$-2\ell/T + 2n/T$
Schwarz Criterion (SC)	$-2\ell/T + n\log T/T$

where $n = k(d + pk)$ is the total number of estimated parameters in the VAR and T the number of usable observations.

The log-likelihood is computed by EViews assuming a multivariate normal distribution

$$\ell = -\frac{Tk}{2}(1 + \log 2\pi) - \frac{T}{2}\log\left|\hat{\Omega}\right| \quad (2.34)$$

where

$$\left|\hat{\Omega}\right| = \det\left(\sum_t \hat{\varepsilon}_t \hat{\varepsilon}_t' / T\right)$$

is the determinant of the residual covariance.

For each of these criteria, the 'best' model has the smallest value for the information criterion.

Various aspects of VARs that are of interest have been described above. It should be noted that some may be applicable to other types of equations as well such as Vector Error Correction Models.

2.7 Granger Causality

Granger Causality is considered to exist if lagged values of one variable (x_t) improve the autoregressive forecast of another variable (y_t). It is considered to be prerequisite before cointegration analysis is performed which will be described in one of the following sections.

The sum of squared residuals (RSS_{UR}) from the unrestricted regression is calculated.

$$y_t = a + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_k y_{t-k} + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \ldots + \beta_k x_{t-k} + e_t \tag{2.35}$$

In the above equation k is the number of lags that is required to remove the serial correlation. Also the sum of squared residuals (RSS_R) from the restricted regression is calculated.

$$y_t = a + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_k y_{t-k} + v_t \tag{2.36}$$

Next S is calculated.

$S = ((RRS_R - RSS_{UR}) / k) / (RSS_{UR} / (T - 3k - 1))$

where T is the sample size and k is the number of lags required for independent residuals.

The null hypothesis is:

$$H_0 = \beta_1 = \beta_2 = \ldots = \beta_k = 0$$

The decision rule is based on the F statistic value F (0.05, k, T – 3k – 1)

Since the null hypothesis maintains no Granger Causality, $p < 0.05$ is considered to mean that Granger Causality existed.

Various assumptions are required to be made. The variable should be stationary. It is assumed that the error terms in the causality tests are uncorrelated. No attempts will be made in the various chapters to correct for this. The justification is that the Granger Causality will be used as an exploratory test and its bias towards proving causality where none exists will be considered when the final models are developed.

Gujarati (p. 698) mentions that "the direction of causality may depend critically on the number of lagged terms included." In his example 17.13 he showed how the direction of causality was evaluated for various numbers of lags. Table 6.6 is an example how Granger Causality is evaluated in this thesis. Each combination of time series will be evaluated in both directions for Granger Causality and this will be applied for 8 lags. The results will be compared with the results of the cointegration analyses.

2.8 Cointegration and Vector Error Correction Models

Cointegration is said to exist if a linear combination of two or more non-stationary series results in a stationary series. In principle this can be seen as the application of matrix algebra and Vector Autoregression (VAR)

VAR

The following VAR of order p applies. The vector $\mathbf{y}_t$ contains a number of unit root processes and the intention is to test whether or not some of them are cointegrated.

$$\mathbf{y}_t = \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{B}\mathbf{x}_t + \boldsymbol{\varepsilon}_t \qquad (2.37)$$

where $\mathbf{y}_t$ is a k-vector of non-stationary I(1) variables, $\mathbf{x}_t$ is a d vector of exogenous deterministic variables, and $\boldsymbol{\varepsilon}_t$ is a vector of innovations.

Two (or more) variables may have unit roots yet they may move in a correlated manner over time. They may have a long-run relationship.

If they are cointegrated then a linear combination is stationary, so $\boldsymbol{\beta}'\mathbf{y}_t = \mathbf{v}_t$ where $\boldsymbol{\beta}$ is the "cointegrating vector". If there are more than two series, there may be more than one cointegrating vector, so if stacked they give a matrix which premultiplies $\boldsymbol{\beta}'\mathbf{y}_t = \mathbf{v}_t$ to give a vector of stationary series.

Such situations can be important from a financial or economic perspective. In principle the above can be tested by three Dickey Fuller tests. This is Engle-Granger Two-Step procedure where two series y_{1t} and y_{2t} exist (Engle and Granger, 1987). Both are tested for unit root. One is regressed on the other and β is estimated. The residual of this regression (v_t) is tested for unit root.
When v_t is tested the constant term in the Dickey Fuller equation must always be included. This procedure has been criticised because β may be biased. Another major drawback is that it can be used for two time series only.

Matrix Algebra

The method developed by Johansen (1990, 1991) as an alternative has become widely used in recent years. It has an unrestricted and a restricted format. The approach by Johansen is based on eigenvalue analysis of an appropriate matrix.

Let **A** be an $(n \times n)$ square matrix with elements a_{ij} and **y** an $(n \times 1)$ vector.
Then scalar λ is the eigenvalue of **A** if:

$$\mathbf{Ay} = \lambda \mathbf{y}\text{, or}$$

$$\mathbf{Ay} - \lambda \mathbf{y} = 0 \qquad (2.38)$$

This can be redefined with an $(n \times n)$ identity matrix **I** as:

$$(\mathbf{A} - \lambda \mathbf{I})\mathbf{y} = 0 \qquad (2.39)$$

If the values of **y** are not 0, then the rows of $(\mathbf{A} - \lambda \mathbf{I})$ must be linearly independent.
Therefore the determinant must be zero, ie $|\mathbf{A} - \lambda \mathbf{I}| = 0$. This equation is the characteristic equation of a square matrix (ie determinant = 0) and can be used for finding the eigenvalues.

The characteristic equation is an n^{th} order polynomial of λ. It can be expressed as:

$$\lambda^n + b_1\lambda^{n-1} + b_2\lambda^{n-2} + \cdots + b_{n-1}\lambda + b_n = 0 \qquad (2.40)$$

This shows that an $(n \times n)$ matrix will have n eigenvalues that could be repeating or complex.

The rank of a square $(n \times n)$ matrix **A** is the number of independent rows or columns in the matrix. The matrix **A** is of full rank if rank (**A**) = n.
Therefore the rank of **A** equals its number of non-zero eigenvalues.

This situation is analogous to the DF test described in Section 2.3. The original AR1 model tested $a_1 = 1$. This was changed to testing $\gamma = a_1 - 1 = 0$. Similarly in the cointegration test according to Johansen the VAR is set up in such a way that each non-zero eigenvalue of the matrix being tested corresponds to a cointegrating relationship. This is the reason for the interest in the rank of a matrix.

Johansen methodology of cointegration

The above analysis of the rank of a matrix and the eigenvalues is used in the Johansen procedure.

The time series are described as:

$$\mathbf{y}_t = \mathbf{A}_1\mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t \qquad (2.41)$$

This can be expressed in differenced format as:

$$\begin{aligned} \Delta \mathbf{y}_t &= (\mathbf{A}_1 - \mathbf{I})\mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t \\ &= \boldsymbol{\Pi}\mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t \end{aligned} \tag{2.42}$$

Now the rank of $\boldsymbol{\Pi}$ equals the number of eigenvalues that are not zero (and these correspond to cointegrating relationships between the components of $\mathbf{y}_t$. These eigenvalues are ordered so that $\lambda_1 > \lambda_2 > \cdots > \lambda_n$. The Johansen procedures test the number of eigenvalues that are statistically different from zero.

As with the DF test, we may want to add lagged values of $\mathbf{y}_t$ to remove autocorrelation. In the section on VAR the following equation was discussed:

$$\mathbf{y}_t = \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{B}\mathbf{x}_t + \boldsymbol{\varepsilon}_t \tag{2.43}$$

The term $\mathbf{B}\mathbf{x}_t$ is exogenous and can be left out of the rest of the explanation without any loss when generalising the conclusions.

The differenced form of the above equation is:

$$\Delta \mathbf{y}_t = (\mathbf{A}_1 - \mathbf{I})\mathbf{y}_{t-1} + \mathbf{A}_2\mathbf{y}_{t-2} + \mathbf{A}_3\mathbf{y}_{t-3} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t \tag{2.44}$$

Adding and subtracting $(\mathbf{A}_1 - \mathbf{I})\mathbf{y}_{t-2}$ to the above equation results in:

$$\Delta \mathbf{y}_t = (\mathbf{A}_1 - \mathbf{I})\Delta\mathbf{y}_{t-1} + (\mathbf{A}_2 + \mathbf{A}_1 - \mathbf{I})\mathbf{y}_{t-2} + (\mathbf{A}_3 + \mathbf{A}_2 + \mathbf{A}_1 - \mathbf{I})\mathbf{y}_{t-3} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t \tag{2.45}$$

This procedure can be continued and the following equation will eventuate:

$$\Delta \mathbf{y}_t = \sum_{i=1}^{p-1} \boldsymbol{\Pi}_i \Delta\mathbf{y}_{t-i} + \boldsymbol{\Pi}\mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t \tag{2.46}$$

where

$$\boldsymbol{\Pi}_i = -\left(\mathbf{I} - \sum_{j=1}^{i}\mathbf{A}_j\right) \text{ and } \boldsymbol{\Pi} = -\left(\mathbf{I} - \sum_{i=1}^{p}\mathbf{A}_i\right) \tag{2.47}$$

The above equation is in effect a multivariate form of the Dickey-Fuller test. As in the Dickey-Fuller test the component π plays a critical role. It should be noted that where the Dickey-Fuller test uses π as a coefficient for y_{t-1}, the Johansen procedure as described here relates $\boldsymbol{\Pi}$ to $\mathbf{y}_{t-p}$, which just corresponds to a re-arrangement of the augmented DF equation. EViews on the other hand uses the matrix coefficient of $\mathbf{y}_{t-1}$, which is closer to the usual univariate DF procedure.

The number of independent cointegrating vectors is determined by evaluating the rank of the coefficient matrix $\mathbf{\Pi}$.

If the coefficient matrix $\mathbf{\Pi}$ has reduced rank r < k, then there exist k × r matrices $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ each with rank r such that $\mathbf{\Pi} = \boldsymbol{\alpha\beta}'$ and $\boldsymbol{\beta}'\mathbf{y}_t$ is stationary. The number of cointegrating relations (the cointegrating rank) is r and each column of $\boldsymbol{\beta}$ is the cointegrating vector.

Estimates of the cointegrating vectors are given by each of the columns of the $\boldsymbol{\beta}$ matrix. Normalisation is required for the cointegrating vectors to be identified and EViews solves this for the first r variables in the $\mathbf{y}_t$ vector as a function of the remaining k-r variables.

Similar to the Dickey Fuller tests deterministic trend assumptions must be made. The LR test statistic for the reduced rank has an asymptotic distribution. It does not have the usual χ^2 distribution and it depends on assumptions regarding the deterministic trends of the series and the cointegrating equations.

The following options are used by EViews and they are based on Johansen (1995). The term $\mathbf{Bx}_t$ has been deleted from the left hand side as discussed above.

1 Series y have no deterministic trends and the cointegrating equations do not have intercepts:

$H_2(r)$: $$\mathbf{\Pi y}_{t-1} = \boldsymbol{\alpha\beta}'\mathbf{y}_{t-1} \tag{2.48}$$

2 Series y have no deterministic trends and the cointegrating equations have intercepts:

$H_1^*(r)$: $$\mathbf{\Pi y}_{t-1} = \boldsymbol{\alpha}(\boldsymbol{\beta}'\mathbf{y}_{t-1} + \boldsymbol{\rho}_0) \tag{2.49}$$

3 Series y have linear trends but the cointegrating equations have only intercepts:

$H_1(r)$: $$\mathbf{\Pi y}_{t-1} = \boldsymbol{\alpha}(\boldsymbol{\beta}'\mathbf{y}_{t-1} + \boldsymbol{\rho}_0) + \boldsymbol{\alpha} \perp \boldsymbol{\gamma}_0 \tag{2.50}$$

Here the constant in the VAR cannot be absorbed into the cointegrating equations because it is not in the column space of α. To make the model identifiable, the constant in the cointegrating equations could be omitted. Alternatively, the constant in the VAR can be split into one component of the form $\boldsymbol{\alpha\rho}_0$ and another, here denoted $\boldsymbol{\alpha} \perp \boldsymbol{\gamma}_0$, which is perpendicular to the columns of $\boldsymbol{\alpha}$.

4 Both series y and the cointegrating equations have linear trends

$H^*(r)$: $$\mathbf{\Pi y}_{t-1} = \boldsymbol{\alpha}(\boldsymbol{\beta}'\mathbf{y}_{t-1} + \boldsymbol{\rho}_0 + \boldsymbol{\rho}_1\mathbf{t}) + \boldsymbol{\alpha} \perp \boldsymbol{\gamma}_0 \tag{2.51}$$

5 Series y have quadratic trends and the cointegrating equations have linear trends

$H(r)$: $$\mathbf{\Pi y}_{t-1} = \boldsymbol{\alpha}(\boldsymbol{\beta}'\mathbf{y}_{t-1} + \boldsymbol{\rho}_0 + \boldsymbol{\rho}_1\mathbf{t}) + \boldsymbol{\alpha} \perp (\boldsymbol{\gamma}_0 + \boldsymbol{\gamma}_1\mathbf{t}) \tag{2.52}$$

where $\boldsymbol{\alpha}\perp$ is the (non-unique) $k \times (k-r)$ matrix such that $\boldsymbol{\alpha}'\boldsymbol{\alpha}\perp = \mathbf{0}$ and rank $([\alpha \mid \alpha \perp]) = k$

These five cases are nested from the most restrictive to the least restrictive, given any particular cointegrating rank r.

$\mathbf{H_2(r) \subset H_1^*(r) \subset H_1(r) \subset H^*(r) \subset H(r)}$

EViews mentions that options 1 and 5 are rarely used in practice. It recommends option 2 if none of the series appears to have a trend. If there are trends, case 3 is recommended if all trends are stochastic and 4 if some of the series have a deterministic trend.

EViews presents the eigenvalues and the Likelihood Ratio (LR) test statistic. Johansen's method estimates $\boldsymbol{\Pi}$ in an unrestricted form and this is then it is tested whether the restrictions implied by the reduced rank of $\boldsymbol{\Pi}$ can be rejected.

The trace statistic (Q_T) is calculated as

$$Q_r = -T \sum_{i=r+1}^{k} \log(1-\lambda_i)$$

for r = 0, 1, ..., k-1 where λ_i is the ith largest eigenvalue. The trace statistic tests $H_{1(r)}$ against $H_{1(k)}$. This statistic tests the null hypothesis that the number of cointegrating vectors is less than or equal to *r* against a general alternative.

Johansen suggest a second LR statistic, the maximum eigenvalue statistic. It is calculated from the trace statistic as

$$Q_{\max} = -T\log(1-\lambda_{r+1}) = Q_r - Q_{r+1}$$

This statistic tests $H_{1(r)}$ against $H_{1(r+1)}$ or alternatively worded that the number of cointegrating vectors is r against the alternative of $r + 1$ cointegrating vectors.

If the 5 percent critical value is applied then the following applies. The hypothesis of no cointegration is rejected if the Trace statistic is more than the 5 % Critical Value for the "None" test and if the Max-Eigen statistic is more than its 5 % Critical Value.
Enders makes the point that these two statistics may result in conflicting results (p. 393).

After normalisation of the of the first r series in the $\mathbf{y_t}$ series by EViews the normalised cointegrating equation with the normalised cointegrating coefficients is given. This equation is the long-term relationship $(\boldsymbol{\beta})$ between the cointegrated variables. Also the adjustment coefficients $(\boldsymbol{\alpha})$ are given which show how the variables react to departures from the long-term equilibrium.

2.9 Vector Error Correction Model selection

The intention of the cointegration test is to determine whether series are cointegrated and then to establish the Vector Error Correction Model (VECM).

The VECM is defined as:

$$\mathbf{\Delta y}_t = \gamma_1(\mathbf{y}_{t-1} - \boldsymbol{\alpha} - \boldsymbol{\beta}\mathbf{x}_{t-1}) + \gamma_2\mathbf{\Delta y}_{t-1} + \gamma_3\mathbf{\Delta y}_{t-2} + \gamma_4\mathbf{\Delta x}_{t-1} + \gamma_5\mathbf{\Delta x}_{t-2} + \mathbf{e}_t \quad (2.53)$$

where

$\mathbf{y} - \boldsymbol{\alpha} - \boldsymbol{\beta}\mathbf{x}$ is the cointegrating equation and $\gamma_2\mathbf{\Delta y}_{t-1} + \gamma_3\mathbf{\Delta y}_{t-2} + \gamma_4\mathbf{\Delta x}_{t-1} + \gamma_5\mathbf{\Delta x}_{t-2}$ is the lag part.

If cointegration exists between two time series, then one would expect the adjustment factors in γ_1 to be of opposite sign. If one of them is not significant, then this expectation would not apply. In addition one would expect a negative adjustment factor in the equation for the variable on which the CE was normalized (ie the variable whose CE coefficient is set to 1).

The following chapters will evaluate the appropriate time series in a systematic manner as made possible by EViews. Deliberately no attempt is made to make assumptions *a priori* about the deterministic components in the VECM, the number of lags in the differenced series or the results of he Granger Causality tests. The purpose is to evaluate the results of the tests as applied systematically to the data series and then analyse whether the various tests (eg unit root, Granger Causality and Cointegration) are consistent in their results.

As a first step EViews provides the following options (Table 2.3):

Table 2.3 Johansen Cointegration test. Cointegration Equation and VAR specification as enabled by EViews

Tests assumes no deterministic trend in data:	
Option 1	No intercept or trend in CE or test VAR
Option 2	Intercept (no trend) in CE – no intercept in VAR
Test allows for linear deterministic trend in data:	
Option 3	Intercept (no trend) in CE and test VAR
Option 4	Intercept and trend in CE – no trend in VAR
Test allows for quadratic deterministic trend in data:	
Option 5	Intercept and trend in CE – linear trend in VAR
Summary:	
Option 6	Summarise all 5 sets of assumptions

The CE and data trend assumptions apply to levels. EViews calls the lag part of the VECM the VAR and estimates the tests VAR in differenced form. It is possible in EViews to include exogenous series in the VAR but this option will not be used in this thesis.

The cointegration analyses below will consistently use Option 6 for initial analysis of the data sets. It will be done over a total of eight lags. The data will be displayed as shown in the table 2.4.

Table 2.4 is a copy of table 6.7. It is displayed here to explain the way these tables are set up throughout the thesis. The left-hand column shows the number of lags included in the model and the number of resulting observations that can be used.

The remaining columns contain cells that show the results for the various combinations of Options 1 to 5 as explained above and the number of lags.

Table 2.4 Cointegration analysis of *CD* and *SMD*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 observations	0	1 1.775330 2.159229	1 1.809640 2.236194	2	2
Lag 1 to 2 38 observations	0	0	0	1 1.471763 **2.118179**	2
Lag 1 to 3 37 observations	0	0	0	1 1.417689 2.244917	2
Lag 1 to 4 36 observations	0	0	0	1 1.242105 2.253798	2
Lag 1 to 5 35 observations	0	0	0	1 1.173019 2.372859	2
Lag 1 to 6 34 observations	0	0	0	1 1.016164 2.407846	2
Lag 1 to 7 33 observations	1 1.533997 2.985156	1 1.546635 3.043142	0	1 **0.617478** 2.204683	2
Lag 1 to 8 32 observations	1 1.232091 2.881044	1 0.932344 2.627101	1 0.807655 2.548216	2	2

Note: Period covered 1994:1 – 2004:1.

Each cell contains 3 numbers. The first number is the number of cointegrating equations. The number 0 means there were no cointegrating equations and no further information is displayed in these cells. VAR analyses could be applied to the first differences of the data. The number 2 in this instance where there were 2 time series means none of the series had unit root and a VAR could be specified in terms of the levels of these series. No further information is displayed in these cells. If there are 3 or more time series the number 3 or whatever respective number would have this meaning. If there are less cointegrating equations than the number of analysed series, but more then 0, then more details are displayed. The second number is the Akaike Information Criterion and the last number is the Schwarz Criterion. The lowest AIC and SC (ie the 'best' models) are displayed in bold.

In order to interpret the results $\mathbf{y}_t$ of (2.53) has to be normalised. No standard error is therefore given. EViews provides the standard errors and t statistics for the adjustment factors and the lagged (differenced) time series. Table 2.5 shows the variables for which the standard error is provided in EViews.

Table 2.5 Standard error and t statistic provided in EViews

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Data trend					
Constant			Yes	Yes	Yes
Trend					Yes
CE					
Constant		Yes	No	No	No
Trend				Yes	No

The information criteria have been discussed above. During the analyses that follow it appeared that the SC consistently suggested more parsimonious models than the AIC. For this reason the model with the lowest SC usually was further analysed and not the model with the lowest AIC. Both information criteria depend on the number of usable observations. Consequently the use of the SC for choosing between models with different lags will introduce some bias.

Next the VECM will be computed with EViews with the appropriate options and lags as established above. The results will be displayed in matrix format and any significant coefficients will be displayed in bold typeface. It should be noted that the cointegrating equation has been normalised on the first time series in this equation and consequently this could be considered significant too. The eigenvalues and unnormalised cointegration coefficients are available in EViews but they will not be displayed in this thesis.

The residuals of the VECMs will be evaluated to establish whether they meet the assumptions of the linear model. The tests include the Jarque-Bera tests, inspection of the graphs of the residuals, the ACF and Q statistics, the correlation coefficient and the cross correlogram.

2.10 Impulse Response Functions

The impulse response function evaluates how a shock of an innovation affects the values of the endogenous variables. The following expose is based on Enders (pp. 305 – 310). The computations in the thesis are performed in EViews. When interpreting the discussion by Enders and the results of EViews, it should be noted that where Enders mentions a shock of one unit, EViews refers to a shock of one standard deviation.

As an example take two equations:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \end{bmatrix} \qquad (2.54)$$

This can be rewritten, by successive substitution, in the 'moving average' form as:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} \bar{y}_1 \\ \bar{y}_2 \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^i \begin{bmatrix} e_{1,t-i} \\ e_{2,t-i} \end{bmatrix} \tag{2.55}$$

The error terms $e_{1,t-i}$ and $e_{2,t-i}$ can be written in terms of the original error terms $\{\varepsilon_{1,t}\}$ and $\{\varepsilon_{2,t}\}$ as described in section 2.6.

The moving average form of the above equation then becomes:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} \bar{y}_1 \\ \bar{y}_2 \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \varphi_{11}(i) & \varphi_{12}(i) \\ \varphi_{21}(i) & \varphi_{22}(i) \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-i} \\ \varepsilon_{2,t-i} \end{bmatrix} \tag{2.56}$$

The four φ terms in the above equation are impact multipliers.

A shock of one standard deviation of $\varepsilon_{1,t}$ will affect the current value of $y_{1,t}$. It will not affect the current value of $y_{2,t}$. However there will be an effect on the future values of y_2 since it is influenced by the lagged values of y_1.

If the error terms are correlated a problem arises since it is not known what proportion of the shock is to be attributed to what error. EViews uses the Choleski decomposition which orthogonalises the errors. As a result the covariance matrix of the resulting innovations is diagonal. This method is arbitrary since the sequence of the equations can have a severe impact on the attribution of the results.

If the error terms $e_{1,t}$ and $e_{2,t}$ are correlated then the order in which the time series are entered for the computation will affect the impulse response function. Note that in section 2.6 the comment was made that they usually are and this followed from the way they were derived. Enders suggests that the correlation coefficient is significant if $|\rho_{12}| \succ 0.2$. When two time series are analysed in this thesis, both ordering sequences will be analysed. If more than 2 time series, 2 or more different orders will be used.

2.11 Variance Decomposition

The errors of a model can be considered in terms of a Vector Moving Average (VMA) rather than a VAR model. Over a period *n* the following equation applies:

$$y_{t+n} = \mu + \sum_{i=0}^{\infty} \phi_i \varepsilon_{t+n-i} \tag{2.57}$$

The forecast error after period *n* becomes

$$y_{t+n} - E_t y_{t+n} = \sum_{i=0}^{n-1} \phi_i \varepsilon_{t+n-i} \tag{2.58}$$

As discussed for the impulse response function, in the multivariate case the errors of the variables will influence each other. The Variance Decomposition establishes what proportion of the movements is a series are brought about by its own shocks and what by other shocks (Enders, p. 311).

Now two time series $\{y\}$ and $\{z\}$ are given as discussed in section 2.6 (VAR).

The n-step ahead forecast error of $\{y\}$ is:

$$\begin{aligned} y_{t+n} - E_t y_{t+n} &= \phi_{11}(0)\varepsilon_{y,t+n} + \phi_{11}(1)\varepsilon_{y,t+n-1} + \cdots + \phi_{ii}(n-1)\varepsilon_{y,t+1} \\ &+ \phi_{12}(0)\varepsilon_{z,t+n} + \phi_{12}(1)\varepsilon_{z,t+n-1} + \cdots + \phi_{12}(n-1)\varepsilon_{z,t+1} \end{aligned} \qquad (2.59)$$

The variance of the n-step ahead forecast error of the above equation is:

$$\begin{aligned} \sigma_y(n)^2 = \sigma_y^2 &\left[\phi_{11}(0)^2 + \phi_{11}(1)^2 + \cdots + \phi_{11}(n-1)^2\right] + \\ \sigma_z^2 &\left[\phi_{12}(0)^2 + \phi_{12}(1)^2 + \cdots + \phi_{12}(n-1)^2\right] \end{aligned} \qquad (2.60)$$

This n-step ahead forecast error of $\sigma_y(n)^2$ can be decomposed in terms of the original shocks.

For $\{\varepsilon_{y,t}\}$ the proportion is:

$$\frac{\sigma_y^2\left[\phi_{11}(0)^2 + \phi_{11}(1)^2 + \cdots + \phi_{11}(n-1)^2\right]}{\sigma_y(n)^2} \qquad (2.61)$$

and for $\{\varepsilon_{z,t}\}$ it is:

$$\frac{\sigma_z^2\left[\phi_{12}(0)^2 + \phi_{12}(1)^2 + \cdots + \phi_{12}(n-1)^2\right]}{\sigma_y(n)^2} \qquad (2.62)$$

The problem that constitutes due to the ordering as described in the previous section also exists for Variance Decomposition. In this case to the Choleski decomposition is used. Also similarly various ordering are used during the analysis to establish the impact of the ordering.

The interpretation of a variance decomposition graph is that it shows the percentage of the forecast error variance of a time series at the various time periods that is caused by its own shocks or by the shocks of the other time series.

2.12 Concluding comments

A number of statistical techniques have been discussed above that will be applied to economic time series relating to inflation. At first sight these techniques seem very suitable to explore these time series to arrive at a model that describes some important variables that affect inflation. Inevitably a number of variables cannot be explored for practical reasons. A perfect model would not be possible, since some variables will always be missing.

However the reservations about the suitability go beyond some of the practical concerns. Some of these concerns will be further discussed after the analyses have been performed. It seems appropriate to discuss some now, so that the reader is prepared for a number of the issues that arise during the analysis.

The time series usually covered a period of approximately 10 years where the years were divided in quarters. From a statistical perspective this appeared to be a short period. From an economic perspective it could be argued that time series covering such a period without any major policy changes is probably as good as one can reasonably expect. If so one must wonder whether analysis based on a small number of variables, rather than a large number and extrapolating these a few periods out may be the only feasible alternative.

The Dickey-Fuller tests have evolved somewhat since they were originally developed. This was to correct some violations of statistical assumptions. The result is a test that required test statistics based on simulations. Several other tests have been developed since (eg the Phillips-Perron tests). Nevertheless the DF tests are still widely used. If anything, the history of these tests shows the difficulty of the problem. If straightforward, one would have expected a standardised and widely accepted methodology to have been developed by now.

A similar comment can be made about the Johansen methodology. These tests replaced the Engle-Granger approach to cointegration. However since the Johansen test is an extended form of the DF methodology, similar comments can be made.

This thesis is about applied statistics and concentrates on the application of these tests to a number of economic time series. It attempts to use a standardised method for evaluating these series. Although one might get the impression that this is similar to 'data dredging' there are some important differences between these two methods. The standardised approach evaluates various options and establishes how the results differ as different assumptions are made. Usually there are no preconceived ideas, not even based on inspecting graphs. Data dredging on the other hand may be a matter of going through the available information until the preconceived ideas are 'proven'. The standardised method that is used shows the risks of data dredging. If a sufficient number of options are tested, there is frequently one option that will support the theory that is proposed by an author. One the other hand there is often little guidance available, either from the data or from theoretical considerations, on which option to choose.

The following chapters will at times show that inadmissible results eventuated. For instance the section on the DF tests showed various models as options. Sometimes it turned out that one of these models should be chosen, but further testing showed that some of its variables were not significant when they should be according to the model specification that was used. However, the resulting model that excluded these variables would appear to be inadmissible.

As is common with most if not all statistical tests, some assumptions must be valid for the tests to be reliable. In this case the theory of linear model was important. Consequently a number of diagnostic tests were performed to evaluate whether the assumptions were valid. Inevitably a degree of subjectivity applies to decide whether the assumptions are met. Even worse perhaps is probably that some of the assumptions at times may not have held. Again a subjective judgement is required at times to decide whether to proceed or deem the test inappropriate for the issue that is investigated.

2.13 References

Dickey DA and Fuller WA (1981) Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica. 49(4), 1057-1072

Enders W. Applied Econometric Time Series. New York. John Wiley & Sons. (1995) pp. 433

Engle RF and Granger CWJ (1987) Co-integration and error correction: representation, estimation, and testing. Econometrica. 55(4), 251-276

EViews 3.1 Student Version . Quantitative Micro Software, LLC, Irvine CA

Gujarati DN (2003) Basic Econometrics, 4th ed., McGraw-Hill, Boston

Johansen S and Juselius K (1990) Maximum likelihood estimation and inference on cointegration – with applications to the demand for money. Oxford Bulletin of Economics and Statistics. 52(2), 169-210

Johansen S (1991) Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica. 59(6), 1551-1580

Johansen S (1995) Likelihood-based inference in cointegrated vector autoregressive models. Oxford University Press

CHAPTER 3

ECONOMIC ASPECTS OF INFLATION

3.1 Recent history of inflation in New Zealand

The CPI in the period 1955-1965 was generally below 5%. However since the early 1960s inflation started to increase and in 1975 it exceeded 10%. Since then until 1988 it was generally above 10%. Exceptions were 1984 and 1985 when the CPI was lower due to wage and price freezes in previous years. In 1986 the GST was introduced and the GST rate was increased in 1989. Both events coincided with increases of inflation.

The history above illustrates the need that existed to manage inflation in a consistent and effective manner. In 1989 the Reserve Bank of New Zealand Act was promulgated in response to this need. This Act provides a large degree of autonomy for the Reserve Bank of New Zealand (RBNZ). The degree of independence of the RBNZ of influences by government will ensure that no decisions are made that would jeopardise inflation targets as a trade-off for short-term political gain. One of the main tasks of the RBNZ was to ensure low levels of inflation and the policies put in place to achieve this are called "Inflation targeting". It intends to achieve low stable inflation as the main long-run goal for monetary policies. The main pillars of this policy are communication to the public, transparency of its actions and credibility of its intentions.

Initially the objective was to achieve inflation that fell in the region of 0 to 3 percent. This was set out in the Policy Trade Agreements (PTAs) as agreed to between the Minister of Finance and the Governor of the Reserve bank. In 1999 this was changed from 2 to 3 percent. The government can change the targets if it considers this necessary but checks are in place to ensure that this does not occur for political expediency.

3.2 Inflation Theories

A number of theories exist that attempt to explain the causes of inflation. At times these theories may be complementary to each rather than mutually exclusive. For instance the combination of knowledge of interest rates and of monetary aggregates might better explain inflation rates than either of them in isolation.

Sometimes inflation theories might considerably overlap each other and the way a theory is described may reflect the author's view of the world rather than a real difference. For instance a theory can advocate the importance of interest rates. Increasing interest rates will reduce investment thereby causing unemployment, followed by a reduction in inflation.

The classification of inflation that is used in this chapter is based on the data sets that will be analysed. It is not intended to be comprehensive. Rather it intends to provide the context in which the econometric analysis of the data sets should be considered. No preconceived views regarding their economic importance should be read into the sequence of analysis. Furthermore, any final conclusions from the econometric analysis should be considered with caution. This is because of issues related to the statistical techniques used, the relative shortness of the time series and the data collection processes. It cannot be expected that the time series analyses will provide the definitive answer to the perennial question "What causes inflation?". In addition to the factors listed above, the political and social circumstances of a country are important. They are likely to heavily affect the impact of the various variables that will be analysed. Consequently it was deemed appropriate to discuss in section 3.3 some of the issues that in the recent past occurred in New Zealand and that may very well have a severe influence on the current inflation rate.

Imported inflation

An increase in the cost of goods and services imported into a country is likely to influence the inflation rate of the importing country. Importers may for some time absorb the increased cost (as expressed in NZ dollars) but they may ultimately be forced to pass on the costs to the buyers of their products. Increased inflation eventuates. The most important good is arguably oil. An increased (or decreased) cost will not only affect the direct users of petrol but also those who use it for manufacturing goods produced from oil and the cost of transporting goods will increase as well.

The cost of imported goods also works through a different channel. The cost of transport and insurance make an imported good more costly than a domestically produced good, *ceteris paribus*. If the prices of domestically produced goods rise faster than those of imported goods, then domestic buyers are likely to increasingly switch to the imported goods. This will have a dampening effect on inflation.

This thesis will not evaluate imported inflation in detail. However in Chapter 4 it will discuss the relationship between tradable and non-tradable inflation as defined by the RBNZ.

Quantity Theory of Money

"Virtually every quantity theorist has recognised that changes in the quantity of money that correspond to changes in the volumes of trade or of the output have no tendency to produce changes in prices." (Milton Friedman quoted in Dornbusch and Fisher p. 372).

The quantity theory of money links the monetary aggregates to inflation. In its most extreme form it states that the price level is fully determined by the increase in the stock of money. This strict interpretation is not commonly accepted any longer.

In Chapter 5 and 7 this thesis will analyse M1, M2 and M3R as defined by the RBNZ. Since M2 includes M1 and M3R includes M2, the increases from M1 to M2 and from M2 to M3 will be analysed. The data provided by the RBNZ are not inflation adjusted. Some analyses were performed with unadjusted log transformed time series and while other ones were CPI adjusted first before log transformation.

It should be appreciated there are difficulties measuring money (Collins *et al.*, 1999). The same would no doubt apply to some of the other time series that have been used and this should again serve as a warning to interpret the results of econometric analysis with caution.

Output gap and interest rates

The thinking about maintaining low inflation rates in New Zealand has been dominated in recent times by the philosophy of inflation targeting. This philosophy is based on the belief that when demand exceeds production too much, inflationary pressures become too high. The excess demand is measured by the output gap. A reduction in demand is brought about by the banks increasing their interest rates. The main tool used by the RBNZ to bring this about is using the Official Cash Rate (OCR). The RBNZ pays financial institutions an interest rate that is 0.25 percent below the OCR and charges them interest at 0.25 percent above the OCR. Consequently the short-term loans and borrowing by the banks to the public will be `in a range that is closely associated with the OCR.

In Chapter 6 this thesis will analyse the relationship between Gross Domestic Product and the interest rates.

3.3 Some factors currently affecting inflation in New Zealand

A number of specific events in recent years are affecting the inflation rates in New Zealand. To some degree these factors may affect inflation through mechanisms as explained by the theories discussed above.

The issues listed below are just a selection of tentative factors and to investigate their effects in detail is outside the scope of this thesis. In some cases redistribution of wealth has occurred. Two main categories of variables that affect inflation are identified below. The first category includes factors that affect discretionary spending. Discretionary spending is defined here as the amount of money that remains available at the discretion of the holders for buying goods and services after payments of taxes, goods and services that "must" be made. The word "must" applies where either the payments are imposed or the holders are committed to them based on their decisions in the past. The second group of variables relate to the importance of the output gap.

- The Employment Contacts Act (1991)

The Employment Contracts Act (1991) reduced the ability of the lower paid workers to maintain or increase their purchasing power. Consequently the ownership of money resulting from the increase of the monetary aggregates may not have been evenly distributed over the population. It could be argued that the 'bidding' process for a number of goods might not have occurred to any significant degree since the lower and middle socio-economic groups of New Zealand society at times benefited little from the economic reforms.

The average hourly earnings might be used as a proxy for some of the effects of the ECA. However, it might be more appropriate to use an index that covers the bottom 80 percent of earners of society.

- Abolishment of import licensing and tariffs

The abolishment of import licensing and tariffs for many goods has made it easier to import goods from overseas. Therefore if the demand for certain goods increases, there would not necessarily be an increased pressure on production facilities and the output gap would not necessarily widen. Rather goods could be imported. This process has gone one step further because these imports are frequently from low cost countries. An example of this would be the imports of cheap clothes and second-hand automobiles.

- Black market economy

There is a wide range of activities that are not reflected in the 'official economy'. They range from tradesmen being paid 'under the table' to income from criminal activities. These activities are commonly paid for with notes and changes in patterns of these activities may influence the effect of M1 on inflation.

- Housing

The price of houses has increased considerably in recent years. This may have absorbed a large proportion of increase of the monetary aggregates. The increase in house prices has been of concern to the Governor of the Reserve Bank because of its inflationary effects.

However it should also be considered that people with (large) mortgages will have less discretionary money because of repayment obligations. Consequently less money will be available to fuel inflation by purchasing other goods and services.

- Household indebtedness

Current household debt levels in New Zealand are high. The debt levels could be interpreted in various ways. Initial indebtedness might increase inflation since more money is available for spending. However, once debt needs to be repaid this may slow down inflation due to reduced discretionary money being available.

- Virtual monopolies, compliance costs and tax drag

There are a number of virtual monopolies such as utilities and city/district councils. Consumers do not have an option but to pay the charges or taxes (rates, assessment and compliance costs, etc.) imposed by these organisations. This leads to a reduction in money available for discretionary spending. Although to some degree these increases will be reflected in the CPI, it also means that the output gap does not come under pressure since the discretionary spending is reduced. The way in which these organisations spend their money will determine their effect on inflation. This example illustrates how the various pathways that may lead to increases in inflation.

Similarly as some compensation for inflation occurs, this compensation may be partially taxed away if people fall into a higher tax bracket.

- Student loans

The repayment of loans to an extent that did not exist in the past is likely to affect the discretionary income of some socio-economic groups.

The issues raised above may have had some impact on the low levels of inflation in recent times. There are only a small number of quarterly observations available and there are many variables that may, to a smaller or larger degree, influence inflation. The list of examples above is not comprehensive but serves to show that there are many specific factors as part of or in addition to the interest rates and monetary aggregates that may have contributed to the low inflation rates in recent times.

3.4 References

Collins, S, Thorp, C and White, B (1999) Defining money and credit aggregates: theory meets practice. Reserve Bank of New Zealand: Bulletin Vol. 62, No 2, 5 - 23

Dornbusch R and Fischer S (1984) Macroeconomics, 3th edition. McGraw-Hill International Book Company, New York

CHAPTER 4

TIME SERIES ANALYSES OF INFLATION

Introduction

This chapter will analyse various time series of inflation in New Zealand. Below the abbreviations are described and the way in which various aspects of the analyses have been denoted.

LOGCPI	Natural logarithm of the CPI
CPI	Consumer Price Index
LOGCPIX	Natural logarithm of the CPI excluding credit services
LOGNT	Natural logarithm of CPI Non-Tradable Inflation
LOGT	Natural logarithm of CPI Tradable Inflation
LOGLC	Natural logarithm of Labour Cost Inputs
LOGHE	Natural logarithm of Average Hourly Earnings

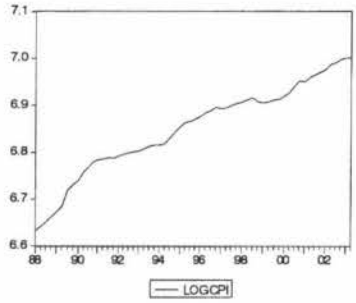
The univariate and multivariate analyses will be carried out as explained in Chapter 3. The τ and ϕ statistics are as described by Dickey and Fuller (1981). The coefficient of the constant term is denoted as a_0 and that of the linear trend term is described as a_2. The standard errors are put in parentheses below each equation. The terms ΔY_{t-i} were used in the models if they were significant. In some instances a term may have been included if not significant, if the higher order term(s) was (were) significant (See Chapter 2 for details). Note that critical values for tests are based on n = 50 as this is the closest tabulated value in Dickey and Fuller (1981). Since our sample sizes are slightly larger the test will be slightly conservative. The data consists of quarterly values. This is reflected in the notation used (eg 1991:4 is the fourth quarter of 1991). In subsequent chapters cointegration tests will be performed with *LOGCPI*. The time series used in the subsequent chapters will be shorter than the time series used in the DF tests of this chapter.

LOGCPI

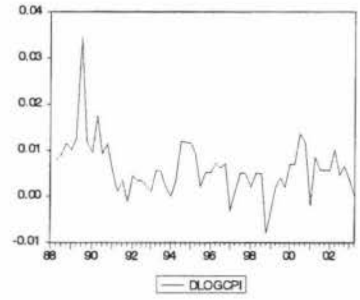
This section analyses the time series that consists of the natural logarithm of the Statistics New Zealand All Groups Consumer Price Index (LOGCPI). The data are derived through the RBNZ from Statistics New Zealand. The base was June 1999 = 1000. From September 1999 this index excludes interest charges and section prices. It is always unfortunate if changes have occurred to the collection of a data series. A breakpoint test will be performed to see whether a breakpoint at this point in time can be demonstrated. The time series has an upward trend (Figure 4.1). The variance seems to be constant. The ACF dies down slowly. The

differenced series shows one large peak early in the series. After a subsequent decline the series seems more or less stationary with considerable variation.
The time series covers the period from 1988:1 to 2003:2.

Figure 4.1 Time series and differenced time series of *LOGCPI*



Time series of *LOGCPI*



Differenced time series of *LOGCPI* (*DLOGCPI*)

DF Models of *LOGCPI*

The time series of LOGCPI was tested for stationarity in (4.1) to (4.5) by using the Dickey-Fuller equations as outlined in Chapter 2.

Model 1

$$\underset{}{\Delta LOGCPI_t} = \underset{(0.2185)}{0.7392} + \underset{(0.0002)}{0.0005t} - \underset{(0.0326)}{0.1096 LOGCPI_{t-1}} + \underset{(0.1129)}{0.3522 \Delta LOGCPI_{t-1}} + \varepsilon_t \qquad (4.1)$$

Model 2

$$\Delta LOGCPI_t = \underset{(0.0531)}{0.1302} - \underset{(0.0071)}{0.0185 LOGCPI_{t-1}} + \underset{(0.1197)}{0.3683 \Delta LOGCPI_{t-1}} + \varepsilon_t \qquad (4.2)$$

Model 2R

$$\Delta LOGCPI_t = \underset{(0.001)}{0.0032} + \underset{(0.1177)}{0.4614 \Delta LOGCPI_{t-1}} + \varepsilon_t \qquad (4.3)$$

Model 3

$$\Delta LOGCPI_t = \underset{(0.0002)}{0.0005 LOGCPI_{t-1}} + \underset{(0.1174)}{0.4673 \Delta LOGCPI_{t-1}} + \varepsilon_t \qquad (4.4)$$

Model 3R

$$\Delta LOGCPI_t = \underset{(0.0876)}{0.7303 \Delta LOGCPI_{t-1}} + \varepsilon_t \qquad (4.5)$$

The RSS and the information criteria of (4.1) to (4.5) are shown in Table 4.1.

Table 4.1 RSS and information criteria of Dickey-Fuller models of *LOGCPI*

	RSS	AIC	SC	Adj. R^2
Model 1	0.00133	-7.7483	-7.6087	0.3399
Model 2	0.0015	-7.645	-7.5403	0.2566
Model 2R	0.0017			
Model 3	0.0017	-7.5780	-7.5082	0.1922
Model 3R	0.001963			

The various statistics of the DF models (4.1) to (4.5) are displayed in Table 4.2.

Table 4.2 Summary of the Dickey-Fuller tests of *LOGCPI*

Model	Test Statistic	Value	Critical Value (p-value, n[#])	Hypothesis
1	τ_τ	-3.36	-3.48 (0.05)	$\gamma = 0$
			-3.17 (0.1)	
	$\tau_{\alpha\tau}$	3.38	3.14 (0.05, 50)	$a_0 = 0$ *given* $\gamma = 0$
			3.47 (0.025, 50)	
	$\tau_{\beta\tau}$	2.86	2.81 (0.05, 50)	$a_2 = 0$ *given* $\gamma = 0$
			3.18 (0.025, 50)	
	ϕ_2	8.95	7.02 (0.01, 50)	$a_0 = \gamma = a_2 = 0$
	ϕ_3	7.32	6.73 (0.05, 50)	$\gamma = a_2 = 0$
			7.81 (0.025, 50)	
2	τ_μ	-2.39	-2.59 (0.1)	$\gamma = 0$
	$\tau_{\alpha\mu}$	2.45	2.18 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
	ϕ_1	8.28	7.06 (0.01, 50)	$a_0 = \gamma = 0$
3	τ	3.12	-1.62 (0.1)	$\gamma = 0$

[#] n listed if p-value for precise sample size of time series not known

Model 2 has a unit root. Model 1 suggests unit root ($p > 0.05$). However the evidence is not strong. Model 3 does not have a unit root.

Model 1

The ACF of equation (4.1) does not show significant lags (28 lags included). There are no significant Q statistics.

Both deterministic components (τ statistics) of Model 1 are significant ($p < 0.05$) if the hypothesis of unit root is accepted. Here too the evidence is not strong.

There are 60 usable observations ($T = 60$) and 4 parameters in the unrestricted model ($k = 4$) of ϕ_2 (3 restrictions) and ϕ_3 (2 restrictions).

The unrestricted and restricted equations for ϕ_2 (4.1) are and (4.5) respectively.

The null hypothesis is rejected. This can be interpreted as meaning that if the process is unit root, than a_0 and/or a_2 are significant which supports the conclusion based on the $\tau_{\alpha\tau}$ and $\tau_{\beta\tau}$ statistics.

The unrestricted equation and restricted equations for ϕ_3 are (4.1) and (4.3) respectively. Hence it is possible to reject the null hypothesis ($p < 0.05$) but it should be considered that the evidence is not strong. This can be interpreted as meaning that if the process has a unit root, then a_2 is significant.

Figures 4.1 and 4.2 show that structural breaks could have occurred. If so this would have made the inclusion of deterministic components in the differenced equations more likely. One point in Figure 4.2 stands out (1989:3) and it will be further investigated with the Chow test.

The Chow Breakpoint Test was performed on Model 1 (4.1) and the results are shown in Table 4.3

Table 4.3 Chow Breakpoint Test of DF Model 1 of *LOGCPI*

	Value	Probability
1989:3		
F - statistic	2.99	0.03
Log Likelihood ratio	12.41	0.01
1999:3		
F - statistic	0.81	0.52
Log Likelihood ratio	3.66	0.45

There is evidence for a breakpoint at 1989:3. This may impact on some of the conclusions of Model 1. Note though that the choice of possible breakpoint was determined by examining the data, and this to some extent compromises the validity of the test. No breakpoint could be detected at 1999:3 when the section prices and interest rates were no longer included.

The conclusion from analysing Model 1 is that the hypothesis of a unit root in the time series *LOGCPI* is not rejected. The DF model has a constant and a deterministic trend. Figure 4.2 supports a constant. The deterministic trend may be caused by the large peak and as such should be interpreted with caution. The DF model infers a quadratic trend in the undifferenced time series, or equivalently a deterministic linear trend in the rate of inflation. Figures 4.1 and 4.2 do not seem to fully support this impression.

Model 2

This model suggests a unit root ($p > 0.1$). The ACF of equation (4.2) does not show significant lags (28 lags included). There are no significant Q statistics.

The constant (a_0) is significant at the 5% significance level.

The unrestricted and the restricted equations for ϕ_1 are (4.2) and (5.5) respectively. There are 60 usable observations (T=60) and 3 parameters (k=3) in the unrestricted model. There are 2 restrictions.

This null hypothesis ($a_0 = \gamma = 0$) is rejected. Therefore the constant term (a_0) is significant if the process is unit root. The Chow Breakpoint Tests failed to demonstrate a significant breakpoint (Table 4.4).

Table 4.4 Chow Breakpoint Test of DF Model 2 of *LOGCPI*

	Value	Probability
1989:3		
F - statistic	0.06	0.98
Log Likelihood ratio	0.21	0.98
1999:3		
F - statistic	2.08	0.11
Log Likelihood ratio	6.56	0.09

In view of these results it would appear that Model 2 is indeed preferable. It is assumed that the exclusion of interest rates and section prices from this index since 1999:3 is of a minor nature.

These results are interpreted to mean that the process has a unit root with a constant in the DF equation. This implies that the inflation rate (rate of change of the CPI) fluctuates randomly around a constant level.

Selection of LOGCPI DF model

The process seems unit root but only if deterministic components are included. Based on the information criteria, Model 1 would be favoured. However, the extreme values, early in the time series may have caused this situation. The Chow Breakpoint test also supports that view.

Since Model 2 is not rejected and more plausible from an economic perspective itwould appear to be the preferred model.

A number of simulations were performed using the chosen model (ie unit root and a_0 = 0.13)(Figure 4.2). No autocorrelated terms Δy_{t-i} were used during these simulations since the error terms were not correlated anyway. Some graphs are shown below for illustrative purposes.

Figure 4.2 Simulated graphs of (4.2)

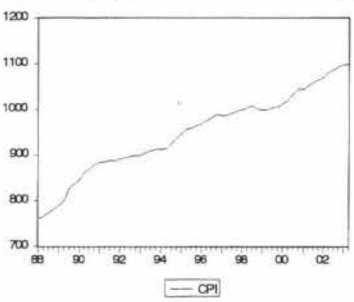
The conclusion is that the inflation rate (rate of change of CPI) fluctuates randomly around a constant level, while the actual price level increases over time in a more or less constant manner. It should be noted that the model allows for declines of a magnitude that the actual data set (*LOGCPI*) did not display.

CPI

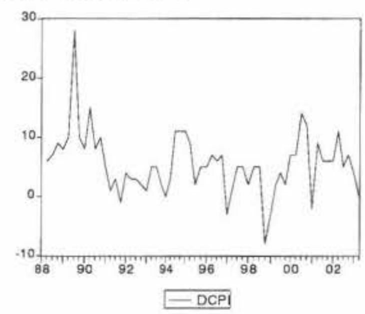
This section analyses the time series of the Consumer Price Index (CPI). This index is described in the previous section. The time series covers the period from 1988:1 to 2003:2.

This is the same series as the one that was analysed in the previous section. The difference is that this series was not log transformed. The intention is to see whether the conversion might have lead to different conclusions. See Chapter 2 for further comments on log transformation. The time series *CPI* has an upward trend (Figure 4.4). The variance does not appear to increase over time. The ACF decays slowly over time. Figure 4.4 shows one large peak around 1989:3. After that peak a considerable decline occurs. The rest of the series displays considerable variation.

Figure 4.3 Time series and differenced time series of *CPI*



Time series of *CPI*



Differenced time series of *CPI* (*DCPI*)

DF models of CPI

The time series of CPI was tested for stationarity in (4.6) to (4.10) by using the Dickey-Fuller equations as outlined in Chapter 2.

Model 1

$$\Delta CPI_t = 99.2211 + 0.5276t - 0.1184CPI_{t-1} + 0.3789\Delta CPI_{t-1} + \varepsilon_t \qquad (4.6)$$
$$(30.3589) \quad (0.1869) \quad (0.0380) \quad (0.1145)$$

Model 2

$$\Delta CPI_t = 15.6869 - 0.0129CPI_{t-1} + 0.3708\Delta CPI_{t-1} + \varepsilon_t \qquad (4.7)$$
$$(7.1452) \quad (0.0073) \quad (0.1212)$$

Model 2R

$$\Delta CPI_t = 3.2077 + 0.4128\Delta CPI_{t-1} \qquad (4.8)$$
$$(0.9228) \quad (0.121)$$

Model 3

$$\Delta CPI_t = 0.0031CPI_{t-1} + 0.4472\Delta CPI_{t-1} + \varepsilon_t \qquad (4.9)$$
$$(0.0001) \quad (0.1199)$$

Model 3R

$$\Delta CPI_t = 0.7235\Delta CPI_{t-1} + \varepsilon_t \quad (4.10)$$
$$(0.0889)$$

The RSS and various information criteria of (4.6) to (4.10) are displayed in Table 4.5. Model 1 seems the preferred model if the decision were based on the information criteria.

Table 4.5 RSS and information criteria of Dickey-Fuller models of *CPI*

	RSS	AIC	SC	Adj. R^2
Model 1	1118.15	5.8963	6.0359	0.2714
Model 2	1277.17	5.9959	6.1007	0.1824
Model 2R	1346.635			
Model 3	1385.168	6.0438	6.1136	0.1286
Model 3R	1627.173			

The various τ and ϕ statistics of (4.6) to (4.10) are shown in table 4.6. Both Model 1 and Model 2 have a unit root but Model 3 does not have a unit root.

Table 4.6 Summary of the Dickey-Fuller tests of CPI

Model	Test Statistic	Value	Critical Value (p-value, n[#])	Hypothesis
1	τ_τ	-3.11	-3.17 (0.1)	$\gamma = 0$
	$\tau_{\alpha\tau}$	3.27	3.14 (0.05, 50)	$a_0 = 0$ *given* $\gamma = 0$
			3.47 (0.025, 50)	
	$\tau_{\beta\tau}$	2.82	2.81 (0.05, 50)	$a_2 = 0$ *given* $\gamma = 0$
			3.18 (0.025, 50)	
	ϕ_2	8.50	7.02 (0.01, 50)	$a_0 = \gamma = a_2 = 0$
	ϕ_3	5.72	5.61 (0.1, 50)	$\gamma = a_2 = 0$
			6.73 (0.05, 50)	
2	τ_μ	-1.76	-2.59 (0.1)	$\gamma = 0$
	$\tau_{\alpha\mu}$	2.20	2.18 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
	ϕ_1	7.81	7.06 (0.01, 50)	$a_0 = \gamma = 0$
3	τ	3.18	-1.62 (0.1)	$\gamma = 0$

[#] n listed if p-value for precise sample size of time series not known

Model 1

The model suggests unit root ($p > 0.1$). The ACF of equation (4.6) does not show significant lags (28 lags included). There are no significant Q statistics.

Both deterministic components ($\tau_{\alpha\tau}$ and $\tau_{\beta\tau}$) are significant ($p < 0.05$) if the hypothesis of unit root is accepted. Again the evidence is not strong.

The unrestricted and the restricted equations for ϕ_2 are (4.6) and (4.10) respectively. For ϕ_3 these equations are (6.1) and (6.3). There are 60 usable observations (T=60) and 4 parameters (k=4) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3.

The null hypothesis for ϕ_2 is rejected . This can be interpreted as meaning that if the process is unit root, than a_0 and/or a_2 are significant which supports the conclusion based on the $\tau_{\alpha\tau}$ and $\tau_{\beta\tau}$ statistics.

It is questionable whether the null hypothesis for ϕ_3 should be rejected. It is possible that a_2 is zero.

Figure 4.3 shows that a structural break could have occurred. If so this would have made the inclusion of deterministic components in the differenced equations more likely. One point stands out and they will be further investigated with the Chow Breakpoint Test. The Chow Breakpoint Test was performed 1989:3 (Table 4.7). A breakpoint was not demonstrated with this test.

Table 4.7 Chow Breakpoint Test of DF Model 1 of *CPI* at 1989:3

	Value	Probability
F - statistic	1.658489	0.173736
Log Likelihood ratio	7.204219	0.125482

Model 2

This model suggests a unit root ($p > 0.1$). The ACF of this equation does not show significant lags (28 lags included). There are no significant Q statistics.

The constant (a_0) is significant at the 10% but not at the 5% significance level. Therefore the evidence is not strong.

The unrestricted and the restricted equations for ϕ_1 are (4.7) and (4.10) respectively. There are 60 usable observations (T=60) and 3 parameters (k=3) in the unrestricted model. There are 2 restrictions..

The null hypothesis ($a_0 = \gamma = 0$) is rejected. Therefore the constant term is significant if the process is unit root. The $\tau_{\alpha\mu}$ and the ϕ_1 statistics are not in good agreement.

The Chow Breakpoint Test was performed on Model 2 (Table 4.8). A breakpoint was not demonstrated with this test.

Table 4.8 Chow Breakpoint Test of DF Model 2 of *CPI* at 1989:3

	Value	Probability
F - statistic	0.05	0.99
Log Likelihood ratio	0.16	0.98

Selection of CPI DF model

The process seems to have a unit root but deterministic components should be included. Both Model 1 and Model 2 have statistics that could be interpreted as rejecting either model. Based on the information criteria, Model 1 seemed the best model. However, ϕ_3 did not provide strong support for a_2 being significant.

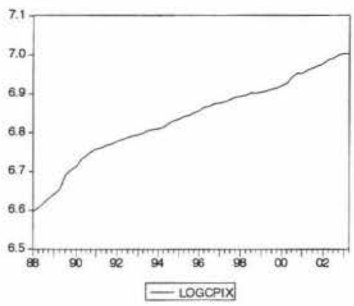
Similar to the analysis of the *LOGCPI* models, the extreme value at 1989:3 is of concern. Chow Breakpoint tests were carried out and the hypothesis of no breakpoint at the most probable time was accepted.

The selection of Model 1 means that the time series *CPI* has a deterministic quadratic trend. This is not very plausible from an economic perspective. Also Figure 4.3 does not provide much support for this model. In the case of this time series, further use for cointegration analysis is not intended since log transformed series seem more appropriate. It is of interest to note that the model for *CPI* differs from the one selected for *LOGCPI*.

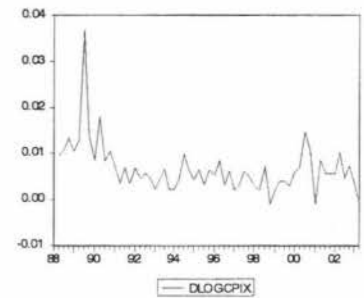
LOGCPIX

This section analyses the natural logarithm of the Statistics New Zealand All Groups Consumer Price Index excluding the Credit Services Group. From September 1999, the credit services group excludes interest rates. The time series covers the period 1988:1 to 2003:2. The series has an upward trend (Figure 4.4). The variance seems to be constant. The ACF dies down slowly. The time series *DLOGCPIX* show a large peak at 1989:3.

Figure 4.4 Time series and differenced time series of *LOGCPIX*



Time series of *LOGCPIX*



Differenced time series of *LOGCPIX* (*DLOGCPIX*)

DF Models of *LOGCPIX*

The standard approach as outlined in Chapter 2 for establishing the number of lags was followed. In the equations below three lags were necessary for carrying out the tests with the restricted models. Once the most appropriate model has been identified given the standardised approach, a further analysis will be performed to see whether some further improvements can be made to this model. This may influence the final conclusion which it the preferred model.

Model 1:

$$\underset{}{\Delta LOGCPIX_t} = \underset{(0.2430)}{1.1194} + \underset{(0.0002)}{0.0008t} - \underset{(0.0364)}{0.1669LOGCPIX_{t-1}} + \underset{(0.1153)}{0.0888\Delta LOGCPIX_{t-1}} -$$

$$\underset{(0.1154)}{0.3669\Delta LOGCPIX_{t-2}} + \underset{(0.1125}{0.2812\Delta LOGCPICX_{t-3}} + \varepsilon_t \qquad (4.11)$$

Model 2

$$\Delta LOGCPIX_t = \underset{(0.0540)}{0.1053} - \underset{(0.0078)}{0.0149LOGCPIX_{t-1}} + \underset{(0.1298)}{0.1889\Delta LOGCPIX_{t-1}} + \underset{(0.1322)}{0.0057\Delta LOGCPIX_{t-2}}$$

$$+ \underset{(0.1294)}{0.2866\Delta LOGCPIX_{t-3}} + \varepsilon_t \qquad (4.12)$$

Model 2R

$$\Delta LOGCPIX_t = \underset{(0.0012)}{0.0019} + \underset{(0.1284)}{0.2536}\Delta LOGCPIX_{t-1} + \underset{(0.1326)}{0.0579}\Delta LOGCPIX_{t-2} +$$

$$\underset{(0.1282)}{0.3493}\Delta LOGCPIX_{t-3} + \varepsilon_t \qquad (4.13)$$

Model 3

$$\Delta LOGCPIX_t = \underset{(0.0002)}{0.0003}LOGCPIX_{t-1} + \underset{(0.1283)}{0.2566}\Delta LOGCPIX_{t-1} + \underset{(0.1326)}{0.0605}\Delta LOGCPIX_{t-2}$$

$$+ \underset{(0.1281)}{0.3524}\Delta LOGCPIX_{t-3} + \varepsilon_t \qquad (4.14)$$

Model 3R

$$\Delta LOGCPIX_t = \underset{(0.1221)}{0.3255}\Delta LOGCPIX_{t-1} + \underset{(0.1281)}{0.1225}\Delta LOGCPIX_{t-2} + \underset{(0.1213)}{0.4238}\Delta LOGCPIX_{t-3} + \varepsilon_t \qquad (4.15)$$

The RSS and various information criteria that apply to *LOGCPIX* are displayed in Table 4.9. Model 1 would appear to be the best model

Table 4.9 RSS and information criteria of Dickey-Fuller models of *LOGCPIX*

	RSS	AIC	SC	Adj. R^2
Model 1 (4.11)	0.0009	-8.0717	-7.8586	0.4453
Model 2 (4.12)	0.001162	-7.8076	-6.6300	0.2664
Model 2R (4.13)	0.0012			
Model 3 (4.14)	0.0012	-7.7726	-7.6305	0.2282
Model 3R (4.15)	0.001302			

The various τ and ϕ statistics of (4.11) to (4.15) are displayed in table 4.10). Neither Model 1 nor Model 3 support a unit root.

Table 4.10 Summary of the Dickey-Fuller tests of *LOGCPIX*

Model	Test Statistic	Value	Critical Value (p-value, n#)	Hypothesis
1	τ_τ	-4.59	-4.12 (0.01)	$\gamma = 0$
2	τ_μ	-1.92	-2.59 (0.1)	$\gamma = 0$
	$\tau_{\alpha\mu}$	1.95	2.18 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
			2.56 (0.05, 50)	
	ϕ_1	3.19	3.94 (0.1, 50)	$a_0 = \gamma = 0$
3	τ	1.56	-1.62 (0.1)	$\gamma = 0$

n listed if p-value for precise sample size of time series not known

Model 2

The ACF of equation (4.12) does not show significant lags (28 lags included). There are no significant Q statistics.

The constant (a_0) is significant at the 10% but not at the 5% significance level and therefore the evidence is not strong.

The unrestricted and the restricted equation for ϕ_1 are (4.12) and (4.15) respectively There are 58 usable observations (T = 58) and 5 parameters (k = 5) in the unrestricted models. There are 2 restrictions. The null hypothesis of unit root and $a_0 = 0$ is not rejected. If the process is unit root, then the term a_0 is not significant.

Selection of *LOGCPIX* DF Model

Model 1 and Model 3 reject the unit root hypothesis. Model 2 accepted unit root but also considered a_0 not being different from zero. This would in effect result in Model 3 being unit root but this was rejected. Consequently the results are ambiguous.

Since unit root is essential for the proposed course of action with multivariate analysis Model 2 is selected. A further analysis was carried out with model 2 but with fewer lags.

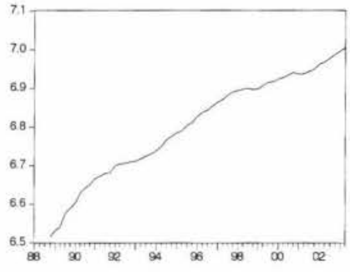
Model 2 with 2 lags had an ADF statistic -2.6916 (critical value -2.9109, p =0.05). Both coefficients of the lagged terms are not significant (p > 0.10).
Model 2 with 1 lag had an ADF statistic -3.0705 (critical value -3.5417, p = 0.01; critical value -2.9101, p = 0.05). The p- value of the coefficient of lagged term is 0.0601.
Model 2 with no lags did not have a unit root (p , 0.01). Consequently Model 2 with 1 lag seems the best model available. Its test statistics for a_0 is $\tau_{\alpha\mu} = 3.1543$ with critical value 2.89 for n = 50 and p = 0.025. The ACF at lag 3 is significant or close to significance but the other lags are not significant. There are no significant Q statistics.

The limits of Model 2 with 1 lag are to be noted. The process is not convincingly unit root. However it is similar to the model selected for *LOGCPI* which is a positive point. VAR may be considered if deemed appropriate given other time series under investigation. As a concluding comment it could be considered that the analysis process of time series using the commonly used Dickey Fuller approach is far from perfect.

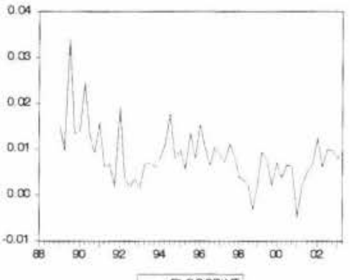
LOGCPINT

This section analyses the time series that consist of natural logarithm of the CPI Non-tradables Inflation. This is a time series that is created by the RBNZ and it includes all the goods and services in the CPI that are not exposed to foreign competition such as government charges. Interest rates are excluded. The time series covers the period from 1988:4 to 2003:2. This time series will be denoted as *LOGCPINT* or *LOGNT* in this section. The undifferenced series has an upward trend (Figure 4.5). There do not appear to be structural breaks. The ACF dies down slowly. The differenced series seems to indicate an initial decrease followed by a more constant pattern.

Figure 4.5 Time series and differenced time series of *LOGNT*



Time series of *LOGNT*



Differenced time series of *LOGNT* (*DLOGNT*)

DF models of *LOGNT*

In all three models the augmented term $\Delta LOGNT_{t-3}$ was significant or it was close to significance with the terms $\Delta LOGNT_{t-1}$ and $\Delta LOGNT_{t-2}$ not being significant. This situation is very similar to *LOGCPIX*.

Model 1

$$\underset{}{\Delta LOGNT_t} = \underset{(0.2352)}{0.5182} + \underset{(0.0003)}{0.0005t} - \underset{(0.035778)}{0.0782LOGNT_{t-1}} +$$

$$\underset{(0.1119)}{0.1189\Delta LOGNT_{t-1}} + \underset{(0.1096)}{0.1190\Delta LOGNT_{t-2}} + \underset{(0.1111)}{0.2414\Delta LOGNT_{t-3}} + \varepsilon_t \qquad (4.16)$$

Model 2

$$\Delta LOGNT_t = \underset{(0.0456)}{0.0379} - \underset{(0.0066)}{0.0050LOGNT_{t-1}} + \underset{(0.1145)}{0.1509\Delta LOGNT_{t-1}} +$$

$$\underset{(0.1131)}{0.1189\Delta LOGNT_{t-2}} + \underset{(0.1143)}{0.2210\Delta LOGNT_{t-3}} + \varepsilon_t \qquad (4.17)$$

Model 2R

$$\Delta LOGNT_t = \underset{(0.0013)}{0.0031} + \underset{(0.1098)}{0.1745}\Delta LOGNT_{t-1} + \underset{(0.1084)}{0.1425}\Delta LOGNT_{t-2} + \underset{(0.1086)}{0.2471}\Delta LOGNT_{t-3} + \varepsilon_t \quad (4.18)$$

Model 3

$$\Delta LOGNT_t = \underset{(0.0004)}{0.0004}LOGNT_{t-1} + \underset{(0.1096)}{0.1775}\Delta LOGNT_{t-1} + \underset{(0.1455)}{0.1455}\Delta LOGNT_{t-2} +$$

$$\underset{(0.1084)}{0.2503}\Delta LOGNT_{t-3} + \varepsilon_t \quad (4.19)$$

Model 3R

$$\Delta LOGNT_t = \underset{(0.1080)}{0.2672}\Delta LOGNT_{t-1} + \underset{(0.1056)}{0.2403}\Delta LOGNT_{t-2} + \underset{(0.1067)}{0.3398}\Delta LOGNT_{t-3} + \varepsilon_t \quad (4.20)$$

The RSS and various information criteria of LOGNT are shown in Table 4.11. The various criteria are indicating different optimal models.

Table 4.11 RSS and information criteria of Dickey-Fuller models of *LOGNT*

	RSS	AIC	SC	Adj. R^2
Model 1 (4.16)	0.000994	-7.8654	-7.6464	0.2676
Model 2 (4.17)	0.001081	-7.8172	-7.6347	0.2190
Model 2R (4.18)	0.001094			
Model 3 (4.19)	0.001096	-7.8399	-7.6939	0.2237
Model 3R (4.20)	0.001224			

The τ and the ϕ statistics of (4.16) to (4.20) are shown in Table 4.12. Both Model 1 and Model 2 have a unit root (p > 0.1) but Model 3 does not.

Table 4.12 Summary of the Dickey-Fuller tests of *LOGNT*

Model	Test Statistic	Value	Critical Value (p-value, n[#])	Hypothesis
1	τ_τ	-2.19	-3.17 (0.1)	$\gamma = 0$
	$\tau_{\alpha\tau}$	2.20	2.75 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
	$\tau_{\beta\tau}$	2.08	2.38 (0.1, 50)	$a_2 = 0$ *given* $\gamma = 0$
	ϕ_2	3.78	4.31 (0.1, 50)	$a_0 = \gamma = a_2 = 0$
	ϕ_3	2.14	5.61 (0.1, 50)	$\gamma = a_2 = 0$
2	τ_μ	-0.76	-2.59 (0.1)	$\gamma = 0$
	$\tau_{\alpha\mu}$	0.83	2.18 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
	ϕ_1	3.31	3.94 (0.1, 50)	$a_0 = \gamma = 0$
3	τ	2.44	$\gamma \succ 0$	$\gamma = 0$

[#] n listed if p-value for precise sample size of time series not known

Model 1

The ACF of (4.16) does not show significant lags (24 lags included). There are no significant Q statistics.

Both deterministic components ($\tau_{\alpha\tau}$ and $\tau_{\beta\tau}$) are not significant ($p > 0.1$) if the hypothesis of unit root is accepted.

The unrestricted and the restricted equation for ϕ_2 are (4.16) and (4.20) respectively. For ϕ_3 these equations are (4.21) and (4.23). There are 55 usable observations (T = 55) and 6 parameters (k = 6) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3.

The null hypothesis that $a_0 = \gamma = a_2 = 0$ is not rejected. If the process is unit root, then both a_0 and a_2 are not significantly different from 0 which is in line with the $\tau_{\alpha\tau}$ and $\tau_{\beta\tau}$ statistics. Also the null hypothesis that $\gamma = a_2 = 0$ is not rejected. This means that the process is unit root and a_2 is 0.

Although Model 1 has a unit root, a further analysis of the τ and the ϕ statistics has shown they are not significantly different from 0. Therefore Model 1 is not an adequate model.

Model 2

The ACF of equation (4.17) does not have significant lags (24 lags included). There are no significant Q statistics.

The constant a_0 of Model 2 is not significant at the 10% level.

The unrestricted and the restricted equation for ϕ_1 are (4.17) and (4.20) respectively There are 55 usable observations (T = 55) and 5 parameters (k = 5) in the unrestricted models. There are 2 restrictions. The null hypothesis of unit root and $a_0 = 0$ is not rejected. Both $\tau_{\alpha\tau}$ and the ϕ_1 statistics agree that a_0 is not significant.

Comments on unit root model selection at this stage

At this stage no satisfactory unit root model has been found. Other models with fewer augmented terms are evaluated in Table 4.13.

Table 4.13 Summary of additional Dickey-Fuller tests of *LOGNT*

Model (&)	Test Statistic	Value	Critical Value (p-value, n#)	Hypothesis
1(2)	τ_τ	-3.70	-4.13 (0.01) -3.49 (0.05)	$\gamma = 0$
1(2)	AIC	-7.63		
1(1)	τ_τ	**-3.12**	-3.17 (0.1)	$\gamma = 0$
1(1)	AIC	-7.57		
1(1)	$\tau_{\alpha\tau}$	3.16	3.14 (0.05, 50) 3.47 (0.025, 50)	$a_0 = 0$ *given* $\gamma = 0$
1(1)	$\tau_{\beta\tau}$	2.61	2.81 (0.05, 50) 2.38 (0.1, 50)	$a_2 = 0$ *given* $\gamma = 0$
1(0)	τ_τ	-3.25	-3.49 (0.05) -3.17 (0.1)	$\gamma = 0$
1(0)	AIC	-7.59		
1(0)	$\tau_{\alpha\tau}$	3.32	3.14 (0.05, 50) 3.47 (0.025, 50)	$a_0 = 0$ *given* $\gamma = 0$
1(0)	$\tau_{\beta\tau}$	2.57	2.38 (0.1, 50) 2.81 (0.05, 50)	$a_2 = 0$ *given* $\gamma = 0$
2 (2)	τ_μ	**-2.34**	-2.59 (0.1)	$\gamma = 0$
2(2)	AIC	-7.49		
2(2)	$\tau_{\alpha\mu}$	2.42	2.18 (0.1, 50) 2.56 (0.05, 50)	$a_0 = 0$ *given* $\gamma = 0$
2(1)	τ_μ	-2.85	-2.91 (0.05) -2.59 (0.1)	$\gamma = 0$
2(1)	AIC	-7.49		
2(0)	τ_μ	-4.00	-3.55 (0.01)	$\gamma = 0$
3	τ	For all lags: $\gamma > 0$		$\gamma = 0$

n listed if p-value for precise sample size of time series not known
(&)Lagged differences

For selection of the best unit root model, the ADF statistic is evaluated first. Only Model 1(1) and Model 2(2) appeared to have a clear unit root ($p > 0.1$). Both these Models had a τ statistic that was not significant at $p < 0.05$.

All three Models 1 had residuals that were significant or close to significance at lag 3. Model 2(2) did not have significant lags in the ACF nor were its Q statistics significant.

Again no model eventuated that was acceptable in all regards.

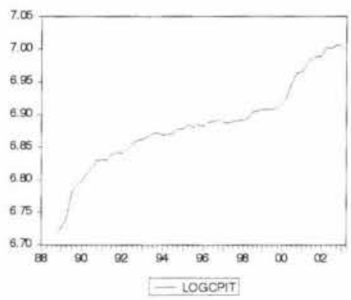
The intercept only model with two lagged differences seemed preferable as there was strong evidence for unit root and there was no autocorrelation left in the residuals. The evidence supporting a_0 being significant was weak. However, there will be a need for consistency of lags for the cointegration tests that will follow. The model with the intercept only and 1 lag was acceptable since it had arguably unit root, a significant a_0 and acceptable Q statistics.

The conclusion is that the inflation rate for the CPI of non-tradable inflation fluctuates randomly around a constant level, while the actual CPINT increases over time in a more or less constant manner.

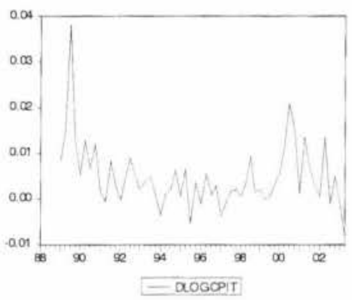
LOGCPIT

This section analyses the natural logarithm of the Consumer Price Index of Tradable Inflation (denoted as *LOGCPIT* or *LOGT*). This series is calculated by the RBNZ and consists of all goods and services in the *CPI* that are imported or that are in competition with foreign goods either in the domestic or the foreign markets. *LOGCPIT* is a quarterly series that starts in 1988:4 and finishes in 2003:2. The time series has an upward trend but this trend differs considerably from the CPI and CPIX trends (Figure 4.6). There may have been one or more structural breaks but the graph is not clear in this regard. The ACF decays slowly over time. The differenced series shows a large peak at 1989:3.

Figure 4.6 Time series and differenced time series of *LOGCPIT*



Time series of *LOGCPIT*



Differenced time series of *LOGCPIT* (*DLOGCPIT*)

DF models of *LOGCPIT*

The time series LOGCPIT was tested for stationarity in (4.21) to (4.25) by using the Dickey-Fuller equations as outlined in Chapter 2.

Model 1

$$\underset{}{\Delta LOGCPIT_t} = \underset{(0.2825)}{0.9775} + \underset{(0.0002)}{0.0004t} - \underset{(0.0417)}{0.1436LOGCPIT_{t-1}} + \underset{(0.1191)}{0.3315\Delta LOGCPIT_{t-1}} + \varepsilon_t \qquad (4.21)$$

Model 2

$$\Delta LOGCPIT_t = \underset{(0.0960)}{0.2234} - \underset{(0.1392)}{0.032LOGCPIT_{t-1}} + \underset{(0.1265)}{0.3314\Delta LOGCPIT_{t-1}} + \varepsilon_t \qquad (4.22)$$

Model 2R

$$\Delta LOGCPIT = \underset{(0.0011)}{0.0028} + \underset{(0.1285)}{0.3921\Delta LOGCPIT_{t-1}} + \varepsilon_t \qquad (4.23)$$

Model 3

$$\Delta LOGCPIT_t = \underset{(0.0002)}{0.0004LOGCPIT_{t-1}} + \underset{(0.1285)}{0.3947\Delta LOGCPIT_{t-1}} + \varepsilon_t \qquad (4.24)$$

Model 3R

$$\Delta LOGCPIT_t = \underset{(0.1085)}{0.5840}\Delta LOGCPIT_{t-1} + \varepsilon_t \qquad (4.25)$$

The RSS and information criteria of (4.21) to (4.25) are displayed in Table 4.14. Model 1 has the best information criteria.

Table 4. 14 RSS and information criteria of Dickey-Fuller models of *LOGCPIT*

	RSS	AIC	SC	Adj. R^2
Model 1 (4.21)	0.0019	-7.3119	-7.1685	0.2841
Model 2 (4.22)	0.0022	-7.2074	-7.0998	0.1921
Model 2R (4.23)	0.0024444			
Model 3 (4.24)	0.0024	-7.1469	-7.0752	0.1429
Model 3R (4.25)	0.0027727			

The various τ and ϕ statistics of Models 1 to 3 are displayed in Table 4.15. There is weak evidence against unit root in Model 1. Model 2 has a unit root and Model 3 does not have a unit root.

Table 4.15 Summary of the Dickey-Fuller tests of *LOGCPIT*

Model	Test Statistic	Value	Critical Value (p-value, n[#])	Hypothesis
1	τ_τ	-3.44	-3.49 (0.05)	$\gamma = 0$
			-3.17 (0.1)	
	$\tau_{\alpha\tau}$	3.46	3.14 (0.05, 50)	$a_0 = 0$ *given* $\gamma = 0$
			3.47 (0.025, 50)	
	$\tau_{\beta\tau}$	2.82	2.81 (0.05, 50)	$a_2 = 0$ *given* $\gamma = 0$
	ϕ_2	7.64	7.02 (0.01, 50)	$a_0 = \gamma = a_2 = 0$
	ϕ_3	6.96	6.73 (0.05, 50)	$\gamma = a_2 = 0$
			7.81 (0.025, 50)	
2	τ_μ	-2.30	-2.59 (0.1)	$\gamma = 0$
	$\tau_{\alpha\mu}$	2.33	2.18 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
			2.56 (0.05, 50)	
	ϕ_1	6.50	5.80 (0.025, 50)	$a_0 = \gamma = 0$
			7.06 (0.01, 50)	
3	τ	2.50	$\gamma \succ 0$	$\gamma = 0$

[#] n listed if p-value for precise sample size of time series not known

Model 1

The ACF of equation (4.21) does not display any significant lags (24 lags included). There are no significant Q statistics.

Both deterministic components ($\tau_{\alpha\tau}$ and $\tau_{\beta\tau}$) are significant at $p < 0.05$ but not at $p < 0.025$ if the hypothesis of unit root is accepted. Here too the evidence is not strong.

The unrestricted and the restricted equation for ϕ_2 are (4.21) and (4.25) respectively. For ϕ_3 these equations are (4.21) and (4.23). There are 57 usable observations (T = 57) and 4 parameters (k = 4) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3. If Model 1 is unit root, then one or both deterministic components are significant. Hence it is possible to reject the null hypothesis. This can be interpreted as meaning that if the process is unit root, then a_0 and/or a_2 are significant which supports the conclusion based on the $\tau_{\alpha\tau}$ and the $\tau_{\beta\tau}$ statistics.

If Model 1 is unit root, then a_2 is significant at $p < 0.05$ but the evidence is not strong.

Figure 4.6 suggested various breakpoints. The Chow Breakpoint test could not be performed on the first suspected breakpoint because the time series before that point was to short. Instead 1990: 2 was chosen. Both at 1990:2 and 2000:3 breakpoints were identified (Table 4.16). The existence of these breakpoints is likely to have created a bias toward acceptance of this unit root model (Model 1).

Table 4.16 Chow Breakpoint tests of DF Model 1of *LOGCPIT*

	Value	Probability
Breakpoint 1990:2		
F-statistic	5.3211	0.0012
Log likelihood ratio	20.5619	0.00038
Breakpoint 2000:3		
F-statistic	9.2683	0.000012
Log likelihood ratio	32.1126	0.000002

Model 2

The ACF of the residuals of Model 2 is not significant at any lag up to 28.

The evidence that the deterministic component a_0 is significant is weak.

The unrestricted and the restricted equation for ϕ_1 are (4.22) and (4.25) respectively There are 57 usable observations (T = 57) and 3 parameters (k = 3) in the unrestricted models There are 2 restrictions. If *LOGCPIT* is unit root then a_0 is significant ($p < 0.025$).

Based on the concerns of structural beaks as suggested by Figure 4.6 Chow Breakpoint Tests were performed. Again two breakpoints were identified (Table 4.17).

Table 4.17 Chow Breakpoint test of DF Model 2 of *LOGCPIT*

	Value	Probability
Breakpoint 1990:1		
F-statistic	9.6854	0.000036
Log likelihood ratio	25.7015	0.00011
Breakpoint 2000:3		
F-statistic	9.4428	0.000046
Log likelihood ratio	25.1809	0.000014

Comparison of *LOGCPIT* models

Both Model 1 and 2 were acceptable if only the ADF, τ and ϕ statistics were considered. However, the Chow Breakpoint Tests indicated the existence of breakpoint as suggested by the Figure 4.6. Later in this chapter it will be investigated whether a cointegration relationships exists with *LOGCPINT*. Unless other series had similar breakpoints a cointegrating relationship could not exist.

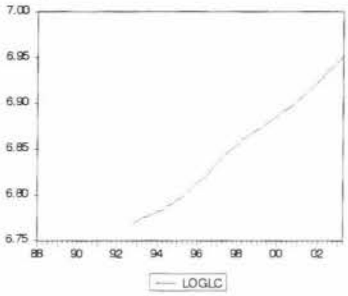
Model 1 would suggest that *LOGCPIT* has a quadratic trend. Its differenced version would suggest that it increases with a linear trend. This is hard to accept this from an economic perspective unless it covers a very short period.

Model 2 would suggest that the rate of change of *LOGCPIT* fluctuates randomly around a constant level, while the actual price level increases over time in a more or less constant manner.

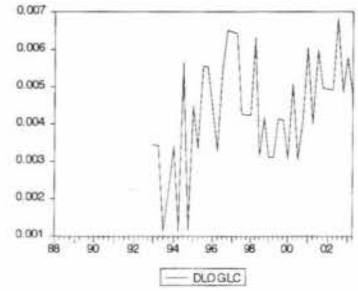
LOGLC

This section analyses the time series that consists of the natural logarithm of the Labour Cost. The time series covers the period 1992:4 to 2003:2. It is shorter than the other inflation time series that have been analysed. The undifferenced series has an upward trend (Figure 4.7). The variance seems to be constant. The ACF dies down slowly. The differenced series shows an increase over time. There may have been a structural break around 1996:2.

Figure 4.7 Time series and differenced time series of *LOGLC*



Time series of *LOGLC*



Differenced time series of *LOGLC* (*DLOGLC*)

DF Models of LOGLC

The time series LOGLC was tested for stationarity in (4.26) to (4.30) by using the Dickey-Fuller equations as outlined in Chapter 2.

Model 1

$$\underset{}{\Delta LOGLC_t} = \underset{(0.4132)}{1.3422} + \underset{(0.0003)}{0.0009t} - \underset{(0.0620)}{0.2011LOGLC_{t-1}} + \underset{(0.1382)}{0.0647\Delta LOGLC_{t-1}} +$$

$$\underset{(0.1387)}{0.4067\Delta LOGLC_{t-2}} + \varepsilon_t \qquad (4.26)$$

Model 2

$$\Delta LOGLC_t = \underset{(0.0318)}{-0.0358} + \underset{(0.0047)}{0.00056LOGLC_{t-1}} + \underset{(0.1565)}{0.0518\Delta LOGLC_{t-1}} + \underset{(0.1568)}{0.3808\Delta LOGLC_{t-2}} + \varepsilon_t \qquad (4.27)$$

Model 2R

$$\Delta LOGLC_t = \underset{(0.0008)}{0.0020} + \underset{(0.1470)}{0.1180\Delta LOGLC_{t-1}} + \underset{(0.1482)}{0.4443\Delta LOGLC_{t-2}} + \varepsilon_t \qquad (4.28)$$

Model 3

$$\Delta LOGLC_t = 0.0003LOGLC_{t-1} + 0.1119\Delta LOGLC_{t-1} + 0.4384\Delta LOGLC_{t-2} + \varepsilon_t$$
$$(0.0001) \qquad (0.1475) \qquad (0.1487) \qquad (4.29)$$

Model 3R

$$\Delta LOGLC_t = 0.3305\Delta LOGLC_{t-1} + 0.6568\Delta LOGLC_{t-2} + \varepsilon_t \qquad (4.30)$$
$$(0.1237) \qquad (0.1254)$$

The RSS and various information criteria of (4.26) to (4.30) are shown in Table 4.18. Based on any of the three information criteria Model 1 would appear to be the best one.

Table 4.18 RSS and information criteria of Dickey-Fuller models of *LOGLC*

	RSS	AIC	SC	Adj. R^2
Model 1 (4.26)	0.0000479	-10.5480	-10.3369	0.3762
Model 2 (4.27)	0.0000631	-10.321	-10.1521	0.2000
Model 2R (4.28)	0.0000656			
Model 3 (4.29)	0.0000654	-10.3366	-10.2099	0.1943
Model 3R (4.30)	0.0000757			

The various τ and ϕ statistics of (4.26) to (4.30) are shown in Table 4.19. Both Model 2 and Model 3 do not have a unit root.

Table 4.19 Summary of the Dickey-Fuller tests *of LOGLC*

Model	Test Statistic	Value	Critical Value (p-value, n[#])	Hypothesis
1	τ_τ	-3.24	-3.52 (0.05)	$\gamma = 0$
			-3.19 (0.1)	
	$\tau_{\alpha\tau}$	3.25	3.14 (0.05, 50)	$a_0 = 0$ *given* $\gamma = 0$
			3.47 (0.025, 50)	
	$\tau_{\beta\tau}$	3.34	3.18 (0.025, 50)	$a_2 = 0$ *given* $\gamma = 0$
			3.60 (0.01, 50)	
	ϕ_2	6.77	6.75 (0.025, 25)	$a_0 = \gamma = a_2 = 0$
			5.94 (0.025, 50)	
	ϕ_3	6.47	5.91 (0.1, 25)	$\gamma = a_2 = 0$
			7.24 (0.05, 25)	
			5.61 (0.1, 50)	
			6.73 (0.05, 50)	
2	τ_μ	1.18	$\gamma \succ 0$	$\gamma = 0$
3	τ	2.42	$\gamma \succ 0$	$\gamma = 0$

n listed if p-value for precise sample size of time series not known

Model 1

The ACF equation (4.26) does not show significant lags up to and including lag 28. However, there are a number of significant ($p < 0.05$) Q statistics (Lag 14, 17, 18 and 19).

The model suggests there is weak evidence against the unit root ($p > 0.05$).

Both deterministic components ($\tau_{\alpha t}$ and $\tau_{\beta\tau}$) are significant ($p < 0.05$), if the hypothesis of unit root is accepted.

The unrestricted and the restricted equation for ϕ_2 are (4.26) and (4.30) respectively. For ϕ_3 these equations are (4.26) and (4.28). There are 40 usable observations ($T = 40$) and 5 parameters ($k = 5$) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3.

The null hypothesis can be rejected. This can be interpreted as meaning that if *LOGLC* is unit root, then a_0 and/or a_2 are significant which supports the conclusion based on the $\tau_{\alpha\tau}$ and $\tau_{\beta\tau}$ statistics.

There is weak support that *LOGLC* is unit root and that a_2 is significant.

Based on Figure 4.12 there was some concern that that structural change might have occurred around 1996:2. The Chow Breakpoint test does not suggest evidence for a breakpoint around 1996:2 (Table 4.20).

Table 4.20 Chow Breakpoint Tests of DF Model 1 of *LOGLC*

	Value	Probability
F-statistic	1.3662	0.2647
Log likelihood ratio	8.2058	0.1453

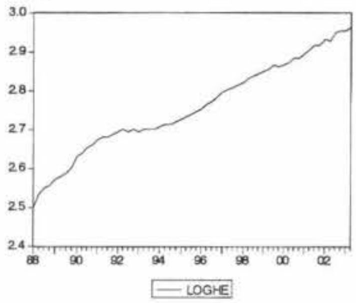
Selection of the appropriate *LOGLC* Model

Model 1 is the only model that was not rejected. The differenced equation has two deterministic components. Consequently the original (undifferenced) equation is quadratic. This means that the natural log of the labour cost increases in an explosive manner. This is not particularly plausible from an economic perspective. However, one has to consider that the time series is short and the test may have been affected by breakpoint as well. However, the Chow test did not suggest a breakpoint in the quarter that was considered the most likely one based on visual inspection of Figure 4.12. Inspection of Figure 4.11 would suggest a linear rather than a quadratic process.

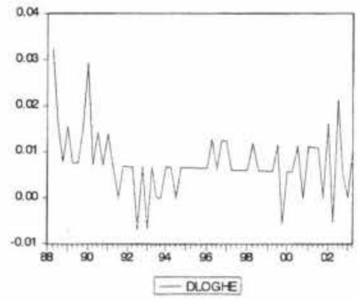
LOGHE

This section analyses the time series that consists of the natural logarithm of the Hourly Earnings. The time series covers the period 1988:1 to 2003:2. Figure 4.8 shows a time series with an upward trend. The variance seems to be constant. The ACF dies down slowly. The mean of the differenced series appears stationary but the variance seems to vary somewhat, with more variation in the beginning and at the end of the time series.

Figure 4.8 Time series and differenced time series of *LOGHE*



Time series of *LOGHE*



Differenced time series of *LOGHE* (*DLOGHE*)

DF models of *LOGHE*

The time series LOGHE was tested for stationarity in (4.31) to (4.35) by using the Dickey-Fuller equations as outlined in Chapter 2. The various DF models had augmented terms that were not significant at lag 1 but they were significant at lag 2.

Model 1

$$\underset{}{\Delta LOGHE_t} = \underset{(0.1347)}{0.2881} + \underset{(0.0003)}{0.0007t} - \underset{(0.0526)}{0.1100 LOGHE_{t-1}} - \underset{(0.1245)}{0.0784 \Delta LOGHE_{t-1}} +$$

$$\underset{(0.1129)}{0.2344 \Delta LOGHE_{t-2}} + \varepsilon_t \qquad (4.31)$$

Model 2

$$\Delta LOGHE_t = \underset{(0.0210)}{0.0204} - \underset{(0.0075)}{0.0053 LOGHE_{t-1}} - \underset{(0.1272)}{0.1033 \Delta LOGHE_{t-1}} + \underset{(0.1159)}{0.2444 \Delta LOGHE_{t-2}}$$

$$+ \varepsilon_t \qquad (4.32)$$

Model 2R

$$\Delta LOGHE_t = \underset{(0.0015)}{0.0058} - \underset{(0.1253)}{0.0904 \Delta LOGHE_{t-1}} + \underset{(0.1125)}{0.2625 \Delta LOGHE_{t-2}} + \varepsilon_t \qquad (4.33)$$

Model 3

$$\Delta LOGHE_t = 0.0020 LOGHE_{t-1} - 0.0804 \Delta LOGHE_{t-1} + 0.2737 \Delta LOGHE_{t-2} + \varepsilon_t$$
$$(0.0005) \qquad (0.125) \qquad (0.1119) \qquad (4.34)$$

Model 3R

$$\Delta LOGHE_t = 0.2018 \Delta LOGHE_{t-1} + 0.5157 \Delta LOGHE_{t-2} + \varepsilon_t$$
$$(0.1117) \qquad (0.1022) \qquad (4.35)$$

The RSS and information criteria of (4.31) to (4.35) are shown in Table 4.21.

Table 4.21 RSS and information criteria of Dickey-Fuller models of *LOGHE*

	RSS	AIC	SC	Adj. R^2
Model 1 (4.31)	0.0019	-7.3392	-7.1632	0.1042
Model 2 (4.32)	0.0020	-7.3010	-7.1601	0.0547
Model 2R (4.33)	0.00201			
Model 3 (4.34)	0.002071	-7.3179	-7.2122	0.0556
Model 3R (4.35)	0.002604			

Model 3 is the best model according to the SC. The small Adj. R^2 values show that none of the models is particularly good. The various τ and ϕ statistics of the DF models are shown in Table 4.22.

Table 4.22 Summary of the Dickey-Fuller tests of *LOGHE*

Model	Test Statistic	Value	Critical Value (p-value, n[#])	Hypothesis
1	τ_τ	-2.09	-3.17 (0.1)	$\gamma = 0$
	$\tau_{\alpha\tau}$	2.14	2.75 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
	$\tau_{\beta\tau}$	2.01	2.38 (0.1, 50)	$a_2 = 0$ *given* $\gamma = 0$
	ϕ_2	6.87	5.94 (0.025, 50)	$a_0 = \gamma = a_2 = 0$
			7.02 (0.01, 50)	
	ϕ_3	2.32	1.37 (0.9, 50)	$\gamma = a_2 = 0$
			5.61 (50, 0.1)	
2	τ_μ	-0.70	-2.59 (0.1)	$\gamma = 0$
	$\tau_{\alpha\mu}$	0.97	2.18 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
	ϕ_1	7.81	7.06 (0.01, 50)	$a_0 = \gamma = 0$
3	τ	3.80	$\gamma \succ 0$	$\gamma = 0$

[#] n listed if p-value for precise sample size of time series not known The time series has > 50 observations.

Both Model 1 and Model 2 have a unit root (p > 0.1) but Model 3 does not.

Model 1

The ACF of (4.31) does not display any significant values up to and including lag 28. There are no significant Q statistics.

Both deterministic components ($\tau_{\alpha\tau}$ and $\tau_{\beta\tau}$) are not significant (p > 0.1).

The unrestricted and the restricted equation for ϕ_2 are (4.31) and (4.35) respectively. For ϕ_3 these equations are (4.33) and (4.31). There are 59 usable observations (T = 59) and 4 parameters (k = 4) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3.

Hence at $p < 0.025$ the null hypothesis is rejected that there is a unit root and both a_0 and a_2 are 0. However this is not the case at $p < 0.01$.

If one considers the test statistic ϕ_3, the null hypothesis is not rejected that there is a unit root and a_2 equals 0.

Model 2

The ACF of the residuals of (4.32) is not significant at any lag up to 28. There are no significant Q statistics.

The constant (a_0) is not significant at the 10% significance level based on $\tau_{\alpha\mu}$.

The unrestricted and the restricted equation for ϕ_1 are (4.32) and (4.35) respectively There are 59 usable observations (T = 59) and 3 parameters (k = 3) in the unrestricted models There are 2 restrictions. The null hypothesis that $a_0 = \gamma = 0$ is rejected. Therefore the constant term (a_0) is significant if the process is unit root. This finding is not in line with the $\tau_{\alpha\mu}$ statistic.

The differenced series showed a peak at 1989:4. There may have been a breakpoint and this is assessed with the Chow Breakpoint test for that point in time. The tests does not suggest a breakpoint in 1989:4 (Table 4.23)

Table 4.23 Chow Breakpoint test of DF Model 2 of *LOGHE* at 1989:4

	Value	Probability
F-statistic	0.4664	0.7600
Log likelihood ratio	2.1198	0.7137

Selection of *LOGHE* DF Model

Model 2 with two lags seems the most appropriate model although the result of the $\tau_{\alpha\mu}$ statistic is of concern. A further analysis was performed on Model 2 with fewer lags

Model 2 with 1 lag had ADF -1.4045 (critical value -2.5923, p = 0.1). The lagged term $DLOGHE_{t-1}$ of this model was not significant (p = 0.7635).

Model 2 with no lags had ADF -2.2521 (critical value -2.2919, p = 0.1). None of lagged values in the ACF and of the Q statistics were significant.
$\tau_{\alpha\mu}$ = 1.7465, for n = 50 and p = 0.1 the critical value is 2.17. The preferred choice is still Model 2 with 2 lags, although the $\tau_{\alpha\mu}$ remains of concern.

The conclusion is that the inflation rate of the differenced hourly earnings fluctuates around a constant level while the actual hourly earnings increase over time in a more or less constant manner.

In should be kept in mind that the focus of this section is to find unit root so that for instance Model 3 was rejected. Possibly VAR analysis could be attempted on other similar inflation time series.

Summary of Dickey-Fuller Tests

A number of DF tests have been performed. They were intended to analyse the various time series at a univariate level. In addition it was to evaluate whether they could be used for cointegration tests. Table 4.24 summarises the findings. Since a number of these inflation indices are in a sense part of the *CPI*, no attempt will be made to establish cointegrating relationships between them. In the case of *LOGCPIT* and *LOGCPINT* this situation is different. They make up the CPI together but are different aspects of inflation.

Table 4.24 Summary of DF models of inflation indices

Variable	Model	Lag(s)
LOGCPI	2	1
CPI	1	1
LOGCPIX	2	1
LOGCPINT	2	1
LOGCPIT	2	1
LOGLC	1	2
LOGHE	2	2

The data are usually best described by a Model 2. As explained previously, the time series *CPI* will not be used for cointegration analysis.

The time series *LOGLC* appears different from the others. An attempt to fit it to a Model 2 Lag1 was unsuccessful since the coefficient of $LOGLC_{t-1}$ was positive resulting in a rejection of unit root.

The best model for variable *LOGHE* had two lags. The Model 2 version with 1 lag was re-evaluated. The ACF appeared to show significant values at lags 2 and 4. The Q statistics were significant at many lags.

It is of interest to note that both *LOGLC* and *LOGHE* are labour cost related variables and these time series appear to show a pattern that is different from the other time series that were evaluated in this chapter.

Granger Causality of tradable and non-tradable inflation

The various inflation indices that were analysed above all related to each other in various ways. A point of research in this thesis is to identify factors that drive inflation.

The p values for Granger Causality tests for LOGCPIT and LOGCPINT are displayed in Table 4.25. The null hypothesis tested in Table 4.25 is that the left hand column (eg *LOGCPIT*) does not Granger Cause the second column from the left (eg *LOGCPINT*). The next row of data in this table calculates Granger Causality in the opposite direction (eg does *LOGCPINT* Granger Cause *LOGCPIT*?). EViews calculates these regressions as follows:

$$LOGCPIT_t = \alpha_0 + \alpha_1 LOGCPIT_{t-1} + ... + \alpha_l LOGCPIT_{t-l} + \beta_1 LOGCPINT_{t-1} + ... + \beta_l LOGCPINT_{t-l}$$

$$LOGCPINT_t = \alpha_0 + \alpha_1 LOGCPINT_{t-1} + ... + \alpha_l LOGCPINT_{t-l} + \beta_1 LOGCPIT_{t-1} + ... + \beta_l LOGCPIT_{t-l}$$

It reports F-statistics are the Wald statistics for the joint hypotheses: $\beta_1 = \cdots = \beta_l = 0$

Table 4.25 P values of Granger Causality analysis of tradable and non-tradable inflation.

		Lags							
		1	2	3	4	5	6	7	8
LOGCPIT	*LOGCPINT*	0.68	0.90	0.84	0.19	0.29	0.13	0.10	0.11
LOGCPINT	*LOGCPIT*	0.67	0.43	0.57	0.65	0.23	0.28	0.25	0.07

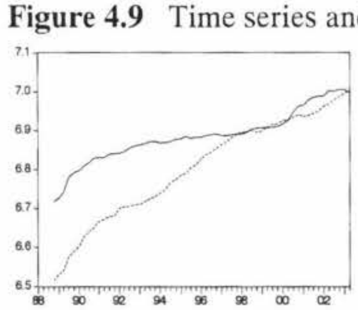
Note: Period covered Period 1988:1 2003:2

Table 4.25 does not support the hypothesis that non-tradable inflation and tradable inflation Granger Cause each other.

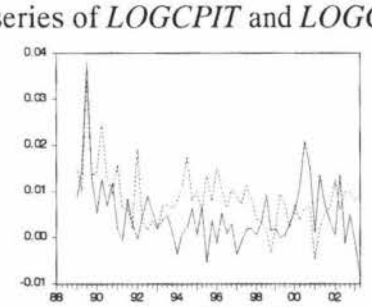
Cointegration analysis of tradable and non-tradable inflation

Although the Granger Causality tests did not suggest a relationship between tradable and non-tradable inflation, it was still decided to perform a cointegration analysis. This was done to evaluate how these tests performed from a statistical perspective. Figure 4.9 shows that both time series have an upward trend. The slope of *LOGCPINT* is steeper than that of *LOGCPIT*. The differenced series show that both time series initially decline and then become stationary.

Figure 4.9 Time series and differenced time series of *LOGCPIT* and *LOGCPINT*



Time series of *LOGCPIT* and *LOGCPINT*



Differenced time series of *LOGCPIT* and *LOGCPINT*

Table 4. 26 below analyses the VECMs of tradable and non-tradable inflation. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM (relating to deterministic components in the Cointegrating Equation and the VAR component) and 8 lags. The resulting cells contain from top to bottom the number of cointegrating equations, AIC and the SC in this order.

Table 4.26 Cointegration analysis of *LOGCPINT* and *LOGCPIT*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1, 57 obser- vations	1 -14.61782 -14.33108	1 -14.60181 -14.27922	0	1 -14.98213 -14.58786	1 -14.97042 -14.54031
Lag 1 to 2 56 obser- vations	1 -14.54489 -14.11088	0	0	1 **-15.33927** **-14.79676**	2
Lag 1 to 3 55 observations	0	0	0	0	2
Lag 1 to 4 54 observations	0	0	0	0	2
Lag 1 to 5 53 observations	0	0	0	0	2
Lag 1 to 6 52 obser-vations	1 -15.11137 -14.06070	1 -15.09834 -14.01015	0	0	2
Lag 1 to 7 51 obser-vations	1 -14.96823 -13.75611	2	1 -15.21116 -13.92327	0	2
Lag 1 to 8 50 obser-vations	1 -15.06838 -13.69172	2	0	0	0

Note: Period covered 1988:4 2003:2

Although no relationship was suggested by Granger Causality, the cointegration tests did suggest that several were possible. Both the SC and the AIC selected Option 4 with 2 lags.

VECM of *LOGCPINT* and *LOGCPIT*

The best VECM according to Table 4.26 is:

$$\begin{bmatrix}\Delta LOGCPINT_t \\ \Delta LOGCPIT_t\end{bmatrix} = \begin{bmatrix}\mathbf{-0.2125} \\ \mathbf{-0.2300}\end{bmatrix}\left[LOGCPINT_{t-1} + \mathbf{0.6608}LOGCPIT_{t-1} - \mathbf{0.0093}t - 11.0523\right]$$

$$\begin{bmatrix}0.1547 & -0.1200 \\ -0.1135 & 0.0687\end{bmatrix}\begin{bmatrix}\Delta LOGCPINT_{t-1} \\ \Delta LOGCPIT_{t-1}\end{bmatrix} + \begin{bmatrix}\mathbf{0.2324} & \mathbf{-0.2489} \\ -0.0038 & -0.0867\end{bmatrix}\begin{bmatrix}\Delta LOGCPINT_{t-2} \\ \Delta LOGCPIT_{t-2}\end{bmatrix}$$

$$+\begin{bmatrix}\mathbf{0.0073} \\ \mathbf{0.0056}\end{bmatrix} + \begin{bmatrix}\varepsilon_{LOGCPINT,t} \\ \varepsilon_{LOGCPIT,t}\end{bmatrix} \qquad (4.36)$$

where the significant coefficients are in bold.

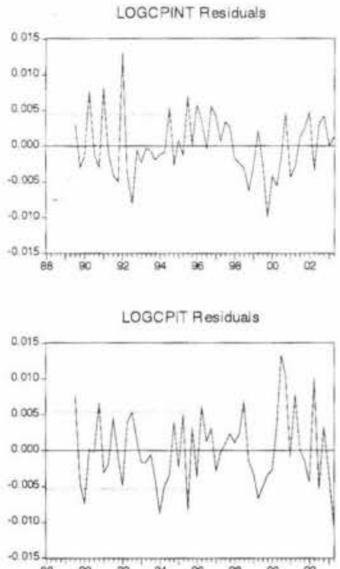
Both adjustment factors are significant, indicating that the correction is performed by both time series. Both time series react with a negative adjustment to a departure of the long-term equilibrium. It is rather unusual to have two adjustment factors with the same sign. It means that the combination of the two series has a linear trend. Consequently if either of the two series was too high in the previous period relative to the trend, they both compensate by reducing the increases in the current period.

Residual analysis of the VECM of *LOGCPINT* and *LOGCPIT*

The residuals of the VECM were analysed to evaluate whether they might have caused the inadmissible results.

The Jarque-Bera value of the residuals of Δ*LOGCPIT* is 1.380913 ($p = 0.501347$)
The Jarque-Bera value of Δ*LOGCPNIT* is 2.473014 ($p = 0.290397$)
The residuals of both time series appear stationary (Figure 4.10), although it could be argued that the variance of *LOGCPINT* varied somewhat over time..

Figure 4.10 Residuals of VECM of *LOGCPINT* and *LOGCPIT*

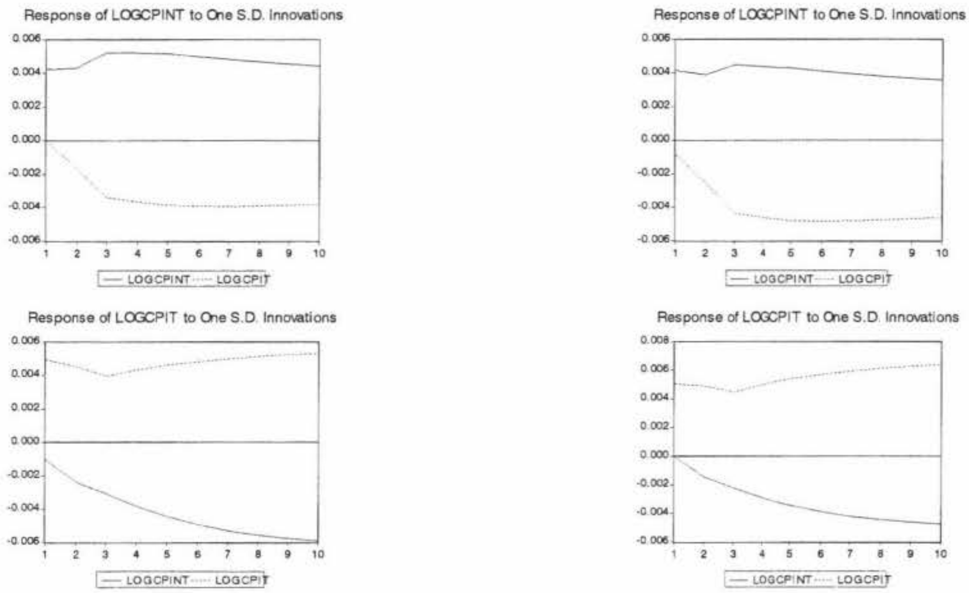


The ACF of the residuals of Δ*LOGCPINT* are close to significant at various lags (eg 3, 4, 11 and 12). The Q statistics of the residuals of Δ*LOGCPINT* become significant starting after lag 11. The ACF and the Q statistics of Δ*LOGCPIT* are not significant. It is of concern that the residuals of Δ*LOGCPINT* are not well behaved since it may invalidate the model.
The correlation coefficient of the residuals of Δ*LOGCPIT* and Δ*LOGCPINT* is -0.199072
The cross-correlogram of the two series of residuals does not show significant correlations.

Innovation Accounting

The Impulse Response Function does not appear to be sensitive to the order in which the time series were entered (Figure 4.11). Both times series seem to be considerably influenced by each others innovations.

Figure 4.11 Impulse Response Function of VECM of *LOGCPINT* and *LOGCPIT*



Order *LOGCPINT LOGCPIT*   Order *LOGCPIT LOGCPINT*

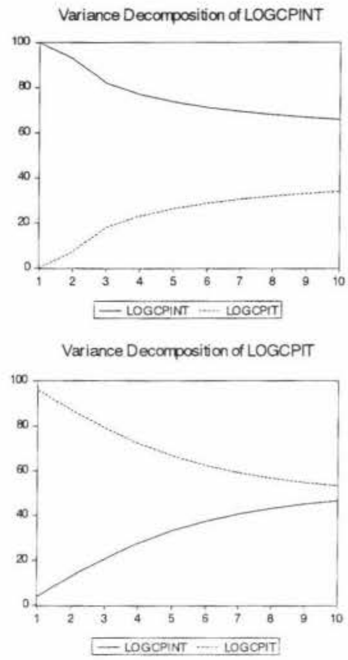
The variance of both after 10 periods seems to have a considerable proportion caused by the other (Figure 4.12). The order of entering the time series does seem to have a considerable effect on the Variance Decomposition.

Interpretation of relationship between *LOGCPIT* and *LOGCPINT*

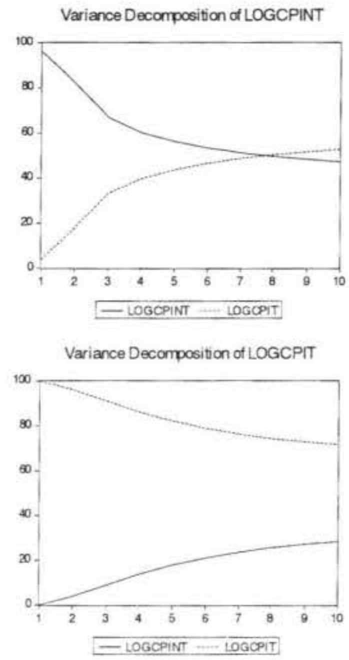
The above analysis resulted in various VECMs as shown in Table 4.26. This appears to be different from what was expected after performing the Granger Causality tests. The DF models had 1 lag while the best VECM had two lags. However, VECMs with 1 lag in the data were possible too according to Table 4.26. The DF tests indicated a Model 2 for both time series and this is similar to the Option 4 that was chosen by the cointegration analysis.

The economic interpretation of the results appears less than straightforward. It tended to indicate that both forms of inflation react to a deviation from their long-term equilibrium with a trend, regardless whether the departure was caused by one or the other. A possible explanation is that if inflation is too high, monetary policy and/or some other factors will force both types of inflation down.

Figure 4.12 Variance Decomposition of *LOGCPINT* and *LOGCPIT*



Order *LOGCPINT LOGCPIT*



Order *LOGCPIT LOGCPINT*

CHAPTER 5

TIME SERIES ANALYSIS OF MONETARY AGGREGATES

Introduction

Monetary aggregates are of importance for causing inflation according to the Quantity Theory of Money. The increased amount of money that is present in the economy would enable people to bid more money for the available resources. A review of the discussions regarding this theory over the last few centuries is provided by Laidler (1991). This would result in increased inflation. A number of monetary aggregates are being monitored by the RBNZ. The following will be analysed in this chapter.

M1	Notes and coins held by the public plus chequeable deposits, minus inter-institutional chequeable deposits, and minus central government deposits.
M2	M1 plus all non-M1 funding (call funding includes overnight money and funding on terms that can of right be broken without break penalties) minus inter-institutional non-M1 call funding.
M3	Notes and coins held by the public plus NZ dollar funding minus inter-M3 institutional claims and minus central government deposits.
M3(R)	Same as M3, less funding from non-residents.
M3 excluding repurchase agreements	NZ dollar funding excluding securities sold under agreements to repurchase.
M3(R) excluding repurchase agreements	NZ dollar funding from New Zealand residents excluding securities sold under agreements to repurchase.

Since there is a natural progression when one considers these categories, from a statistical perspective it is more appropriate in some instances to analyse the monetary aggregates based on their differences.

The following categories and abbreviations will be used throughout this chapter.

M1	M1
M2R	M2 – M1
M3RR	M3(R) – M2

Some of the time series showed considerable seasonal patterns. Consequently some of the time series were seasonally adjusted after log transformation. The adjustment method was additive, it was the difference from the moving average. Seasonal adjustment will be denoted by "SA". The "A" has been added where the series have been adjusted for inflation. Details of the seasonal adjustment and the CPI adjustment are given in Chapter 2.

The monetary aggregates are collected on a monthly basis, while the inflation indices are collected on a quarterly basis. Initially this chapter will analyse the various monetary data series at a univariate level. Subsequent to these analyses, cointegration analyses are performed. The price surveys for the CPI are mainly performed at the middle of each quarter, although some weekly and some monthly surveys are also performed. In fact some items are monitored throughout the quarter. The monetary aggregates are measured at the last day of each month. Under these circumstances a perfect match of data is not immediately obvious. It was decided to use the mean of the three months of each quarter as the value that covers the quarterly period.

The univariate and multivariate analyses will be carried out as explained in Chapter 2.The standard errors are put in parentheses below each DF equation. The criterion for rejecting a unit root is $p < 0.1$. The criterion for rejecting the τ and ϕ statistics is $p < 0.05$. Dickey and Fuller (1981) provided critical values for these latter two test statistics. Regrettably if the sample size of this chapter is considered only the sample sizes of 25 and 50 are relevant. Consequently various critical values are required to be shown at times for one tests statistic to decide whether a hypothesis is to be rejected or not.

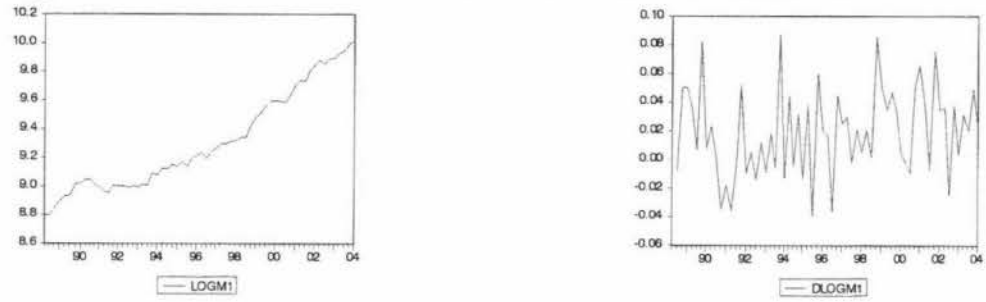
The following DF models were evaluated:

- LOGM1
- LOGM2R
- LOGM3RR

LOGM1

This section analyses the time series that consists of the natural logarithm of M1. The data are derived from the RBNZ. The data are quarterly figures that are based on averaging the three months in each quarter. The time series covers the period from 1988:2 to 2004:1. The time series *LOGM1* has an upward trend (Figure 5.1). The period 1990 to 1994 does not show the upward trend. The variance seems to be constant. The ACF dies down slowly. The differenced series *LOGM1* appears stationary.

Figure 5.1 Time series and differenced time series of *LOGM1*



Time series of *LOGM1* — Differenced series of *LOGM1* (*DLOGM1*)

DF Models of *LOGM1*

The possible stationarity of the series before 1994:1 was reason for concern. A Chow Breakpoint Test was performed with 1994:1 as breakpoint on what would have been Model 1 (Table 5.1).

Table 5.1 Chow Breakpoint Test of DF Model 1 at 1994:1

	Value	Probability
F - statistic	2.9252	0.02
Log Likelihood ratio	15.3807	0.009

As the Chow test shows significant evidence of a break point, it was decided to continue the analysis with the dataset from 1994:1 to 2004:1. There are some reservations about the use of the Chow test this way and they are discussed in Chapter 2.

The time series of *LOGM1* was tested for stationarity in (5.1) to (5.5) by using the Dickey-Fuller equations as outlined in Chapter 2.

Model 1

$$\Delta LOGM1_t = \underset{(0.8376)}{1.8968} + \underset{(0.0023)}{0.0055t} - \underset{(0.0932)}{0.2093LOGM1_{t-1}} + \varepsilon_t \qquad (5.1)$$

RSS = 0.026836 AIC = -4.3190 SC = -4.1924 Adj. R^2 = 0.0969

Model 2

$$\Delta LOGM1_t = -0.0748 + 0.0140 LOGM1_{t-1} + \varepsilon_t \qquad (5.2)$$
$$(0.1507) \quad (0.0159)$$

Model 2R

$$\Delta LOGM1_t = 0.0234 + \varepsilon_t \qquad (5.3)$$
$$(0.0045)$$

RSS = 0.031320

Model 3

$$\Delta LOGM1_t = 0.0025 LOGM1_{t-1} + \varepsilon_t \qquad (5.4)$$
$$(0.0005)$$

Model 3R

$$\Delta LOGM1_t = 0 + \varepsilon_t \qquad (5.5)$$

RSS = 0.053279

Analysis of DF models

Some DF statistics of models (5.1) to (5.5) are shown in Table 5.2. Model 1 is the only model that has a unit root.

The unrestricted and the restricted equations for ϕ_2 are (5.1) and (5.5) respectively. For ϕ_3 these equations are (5.1) and (15.3). There are 40 usable observations (T=40) and 3 parameters (k=3) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3 .

The statistics $\tau_{\alpha\tau}$ and $\tau_{\beta\tau}$ as well as ϕ_3 are not significant. This indicates that the deterministic components were not significantly different from 0, but the two other models are not in agreement with this finding by not having a unit root. The ϕ_2 statistic however appeared to be highly significant. This finding was surprising given the other statistics.

Table 5.2 Summary of the Dickey-Fuller tests of *LOGM1*

Model	Test Statistic	Value	Critical Value (p-value, n[#])	Hypothesis
1	τ_τ	-2.25	-3.19 (0.1)	$\gamma = 0$
	$\tau_{\alpha\tau}$	2.26	2.75 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
	$\tau_{\beta\tau}$	2.39	2.38 (0.1, 50)	$a_2 = 0$ *given* $\gamma = 0$
			2.81 (0.05, 50)	
	ϕ_2	12.15	8.21 (0.01, 25)	$a_0 = \gamma = a_2 = 0$
	ϕ_3	3.09	5.61 (0.1, 50)	$\gamma = a_2 = 0$
2	τ_μ	0.65	$\gamma \succ 0$	$\gamma = 0$
3	τ	5.26	$\gamma \succ 0$	$\gamma = 0$

n listed if p-value for precise sample size of time series not known

The ACF of the residuals of Model 1 shows that lags 3, 4 and 5 are significant. Also the Q statistics from lag 3 onward are significant. A seasonally adjusted series was computed in order to remove the autocorrelation of the residuals in the model. Another option would have been the inclusion of more lags in the model. However the time series are relatively short and this would have resulted in a considerable loss of degrees of freedom. When attempted it appeared that lag 1 to 4 would not be significant but lag 5 would be. The seasonally adjustment is additive based on the difference from the moving average and details are provided in Chapter 2.

Model 1 (SA)

$$\Delta LOGM1SA_t = 1.1511 + 0.0034t - 0.1263LOGM1SA_{t-1} + \varepsilon_t \qquad (5.1SA)$$

$$(0.6344) \quad (0.0017) \quad (0.0706)$$

RSS = 0.014411 AIC = -4.9408 SC = -4.8141 Adj. R^2 = 0.0703

$$\Delta LOGM1SA_t = 0.023430 + \varepsilon_t \qquad (5.3SA)$$

$$(0.0032)$$

RSS = 0.016339

$$\Delta LOGM1SA_t = 0 + \varepsilon_t \qquad (5.5SA)$$

RSS = 0.036657

The ACF of the residuals of the seasonally adjusted Model 1 does not show significant lags (20 lags included). There are no significant Q statistics. The τ statistics of the seasonally adjusted models are shown in Table 5.3. Note that the data set contained less than 50 data points. Both deterministic components are not significant ($p > 0.1$) if the hypothesis of unit root is accepted.

The unrestricted and the restricted equations for ϕ_2 are (5.1*SA*) and (5.5SA) respectively. For ϕ_3 these equations are (5.1SA) and (15.3SA). There are 40 usable observations (T=40) and 3 parameters (k=3) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3. Similar to the previous models that were not seasonally adjusted the τ statistics and ϕ_3 were not significant while the ϕ_2 statistic was highly significant.

Again Models 2 and 3 did not have a unit root.

Models 2 and 3 were rejected as unit root models, and therefore only Model 1 remained. The residuals of the model did not show autocorrelation after seasonal adjustment. However, this model was not very satisfactory since the hypothesis of significant deterministic components was rejected, while Models 2 and 3 with one and no deterministic components respectively were rejected.

Table 5.3 Summary of the Dickey-Fuller tests of *LOGM1SA*

Model	Test Statistic	Value	Critical Value (p-value, n#)	Hypothesis
1	τ_τ	-1.79	-3.19 (0.1)	$\gamma = 0$
	$\tau_{\alpha\tau}$	1.81	2.75 (0.1, 50)	$a_0 = 0 \;\; given \;\; \gamma = 0$
	$\tau_{\beta\tau}$	1.97	2.38 (0.1, 50)	$a_2 = 0 \;\; given \;\; \gamma = 0$
	ϕ_2	19.04	8.21 (0.01, 25)	$a_0 = \gamma = a_2 = 0$
	ϕ_3	2.48	5.61 (0.1, 50)	$a_0 = \gamma = a_2 = 0$
2	τ_μ	0.99	$\gamma \succ 0$	$\gamma = 0$
3	τ	7.30	$\gamma \succ 0$	$\gamma = 0$

n listed if p-value for precise sample size of time series not known

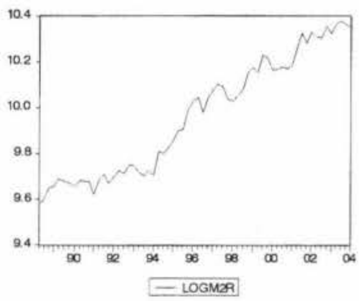
It is rather unsatisfactory that one test appears to suggest a certain model (ie unit root without deterministic components) while a related test rejects this model. This appears to add to the evidence that these tests are at times problematic when applied to certain (existing) time series.

The selected seasonally adjusted model implies a quadratic trend in the undifferenced time series of *LOGM1*. Although possibly plausible over a short time period, this would not be plausible over an extended period of time.

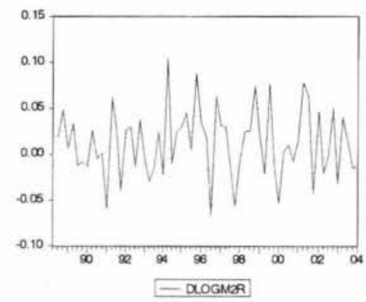
LOGM2R

This section analyses the natural logarithm of the M2 with the M1 excluded (*LOGM2R*). Similar to *LOGM1* the time series was analysed from 1994:1 to 2004:1. The time series *LOGM2R* has an upward trend (Figure 5.2). There seems some variation in the variance. The ACF dies down slowly. The differenced series appears stationary.

Figure 5.2 Time series and differenced time series of *LOGM2R*



Time series of *LOGM2R*



Differenced time series of *LOGM2R* (*DLOGM2R*)

DF models of *LOGM2R*

The time series of *LOGM2R* was tested for stationarity in (5.6) to (5.10) by using the Dickey-Fuller equations as outlined in Chapter 2.

Model 1

$$\Delta LOGM\,2R_t = \underset{(1.1472)}{4.2038} + \underset{(0.0018)}{0.0055t} - \underset{(0.1168)}{0.4249} LOGM\,2R_{t-1} + \varepsilon_t \qquad (5.6)$$

Model 2

$$\Delta LOGM\,2R_t = \underset{(0.3522)}{0.8020} - \underset{(0.0348)}{0.0777} LOGM\,2R_{t-1} + \varepsilon_t \qquad (5.7)$$

Model 2R

$$\Delta LOGM\,2R_t = \underset{(0.0064)}{0.0161} + \varepsilon_t \qquad (5.8)$$

Model 3

$$\Delta LOGM\,2R_t = \underset{(0.0006)}{0.0016} LOGM\,2R_{t-1} + \varepsilon_t \qquad (5.9)$$

Model 3R

$$\Delta LOGM\,3R_t = 0 + \varepsilon_t \qquad (5.10)$$

Table 5.4 Summary of the Dickey-Fuller tests of *LOGM2R*

Model	Test Statistic	Value	Critical Value (p-value, n[#])	Hypothesis
1	τ_τ	-3.63	-3.19 (0.1)	$\gamma = 0$
			-3.52 (0.05)	
	$\tau_{\alpha\tau}$	3.66	3.20 (0.05, 25)	$a_0 = 0$ *given* $\gamma = 0$
	$\tau_{\beta\tau}$	3.08	2.85 (0.05, 25)	$a_2 = 0$ *given* $\gamma = 0$
	ϕ_2	8.06	6.75 (0.025, 25)	$a_0 = \gamma = a_2 = 0$
	ϕ_3	7.81	5.61 (0.1, 50)	$\gamma = a_2 = 0$
2	τ_μ	-2.23	-2.60 (0.1)	$\gamma = 0$
	$\tau_{\alpha\mu}$	2.28	2.18 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
	ϕ_1	5.97	5.18 (0.05, 25)	$a_0 = \gamma = 0$
3	τ	2.47	$\gamma \succ 0$	$\gamma = 0$

n listed if p-value for precise sample size of time series not known. Time series has 40 observations after adjusting endpoints

The various τ statistics for Models 1 to 3 are shown in Table 5.4. There is weak support for unit root in Model 1. Model 2 has a unit root and Model 3 does not have a unit root.

The ACFs of the residuals of Model 1 and Model 2 do not show significant lags (40 observations included). There are no significant Q statistics. The τ statistics for both Model 1 and Model 2 are significant. The unrestricted and the restricted equations for ϕ_2 are (5.6) and (5.10) respectively. For ϕ_3 these equations are (5.6) and (5.8). There are 40 usable observations (T=40) and 3 parameters (k=3) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3 . The ϕ statistics of Model 1 were both significant as well.

The unrestricted and the restricted equations for ϕ_1 are (5.7) and (5.10) respectively. There are 40 usable observations (T=40) and 3 parameters (k=3) in the unrestricted model. There are 2 restrictions. The ϕ_1 statistic was significant.

Table 5.5 is required to make a judgement regarding the best model. This would appear to be Model 1 based on the information criteria. Note the Adjusted R^2 of Model 3 which is negative. This is another reason to reject this model.

Table 5.5 RSS and information criteria of Dickey-Fuller models of *LOGM2R*

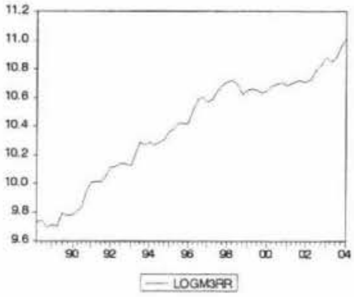
	RSS	AIC	SC	Adj. R^2
Model 1	0.044922	-3.8038	-3.6772	0.2589
Model 2	0.0565	-3.6247	-3.5403	0.0926
Model 2R	0.063893			
Model 3	0.0642	-3.5468	-3.5046	-0.0048
Model 3R	0.074264			

The selected model implies a quadratic trend in the undifferenced time series. Although possibly plausible over a short time period, this would not be plausible over an extended period of time.

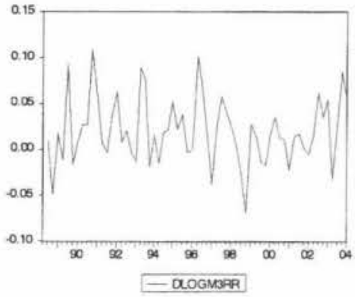
LOGM3RR

This section analyses the time series that consists of the natural logarithm of *M3RR*. The analysis covers the period from 1994:1 to 2004:1 in quarters. The time series *LOGM3RR* has an upward trend (Figure 5.3). The variance seems constant. The ACF dies down slowly although faster than many of the other time series analysed so far. The differenced time series (*DLOGM3RR*) seems stationary.

Figure 5.3 Time series and differenced time series of *LOGM3RR*



Time series of *LOGM3RR*



Differenced time series of *LOGM3RR* (*DLOGM3RR*)

DF models of LOGM3RR

The time series of LOGM3RR was tested for stationarity in (5.11) to (5.15) by using the Dickey-Fuller equations as outlined in Chapter 2.

Model 1

$$\underset{}{\Delta LOGM3RR_t} = \underset{(0.8433)}{1.8490} + \underset{(0.0012)}{0.0024t} - \underset{(0.0815)}{0.1774 LOGM3RR_{t-1}} + \underset{(0.1586)}{0.3534 \Delta LOGM3RR_{t-1}} + \varepsilon_t \qquad (5.11)$$

Model 2

$$\Delta LOGM3RR_t = \underset{(0.3464)}{0.2850} - \underset{(0.0326)}{0.0255 LOG3RR_{t-1}} + \underset{(0.1605)}{0.2773 \Delta LOGM3RR_{t-1}} + \varepsilon_t \qquad (5.12)$$

Note that lag 1 was used for Model 2 to enable the calculation of ϕ statistics. The coefficient of the term $LOGM3RR_{t-1}$ is not significant and could therefore be removed from the model. However the ϕ statistics are based on evaluating a restricted and an unrestricted model with regard to the deterministic components and having different lags included in the model would result in additional differences between the models.

Model 2R

$$\Delta LOGM3RR = \underset{(0.0060)}{0.01449} + \underset{(0.1588)}{0.2642 \Delta LOGM3RR_{t-1}} + \varepsilon_t \qquad (5.13)$$

Model 3

$$\Delta LOGM3RR_t = \underset{(0.0006)}{0.0014} LOGM3RR_{t-1} + \underset{(0.1590)}{0.2646} \Delta LOGM3RR_{t-1} + \varepsilon_t \qquad (5.14)$$

Model 3R

$$\Delta LOGM3RR_t = \underset{(0.0472)}{0.4407} \Delta LOGM3RR_{t-1} + \varepsilon_t \qquad (5.15)$$

The RSS of the various models which are required for the calculation of the ϕ statistics are displayed in Table 5.6 as well as the various information criteria.

Table 5.6 RSS and information criteria of Dickey-Fuller models of *LOGM3RR*

	RSS	AIC	SC	Adj. R^2
Model 1	0.035867	-3.9485	-3.7779	0.1103
Model 2	0.040041	-3.8897	-3.7617	0.0343
Model 2R	0.040719			
Model 3	0.040793	-3.9224	-3.837044	0.0428
Model 3R	0.047179			

The various τ and ϕ statistics of Models (5.11) to (5.15) are displayed in Table 5.7. Models 1 and 2 have a unit root but Model 3 does not have a unit root. In the case of Model 3 the unit root tests were performed with up to 5 lags. In all cases $\gamma > 0$ and consequently all these models were rejected.

The ACF of Model 1 and Model 2 do not have significant lags and the Q statistics are not significant either (16 lags included).

Table 5.7 Summary of the Dickey-Fuller tests of *LOGM3RR*

Model	Test Statistic	Value	Critical Value (p-value, $n^{\#}$)	Hypothesis
1	τ_τ	-2.18	-3.19 (0.1)	$\gamma = 0$
	$\tau_{\alpha\tau}$	2.19	2.75 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
	$\tau_{\beta\tau}$	2.02	2.38 (0.1, 50)	$a_2 = 0$ *given* $\gamma = 0$
	ϕ_2	3.68	4.31 (0.1, 50)	$a_0 = \gamma = a_2 = 0$
	ϕ_3	2.37	5.61 (0.1, 50)	$\gamma = a_2 = 0$
2	τ_μ	-0.78	-2.60 (0.1)	$\gamma = 0$
	$\tau_{\alpha\mu}$	0.82	2.18 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
	ϕ_1	3.12	3.94 (0.1, 50)	$a_0 = \gamma = 0$
3	τ	2.40	$\gamma \succ 0$	$\gamma = 0$

\# n listed if p-value for precise sample size of time series not known The time series has 39 observations after adjusting the endpoints.

The remaining τ statistics of Model 1 and Model 2 were not significant. This is in contradiction with the models chosen with this methodology because they are supposed to have deterministic components.

The unrestricted and the restricted equations for ϕ_2 are (5.11) and (5.15) respectively. For ϕ_3 these equations are (5.11) and (15.13). There are 39 usable observations (T=39) and 4 parameters (k=4) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3 .

It is not possible to reject the null hypotheses based on ϕ_2 or ϕ_3. This can be interpreted as meaning that if the process is unit root, then a_0 and a_2 are not significant. This is in line with the τ statistics, but of concern since they should be significant in Model 1.

The unrestricted and the restricted equations for ϕ_1 are (5.12) and (15.15) respectively. There are 39 usable observations (T=39) and 3 parameters (k=3) in the unrestricted model. There are 2 restrictions. Again the null hypothesis is not rejected meaning that the constant is not significant.

The Chow Breakpoint test was performed to evaluate the existence of breakpoints. There appeared to be a breakpoint at 1998:1 (Table 5.8) for Model 1. This too is of concern as it might invalidate the DF models.

Table 5.8 Chow Breakpoint Tests of *LOGM3RR*

	Value	Probability
Model 1		
F – statistic (1998:1)	3.6703	0.0147
Log Likelihood ratio (1998:1)	15.1204	0.0044
F – statistic (2002:2)	3.0037	0.0332
Log Likelihood ratio (2002:2)	12.7747	0.0124
Model 2		
F – statistic (1998:1)	0.8683	0.4673
Log Likelihood ratio (1998:1)	2.9631	0.3974
F – statistic (2002:2)	2.3353	0.0918
Log Likelihood ratio (2002:2)	7.5082	0.0573

Both Model 1 and Model 2 supported the unit root hypothesis. However also in both cases the deterministic components did not appear to be significant. In addition the Chow test especially for Model 1 indicated a breakpoint. Model 3 however did not support unit root. Therefore there was no satisfactory DF model.

Granger Causality of inflation and monetary aggregates

According to the Quantity Theory of Money an increase of available money stock would result in an increasing inflation rate. Consequently it is of interest to test this theory with the three monetary aggregates that have been discussed in the previous sections by using Granger Causality tests. Various p values for Granger Causality tests for monetary aggregates and inflation are displayed in Table 5.9. The null hypothesis tested in Table 5.9 is that the left hand column (eg *LOGM1SA*) does not Granger Cause the second column from the left (eg *LOGCPI*). The next row of data in this table calculates Granger Causality in the opposite direction (eg does *LOGCPI* Granger Cause *LOGM1SA*?). EViews calculates these regressions as follows:

$$LOGM1SA_t = \alpha_0 + \alpha_1 LOGM1SA_{t-1} + ... + \alpha_l LOGM1SA_{t-l} + \beta_1 LOGCPI_{t-1} + ... + \beta_l LOGCPI_{t-l}$$

$$LOGCPI_t = \alpha_0 + \alpha_1 LOGCPI_{t-1} + ... + \alpha_l LOGCPI_{t-l} + \beta_1 LOGM1SA_{t-1} + ... + \beta_l LOGM1SA_{t-l}$$

It reports F-statistics are the Wald statistics for the joint hypotheses: $\beta_1 = \cdots = \beta_l = 0$

Inspection of Table 5.9 shows that many combinations of the time series display Granger Causality. The Granger Causality is not limited to the monetary aggregates Granger Causing the inflation indices. The reverse also occurs.

There is strong support for *LOGM1SA* Granger Causing various forms of inflation when the lag period is short. This is in line with the Quantity Theory of Money. However he opposite also occurs where *LOGCPINT* Granger Causes *LOGM1SA* after 3 to 8 lags. It becomes highly significant at 6 and 7 lags.

It is striking when considering *LOGM2R* and *LOGM3RR* that the Granger Causality is more often in the direction that is opposite to that expected by the Quantity Theory. This relationship is called 'reverse causation' and is discussed by Laidler (1991). Increased inflation appears to generate increased values of these two monetary aggregates. It could be hypothesised that the monetary aggregates are increasing in value to enable transactions to take place under the higher demand for money caused by inflation.

Table 5.9 P values of Granger Causality analysis of monetary aggregates and inflation rates

Time series		Lags							
		1	2	3	4	5	6	7	8
M1									
M1SA	CPI	0.004**	0.0005**	0.005**	0.015*	0.06	0.15	0.09	0.15
CPI	M1SA	0.63	0.14	0.21	0.55	0.64	0.57	0.62	0.52
M1SA	CPIX	0.015*	0.014**	0.07	0.07	0.12	0.23	0.13	0.09
CPIX	M1SA	0.27	0.07	0.07	0.26	0.50	0.46	0.61	0.70
M1SA	CPINT	0.008**	0.06	0.30	0.21	0.32	0.08	0.06	0.004**
CPINT	M1SA	0.46	0.30	0.03*	0.02*	0.0109*	0.0008**	0.008**	0.04*
M1SA	CPIT	0.24	0.17	0.11	0.04*	0.048*	0.16	0.21	0.02*
CPIT	M1SA	0.60	0.70	0.04*	0.14	0.12	0.20	0.39	0.43
M2									
M2R	CPI	0.88	0.76	0.66	0.39	0.03*	0.06	0.09	0.16
CPI	M2R	0.006**	0.006**	0.02*	0.06	0.15	0.25	0.36	0.13
M2R	CPIX	0.94	0.94	0.86	0.78	0.46	0.71	0.86	0.76
CPIX	M2R	0.006**	0.008**	0.015*	0.04*	0.06	0.19	0.16	0.15
M2R	CPINT	0.07	0.11	0.10	0.09	0.09	0.006**	0.004**	0.006*
CPINT	M2R	0.047*	0.14	0.12	0.20	0.22	0.07	0.06	0.20
M2R	CPIT	0.79	0.85	0.37	0.18	0.09	0.17	0.40	0.25
CPIT	M2R	0.02*	0.10	0.03*	0.03*	0.007**	0.03*	0.06	0.12
M3									
M3RR	CPI	0.014*	0.07	0.15	0.15	0.26	0.31	0.31	0.46
CPI	M3RR	0.04*	0.02*	0.08	0.16	0.07	0.03*	0.04*	0.04*
M3RR	CPIX	0.049*	0.12	0.31	0.37	0.46	0.41	0.46	0.54
CPIX	M3RR	0.09	0.07	0.22	0.33	0.32	0.13	0.11	0.048*
M3RR	CPINT	0.17	0.46	0.65	0.73	0.61	0.56	0.64	0.69
CPINT	M3RR	0.02*	0.008**	0.009**	0.0009**	0.002**	0.0007**	0.003**	0.0002**
M3RR	CPIT	0.84	0.80	0.55	0.63	0.78	0.75	0.72	0.28
CPIT	M3RR	0.22	0.14	0.053	0.048*	0.07	0.049*	0.14	0.11

Note: Period covered 1994:1 – 2004:1. All time series are log transformed. * (**) denotes rejection of the hypothesis at the 5% (1%) significance level.

Cointegration analyses of inflation and monetary aggregates

It is of interest to evaluate whether the different patterns displayed by the Granger Causality tests of the previous section can be captured with Vector Error Correction Models. A number of combinations of time series will be analysed below since they are of interest from an economic perspective.

The following Vector Error Correction Models will be explored in varying degrees of detail.

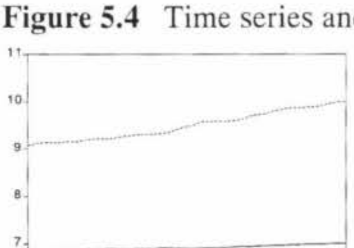
- LOGCPI LOGM1SA
- LOGCPI LOGM2R
- LOGCPI LOGM3RR
- LOGCPI LOGM1SA LOGM2R
- LOGCPI LOGM1SA LOGM2R LOGM3RR

where SA denotes seasonal adjustment

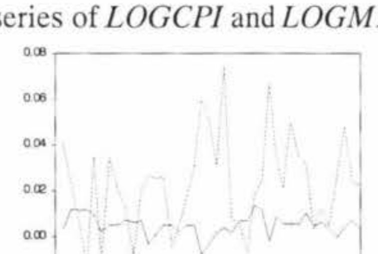
Cointegration analysis of *LOGCPI* and *LOGM1SA*

The monetary aggregate denoted by *LOGM1SA* is an obvious option to explore the Quantity Theory of Money as became obvious when it was tested for Granger Causality. The more readily accessible money is available in the market, the more the price level will increase. The time series *LOGCPI* and *LOGM1SA* both show an increase over time (Figure 5.4). However the slope of *LOGM1SA* is steeper. Both series show little variation in the undifferenced series. The differenced series show more variation in *LOGM1SA* than in *LOGCPI*.

Figure 5.4 Time series and differenced time series of *LOGCPI* and *LOGM1SA*



Time series of *LOGCPI* and *LOGM1SA*



Differenced time series of *LOGCPI* and *LOGM1SA*

The various cointegration analyses of *LOGCPI* and *LOGM1SA* are displayed in Table 5.10. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The VECM options include options for the data trend and the Cointegrating Equation (CE). The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order.

Table 5.10 Cointegration analysis of *LOGCPI* and *LOGM1SA*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 obser-vations	1 -12.91587 -12.57463	2	1 **-13.24858** **-12.82203**	0	1 -13.22962 -12.71776
Lag 1 - 2 38 obser-vations	0	1 -12.89986 -12.33963	0	0	1 -13.05828 -12.36877
Lag 1 – 3 37 obser-vations	0	1 -12.71074 -11.97058	0	0	0
Lag 1 – 4 36 obser-vations	0	0	0	0	0
Lag 1 – 5 35 obser-vations	0	0		1 -12.77741 -11.30016	2
Lag 1 – 6 34 obser-vations	0	0	0	2	2
Lag 1 – 7 33 obser-vations	0	0	0	1 -12.68344 -11.09623	2
Lag 1 – 8 32 obser-vations	1 -12.30683 -10.65787	2	2	1 -12.61018 -10.82381	2

Note: Period covered 1994:1 – 2004:1.

The Granger Causality analysis only showed a significant relationship up to and including 4 lags. The cointegration analysis showed some VECMs at higher lags. Both information criteria suggest that Option 3 with 1 lag is the optimal model.

VECM of *LOGCPI* and *LOGM1SA*

A VECM as suggested by Table 5.3 is displayed in (5.16).

$$\begin{bmatrix} \Delta CPI_t \\ \Delta M1_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.199694} \\ 0.253765 \end{bmatrix} \left[CPI_{t-1} - \mathbf{0.178927} M1_{t-1} - 5.22228 \right] +$$

$$\begin{bmatrix} 0.165603 & \mathbf{-0.074886} \\ -1.140289 & 0.172407 \end{bmatrix} \begin{bmatrix} \Delta CPI_{t-1} \\ \Delta M1_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{0.005987} \\ \mathbf{0.024720} \end{bmatrix} + \begin{bmatrix} \varepsilon_{CPI,t} \\ \varepsilon_{M1,t} \end{bmatrix} \qquad (5.16)$$

where *CPI* is *LOGCPI*, *M1* is *LOGM1SA* and significant coefficients are in bold.

Equation (5.16) shows that adjustment to the long-term equilibrium is done by $\Delta LOGCPI$. If the value for *LOGM1SA* is too large in the previous period for the equilibrium, *LOGCPI* compensates by increasing relatively more. This is in support of Quantity Theory of Money.

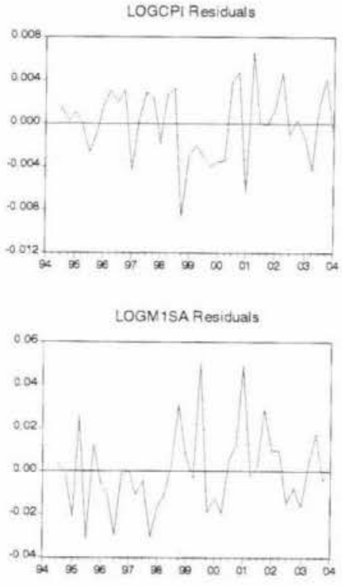
$\Delta LOGCPI_y$ also shows a significant negative correlation with $\Delta LOGM1SA_{t-1}$. Relative to the increase of the amount of money in the previous period, the CPI will decrease in the current period. This is not what one would expect according to the Quantity Theory.

Analysis of residuals of VECM of *LOGCPI* and *LOGM1SA*

Various tests were performed on the residuals to ensure that the assumptions for the linear model were met. If not the model may give misleading information about the system being modelled.

The Jarque-Bera value of the residuals of $\Delta LOGCPI$ is 0.9886 (p = 0.6100)
The Jarque-Bera value of the residuals of $\Delta LOGM1SA$ is 5.0022 (p = 0.0820)

Figure 5.5 Residuals of VECM of *LOGCPI* and *LOGM1SA*



Whether or not the residuals of both time series are stationary is questionable (Figure 5.5). There may have been more variation in the last part of $\Delta LOGCPI$. In the case of $\Delta LOGM1SA$ the mean may have shifted as well.

The ACF of the residuals of $\Delta LOGCPI$ may have been significant at lag 10 but the Q statistics did not have significant values. The ACF of the residuals of $\Delta LOGM1SA$ and its Q statistics did not have significant values.

The residuals did not appear to be well behaved. To what degree it may have invalidated the model cannot be determined.

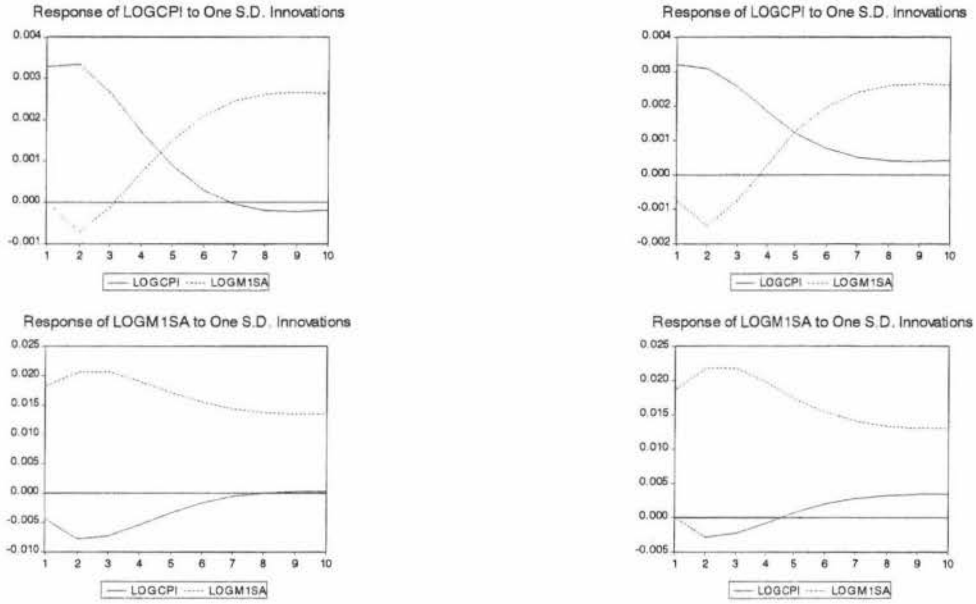
The correlation coefficient between the two time series was -0.2316 and there were no significant lags or leads in the cross-correlogram.

Innovation Accounting

The Impulse Response Function and the Variance Decomposition show similar patterns regardless of the order in which the time series were placed. The values differ slightly.

The inflation shows a strong reaction to a shock to the monetary aggregate after 10 periods (Figure 5.6). The reverse is not the case

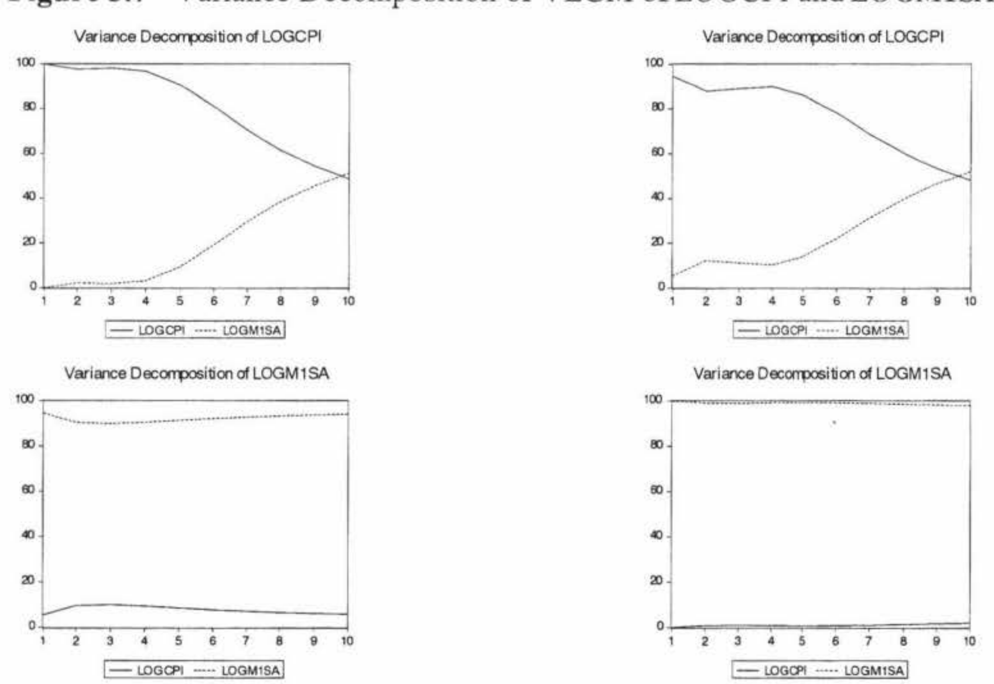
Figure 5.6 Impulse Response Function of VECM of *LOGCPI* and *LOGM1SA*



Order *LOGCPI LOGM1SA* Order *LOGM1SA LOGCPI*

The variance of inflation is equally made up of inflation and the monetary aggregate after 10 periods (Figure 5.7). On the other hand there appears no influence of the inflation on the variance of $\Delta LOGM1SA$.

Figure 5.7 Variance Decomposition of VECM of *LOGCPI* and *LOGM1SA*



Order *LOGCPI LOGM1SA* Order *LOGM1SA LOGCPI*

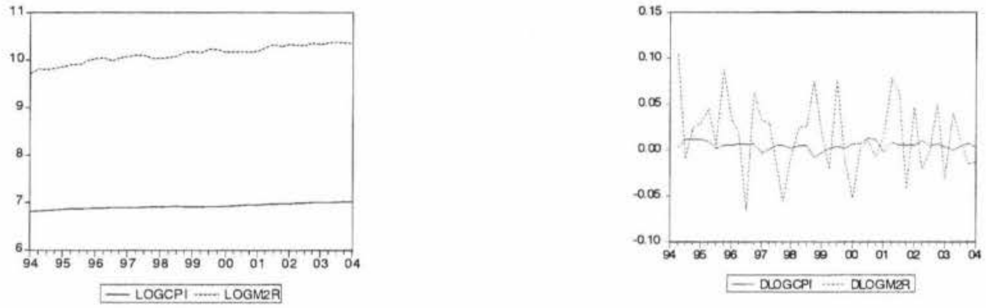
Interpretation of VECM of *LOGCPI* and *LOGM1SA*

LOGCPI will react more strongly to movements away from the equilibrium than *LOGM1* will. The adjustment parameter in the VECM for $LOGCPI_t$ is significant. Therefore the conclusion is that *LOGCPI* reacts to changes of *LOGM1SA*. The IRF and the VD also showed a sensitivity of *LOGCPI* to *LOGM1SA* but not the other way. The results are in agreement with the Granger Causality tests. The negative significant lag term in (5.16) does not fit in with the hypothesis of the Quantity Theory well. The residuals of the VECM were not well behaved and this is of some concern. It cannot be determined whether it was to an unacceptable degree.

Cointegration analysis of *LOGCPI* and *LOGM2R*

The time series *M2R* constitutes *M2 – M1*. The reasons for analysing the time series *M2R* rather than *M2* are explained in the introduction. It is of considerable interest that the Granger Causality tests showed that between *LOGM2R* and *LOGCPI* on the one hand and *LOGM1SA* and *LOGCPI* on the other hand were in different directions. It seems to indicate that different economic patterns exist between inflation (*LOGCPI*) and the two monetary aggregates in question.
Both *LOGCPI* and *LOGM2R* increase over time (Figure 5.8). The slope of *LOGM2R* is steeper than that of *LOGCPI.*

Figure 5.8 Time series and differenced time series of *LOGCPI* and *LOGM2R*



Time series of *LOGCPI* and *LOGM2R*

Differenced time series of *LOGCPI* and *LOGM2R*

The various cointegration analyses of *LOGCPI* and *LOGM2R* are displayed in Table 5.11. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The VECM options include options for the data trend and the Cointegrating Equation (CE). The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order.

Table 5.11 shows that the best model according to the SC is very different from the model according to the AIC. The model suggested by the SC is considerably more parsimonious with fewer deterministic components and only 1 lag in the data series rather than the 8 lags for the other model.

VECM of *LOGCPI* and *LOGM2R*

A VECM as suggested by the SC is displayed in (5.17)

$$\begin{bmatrix} \Delta M2R_t \\ \Delta CPI_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.1018} \\ \mathbf{-0.0113} \end{bmatrix} \left[M2R_t - \mathbf{1.5037} CPI_{t-1} \right] +$$

$$\begin{bmatrix} -0.1601 & -1.9656 \\ -0.0017 & 0.3285 \end{bmatrix} \begin{bmatrix} \Delta \mathrm{M2R}_{t-1} \\ \Delta \mathrm{CPI}_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{M2R,t} \\ \varepsilon_{CPI,t} \end{bmatrix} \qquad (5.17)$$

where *CPI* is *LOGCPI* and *M2R* is *LOGM2R* and the significant coefficients are in bold.

Table 5.11 Cointegration analysis of *LOGCPI* and *LOGM2R*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 obser-vations	1 -11.58583 **-11.24459**	1 -11.60212 -11.21822	0	0	2
Lag 1 - 2 38 obser-vations	1 -11.44350 -10.92636	1 -11.44965 -10.88942	0	0	2
Lag 1 – 3 37 obser-vations	0	0	0	0	0
Lag 1 – 4 36 obser-vations	0	0	0	0	2
Lag 1 – 5 35 obser-vations	0	0	0	1 -11.53755 -10.33771	2
Lag 1 – 6 34 obser-vations	0	0	0	1 -11.66045 -10.26877	2
Lag 1 – 7 33 obser-vations	0	1 -11.28874 -9.79228	1 -11.35626 -9.814400	2	2
Lag 1 – 8 32 obser-vations	0	0	0	1 **-11.98371** -10.19734	2

Note: Period covered 1994:1 – 2004:1.

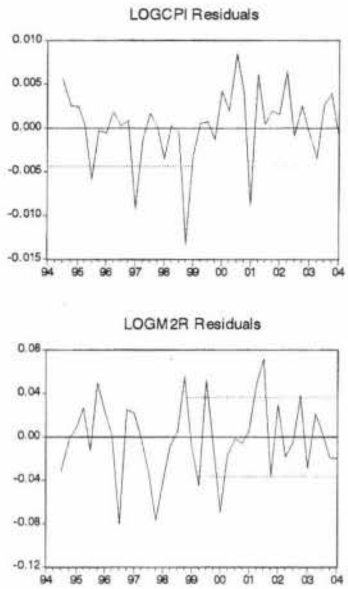
Model (5.17) shows that both time series have significant adjustment coefficients.
The VECM suggest that the current *LOGM2R* increases if the *LOGCPI* in the previous period had been high. However, *LOGCPI* react similarly to this situation. The overall economic interpretation that should be given to (5.17) is not immediately obvious.
The residuals therefore seem to be reasonably well behaved.

Although none of the lagged terms appeared significant, the coefficient 0.3285 came close to significance.

Analysis of residuals of VECM of LOGCPI and LOGM2R

Various tests were performed on the residuals to ensure that the assumptions for the linear model were met. If not the model may give misleading information about the system being modelled.
The Jarque-Bera value of the residuals of $\Delta LOGM2R$ is 0.1572 (p = 0.9244).
The Jarque-Bera value of the residuals of $\Delta LOGCPI$ is 1.2558 (p = 0.5337).
The residuals of the VECM appear stationary although it could be argued that the mean of *LOGCPI* may have shifted somewhat over time (Figure 5.9).

Figure 5.9 Residuals of VECM of *LOGCPI* and *LOGM2R*



The ACF of neither of the residuals shows significant findings. The Q statistics are not significant either.

The correlation between the residuals of $\Delta LOGM2R$ and $\Delta LOGCPI$ is -0.2000
The cross-correlogram shows a significant positive value at lag 4.

Innovation Accounting

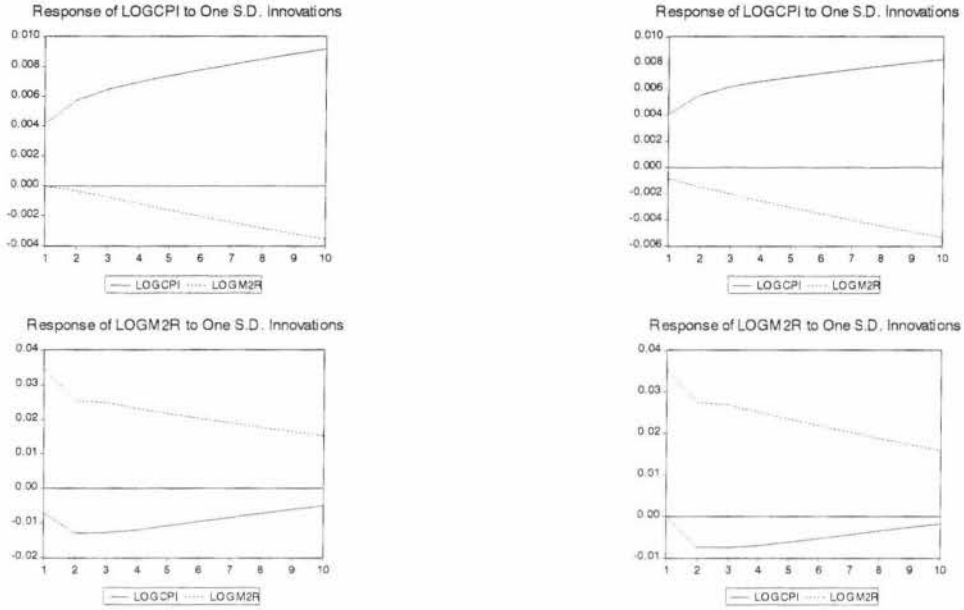
The order in which the time series have been entered into the IRF and VD does not appear to be important. After 10 periods both time series react stronger to shocks to their own series than shocks to the other series (Figure 5.10). This is most apparent for $\Delta LOGCPI$. In addition in the case of $\Delta LOGCPI\ I$ this effect seems to be increasing over time while for $\Delta LOGM2R$ it seems to be decreasing.

The variance of both time series is mainly determined by themselves with little effect of the other series (Figure 5.11).

Interpretation of the VECM of *LOGCPI* and *LOGM2R*

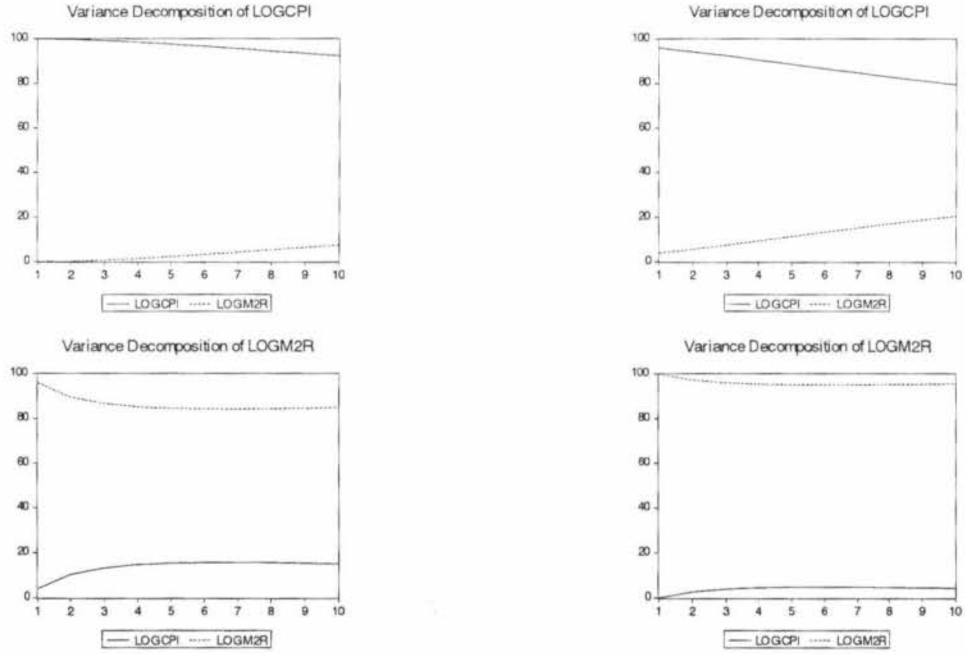
Both adjustment parameters of the VECM are significant. This is not in line with the Granger Causality analysis. Furthermore, both adjustment coefficients have the same sign which is difficult to explain in economic terms.
The term $\Delta LOGCPI_{t-1}$ comes close to significance for $\Delta LOGCPI_t$. This means that the inflation in the previous period still influences the current period.

Figure 5.10 Impulse Response Function of VECM of *LOGCPI LOGM2R*



Order *LOGCPI LOGM2R* Order *LOGM2R LOGCPI*

Figure 5.11 Variance Decomposition of VECM of *LOGCPI LOGM2R*

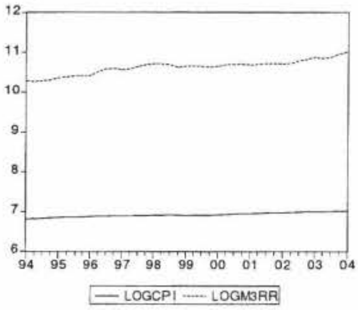


Order *LOGCPI LOGM2R* Order *LOGM2R LOGCPI*

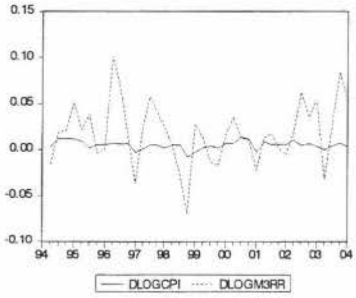
Cointegration analysis of *LOGCPI* and *LOGM3RR*

Both time series show an upward trend with the slope of *LOGM3RR* steeper than that of *LOGCPI* (Figure 5.12). There appears little variation. The differenced series of *LOGM3RR* shows more variation than that of *LOGCPI*.

Figure 5.12 Time series and differenced time series of *LOGCPI* and *LOGM3RR*



Time series of *LOGCPI* and *LOGM3RR*



Differenced Time series of *LOGCPI* and *LOGM3RR*

The various cointegration analyses of *LOGCPI* and *LOGM3RR* are displayed in Table 5.12. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The VECM options include options for the data trend and the Cointegrating Equation (CE). The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order. Both information criteria propose the same model which consists of Option 4 with 1 lag.

Table 5.12 Cointegration analysis of *LOGCPI* and *LOGM3RR*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 obser- vations	1 -12.11835 -11.77710	1 -12.16829 -11.78439	0	1 **-12.31267** **-11.84346**	2
Lag 1 – 2 38 obser- vations	0	0	0	1 -12.22009 -11.57367	2
Lag 1 – 3 37 observations	0	0	0	0	2
Lag 1 – 4 36 obser- vations	0	1 -11.85050 -10.92678	0	2	2
Lag 1 – 5 35 obser- vations	0	1 -11.75740 -10.64644	1 -11.88737 -10.73197	2	2
Lag 1 – 6 34 obser- vations	0	1 -11.81437 -10.51247	1 -11.96286 -10.61607	2	2
Lag 1 – 7 33 obser- vations	0	1 -11.85257 -10.35606	1 -12.04405 -10.50219	1 -12.07093 -10.48372	2
Lag 1 – 8 32 obser- vations	0	2	1 -11.98925 -10.24869	1 -11.93190 -10.14554	2

Note: Period covered 1994:1 – 2004:1.

VECM of LOGCPI and LOGM3RR

A VECM as suggested by the SC is displayed in (5.18).

$$\begin{bmatrix} \Delta CPI_t \\ M3RR_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.128616} \\ -0.447881 \end{bmatrix} \left[CPI_{t-1} + 0.269462 M3RR_{t-1} - \mathbf{0.007695t} - 9.624383 \right] +$$

$$\begin{bmatrix} 0.046026 & \mathbf{0.057441} \\ -1.445020 & \mathbf{0.461610} \end{bmatrix} \begin{bmatrix} \Delta CPI_{t-1} \\ \Delta M3RR_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{0.003843} \\ \mathbf{0.018387} \end{bmatrix} + \begin{bmatrix} \varepsilon_{CPI,t} \\ \varepsilon_{M3RR,t} \end{bmatrix} \qquad (5.18)$$

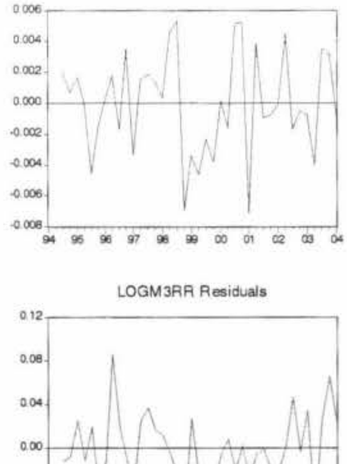
where *CPI* is *LOGCPI*, *M3RR* is *LOGM3RR* and the significant coefficients are in bold.

Although (5.18) contains one significant adjustment coefficient, the coefficient of $M3RR_{t-1}$ is not significant and consequently this equation is of little use as a VECM for economic model building. Nevertheless the equation will be evaluated below to determine whether this can be explained by some statistical issues.

Residual analysis of VECM of *LOGCPI* and *LOGM3RR*

Various tests were performed on the residuals to ensure that the assumptions for the linear model were met. This is of special interest in this case with the non-significant term as explained above.
The Jarque-Bera value of the residuals of $\Delta LOGCPI$ is 0.1572 (p = 0.9244).
The Jarque-Bera value of the residuals of $\Delta LOGM3RR$ is 1.2558 (p = 0.5337).
The residuals of the VECM appear stationary (Figure 5.13).

Figure 5.13 Residuals of VECM of *LOGCPI* and *LOGM3RR*



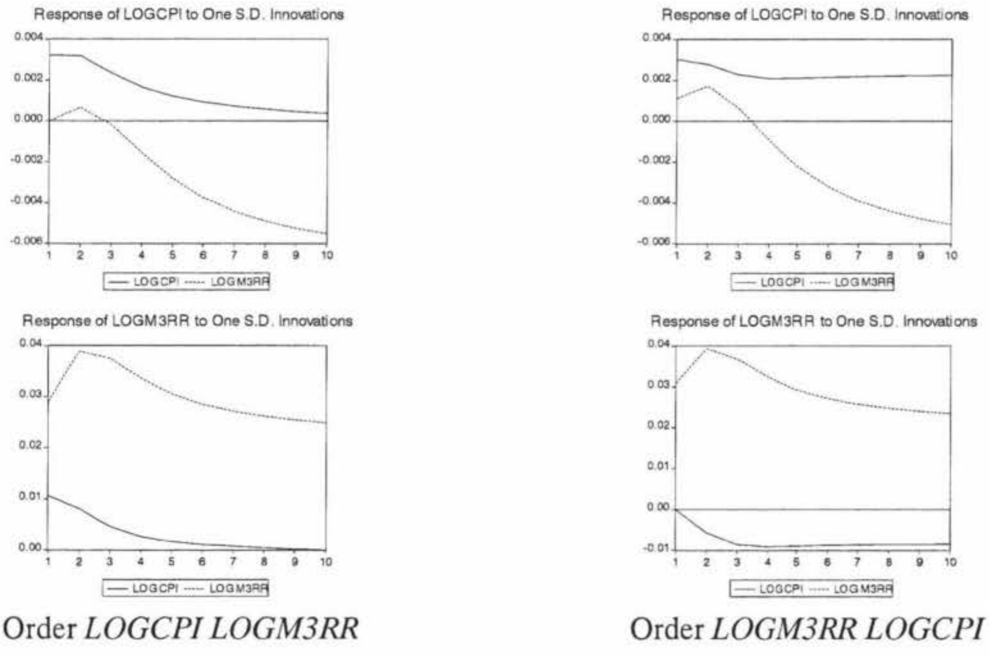
The ACF of neither of the residuals shows significant findings. The Q statistics are not significant either.
The residuals of the VECM seemed well behaved.

The correlation coefficient of the two series is 0.3437. The cross correlogram of the residuals does not show significant results.

Innovation Accounting

Both the IRF and the VD differ depending on the order in which the two time series were entered. This was as expected based on the correlation coefficient. The difference was more a matter of degree rather than different patterns However in the case of the IRF of $\Delta LOGM3RR$ the reaction to a shock of $\Delta LOGCPI$ changed from barely a response to a negative response after 10 periods (Figure 5.14). The $\Delta LOGCPI$ showed a negative response to a shock to $\Delta LOGM3RR$ after 10 periods.

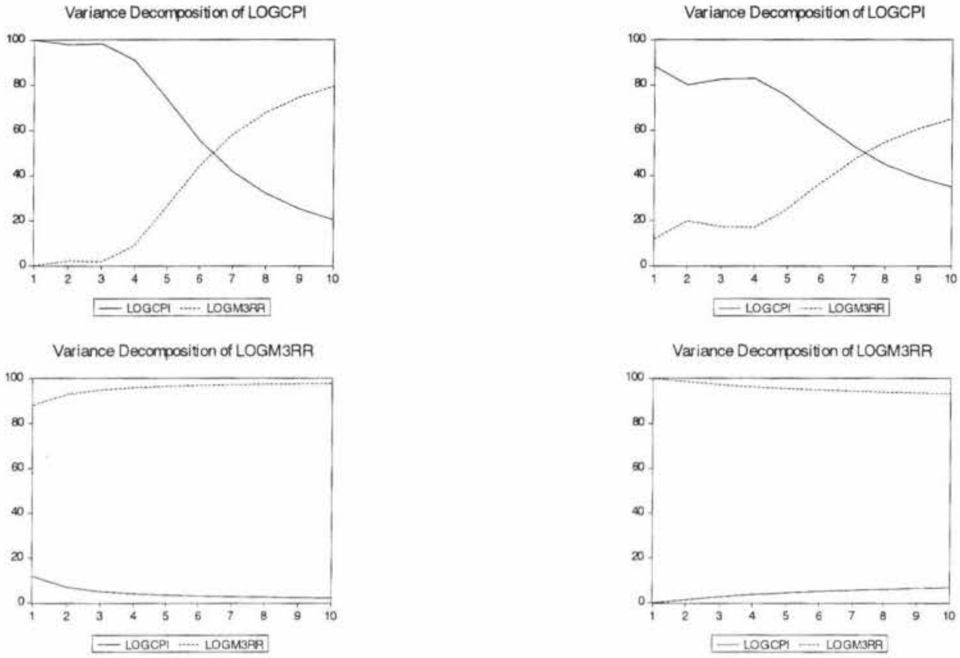
Figure 5.14 Impulse Response Function of VECM of *LOGCPI* and *LOGM3RR*



Order *LOGCPI LOGM3RR* Order *LOGM3RR LOGCPI*

The VD of $\Delta LOGM3RR$ showed little effect of $\Delta LOGCPI$ at all periods (Figure 5.15). However, the VD of $\Delta LOGM3RR$ showed a greater effect of $\Delta LOGCPI$ than of its own time series after 10 periods.

Figure 5.15 Variance Decomposition of VECM of *LOGCPI* and *LOGM3RR*



Order *LOGCPI LOGM3RR* Order *LOGM3RR LOGCPI*

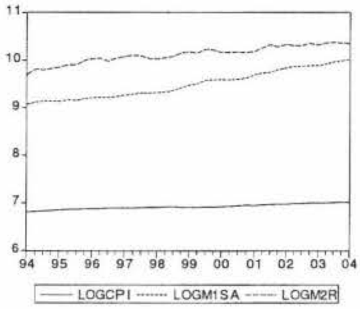
Interpretation of VECM of *LOGCPI* and *LOGM3RR*

One of the adjustment parameters of the VECM is significant. However, the coefficient of the term $\Delta LOGM3RR_{t-1}$ is not significant. Therefore the model cannot be used as a VECM. The term $\Delta LOGM3RR_{t-1}$ is significant for both $\Delta LOGCPI_t$ and $\Delta LOGM3RR_t$. This is interpreted as meaning that it is associated with an increased inflation and an increase of its own value. These results of the innovation accounting would have been of great interest but the problems with the VECM renders their value questionable.
The cointegration analysis appeared to provide a significant result at Option 4 with lag 1. Further analysis demonstrated that the VECM did not meet the criteria of an Option 4 VECM. This seems to point to a weakness in the methodology.

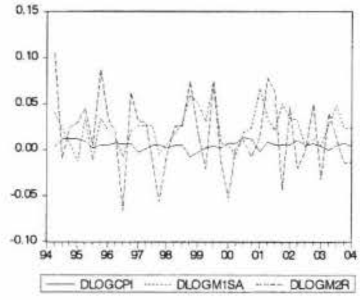
Cointegration analysis of *LOGCPI, LOGM1SA* and *LOGM2R*

M2 as is commonly used constitutes *M1* and *M2R* (See introduction of this chapter). It is of interest to see whether by bringing these two time series together (albeit with a seasonally adjusted *M1*) will result in new insights when cointegration analyses are performed with *LOGCPI*. It would appear that *LOGM1SA* and *LOGM2R* increase in a similar manner (Figure 5.16). However the differenced series show some differences between these two with the *LOGM2R* initially having more variation than *LOGM1SA*.

Figure 5.16 Time series and differenced time series of *LOGCPI, LOGM1SA* and *LOGM2R*



Time series of *LOGCPI, LOGM1SA* and *LOGM2R*



Differenced time series of *LOGCPI, LOGM1SA* and *LOGM2R*

The various cointegration analyses of the above time series are displayed in Table 5.13. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The VECM options include options for the data trend and the Cointegrating Equation (CE). The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order.

Both information criteria suggested one lag. However the SC had Option 4 with one cointegrating equation while the AIC had Option 3 with two cointegrating equations.

VECM of LOGCPI, LOGM1SA and LOGM2R

Various versions of this VECM were possible. The complete VECM of one model is displayed in (5.19).

$$\begin{bmatrix} \Delta CPI_t \\ M1_t \\ M2R_{t-1} \end{bmatrix} = \begin{bmatrix} \mathbf{-0.072420} \\ 0.121926 \\ -0.162041 \end{bmatrix} \left[CPI_{t-1} - 0.6322M1_{t-1} + 0.3155M2R_{t-1} + 0.0076t - 4.2735 \right] +$$

$$\begin{bmatrix} 0.0285 & -0.0502 & -0.0006 \\ -0.8565 & 0.1346 & 0.0211 \\ -1.6209 & -0.1981 & -0.1016 \end{bmatrix} \begin{bmatrix} \Delta CPI_{t-1} \\ \Delta M1_{t-1} \\ \Delta M2R_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{0.0061} \\ \mathbf{0.0238} \\ 0.0284 \end{bmatrix} + \begin{bmatrix} \varepsilon_{CPI,t} \\ \varepsilon_{M1,t} \\ \varepsilon_{M2R,t} \end{bmatrix} \qquad (5.19)$$

where *CPI* is *LOGCPI, M1* is *LOGM1SA* and *M2R* is *LOGM2R* and the significant coefficients are in bold.

Table 5.13 Cointegration analysis of *LOGCPI* , *LOGM1SA* and *LOGM2R*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1	2	3	2	1	3
39 obser-vations	-16.72587		**-16.93376**	-16.81070	
	-15.83011		-15.91003	**-16.00025**	
Lag 1 – 2	2	2	1	1	3
38 obser-vations	-16.49087	-16.49100	-16.60087	-16.67914	
	-15.19804	-15.11198	-15.43732	-15.47249	
Lag 1 – 3	1	2	1	1	3
37 obser-vations	-16.13590	-16.08942	-16.20668	-16.47294	
	-14.69914	-14.30435	-14.63930	-14.86202	
Lag 1 – 4	1	1	1	1	3
36 obser-vations	-16.31807	-16.31277	-16.35374	-16.58896	
	-14.47063	-14.42134	-14.37434	-14.56558	
Lag 1 – 5	0	1	1	2	3
35 obser-vations		-16.42975	-16.43657	-16.69484	
		-14.11895	-14.03689	-13.93965	
Lag 1 – 6	1	2	2	3	3
34 obser-vations	-16.23813	-16.52129	-16.60941		
	-13.54455	-13.46857	-13.51179		
Lag 1 – 7	1	3	2	3	3
33 obser-vations	-16.34548		-16.75483		
	-13.21642		-13.21763		
Lag 1 – 8					
32 obser-vations	Insufficient number of observations				

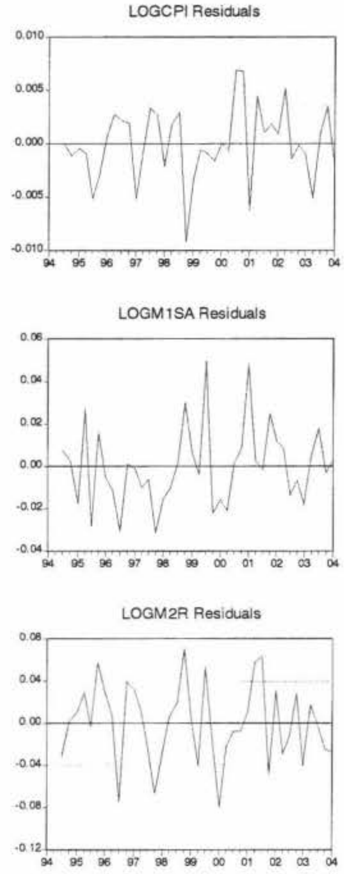
Note: Period covered 1994:1 – 2004:1.

Although (5.19) has one significant adjustment factor, the coefficients of the two monetary aggregates in the CE are not significant. In addition none of the lagged terms had a significant coefficient. Consequently this VECM is not of use as an economic model. Nevertheless the model will be evaluated to see whether some statistical aspects are of interest.

Residual analysis of VECM of LOGCPI, *LOGM1SA* and *LOGM2R*

Various tests were performed on the residuals to check whether the assumptions for the linear model were met.
The Jarque-Bera value of the residuals of $\Delta LOGCPI$ is 0.7800 (p = 0.6718)
The Jarque-Bera value of the residuals of $\Delta LOGM1SA$ is 3.8726 (p = 0.1442
The Jarque-Bera value of the residuals of $\Delta LOGM2R$ is 0.4315 (p = 0.8059)
The residuals of the VECM appear stationary (Figure 5.17).

Figure 5.17 Residuals of VECM of *LOGCPI* and *LOGM1SA* and *LOGM2R*



The ACF of none of the residuals shows significant findings. The Q statistics are not significant either. The residuals of the VECM seem well behaved.

Table 5.14 Correlation coefficients of the residuals of the VECM of *LOGCPI*, *LOGM1SA* and *LOGM2R*

		Correlation coefficient
$\Delta LOGCPI$	$\Delta LOGM1SA$	-0.2035
$\Delta LOGCPI$	$\Delta LOGM2R$	-0.2718
$\Delta LOGM1SA$	$\Delta LOGM2R$	0.4891

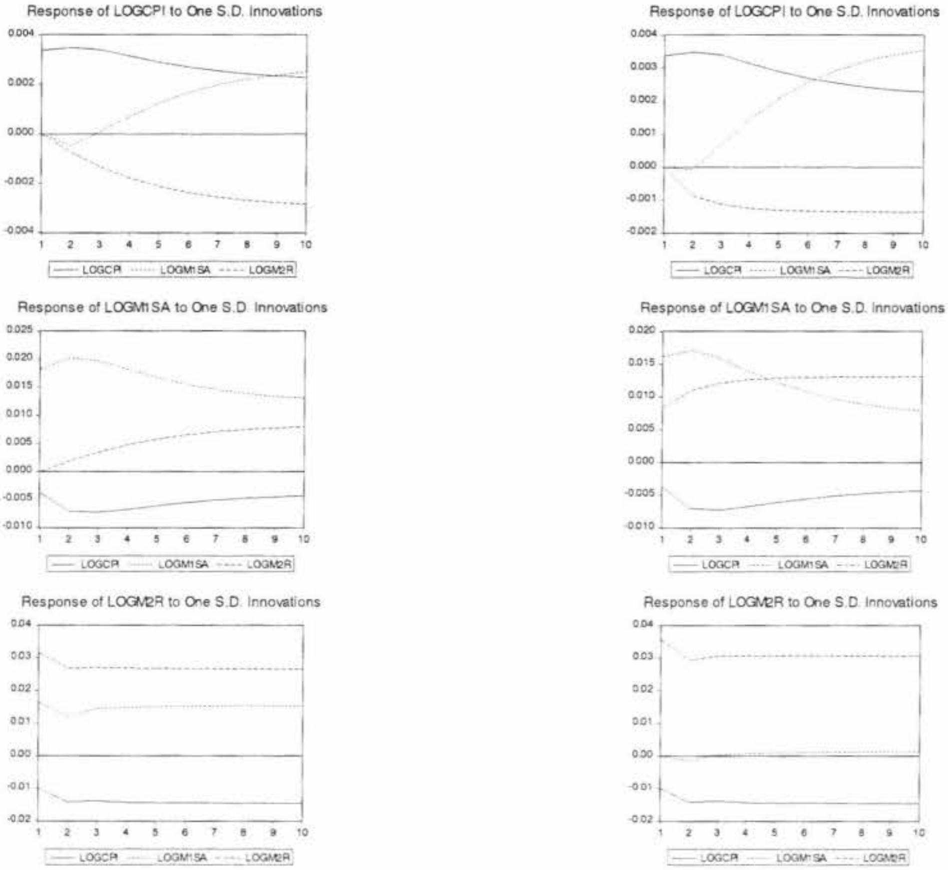
The cross-correlogram may have shown a positive correlation between the residuals of $\Delta LOGCPI$ and $\Delta LOGM2R$ at lag 4. Table 5.14 shows the high value of the correlation coefficient of the two monetary aggregates. This may affect the innovation accounting analysis.

Innovation Accounting

Since there are three time series, there are six different orders that can be used for entering the series into the Impulse Response Function and the Variance Decomposition. Two are shown below for illustrative purposes (Figure 5.18 and 5.19).

The IRF of $\Delta LOGCPI$ shows a strong positive response to shocks to $\Delta LOGM1SA$ and a negative response to $\Delta LOGM2R$. The order in which the two monetary aggregates are entered clearly affect the response of $\Delta LOGCPI$ they create.

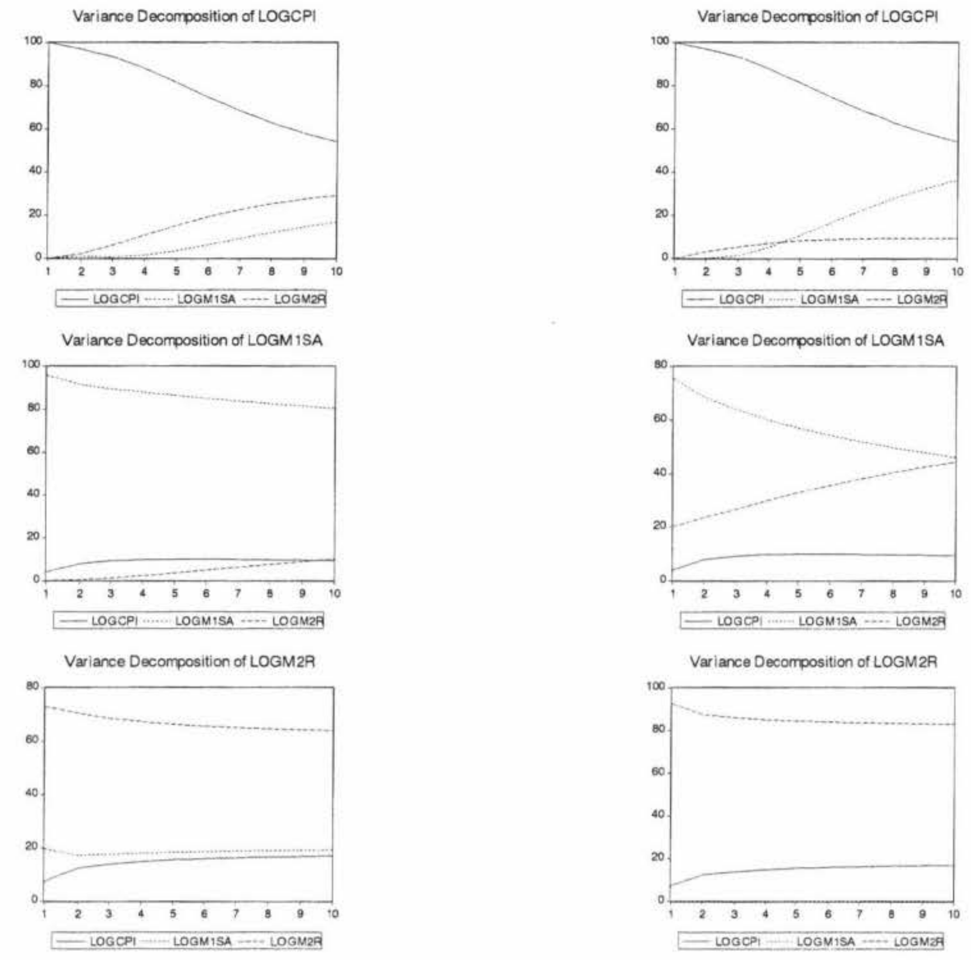
Figure 5.18 Impulse Response Function of VECM of *LOGCPI, LOGM1SA* and *LOGM2R*



Order *LOGCPI LOGM1SA LOGM2R* Order *LOGCPI LOGM2R LOGM1SA*

The order in which the two monetary aggregates are entered matters much when the VD of $\Delta LOGM1SA$ is considered. If *LOGM2R* is entered before *LOGM1SA*, then both these time series contribute approximately the same proportion to the variance of $\Delta LOGM1SA$. If the order is reversed (left hand site of Figure 3.33) then the contribution becomes similar to that by $\Delta LOGCPI$ which is about 10% after 10 periods.

Figure 5.19 Variance Decomposition of VECM of *LOGCPI*, *LOGM1SA* and *LOGM2R*



Order *LOGCPI LOGM1SA LOGM2R* Order *LOGCPI LOGM2R LOGM1SA*

Interpretation of VECM of *LOGCPI* and *LOGM1SA* and *LOGM2R*

The adjustment parameter of $\Delta LOGCPI_t$ is significant. However, none of the components of the error correction term (including the trend term) is significant. In the case of the data trend none of the lagged terms is significant. Again the results of the innovation accounting would have been of interest from an economic perspective but this is largely rendered by the problems of non-significant values in the CE.

VECM of *LOGCPI* and *LOGM1SA* and *LOGM2R* (2 cointegrating equations)

In an attempt to establish whether a more meaningful VECM could be detected the best model according to the AIC was evaluated in (5.20). By using two CEs there is also the possibility that perhaps the Quantity Theory might be modelled for *M1* and reverse causation for *M2R*.

$$\begin{bmatrix} \Delta LOGCPI_t \\ \Delta LOGM1SA_t \\ \Delta LOGM2R_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.1792} & \mathbf{0.0387} \\ 0.2442 & -0.0368 \\ \mathbf{1.1318} & 0.0259 \end{bmatrix} \begin{bmatrix} LOGCPI_{t-1} - \mathbf{0.3691} LOGM2R_{t-1} - 3.1826 \\ LOGM1SA_{t-1} - \mathbf{1.9986} LOGM2R_{t-1} + 10.7483 \end{bmatrix} +$$

$$\begin{bmatrix} 0.1132 & \mathbf{-0.0769} & 0.0066 \\ -1.2325 & 0.1695 & 0.0099 \\ -2.8523 & 0.2529 & -0.0889 \end{bmatrix} \begin{bmatrix} \Delta LOGCPI_{t-1} \\ \Delta LOGM1SA_{t-1} \\ \Delta LOGM2R_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{0.0062} \\ \mathbf{0.0251} \\ 0.0238 \end{bmatrix} + \begin{bmatrix} \varepsilon_{LOGCPI,t} \\ \varepsilon_{LOGM1SA,t} \\ \varepsilon_{LOGM2r,t} \end{bmatrix} \quad (5.20)$$

The difference between (5.20) and (5.19) is striking at this stage. Equation (5.20) appears to have at least a significant coefficient in each cointegration equation which may make it meaningful from an economic perspective.

Three long-term relationships can be distinguished. Both *LOGCPI* and *LOGM2R* show short-term corrections to departures from their long-term equilibrium. They have opposite signs of their adjustment coefficients and this seems to make more economic sense than VECM of these two time series only that was discussed at an earlier stage.

In addition *LOGCPI* also appears to react to a departure of the long-term equilibrium between the two monetary aggregates. As LOGM1SA increases from its long-term equilibrium with *LOGM2R*, *LOGCPI* will increase more.

Residual analysis of VECM of LOGCPI, *LOGM1SA* and *LOGM2R* (2 cointegrating equations)

Various tests were performed on the residuals to check whether the assumptions for the linear model were met.
The Jarque-Bera value of the residuals of $\Delta LOGCPI$ is 1.1074 ($p = 0.5748$)
The Jarque-Bera value of the residuals of $\Delta LOGM1SA$ is 5.4240 ($p = 0.0664$)
The Jarque-Bera value of the residuals of $\Delta LOGM2R$ is 0.5145 ($p = 0.7732$)
The residuals of the monetary aggregates in the VECM may have shown a slight upward ternd of the mean (Figure 5.20).

The ACF of the residuals of $\Delta LOGCPI$ may have been significant at lag 10, but the other time series did not show significant findings. The Q statistics of none of the series was significant either.
The residuals seemed reasonably well behaved.

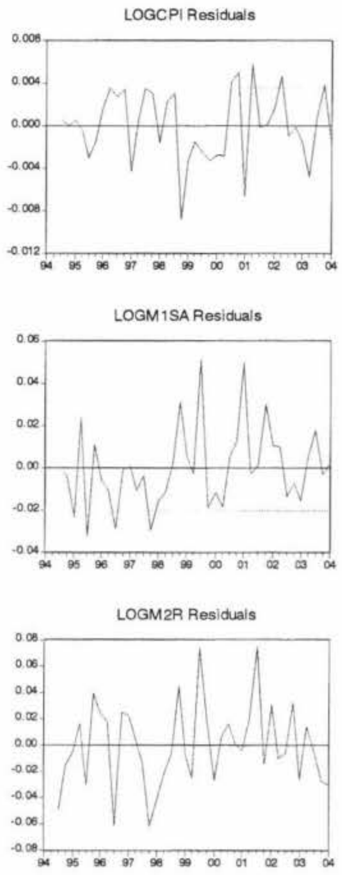
Table 5.15 Correlation coefficients of the residuals of the VECM of *LOGCPI*, *LOGM1SA* and *LOGM2R*

		Correlation coefficient
$\Delta LOGCPI$	$\Delta LOGM1SA$	-0.2585
$\Delta LOGCPI$	$\Delta LOGM2R$	-0.1803
$\Delta LOGM1SA$	$\Delta LOGM2R$	0.4893

The correlation coefficient of especially the two monetary aggregates in Table 5.15 is very similar to the one identified in the VECM with one CE only.

The cross-correlogram between the residuals of $\Delta LOGCPI$ and $\Delta LOGM2R$ showed a significant negative lead 7. The remaining values of the cross-correlograms were not significant.

Figure 5.20 Residuals of VECM of *LOGCPI*, *LOGM1SA* and *LOGM2R*

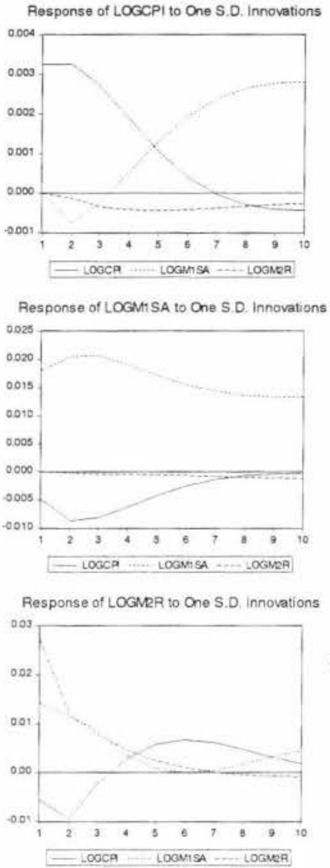


Innovation Accounting

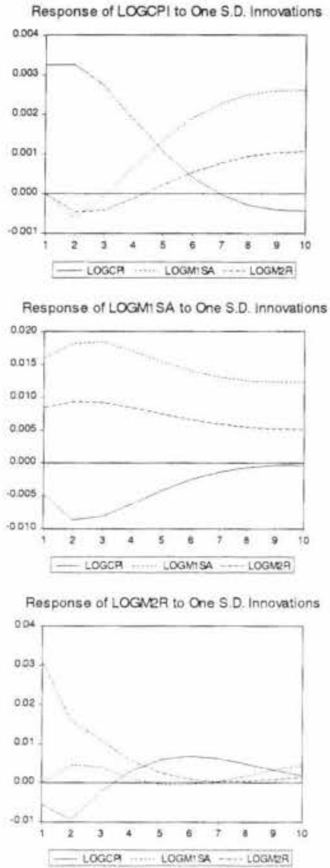
The high correlation coefficient between the two monetary aggregates clearly influences the IRF (5.21) and the VD (5.22). The response of $\Delta LOGCPI$ to shocks to $\Delta LOGM1SA$ is obvious regardless of the ordering and this is an important finding.

The VD too shows the importance of $\Delta LOGM1SA$ with regard to $\Delta LOGCPI$.

Figure 5.21 Impulse Response Function of VECM of *LOGCPI, LOGM1SA* and *LOGM2R*



Order *LOGCPI LOGM1SA LOGM2R*

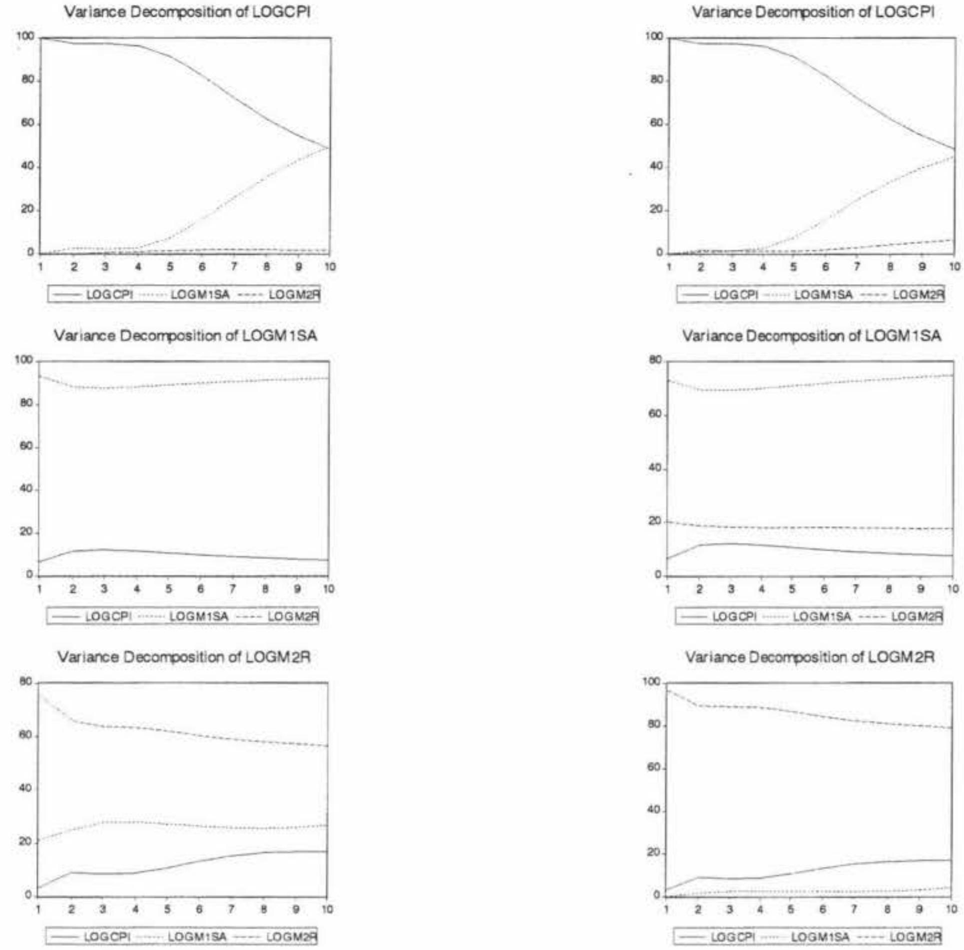


Order *LOGCPI LOGM2R LOGM1SA*

Comments on the VECMs of *LOGCPI, LOGM1SA, LOGM2R*

The VECM with two cointegrating equations was of more use than the one with one CE only. Although it is encouraging to have results that can be interpreted in a meaningful economic sense it is reason for concern too. At first sight there was no good reason to choose (5.20) rather than (5.19). Both should have resulted in admissible models. The information criterion chosen cannot be used for 'weeding out' the first model. Equation (5.20) showed the importance of the relationship between *LOGCPI* and *LOGM2R*. However the innovation accounting seemed to show that the relationship between *LOGCPI* and *LOGM2R* was of more importance.

Figure 5.22 Variance Decomposition of VECM of *LOGCPI*, *LOGM1SA* and *LOGM2R*

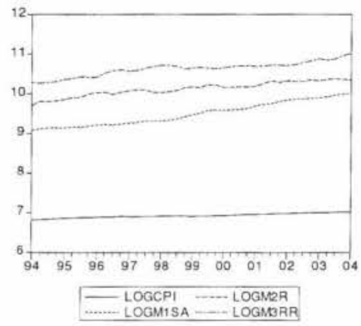


Order *LOGCPI LOGM1SA LOGM2R* Order *LOGCPI LOGM2R LOGM1SA*

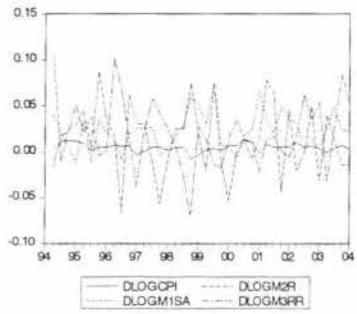
Cointegration analysis of *LOGCPI, LOGM1SA, LOGM2R* and *LOGM3RR*

Finally of interest is a cointegration analysis that evaluates the three monetary aggregates that have been used so far and *LOGCPI*. Figure 5.23 gives the impression that the slope of the monetary aggregates is steeper than that of the inflation. The monetary aggregates also display more variation.

Figure 5.23 Time series and differenced time series of *LOGCPI* , *LOGM1SA*, *LOGM2R* and *LOGM3RR*



Time series of *LOGCPI* , *LOGM1SA*, *LOGM2R* and *LOGM3RR*



Differenced time series of *LOGCPI*, *LOGM1SA*, *LOGM2R* and *LOGM3RR*

The various cointegration analyses of the above time series are displayed in Table 5.16. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The VECM options include options for the data trend and the Cointegrating Equation (CE). The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order.

The large number of time series relative to the length of the time series resulted in models with 5 lags at the most. All possible VECMs with one exception had 2 or 3 Cointegration Equations. The SC selected this VECM with the 1 CE as the best model. It probably illustrates the parsimonious nature of the information criterion. However, it also raises some doubts whether a criterion based on parsimony is necessarily the best way to select a model. This issue will be further discussed in the general discussion.

VECM of *LOGCPI, LOGM1SA, LOGM2R* and *LOGM3RR*

Since there were 4 time series and 1 CE was deemed to exist, there were 4 possible ways of displaying the CE. One model is displayed in full (5.21) and the CEs of the remaining models are displayed in (5.22) to (5.24). Although all 4 versions had negative significant adjustment coefficients, none had a significant coefficient of a time series in the CE.

Table 5.16 Cointegration analysis of *LOGCPI*, *LOGM1SA*, *LOGM2R* and *LOGM3RR*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 observations	2 -20.98558 -19.62060	3 -20.96893 -19.13474	2 -21.22277 19.68718	1 -21.07200 **-19.83500**	2 -21.19454 -19.48832
Lag 1 – 2 38 observations	2 -20.73326 -18.66473	3 -20.67425 -18.13168	1 -20.85088 -18.95473	3 -20.91012 -18.19517	3 -20.98999 -18.23195
Lag 1 – 3 37 observations	2 -20.43916 -17.65270	3 -20.43733 -17.17196	3 -20.47874 -17.16983	4	3 -20.83995 -17.35688
Lag 1 – 4 36 observations	3 -20.43876 -16.56793	3 -20.60108 -16.59830	4	4	3 -21.10051 -16.87779
Lag 1 – 5 35 observations	2 -21.14468 -16.87858	2 -21.19747 -16.84249	2 -21.30396 -16.86010	3 -22.06981 -17.13714	2 **-22.29890** -17.67730
Lag 1 – 6 34 observations					
Lag 1 – 7 33 observations					
Lag 1 – 8 32 observations	Insufficient number of observations				

Note: Period covered 1994:1 – 2004:1.

The significant adjustment coefficient applied in all cases to *LOGCPI*. Interestingly, the trend was significant in (5.24) but not in any of the other ones. This illustrates that although the same space may be spanned by the vectors, the conclusions can still differ if one uses 'significance' for making decisions regarding the meaning of a model. It was decided not to further explore this model because it was not informative.

$$\begin{bmatrix} \Delta CPI_t \\ \Delta M1_t \\ \Delta M2R_t \\ \Delta M3RR_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.0016} \\ 0.0009 \\ -0.0069 \\ -0.004706 \end{bmatrix}$$

$$\left[CPI_{t-1} + 4.2396M1_{t-1} + 19.8010M2R_{t-1} + 23.6496M3RR_{t-1} - 0.6675t - 485.1551\right]$$

$$+\begin{bmatrix} -0.1024 & -0.0150 & 0.0042 & 0.0469 \\ -0.6544 & -0.0193 & -0.0304 & -0.2262 \\ -1.7205 & -0.3461 & -0.1915 & -0.26591 \\ -1.5462 & 0.2423 & 0.0582 & \mathbf{0.5144} \end{bmatrix}\begin{bmatrix} \Delta CPI_{t-1} \\ \Delta M1_{t-1} \\ \Delta M2R_{t-1} \\ \Delta M3RR_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{0.0051} \\ \mathbf{0.0311} \\ \mathbf{0.0384} \\ 0.0113 \end{bmatrix} + \begin{bmatrix} \varepsilon_{CPI,t} \\ \varepsilon_{M1,t} \\ \varepsilon_{M2R,t} \\ \varepsilon_{M3EE,t} \end{bmatrix} \quad (5.21)$$

$$\begin{bmatrix} 0.0038 \\ -0.0292 \\ -0.0200 \\ \mathbf{-0.0068} \end{bmatrix} \begin{bmatrix} M1SA_{t-1} + 4.6705M2R_{t-1} + 5.5783M3RR_{t-1} + 0.2359CPI_{t-1} \\ -0.1574t - 114.4344 \end{bmatrix} \tag{5.22}$$

$$\begin{bmatrix} -0.1365 \\ -0.0932 \\ \mathbf{-0.0320} \\ 0.0178 \end{bmatrix} \begin{bmatrix} M2R_{t-1} + 1.1944M3RR_{t-1} + 0.0505CPI_{t-1} + 0.2141M1SA_{t-1} \\ -0.0337t - 24.5016 \end{bmatrix} \tag{5.23}$$

$$\begin{bmatrix} -0.1113 \\ \mathbf{-0.0382} \\ 0.0212 \\ -0.1630 \end{bmatrix} \begin{bmatrix} M3RR_{t-1} + 0.0423CPI_{t-1} + 0.1793M1SA_{t-1} + 0.8373M2R_{t-1} \\ \mathbf{-0.0282}t - 20.5143 \end{bmatrix} \tag{5.24}$$

where *CPI* is *LOGCPI*, *M1* is *LOGM1SA*, *M2R* is *LOGM2R*, *M3RR* is *LOGM3RR* and the significant coefficients are in bold.

Discussion

Money can be defined in various ways and three different monetary aggregates were evaluated in this Chapter.

VECMs for *LOGCPI, LOGM1SA* and *LOGM2R* seemed to provide results that were informative and can be used for model building. However, the meaning of some of the results (eg equation (5.17)) was not immediately clear. Further research may be able to clarify what caused the results. The standardised manner of finding the best model would have resulted in (5.19). This model was not informative. However model (5.20) was quite informative. This again raises the issue how to find an appropriate model without 'data dredging' until a model is found that appeals to the analyst.

This discussion on the importance of the monetary aggregates will be continued later when the interest rates and the GDP are evaluated.

References

Laidler D (1991) The Quantity Theory is always and everywhere controversial – Why? The Economic Record, 289-306.

CHAPTER 6

TIME SERIES ANALYSES OF INTEREST RATES

Introduction

In recent times NZ governments have been committed to keeping inflation within bounds. A number of tools can be used to control inflation. Some of these will be in the hands of government (eg affecting employment) while other tools are available to the RBNZ. The government has made inflation control a main task of the RBNZ as set out in an agreement between these two parties. Currently it is 1 to 3 percent over the medium term. The tools available to the RBNZ include the manipulation of the monetary base and the interest rates. The RBNZ uses the Official Cash Rate (OCR) as its primary tool to control inflation.

A sign of success to reduce inflation could be considered the CPI figure of the second quarter of 1991 when for the first time in recent history the yearly inflation rate was less than 3.0% (ie 2.8%). The difference in inflation rates before and after June 1991 offers, from an analysis perspective, opportunities as well as disadvantages. An analysis of the economy under different economic conditions that are characterised by high as well as low inflation has advantages as well as disadvantages. Issues with potential profound economic effects should preferably be considered under varying conditions. The main disadvantage of the considerable difference in inflation rates is that the actual time series available for analysis has now become divided into two relatively short time series which make it more difficult to make robust inferences. In order to be consistent with some other chapters the analysis in this chapter will cover the quarters over the period 1994:1 – 2004:1.

Interest rates compete with a number of other investment vehicles (eg share market and real estate) for available resources. Consequently one would expect some form of return between these investment vehicles after taking into account such matters as risk premiums, taxation distortions and investment fashions. If one of these types of investment became more profitable than the other ones, more resources would be allocated to this type of investment, reducing its returns and lifting that of the others. However the setting of the OCR by the RBNZ distorts this mechanism.

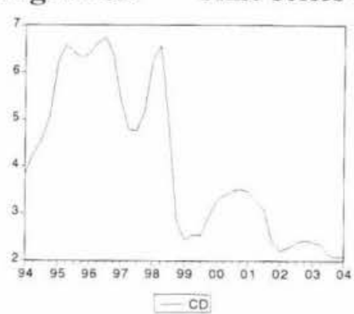
This chapter analyses two interest rates: the Call Deposit Rate (CD) and the Six Month Deposit Rate (SMD). The longer money is lent, *ceteris paribus*, the higher the interest rate should be because the lender is foregoing the consumption of the resources for a longer period. In addition there is a greater risk of unforeseen inflation rate changes. The latter would not matter if both lender and borrower are risk neutral and the inflation rate can accelerate or decelerate with equal probabilities and at similar speeds. In reality the lender may be more risk averse the longer the period the money is not available to him, ie more reluctant to accept the current inflation rate as fixed if it is low. One would also expect that both the lender and the borrower have a better knowledge of the inflation rate in the immediate term than in the medium or long term.

The univariate and multivariate analyses will be carried out as explained in Chapter 2.The standard errors are put in parentheses below each DF equation. The criterion for rejecting a unit root is $p < 0.1$ and the criterion for rejecting the τ and ϕ statistics is $p < 0.05$ (See Chapter 2). Dickey and Fuller (1981) provided critical values for these latter two test statistics. Regrettably if the sample size of this chapter is considered only the sample sizes of 25 and 50 are relevant. Consequently various critical values are required to be shown at times for one tests statistic to decide whether a hypothesis is to be rejected or not.

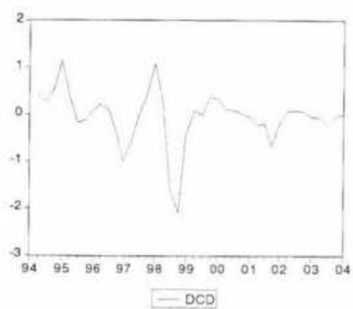
Call Deposit Rate *(CD)*

The time series of the call deposit interest rates covers the period 1994:1 to 2004:1 in quarterly time periods. The *CD* time series starts at a level of less than 4 percent (Figure 6.1). After a steep increase it remains at a level of approximately 6.5 percent for a number of years. There is a steep decline after 1998 and the interest rates remain at a lower level until the end of the series. The differenced series is more or less stationary although a large peak and a large trough can be distinguished.

Figure 6.1 Time series and differenced time series of *CD*



Time series of *CD*



Differenced time series of *CD* (*DCD*)

DF Models of *CD*

The time series of *CD* was tested for stationarity in (6.1) to (6.5) by using the Dickey-Fuller equations as outlined in Chapter 2.

Model 1

$$\underset{}{\Delta CD_t} = \underset{(0.5460)}{1.9079} - \underset{(0.0110)}{0.0386t} - \underset{(0.0782)}{0.2701CD_{t-1}} + \underset{(0.1203)}{0.8124\Delta CD_{t-1}} - \underset{(0.1371)}{0.3638\Delta CD_{t-2}} + \varepsilon_t \qquad (6.1)$$

Model 2

$$\Delta CD_t = \underset{(0.1969)}{0.0886} - \underset{(0.0443)}{0.0312CD_{t-1}} + \underset{(0.1379)}{0.8637\Delta CD_{t-1}} - \underset{(0.1468)}{0.5439\Delta CD_{t-2}} + \varepsilon_t \qquad (6.2)$$

Model 2R

$$\Delta CD_t = -0.0415 + 0.8638\Delta CD_{t-1} - 0.5815\Delta CD_{t-2} + \varepsilon_t \qquad (6.3)$$

$$\quad (0.0669) \quad (0.1369) \qquad (0.1357)$$

Model 3

$$\Delta CD_t = -0.0124CD_{t-1} + 0.8624\Delta CD_{t-1} - 0.5670\Delta CD_{t-2} + \varepsilon_t \qquad (6.4)$$

$$\quad (0.0150) \qquad (0.1363) \qquad (0.1359)$$

Model 3R

$$\Delta CD_t = 0.8696\Delta CD_{t-1} - 0.5791\Delta CD_{t-2} + \varepsilon_t \qquad (6.5)$$

$$\quad (0.1354) \qquad (0.1345)$$

The RSS and the information criteria of DF models (6.1) to (6.5) are shown in Table 6.1.

Table 6.1 RSS and information criteria of Dickey-Fuller models of *CD*

	RSS	AIC	SC	Adj. R^2
Model 1 (6.1)	4.222452	0.9039	1.1193	0.6282
Model 2 (6.2)	5.796736	1.1681	1.3405	0.5046
Model 2R (6.3)	5.8811			
Model 3 (6.4)	5.8313	1.1214	1.2507	0.5159
Model 3R (6.5)	5.945881			

The various DF statistics of (6.1) to (6.5) are displayed in Table (6.2).

Table 6.2 Summary of the Dickey-Fuller tests of *CD*

Model	Test Statistic	Value	Critical Value (p-value, n[#])	Hypothesis
1	τ_τ	-3.45	-3.53 (0.05)	$\gamma = 0$
			-3.20 (0.1)	
	$\tau_{\alpha\tau}$	3.49	3.20 (0.05, 25)	$a_0 = 0$ *given* $\gamma = 0$
			3.59 (0.025, 25)	
	$\tau_{\beta\tau}$	-3.51	3.25 (0.025, 25)	$a_2 = 0$ *given* $\gamma = 0$
			3.74 (0.01, 25)	
	ϕ_2	4.49	4.67 (0.1, 25)	$a_0 = \gamma = a_2 = 0$
			5.68 (0.05, 25)	
			5.13 (0.05, 50)	
	ϕ_3	6.48	5.61 (0.1, 50)	$\gamma = a_2 = 0$
			6.73 (0.05, 50)	
2	τ_μ	-0.70	-2.61 (0.1)	$\gamma = 0$
	$\tau_{\alpha\mu}$	0.45	2.18 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
	ϕ_1	0.42	3.94 (0.1, 50)	$a_0 = \gamma = 0$
3	τ	-0.83	-1.62 (0.1)	$\gamma = 0$

[#] n listed if p-value for precise sample size of time series not known, time series has 38 observations after adjusting endpoints

Model 1

The model suggests unit root ($p > 0.05$). However the evidence is not strong. The ACF of the residuals of (6.1) does not show significant lags (16 lags included). There are no significant Q statistics.

There was concern about a possible breakpoint and therefore the Chow Breakpoint test was performed (Table 6.3). According to this test there is no evidence for a breakpoint at 1998:1.

Table 6.3 Chow Breakpoint Test of DF Model 1 of CD at 1998:1

	Value	Probability
F - statistic	0.64	0.67
Log Likelihood ratio	4.13	0.53

Both deterministic components ($\tau_{\alpha\tau}$ and $\tau_{\beta\tau}$) are significant ($p < 0.05$) if the hypothesis of unit root is accepted.

The unrestricted and the restricted equations for ϕ_2 are (6.1) and (6.5) respectively. For ϕ_3 these equations are (6.1) and (6.3). There are 38 usable observations (T=38) and 5 parameters (k=5) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3 .

The null hypothesis for ϕ_2 is not rejected. This can be interpreted as meaning that if the process is unit root, then a_0 and/or a_2 may be zero too. This is not in line with the τ statistics. The null hypothesis of ϕ_3 is not rejected either ($p > 0.05$). This can be interpreted as meaning that if the process is unit root, then a_2 is not significantly different from 0.

The results of the tests are ambiguous. Although the process is unit root, the deterministic components are not always considered to be significant. This tends to indicate that a better model without deterministic components should exist.

Model 2

Model 2 has a unit root ($p > 0.1$). The ACF of (6.2) seems to show a significant lag (lag 15) and the Q statistics of lags 15 and 16 are significant (16 lags included). Given the multiple use of p values it is not unexpected that by chance at times seemingly significant findings occur. If for instance 20 tests are performed at 0.05, one spurious significant result can be expected.

The constant (a_0) is not significant at the 10% significance level as shown by $\tau_{\alpha\mu}$.

The unrestricted and the restricted equations for ϕ_1 are (6.2) and (6.5) respectively. There are 38 usable observations (T=38) and 4 parameters (k=5) in the unrestricted model. There are 2 restrictions. The null hypothesis for ϕ_1 is not rejected, meaning that a_0 is not significant.

Similar to Model 1 a time series with unit root is identified that initially seems to have deterministic component(s). On closer examination the constant in Model 2 appears not significant.

Model 3

Model 3 appears to have a unit root (p > 0.1). The ACF of the residuals of (6.4) appears significant at lag 15 and the Q statistics are significant at lag 15 and 16 (16 lags included). A possible explanation for these significant values has been given above in Model 1.

Selection of the best CD DF Model

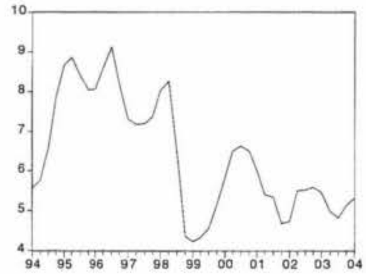
Model 3 seems the best model. It includes two lags. The information criteria of Model 1 were smaller but the lack of significance of the deterministic components was of concern.

This means that the *CD* has a unit root, it displays a pattern that could be taken to be a random walk without a drift. Therefore the value of *CD* in the next period will be close to the current value. However long term predictions of the *CD* cannot be made confidently if based on its own values only.

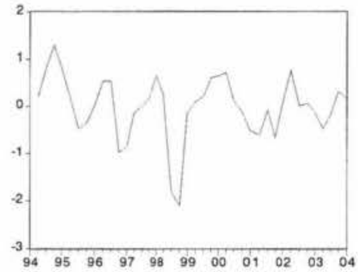
Sixth Month Deposit Rate (*SMD*)

The quarterly time series of the *SMD* covers the period 1994:1 to 2004:1. The time series SMD shows a sharp increase at the beginning (Figure 6.2). After that initial increase there appears a continuous decline, with one sharp drop in the beginning of 1998 followed by an increase. The differenced time series appears stationary with the exception of a deep through in 1998.

Figure 6.2 Time series and differenced time series of *SMD*



Time series of *SMD*



Differenced time series of *SMD* (*DSMD*)

DF Models of *SMD*

The time series of *SMD* were tested for stationarity in (6.6) to (6.10) by using the Dickey-Fuller equations as outlined in Chapter 2.

Model 1

$$\Delta SMD_t = \underset{(0.8318)}{2.5852} - \underset{(0.0115)}{0.0315t} - \underset{(0.0957)}{0.2995SMD_{t-1}} + \underset{(0.1320)}{0.7011\Delta SMD_{t-1}}$$

$$- \underset{(0.1554)}{0.2213\Delta SMD_{t-2}} + \varepsilon_t \qquad (6.6)$$

Model 2

$$\Delta SMD_t = \underset{(0.4249)}{0.5710} - \underset{(0.0643)}{0.0929SMD_{t-1}} + \underset{(0.1435)}{0.7347\Delta SMD_{t-1}} - \underset{(0.1593)}{0.3680\Delta SMD_{t-2}} + \varepsilon_t \qquad (6.7)$$

Model 2R

$$\Delta SMD_t = \underset{(0.0847)}{-0.0305} + \underset{(0.1457)}{0.7347\Delta SMD_{t-1}} - \underset{(0.1460)}{0.4669\Delta SMD_{t-2}} + \varepsilon_t \qquad (6.8)$$

Model 3

$$\Delta SMD_t = \underset{(0.0128)}{-0.0081SMD_{t-1}} + \underset{(0.1451)}{0.7343\Delta SMD_{t-1}} - \underset{(0.1458)}{0.4590\Delta SMD_{t-2}} + \varepsilon_t \qquad (6.9)$$

Model 3R

$$\Delta SMD_t = \underset{(0.1439)}{0.7353\Delta SMD_{t-1}} - \underset{(0.1442)}{0.4659\Delta SMD_{t-2}} + \varepsilon_t \qquad (6.10)$$

The RSS and various information criteria of DF models (6.6) to (6.10) are shown in Table 6.4. The various DF statistics of (6.6) to (6.10) are displayed in Table 6.5.

Table 6.4 RSS and information criteria of Dickey-Fuller models of *SMD*

	RSS	AIC	SC	Adj. R^2
Model 1	7.310513	1.4528	1.6682	0.5061
Model 2	8.9736	1.6051	1.7775	0.4115
Model 2R	9.5237			
Model 3	9.4502	1.6042	1.7335	0.3980
Model 3R	9.5590			

Model 1

The standardised procedures that are outlined in Chapter 2 would initially have resulted in the equation below because the second lag is not significant.

$$\Delta SMD_t = \underset{(0.6449)}{2.9936} - \underset{(0.0096)}{0.0345t} - \underset{(0.0750)}{0.3532SMD_{t-1}} + \underset{(0.1172)}{0.6086\Delta SMD_{t-1}} + \varepsilon_t$$

RSS = 7.8189 AIC = 1.4360 SC = 1.6066 Adj. R^2 = 0.5085

However, the standardised procedures also require that all DF models have an equal number of lags which is two lags in this case. This is because the ϕ statistics are based on a nested

Table 6.5 Summary of the Dickey-Fuller tests of *SMD*

Model	Test Statistic	Value	Critical Value (p-value, n[#])	Hypothesis
1	τ_τ	-3.13	-3.20 (0.1)	$\gamma = 0$
	$\tau_{\alpha\tau}$	3.11	3.14 (.05, 50)	$a_0 = 0 \ given \ \gamma = 0$
	$\tau_{\beta\tau}$	-2.74	2.81 (0.05, 50)	$a_2 = 0 \ given \ \gamma = 0$
	ϕ_2	3.38	4.31 (0.1, 50)	$a_0 = \gamma = a_2 = 0$
	ϕ_3	1.08	1.37 (0.1, 50)	$\gamma = a_2 = 0$
2	τ_μ	-1.44	-2.61 (0.1)	$\gamma = 0$
	$\tau_{\alpha\mu}$	0.57	2.18 (0.1, 50)	$a_0 = 0 \ given \ \gamma = 0$
	ϕ_1	5.00	5.18 (0.05, 25)	$a_0 = \gamma = 0$
			4.86 (0.05, 50)	
3	τ	-0.63	-1.62 (0.1)	$\gamma = 0$

[#] n listed if p-value for precise sample size of time series not known, time series has 38 observations after adjusting endpoints

approach. Therefore the same number of lags is required for all models and consequently (6.6) was computed.

The model suggests unit root (p > 0.1). The ACF of the residuals of (6.6) does not show significant lags (16 lags included). There are no significant Q statistics. There was some concern a breakpoint might exist and a Chow Breakpoint Test was performed (Table 6.6). According to this test there is no evidence for a breakpoint at 1998:1.

Table 6.6 Chow Breakpoint Test of DF Model 1 of *SMD* at 1998:1

	Value	Probability
F - statistic	1.16	0.35
Log Likelihood ratio	7.16	0.21

Neither the null hypothesis of $\tau_{\alpha\tau}$ nor $\tau_{\beta\tau}$ and rejected. Consequently the deterministic components are not deemed significant.

The unrestricted and the restricted equations for ϕ_2 are (6.6) and (6.10) respectively. For ϕ_3 these equations are (6.6) and (6.8). There are 38 usable observations (T=38) and 5 parameters (k=5) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3 .

The null hypothesis of ϕ_2 is not rejected (p > 0.1). This can be interpreted as meaning that if the process is unit root, then a_0 and a_2 are zero too. The null hypothesis for ϕ_3 is not rejected either (p > 0.1). This can be interpreted as meaning that if the process is unit root, then a_2 is not significantly different from 0.

Consequently the initial test showed a unit root model with deterministic components. The deterministic components were subsequently deemed to be not significant.

Model 2

Model 2 has a unit root ($p > 0.1$). The ACF of the residuals of (6.7) does not show significant lags (16 lags included). There are no significant Q statistics.

The deterministic component ($\tau_{\alpha\mu}$) is not significant ($p > 0.1$) if the hypothesis of unit root is accepted.

The unrestricted and the restricted equations for ϕ_1 are (6.7) and (6.10) respectively. There are 38 usable observations (T=38) and 4 parameters (k=5) in the unrestricted model. There are 2 restrictions. Since the value of the test statistic ϕ_1 falls between the critical values at p=0.05 for a sample size of 25 and a sample size of 50, the decision is not clear-cut. The evidence for rejecting the null hypothesis is weak.

The initial test indicated a unit root model with a deterministic component. The test based on $\tau_{\alpha\mu}$ rejected the deterministic component being different from 0 and ϕ_1, although less clear, appeared do the same.

Model 3

Model 3 has a unit root ($p > 0.1$). The ACF of the residuals of Equation (6.9) does not show significant lags (16 lags included). There are no significant Q statistics.

There was some concern a breakpoint might exist and a Chow Breakpoint Test was performed (Table 6.7). According to this test there is no evidence for a breakpoint at 1998:1.

Table 6.7 Chow Breakpoint Test of DF Model 3 of *SMD* at 1998:1

	Value	Probability
F - statistic	0.29	0.83
Log Likelihood ratio	1.01	0.80

Selection of DF *SMD* model

All three models suggested unit root. Based on the statistics for the deterministic components Model 3 seemed the best model. This is despite the information criteria indicating that Model 1 might be a better model.

This means that the *SMD* has a unit root, it displays a random walk without a drift. Therefore the value of *SMD* in the next period will be close to the current value. However long term predictions of the *SMD* cannot be made confidently if based on its own values only.

Summary of DF test of interest rates

Model 3 was the best DF model for both *CD* and *SMD*. In both cases there were 2 lags. Both analyses initially permitted the use of models that included either 1 or 2 deterministic components. Had either the AIC, the SC or Adj. R^2 been used as a criterion for selecting the optimal model, then in both cases the Model 1 would have been chosen incorrectly. The usual t-statistics and F-statistics do not apply and the critical values provided by Dickey and Fuller (1981) must be used. There are only two options available (sample sizes 25 and 50) that may be of use in the case of the sample size that was used. This resulted in one of the decisions regarding rejecting the null hypothesis or not, not being entirely clear. However it should always be kept in mind that the selection of the p value itself that is used for decision making is a subjective decision too.

Granger Causality of inflation and interest rates

The DF models chosen for *CD* and *SMD* were the same. This was not unexpected when one considers the nature of the time series. One would expect the patterns of the returns of the two interest rates to be similar but with a greater return for the *SMD* because the lender has to forgo the use of his/her assets for a longer period of time. One would also expect that if changes occur, then they would first be noticed in the *CD* rate and they would possibly occur later in the *SMD*. Also because the *SMD* occurs over a longer period of time the curve might have a more smoothed appearance than that of the *CD*.

The RBNZ manipulates the interest rates through the use of the OCR. If the OCR goes up, so will the interest rates. By raising (or lowering) the interest rates, the national production is reduced (or increased) which should result in a reduction (or increase) of inflation (*CPI* in this thesis). Consequently it will be of interest to see what relationship can be detected between two interest rates that are likely to react swiftly to changes of the OCR and the *CPI*.

Given the above considerations Granger Causality tests and Cointegration tests will be performed on the interest rates and inflation.

Various p values for Granger Causality tests for interest rates and inflation are displayed in Table 6.8. The null hypothesis tested in Table 6.8 is that the left hand column (eg *CD*) does not Granger Cause the second column from the left (eg *SMD*). The next row of data in this table calculates Granger Causality in the opposite direction (eg does *CD* Granger Cause *SMD*?). EViews calculates these regressions as follows:

$$CD_t = \alpha_0 + \alpha_1 CD_{t-1} + ... + \alpha_l CD_{t-l} + \beta_1 SMD_{t-1} + ... + \beta_l SMD_{t-l}$$

$$SMD_t = \alpha_0 + \alpha_1 SMD_{t-1} + ... + \alpha_l SMD_{t-l} + \beta_1 CD_{t-1} + ... + \beta_l CD_{t-l}$$

It reports F-statistics are the Wald statistics for the joint hypotheses: $\beta_1 = \cdots = \beta_l = 0$

Table 6.8 P values of Granger Causality tests of interest and inflation rates

Time series		Lags							
		1	2	3	4	5	6	7	8
CD	SMD	0.75	0.22	0.56	0.17	0.33	0.47	0.65	0.31
SMD	CD	0.15	0.19	0.43	0.42	0.49	0.66	0.64	0.09
LOG-CPI	CD	0.008**	0.011*	0.001**	0.09	0.50	0.18	0.21	0.26
CD	LOG-CPI	0.31	0.001**	0.007**	0.007**	0.03*	0.052	0.07	0.0504
LOG-CPI	SMD	0.015*	0.0108*	0.08	0.39	0.57	0.60	0.22	0.51
SMD	LOG-CPI	0.97	0.0002*	0.001**	0.001**	0.007**	0.009**	0.004**	0.011*

Note: Period covered 1994:1 – 2004:1. *(**) denotes rejection of the hypothesis at the 5%(1%) significance level.

There were no significant lags for *CD* and *SMD* (8 lags included). This means that one time series is not Granger Causing the other. They may still react simultaneously to the same stimuli.

The pattern of *SMD* or *CD* on the one hand and CPI on the other hand is quite similar. When the lag number is small *LOGCPI* is Granger Causing *CD* or *SMD*. However, starting from 2 lags, *CD* or *SMD* are Granger Causing *LOGCPI*. The observation that *LOGCPI* Granger Causes either CD or SMD may be explained by the increase in inflation resulting in an increase in the OCR. The latter observation is encouraging because it may mean that the interest rates are indeed associated with reducing or increasing the CPI at a later stage. Obviously both explanations are tentative and confirmation would be subject to further analysis.

Cointegration Analysis

The rationale for carrying out cointegration analyses was explained in the previous section on Granger Causality. Cointegration analysis was performed of the following time series.

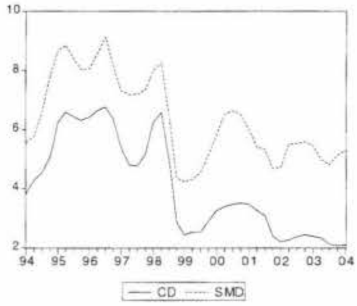
- *CD* *SMD*
- *LOGCPI* *CD*
- *LOGCPI* *SMD*
- *LOGCPI* *CD* *SMD*

The dataset that was used is shown in the appendix. Note that *LOGCPI* in the Vector Error Correction Model (VECM) calculations of contained 4 instead 6 significant digits. The differences in the results are of a minor nature.

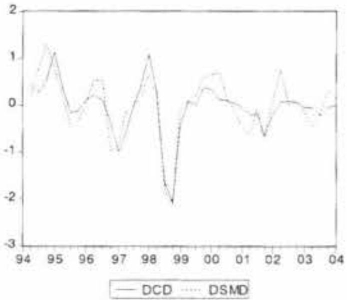
Cointegration analysis of *CD* and *SMD*

Figure 6.3 shows the similar patterns of the original and the differenced time series of *CD* and *SMD*. The return on the *SMD* is consistently better than on the *CD*.

Figure 6.3 Time series and differenced time series of *CD* and *SMD*



Time series of *CD* and *SMD*



Differenced time series of *CD* and *SMD*

Table 6.9 analyses the VECMs of *CD* and *SMD*. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The VECM options include options for the data trend and the Cointegrating Equation (CE). The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order. The best VECM using the SC is Option 4 with 2 lags (Table 6.9). Although these time series did not show any Granger Causality ($p > 0.05$) in Table 6.8, various VECMs were identified in Table 6.9. In fact every one of the 5 options and every lag seemed to be possible, but not every combination of these two.

VECM of *CD* and *SMD*

The best VECM of Table 6.7 according to the SC is displayed in (6.11)

$$\begin{bmatrix} \Delta CD_t \\ \Delta SMD_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.9100} \\ \mathbf{-0.6837} \end{bmatrix} \left[CD_{t-1} - \mathbf{0.7808} SMD_{t-1} + \mathbf{0.0567}t - 0.2983 \right] +$$

$$\begin{bmatrix} \mathbf{0.8851} & -0.3770 \\ 0.4578 & 0.2194 \end{bmatrix} \begin{bmatrix} \Delta CD_{t-1} \\ \Delta SMD_{t-1} \end{bmatrix} + \begin{bmatrix} -0.1702 & -0.3770 \\ -0.1049 & -0.5050 \end{bmatrix} \begin{bmatrix} \Delta CD_{t-2} \\ \Delta SMD_{t-2} \end{bmatrix} + \begin{bmatrix} -0.0321 \\ -0.0182 \end{bmatrix} +$$

$$\begin{bmatrix} \varepsilon_{CD,t} \\ \varepsilon_{SMD,t} \end{bmatrix} \qquad (6.11)$$

where the significant coefficients are in bold typeface.

VECM (6.11) has two significant adjustment factors. However, they are both negative. It is hard to reconcile that these coefficients are both of the same sign, indicating a correction for both time series in the same direction if the series are not in equilibrium.

The significant coefficient of the time-dependent term in the error correction term is difficult to interpret from an economic perspective. Such a term would indicate ongoing divergence which does not make sense for the time series in question where *CD* grows at a faster rate than *SMD*. The shortness of the time series might lead to this type of situations. At the same time there is a constant negative component in the cointegration equation. This may have compensated for the positive trend.

Table 6.9 Cointegration analysis of *CD* and *SMD*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 obser-vations	0	1 1.775330 2.159229	1 1.809640 2.236194	2	2
Lag 1 to 2 38 obser-vations	0	0	0	1 1.471763 **2.118179**	2
Lag 1 to 3 37 obser-vations	0	0	0	1 1.417689 2.244917	2
Lag 1 to 4 36 obser-vations	0	0	0	1 1.242105 2.253798	2
Lag 1 to 5 35 obser-vations	0	0	0	1 1.173019 2.372859	2
Lag 1 to 6 34 obser-vations	0	0	0	1 1.016164 2.407846	2
Lag 1 to 7 33 obser-vations	1 1.533997 2.985156	1 1.546635 3.043142	0	1 **0.617478** 2.204683	2
Lag 1 to 8 32 obser-vations	1 1.232091 2.881044	1 0.932344 2.627101	1 0.807655 2.548216	2	2

Note: Period covered 1994:1 – 2004:1.

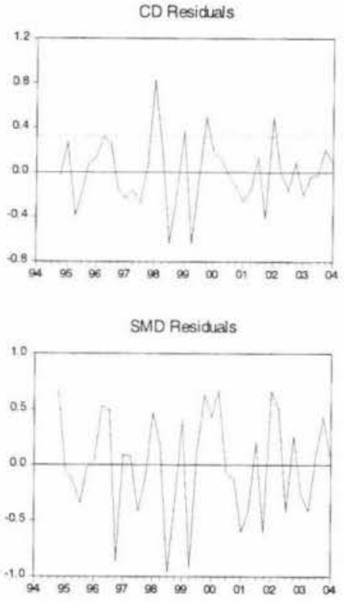
Although the best model included 2 lags, the second lag did not have significant coefficients in VECM (6.11). The only lagged term that was significant in the VECM applied to *CD* at 1 lag. This coefficient indicated a positive correlation.

Residual analysis of VECM of *CD* and *SMD*

Various tests were performed on the residuals to verify that the assumptions for the linear model were met. If not, the model may give misleading information about the system being modelled. Since the VECM was not satisfactory it was considered important to evaluate any deviations of the residuals from the usual assumptions.

The Jarque-Bera value of the residuals of ΔCD is 0.7913 ($p = 0.6733$).
The Jarque-Bera value of the residuals of ΔSMD is 1.5004 ($p = 0.4723$).
The residuals of the VECM appear stationary (Figure 6.4).

Figure 6.4 Residuals of VECM of *CD* and *SMD*



The ACF of the residuals of ΔCD_t appears significant at 2, 7, 11 and 16 lags and the Q statistics at lag 5 and from lag 7 onward are significant (16 lags included). The ACF of the residuals of ΔSMD_t appears significant at lag 7 and the Q statistics at lag 7 and from lag 10 onward are significant (16 lags included).

The correlation coefficient of the residuals of ΔCD_t and ΔSMD_t is 0.7900. They are also positively cross-correlated at lag 7 and lead 16, and negatively at lead 11..

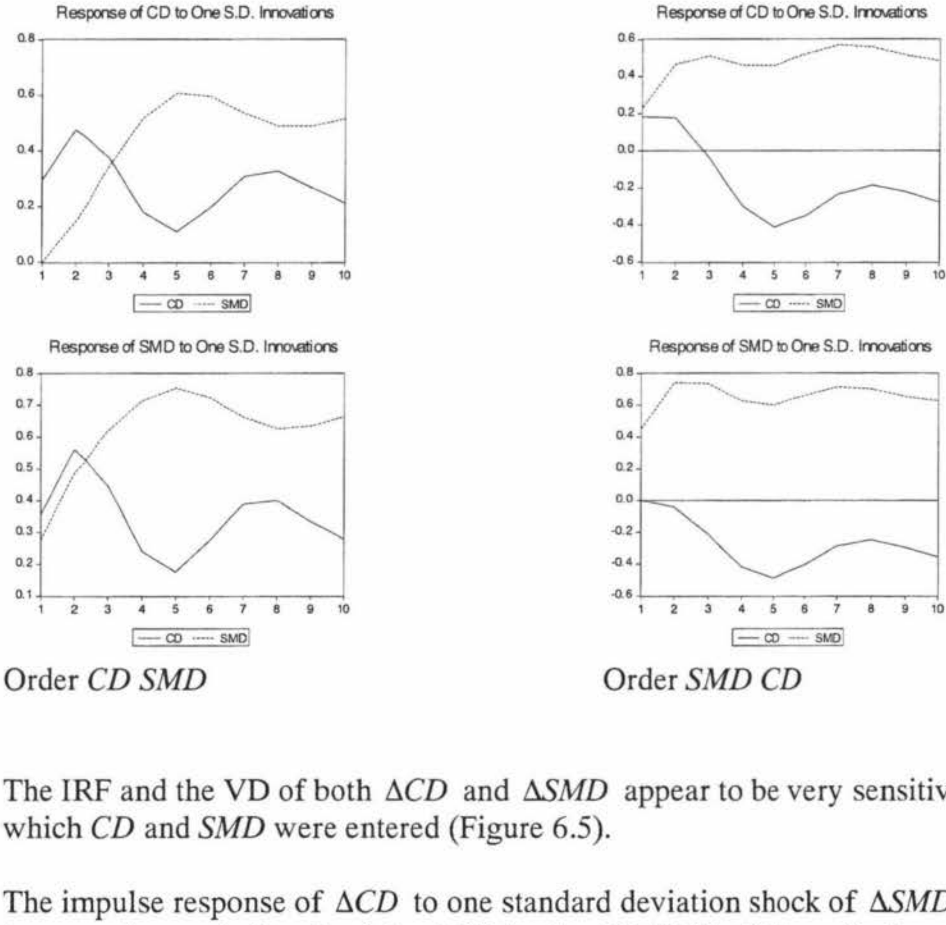
The autocorrelations of the residuals of VECM (6.11) is of concern since it may be associated with the problems identified in the VECM. Consequently VECMs with 1 to 3 lags and 1 cointegration equation were attempted. In all cases a considerable degree autocorrelation of the residuals of ΔCD_t remained. The cross-correlations remained high, especially at lag 0. None of these models was considered a suitable replacement for (6.11).

A model with 4 lags did not have ACFs of the residuals with significant lags. Neither were there significant Q statistics. The cross-correlation of the residuals at lag 0 remained high. This model might be better than (6.11). However it was considered that it eventuated from a less than desirable approach and the accusation of data dredging could be made.

Innovation Accounting

Despite the problems with the residuals that are explained above the Impulse Response Function and the Variance Decomposition were evaluated. As explained above, the correlation coefficient of the residuals of (6.11) is 0.789958. This number is very high and is likely to affect the results of the Impulse Response Function (IRF) and the Variance Decomposition (VD).

Figure 6.5 Impulse Response Function of VECM of *CD* and *SMD*

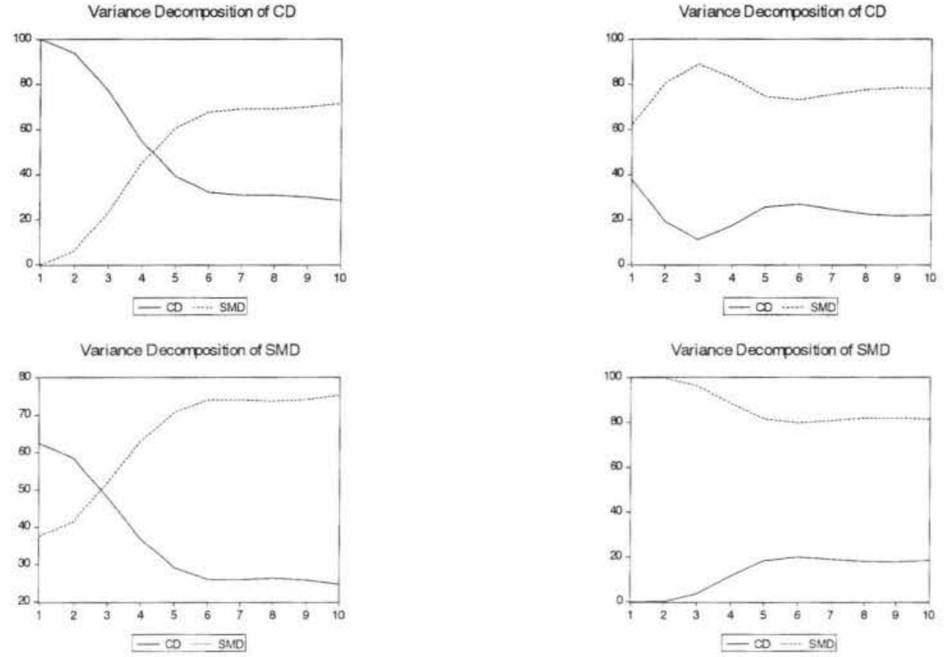


Order *CD SMD* | Order *SMD CD*

The IRF and the VD of both ΔCD and ΔSMD appear to be very sensitive to the order in which *CD* and *SMD* were entered (Figure 6.5).

The impulse response of ΔCD to one standard deviation shock of ΔSMD is greater in the long run than a similar shock by ΔCD (order *CD SMD*). If the order is reversed the response for one is positive and the other is negative. The impulse responses of ΔSMD for both orders show they react stronger to one SD innovation of ΔSMD than ΔCD after several periods (Order *CD SMD*). Again, if the order is reversed a positive and a negative response eventuate. One would expect that shocks to the very short term interest rate (*CD*) has a larger impact on either of the time series than a shock to the longer term interest rate. However this is not what the IRF seems to suggest.

Figure 6.6 Variance Decomposition of VECM of *CD* and *SMD*



Order *CD SMD* Order *SMD CD*

The variance decomposition of ΔCD (order *CD SMD*) is initially mainly taken up by *CD* but later *SMD* dominates. If the order is reversed *SMD* seems to be determining most of the variance from the beginning. In the long run both orders show some agreement.
At the early lags the variance decomposition of ΔSMD also shows considerable differences between the two different orders. At the later lags the results become more similar.
In both cases in the long run the variance of each time series is mainly caused by *SMD*.

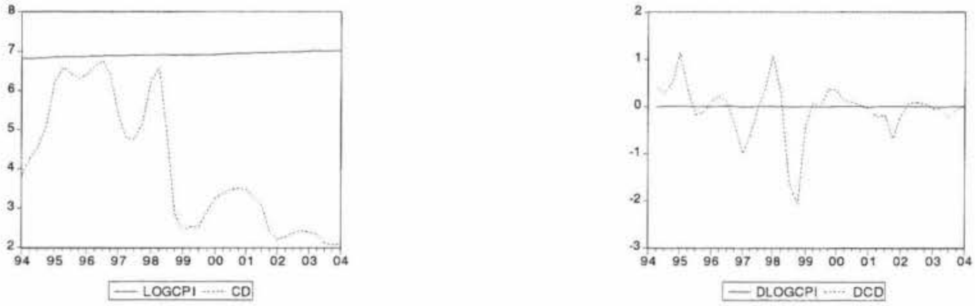
Discussion of VECM of *CD* and *SMD*

The standard approach to find an acceptable VECM resulted in (6.11) However, this VECM appeared to be rather unsatisfactory both from a statistical and from an economic perspective. Some other models were explored (data not shown) that were not satisfactory either. The intention was to arrive at a model by using a structured approach. Without pre-empting the discussion on this topic in the general discussion it can already be stated that this seemed not very successful in this case. The alternative to try models in a haphazard way until a reasonable model eventuates seems a questionable approach from an economic perspective. It should be considered that Granger Causality did not result in any significant results. The intention of this thesis includes contrasting Granger Causality results with Cointegration results. The outcome may be that Granger Causality is to be used to make some cointegration tests inadmissible. The DF tests for both time series had suggested they had a unit root without a constant or trend and with two lags. The VECM indicated two lags but the second lag did not have any significant coefficients. The VECM also indicated a constant which was not in agreement with the DF models.

Cointegration analysis of *LOGCPI* and *CD*

One might expect that an association exists between inflation and interest rates. A rise in inflation may result in higher interest rates. This is because the RBNZ tries to dampen inflation by increasing the OCR. Also higher interest rates may be required to compensate for the diminished real returns. The analysis below was performed to see whether such an association could be distinguished. Figure 6.7 gives the impression there is little or no association between *LOGCPI* and *CD*. However, Table 6.1 has already provided strong support for Granger Causality.

Figure 6.7 Time series and differenced time series of *LOGCPI* and *CD*



Time series of *LOGCPI* and *CD* Differenced time series of *LOGCPI* and *CD*

Table 6.10 analyses the VECMs of *LOGCPI* and *CD*. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order. The best VECM using both the SC and the AIC is Option 4 with 1 lag (Table 6.10). As with previous analyses of other time series, the vast array of VECMs with different options and lags is of concern.

VECM of *CD* and *LOGCPI*

The best VECM of Table 6.8 according to the SC and AIC is displayed in (6.12)

$$\begin{bmatrix} \Delta CD_t \\ \Delta LOGCPI_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.4887} \\ -0.0016 \end{bmatrix} \left[CD_{t-1} - \mathbf{43.2862} LOGCPI_{t-1} + \mathbf{0.3144} t + 288.8693 \right] +$$

$$\begin{bmatrix} \mathbf{0.7419} & -16.0997 \\ \mathbf{0.0048} & 0.0381 \end{bmatrix} \begin{bmatrix} \Delta CD_{t-1} \\ \Delta LOGCPI_{t-1} \end{bmatrix} + \begin{bmatrix} 0.0590 \\ \mathbf{0.0051} \end{bmatrix} + \begin{bmatrix} \varepsilon_{CD,t} \\ \varepsilon_{LOGCPI,t} \end{bmatrix} \qquad (6.12)$$

where the significant coefficients are in bold typeface.

Table 6.10 Cointegration analysis of *LOGCPI* and *CD*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 obser-vations	1 -6.771203 -6.429959	2	1 -7.083172 -6.656618	1 **-7.227654** **-6.758444**	2
Lag 1 to 2 38 obser-vations	1 -7.068689 -6.551556	2	0	0	0
Lag 1 to 3 37 obser-vations	1 -7.004621 -6.308008	1 -6.950568 -6.210416	0	0	0
Lag 1 to 4 36 obser-vations	0	0	0	0	0
Lag 1 to 5 35 obser-vations	0	1 -6.772333 -5.661370	0	1 -7.166540 -5.966700	2
Lag 1 to 6 34 obser-vations	1 -6.679233 -5.422230	2	0	1 -6.950907 -5.559225	2
Lag 1 to 7 33 obser-vations	0	0	0	0	2
Lag 1 to 8 32 obser-vations	0	1 -6.725835 -5.031077	1 -6.865532 -5.124970	1 -6.804697 -5.018331	2

Note: Period covered 1994:1 – 2004:1

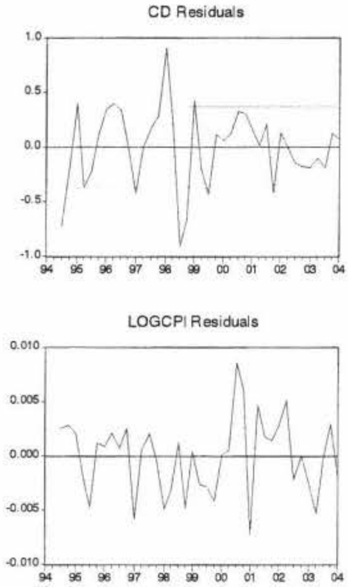
The CE shows that *CD* reacts to changes of divergence of the *LOGCPI* and *CD* series. The reverse does not appear to be the case in (6.12). Both differenced time series show a correlation with ΔCD_{t-1}. Similar to VECM (6.11) there is a time-dependence in the error correction term. However both coefficients of these deterministic components in the CE are positive. The increase in their difference therefore increases in a quadratic manner over time which does not appear plausible in an economic sense in the long term. The constant term in the data for $\Delta LOGCPI$ is plausible since it indicates an ongoing constant increase.

Analysis of residuals of VECM of *CD* and *LOGCPI*

The Jarque-Bera value of the residuals of ΔCD CD is 0.0922 (p = 0.9522)
The Jarque-Bera value of the residuals of $\Delta LOGCPI$ is 1.1755 (p = 0.5556)
The residuals of VECM (6.12) appear stationary (Figure 6.8).

The ACF of the residuals of $\Delta LOGCPI_t$ and ΔCD_t do not appear significant with the possible exceptions lag 10 for $\Delta LOGCPI_t$ and lag 16 for ΔCD_t. The Q statistics are not significant. The correlation coefficient at lag 0 was 0.1690. The rest of the cross-correlogram shows a significant value after a lead of 8 periods and possibly a lag of 4 periods and a lead of 10 periods. It is concluded that although not perfect, the residuals appear to behave in an acceptable manner.

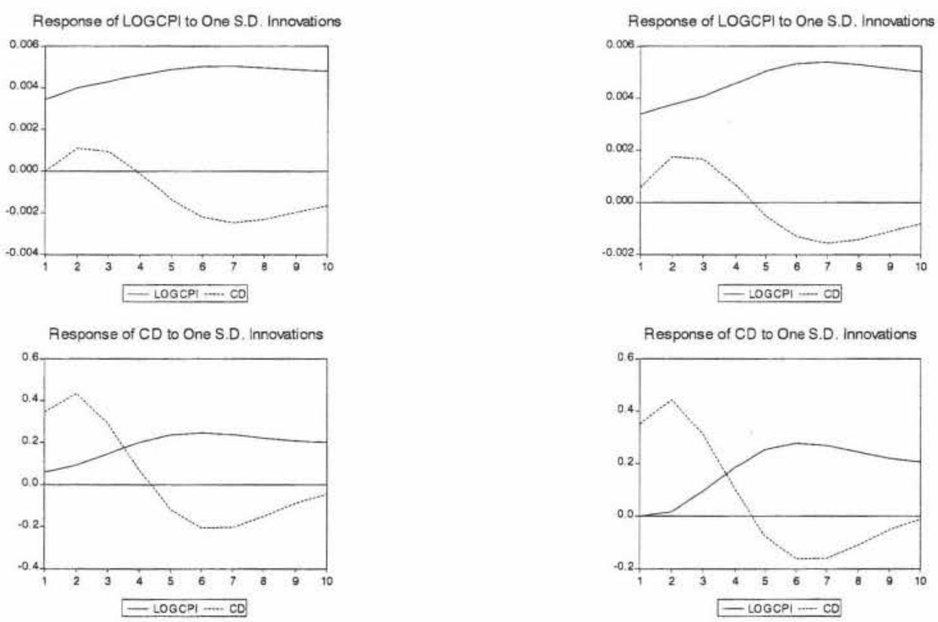
Figure 6.8 Residuals of VECM of *CD* and *LOGCPI*



Innovation accounting

The correlation coefficient of $\Delta LOGCPI_t$ and ΔCD_t is 0.1690. This number is relatively low and not likely to affect the results of the Impulse Response Function and the Variance Decomposition. This is borne out by Figures 6.9 and 6.10.

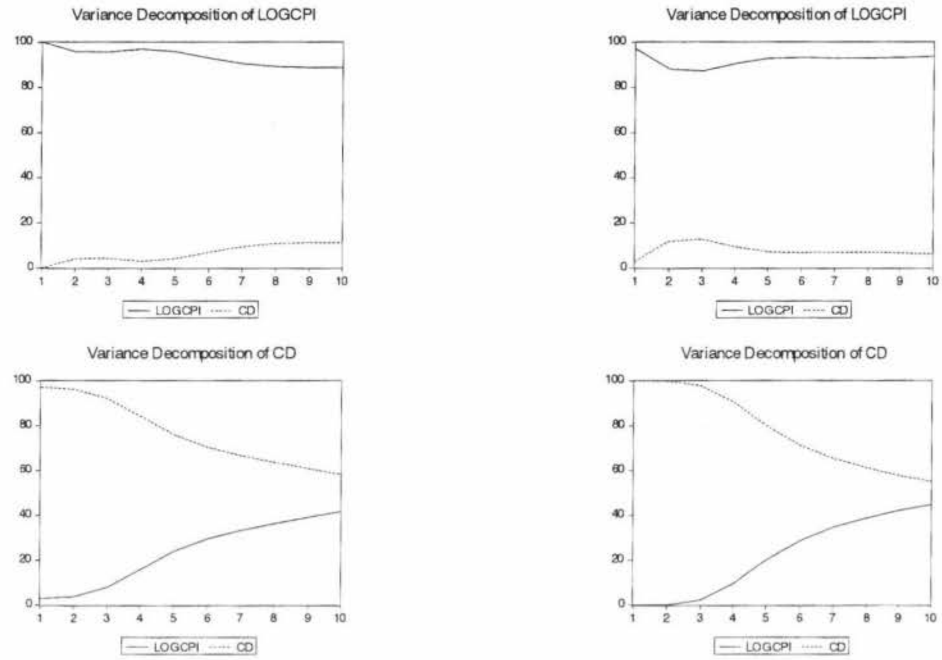
Figure 6.9 Impulse Response Function of VECM of *LOGCPI* and *CD*



Order LOGCPI CD | Order CD LOGCPI

The response of $\Delta LOGCPI$ seems susceptible to shocks to $\Delta LOGCPI$ but little to shocks to ΔCD. The response of ΔCD in the long-run is greater if shocks are applied to $\Delta LOGCPI$ than shocks to ΔCD.

Figure 6.10 Variance Decomposition of VECM of *LOGCPI* and *CD*



Order *LOGCPI CD* Order *CD LOGCPI*

The variance of $\Delta LOGCPI$ is mainly determined by its own past. However the variance of ΔCD is influenced by $\Delta LOGCPI$ to a considerable degree.

Discussion of VECM *LOGCPI* and *CD*

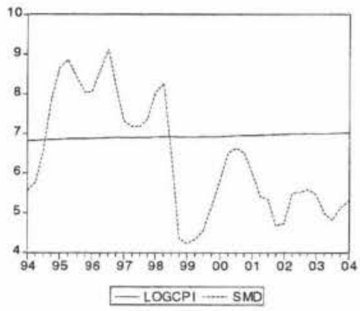
VECM (6.12) seemed better behaved than (6.11). The model seems acceptable from a statistical perspective and plausible from an economic perspective. The main impression is that *CD* reacts to *LOGCPI* but not the other way. This reflects RBNZ policy of increasing the OCR (and consequently *CD*) if inflation accelerates. Granger Causality also showed an effect of *CD* on *LOGCPI*. Had a VECM been chosen with more lags this effect might have been evident. However, the structured approach that is attempted throughout this thesis does not permit for this situation.

Model 2 had been chosen for LOGCPI, although this was for a longer time series. A constant was also identified in (6.12). However there was no significant lagged difference term for LOGCPI in (6.12).

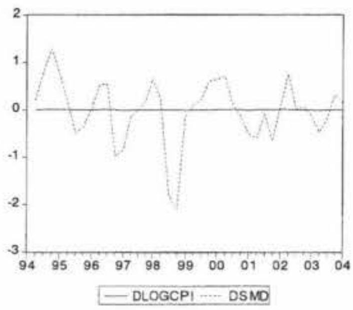
Cointegration analysis of *LOGCPI* and *SMD*

Figure 6.11 gives the impression there is little or no association between *LOGCPI* and *SMD*. However, Table 6.8 has already provided strong support for Granger Causality. Therefore it is still of interest to further investigate the relationship between these two time series. The apparent conflict cannot be explained easily. If anything it should be seen as an encouragement to perform statistical tests in addition to inspecting figures.

Figure 6.11 Time series and differenced time series of *LOGCPI* and *SMD*



Time series of *LOGCPI* and *SMD*



Differenced time series of *LOGCPI* and *SMD*

Table 6.11 analyses the VECMs of *LOGCPI* and *SMD*. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order. The best VECM using the SC is Option 5 with 1 lag (Table 6.11). The AIC leads to the same conclusion.

VECM of *LOGCPI* and *SMD*

The optimal model according to the information criteria is displayed in (6.13).

$$\begin{bmatrix} \Delta SMD_t \\ \Delta LOGCPI_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.5273} \\ -0.0004 \end{bmatrix} \left[SMD_{t-1} - \mathbf{47.911} LOGCPI_{t-1} + 0.3050t + 318.7660 \right] +$$

$$\begin{bmatrix} \mathbf{0.7640} & -9.5975 \\ \mathbf{0.0048} & -0.0335 \end{bmatrix} \begin{bmatrix} \Delta SMD_{t-1} \\ \Delta LOGCPI_{t-1} \end{bmatrix} + \begin{bmatrix} 0.0625 \\ \mathbf{0.0055} \end{bmatrix} + \begin{bmatrix} -0.0008 \\ -7.79^{-6} \end{bmatrix} t + \begin{bmatrix} \varepsilon_{SMD,t} \\ \varepsilon_{LOGCPI,t} \end{bmatrix} \quad (6.13)$$

where the significant coefficients are in bold typeface.

The model shows that the *SMD* reacts to a deviation of the long-term equilibrium between *SMD* and *LOGCPI*. The intercept and trend in the cointegrating equation are difficult to support from an economic perspective. Both *SMD* and *LOGCPI* are correlated with the *SMD* at one lag.

Table 6.11 Cointegration analysis of *LOGCPI* and *SMD*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 observations	2	2	0	0	1 **-6.990251** **-6.478386**
Lag 1 to 2 38 observations	1 -6.703897 -6.186765	1 -6.684411 -6.124184	0	0	0
Lag 1 to 3 37 observations	0	0	0	0	2
Lag 1 to 4 36 observations	0	0	0	0	1 -6.826038 -5.770359
Lag 1 to 5 35 observations	0	0	0	1 -6.825508 -5.625668	2
Lag 1 to 6 34 observations	1 -6.481605 -5.224603	1 -6.513921 -5.212026	0	2	2
Lag 1 to 7 33 observations	0	0	0	1 -6.748331 -5.161126	2
Lag 1 to 8 32 observations	0	1 -6.363757 -4.669000	1 -6.501365 -4.760804	2	2

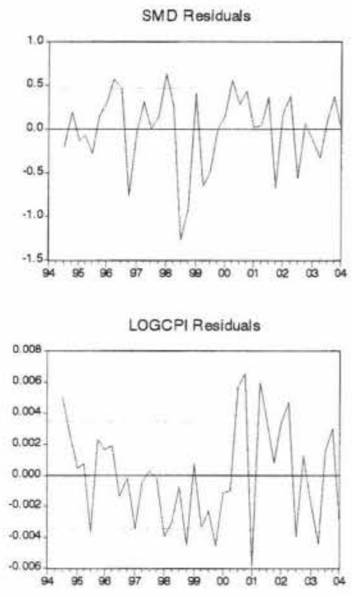
Note: Period covered 1994:1 – 2004:1

Although the VECM of *SMD* and *LOGCPI* (6.13) is different from the VECM of *CD* and *LOGCPI* (6.12), the significant coefficients (in bold) are very similar. Although option 5 indicates a significant quadratic trend in the data, this does not appear to be the case in (6.13). This makes the model more plausible from an economic perspective. However, it calls in question the statistical aspects as to why this option was selected in the first place.

Residual analysis of the VECM of *SMD* and *LOGCPI*

The Jarque-Bera value of the residuals of ΔSMD is 6.601424 (p = 0.036857). This suggests the residuals are not normally distributed.
The Jarque-Bera value of the residuals of $\Delta LOGCPI_t$ is 1.393896 (p = 0.4981).
The residuals of $\Delta LOGCPI_t$ do not appear stationary (Figure 6.12). Especially the mean seems to change over time. The variance of residuals of ΔSMD does not appear to be constant either (Figure 6.12).

Figure 6.12 Residuals of VECM of *LOGCP*I and *SMD*



The ACF of the residuals of ΔSMD_t are not significant. The Q statistics are not significant either. The ACF of the residuals of $\Delta LOGCPI_t$ appears significant at lag 10 and at from lag 10 onward the Q statistics become significant as well (except lag 13).

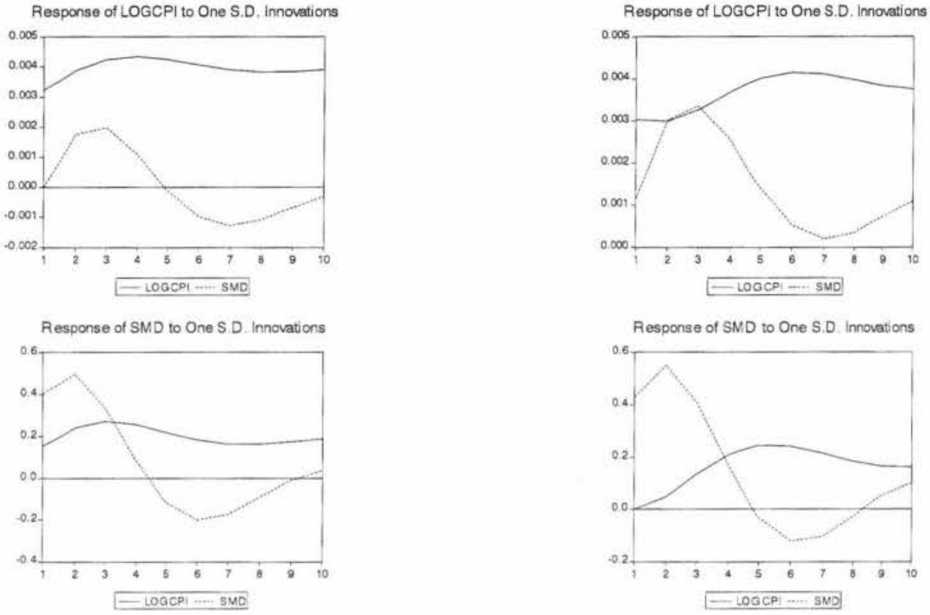
The correlation coefficient of the residuals of $\Delta LOGCPI_t$ and ΔSMD_t is 0.355543. The rest of the cross correlogram does not show significant values with the exception of the lead at period 8.

The residuals of VECM (6.13) are not well-behaved. Since this violates some of the assumptions of the linear model (ie normality), this calls in question the validity of the model. The VECM of *CD* and *LOGCPI* on the one hand and SMD and LOGCPI on the other hand appeared very similar. It is of interest that the residuals of the first one were so well behaved but not those of the second one.

Innovation accounting

The large correlation coefficient may lead to the order in which the series are entered being quite important with regard to the IRF and the VD. The order appears to have some influence but the basic conclusions remain unchanged. In the long run $\Delta LOGCPI$ react strongly to its own shocks but not to those of ΔSMD (Figure 6.13). In the long run ΔSMD responds more to innovations of $\Delta LOGCPI$ than of ΔSMD .

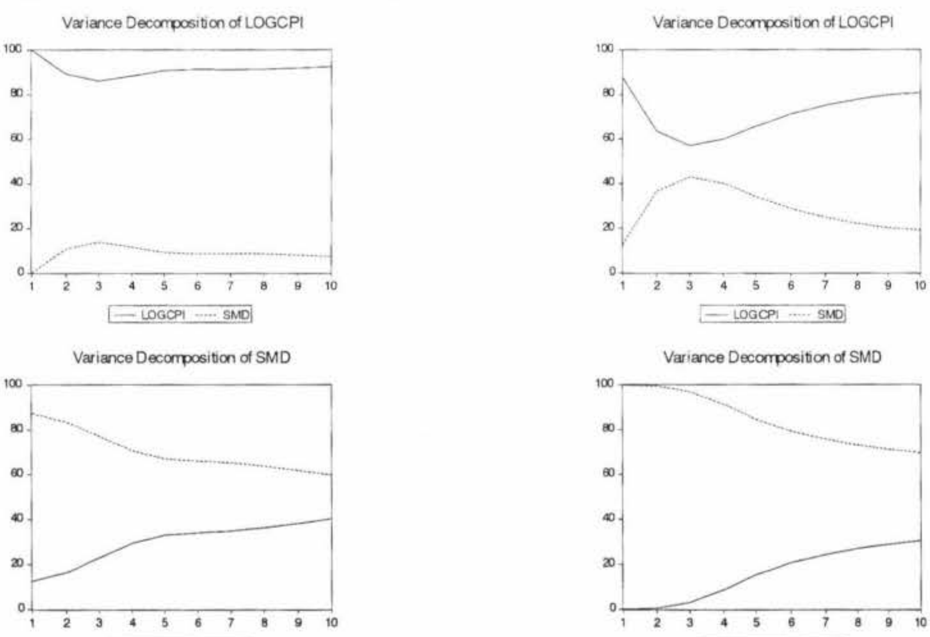
Figure 6.13 Impulse Response Function of VECM of *LOGCPI* and *SMD*



Order *LOGCPI SMD* Order *SMD LOGCPI*

Figure 6.14 shows that the order has a certain influence of the variance decomposition of both $\Delta LOGCPI$ as well as ΔSMD although the general impression remains largely unchanged. The variance of $\Delta LOGCPI$ is mainly determined by its past values, while the variance of ΔSMD is also influenced by the past values of $\Delta LOGCPI$.

Figure 6.14 Variance Decomposition of *LOGCPI* and *SMD*



Order *LOGCPI SMD* Order *SMD LOGCPI*

Discussion of VECM *LOGCPI* and *SMD*

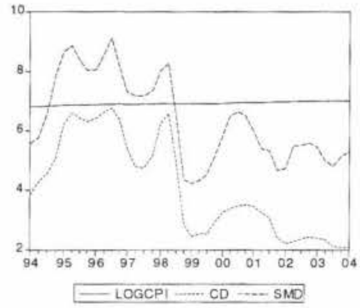
The large number of parameters in VECM (6.13) seem unnecessary and not plausible from an economic perspective. There are considerable similarities with Model (6.14) which is in line with the similarities that are shown in the various previous figures and Figure 6.15.

The *SMD* reacts to changes of *LOGCPI*. This probably reflects economic policy by the RBNZ where the OCR is increased when the inflation rate is deemed to increase too much.

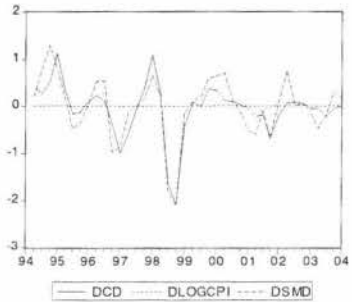
Cointegration analysis of *CD*, *SMD* and *LOGCPI*

Both the *CD* and the *SMD* have shown to have VECMs with *LOGCPI* in the previous two sections. It will now be of interest to enter all three time series in one VECM to evaluate whether or not only one of the two interest rates matters more in such a situation. Figure 6.15 shows that *CD* and *SMD* have a very similar pattern. They do not appear to have an association with *LOGCPI*.

Figure 6.15 Time series and differenced time series of *LOGCPI*, *CD* and *SMD*



Time series of *LOGCPI*, *CD* and *SMD*



Differenced time series of *LOGCPI*, *CD* and *SMD*

Table 6.12 analyses the VECMs of *LOGCPI* and *SMD*. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order. Admissible models can be seen for all options and at all lags. The best VECM using the SC is option 4 with 1 lag (Table 6.12). Both SC and AIC would lead to Option 4 but there is a large difference in the number of lags.

VECM of *CD*, *SMD* and *LOGCPI* (1 cointegrating equation)

The best VECM according to Table 6.12 is:

$$\begin{bmatrix} \Delta CD_t \\ \Delta SMD_t \\ \Delta LOGCPI_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.7476} \\ \mathbf{-0.8209} \\ -0.0016 \end{bmatrix} \left[CD_{t-1} - \mathbf{0.4406} SMD_{t-1} - 20.7467 LOGCPI_{t-1} + \mathbf{0.1750}\, t + 138.6307 \right]$$

$$+ \begin{bmatrix} \mathbf{0.5625} & 0.1041 & \mathbf{-32.1698} \\ 0.2990 & 0.3026 & -42.4272 \\ 0.0010 & 0.0037 & -0.0693 \end{bmatrix} \begin{bmatrix} \Delta CD_{t-1} \\ \Delta SMD_{t-1} \\ \Delta LOGCPI_{t-1} \end{bmatrix} + \begin{bmatrix} 0.1334 \\ 0.2196 \\ \mathbf{0.0055} \end{bmatrix} + \begin{bmatrix} \varepsilon_{CD,t} \\ \varepsilon_{SMD,t} \\ \varepsilon_{LOGCPI,t} \end{bmatrix} \qquad (6.14)$$

where the significant coefficients are in bold typeface.

Table 6.12 Cointegration analysis of *LOGCPI, CD* and *SMD*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1	2	3	2	1	2
39 obser-vations	-6.512965		-6.818658	-6.692002	-6.842001
	-5.617201		-5.794928	**-5.881549**	-5.690304
Lag 1 to 2	1	3	0	0	1
38 obser-vations	-6.497767				-6.658121
	-5.463502				-5.365290
Lag 1 to 3	0	1	1	1	1
37 obser-vations		-6.745071	-6.901029	-6.849970	-6.789218
		-5.264768	-5.333649	-5.239053	-5.091223
Lag 1 to 4	0	1	1	2	3
36 obser-vations		-6.986905	-7.124715	-7.343868	
		-5.095480	-5.145317	-5.012576	
Lag 1 to 5	0	1	1	2	3
35 obser-vations		-7.045030	-7.170906	-7.648715	
		-4.734227	-4.77126	-4.893527	
Lag 1 to 6	0	2	1	2	3
34 obser-vations		-7.534406	-7.746423	**-8.054219**	
		-4.481685	-4.918167	-4.866819	
Lag 1 to 7	1	2	2	3	3
33 obser-vations	-7.403216	-7.689392	-7.761725		
	-4.274155	-4.197541	-4.224525		
Lag 1 to 8					
32 obser-vations			Insufficient number of observations		

Note: Period covered 1994:1 – 2004:1

Equation (6.14) has 2 significant adjustment coefficients. They apply to ΔCD_t and ΔSMD_t. Therefore any adjustment to restore to the long-term relationship is done by the interest rates.

The coefficient of $LOGCPI_{t-1}$ in the cointegrating equation is not significant. Therefore the adjustments apply to the interest rates only. It is of interest that the relationships that were found previously between either of the two interest rates and the inflation rate cannot be detected in this VECM. The trend in the CE has a significant coefficient. In essence the VECM has now been reduced to the VECM which was analysed previously (6.11). The second negative adjustment factor (-0.8209) is problematic. One would expect that the adjustment coefficient of ΔSMD_t be positive to restore the series to its long term equilibrium.

No further analysis of this model is required because of its similarity with (6.11).

VECM of *CD, SMD* and *LOGCPI* (2 cointegrating equations)

Since *LOGCPI* was found to have significant coefficients in the VECM when evaluated with *CD* or *SMD* but not with both of these together, it was deemed of interest to evaluate the next best model according the SC on Table 6.12. This VECM was Option 3 with 1 lag. It had 2 cointegrating equations.

$$\begin{bmatrix} \Delta LOGCPI_t \\ \Delta CD_t \\ \Delta SMD_t \end{bmatrix} = \begin{bmatrix} -0.0345 & -0.0025 \\ \mathbf{-8.8153} & \mathbf{-0.6883} \\ \mathbf{-8.4101} & -0.2772 \end{bmatrix} \begin{bmatrix} LOGCPI_{t-1} + \mathbf{0.0474} SMD_{t-1} - 7.2266 \\ CD_{t-1} - \mathbf{1.3377} SMD_{t-1} + 4.4873 \end{bmatrix} +$$

$$\begin{bmatrix} -0.0613 & 0.0014 & 0.0028 \\ -30.2286 & 0.4440 & 0.0762 \\ -13.7795 & 0.1736 & 0.3886 \end{bmatrix} \begin{bmatrix} \Delta LOGCPI_{t-1} \\ \Delta CD_{t-1} \\ \Delta SMD_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{0.0055} \\ 0.1178 \\ 0.0698 \end{bmatrix} + \begin{bmatrix} \varepsilon_{LOGCPI,t} \\ \varepsilon_{CD,t} \\ \varepsilon_{SMD,t} \end{bmatrix} \tag{6.15}$$

The adjustments in (6.15) are done by the interest rates. In the case of the first CE, if either *LOGCPI* or *SMD* are too high, then a decrease of *CD* and a decrease by *SMD* will occur. *CD* also makes the adjustment if there is a disequilibrium between *CD* and *SMD*. None of the coefficients of the lagged differenced terms is significant. This is surprising since one would have expected some autocorrelation in these time series.

Although the equations should be the same it was considered of interest to change the order in which the time series were placed in the VECM.

$$\begin{bmatrix} \Delta CD_t \\ \Delta SMD_t \\ \Delta LOGCPI_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.6883} & \mathbf{0.5027} \\ -0.2774 & -0.0277 \\ -0.0025 & 0.0017 \end{bmatrix} \begin{bmatrix} CD_{t-1} + \mathbf{28.2095} LOGCPI_{t-1} - 199.3711 \\ \mathrm{SMD}_{t-1} + \mathbf{21.0888} LOGCPI_{t-1} - 152.4001 \end{bmatrix}$$

$$\begin{bmatrix} 0.4440 & 0.0762 & -30.2286 \\ 0.1736 & 0.3886 & -13.7795 \\ 0.0014 & 0.0028 & -0.0613 \end{bmatrix} \begin{bmatrix} \Delta CD_{t-1} \\ \Delta SMD_{t-1} \\ \Delta LOGCPI_{t-1} \end{bmatrix} + \begin{bmatrix} 0.1178 \\ 0.0698 \\ \mathbf{0.0055} \end{bmatrix} + \begin{bmatrix} \varepsilon_{CD,t} \\ \varepsilon_{SMD,t} \\ \varepsilon_{LOGCPI,t} \end{bmatrix} \tag{6.16}$$

Equation (6.16) shows that *CD* is now the only variable that reacts to a disturbance of the long-term equilibrium of the three time series. The long-term equilibria apply to *CD* and *LOGCPI* in the first CE, and *SMD* and *LOGCPI* in the second CE. In both CEs the equilibrium consists of an interest rate plus the inflation being constant. If one views Figure 6.15 one could hypothesise that because the pattern of *CD* and *SMD* appears similar, the adjustment mechanisms would be similar too. However this is not the case in (6.16) where the adjustment coefficient is positive in one CE and negative in the other one. In the first CE, if *LOGCPI* increases, then the long-term equilibrium is restored by a decrease in *CD*. In the bottom CE an increase of *CD* occurs. This latter finding appears hard to explain.

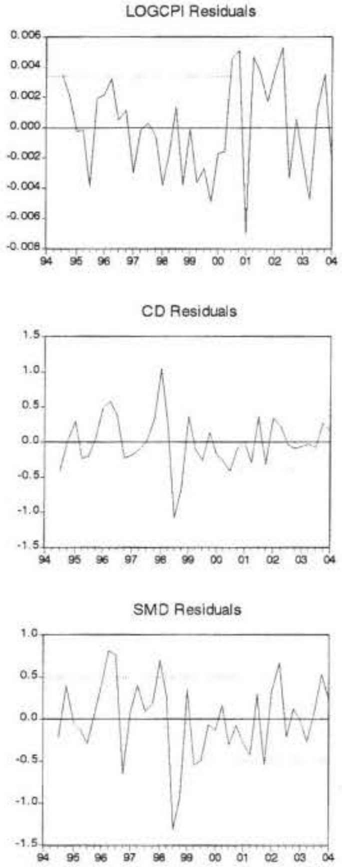
Analysis of residuals of VECM of *LOGCPI*, *CD* and *SMD*

Various tests were performed on the residuals to verify that the assumptions for the linear model were met. If not the model may give misleading information about the system being modelled.

The Jarque-Bera value of the residuals of $\Delta LOGCPI$ is 1.2948 (p = 0.5234)
The Jarque-Bera value of the residuals of ΔCD is 3.9457 (p = 0.1391)
The Jarque-Bera value of the residuals of ΔSMD is 2.0235 (p = 0.3636)

The residuals of $\Delta LOGCPI$ and ΔSMD seem to show that their variances are not constant (Figure 6.16). The mean of all residuals appear constant.

Figure 6.16 Residuals of VECM of *LOGCPI*, *CD* and *SMD*



The ACF of the residuals of $\Delta LOGCPI$ may be significant at lag 10, but the Q statistics are not significant. The ACF of ΔCD appears significant at lag 2. Its Q statistics are significant at lags 2, 3, 7, 9 to 11, 15 and 16. The ACF and the Q statistics of ΔSMD did not show any significant lags. In the case of all these series 16 lags were included.

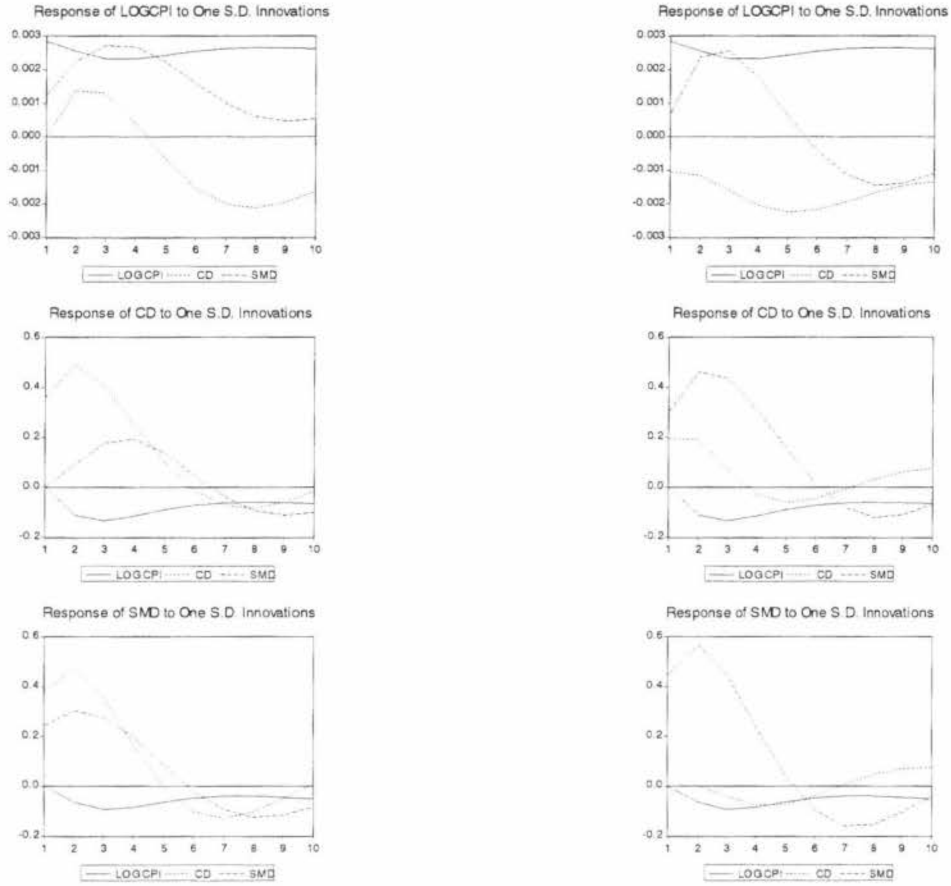
The correlation between the residuals of $\Delta LOGCPI$ and ΔCD is 0.0190.
The correlation between the residuals of $\Delta LOGCPI$ and ΔSMD is 0.2367.
The correlation between the residuals of ΔCD and ΔSMD is 0.8403.

In addition to the above, $\Delta LOGCPI$ and ΔCD seem negatively cross correlated at 8. $\Delta LOGCPI$ and ΔSMD are positively cross-correlated at lead 6. ΔCD and ΔSMD are cross-correlated at lag 7.

The residuals are not particularly well behaved and the sequence of entering ΔCD and ΔSMD is likely to have a considerable effect on the innovation accounting.

Because there are three time series, the time series can be entered into the IRF and the VD in six different orders. For illustrative purposes two different ones will be used.

Figure 6.17 Impulse Response Function of VECM of *LOGCPI*, *CD* and *SMD*



Order *CD*, *SMD*, *LOGCPI*

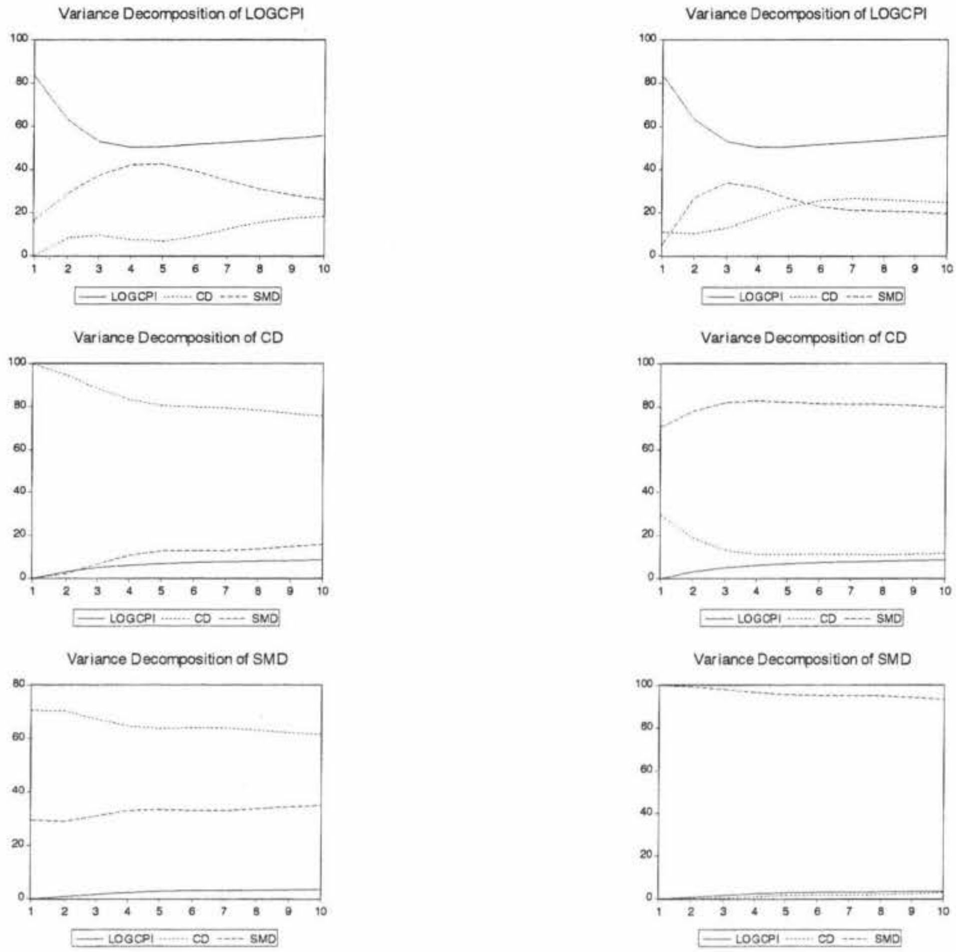
Order *SMD*, *CD*, *LOGCPI*

Regardless of the order, $\Delta LOGCPI$ shows a greater response to shocks to its own time series, than to responses to the other series.

The pattern of response of ΔCD and ΔSMD to shocks to the three times series is the same in the bottom two left hand figures. The same applies to the right hand figures. The peaks in the bottom two figures (both left hand and right hand) after 2 periods for both orders are notable. It is related to the time series (either CD or SMD) that was first entered. After 10 periods this effect has disappeared. Neither Granger Causality nor the VECM can be used to decide which series should be entered first.

The left hand figures show that the VD of the ΔCD is largely made up from shocks to its own series. The same applies for ΔSMD in the right hand figure. The VD of the interest rate that was not entered first is still largely determined by the other interest rate. It illustrates the importance of the order. It also shows that if it is not known which order to use first no robust conclusions can be drawn

Figure 6.18 Variance Decomposition of VECM of *LOGCPI, CD* and *SMD*



Order *CD, SMD, LOGCPI*

Order *SMD, CD, LOGCPI*

Discussion

No Granger Causality was shown to exist between *CD* and *SMD*. The figures and the correlation coefficient showed that these two time series were highly correlated. Although not demonstrated here, they both react strongly and similarly to changes of the OCR.

The VECMs that were analysed showed that both the CD and the SMD reacted to changes of LOGCPI. This makes sense from an economic perspective. There was "no evidence" of the reverse that the inflation rate reacts to changes of the interest rates. This had been shown with Granger causality but was not demonstrated with the VECMs. This may partially be explained by the SC criterion which was parsimonious by choosing models with small numbers of lags (1 or 2) only. However the parsimony did not apply to the options chosen (4 and 5) which included time-dependence.

The time-dependence in the cointegrating equations was not very plausible from an economic perspective. The fact that these factors at times lost their significance when further evaluated was of concern from a statistical perspective.

A large number of VECMs appeared admissible. This is of some concern because it may carry the risk of hypotheses being supported as a result of data dredging. However, it cannot be ruled either that various models may at times be applicable. It should also be considered that the lack of rejection of a model does not mean that the model is correct. It may mean that the time series may not have been large enough to result in rejection.

The residuals were not always well behaved. The raises the question whether one should still consider a hypothesis as not rejected since some of the assumptions did not hold.

CHAPTER 7

TIME SERIES ANALYSES OF GROSS DOMESTIC PRODUCT

Introduction

The Gross Domestic Product and the Output gap play an important role in the management of the inflation by the RBNZ. The basic philosophy is that when the output is too large for the nationally available resources, inflationary pressures will start to increase. This is because a 'bidding war' will start by the various users of these resources. Consequently prices for these resources will increase.

A way to dampen the demand for resources is to increase interest rates. This will make it less attractive to borrow funds for production and expansion of production. The mechanism used by the RBNZ is to the set the level of the Official Cash Rate (OCR). An increase in OCR will result in an increase in interest rates, and in due course a decrease of GDP and a decrease of inflation. Consequently an analysis of these variables in the context of cointegration analysis will be of interest both from a statistical and an economic perspective.

The following two measurements of GDP will be analysed in this chapter.

LOGEGDP	Natural logarithm ($m) of expenditure-based real Gross Domestic Product in 1995/96 dollars. A measure of total final purchases in the economy. It includes stock building.
LOGPGDP	Natural logarithm ($m) of production-based real Gross Domestic Product in 1995/96 dollars. A measure of total value-added in the economy.

The Department of Statistics' web site mentions that the two GDP series are conceptually the same. However different estimation techniques are used. It is interesting from both a statistical and an economic perspective to evaluate to what degree they diverge. Also of interest is to establish whether different conclusions will be arrived at by using the different series.

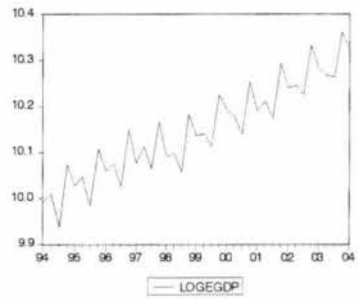
The univariate and multivariate analyses will be carried out as explained in Chapter 2.The standard errors are put in parentheses below each DF equation. The criterion for rejecting a unit root is $p < 0.1$ and the criterion for rejecting the τ and ϕ statistics is $p < 0.05$ (See Chapter 2). Dickey and Fuller (1981) provided critical values for these latter two test statistics. Regrettably if the sample size of this chapter is considered only the sample sizes of 25 and 50 are relevant. Consequently various critical values are required to be shown at times for a test statistic to decide whether a hypothesis is to be rejected or not.

Some of the analyses below may at first sight appear uninformative from an economic perspective. However, they were performed to show the risk of 'data dredging'. By using the standardised techniques that are advocated in this thesis it becomes apparent that at times various hypotheses can be supported. Data dredging is definitely not advocated in this thesis.

Expenditure-based real GDP, seasonally adjusted *(LOGEGDP)*

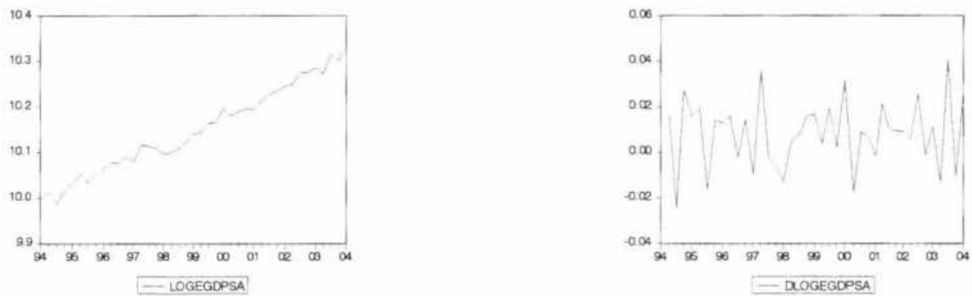
The quarterly time series *LOGEGDP* covers the period 1994:1 to 2004:1 in quarterly periods.

Figure 7.1 Time series of *LOGEGDP*



The time series has an upward trend and displays a seasonal pattern (Figure 7.1). An additive seasonal adjustment as described in Chapter 2 was performed in EViews on the log transformed series.

Figure 7.2 Time series and differenced time of *LOGEGDP* after seasonal adjustment



Time series of *LOGEGDPSA* | Differenced series of *LOGEGDPSA* (*DLOGEGDPSA*)

The seasonally adjusted series (*LOGEGDPSA*) has an upward trend. The variance seems to be constant. The ACF dies down slowly. The differenced series (*DLOGEGDPSA*) appears stationary.

DF Models of *LOGEGDPSA*

The time series of *LOGEGDPSA* was tested for stationarity in (7.1) to (7.5) by using the Dickey-Fuller equations as outlined in Chapter 2.

To keep the description of models (7.1) to (7.5) concise, *LOGEGDPSA* will be denoted as *EGDP* in the equations below.

Model 1

$$\Delta EGDP_t = 6.3609 + 0.0051t - 0.6364EGDP_{t-1} + \varepsilon_t \qquad (7.1)$$
$$(1.5956) \quad (0.0013) \quad (0.1598)$$

Model 2

$$\Delta EGDP_t = -0.1330 + 0.0143EGDP_{t-1} - \Delta EGDP_{t-1} + \varepsilon_t \qquad (7.2)$$
$$(0.2445) \quad (0.0241) \quad (0.1455)$$

Model 2R

$$\Delta EGDP_t = 0.0082 - 0.0124\Delta EGDP_{t-1} + \varepsilon_t \qquad (7.3)$$
$$(0.0025) \quad (0.0360)$$

Model 3

$$\Delta EGDP_t = 0.001206EGDP_{t-1} - 0.5231\Delta EGDP_{t-1} + \varepsilon_t \qquad (7.4)$$
$$(0.0002) \quad (0.1433)$$

Model 3R

$$\Delta EGDP_t = -0.1786\Delta EGDP_{t-1} + \varepsilon_t \qquad (7.5)$$
$$(0.1629)$$

The RSS and various information criteria of these DF tests are displayed in Table 7.1. Model 1 appears to be the best if the information criteria are inspected without considering other issues.

Table 7.1 RSS and information criteria of Dickey-Fuller models of *LOGEGDPSA*

	RSS	AIC	SC	Adj. R^2
Model 1 (7.1)	0.006146	-5.7929	-5.6663	0.2670
Model 2 (7.2)	0.006397	-5.7237	-5.5957	0.2305
Model 2R (7.3)	0.0087			
Model 3 (7.4)	0.0065	-5.7668	-5.6815	0.2451
Model 3R (7.5)	0.011000			

The ADF of (7.1) is -3.9827 (p = 0.01, critical value -4.2023; p = 0.05, critical value -3.5247). There is weak evidence against a unit root in (7.1). The ACF of the residuals of (7.1) does not show significant lags (20 lags included). There are no significant Q statistics.

Model 1 (7.1) is the only model listed above that did not have a significant value for $\Delta EGDP_{t-1}$. This creates problems with the following analyses where a lagged differenced value is required. Consequently the equation with $\Delta EGDP_{t-1}$ included was re-evaluated.

$$\Delta EGDP_t = 4.4716 + 0.0037t - 0.4471EGDP_{t-1} - 0.3016\Delta EGDP_{t-1} + \varepsilon_t \qquad (7.1a)$$
$$(1.8881) \quad (0.0015) \quad (0.1891) \quad (0.1653)$$

RSS = 0.005456 AIC = -5.8315 SC = -5.6609 Adj. R^2 = 0.3249

The DF statistics of Models 1 to 3 of *LOGEGDPSA* are displayed in Table 7.2

Table 7.2 Summary of the Dickey-Fuller tests of *LOGEGDPSA*

Model	Test Statistic	Value	Critical Value (p-value, n[#])	Hypothesis
1 (7.1a)	τ_τ	-2.36	-3.19 (.1)	$\gamma = 0$
	$\tau_{\alpha\tau}$	2.37	2.77 (0.1, 25)	$a_0 = 0$ *given* $\gamma = 0$
			2.75 (0.1, 50)	
	$\tau_{\beta\tau}$	2.46	2.85 (0.05, 25)	$a_2 = 0$ *given* $\gamma = 0$
			2.39 (0.1, 25)	
	ϕ_2	11.85	8.21 (0.01, 25)	$a_0 = \gamma = a_2 = 0$
	ϕ_3	10.41	8.65 (0.025, 25)	$\gamma = a_2 = 0$
			10.61 (0.01, 25)	
			9.31 (0.01, 50)	
2	τ_μ	0.59	$\gamma \succ 0$	$\gamma = 0$
3	τ	5.11	$\gamma \succ 0$	$\gamma = 0$

[#] n listed if p-value for the precise sample size of the time series not known

There appears to be strong support for unit root in the new Model 1 (7.1a). Neither Model 2 nor Model 3 had a unit root.

The ACF of the residuals of (7.1a) does not show significant lags (16 lags included). There are no significant Q statistics.

It is of concern that the strength of conviction of unit root is considerably increased by adding a non-significant term to an equation. Nevertheless, (7.1a) rather than (7.1) will be used for evaluating Model 1.

There are 39 observations after adjusting endpoints. The deterministic component $\tau_{\alpha\tau}$ is not significant ($p > 0.1$) if the hypothesis of unit root is accepted. Whether the term $\tau_{\beta\tau}$ is significant or not is debatable.

The unrestricted and the restricted equations for ϕ_2 are (7.1a) and (7.5) respectively. For ϕ_3 these equations are (7.1a) and (7.3). There are 39 usable observations (T=39) and 4 parameters (k=4) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3 .

It is possible to reject the null hypothesis based on ϕ_2. This can be interpreted as meaning that if the process is unit root, then a_0 and/or a_2 are significant which may be seen as further clarification of the conclusions based on the $\tau_{\alpha\tau}$ and $\tau_{\beta\tau}$ statistics. It is possible to reject the null hypothesis of ϕ_3 ($p < 0.05$). This can be interpreted as meaning that if the process is unit root, then a_2 is significant.

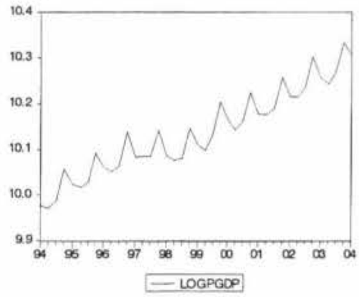
Figure 7.2 did not provide any indication of a breakpoint and the Chow Breakpoint test does not appear required.

Model 1 as described in Equation (7.1a) is the only model that was not rejected as a DF model. The DF model infers a quadratic trend in the undifferenced time series. From an economic perspective this would only be plausible if applied to a short period of time. In the long run a quadratic growth of *LOGEGDPSA* would not be sustainable. However, the constant in this DF model according to the $\tau_{\alpha\tau}$ statistics does not appear significant which largely brings this conclusion in question. The essence of Model 1 is that it contains two deterministic components. In a sense if one of these is not significant, then it can be argued that Model 1 is no longer an appropriate model.

Production-based real GDP, seasonally adjusted *(LOGPGDP)*

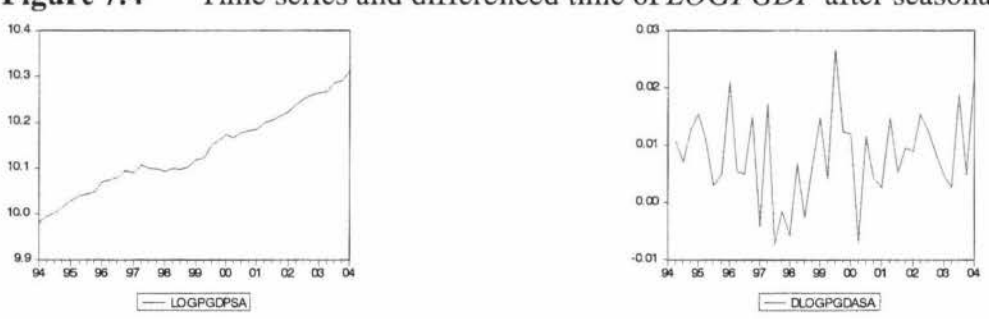
The quarterly time series *LOGPGDP* covers the period from 1994:1 to 2004:1. The series LOGPGDP has an upward trend (Figure 7.3). There is a seasonal pattern.

Figure 7.3 Time series of *LOGPGDP*



The seasonally adjusted series has an upward trend (Figure 7.4). The variance seems to be constant. The ACF dies down slowly. The differenced series of *LOGPGDPSA* (*DLOGPGDPSA*) appears stationary.

Figure 7.4 Time series and differenced time of *LOGPGDP* after seasonal adjustment



Time series of *LOGPGDPSA* | Differenced series of *LOGPGDPSA* (*DLOGPGDPSA*)

DF Models of *LOGPGDPSA*

The time series of *LOGPGDPSA* was tested for stationarity in (7.6) to (7.10) by using the Dickey-Fuller equations as outlined in Chapter 2. To keep the description of models (7.6) to (7.10) concise, *LOGPGDPSA* will be denoted as *PGDP* in the equations below.

Model 1

$$\Delta PGDP_t = 1.8998 + 0.0014t - 0.1899PGDP_{t-1} + 0.0112\Delta PGDP_{t-1} + 0.3837\Delta PGDP_{t-2} + \varepsilon_t$$
$$(1.0775)\,(0.0008)\quad(0.1080)\qquad(0.1778)\qquad(0.1746)\qquad(7.6)$$

Model 2

$$\Delta PGDP_t = -0.0634 + 0.0069PGDP_{t-1} - 0.1036\Delta PGDP_{t-1} + 0.2865\Delta PGDP_{t-2} + \varepsilon_t$$
$$(0.1670)\quad(0.0165)\qquad(0.1723)\qquad(0.1722)\qquad(7.7)$$

Model 2R

$$\Delta PGDP = 0.0066 - 0.0960\Delta PGDP_{t-1} + 0.2935\Delta PGDP_{t-2} + \varepsilon_t$$
$$(0.0024)\quad(0.1693)\qquad(0.1694)\qquad(7.8)$$

Model 3

$$\Delta PGDP_t = 0.0007PGDP_{t-1} - 0.0973\Delta PGDP_{t-1} + 0.2923\Delta PGDP_{t-2} + \varepsilon_t$$
$$(0.0002)\qquad(0.1694)\qquad(0.1694)\qquad(7.9)$$

Model 3R

$$\Delta PGDP_t = 0.1967\Delta PGDP_{t-1} + 0.5910\Delta PGDP_{t-2} + \varepsilon_t$$
$$(0.1450)\qquad(0.1435)\qquad(7.10)$$

The RSS and various information criteria of (7.6) to (7.10) are displayed in Table 7.3. The Adj. R^2 value seems particularly small, indicating that many aspects of this time series are not captured by these models.

Table 7.3 RSS and information criteria of Dickey-Fuller models of *LOGEGDPSA*

	RSS	AIC	SC	Adj. R^2
Model 1	0.002004	-6.7494	-6.5339	0.0826
Model 2	0.002210	-6.704044	-6.5317	0.0179
Model 2R	0.0022221			
Model 3	0.0022	-6.7524	-6.6232	0.0419
Model 3R	0.002716			

The various DF statistics of (7.6) to (7.10) are displayed in Table 7.4

Table 7.4 Summary of the Dickey-Fuller tests of *LOGEGDPSA*

Model	Test Statistic	Value	Critical Value (p-value, n[#])	Hypothesis
1	τ_τ	-1.76	-3.20 (0.1)	$\gamma = 0$
	$\tau_{\alpha\tau}$	1.76	2.75 (0.1, 50)	$a_0 = 0$ *given* $\gamma = 0$
	$\tau_{\beta\tau}$	1.84	2.38 (0.1, 50)	$a_2 = 0$ *given* $\gamma = 0$
	ϕ_2	3.91	4.31 (0.1, 50)	$a_0 = \gamma = a_2 = 0$
	ϕ_3	1.20	5.61 (0.1, 50)	$\gamma = a_2 = 0$
2	τ_μ	0.42	$\gamma \succ 0$	$\gamma = 0$
3	τ	2.80	$\gamma \succ 0$	$\gamma = 0$

[#] n listed if p-value for the precise sample size of the time series not known

Model 1 was the only model that had a unit root. In the case of both Model 2 and Model 3 the unit root was rejected because $\gamma \succ 0$. Model 2 as displayed in (7.7) and in its restricted form (7.8) contains 2 lags. Although not significant they were left in the equations in order to be able to derive the ϕ statistics for Model 1. If the lags were removed from Model 2, the time series still would not have a unit root ($\gamma \succ 0$). Similar to Model 2, Model 3 as displayed in (7.9) and in its restricted form (7.10) contains 2 lags. Although not significant they were left in the equations in order to be able to derive the ϕ statistics. In this case too, removal of the lags did not result in a time series with a unit root ($\gamma \succ 0$).

The ACF of Model 1 (7.6) does not show significant lags (16 lags included). There are no significant Q statistics.

Both deterministic components ($\tau_{\alpha\tau}$ and $\tau_{\beta\tau}$) are not significant ($p > 0.1$) if the hypothesis of unit root is accepted.

The unrestricted and the restricted equations for ϕ_2 are (7.6) and (7.10) respectively. For ϕ_3 these equations are (7.6) and (7.8). There are 38 usable observations (T=38) and 5 parameters (k=5) in the unrestricted models of ϕ_2 and ϕ_3. There are 3 restrictions in ϕ_2 and 2 in ϕ_3.

The null hypothesis that uses ϕ_2 as the test statistic is not rejected. If the process is unit root, then both a_0 and a_2 are not significantly different from 0. The null hypothesis based on ϕ_3 that the process is unit root and a_2 equals 0 is not rejected.

No satisfactory unit root model was identified. Although Model 1 was unit root, the deterministic components appeared not significantly different from 0. Consequently Model 2 or 3 should have been unit root. This was not the case. So yet another failure of the methodology appears to have occurred. It is unclear whether an attempt should be made to explain the model in economic terms. This is because the quadratic trend of the undifferenced time series which Model 1 indicates is not supported by significant deterministic components.

Comparison of DF Models of *LOGEGDPSA* and *LOGPGDPSA*

The Dickey-Fuller analyses of *LOGEGDPSA* and *LOGPGDPSA* resulted in different conclusions. In both cases a form of Model 1 was chosen. *LOGEGDPSA* used one lag while *LOGPGDPSA* used two lags. There was a difference in the degree of significance of the τ and the ϕ statistics. Since both time series are conceptually the same, the difference between them should have been minor. It was acknowledged by the Department of Statistics that timing and valuation problems cause more problems for the expenditure-based GDP than the production-based GDP.

Granger Causality of GDP, inflation and interest rates

The interaction between *GDP*, interest rates and inflation are deemed to be particularly important when monetary policy is set by the RBNZ. Granger Causality tests are performed below to see whether any association can be distinguished (Table 7.5).

The null hypothesis tested in Table 7.5 is that the left hand column (eg *LOGPGDPSA*) does not Granger Cause the second column from the left (eg *LOGEGDPSA*). The next row of data in this table calculates Granger Causality in the opposite direction (eg does *CD* Granger Cause *SMD*?). EViews calculates these regressions as follows:

$$
\begin{aligned}
LOGPGDPSA_t &= \alpha_0 + \alpha_1 LOGPGDPSA_{t-1} + \ldots + \alpha_l LOGPGDPSA_{t-l} + \\
&\quad \beta_1 LOGEGDPSA_{t-1} + \ldots + \beta_l LOGEGDPSA_{t-l} \\
LOGEGDPSA_t &= \alpha_0 + \alpha_1 LOGEGDPSA_{t-1} + \ldots + \alpha_l LOGEGDPSA_{t-l} + \\
&\quad \beta_1 LOGPGDPSA_{t-1} + \ldots + \beta_l LOGPGDPSA_{t-l}
\end{aligned}
$$

It reports F-statistics are the Wald statistics for the joint hypotheses: $\beta_1 = \cdots = \beta_l = 0$

An increase in production-based GDP (*LOGPGDPSA*) appears to 'cause' an increase in expenditure-based GDP (*LOGEGDPSA*). Conceptually the datasets are identical, so this could be considered an anomaly. However, it is also possible that there is some sort of a lag in measuring the LOG*EGDPSA* that is reflected in the Granger Causality tests.

The pattern for *LOGCPI* on the one hand and either *LOGEGDPSA* or *LOGPGDPSA* was very similar. The above tests suggest that both the expenditure-based and the production-based real *GDP* Granger Cause inflation. This can be interpreting as supporting the RBNZ's view of the main cause of inflation. The overheating of the economy (an increase in the output gap) is considered to be a main cause of inflation.

The relationship between the *GPD* indicators and the interest rates appeared to be very similar for the combinations that were used. An increase in *GDP* Granger Causes an increase in interest rates. This can be explained by an increase that is more than deemed desirable by the RBNZ resulting in an increase of the OCR. This in turn results in higher interest rates. It should be noted that the OCR was only used in the latter part of the time series that were evaluated. The Granger Causality tests did not show that higher interest rates result in a reduction of GDP. Various hypotheses might be used to explain these findings. One is that an effect of a variable cannot be seen if this variable is constantly adjusted. Another hypothesis is that the tool in not effective to achieve the results for which it is used.

Table 7.5 P values of Granger causality tests of GDP, interest rates and inflation

Time series		Lags							
		1	2	3	4	5	6	7	8
GDP									
LOG PGDPSA	*LOG EGDPSA*	0.0003**	0.016*	0.10	0.09	0.06	0.13	0.11	0.11
LOG EGDPSA	*LOG PGDPSA*	0.46	0.13	0.20	0.17	0.28	0.44	0.48	0.06
***GDP* and inflation**									
LOG EGDPSA	*LOG CPI*	0.03*	0.007**	0.03*	0.04*	0.06	0.07	0.02*	0.046*
LOG CPI	*LOG EGDPSA*	0.04*	0.36	0.75	0.69	0.49	0.34	0.63	0.86
LOG PGDPSA	*LOG CPI*	0.003**	0.004**	0.012*	0.03*	0.06	0.09	0.04*	0.08
LOG CPI	*LOG PGDPSA*	0.93	0.73	0.70	0.53	0.71	0.72	0.82	0.89
***GDP* and interest rates**									
CD	*LOG EGDPSA*	0.31	0.25	0.21	0.10	0.32	0.26	0.11	0.24
LOG EGDPSA	*CD*	0.03*	0.012*	0.09	0.02*	0.15	0.22	0.04*	0.10
SMD	*LOG EGDPSA*	0.36	0.50	0.26	0.21	0.33	0.24	0.36	0.66
LOG EGDPSA	*SMD*	0.06	0.0195*	0.25	0.24	0.23	0.19	0.012*	0.009**
CD	*LOG PGDPSA*	0.051	0.11	0.26	0.48	0.83	0.85	0.27	0.23
LOG PGDPSA	*CD*	0.03*	0.02*	0.12	0.02*	0.11	0.13	0.03*	0.10
SMD	*LOG PGDPSA*	0.06	0.09	0.22	0.43	0.70	0.65	0.69	0.69
LOG PGDPSA	*SMD*	0.07	0.02*	0.22	0.23	0.11	0.11	0.046*	0.02*

Note: Period covered 1994:1 – 2004:1. *(**) denotes rejection of the hypothesis at the 5%(1%) significance level.

Cointegration Analysis

Cointegration analyses were performed with time series reflecting GDP, CPI, M1 and interest rates. The intention was in particular to analyse what variables affect GDP and CPI and to what degree. It is appreciated that the DF tests above did not explain the presence or absence of a unit root in the time series particularly well. From an economic perspective the existence of a unit root seems quite plausible. These aspects together make it of particular interest to apply cointegration tests to the time series. The combinations of time series that will be analysed are:

GDP
- *LOGEGDPSA* *LOGPGDPSA*

CPI and GDP
- *LOGCPI* *LOGEGDPSA*
- *LOGCPI* *LOGPGDPSA*
- *LOGCPI* *LOGEGDPSA* *LOGPGDPSA*

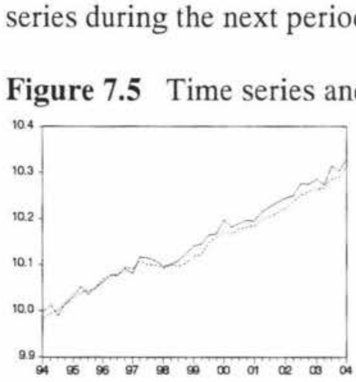
CPI, EGDP and M1
- *LOGCPI* *LOGEGDPSA* *LOGM1SA*
- *LOGCPI* *LOGEGDPSA* *LOGM1SA*

EGDP and interest rates
- *LOGEGDPSA* *CD*
- *LOGEGDPSA* *SMD*

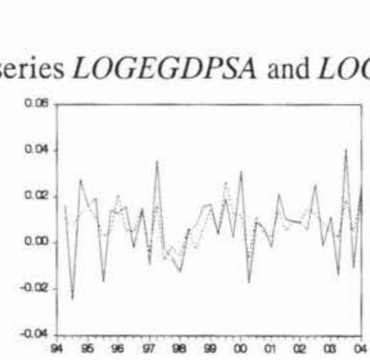
Cointegration analysis of *LOGEGDPSA* and *LOGPGDPSA*

Figure 7.5 shows that *LOGEGDPSA* and *LOGPGDPSA* appear to be moving closely together over time. This is as expected since they are supposed to measure the same. There generally appears to be more variation in the expenditure-based GDP than in the production-based GDP and the reasons were explained when the DF models were discussed. It is questionable whether cointegration tests for these time series will assist much in elucidating basic economic processes. However, it is interesting from the perspective of cointegration analysis of two series that should not diverge too much from each other since they measure the same. The more one series is underestimated at one stage, the more it should move back to the other series during the next period.

Figure 7.5 Time series and differenced time series *LOGEGDPSA* and *LOGPGDPSA*



Time series of *LOGEGDPSA* and *LOGPGDPSA*



Differenced time series of *LOGEGDPSA* and *LOGPGDPSA*

The various cointegration analyses of *LOGEGDPSA* and *LOGPGDPSA* are displayed in Table 7.6. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The VECM options include options for the data trend and the Cointegrating Equation (CE). The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order.

Table 7.6 Cointegration analysis of *LOGEGDPSA* and *LOGPGDPSA*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 obser-vations	2	2	0	1 -13.64279 -13.17356	1 -13.60860 -13.09673
Lag 1 to 2 38 obser-vations	2	0	0	1 -13.89800 **-13.25159**	1 -13.87374 -13.18423
Lag 1 to 3 37 obser-vations	1 -13.33783 -12.64122	0	0	1 -13.72571 -12.89848	2
Lag 1 to 4 36 obser-vations	1 -13.30748 -12.42775	0	0	0	1 -13.61457 -12.55889
Lag 1 to 5 35 obser-vations	1 -13.09958 -12.03306	0	0	0	1 -13.55452 -12.31025
Lag 1 to 6 34 obser-vations	2	1 -13.02875 -11.72685	0	0	0
Lag 1 to 7 33 observations	2	2	0	1 -13.61147 -12.02427	1 -13.66650 -12.03395
Lag 1 to 8 32 obser-vations	2	1 -14.07481 -12.38005	2	2	1 **-14.87658** -13.04441

Note: Period covered 1994:1 – 2004:1.

With the exception of Option 3, all four other options were possible according to the use of cointegration analyses. Similarly all lags were possible as well. The two optimal models based on the SC and the AIC were quite different. The SC was considerably more parsimonious than the AIC.

VECM of *LOGEGDPSA* and *LOGPGDPSA*

To keep the description of the VECM (7.11) concise, *LOGEGDPSA* will be denoted as *EGDP* and *LOGPGDPSA* as *PGDP*.

$$\begin{bmatrix} \Delta EGDP_t \\ \Delta PGDP_t \end{bmatrix} = \begin{bmatrix} \mathbf{-2.0293} \\ -0.3374 \end{bmatrix} \left[EGDP_{t-1} - \mathbf{0.6822} PGDP_{t-1} - \mathbf{0.0029} t - 3.1718 \right] +$$

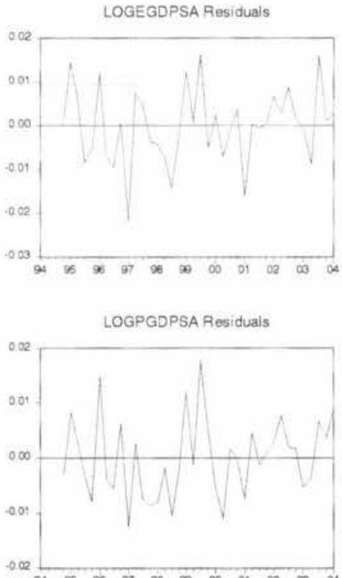
$$\begin{bmatrix} 0.4275 & 0.0745 \\ -0.0612 & 0.0953 \end{bmatrix} \begin{bmatrix} \Delta EGDP_{t-1} \\ \Delta PGDP_{t-1} \end{bmatrix} + \begin{bmatrix} 0.3753 & 0.2643 \\ -0.0191 & 0.3692 \end{bmatrix} \begin{bmatrix} \Delta EGPD_{t-2} \\ \Delta PGDP_{t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{EGDP,t} \\ \varepsilon_{PGDP,t} \end{bmatrix} \tag{7.11}$$

where the significant coefficients are in bold typeface.
The results of the Granger Causality test seem reflected in the VECM in that *LOGEGDPSA* reacts to changes in *LOGPGDPSA*. Equation (7.11) has two lags according to the cointegration analysis but no significant coefficients were identified in these lags.

Residual analysis of VECM of *LOGEGDPSA* and *LOGPGDPSA*

Various tests were performed on the residuals to ensure that the assumptions for the linear model were met. If not the model may give misleading information about the system being modelled.
The Jarque-Bera value of the residuals of $\Delta LOGEGDPSA$ is 0.1572 ($p = 0.9244$).
The Jarque-Bera value of the residuals of $\Delta LOGPGDPSA$ is 1.2558 ($p = 0.5337$).
The residuals of the VECM appear stationary (Figure 7.6).

Figure 7.6 Residuals of VECM of *LOGEGDPSA* and *LOGPGDPSA*



The ACF of the residuals of $\Delta LOGEGDPSA$ and of $\Delta LOGPGDPSA$ at up to 16 lags appear not significant and their Q statistics are not significant either. The assumptions that underlie the linear model seem justified.

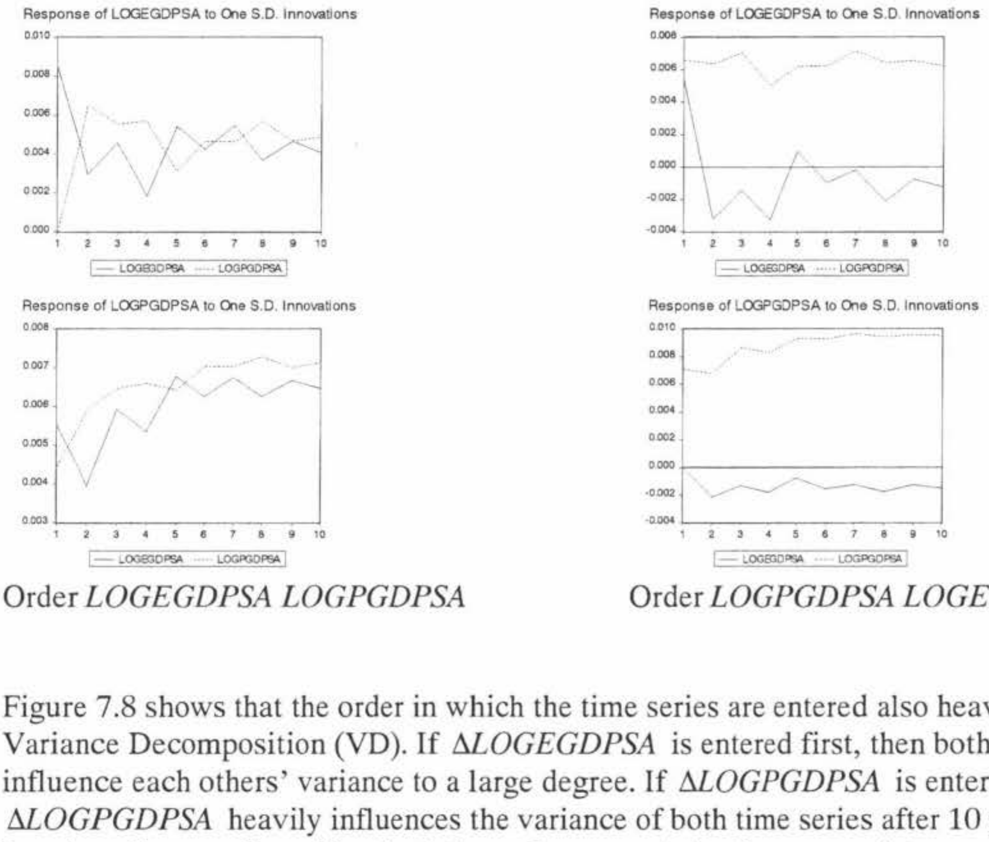
The correlation coefficient of the residuals of $\Delta LOGEGDPSA$ and $\Delta LOGPGDPSA$ is 0.7784. They are not cross-correlated at the other lags of the cross-correlogram.

Innovation accounting

The order in which the time series are entered results in a large difference between the Impulse Response Functions (IRF) (Figure 7.7). This is a result of the high correlation coefficient.

If *LOGPGDPSA* is entered first, then the response of both $\Delta LOGPGDPSA$ and $\Delta LOGEGDPSA$ to innovations of $\Delta LOGPGDPSA$ is large. Their response to an innovation from $\Delta LOGEGDPSA$ is small. Granger Causality would suggest this is the proper order to put the time series in. If the other option was taken ($\Delta LOGEGDPSA$ first) then the conclusion would have been quite different. Both time series react in a similar manner to the innovations.

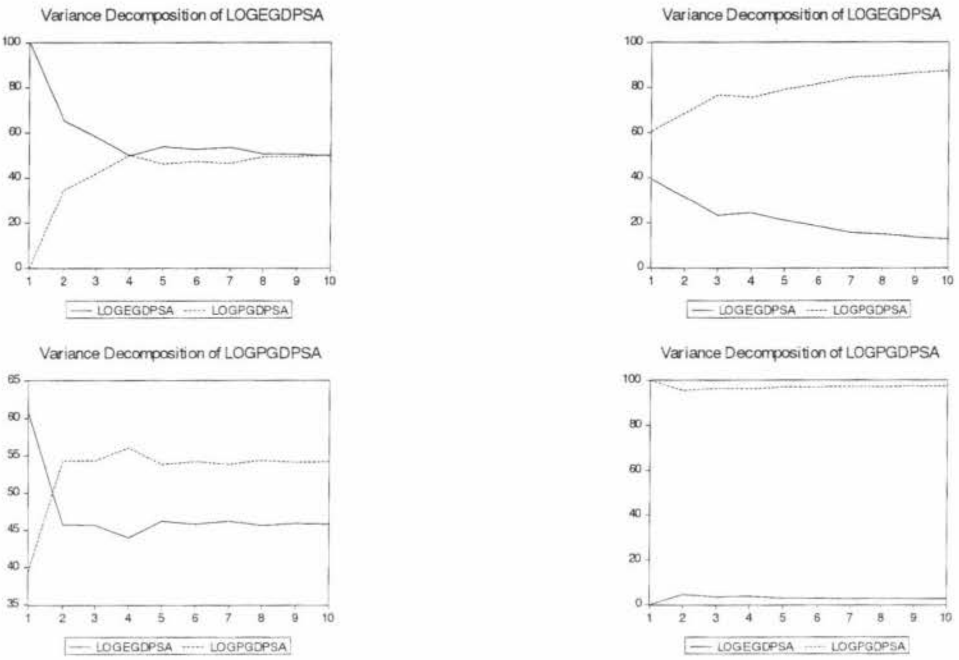
Figure 7.7 Impulse Response Function of VECM of *LOGEGDPSA* and LOGPGDPSA



Order *LOGEGDPSA LOGPGDPSA* Order *LOGPGDPSA LOGEGDPSA*

Figure 7.8 shows that the order in which the time series are entered also heavily influences the Variance Decomposition (VD). If $\Delta LOGEGDPSA$ is entered first, then both time series influence each others' variance to a large degree. If $\Delta LOGPGDPSA$ is entered first, then $\Delta LOGPGDPSA$ heavily influences the variance of both time series after 10 periods. Again, based on Granger Causality, the latter order seems to be the appropriate one.

Figure 7.8 Variance Decomposition of VECM of *LOGEGDPSA* and *LOGPGDPSA*



Order *LOGEGDPSA LOGPGDPSA* Order *LOGPGDPSA LOGEGDPSA*

Discussion of VECM of *LOGEGDPSA* and *LOGPGDPSA*

Table 7.6 showed that a large number of VECMs could be admissible. The best model according to the AIC would have been option 5 with 8 lags. Since the data of the GDP series basically measure the same, this lag does not appear plausible. The SC resulted in a model with a considerably smaller number of variables. This was in line with the results of the Granger Causality test. Eight lags with 32 remaining observations would have used up a lot of degrees of freedom too!

However, VECM (7.11) was rather unsatisfactory with the lag values that were not significant. The residuals were well behaved.

The strong correlation between the residuals of the VECM made the interpretation of the IRF and the VD rather difficult. Granger Causality was of assistance to make a justifiable decision to place most trust in the option where LOGPGDPSA was used first.

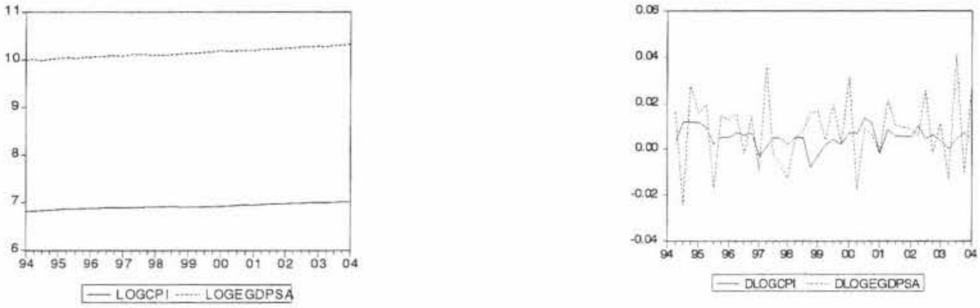
The tests show $\Delta LOGEGDPSA$ reacts to changes in $\Delta LOGPGDPSA$. The IRF and VD also clearly showed the importance of $\Delta LOGPGDPSA$ on $\Delta LOGEGDPSA$ over time.

The conclusion is reached that production-based GDP has a large impact on expenditure-based GDP. Reducing the first one will affect the second one. The opposite does not appear to be the case. An economic explanation cannot be given in principle since the data series are intended to be the same. However the findings may reflect the data collection process and this would constitute an important finding. The results indicate that the different methodologies result in different interpretations which in turn might affect economic policy.

Cointegration analysis *LOGCPI* and *LOGEGDPSA*

The output gap may considerably affect inflation and the cointegration analyses below use *LOGCPI* and *LOGEGDPSA* to evaluate this. Both undifferenced time series in Figure 7.9 are trending upward with apparently little variation. However, the differenced time series which have stationary means show that the variation of *DLOGEGDPSA* is greater than that of *DLOGCPI*.

Figure 7.9 Time series and differenced time series of *LOGCPI* and *LOGEGDPSA*



Time series of *LOGCPI* and *LOGEGDPSA* — Differenced time series of *LOGCP*I and *LOGEGDPSA*

Table 7.7 shows the results of the cointegration analyses of *LOGCPI* and *LOGEGDPSA*. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The VECM options include options for the data trend and the Cointegrating Equation (CE). The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order. The best model according to the SC is Model 3 with 1 lag only. All 5 models were possible in principle. The model chosen by the SC and the AIC were quite different.

VECM of *LOGCPI* and *LOGEGDPSA*

VECM (7.12) shows that the differenced *LOGCPI* reacts to the difference between *LOGCPI* and *LOGEGDPSA* (ie the cointegration equation). In addition it reacts to the lagged differenced values of both *LOGCPI* and *LOGEGDPSA*. The association with its own lagged differenced observation is a positive one. The association with the *LOGEGDPSA* time series is negative. Both differenced time series have a constant term indicating a linear trend over time.

The *LOGEGDPSA* was not sensitive to the cointegration equation.

$$\begin{bmatrix} \Delta CPI_t \\ \Delta EGDP_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.2257} \\ 0.2821 \end{bmatrix} \left[CPI_{t-1} \quad \mathbf{-0.5439 EGDP_{t-1}} \quad -1.4007 \right] +$$

$$\begin{bmatrix} \mathbf{0.3485} & \mathbf{-0.0898} \\ -0.4222 & \mathbf{-0.4311} \end{bmatrix} \begin{bmatrix} \Delta CPI_{t-1} \\ \Delta EGDP_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{0.0040} \\ \mathbf{0.0136} \end{bmatrix} + \begin{bmatrix} \varepsilon_{CPI,t} \\ \varepsilon_{EGDP,t} \end{bmatrix} \qquad (7.12)$$

where *CPI* is *LOGCPI*, *EGDP* is *LOGEGDPSA* and significant coefficients are in bold typeface.

Table 7.7 Cointegration analysis *LOGCPI* and *LOGEGDPSA*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 obser- vations	1 -13.62252 -12.28128	2	1 -13.91596 **-13.48941**	0	1 -13.88934 -13.37748
Lag 1 to 2 38 obser- vations	1 -13.64424 -13.12710	1 -13.68436 -13.12413	0	0	1 **-13.92218** -13.23231
Lag 1 to 3 37 obser- vations	1 -13.6554 -12.9588	1 -13.6784 -12.9383	0	0	0
Lag 1 to 4 36 obser- vations	1 -13.6016 -12.72186	2	0	0	0
Lag 1 to 5 35 observations	0	0	0	0	0
Lag 1 to 6 34 observations	0	0	0	0	2
Lag 1 to 7 33 obser- vations	0	0	0	1 -13.5077 -11.9205	2
Lag 1 to 8 32 obser- vations	1 -13.1321 -11.4832	2	1 -13.5245 -11.7839	1 -13.4720 -11.6856	2

Note: Period covered 1994:1 – 2004:1

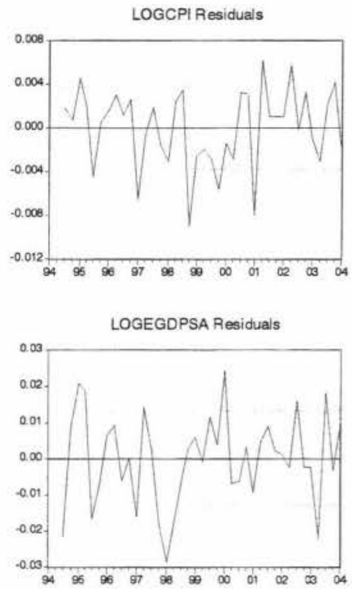
The Granger Causality test allowed for Granger Causality in both directions. However generally (ie when one considers the various lags) *LOGEGDPSA* Granger Causes *LOGCPI*.

Residual Analysis of VECM of *LOGCPI* and *LOGEGDPSA*

Various tests were performed on the residuals to ensure that the assumptions for the linear model were met. If not the model may give misleading information about the system being modelled.

The Jarque-Bera value of the residuals of *LOGCPI* is 2.587541 ($p = 0.274235$).
The Jarque-Bera value of the residuals of *LOGEGDPSA* is 0.677616 ($p = 0.712619$).
The residuals of the *LOGEGDPSA* appear stationary (Figure 7.10), although it could be argued that the mean of the residuals of *LOGCPI* seems to change somewhat over time. This again demonstrates the difficulty of making inferences based on inspecting figures.

Figure 7. 10 Residuals of VECM of *LOGCPI* and *LOGEGDPSA*



The ACF of none of the residuals shows significant findings. Their Q statistics are not significant either. The assumptions for the linear model seem to hold.

The correlation between the residuals of LOGEGDPSA and LOGCPI is 0.235768. The cross-correlogram of the residuals does not appear to have significant values at the other lags.

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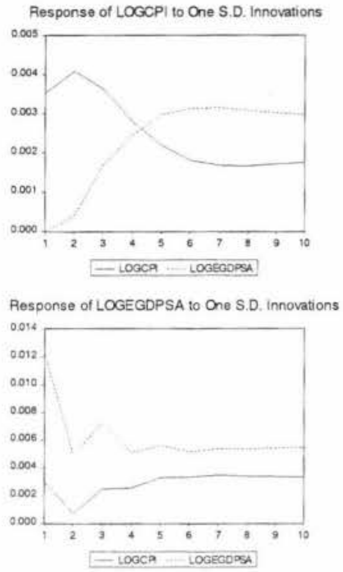
The patterns in Figure 7.11 appear similar for both orders used. However, entering *LOGEGDPSA* seems to result in a larger difference between the time series as plotted in the figure. Granger Causality (Table 7.1) and economic theory would suggest that *LOGEGDPSA* should be entered first.

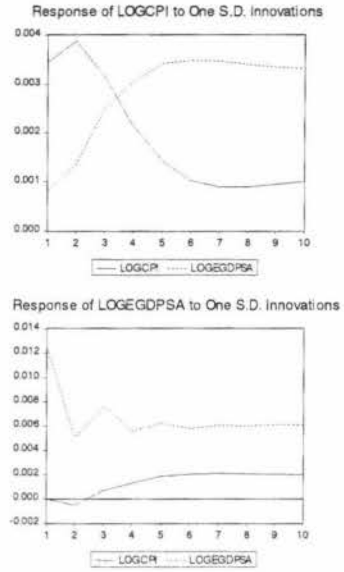
The inflation (*LOGCPI*) seems sensitive to shocks of inflation (*LOGCPI*) in the shorter term and becomes sensitive to the shocks of the GPD (*LOGEGDPSA*) in the longer term. The *LOGEGDPSA* does hardly react to shocks of *LOGCPI* but shows a direct reaction to shocks of *LOGEGDPSA*.

Similar to the IRF, the effect of ordering is present but seems minor for the VD (Figure 7.12). Over time the variance of *LOGCPI* is more or less equally influenced by *LOGCPI* and *LOGEGDPSA*. As expected, the variance of *LOGEGDPSA* shows little contribution from *LOGCPI*.

Figure 7. 11 Impulse Response Function of VECM of *LOGCPI* and *LOGEGDPSA*

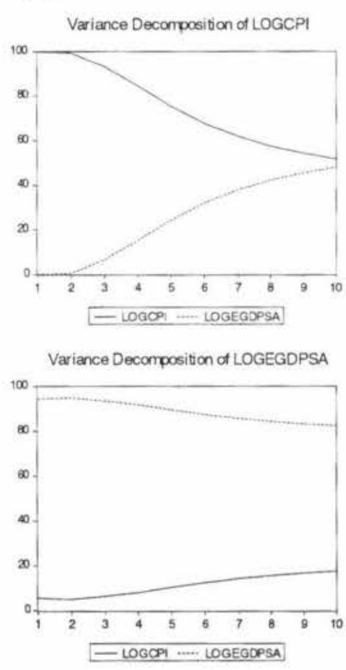


Order *LOGCPI LOGEGDPSA*

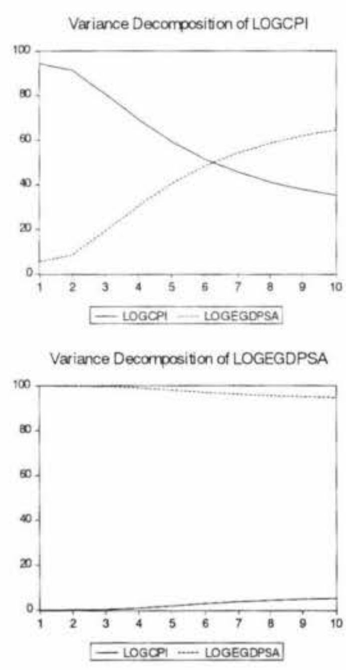


Order *LOGEGDPSA LOGCPI*

Figure 7. 12 Variance Decomposition of VECM of *LOGCPI* and *LOGEGDPSA*



Order *LOGCPI LOGEGDPSA*



Order *LOGEGDPSA LOGCPI*

Similar to the IRF, the effect of ordering is present but seems minor for the VD (Figure 7.12).

Discussion of VECM of *LOGCPI* and *LOGEGDPSA*

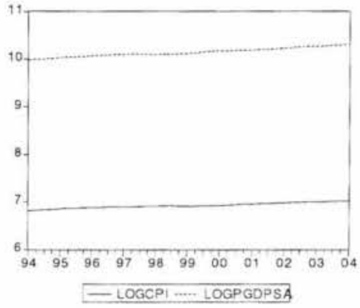
As far as the GDP variable is concerned, the constant term that was not significant in the DF test of Model 1 (7.1a) has now become significant. The trend term however has disappeared from the model. In addition the term $\Delta EGDP_{t-1}$ was not significant in its DF model but has now become significant.

The CE seemed to indicate that *LOGCPI* reacts to departures of the long term equilibrium with *LOGEGDPSA* Although this was possible according to the Granger Causality tests at lag 1, the GC tests seemed to provide more evidence for the opposite at lag 1 and the other lags. This VECM in effect is saying that the CPI reacts to deviations from the long term equilibrium between CPI and GDP. This is in line with economic thinking.

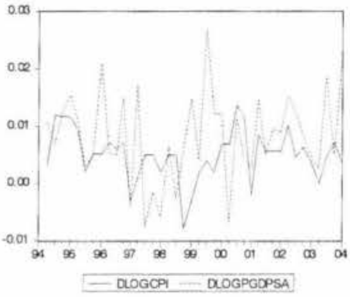
Cointegration analysis *LOGCPI* and *LOGPGDPSA*

The impression one acquires from Figure 7.13 is very similar to that of Figure 7.9 as should be the case since both time series are intended to measure the same. The undifferenced time series are trending up with little apparent variation. The differenced time series of *LOGPGDPSA* shows more variation than the differenced series of *LOGCPI*.

Figure 7.13 Time series and differenced time series of *LOGCPI* and *LOGPGDPSA*



Time series of *LOGCPI* and *LOGPGDPSA*



Differenced time series of *LOGCPI* and *LOGPGDPSA*

Table 7.8 shows the results of the cointegration analyses of *LOGCPI* and *LOGPGDPSA*. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The VECM options include options for the data trend and the Cointegrating Equation (CE). The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order. Table 7.7 and Table 7.8 show considerable differences. The SC and the AIC in Table 7.7 suggest the same model. This is Option 3 with 2 lags. This was not an admissible option in Table 7.8.

VECM of *LOGCPI* and *LOGPGDPSA*

The optimal VECM as identified in Table 7.8 is displayed in (7.13)

$$\begin{bmatrix} \Delta CPI_t \\ \Delta PGDP_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.344470} \\ 0.064899 \end{bmatrix} + \left[CPI_{t-1} - \mathbf{0.604780}PGDP_{t-1} - 0.790137\right] +$$

$$\begin{bmatrix} \mathbf{0.333856} & -0.145224 \\ -0.384663 & 0.003414 \end{bmatrix} \begin{bmatrix} \Delta CPI_{t-1} \\ \Delta PGDP_{t-1} \end{bmatrix} + \begin{bmatrix} 0.108384 & -0134533 \\ 0.173444 & 0.334565 \end{bmatrix} \begin{bmatrix} \Delta CPI_{t-2} \\ \Delta PGDP_{t-2} \end{bmatrix} +$$

$$\begin{bmatrix} \mathbf{0.00481} \\ \mathbf{0.00609} \end{bmatrix} + \begin{bmatrix} \varepsilon_{CPI,t} \\ \varepsilon_{CPI,t} \end{bmatrix} \qquad (7.13)$$

where *CPI* is *LOGCPI*, *PGDP* is *LOGPGDPSA* and the significant coefficients are in bold typeface.

Table 7.8 Cointegration analysis of *LOGCPI* and *LOGPGDPSA*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 observations	1 -14.7009 -14.0704	2	0	0	0
Lag 1 to 2 38 observations	2	1 -14.79130 -14.23108	1 **-14.89909** **-14.29577**	0	1 -14.83551 -14.14600
Lag 1 to 3 37 observations	0	1 -14.62402 -13.88386	0	0	0
Lag 1 to 4 36 observations	0	0	0	0	0
Lag 1 to 5 35 observations	0	0	0	0	0
Lag 1 to 6 34 observations	0	0	0	0	2
Lag 1 to 7 33 observations	0	0	0	0	2
Lag 1 to 8 32 observations	1 -14.25631 -12.60735	2	2	1 -14.73695 -12.95058	2

Note: Period covered 1994:1 – 2004:1.

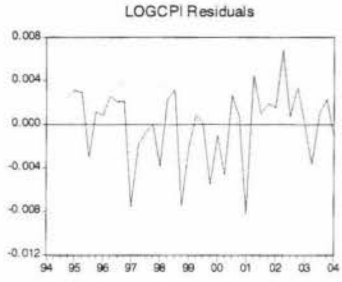
VECM (7.13) has coefficients that are similar to the VECM of *LOGCPI* and *LOGEGDPSA* (7.12). The main differences apply to two significant coefficients in the first differenced lag of (7.12). Although a second lag of the differenced component was suggested by the cointegration analysis, VECM (7.13) did not contain significant values. Consequently the similarity between the (7.12) and (7.13) is better than expected initially which is encouraging. However the issue remains that models that are admissible for one data collection system are not so for the other one.

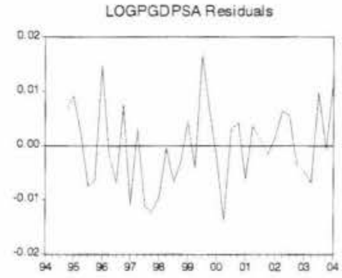
Residual analysis of VECM of *LOGCPI* and *LOGPGDPSA*

Various tests were performed on the residuals to ensure that the assumptions for the linear model were met. If not the model may give misleading information about the system being modelled.

The Jarque-Bera value of the residuals of $\Delta LOGCPI$ is 4.098450 ($p = 0.128835$).
The Jarque-Bera value of the residuals of $\Delta LOGPGDPSA$ is 0.823137 ($p = 0.662610$).
The residuals of the VECM appear more or less stationary (Figure 7.14). Similar to the residuals of $\Delta LOGCPI$ in Figure 7.10, the mean of the residuals of $\Delta LOGCPI$ in Figure 7.14 seems to vary somewhat, but it is not to the same degree.

Figure 7.14 Residuals of VECM of *LOGCPI* and *LOGPGDPSA*





The ACF of neither of the residuals shows significant findings. Their Q statistics are not significant either. The assumptions for the linear model seem to hold.

The correlation coefficient of the residuals of $\Delta LOGCPI$ and $\Delta LOGPGDPSA$ is 0.366008 The cross-correlogram of residuals also seems to show a significant value at lag 10. If a large number of lags are evaluated it is to be expected that at times a lag appears to be significant, so this finding is deemed to be of no relevance.

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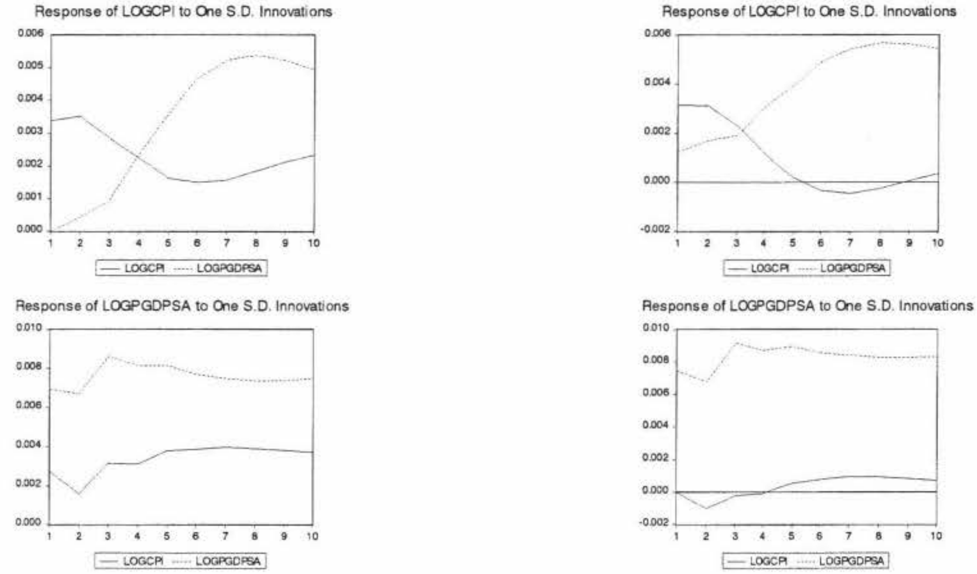
Both the IRF and the VD patterns of $\Delta LOGEGDPSA$ and $\Delta LOGPGDPSA$ seem similar although some quantitative differences exist. Based on Granger Causality *LOGPGDPSA* should be entered before *LOGCPI*.

The patterns of the IRF do not seem to be greatly affected by the ordering (Figure 7.15). After 10 periods $\Delta LOGCPI$ is more affected by innovations of $\Delta LOGPGDPSA$ than by its own innovations. $\Delta LOGPGDPSA$ is considerably influenced by its own innovations but not so much by the innovations of $\Delta LOGCPI$.

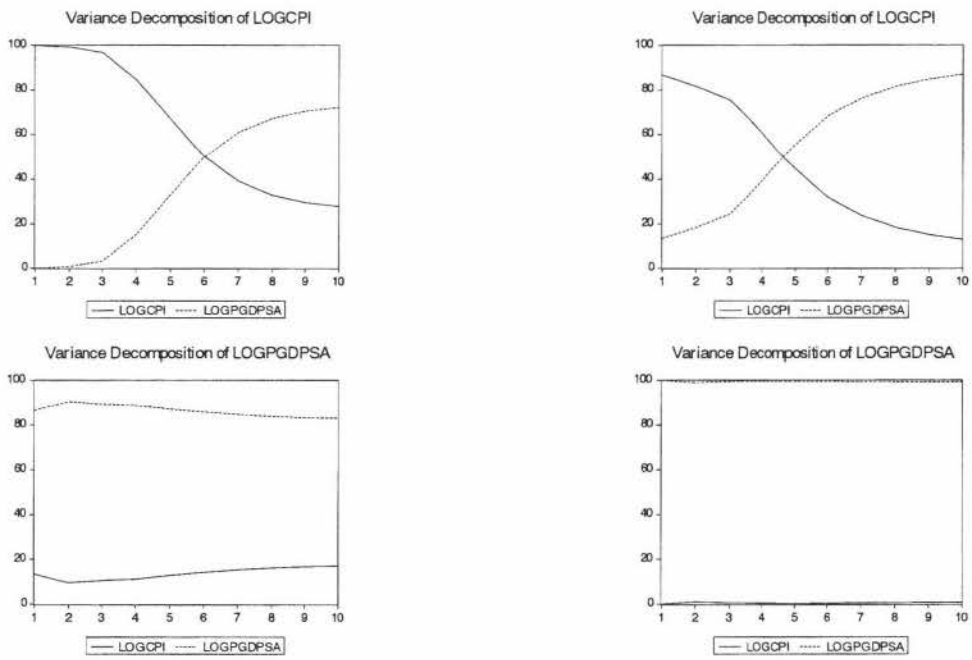
Figure 7.15 Impulse Response Function of VECM of *LOGCPI* and *LOGPGDPSA*



Order *LOGCPI LOGPGDPSA* Order *LOGPGDPSA LOGCPI*

Both the variance of $\Delta LOGCPI$ and $\Delta LOGPGDPSA$ are heavily influenced by $\Delta LOGPGDPSA$ after 10 periods regardless of the ordering (Figure 7.16).

Figure 7.16 Variance Decomposition of VECM of *LOGCPI* and *LOGPGDPSA*



Order *LOGCPI LOGPGDPSA* Order *LOGPGDPSA LOGCPI*

Comments on the relationship of *LOGCPI* and *LOGPGDPSA*

The DF unit root analysis resulted in Model 1 but the deterministic components were not significant. The VECM (7.13) does have a significant constant term. Both the DF tests and the VECM included two lags. However, in the case of the VECM the second lag did not contain a significant coefficient.

The adjustment coefficient and the coefficient of $PGDP_{t-1}$ of the cointegration equation were both significant. This is encouraging since a meaningful economic model has now eventuated as described above.

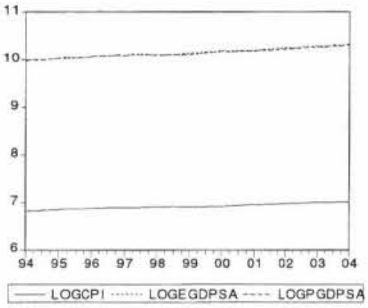
It is claimed at times that economic models are to be developed '*a priori*' and statistical tests can be used to reject these models or not. There is a risk that if a model is rejected by a test an analyst might try other models that closely resembles the first one until the statistical test results in not rejecting that model. This analysis has shown a different aspect. If an analysis does not succeed with one variable a closely resembling variable can be used instead. In this case the same optimal model was arrived at if the issue of the lags is ignored. Usually the analysis strategy of Table 7.4 would not be used. In that case the final VECM used could differ quite a lot depending on what variable (*LOGEGDPSA* or *LOGPGDPSA*) is used.

Cointegration analysis *LOGCPI, LOGEGDPSA* and *LOGPGDPSA*

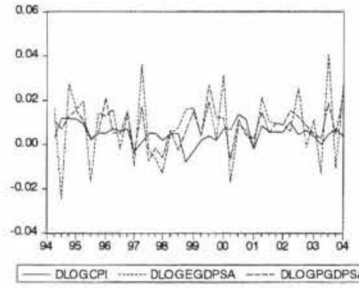
Although *LOGEGDPSA* and *LOGPGDPSA* are conceptually the same it is of interest from a statistical perspective to assess whether the VECM changes if both time series are used concurrently for evaluating their association with *LOGCPI.*

Figure 7.17 combines Figures 7.9 and 7.13 and comments can be found in the sections of these two figures.

Figure 7.17 Time series and differenced time series of *LOGCPI, LOGEGDPSA* and *LOGPGDPSA*



Time series of *LOGCPI, LOGEGDPSA* and *LOGPGDPSA*



Differenced time series of *LOGCPI, LOGEGDPSA* and *LOGPGDPSA*

Table 7.9 shows the results of the cointegration analyses of *LOGCPI, LOGEGDPSA and LOGPGDPSA*. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The VECM options include options for the data trend and the Cointegrating Equation (CE). The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order. Since there are now 3 time series there could be 2 cointegrating equations. Various options can be distinguished with 2 cointegrating equations. However the preferred model (7.14) as identified in Table 7.9 only has one cointegrating equation. If the AIC is used, then 2 cointegrating equations are used in the model. However, again a large number of lags would be required.

VECM of *LOGCPI, LOGEGDPSA* and *LOGPGDPSA*

A VECM of *LOGCPI, LOGEGDPSA* and *LOGPGDPSA* is shown in (7.14). Since there are 3 time series they can be entered in 6 different orders. The main issue however, is the variable they are normalised on. The model mainly shows the reaction of Δ*LOGEGDPSA* to its divergence from Δ*LOGPGDPSA* in the previous period. Apart from the constant term (7.14) is very similar to (7.11) and will not be analysed any further.

$$\begin{bmatrix} \Delta EGDP_t \\ \Delta PGDP_t \\ \Delta CPI_t \end{bmatrix} = \begin{bmatrix} \mathbf{-1.3372} \\ -0.0803 \\ 0.2057 \end{bmatrix} \left[EGDP_{t-1} - \mathbf{0.7231} PGDP_{t-1} - 0.0205 CPI_{t-1} - \mathbf{0.0026} t - 2.6224 \right] +$$

$$\begin{bmatrix} -0.1521 & 0.4018 & -0.5385 \\ -0.2047 & 0.2001 & -0.2829 \\ -0.1638 & 0.1850 & 0.2946 \end{bmatrix} \begin{bmatrix} \Delta EGDP_{t-1} \\ \Delta PGDP_{t-1} \\ \Delta CPI_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{0.0089} \\ \mathbf{0.0096} \\ \mathbf{0.0034} \end{bmatrix} + \begin{bmatrix} \varepsilon_{EGDP,t} \\ \varepsilon_{PGDP,t} \\ \varepsilon_{CPI,t} \end{bmatrix} \qquad (7.14)$$

where *EGDP* is *LOGEGDPSA*, *PGDP* is *LOGPGDPSA* and *CPI* is *LOGCPI*.

Table 7.9 Cointegration analysis of *LOGCPI*, *LOGEGDPSA* and *LOGPGDPSA*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 observations	3	2 -21.10202 -20.12094	1 -21.32548 -20.55769	1 -21.57206 **-20.76161**	1 -21.49369 -20.59793
Lag 1 to 2 38 observations	3	2 -21.03661 -19.65759	0	1 -21.79110 -20.58446	1 -21.71335 -20.42052
Lag 1 to 3 37 observations	1 -21.24822 -19.81145	0	0	0	1 -21.55467 -19.85667
Lag 1 to 4 36 observations	1 -21.05436 -19.20692	0	0	0	0
Lag 1 to 5 35 observations	1 -20.98094 -18.71457	0	0	0	0
Lag 1 to 6 34 observations	3	2 -21.00652 -17.95380	1 -21.15051 -18.32225	2 -21.55986 -18.37246	3
Lag 1 to 7 33 observations	3	2 -21.57429 -18.08244	1 -21.70160 -18.43649	2 **-22.04973** -18.42183	3
Lag 1 to 8 32 observations	Insufficient number of observations.				

Note: Period covered 1994:1 – 2004:1.

VECM of *LOGCPI*, *LOGEGDPSA* and *LOGPGDPSA* (2 cointegration equations)

The best model according to the SC in Table 7.9 with 2 cointegration equations was evaluated. This was Option 2 with 1 lag. Two forms of this VECM are shown (7.15 and 7.16).

$$
\begin{bmatrix} \Delta EGDP_t \\ \Delta CPI_t \\ \Delta PGDP_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.7264} & 0.0671 \\ 0.1235 & \mathbf{-0.1685} \\ -0.1022 & \mathbf{-0.2078} \end{bmatrix} \begin{bmatrix} EGDP_{t-1} - 1.0966PGDP_{t-1} + \mathbf{0.9499} \\ CPI_{t-1} - \mathbf{0.6186}PGDP_{t-1} - 0.6882 \end{bmatrix} +
$$

$$
\begin{bmatrix} \mathbf{-0.4515} & -0.7381 & 0.5082 \\ -0.1084 & \mathbf{0.3070} & 0.0570 \\ -0.1805 & -0.2350 & 0.0789 \end{bmatrix} + \begin{bmatrix} \varepsilon_{EGDP,t} \\ \varepsilon_{CPI,t} \\ \varepsilon_{PGDP,t} \end{bmatrix} \qquad (7.15)
$$

Based on the t-statistics of the adjustment coefficients this model is full rank and consequently inappropriate. The model that has the initial order of *LOGEGDPSA* and *LOGCPI* reversed is the same.

The VECMs that have the order *LOGEGDPSA – LOGPGDPSA – LOGCPI* or *LOGPGDPSA– LOGEGDPSA – LOGCPI* only have one negative significant adjustment coefficient. They will not be further evaluated.

Finally the models with order *LOGPGDPSA– LOGCPI – LOGEGDPSA* or *LOGCPI – LOGPGDPSA –LOGEGDPSA* are available for evaluation.

$$
\begin{bmatrix} \Delta PGDP_t \\ \Delta CPI_t \\ \Delta EGDP_t \end{bmatrix} = \begin{bmatrix} 0.2406 & \mathbf{-0.2078} \\ -0.0312 & \mathbf{-0.1685} \\ +\mathbf{0.7551} & 0.0671 \end{bmatrix} \begin{bmatrix} PGDP_{t-1} - \mathbf{0.9119}EGDP_{t-1} - \mathbf{0.8662} \\ CPI_{t-1} - \mathbf{0.5641}EGDP_{t-1} - \mathbf{1.2240} \end{bmatrix} +
$$

$$
\begin{bmatrix} 0.0786 & -0.2350 & -0.1805 \\ 0.0570 & \mathbf{0.3070} & -0.1084 \\ 0.5082 & -0.7381 & \mathbf{-0.4515} \end{bmatrix} + \begin{bmatrix} \varepsilon_{PGDP,t} \\ \varepsilon_{CPI,t} \\ \varepsilon_{EGDP,t} \end{bmatrix} \qquad (7.16)
$$

The last VECM (7.16) is also inadmissible. It contains 3 significant adjustment coefficients.

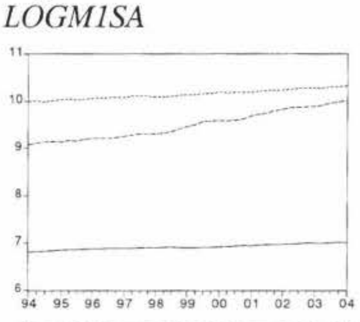
In summary, it has not been possible to develop a VECM that brings the 3 factors together. In a sense the above analysis was mainly of statistical interest rather than economic. It was already decided that two of the time series (*LOGEGDPSA* and *LOGPGDPSA*) were more or less similar. However it is of importance to evaluate how the cointegration analysis dealt with the series that were largely the same.

Cointegration analysis *LOGCPI*, *LOGEGDPSA* and *LOGM1SA*

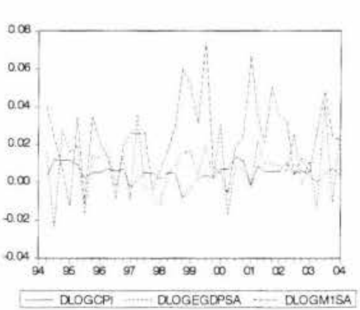
Over the years there has been an ongoing debate whether the output gap or the velocity of money are the main cause of inflation. Cointegration analysis with an inflation index and time series reflecting the output gap and monetary aggregates seem a good way to evaluate this issue. The monetary aggregate (*LOGM1SA*) that is used in this cointegration analysis is seasonally adjusted but it has not been adjusted for the CPI. The next section will use a CPI-adjusted form. This approach is similar to that used in Chapter 5.

Figure 7.18 gives the impression that *LOGM1SA* has a trend that is quite different from *LOGCPI* and *LOGEGDPSA*. Also the differenced series *DLOGM1SA* displays more variation than the other two time series.

Figure 7.18 Time series and differenced time series of *LOGCPI*, *LOGEGDPSA* and *LOGM1SA*



Time series of *LOGCPI*, *LOGEGDPSA* and *LOGM1SA*



Differenced time series of *LOGCPI*, *LOGEGDPSA* and *LOGM1SA*

Table 7.10 shows the results of the cointegration analysis of these 3 time series. The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The VECM options include options for the data trend and the Cointegrating Equation (CE). The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order. Both the SC and the AIC criterion suggest Model 4. However where the SC chooses a series with 1 lag only the AIC chooses the model with 7 lags. In addition the AIC indicates 2 cointegrating equations while the SC only indicates 1.

VECM of *LOGCPI*, *LOGEGDPSA* and *LOGM1SA*

The optimal VECM according to the SC is shown in (7.17).

$$\begin{bmatrix} \Delta CPI_t \\ \Delta M1_t \\ \Delta EGDP_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.163203} \\ \mathbf{0.552232} \\ 0.178656 \end{bmatrix} \left[LOGCPI_{t-1} - 0.105350M1_{t-1} - \mathbf{0.949562}EGDP_{t-1} + 0.0057t + 3.5919 \right]$$

$$+ \begin{bmatrix} 0.217239 & -0.019717 & \mathbf{-0.103074} \\ -0.874074 & 0.158989 & 0.086213 \\ -0.140503 & 0.096995 & \mathbf{-0.457865} \end{bmatrix} \begin{bmatrix} \Delta CPI_{t-1} \\ \Delta M1_{t-1} \\ \Delta EGDP_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{0.005242} \\ \mathbf{0.023010} \\ \mathbf{0.010156} \end{bmatrix} + \begin{bmatrix} \varepsilon_{CPI,t} \\ \varepsilon_{M1,t} \\ \varepsilon_{EGDP,t} \end{bmatrix} \quad (7.17)$$

where *CPI* is *LOGCPI*, *M1* is *LOGM1SA* and *EGDP* is *LOGEGDPSA* and the significant coefficients are in bold.

Table 7.10 Cointegration analysis of *LOGCPI*, *LOGEGDPSA* and *LOGM1SA*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 observations	2 -18.67945 -17.78368	2 -18.87827 -17.89720	2 -18.97544 -17.95171	1 -18.86192 **-18.05147**	3
Lag 1 to 2 38 observations	1 -18.60654 -17.57228	2 -18.68953 -17.31051	2 -18.81822 -17.39610	1 -18.90072 -17.69408	3
Lag 1 to 3 37 observations	0	1 -18.57653 -17.09622	0	1 -18.86773 -17.25681	1 -18.82732 -17.12932
Lag 1 to 4 36 observations	0	0	0	2 -19.01699 -16.24048	3
Lag 1 to 5 35 observations	0	0	0	1 -19.02152 -16.57740	3
Lag 1 to 6 34 observations	2 -18.49347 -15.53054	1 -18.41125 -15.67278	1 -18.61206 -15.78381	2 -18.97134 -15.78394	3
Lag 1 to 7 33 observations	2 -18.82694 -15.42578	3	1 -19.16376 -15.89866	2 **-19.42112** -15.79322	3
Lag 1 to 8 32 observations	Insufficient number of observations				

Note: Period covered 1994:1 – 2004:1.

The model that was selected (7.17) had two significant adjustment coefficients. They were for *LOGCPI* and *LOGM1SA*.

Inflation (*LOGCPI*) is showing association with GDP (*LOGEGDPSA*) at two levels. There is a negative association if one considers the lag in the model. In addition there is also an association through the cointegrating equation. If the long-run equilibrium is disturbed some factor brings them together again. This may be the monetary policy and the way it manipulates interest rates.

The significant adjustment factor for *LOGM1SA* is difficult to explain, especially since the significant coefficients in the cointegrating equation are for *LOGCPI* and *LOGEGDPSA*. It may be explained that if the EGDP is too high for the equilibrium with the inflation rate, M1 is increases.
The trend in the cointegrating equation was not significant which is contrary to the specifications of the model chosen from Table 7.10.

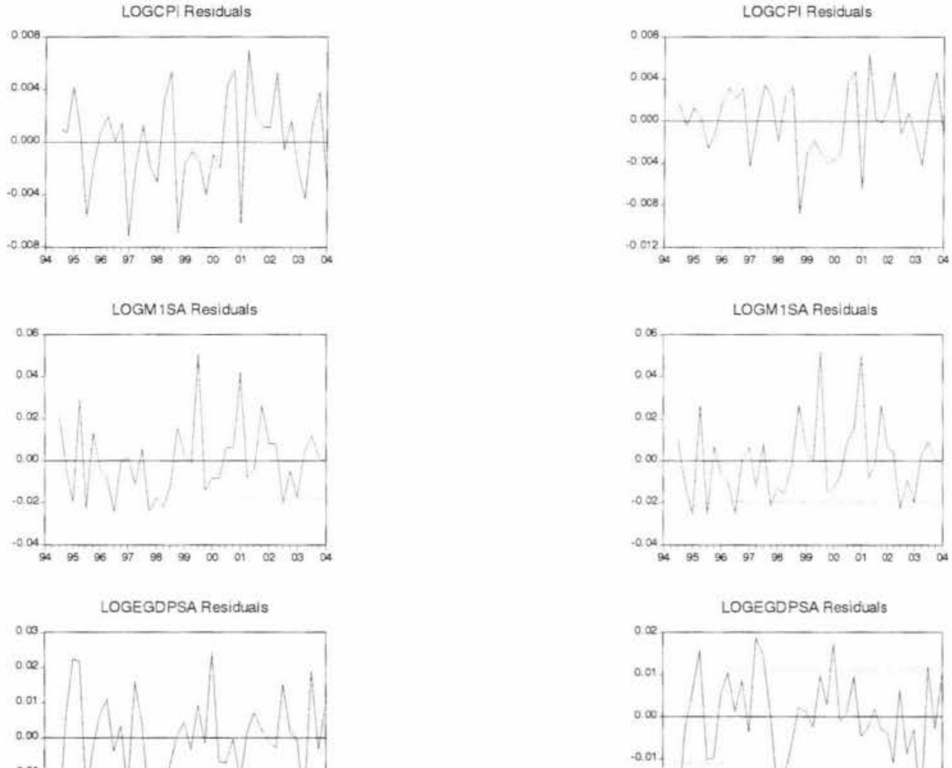
Analysis of the residuals of VECM of *LOGCPI*, *LOGEGDPSA* and *LOGM1SA*

The residuals of the VECM were evaluated to verify that the assumptions for the linear model were not violated.
The Jarque-Bera value of the residuals of $\Delta LOGCPI$ is 0.480682 (p = 0.786360)
The Jarque-Bera value of the residuals of $\Delta LOGM1SA$ is 6.460324 (p = 0.039551)
The Jarque-Bera value of the residuals of $\Delta LOGEGDPSA$ is 0.291465 (p = 0.864389)

The residuals of $\Delta LOGM1SA$ are therefore not normally distributed according to the Jarque-Bera test. This means that an important assumption has been violated. To what degree it renders the model invalid cannot be established.

The means of $\Delta LOGCPI$ and $\Delta LOGM1SA$ seem to vary somewhat over time according to Figure 7.19.

Figure 7.19 Residuals of VECM (7.17) of *LOGCPI*, *LOGEGDPSA* and *LOGM1SA*



1 cointegrating equation | 2 cointegrating equations*

* A VECM with 2 significant cointegration equations according to Table 7.4 will be discussed in the next section

The ACF of none of the residuals shows significant findings. Their Q statistics are not significant either

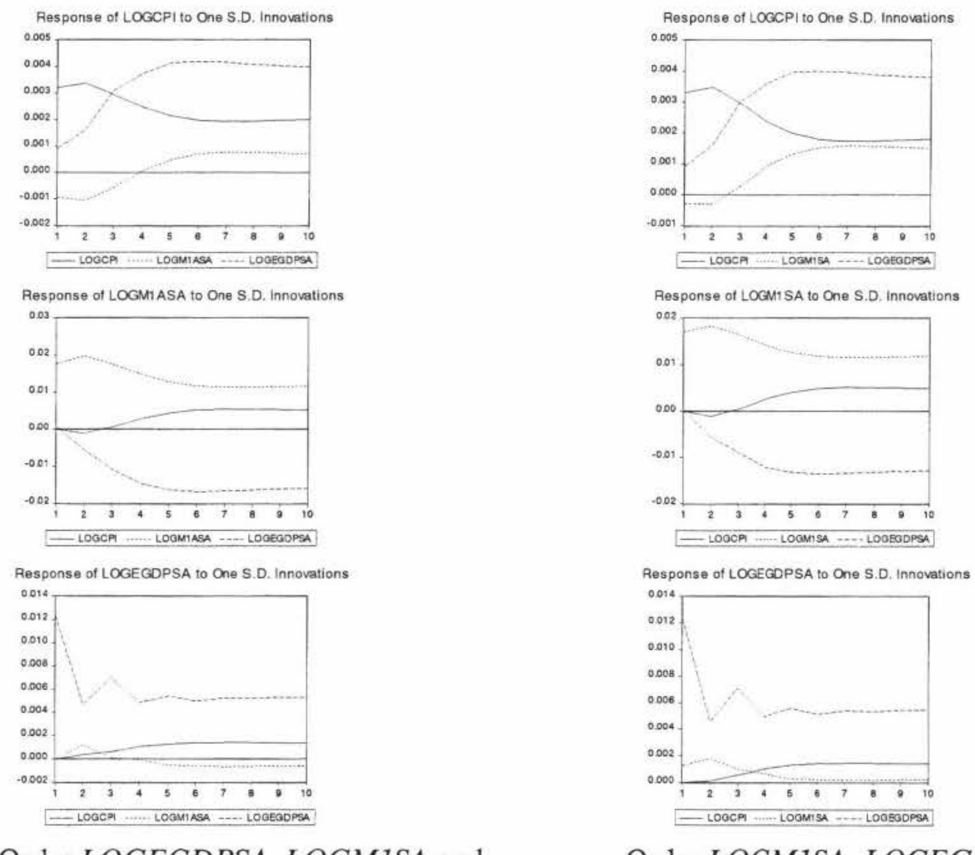
The cross-correlogram may have shown significant findings at lags 2 and 12 for the residuals of *LOGM1SA* and *LOGEGDPSA*.

The correlation between the residuals of $\Delta LOGCPI$ and $\Delta LOGM1SA$ is -0.087449
The correlation between the residuals of $\Delta LOGCPI$ and $\Delta LOGEGDPSA$ is 0.258852
The correlation between the residuals of $\Delta LOGM1SA$ and $\Delta LOGEGDPSA$ is 0.103689

Innovation Accounting

Since three time series are analysed six different orders were possible. Two of these are shown in Figures 7.20 and 7.21. The correlation between the residuals of the 3 time series was small and therefore the order should not matter much. Indeed the IRF did not appear to be sensitive to the two orders that are shown. After 10 periods $\Delta LOGCPI$ seems particularly sensitive to innovations of $\Delta LOGEGDPSA$. This illustrates how shocks to the GDP affect inflation. Figure 7.23 also shows that $\Delta LOGM1SA$ displayed a negative response after 10 periods to innovations of $\Delta LOGEGDPSA$.

Figure 7.20 Impulse Response Function of VECM (7.17) of *LOGCPI, LOGEGDPSA* and *LOGM1SA*

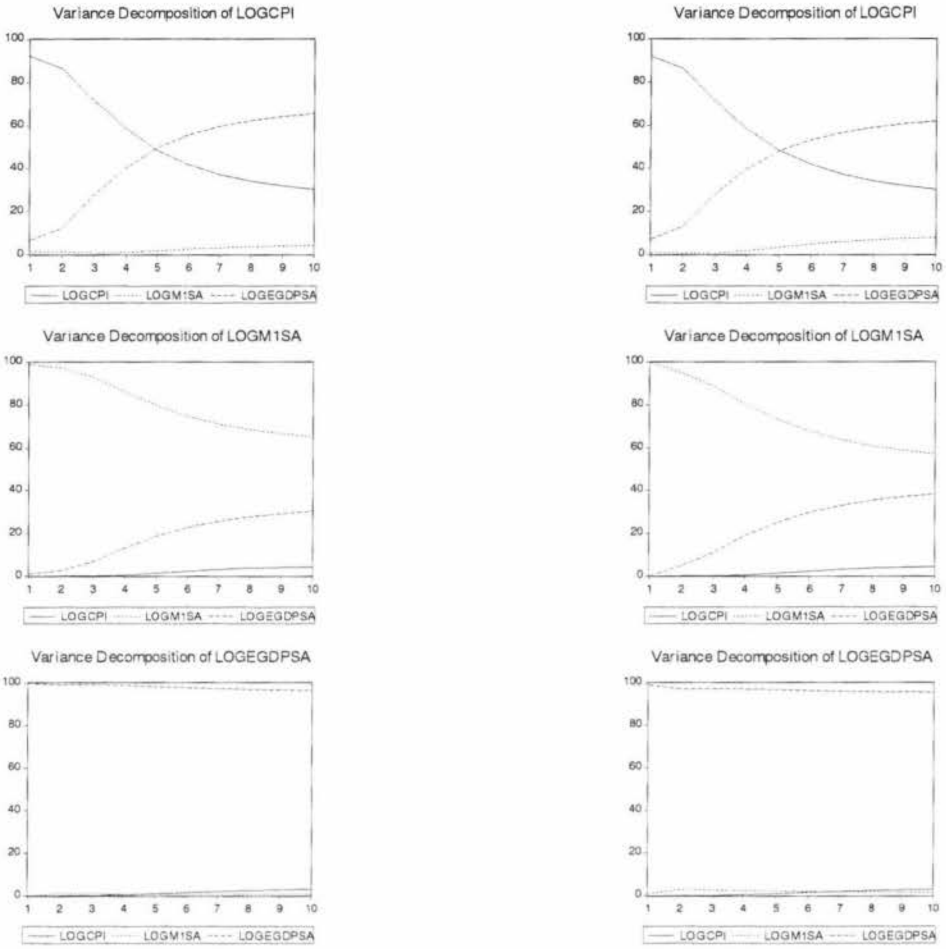


Order *LOGEGDPSA*, *LOGM1SA* and *LOGCPI*

Order *LOGM1SA*, *LOGEGDPSA* and *LOGCPI*

Figure 7.21 showed that the order had little effect on the Variance Composition. This is similar to Figure 7.20 and is explained by the small correlation coefficients.

Figure 7.21 Variance Decomposition of VECM (7.17) of *LOGCPI*, *LOGEGDPSA* and *LOGM1SA*



Order *LOGEGDPSA*, *LOGM1SA* and *LOGCPI*

Order *LOGM1SA*, *LOGEGDPSA* and *LOGCPI*

There was little influence of $\Delta LOGM1SA$ on the variance of the other two time series. However, $\Delta LOGEGDPSA$ did have an large effect on the variance of $\Delta LOGCPI$ after 10 periods.

Comments of the relationship of VECM of *LOGCPI*, *LOGEGDPSA* and *LOGM1SA*

The VECM had two significant coefficients (ie adjustment factors). There should have been a significant trend in the cointegrating equation but there was none. The data series indicated an effect of $\Delta LOGEGDPSA_{t-1}$ on $\Delta LOGCPI$. A departure from the long-term equilibrium between the CPI and the GDP is corrected by the CPI. The effect of $\Delta LOGEGDPSA$ on $\Delta LOGM1SA$ according to the innovation accounting was greater than expected.

VECM of *LOGCPI, LOGM1SA* and *LOGEGDPSA* (2 cointegrating equations)

In addition to the optimal model as established according the Schwarz Criterion above the second best model was evaluated. This was the Option 3 with 1 lag as shown in (7.18). This was done because it had two cointegrating equations and the specification without the trend in the cointegration equation appeared more plausible from an economic perspective. There was little difference between the values of the two SCs. In both cases VECMs were not rejected and it is of interest whether the coefficients of these two models are materially different or might in fact result in a model that explained the three time series better in relation to each other.

$$\begin{bmatrix} \Delta CPI_t \\ \Delta M1_t \\ \Delta EGDP_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.197573} & \mathbf{0.036462} \\ 0.570941 & 0.059583 \\ \mathbf{0.452869} & \mathbf{0.192841} \end{bmatrix} \begin{bmatrix} CPI_{t-1} - \mathbf{0.546028}EGDP_{t-1} - 1.379552 \\ M1 - \mathbf{3.057569}EGDP_{t-1} + 21.53602 \end{bmatrix} +$$

$$\begin{bmatrix} 0.173970 & -0.071364 & -0.015376 \\ -1.382577 & 0.094319 & 0.045347 \\ -0.925592 & -0.143520 & -0.124675 \end{bmatrix} \begin{bmatrix} \Delta CPI_{t-1} \\ \Delta M1_{t-1} \\ \Delta EGDP_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{0.005983} \\ \mathbf{0.027421} \\ \mathbf{0.017152} \end{bmatrix} + \begin{bmatrix} \varepsilon_{CPI,t} \\ \varepsilon_{M1,t} \\ \varepsilon_{EGDP,t} \end{bmatrix} \quad (7.18)$$

where *CPI* is *LOGCPI*, *M1* is *LOGM1SA*, *EGDP* is *LOGEGDPSA* and the significant coefficients are in bold typeface.

The significant adjustment coefficients apply to $\Delta LOGCPI$ and $\Delta LOGEGDPSA$. $\Delta LOGCPI$ reacts to departures of its long term equilibrium with LOGEGDPSA as has been seen previously by decreasing. In addition it also reacts by increasing when the GDP increases too much in relation to the money supply.
This time GDP reacts to departures from its long-term equilibrium with CPI. It reacts by increasing. This means that if inflation is too high in the previous period, the GDP will increase more to compensate. The second Cointegrating Equation shows that if the money aggregate is too high for the GDP, the GDP will correct by increasing.

Other ways of displaying the chosen model were options (7.19) and (7.20)

$$\begin{bmatrix} \Delta CPI_t \\ \Delta EGDP_t \\ \Delta M1_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.1976} & -0.0036 \\ \mathbf{+0.4529} & \mathbf{-0.8369} \\ 0.5709 & -0.4939 \end{bmatrix} \begin{bmatrix} CPI_{t-1} - \mathbf{0.1786}M1_{t-1} - 5.2255 \\ EGDP_{t-1} - \mathbf{0.3271}M1 - 7.0435 \end{bmatrix} +$$

$$\begin{bmatrix} 0.1740 & -0.0154 & -0.0714 \\ -0.9256 & -0.1247 & -0.1435 \\ -1.3826 & 0.0453 & 0.0943 \end{bmatrix} \begin{bmatrix} \Delta CPI_{t-1} \\ \Delta EGDP_{t-1} \\ \Delta M1_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{0.0060} \\ \mathbf{0.0172} \\ \mathbf{0.0274} \end{bmatrix} + \begin{bmatrix} \varepsilon_{CPI,t} \\ \varepsilon_{EGDP,t} \\ \varepsilon_{M1,t} \end{bmatrix} \quad (7.19)$$

$$\begin{bmatrix}\Delta EGDP_{t-1}\\ \Delta M1_{t-1}\\ \Delta CPI_{t-1}\end{bmatrix}=\begin{bmatrix}\mathbf{-0.8369} & \mathbf{+0.1928}\\ -0.4939 & 0.0596\\ -0.0036 & \mathbf{+0.0365}\end{bmatrix}\begin{bmatrix}EGDP_{t-1}-\mathbf{1.8314}CPI_{t-1}+2.5265\\ M1_{t-1}-\mathbf{5.5997}CPI_{t-1}+29.1610\end{bmatrix}+$$

$$\begin{bmatrix}-0.1247 & -0.1435 & -0.9256\\ 0.0453 & 0.0943 & -1.3826\\ -0.0154 & -0.0714 & 0.1740\end{bmatrix}\begin{bmatrix}\Delta EGDP_{t-1}\\ \Delta M1_{t-1}\\ \Delta CPI_{t-1}\end{bmatrix}+\begin{bmatrix}\mathbf{0.0172}\\ \mathbf{0.0274}\\ \mathbf{0.0060}\end{bmatrix}+\begin{bmatrix}\varepsilon_{EGDP,t}\\ \varepsilon_{M1,t}\\ \varepsilon_{CPI,t}\end{bmatrix} \qquad (7.20)$$

Although all these three equations are equivalent, it is of interest to note that (7.18) has four significant adjustment coefficients and (7.19) and (7.20) only have three. When there are two cointegrating vectors, essentially two vectors are chosen which span a space. The way in which the algorithm makes its choice depends on the order in which it is given the variables. Thus the long-run relationships can come in different forms. Any linear combination of these is also a long-run relationship. The number of significant adjustment coefficients may depend on the choice of the two cointegrating vectors to span the "cointegrating space".
The following discussions are based on (7.18) although parts may equally apply to the other equations. None of the lagged values in the data series is significant nor are the adjustment factor of *M1SA*.

Analysis of residuals of VECM of *LOGCPI*, *LOGM1SA* and *LOGEGDPSA* (2 cointegrating equations)

Various tests were performed on the residuals to verify that the assumptions for the linear model were met. If they are not, the model may give misleading information about the system being modelled.

The Jarque-Bera value of the residuals of $\Delta LOGCPI$ is 1.0108 ($p = 0.6033$).
The Jarque-Bera value of the residuals of $\Delta LOGM1SA$ is 8.8230 ($p = 0.0121$).
The Jarque-Bera value of the residuals of $\Delta LOGEGDPSA$ is 0.8122 ($p = 0.6662$).
The Jarque-Bera value for the residuals of $\Delta LOGM1SA$ is too high. They do not display a normal distribution.

The residuals of this VECM (7.15) and VECM (7.16) are very similar (Figure 7.22).
The ACF of none of the residuals shows significant findings. Their Q statistics are not significant either.

The correlation between $\Delta LOGCPI$ and $\Delta LOGM1SA$ is	-0.254940
The correlation between $\Delta LOGCPI$ and $\Delta LOGEGDPSA$ is	0.067158
The correlation between $\Delta LOGM1SA$ and $\Delta LOGEGDPSA$ is	0.071862

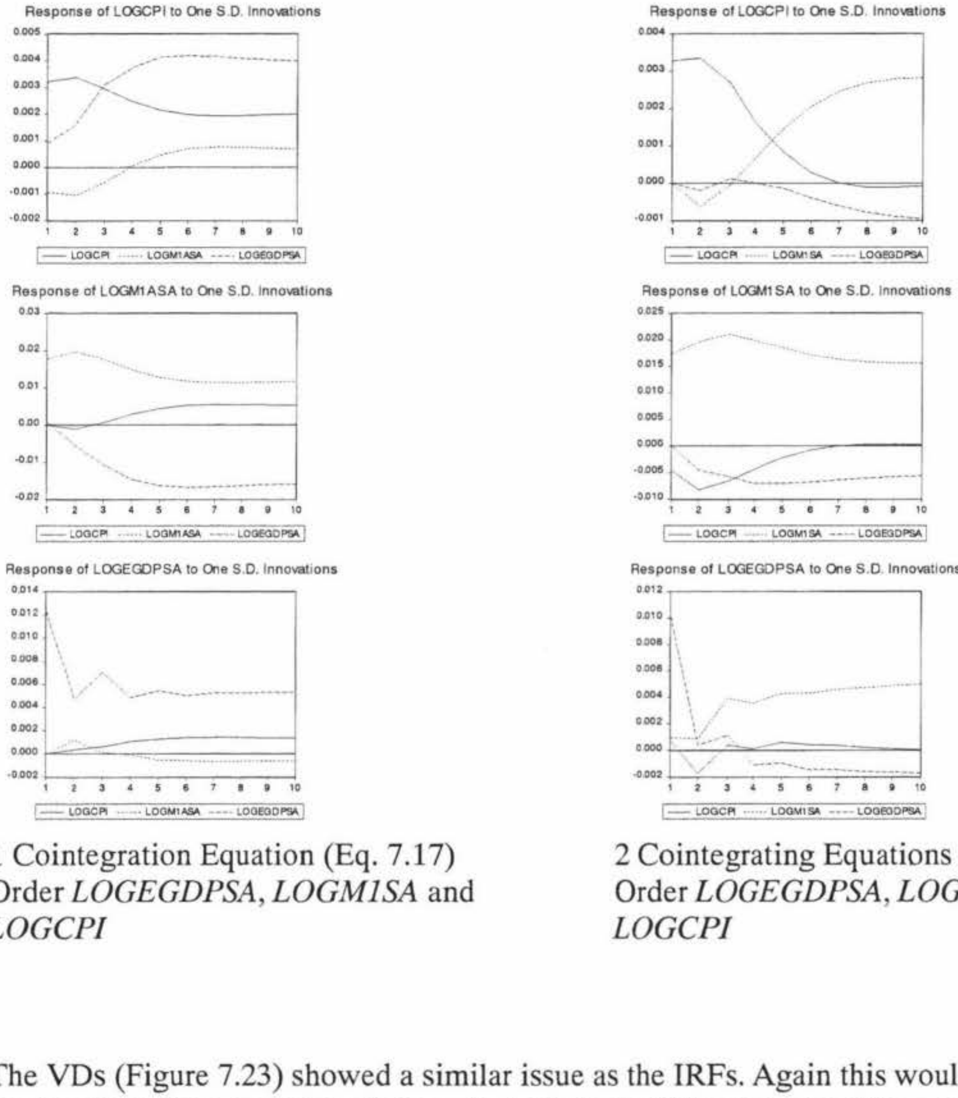
The order in which the times series will be entered for innovation accounting is not likely to be influential with regard to the results.

The cross-correlogram of the three residuals does not show significant findings.

Innovation accounting

Figure 7.22 compares the IRF of the VECMs (7.17) and (7.18). The order used was the same for both figures. Although the patterns of the individual series have remained the same, the position of the lines in relation to each other has shifted. If one were willing to accept both models, then the ramifications for economic policy would become different.

Figure 7.22 Impulse Response Function of VECMs of *LOGCPI, LOGEGDPSA* and *LOGM1SA*

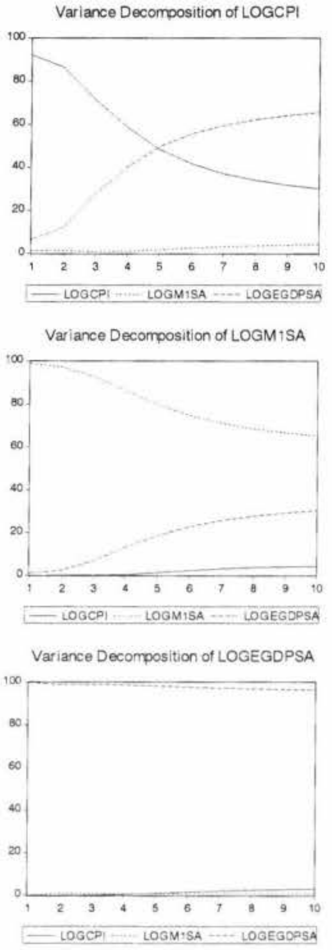


1 Cointegration Equation (Eq. 7.17)
Order *LOGEGDPSA, LOGM1SA* and *LOGCPI*

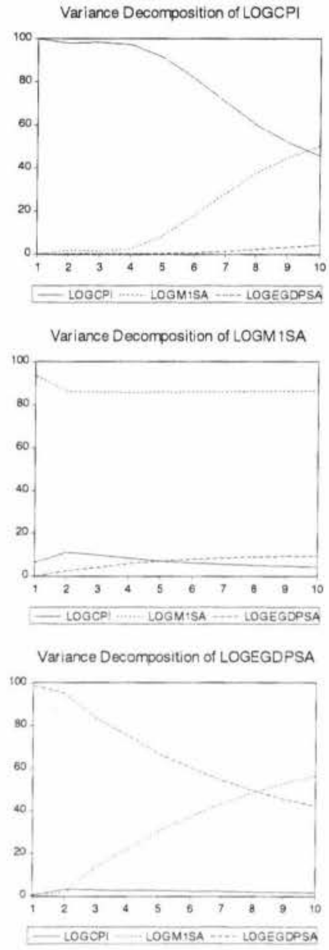
2 Cointegrating Equations (Eq. 7.18)
Order *LOGEGDPSA, LOGM1SA* and *LOGCPI*

The VDs (Figure 7.23) showed a similar issue as the IRFs. Again this would have implications for economic policies. A shock to the CPI would result in a response of the CPI after 10 periods according to the VECM with 1 cointegrating equation but no response according to the VECM with 2 cointegrating equations.

Figure 7.23 Variance Decomposition of VECMs of *LOGCPI*, *LOGEGDPSA* and *LOGM1SA*



1 Cointegration Equation (Eq. 7.17)
Order *LOGEGDPSA*, *LOGM1SA* and *LOGCPI*



2 Cointegrating Equations (Eq. 7.18)
Order *LOGEGDPSA*, *LOGM1SA* and *LOGCPI*

Comments on the differences between the two VECMs

Although both VECMs were admissible according to Table 7.21, the actual equations differed considerably. The different IRFs and VDs have quite different meanings in an economic sense. The differences that were shown would be of concern since the economic interpretation of the two VECMs differs so much.

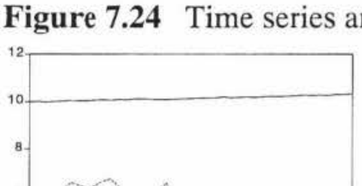
In the section on the VECM with the two CEs, a number of economic ramifications were discussed. Since the residuals of the monetary aggregate this models were not normally distributed, there is a concern the inferences may not be valid.

Cointegration analysis of *LOGEGDPSA* and *CD*

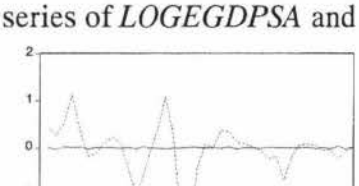
When the RBNZ is of the opinion that the output gap becomes too large and production has become more than the economy can sustain, it increases the OCR. Since retail banks loan and borrow from the RBNZ based on the OCR, they will adjust their lending rates to the public in accordance with changes to the OCR. This in turn should lead to an increase or decrease of the GDP. In this case the Call Deposit Rate (*CD*) was chosen as an example of an interest rate since it was considered to be very sensitive to changes of the OCR.

The time series *LOGEGDPSA* shows a steady increase (Figure 7.24). The time series of *CD* is very irregular with a sharp decline. Both differenced time series appear stationary. There is a large through in the differenced time series of *CD* (*DCD*).

Figure 7.24 Time series and differenced time series of *LOGEGDPSA* and *CD*



Time series of *LOGEGDPSA* and *CD*



Differenced time series of *LOGEGDPSA* and *CD*

A cointegration analysis was performed to evaluate the relationship between *LOGEGDPSA* and *CD* (Table 7.11). The setup of the table is explained in section 2.9. Briefly there are five options for the VECM and 8 lags. The VECM options include options for the data trend and the Cointegrating Equation (CE). The resulting cells contain from top to bottom the number of cointegrating equations, the AIC and the SC in this order. All 5 options seemed to be possible. Both information criteria select Model 4, but the SC uses 2 lags while the AIC uses 6 lags.

VECM of *LOGEGDPSA* and *CD*

A VECM as suggested by the SC is displayed in (7.21).

$$\begin{bmatrix} \Delta CD_t \\ \Delta EGDP_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.3565} \\ 0.0008 \end{bmatrix} \left[CD_{t-1} - \mathbf{67.7135} EGDP_{t-1} + \mathbf{0.6671} t + 669.0170 \right] +$$

$$\begin{bmatrix} \mathbf{0.6837} & \mathbf{-20.2785} \\ -0.0026 & \mathbf{-0.4815} \end{bmatrix} \begin{bmatrix} \Delta CD_{t-1} \\ \Delta EGDP_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{-0.3495} & \mathbf{-14.3314} \\ -0.0035 & 0.0280 \end{bmatrix} \begin{bmatrix} \Delta CD_{t-2} \\ \Delta EGDP_{t-2} \end{bmatrix} +$$

$$\begin{bmatrix} \mathbf{0.2331} \\ \mathbf{0.0121} \end{bmatrix} + \begin{bmatrix} \varepsilon_{CD,t} \\ \varepsilon_{EGDP,t} \end{bmatrix} \qquad (7.21)$$

where the significant coefficients are in bold type face and *EGDP* is *LOGEGDPSA*.

Table 7.11 Cointegration analysis of *LOGEGDPSA* and *CD*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1	1	2	0	1	2
39 obser-	-4.1723			-4.6212	
vations	-3.8310			-4.1520	
Lag 1 to 2	1	1	0	1	2
38 obser-	-4.4567	-4.5569		-5.1186	
vations	-3.9396	-3.9966		**-4.4722**	
Lag 1 to 3	1	2	0	1	1
37 obser-	-4.7137			-5.2859	-5.2383
vations	-4.0171			-4.4587	-4.3675
Lag 1 to 4	1	1	0	0	1
36 obser-	-4.7878	-4.7596			-5.1010
vations	-3.9081	-3.8359			-4.0543
Lag 1 to 5	0	0	0	1	1
35 obser-				-5.2214	-5.1835
vations				-4.0216	-3.9392
Lag 1 to 6	1	1	0	1	2
34 obser-	-5.0178	-5.1157		**-5.2955**	
vations	-3.7608	-3.8138		-3.9038	
Lag 1 to 7	2	1	0	1	2
33 obser-		-4.8218		-5.2239	
vations		-3.3253		-3.6367	
Lag 1 to 8	2	2	1	1	2
32 obser-			-5.0318	-5.1861	
vations			-3.2913	-3.3997	

Note: Period covered 1994:1 – 2004:1.

The interest rate (*CD*) reacts to a divergence of the *GDP* and the *CD*. This can be explained as the interest rates being increased as the GDP becomes too large for the long-term equilibrium in the previous period. This probably reflects monetary policy.

Figure 7.24 shows clearly that *CD* has decreased over time. However the constant (0.2331) in (7.21) and also the coefficient of ΔCD_{t-1} are both positive and significant. CD's coefficients for $\Delta EGDP_{t-1}$, $\Delta EGDP_{t-2}$ and ΔCD_{t-2} are all significant and negative. One cannot but wonder whether the large number of variables allowed a degree of model fitting that does no longer reflect the actual data generating process.

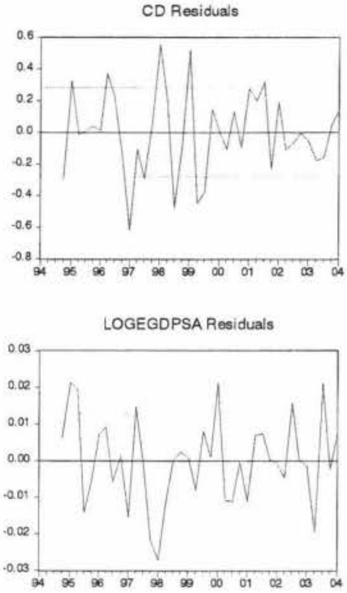
Inspection of Figure 7.24 shows two time series that are moving in different directions. This too does not seem to point to a cointegrating relationship.

Analysis of residuals of VECM of *LOGEGDPSA* and *CD*

Various tests were performed on the residuals to verify that the assumptions for the linear model were met. If not the model may give misleading information about the system being modelled. This is of particular interest in this case because of the positive sign of the significant adjustment factor.

The Jarque-Bera value of the residuals of $\Delta EGDPSA$ is 0.208281 (p = 0.901099).
The Jarque-Bera value of the residuals of ΔCD is 0.070761 (p = 0.965238).
The residuals of $\Delta EGDPSA$ appear stationary (Figure 7.25). The variance of ΔCD appears to decrease over time.

Figure 7.25 Residuals of VECM of *CD* and *LOGEGDPSA*



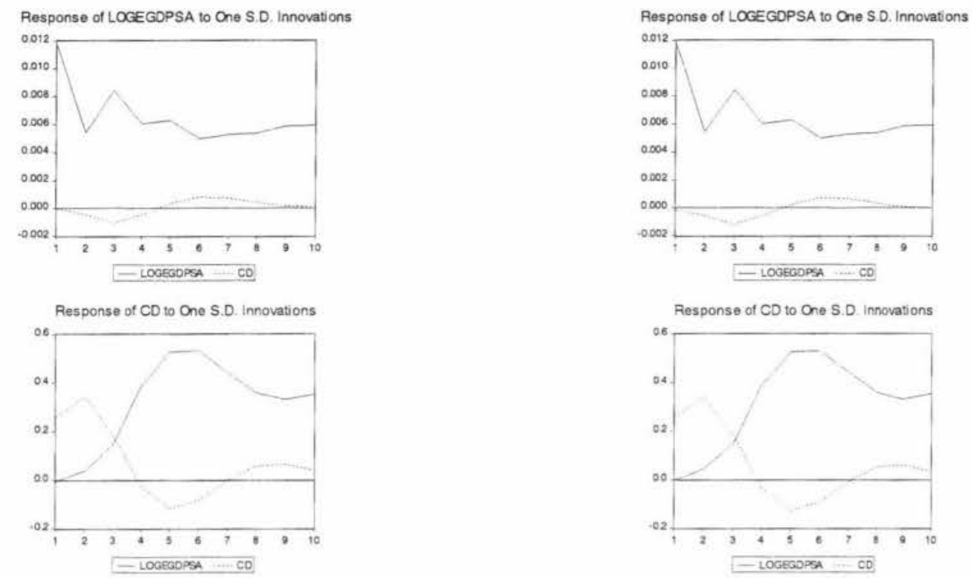
The ACF of the residuals of ΔCD and $\Delta EGDPSA$ do not show significant lags and the Q statistics are not significant either (16 lags included). The assumptions for normality of the residuals seem to hold.

The correlation between the residuals of $\Delta EGDPSA$ and ΔCD is -0.015171.
The residuals of ΔCD and $\Delta EGDPSA$ are correlated after 4, 6 and possibly 14 periods. An inclusion of more lags in the VECM might have been appropriate.

Innovation Accounting

The IRFs are not sensitive to the order in which the time series are entered (Figure 7.26). After 10 periods *CD* appears to be sensitive to innovations of *LOGEGDPSA*. This is more so than to innovations to itself. *LOGEGDPSA* does not appear to be sensitive to innovations to *CD*.

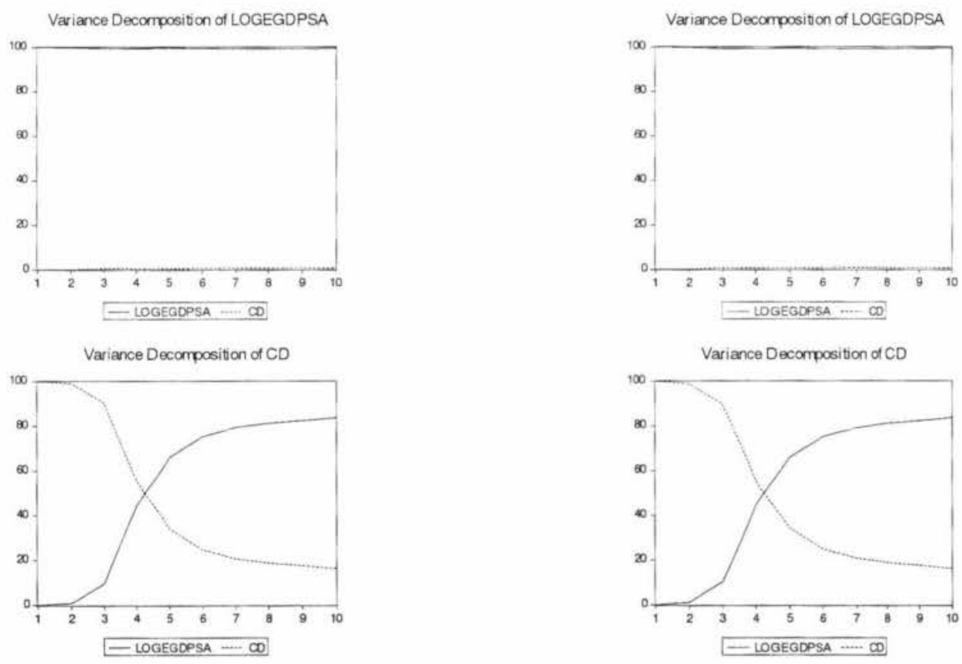
Figure 7.26 Impulse Response Function of VECM of *LOGEGDPSA* and *CD*



Order *LOGEGDPSA CD*   Order *CD LOGEGDPSA*

The Variance Decomposition of *CD* after 10 periods is heavily influenced by *LOGEGDPSA* (Figure 7.27). Here too, the order in which the time series were entered was not important.

Figure 7.27 Variance Decomposition of VECM of *LOGEGDPSA* and *CD*



Order *LOGEGDPSA CD*   Order *CD LOGEGDPSA*

Comments on VECM of *CD* and *LOGEGDPSA*

The analyses have shown that the *CD* reacts strongly to the *LOGEGDP*. This is explained by RBNZ policies of increasing the OCR if it considers that the output gap will become too large. This is in line with the results of the Granger Causality tests.

It was shown that as *LOGEGDPSA* increased, *CD* decreased. This makes a meaningful cointegration relationship less anticipated. The procedures developed in this thesis were nevertheless followed, if anything to detect whether anomalous result might eventuate.

One could also hypothesise that the output gap becomes larger as the interest rates become lower. There was no evidence supporting this hypothesis. This observation may be explained by the effect of the OCR overriding the sensitivity of business to interest rates. However, one may still wonder about the use of the interest rates (through the OCR) for reducing demand and thereby inflation.

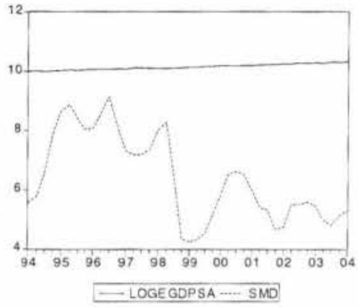
This issue raises the possibility of carrying a full analysis of every option to determine which one is acceptable. The problem becomes that if one attempts sufficient models, at some stage one will comply but this may be a spurious result. The information criterion may be used for choosing the best model, but the models tested with this criterion should be acceptable in the first place.

Cointegration analysis of *LOGEGDPSA* and *SMD*

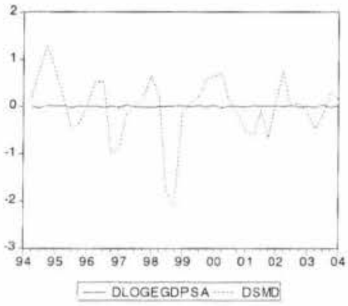
The rationale for evaluating the Sixth Monthly Deposit Rate (*SMD*) is very similar to evaluating the *CD*. The difference is the longer period of time the money will not be available to the depositor. Of particular importance in this analysis is to what degree the effects of *CD* and *SMD* differ and whether the same problems will occur.

Figure 7.28 shows considerable similarities with Figure 7.24. The differenced time series seem stationary. There is one deep trough in the differenced series of *SMD* (*DSMD*).

Figure 7.28 Time series and differenced time series of *LOGEGDPSA* and *SMD*



Time series of *LOGEGDPSA* and *SMD*



Differenced time series of *LOGEGDPSA* and *SMD*

Both information criteria again select Model 4 (Table 7.12). The SC also selected the same number of lags as was chosen in the case of *CD*.

VECM of *LOGEGDPSA* and *SMD*

The VECM suggested in Table 7.12 is shown in (7.22)

$$\begin{bmatrix} \Delta SMD_t \\ \Delta EGDP_t \end{bmatrix} = \begin{bmatrix} \mathbf{-0.4832} \\ 0.0014 \end{bmatrix} \left[SMD_{t-1} - \mathbf{78.5227} EGDP_{t-1} + \mathbf{0.7167} t + 775.3579 \right] +$$

$$\begin{bmatrix} \mathbf{0.5531} & \mathbf{-27.2074} \\ 0.0006 & -0.4100 \end{bmatrix} \begin{bmatrix} \Delta SMD_{t-1} \\ \Delta EGDP_{t-1} \end{bmatrix} + \begin{bmatrix} -0.1606 & \mathbf{-16.1921} \\ -0.0047 & 0.0695 \end{bmatrix} \begin{bmatrix} \Delta SMD_{t-2} \\ \Delta EGDP_{t-2} \end{bmatrix} +$$

$$\begin{bmatrix} \mathbf{0.3155} \\ \mathbf{0.0114} \end{bmatrix} + \begin{bmatrix} \varepsilon_{SMD,t} \\ \varepsilon_{EGDP,t} \end{bmatrix} \qquad (7.22)$$

where *EGDP* is *LOGEGDPSA* and the significant coefficients are in bold typeface.

Table 7. 12 Cointegration analysis of *LOGEGDPSA* and *SMD*

	Five assumption options regarding trend in data and CE				
	1	2	3	4	5
Data trend	None	None	Linear	Linear	Quadratic
CE	No intercept No trend	Intercept No trend	Intercept No trend	Intercept Trend	Intercept Trend
Lag 1 39 obser-vations	2	2	1 -4.0869 -3.6604	1 -4.3760 -3.9068	2
Lag 1 to 2 38 obser-vations	1 -3.9595 -3.4424	1 -3.9888 -3.4286	0	1 -4.5663 **-3.9199**	2
Lag 1 to 3 37 obser-vations	1 -4.0921 -3.3955	1 -4.0803 -3.3401	0	1 **-4.7004** -3.8732	1 -4.6483 -3.7775
Lag 1 to 4 36 obser-vations	1 -4.1905 -3.3108	1 -4.1466 -3.2228	0	0	1 -4.5141 -3.4584
Lag 1 to 5 35 obser-vations	1 -4.1807 -3.1142	0	0	0	1 -4.4843 -3.2401
Lag 1 to 6 34 obser-vations	1 -4.3443 -3.0873	1 -4.3830 -3.0811	0	0	0
Lag 1 to 7 33 obser-vations	1 -4.1810 -2.7298	1 -4.4947 -2.9982	1 -4.5512 -3.0094	1 -4.5119 -2.9247	2
Lag 1 to 8 32 obser-vations	2	1 -4.2319 -2.5371	1 -4.3542 -2.6136	0	2

Note: Period covered 1994:1 – 2004:1.

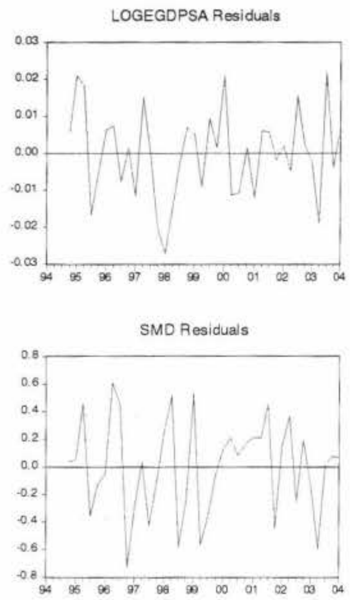
The two equations (7.21 and 7.22) that assess the relationship between the GDP and interest rates are very similar. Not only do they consist of the same model, the size of the coefficients is very similar as well. ΔSMD reacts to departures from the long-run equilibrium between *SMD* and *LOGEGDPSA*.

Analysis of the residuals of the VECM of *LOGEGDPSA* and *SMD*

Various tests were performed on the residuals to verify that the assumptions for the linear model were met. If not the model may give misleading information about the system being modelled.

The Jarque-Bera value of the residuals of $\Delta EGDPSA$ is 0.381673 (p = 0.826268).
The Jarque-Bera value of the residuals of ΔSMD is 1.181938 (p = 0.553790).
The residuals of the VECM appear stationary (Figure 7.29)

Figure 7.29 Residuals of VECM of *LOGEGDPSA* and *SMD*



The ACF of the residuals of $\Delta EGDPSA$ does not show significant lags and the Q statistics are not significant either (16 lags included). The ACF of the residuals of ΔSMD seems to show a significant value at lag 2. However, there are no significant Q statistics (16 lags included).

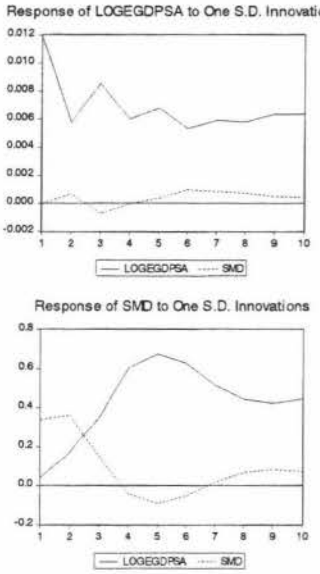
The correlation between the residuals of $\Delta EGDPSA$ and ΔSMD is 0.129065. In contrast with the residuals of VECM (7.21) the residuals of VECM (7.22) are not cross-correlated.

Innovation Accounting

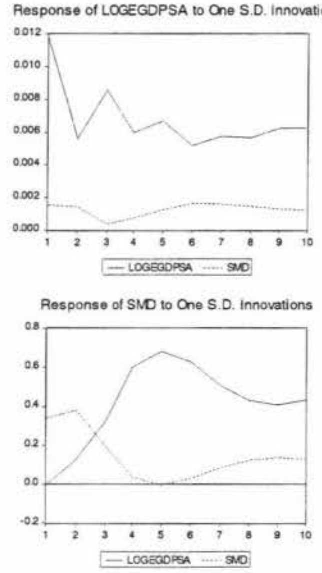
The ordering of the variables does not influence the IRF or VD greatly. Figure 7.30 shows a pattern that is very similar to Figure 7.26. Figure 7.31 shows a pattern that is very similar to Figure 7.27.

Figure 7.30 shows that one SD innovation of $\Delta LOGEGDPSA$ has a severe impact on SMD but the opposite is not the case. Similarly, after 10 periods much of the variance of SMD is derived from LOGEGDPSA.

Figure 7.30 Impulse Response Function of VECM of *LOGEGDPSA* and *SMD*

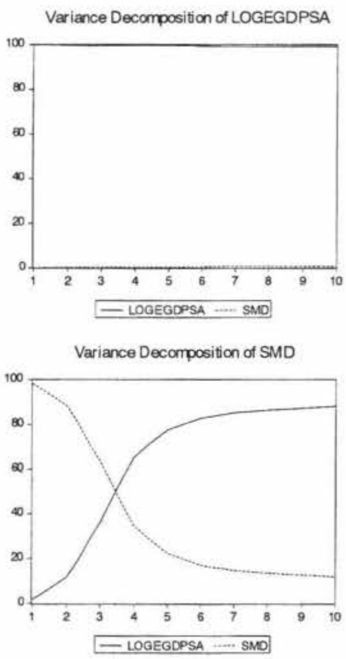


Order *LOGEGDPSA SMD*

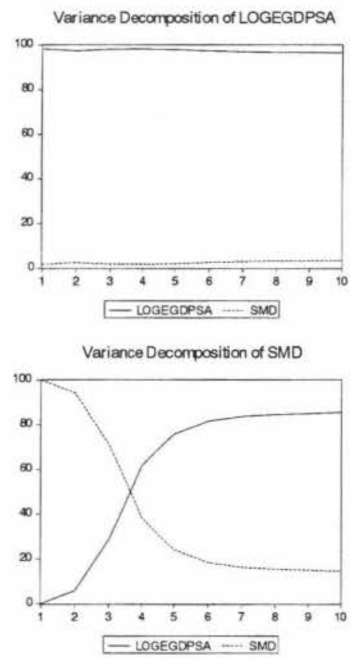


Order *SMD LOGEGDPSA*

Figure 7.31 Variance Decomposition of VECM of *LOGEGDPSA* and *SMD*



Order L*OGEGDPSA SMD*



Order *SMD LOGEGDPSA*

Comments on VECM of LOGEGDPSA and SMD

The VECM of *LOGEGDPSA* and *CD* shows many similarities to the VECM of *LOGEGDPSA* and *CD*. It can be hypothesised that they are largely subject to the same influences. An increase of the GDP will lead to an increase of the interest rates, which will dampen demand. The opposite could not be proven, that interest rates are influencing the GDP.

Comment on the analyses of Gross Domestic Product time series

The GDP plays an important role in monetary policy. If the GDP increases too fast, the risk of an undesirably high level of inflation is considered to be likely to occur in the near future. Dampening demand by raising interest rates through the OCR is used as the main tool to reduce the GDP increase. It should be noted that the OCR has only been in place in the last part of the time series.

The GDP time series showed seasonal patterns which were adjusted. Both series (the expenditure-based GDP and the production-based GDP) measure essentially the same but because measured in a different manner, different conclusions from both a statistical and an economic perspective cannot be ruled out. For both series a DF Model 1 was chosen but there were differences in the lagged terms. The DF models were not satisfactory. This was because in both instances a Model 1 was chosen but for LOGEGDPSA the $\tau_{\alpha\tau}$ did not appear to be significant and for LOGPGDPSA both deterministic components were not significant.

The Granger Causality tests showed similarity in patterns between the GDP series and inflation. This also applied to the GDP series and the interest rates. There was support for the hypothesis that GDP 'drives' inflation. There was also evidence that GDP 'drives' the interest rates, ie it reflects RBNZ's policy. No support was found for the opposite that interest rates in turn affect GDP.

Both Granger Causality and Cointegration Analysis showed relationship between the two GDP measurements. This may reflect the nature of the measurements rather than being based on an economic principle.

The VECM and GC were not in accordance with regard to GDP and CPI. The VECM showed that the CPI was the time series that reacted to the other ones in the CE. However it should be noted that there were also significant lagged differenced values.

Cointegration analysis seems a suitable technique to distinguish between the effect of the output gap and the quantity of money in the circulation on inflation. The cointegrating equations did not show an effect of *LOGEGDPSA* (see 7.17). The clearest effect to restore the long-term equilibrium was by *LOGCPI* and it applied to the combination of *LOGCPI* and *M1SA*. Also M1SA showed an effect in the CE but this was difficult to explain.

The VECMs that evaluated the interest rates and the *EGDPSA* showed that a departure from the long term equilibrium resulted in an adjustment by the interest rates. The opposite could not be established. The figures did not give an indication of cointegration. It is also of interest to not that both ΔCD and ΔSMD had significant negative coefficients for their first and second lag with $\Delta LOGEGDPSA$. This together with the large number of (significant) coefficients in the models is of concern. It gives the impression that the method is quite flexible for fitting a model. However, this model may not be meaningful from an economic perspective.

The cointegration analyses always showed large numbers of admissible VECMs. They would also vary widely with regard to the lags that were included and the option (ie deterministic components) that were included in the models. This is of concern since it creates too m any opportunities to select a model regardless of the economic theory that is used. One may perhaps see this from a different, statistically more correct perspective. The models are not so much accepted; rather they have not been rejected yet. The main reason for this would be the short data series. However, it this is the case, how long should a series be before conclusions can be drawn?

CHAPTER 8

THEORETICAL CONSIDERATIONS OF INFLATION IN AN ECONOMY WHERE VARIOUS CURRENCIES ARE USED CONCURRENTLY

Introduction

The above analyses have considered a number of factors that are commonly associated with inflation. An important issue when analysing factors that affect inflation are the economic policies that are in place. The impact of for instance the monetary aggregates on inflation may change considerably if the economic policies change.

An important factor that may greatly affect inflation is the use of currency substitution. There has been a debate for many years now about a common currency between Australia and New Zealand, the ANZAC dollar. If this does not occur, currency substitution which is a process that appears permitted under New Zealand legislation may become more widespread.

This chapter will discuss some issues raised by currency substitution in a qualitative sense. The contents of this chapter were presented at the Conference of the New Zealand Association of Economists (Inc) in 2003 in Auckland

A conceptual discussion of the concurrent use of multiple currencies in a small open economy

Peter B van der Logt[1], Professor Lawrence C Rose[2] and Dr Geoff Jones[3]

Abstract

Generally goods and services are purchased with a currency that is specific to a country. In recent times dollarisation (ie adopting a foreign currency) and currency unions have been discussed as alternatives to the New Zealand dollar being the legal tender in New Zealand.

Foreign currencies are sometimes accepted by sellers in countries with unstable currencies or in tourist resorts. This paper discusses some ramifications of extending this concept to the whole of a small open economy that does not suffer from any major monetary problems. Buyers and sellers would on a voluntary basis agree what currency (including the NZD) to use for their exchange of goods and services.

In contrast with dollarisation and currency unions, the concurrent use of multiple currencies would constitute a monetary event that does not require a political decision. However, this does not mean this system is without consequences. There are likely to be benefits as well as drawbacks, and in some cases the effect is not overly clear.

A number of these issues will be discussed in this paper on a conceptual basis. They include the spread between buying and selling a currency, insurance against sudden depreciation, facilitating immigration, purchasing expensive assets, hedging, currency risk premium, seignorage, the Official Cash Rate, and the size of the monetary aggregates.

The impact of some of the issues mentioned above might depend on the extent to which various currencies are used at the same time. Quantitative research is currently being carried out to improve the understanding of the impact.

JEL classification: E52, F31

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A conceptual discussion of the concurrent use of multiple currencies in a small open economy

1 Introduction

Normally people will pay with their domestic currency in their own country and with a foreign currency when they are abroad. This situation is taken for granted. People generally convert foreign currency into the domestic currency before making domestic purchases. (Collins *et al.*, 1999). However, Collins *et al.* also mention that at times tourist shops may accept foreign currency as an exception to this rule. There have been periods in the past where foreign money was used for domestic purposes. Pamuk (1997) described how debased European currencies circulated in the seventeenth-century Ottoman empire. Kirschen (1974) stated that the actual precious metal content, rather than their face value mattered when currencies were used abroad. There have also been episodes in the New Zealand history where foreign money was used domestically. For instance in 1931 Australian coins were commonly used which were not legal tender in New Zealand (Matthews, 2003). A number of other events are notable since they show that this situation is not unchangeable. Several countries of the European Union have recently adopted one currency (the Euro) for everyday use. Another example is the acceptance of foreign currencies in countries when their currency is under pressure. Banks may offer their customers the option of keeping accounts in foreign currencies. However, foreign currencies are not legal tender in New Zealand and consequently their widespread use would generally not be expected in New Zealand

This article will discuss a number of aspects of the concept of using foreign currencies from a qualitative perspective. Currently the authors are carrying out research to quantify economic and financial aspects of this approach. Some of the issues raised may be irrelevant from a current New Zealand perspective. However, over time circumstances may change and presently unrealistic issues may become realistic. Therefore this paper is more concerned with potential scenarios than what is actually possible at this point in time.

In recent times there have been many publications in New Zealand on altering the currency currently in use as legal tender (Hargreaves and McDermott, 1999; Grimes *et al.*, 2000, Brash 2000). A common theme in the discussion is either currency union where New Zealand will still have an input into monetary policy or dollarisation where the dollar from another country will be adopted.

Various requirements for entering a currency union have been listed. They include: relative size in world trade, independence of external factors or restrictions, no exchange controls, very liquid primary and secondary markets for currency, stable foreign trade and economic circumstances in each of the countries in the union. Especially the first factor warrants attention. New Zealand's relative size in the world trade is very small, and approximately one fifth of its exports are destined for Australia. Regardless of the argument whether this percentage is considerable or not, it would still leave most of New Zealand's exports not covered by a currency union with Australia. However, it should be considered that, even if a currency union with Australia eventuated, the concurrent use of multiple currencies in the New Zealand economy would still remain an option.

A number of benefits have been listed for a currency union. A concise summary of Mundell's work on currency unions can be found in Grimes *et al.* (2000). The positive effects include the tying of domestic inflation to the partner and convergence of interest rates, an anchor for monetary policy, reducing printing and transactions costs, protection against some domestic lobby groups and speculators, furthering economic integration and a multinational cushion against some shocks. The loss of ability to maintain an independent interest rate, seignorage, exchange rate adjustments to shocks and national sovereignty are described as negative effects. In this publication the authors expand on the relevance of these various issues to New Zealand.

The shock absorber function of exchange rates is an important issue (for more details see section 4.7 below). The optimum-currency-area is much related to this concept. To some degree it requires some form of homogeneity within a region but differences between regions. Some of Mundell's work on this issue is discussed in Levi (1990). If multiple currencies were used concurrently, some of the benefits of an optimum-currency-area might be reduced.

Australia is the most obvious contender for a currency union. Either the USD or the Australian dollar could be considered for dollarisation[4]. The loss of national sovereignty is described above as a negative issue. There is an emotional aspect to this argument. However, at times the loss of sovereignty is specifically applied to the loss of control over monetary policy. This argument is quite relevant from a macroeconomic perspective.

The adoption of the Australian dollar, or any other currency for that matter, as legal tender, can be seen as an economic reform imposed from the top. This article will explore an alternative option of monetary change that can be considered as instigated by the users of the currency rather than by government or the monetary authority, ie a monetary reform from the bottom. Households and firms could start using foreign currencies for the purchase and sale of goods and services. The only requirement would be that both parties to a transaction agreed on the currency to be used. The government would not need to be excluded from this process. Taxes and transfer payments could also be paid in foreign currencies. Therefore, apart from the NZ dollar there would be the option to use the Australian dollar or US dollar, the Euro or whatever other currency on a voluntary basis in the New Zealand economy.

The context of this paper is that of New Zealand being a small open economy. Its nominal GDP for the quarter ending September 2002 was 30,276 million NZ dollars. There are no restrictions on the flows of currencies in and out of the country, apart from reporting requirements if certain amounts are exceeded. The use of other currencies in New Zealand is not likely to affect the value of other currencies because of the New Zealand economy's small size in comparison with its main trading partners. Although New Zealand is used throughout this paper as the country where multiple currencies could be used, in some cases the points made might be more applicable to other countries.

This paper will first outline reasons for using multiple currencies concurrently. This is followed by reasons against doing so. The next section discusses various ways in which monetary matters might be influenced. Finally there is a section on measurement of the inflation rate in a geographic area rather than the measurement of the inflation rate of a currency.

[4] An alternative to dollarisation is a currency board where a country issues its own currency that is fully backed by financial assets denominated in another currency. This structure seems to be less popular now than in the past.

2 Reasons for using foreign currencies

The concurrent use of foreign currencies would be a considerable change for many people. Change would not occur unless some were to benefit. Firms and households may want to use a foreign currency for various reasons and some of these will be discussed below.
The most obvious benefit would be a reduction of the transaction costs. However protection against inflation and/or depreciation might also be important at times. This leads to the wider concept of insurance against adverse movements of the currency by holding wealth in various currencies. Investment might be promoted by seemingly unrelated matters. There is a risk premium attached to the loans in NZD. Also the NZD might appreciate if there is a sudden big demand. At a more basic level, accounting reports of profits and losses may be heavily influenced by exchange rate fluctuations. Their short-term volatility may deter organisations with short-term reporting cycles.

2.1 Transaction costs

If a good is imported into New Zealand, the NZ dollar has to be converted into a foreign currency first. There is a cost to the conversion associated with the buying and selling rates. This cost may not be immediately obvious if one buys from the importer or at a retail level. The cost of conversion has become an invisible part of the purchase price. The removal of the transaction costs will either reduce the cost of the imported good to the user of the good, or it will increase the profit margin of the importer. If it has the effect of reducing the costs of final goods, domestic industries will face increased price pressures. If it reduces the cost of an intermediate good that is used for producing an export product, the domestic industry may be able to produce this good cheaper.

The sale of New Zealand goods in export markets can occur according to various scenarios. A foreign importer may buy NZ dollars, increasing the price in the foreign market of this good produced in New Zealand. An alternative scenario is the foreign importer buying the New Zealand good with a foreign currency, thereby shifting the cost of conversion to the NZ exporter. Whoever converts the money, there will be an additional cost to the NZ product (even before transport costs and insurance costs) which will make it less competitive in export markets. The degree to which the conversion matters will depend on the size of the spread. The spread differs for the various currencies and consequently the benefits will differ. Also the spread will differ for various markets (eg retail and wholesale issues).

The following scenario could be envisaged where conversion is not required. An exporter who acquired USD may use these to buy goods from a New Zealand importer and will pay with USD, which the importer will use to import US goods. A number of additional links between the importer and exporter could be considered increasing the number of people who could potentially be included in the pool of people using foreign currencies. For instance a dairy company sells milk overseas, pays the New Zealand farmers in USD, and the New Zealand farmers will use this money to buy US farm equipment with the USD they received for the milk.

Under these scenarios, the foreign currencies would not be legal tender in New Zealand. A major benefit for using a legal tender is that it reduces the cost of the process required to reach agreement on the price of a good. This argument has been used extensively to show that barter where one good is exchanged for another can be costly because of the effort that is required to find buyers and sellers with complimentary needs. This argument would only moderately apply to multiple currencies. Both parties should be able to establish fairly quickly whether they are willing to trade with the help of a foreign currency. Furthermore the currency, *per se*, would not necessarily affect the price of the good much, if anything.

2.2 Insurance against sudden depreciation

The New Zealand economy is to a large degree dependent on primary industries such as agriculture and forestry. Catastrophes such as the introduction of serious exotic animal diseases would not only affect the profitability of the farming community. In addition they might also result in an immediate depreciation of the NZD. A research paper by the Reserve Bank of New Zealand and the Treasury (Anonymous, 2003) considered that it was difficult to estimate the magnitude of the exchange rate shock. Nevertheless the paper surmised on an initial drop of the NZD of approximately 20 percent in the first quarter. There are other aspects of New Zealand that make its currency vulnerable to sudden depreciation. They include its exposure to geography-associated disasters such as earthquakes (eg Wellington on a fault line) and climate-associated ones such as droughts affecting farming. Consequently it is in the interest of New Zealand residents to hold some of their wealth in foreign currencies that would not be affected by local disasters.

Furthermore, a sudden depreciation would result in an under-valuation of assets denominated in NZD. This would be the ideal situation for overseas interests to buy these assets at depressed prices, before any price corrections had occurred. In other words, other parts of the economy are protected against being sold below 'fair market value'.

It should be noted that there are other ways to protect one's wealth (eg hedging). Like any insurance scheme there is a cost to this and the deliberation above is yet another way of dealing with the risk of holding wealth in a particular currency.

2.3 Immigrants and returning citizens

Large numbers of foreign immigrants have recently arrived in New Zealand. The conversion of their money into NZ dollars can be costly as described above. In addition if people have not decided yet whether or not to stay permanently the decision to convert becomes even more difficult. There is always a concern that the NZ dollar might depreciate suddenly and any higher interest rates would be required for some time to compensate the losses. It is not unusual for lobby groups from export industries to advocate the depreciation of the NZ dollar adding to the immigrants' apprehension. In addition, some immigrants may be reluctant to convert the currency they have used for their entire life and to which they are accustomed.

The ability for immigrants to bring their wealth into the country and use it without having to convert it will encourage some to do so. Some immigrants are currently required to transfer certain minimum amount of investment funds into the country. The result might be that especially these immigrants may bring more wealth into the country than is strictly required as a condition for entry. A reluctance to convert foreign currency that has been acquired overseas may also apply to returning NZ citizens.

The influx of money that is used without conversion may have monetary consequences that are discussed elsewhere.

2.4 Purchase and sale of expensive assets

If a foreign company wishes to buy an asset it will need to acquire NZ dollars. If the asset is very costly and the quantity of NZ dollars available for purchase is relatively small, then the price of NZ dollars will be pushed up depending on the elasticity of supply of the NZ dollar. This could potentially increase the price of the asset in question to such a level that it is no longer profitable to purchase. The ability to pay for this asset with a foreign currency would overcome this issue. It should be noted that the appreciation would not only affect the purchaser of the expensive item but also other buyers who need NZ dollars.

Similarly, the sale of a large asset by a foreign company that subsequent to this sale wants to repatriate the proceeds may bring a glut of NZ dollars onto the foreign exchange market, reducing the value of the NZ dollar and the company's profits.

2.5 Hedging and speculation

Exporters and importers may currently have procedures in place to deal with foreign exchange movements. They may make use of facilities to hedge. Without hedging exporters and importers may make losses or profits as a result of currency movements. These losses or profits could be seen as part of a foreign exchange business rather than part of the core business of importing or exporting.

The benefits and costs of forward contracts should be evaluated with regard to unexpected exchange rate changes as expected changes would already be embedded in differentials (Brookes *et al.*, 2000). They mention that forward contracts are virtually cost-less when wholesale amounts are concerned. There are no bank fees and the bid-ask spreads are not materially different from spot transactions. However, they also explain how a cover for an exporter might be excessive if there is a downturn in sales. The exporter would have to purchase foreign currency in the spot market where it would now be more costly and the sale at the lower forward price that was previously established would constitute a loss. Their observations illustrate that forward contracts can become a position of exposure rather than a hedge. They explain the issue was the result of hedging of anticipated rather than certain cash flows.

Options can be used in which case the bank carries the risk of adverse currency movements and consequently they charge a premium for such a contract. The longer the time period, the more expensive the option. They mention that the up-front cost is a significant proportion of the profit margin. However, since the option will be exercised at various times, the premium should not be considered a cost that is lost[5]. In a competitive market one would expect these

[5] This is an accounting issue to the extent that the cost is often recognised initially but the benefits must wait until the exercise time.

premiums to come down. There are finally two costs associated with this: the unexpected exchange rate movements and the insurance premium.

Doing business by accepting foreign currency and using it for payments would to some degree be another form of hedging. However, some risk would remain. The foreign currency may depreciate (suddenly) against the NZ dollar and against other currencies. The impact on a firm of this depreciation would depend on the degree to which it would be able to continue carrying out business with this foreign currency without having to convert it into NZD or paying to pay a premium to compensate the suppliers. Brookes *et al.* (2000) mention firms making arrangements where the risks are passed on to customers and/or suppliers. The other side of this issue would be to what degree suppliers would benefit if the currency appreciated.

2.6 Currency risk premium

New Zealand interest rates have generally been higher than those in the United States. Ha and Reddell (1998) mentioned that "A(n) ... explanation is that there is a currency-related risk premium embedded into NZ interest rates – something that makes investors relatively less willing to invest in NZ dollar assets than US dollar assets for any given level of interest rates." This observation leads to the conclusion that being able to directly use USD rather than NZD would be to the benefit of companies seeking to borrow money.

Hawkesby *et al.* (2000) investigated the existence of a currency risk premium with regard to the Australian dollar and the US dollar. His analysis suggested that the New Zealand currency risk premium compared with Australia is smaller than the currency risk premium found against interest rates in the United States.

The use of other currencies would therefore be advantageous for borrowers. In contrast, lenders would be disadvantaged. Especially in a case like this one, it would be interesting to try to establish in a quantitative sense what equilibrium levels would eventuate between currency holdings in various denominations.

2.7 Reporting of profits and losses

Private companies and investment funds may work on short-term reporting cycles. Currency fluctuations are reflected in their profits or losses. It may be beneficial for such enterprises to encourage their New Zealand based clients to trade in the domestic currency of these foreign companies and funds so that the short-term volatility of the exchange rate has a reduced impact on the reporting to their overseas owners.

2.8 Protection of capital against erosion due to inflation

The Covered Interest Parity theory states that higher inflation and concomitant depreciation of one currency versus another currency is compensated by higher interest rates. Part of the interest that is received serves to compensate for the erosion of the capital value due to inflation. Interest payments in New Zealand are subject to taxation. It is therefore to the benefit of investors not to invest in a currency that is characterised by a relatively high inflation rate and prone to depreciation, since the compensation for inflation will be 'taxed'.

If anything, this aspect shows the potential for competition between various (groups of) countries issuing a currency. To some degree their ability to maintain price stability would increase the popularity of their currency. This would be tempered by such factors as the interest rates they set (OCR or equivalent) and the 'economic fundamentals' that are in place in these countries.

Fisher (1982) describes the inability of a government to control inflation as an important reason for dollarisation (ie increasing the use of any foreign currency). The NZD has not suffered from high inflation in recent times and consequently there is no need for the NZ government to dollarise for this reason. However, at times it may still be to the benefit of individuals to use another currency instead of the NZD as a store for their wealth.

3 Reasons for not using foreign currencies and some practical issues

The use of foreign currencies may mean that the volatility of the exchange rate is passed on more directly to others who so far were partially shielded from exchange rate volatility. When somebody receives a foreign currency instead of the NZ dollars that he would normally receive, several options are available. The foreign currency can be converted into NZ dollars immediately. Due to the transaction costs there will be a loss that could be prevented by adding a mark-up when the foreign currency is offered instead of the NZD. Another option is to invest the money in a foreign currency bank account or some other financial instrument. The new owner would need to decide what the benefit is of holding the various currencies. Finally the foreign currency could be used for purchasing goods and services with the foreign currency that was just received. In any case, the new owner must develop a strategy for managing foreign currencies, which is presently not required.

The use of bank accounts for various currencies may lead to more fees to be paid. The ability to provide more services may be seen as a positive element by the banking sector. The assessment of one's wealth may also become more complicated if it is expressed in various currencies that appreciate and depreciate against each other on an ongoing basis.

There are some practical issues regarding the use of physical money (ie notes and coins) that need to be considered. Over the years credit cards and EFTPOS have become more popular. Issues such as giving change in shops no longer apply if these cards are used. Smart cards (eg for transport and parking) are becoming increasingly popular, further decreasing the need for notes and coins.

Goods will need to be priced in at least one currency. Preferences may be based on:

- Domestic currency.
- Currency that was used to purchase the goods.
- Strongest currency, ie least likely to depreciate.

The use of credit cards may facilitate the use of multiple currencies. Assume goods in shops are priced in USD. Payment occurs by credit card. Credit card companies will need to purchase USD with NZD. There will be a large demand for USD (probably negligible from a USD perspective) and a large supply of NZD. This has the potential to lead to a considerable depreciation. Depreciation (in the long term) would usually be associated with inflation, which is compensated by higher interest rates. This would not necessarily occur in this case because the depreciation is not inflation driven.

In general, where one party benefits from changes as described in section 2, another party will be negatively affected. Consequently some issues that have been described as being positive will be considered to have a negative effect by others.

4 Impact on monetary matters

Monetary policy, virtually by definition, could be affected if other currencies are used on a wider scale in the domestic economy without conversion. A number of aspects of monetary policy will be briefly discussed below. Again, some of the aspects may be negligible from a practical perspective but this may depend on the circumstances. At times the monetary aspects as discussed below in the various sections will overlap but the angle of approach will differ.

4.1 Seignorage

Various definitions are in existence for seignorage (Kirschen, 1974). The basic concept was the par value of a currency minus the bullion and minting costs. A not uncommon view of seignorage is that it constitutes the interest earned on the real assets received in return for the money issued. Schmitt-Grohé and Uribe (1999) emphasise that inflation and domestic real growth also need to be considered when evaluating the seignorage lost.

Whatever the most appropriate formula, as more foreign money is used, seignorage losses would be incurred by the New Zealand government. If dollarisation was introduced through the adoption of the Australian, the US dollar, or whatever other currency by the New Zealand government, the cost of lost revenue could be estimated. Attempts could be made to receive compensation. If the concurrent use of multiple currencies eventuated on a large scale this issue would be more complicated. There would not be a formal agreement between the various governments and in addition the mix of foreign currencies might change over time.

The loss of seignorage to another country is a negative effect and it was already identified many several centuries ago. Bordo (1986) refers to a publication by Miskimin about a French king who tried periodically and unsuccessfully to prohibit the circulation of foreign coins. This was because it displaced the domestic currency. Although this attempt applied to (debased) commodity money, the same principles would apply to fiat money. If the population believes that its domestic currency is being debased (subject to 'excessive' inflation) it may try to switch to another currency. The prohibition of the use of foreign currency may be difficult to enforce. As mentioned previously, some aspects of the concurrent use of currencies may be irrelevant to New Zealand and this may be one of them.

4.2 Inflation targeting

The Reserve Bank of New Zealand (RBNZ) is required to maintain a stable general level of prices. It uses the Official Cash Rate (OCR) for this purpose. Currently it is possible to have New Zealand bank accounts holding foreign currencies. One would expect that interest rates on such accounts would mainly be guided by the interest rates prevailing in the country that issues the currency if interest parity holds. If not, arbitrage gains could be made. Consequently, the more money is kept in foreign currency accounts rather than NZD accounts, the smaller the impact of OCR and the smaller the influence the RBNZ can exert on the short to medium term inflation rates.

4.3 Monetary aggregates

The money stock is commonly described in terms of M1, M2 and M3. Credit is equally important when assessing the size of the money stock. If foreign money can freely flow into the country and be used without conversion the measurement of the money stock becomes more complicated, if not impossible. The inflation rate may be affected by the increase of money that over time becomes gradually available.

It can be argued that banks can borrow as much money as they wish from the RBNZ, but this comes at a considerable cost. There are practical limits to the amount of money they will require from the RBNZ under the current conditions in New Zealand. However, if large amounts of money can enter the country over a very short period of time without conversion, then the monetary aggregates can change drastically. The question becomes whether large injections of money can have a significant impact on the effect of monetary aggregates on inflation from a practical perspective.

Razzak (2001) has shown a changing relationship between money growth and inflation over an extended period. It is beyond the scope of this paper to analyse the reasons for this. In any case, the potential of an increased inflow of money to affect inflation should be considered.

If large assets are purchased with foreign currencies, and this money stays in New Zealand, then the monetary aggregates will expand. There is at least a theoretical possibility that the monetary aggregates will expand much quicker than the output of the country causing increased demand for goods and services and subsequent inflation.

4.4 Effects on the NZ dollar

Currently when foreigners buy assets in New Zealand they will buy NZ dollars first. A consequence is an appreciation of the NZ dollar. Owners of NZ dollars will not be any worse off if they want to buy other New Zealand assets since the currency they hold has kept its value in terms of assets in New Zealand. However, if conversion does not occur, then there will be an increased money stock and more nominal money will be available to buy the same assets. Consequently the NZ dollar will be worth less. This raises the issue of whether NZ dollars would need to be withdrawn from circulation to compensate for the inflow of foreign money.

The use of multiple currencies may reduce the use of the NZ dollar for international trade purposes (goods and services). Black (1991) modelled the inverse relationship between volume and transaction costs of vehicle currencies. Similarly a reduction in the amount of money continuously available for foreign exchange purposes is likely to increase the spread of the NZD. A vicious circle might eventuate.

Speculation occurs where people are willing to take a risk with a probability of making financial gains. In the past inappropriate pressure may have been placed on currencies in order to reap such gains. This could be successful in the case of fixed exchange rates. These tactics may have been more successful if the amount of money in circulation was small compared with the financial resources available to the speculators. A floating exchange rate as is currently in existence combined with sound economic policies are generally considered to be helpful in preventing crises. Nevertheless, the use of other currencies may provide protection in the sense that larger numbers of people use them. On the downside, the remaining smaller amount of the domestic currency might make it more vulnerable to speculation.

4.5 Surplus/deficit of NZ dollars in the foreign exchange market

The exchange rate is influenced by the balance of imports and exports if one ignores such factors as the financial markets and inflation for the sake of this argument. If exporters decide to keep the foreign currency they acquired (ie not to convert it into NZ dollars) then the balance between the supply by exporters and the demand by others will alter. The excess of NZ dollars could lead to a depreciation which is not based on trade or investment. Once the foreign currency has flown through the New Zealand economy and has started to be acquired by importers the requirements for currencies will go the other way. A process in reverse might occur at that stage where the demand for NZ dollars exceeds its supply.

4.6 Financial markets and foreign debt

The overall effect of the use of multiple currencies would be a reduced use of the NZ dollar in general, unless other countries started to use multiple currencies too. This may also lead to a reduced use of the NZ dollar in the financial markets. A less liquid market is generally more prone to distortions.

The overseas debt of New Zealand residents is considerable. The dependence on foreign capital was discussed by Brash (2002). Increased borrowing by New Zealand residents of foreign currencies without subsequent conversions will have several ramifications. Foreigners may be less willing to be involved in any transactions involving NZ dollars because of the reduced liquidity. However, it may also be possible that it becomes easier for New Zealand residents to borrow money overseas in the foreign denominations.

4.7 Exchange rates as shock absorbers

It has been suggested that the exchange rate functions as a shock absorber when compared with the Australian dollar (Conway and Franulovich, 2002). If exports are slumping, there will be an excess of NZD. This excess will lead to a depreciation of the currency, which in turn will lead to increased competitiveness and more exports. This aspect of currencies has been used as a reason against currency unions. Countries that use the same currency should according to this philosophy have similar business cycles. The shock absorber issue is also worth investigating when multiple currencies are used.

4.8 Competitive depreciation

If some residents are not saving sufficiently to fund others' investment or desired consumption, then money needs to be borrowed from overseas. The foreign debt increases. This increase ultimately needs to be financed. Arguably by exporting more. This could be achieved by becoming more competitive. One way of becoming more competitive is by having a depreciating currency as described above. The words 'competitive depreciation' have been used for this.

If most of the domestic trade is carried out with foreign currencies, depreciation will become less relevant as an option. At a theoretical level it may not be too difficult to distinguish between the shock absorber and the competitive depreciation function. In practice the difference may not always be so obvious.

5 One country, one currency, one inflation rate

Usually country, currency and exchange rate are seen as inextricably related variables. One currency's inflation rate may spill over into another currency due to export prices. However inflation leads to a depreciating currency (*ceteris paribus*) which would to some degree compensate for this.

Now assume Australian goods are sold in New Zealand at the original Australian price plus perhaps additional transport and insurance costs. Inflation in Australia would result in more Australian dollars being demanded for this good in New Zealand too. The New Zealand inflation rate can be measured by converting the AUD prices of goods into NZD. This approach can become problematic if the use of the NZD is reduced to a very low proportion of the currency in circulation. Also if the amount of NZD being traded in the foreign exchange market is becoming smaller, volatility may very well increase. The exchange rates may no longer properly reflect the 'true' value of the currency.

Instead of the NZD the most commonly used currency could be used as a benchmark. Alternatively a formula can be developed that takes into account the proportions of goods in the various categories, the increase in nominal price levels and the various exchange rates to make an estimate of increases of price levels. Therefore the inflation rate would apply to a geographic area, rather than to a currency.

6 Discussion

If multiple currencies were used then the most commonly used ones are likely be the currencies that are used by New Zealand's main trading partners. A certain period of time would be required before sufficient foreign currency had flown into the country to have an effect in any of the areas listed. Such changes would not necessarily be of a permanent nature. For instance, if there were a reduction in the trade with the US and an increase in trade with China, then more of the Chinese currency and less of the USD might circulate in New Zealand.

The scenarios discussed above differ from events driven by and following a currency union. The changes would be driven from the bottom rather than the top. New Zealand legislation states that legal tender notes and coins can be issued solely by the Reserve Bank of New Zealand. The use of foreign currencies by trading partners based on mutual agreement does not appear to be in violation of this legal requirement. Matthews (2003) mentions that "Legal tender is a legally defined means of settling a debt. A creditor is not obliged to accept legal tender, but cannot further pursue the debt if the offer of legal tender is refused."

This paper is of a qualitative nature. The various issues that have been raised are only considered from a qualitative, hypothetical, viewpoint. A number of reasons were given to explain why the use of multiple currencies might benefit some people. Similarly a number of possible ramifications of the use of foreign currencies were discussed. The authors do not express an opinion whether, on balance, the country will benefit or not. As is the case with many economic issues, there are matters of equity and of degree. Quantification of the benefits and the impact on monetary matters are outside the scope of this paper but it will be required at some stage to develop opinions about actual effects. It is clear that the concurrent use of multiple currencies is a complicated matter from a quantitative perspective. If quantified some issues mentioned in the previous sections may appear to be insignificant. The authors are currently carrying out quantitative research to improve their understanding of the impact. This research entails the analysis of time series to acquire a better understanding how the various variables interact. The problem of extrapolating the results of such analyses to a situation that may be quite new is well appreciated. The next stage would be the amendment of an existing model or the development of a new model to make preliminary estimates.

7 References

Anonymous (2003) The macroeconomic impacts of a foot-and-mouth disease outbreak: an information paper for Department of the Prime Minister and Cabinet. Paper prepared by the Reserve Bank of New Zealand and the Treasury.
http://www.rbnz.govt.nz/research/0130346.html

Black SW (1991), Transaction costs and vehicle currencies. Journal of International Money and Finance, 10, 512-526.

Bordo MD (1986) Money, deflation and seigniorage in the fifteenth century: A review essay. Journal of Monetary Economics. Vol. 18, No. 3, 337-346.

Brash DT (2000) The pros and cons of a currency union: A Reserve Bank perspective. An address by Donald T Brash, Governor of the Reserve Bank of New Zealand to the Auckland Rotary Club. Auckland 22 May 2000.

Brash DT (2002) An indebted people. A speech by Donald T Brash, Governor, Reserve Bank of New Zealand to the Canterbury Employers' Chamber of Commerce on 25 January 2002. Reserve Bank of New Zealand: Bulletin Vol. 65, No. 1, 71-80.

Brookes, A., Hargreaves, D., Lucas, C. and White (2000) Can hedging insulate firms from exchange rate risk? Reserve Bank of New Zealand: Bulletin Vol. 63, No 1, 21-34.

Collins S, Thorp C and White B (1999) Defining money and credit aggregates: theory meets practice. Reserve Bank of New Zealand: Bulletin Vol. 62, No. 2, 5-23.

Conway P and Franulovich R (2002) Explaining the NZ-Australian exchange rate. Westpac Trust Institutional Bank, Occasional Paper, April 2002.

Fisher S (1982) Seigniorage and the case for a national money. Journal of Political economy Vol. 90, No. 21, 295-313.

Grimes A, Holmes F and Bowden R (2000) An ANZAC dollar? Currency union and business development. Institute of Policy Studies, Victoria University of Wellington, Wellington, New Zealand.

Ha Y and Reddell M (1998) What do forward interest and exchange rates tell us? Reserve Bank of New Zealand: Bulletin Vol. 61, No. 2, 129-147.

Hargreaves D and McDermott J (1999) Issues relating to optimal currency areas: theory and implications for New Zealand. Reserve Bank of New Zealand: Bulletin Vol. 62, No. 3, 16-29.

Hawkesby C, Smith C and Tether C (2000) New Zealand's currency risk premium. Reserve Bank of New Zealand: Bulletin Vol. 63, No. 3, 30-44.

Kirschen ES (1974) The American external seigniorage. Origin, cost to Europe, and possible defences. European Economic Review 5, 355-378.

Levi MD (1990) International Finance. The markets and financial management of multinational business. McGraw-Hill Book Co. 2nd Ed., New York.

Matthews K, (2003) The legal history of money in New Zealand. Reserve Bank of New Zealand: Bulletin Vol. 66, No. 1, 40-49.

Pamuk Ş (1997) In the absence of domestic currency: debased European coinage in the seventeenth-century Ottoman empire. The Journal of Economic History. Vol. 57, No. 2, 345-366.

Razzak WA (2001) Money in the era of inflation targeting. Reserve Bank of New Zealand Discussion Paper 2001/02.

Schmitt-Grohé S and Uribe M (1999) Dollarization and seignorage: How much is at stake? http://www.econ.upen.edu/~unibe/seignorage.pdf

CHAPTER 9

GENERAL DISCUSSION

The initial chapters of this thesis discussed theoretical statistical and economic aspects of time series analysis and of inflation. The subsequent analyses applied this theory to time series of inflation in New Zealand combined with monetary aggregates, interest rates and gross domestic product. The analyses were initially applied at a univariate level and next multivariate equations were evaluated.

The key research questions for this thesis were stated in the introductory chapter. They applied to economics and statistics. Although the four key questions addressed different issues, some of the answers below will apply to more than one question at the same time.

Before answering the key questions, the principles of hypothesis testing should be considered first to be able to put the results of the analyses in perspective. A (null) hypothesis is formulated and the analysis will reject his hypothesis or not. Two errors can be made. A Type I error is made if the null hypothesis is rejected incorrectly. A Type II error has occurred if the null hypothesis has been accepted when in fact it was incorrect. The probability of committing a type I error is called the level of significance and 0.05 has usually been used in this thesis, but not for unit root testing. Many tests at the 5% significance level have been performed in this thesis. This is likely to lead to some Type I errors. The magnitude of the Type II errors was not known. Consequently, when results of a model become available in this thesis, they should be interpreted as rejecting the null hypothesis or not (yet). A Type II error could have been committed. Also as the sample size increases, the null hypothesis might still be rejected.

This thesis has set out to develop an approach to analysis that was as standardised as possible to reduce any bias. Enders described an approach to establish DF models on pages 256 to 258. This appeared unsatisfactory. It could be argued that it is preferable to have all possible information available at the same time to evaluate which models have not been rejected. Then a decision can still be made which model is deemed to be the 'best' one, for instance by using the Schwartz Criterion or the Akaike Information Criterion. The standardised approach was further extended to Granger Causality Tests and cointegration analyses. However in the process it became clear that frequently various models were possible that were conceptually quite different. No doubt the shortness of the data series was a problem. As described above, models are not so much accepted as being true. Rather models are rejected or not rejected. Consequently having various models not rejected (yet) is not necessarily a sign of a flawed process. It does however illustrate a problem. Two different information criteria were used. Regrettably one got the impression that these two criteria each had their own bias. If ever, and this happened frequently, there were differences between the optimal models, the model chosen by the Schwarz Criterion was more parsimonious than the Akaike Information Criterion. This suggests that the choice of criterion can have an influence on the conclusions reached.

Question 1: Can equations be found that could serve as a backbone for a small model of the New Zealand economy for the period in question?

This thesis was to some degree motivated by Svensson's small economic model (2000). Svensson described a small model that initially seemed suitable for investigating inflation issues. However once research started in this thesis on analysing inflation a comment made by that author became worrisome. He mentioned: "... there is no calibration and/or estimation of the parameters in the current version [of the model]: the only criterion applied is that they must not be a priori unreasonable. As a consequence, the numerical results are only indicative." Then he continued: "although it would be very desirable to test the model's predictions empirically, the short periods of inflation targeting in the relevant countries probably imply that several years of data are necessary for any serious data testing." Although this is a reasonable starting point it does raise some matters of concern in principle. This approach allows an author to try a wide variety of different coefficients until a model eventuates that is in accordance with the thinking of the author. This process can be quite insidious without the author being aware of his/her own bias. Any model that does not conform could be called inadmissible. Consequently some system that is robust with regard to association between variables is required. Rather than using Svensson's model an attempt was made in this thesis to empirically investigate some aspect of inflation in New Zealand in recent years.

A large number of equations were evaluated to this end of which a number were described in this thesis. The most important variable of any small model was going to be inflation and especially the variable *LOGCPI* was used to model inflation. Many equations that are described above appeared unsuitable for a model since they did not have significant coefficients where they were required. However some showed promise. Some equations may be improved in future research by using a related variable instead of the variable used (eg Production-based GDP instead of Expenditure-based GDP). It is appreciated that this again risks introducing an analyst's bias. A few equations are listed below that should be considered for inclusion into a model. Equation (5.20) can be considered when including the monetary aggregates in the model. For the relationship between inflation and interest rates (6.12) can be considered which seems to show the reaction of RBNZ to inflation. Regrettably the standardised way of analysis did not identify an equation for the opposite direction. However Granger Causality tests suggested such equations should be possible. Equation (7.13) addresses the relationship between GDP and inflation. Equation (7.17) had a monetary aggregate added as well. For the relationship between interest rates and GDP (7.21) can be considered. Therefore based on existing New Zealand data some equations were identified that can be used for developing a small model of the economy and inflation in particular. Although they are not 'perfect' for this purpose yet, they can be further developed. It is surmised that models based on empirical analysis have benefits over models based on an analyst's opinion when analysing economic policy.

An important aspect of each model is how many variables should be included. The probable answer is that it should be large enough to give required answers with a known accuracy. It could be argued that some aspects are so important that they should always be included. In the case of the work done, the next priority to improve the model would be the inclusion of equations relating to the exchange rate and inflation of the major trading partners.

Question 2: Can economic and monetary policy be seen reflected in the data sets.

The most important monetary policy tool in New Zealand is the increase or decrease of the OCR and consequently other interest rates as inflation is deemed to move outside the targets. Various equations seemed to show this policy (eg (6.12)). More importantly perhaps is the question whether economic or monetary policies are successful. The VECMs that were analysed did not provide support. The VECMs that were analysed showed that the interest rates reacted to the inflation rate but the opposite was not demonstrated. The thesis did not analyse the OCR but two different interest rates instead. This was because the OCR series is very small, is 6 weekly, and there seems to be an immediate reaction in the market to changes of the OCR. Analysing the relationship between OCR and inflation rate would have been an option. However because of the way the OCR works, retail banks cannot ignore the OCR because they borrow and lend to the RBNZ based on these rates. This is not to say that the policies were not successful. For instance the Granger Causality tests showed that a reaction of the inflation rates to the OCR may be happening if larger lags are used. However, such models were not considered because the Schwartz Criterion seemed to be prone to choose VECMs with a small number of lags. This would be an area for further investigation. Also in this case it should be considered that association and correlation do not necessarily equate to causation. Chapter 3 had already shown in a qualitative manner other variables that may have caused low inflation. There is a need for any policy to be validated and it was regrettable that the cointegration analysis as an example of a validation procedure was not able to provide support for the current policy. In this area too further multivariate analysis seems required to clarify what factors have contributed most to New Zealand's low inflation rate in recent years.

Question 3: How well do standard cointegration techniques work under practical conditions?

The short length of the time series used in this thesis was of concern. The choice was a deliberate one. Policy changes that may affect relationships and trends of time series occur relatively frequently in practice. One need only consider how often the same government is likely to stay in power in a democracy. Government changes are usually accompanied by policy changes. Consequently it will often be more appropriate to evaluate short time series rather than long ones. New Zealand time series of approximately ten years are used to evaluate this issue.

The Chow test for breakpoints was used in this thesis to evaluate the existence of breakpoints possibly due to policy changes. The drawback of this approach was described in Chapter 2. However it seemed to be the most plausible way to verify that breakpoints were not responsible for perceived unit roots in time series.

The issue of the short time series can be rephrased. If these data series are too short for these methodologies, then should these methodologies be used in the first place? Are there other, better techniques available? Is it possible that the results are misleading to such an extent that one would make better decisions without the results of cointegration analyses? A main focus throughout this thesis has been to evaluate how much confidence one can have in the results of the application of these techniques and in particular the Dickey-Fuller tests and cointegration analysis.

The following is a list of statistical issues in which the cointegration analysis was found to be unsatisfactory.

There were a number of Dickey-Fuller tests that indicated a model with unit root and deterministic components. However, based on the τ or ϕ statistics it often appeared that these deterministic components should not be in the model, they were not significant. This situation became even more problematic if the models without deterministic components did not have a unit root.

The τ or ϕ statistics did not always agree with each other.

Granger Causality tests did not show any possible causality, but the cointegration tests did not reject a cointegrating relationship.

The cointegration analyses indicated the inclusion of various significant deterministic components, lags and cointegration equations. At times significance for the relevant variables did not exist.

Despite the various statistical problems some economic conclusions could be reached. One may well wonder whether it is justified to reach these conclusion if statistical aspects are such that they may be misleading.

The number of VECMs that were not rejected according to the cointegration analyses was invariably large and these sometimes had quite different economic implications. A number of reasons are outlined above (eg small number of observations). The correct model might have been among them. Two information criteria were displayed in the tables. Their function is not to reject a hypothesis; they are for finding the best model among all acceptable models. The tables with the cointegration results showed that generally the SC would choose a more parsimonious model than the AIC would. One may wonder whether the use of the SC introduces a bias for model selection by always selection the most parsimonious model while in fact all these models might be rejected as the length of the time series increased.

Where statistical tests are used to evaluate economic policies it is obviously important to validate they are appropriate for the purpose for which they are used. Although the techniques may be impeccable from a mathematical perspective there may be limitations to the degree they can be applied to in a practical context. The analyses that were performed raised a number of issues that are of concern in that regard.

The tests showed a large number of issues that require further research. It may be tempting to reject the use of Dickey-Fuller tests and cointegration analysis on relatively small data series. However the large body of work performed on these techniques tends to indicate that it is likely that alternative, clearly superior, methods are not readily available. This can perhaps be phrased differently: "Is it possible at all to make meaningful statements on the series that were investigated by using statistical techniques?" Are there too many (unknown) factors for such small series? The use of Bayesian statistics could be considered. This would introduce more subjectivity which this thesis has tried to avoid.

The recommended way forward at this stage to further clarify how well the methodologies perform is by simulating time series and then analyzing these. Among other things thus the extent of Type 2 errors can be established.

Question 4: Can an automated approach involving the examination of a large number of possible models produce sensible results?

"Sensible" can be interpreted as meaning that the results of the various models should not contradict each other. In addition the final result of a model, ie a group of equations, should preferably cover the area of interest in a coherent manner.

Over the years there have been many economic theories. The ability of an analyst to support his or her views by intentionally or unintentionally selecting those variables that would support his or her theory are of concern. An automated approach would reduce this concern to some extent. Therefore, one reason for an automated approach is to reduce bias or at least be transparent in the selection of equations for a model. A number of rules are to be established to build a model. An example is "$p < 0.05$" to reject an equation or not. Next the 'best' equation needs to be chosen when several equations are available. There may be an issue of parsimony of rules, the fewer the better, but then too: what are the best rules? This thesis showed that some automation would be possible. However, it is also clear that the process that was used in the thesis was still very time-consuming and further research in this area s advocated.

It has been postulated by some that a model should be developed *a priori* and then this model should be tested with some statistical technique. The large number of significant cointegration equations that were consistently found tended to indicate that testing models that have been established a priori has its drawbacks too. It is altogether too easy to accept a model given the low power of the test. Even if a model were rejected it would usually not be too difficult to find an acceptable model by adding or deleting a lag or a deterministic component in the model.

Concluding comments

At this stage it seems appropriate to bear in mind that the questions and answers discussed in this thesis applied to the methodology as discussed in Chapter 2. Already there may be improvements but they are outside of the scope of this thesis.

At the end of a considerable number of analyses some judgement of the methodologies used may be expected. The analyses showed some worrying problems when the methodology is applied to the New Zealand data series, but at times the results were plausible as well. Research by many is ongoing and improvement of the methodology is likely to occur, and may in fact have occurred already. The critical question when reading this thesis is: What is the probability that the analyses provide incorrect or even misleading results? One gets the impression that the jury is still out whether this methodology is appropriate for the time series to which they were applied. It is strongly recommended at this stage not to rely on the results of these methodologies only when evaluating and formulating economic policy.

References

Enders W. Applied Econometric Time Series. New York. John Wiley & Sons. (1995) pp. 433

Svensson LEO, (2000) Open-economy inflation targeting. Journal of International Economics 50, 155-183

APPENDIX

Time series

Quarter	*LOGCPI*	*LOGCPIX*	*LOGCPINT*	*LOGCPIT*	*LOGLC*	*LOGHE*
1994:1	6.8156	6.8101	6.7380	6.8686	6.7822	2.7081
1994:2	6.8189	6.8145	6.7490	6.8696	6.7833	2.7147
1994:3	6.8309	6.8244	6.7667	6.8718	6.7890	2.7147
1994:4	6.8427	6.8309	6.7748	6.8781	6.7901	2.7213
1995:1	6.8544	6.8352	6.7846	6.8787	6.7946	2.7279
1995:2	6.8638	6.8416	6.7902	6.8854	6.7979	2.7344
1995:3	6.8659	6.8448	6.8040	6.8800	6.8035	2.7408
1995:4	6.8711	6.8512	6.8118	6.8837	6.8090	2.7473
1996:1	6.8763	6.8565	6.8273	6.8826	6.8134	2.7537
1995:2	6.8835	6.8648	6.8378	6.8880	6.8167	2.7663
1996:3	6.8896	6.8680	6.8443	6.8889	6.8222	2.7726
1996:4	6.8967	6.8742	6.8547	6.8917	6.8287	2.7850
1997:1	6.8937	6.8763	6.8635	6.8881	6.8352	2.7973
1997:2	6.8947	6.8794	6.8708	6.8872	6.8416	2.8034
1997:3	6.8997	6.8855	6.8820	6.8890	6.8459	2.8094
1997:4	6.9048	6.8906	6.8906	6.8910	6.8501	2.8154
1998:1	6.9068	6.8937	6.8946	6.8916	6.8544	2.8214
1997:2	6.9117	6.8957	6.8978	6.8951	6.8607	2.8332
1997:3	6.9167	6.9027	6.8998	6.9043	6.8638	2.8391
1997:4	6.9088	6.9017	6.8965	6.9058	6.8680	2.8449
1999:1	6.9058	6.9037	6.8984	6.9077	6.8711	2.8507
1999:2	6.9078	6.9078	6.9078	6.9078	6.8742	2.8565
1999:3	6.9117	6.9117	6.9153	6.9082	6.8783	2.8679
1999:4	6.9137	6.9147	6.9174	6.9110	6.8824	2.8622
2000:1	6.9207	6.9207	6.9245	6.9166	6.8855	2.8679
2000:2	6.9276	6.9276	6.9282	6.9272	6.8906	2.8736
2000:3	6.9412	6.9422	6.9346	6.9481	6.8937	2.8848
2000:4	6.9527	6.9527	6.9412	6.9635	6.8977	2.8848
2001:1	6.9508	6.9518	6.9364	6.9647	6.9037	2.8959
2001:2	6.9594	6.9603	6.9383	6.9783	6.9078	2.9069
2001:3	6.9651	6.9660	6.9435	6.9851	6.9137	2.9178
2001:4	6.9707	6.9717	6.9501	6.9885	6.9187	2.9178
2002:1	6.9763	6.9773	6.9625	6.9890	6.9236	2.9339
2002:2	6.9866	6.9875	6.9686	7.0026	6.9285	2.9285
2002:3	6.9912	6.9921	6.9785	7.0014	6.9354	2.9497
2002:4	6.9976	6.9994	6.9883	7.0063	6.9402	2.9549
2003:1	7.0012	7.0031	6.9964	7.0054	6.9460	2.9549
2003:2	7.0012	7.0022	7.0055	6.9969	6.9508	2.9653
2003:3	7.0058	7.0067	7.0184	6.9925	6.9584	2.9806
2003:4	7.0130	7.0139	7.0333	6.9928	6.9641	2.9857
2004:1	7.0166	7.0184	7.0450	6.9894	6.9679	2.9907

Quarter	*LOGM1*	*LOGM1SA*	*LOGM2R*	*LOGM3RR*
1994:1	9.0809	9.0761	9.7063	10.2863
1994:2	9.1253	9.1166	9.8109	10.2707
1994:3	9.1206	9.1399	9.8012	10.2892
1994:4	9.1523	9.1465	9.8255	10.3104
1995:1	9.1386	9.1338	9.8553	10.3620
1995:2	9.1770	9.1683	9.9008	10.3836
1995:3	9.1378	9.1571	9.9053	10.4216
1995:4	9.1973	9.1915	9.9929	10.4181
1996:1	9.2170	9.2122	10.0265	10.4189
1995:2	9.2337	9.2250	10.0454	10.5208
1996:3	9.1976	9.2169	9.9792	10.5872
1996:4	9.2425	9.2367	10.0418	10.6027
1997:1	9.2675	9.2627	10.0735	10.5656
1997:2	9.2970	9.2883	10.1035	10.5898
1997:3	9.2952	9.3145	10.0920	10.6474
1997:4	9.3161	9.3103	10.0358	10.6888
1998:1	9.3212	9.3164	10.0286	10.7140
1997:2	9.3419	9.3332	10.0535	10.7193
1997:3	9.3434	9.3627	10.0794	10.6925
1997:4	9.4286	9.4228	10.1542	10.6227
1999:1	9.4786	9.4738	10.1742	10.6503
1999:2	9.5136	9.5049	10.1535	10.6639
1999:3	9.5604	9.5797	10.2290	10.6509
1999:4	9.5933	9.5875	10.2171	10.6336
2000:1	9.5978	9.5930	10.1643	10.6496
2000:2	9.5955	9.5868	10.1666	10.6849
2000:3	9.5862	9.6055	10.1773	10.6977
2000:4	9.6358	9.6300	10.1697	10.7081
2001:1	9.7016	9.6968	10.1838	10.6862
2001:2	9.7403	9.7316	10.2617	10.6996
2001:3	9.7334	9.7527	10.3253	10.7169
2001:4	9.8089	9.8031	10.2826	10.7184
2002:1	9.8431	9.8383	10.3292	10.7131
2002:2	9.8792	9.8705	10.3090	10.7296
2002:3	9.8547	9.8740	10.3068	10.7920
2002:4	9.8927	9.8869	10.3566	10.8270
2003:1	9.8963	9.8915	10.3244	10.8812
2003:2	9.9275	9.9188	10.3647	10.8490
2003:3	9.9478	9.9671	10.3782	10.8757
2003:4	9.9966	9.9908	10.3638	10.9603
2004:1	10.0181	10.0133	10.3504	11.0137

Quarter	*CD*	*SMD*	*LOGEGDPSA*	*LOGPGDPSA*
1994:1	3.857	5.566	9.9969	9.9833
1994:2	4.280	5.770	10.0131	9.9940
1994:3	4.557	6.570	9.9888	10.0011
1994:4	5.083	7.863	10.0164	10.0138
1995:1	6.223	8.667	10.0323	10.0292
1995:2	6.590	8.867	10.0518	10.0402
1995:3	6.430	8.390	10.0350	10.0432
1995:4	6.310	8.040	10.0494	10.0481
1996:1	6.413	8.060	10.0623	10.0691
1995:2	6.640	8.593	10.0781	10.0746
1996:3	6.755	9.133	10.0761	10.0795
1996:4	6.380	8.168	10.0905	10.0945
1997:1	5.390	7.313	10.0810	10.0903
1997:2	4.797	7.177	10.1169	10.1075
1997:3	4.763	7.190	10.1145	10.1001
1997:4	5.163	7.366	10.1083	10.0985
1998:1	6.260	8.028	10.0956	10.0927
1997:2	6.577	8.270	10.1006	10.0993
1997:3	4.943	6.457	10.1083	10.0966
1997:4	2.860	4.357	10.1242	10.1028
1999:1	2.440	4.223	10.1407	10.1176
1999:2	2.530	4.323	10.1446	10.1218
1999:3	2.530	4.543	10.1641	10.1486
1999:4	2.913	5.149	10.1665	10.1609
2000:1	3.257	5.797	10.1978	10.1729
2000:2	3.380	6.508	10.1806	10.1661
2000:3	3.477	6.630	10.1895	10.1776
2000:4	3.513	6.507	10.1962	10.1818
2001:1	3.470	5.993	10.1945	10.1845
2001:2	3.257	5.400	10.2158	10.1991
2001:3	3.080	5.330	10.2262	10.2043
2001:4	2.404	4.671	10.2358	10.2139
2002:1	2.203	4.733	10.2448	10.2228
2002:2	2.277	5.500	10.2506	10.2381
2002:3	2.368	5.517	10.2763	10.2507
2002:4	2.430	5.587	10.2750	10.2592
2003:1	2.387	5.460	10.2863	10.2640
2003:2	2.337	4.993	10.2729	10.2666
2003:3	2.120	4.811	10.3141	10.2853
2003:4	2.073	5.130	10.3034	10.2901
2004:1	2.083	5.293	10.3298	10.3126