

Short-term Forecasting
by Univariate Time Series Models
with Application

by

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0. INTRODUCTION

In all situations of life, every choice or decision has future implications. Good decision-making can become better or worse, depending on the quality of the forecasts which underline the decision-making process. At present two types of forecasting techniques are widely used: Econometric Modelling and Time Series Analysis. Econometric models are systems of statistical equations which specify relationships among economic variables based on economic theories. The coefficients of the equations are estimated from past data. The equations are used to quantify assumed structural relationships. They form the basis of forecasts of what will happen to the economy if certain conditions are fulfilled.

The time series analysis approach basically consists of describing a variable as a function of its own past behaviour. One particular form of time series modelling, the Auto-Regressive Integrated Moving Average (ARIMA) model, developed by Box and Jenkins (1970) is widely applied. Although time series models have been studied for many years, Box and Jenkins popularized their use, demonstrated how to extend their application to seasonal data, and made the methodology operational. Consequently, ARIMA models are often referred to as Box-Jenkins models. These models are univariate time series models and do not use explanatory variables or causal variables that are constrained by economic

theory (Vandaele, 1983).

This paper will introduce the technique of ARIMA modelling as outlined by Box and Jenkins, and forecast GDP values for 1989. Comparisons will also be made regarding forecast accuracy between ARIMA models and other popular forecasting methods. The paper is divided into three sections. The first section deals with the theoretical aspects of time series modelling, the second section applies this methodology to forecast gross domestic product, and the third section presents other forecasting models and compares their forecasts with those obtained from time series models. While the theoretical section is generally easy to follow, some highly technical aspects of the discussion are given in the Appendix.

1. MODELLING ARIMA PROCESSES.

Univariate Box-Jenkins (B-J from here on) is a time series modelling process which describes a single series as a function of its own past values. The purpose of the B-J process is to find the equation that reduces a time series with underlying structure to white noise (Box and Jenkins, 1970). Since the equation accounts for the predictable portion of the time series, it can be used to forecast future values of the series.

The modelling procedure itself is a three stage iterative process :

a. Identification:

Choosing a tentative model form by examining a plot of the series and several key statistics.

b. Estimation:

Fitting an appropriate model through some non-linear estimation procedure to the time series under study.

c. Forecasting:

Using the fitted model to predict future values of the time series.

The ARIMA models used for forecasting the time series are of the general multiplicative type (Box, G.E.P. and Jenkins, G.M., 1970), that is:

$$(1.0) \quad \phi_p(B) \phi_p(B^s) \nabla^d \nabla_s^D Z_t = \theta_q(B) \theta_q(B^s) a_t$$

Where s denotes periodicity of the seasonal component (equal to 4 for our series); B denotes the backward operator, i.e:

$$BZ_t = Z_{t-1}; \quad B^s Z_t = Z_{t-s};$$

$\nabla^d = (1-B)^d$ is the ordinary difference operator of order d ; $\nabla_s^D = (1-B^s)^D$ is the seasonal difference operator of order D ; $\phi_p(B)$ and $\phi_p(B^s)$ are stationary autoregressive operators (they are polynomials in B of degree p and in B^s of degree P , respectively); $\theta_q(B)$ and $\theta_q(B^s)$ are invertible moving average operators (they are polynomials in B of degree q and in B^s of degree Q , respectively); a_t is a purely random process.

The general multiplicative model (1.0) is said to be of order (p, d, q) $(P, D, Q)_s$.

1.1 Model Identification

The identification phase entails examining the time series in order to choose a tentative model form. There are several key statistical tools used during this phase. The two most important tools are the autocorrelation function and the partial autocorrelation function of a time series (formal definition of these functions are provided in the appendix). The first step in identification is to make the series stationary (i.e. the mean of the time series, its variance, and its covariance with other values of the series do not depend on time). This implies two types of methods for inducing stationarity. Applying the appropriate differencing factor to a series may create a mean stationary series. By applying the correct power transformation, a variance stationary series may be obtained.

The autocorrelations of a time series provides an indication as to the appropriate level of differencing that is required since the autocorrelations provide us with a means of how much correlation or interdependency there is between neighbouring data points in the series. The need for a power transformation can be ascertained by examining plots of both the original series and the transformed series (Cryer, 1986). If the autocorrelation function

starts out high and decays slowly, it usually implies the need for differencing. To determine the order of the differencing, the number of time periods between the relatively high autocorrelation is usually a good indicator (see figure 1a for example). On the other hand if the series shows a variance that changes over time, transforming the original series may provide a stationary variance series.

The transformation can be obtained from a flexible family of transformations introduced by Box and Cox (1964, Vandaele, 1983). For a given value of λ , the transformation:

$$g(x) = x^\lambda - 1 / \lambda \quad \lambda \neq 0$$

$$= \log(x) \quad \lambda = 0$$

note if λ equals 1, it implies the original series, a value of -1 implies the inverse (of the original series) and so on (see appendix also).

The Box-Cox method is more accurate than just observing the plot of a series. If the type of software allows for Box-Cox test one can estimate a simple mean model with lambda determination option used (AFS, 1986).

Once stationarity is obtained, the autocorrelation and partial autocorrelation functions of the transformed and stationary series (ARMA) will be studied so as to determine the order of the autoregressive and/or moving average process.

1.2 ESTIMATION

From the identification stage a tentative ARIMA model is specified for the data generating process on the basis of the estimated autocorrelation and partial autocorrelation (Box and Jenkins, 1970). The following are some possible results:

- a. For an MA(q) process the autocorrelation $Q_k = 0$ for $k > q$ and the partial autocorrelations taper off. To determine a cut off point to the autocorrelation function the sample autocorrelations are used.
- b. For an AR(p) the partial autocorrelations $\phi_{kk} = 0$ for $k > p$ and the autocorrelations taper off. A cutoff point of the partial autocorrelation function may be determined by comparing the estimates with T , since $(1/T)^{.5}$ is the approximate standard deviation of the estimators ϕ_{kk} for $k > p$.
- c. If neither the autocorrelation nor the partial autocorrelations have a cutoff point, an ARIMA model may be adequate. The AR and the MA degree have to be inferred from the particular pattern of the autocorrelation and partial autocorrelation.

Once the identification is completed, a non-linear least squares or a maximum likelihood estimation based on the Marquardt Algorithm, is employed (Box-Jenkins, 1970, pp 504 - 505). A pure AR(1) process sometimes known as a "random walk" model can be

estimated by linear methods. The non-linear estimation, whether by minimizing least squares or maximizing a likelihood function, makes an appropriate computer software necessary to lessen the labour input and computational time.

The next step after estimation is diagnostic checking. These tests are for necessity, invertibility and sufficiency. Each parameter included in the model should be statistically significant (necessity) and each factor must be invertible (see appendix for detail). In addition, the residuals from the estimated models should be white noise (model sufficiency).

The test for necessity is performed by examining the T-ratios for the individual parameter estimates. Parameters with non-significant coefficients may be deleted from the model in order to have a parsimonious model.

Invertibility is determined by extracting the roots from each factor in the model. All the roots must lie outside of the unit circle. If one of the factors is non-invertible, then the model must be adjusted. The appropriate adjustment is dictated by the type of the factor that is non-invertible. For example, a non-invertible autoregressive factor usually indicates under-differencing, while a non-invertible moving average factor may indicate over differencing. A non-invertible moving average factor could also represent the presence of a deterministic factor. Since the model fixup is not really clear-cut, the overall model must be considered when adjusting for non-invertibility.

The residuals are tested for white noise by studying the autocorrelation and partial autocorrelation of the residuals. Furthermore, a test statistics Q or "portmanteau test" is performed on the residuals autocorrelations of all lags (the test is formally introduced in the appendix). If the model is misspecified or inappropriately fitted, the Q test tends to be inflated (Box-Jenkins, 1970; Vandaele, 1983).

1.3 FORECASTING

The forecasting function of the general multiplicative model (1.0) can be expressed in different forms. For computational purpose, the difference equation form is the most useful. Thus, at time $t+r$ the ARIMA model (1.0) may be written:

$$(1.1) \quad Z_{t+r} = \psi_1 Z_{t+r-1} + \dots + \psi_m Z_{t+r-m} - a_{t+r} - \pi_1 a_{t+r-1} - \dots - \pi_n a_{t+r-n}$$

where $m=p+(s.P)+d+(s.D)$ and $n=q+(s.Q)$; $\psi(B) = \phi_p(B^s) \nabla^d \nabla_s^D$ is the general autoregressive operator; $\pi(B) = \theta_q(B) \theta_0(B)$ is the general moving average operator. For example, if the ARIMA model is of order $(0,1,1)(0,1,1)_{12}$ the difference equation that generates the observations Z_{t+r} , is:

$$(1.2) \quad Z_{t+r} = Z_{t+r-1} + Z_{t+1-12} - Z_{t+r-13} + a_{t-r} - \theta a_{t+r-1} \\ - \theta a_{t+r-12} - \theta \theta a_{t+r-13}$$

Standing at origin t , to make a forecast $Z_t^f(r)$ of Z_{t+r} , the conditional expectation of (1.1) is taken at time t with the following assumptions:

$$(1.3) \quad E_t(Z_{t+j}) = Z_{t+j}, \quad j=0 ; \quad E_t(Z_{t+j}) = Z_t^f(j), \quad j>0$$

$$(1.4) \quad E_t(a_{t+j}) = a_{t+j}, \quad j \leq 0 ; \quad E_t(a_{t+j}) = 0, \quad j > 0$$

where $E_t(Z_{t+j})$ is the conditional expectation of Z_{t+j} taken at origin t . Thus, the forecasts $Z_t^f(r)$ for each lead time are computed from previous observed Z 's, previous forecasts of Z 's and current and previous random shocks a 's. The unknown a 's are replaced by zeroes.

In general, if the moving average operator $\pi(B) = \theta(B)\theta(B^s)$ is of degree $q+(s.Q)$, the forecast equations for $Z_t^f(1)$, $Z_t^f(2)$, ..., $Z_t^f(q+(s.Q))$ will depend directly on the a 's but forecasts at longer lead times will not. The latter will receive indirectly, the impact of the a 's by means of the previous forecasts. In effect, $Z_t(q+(s.Q)+1)$ will depend on the $q+(s.Q)$ previous Z_t , which in turn will depend on the a 's.

From the view point of studying the nature of the forecasts, it is important to consider the explicit form of the forecasting function. For $r > n = q+(s.Q)$, the conditional expectation of (1.1) at time t is:

$$(1.5) \quad Z_t^f(r) - \psi_1 Z_t^f(r-1) - \dots - \psi_m Z_t^f(r-m) = 0 \quad r > m$$

and the solution of this difference equation is:

$$(1.6) \quad Z_t^f(r) = b_0(t) f_0(r) + b_1^{(t)} f_1(r) + \dots + b_{m-1}^{(t)} f_{m-1}^{(r)} \quad r > n-m$$

This function is called the "eventual forecast function", eventual because when $n > m$, it supplies the forecasts only for lead times $r > n-m$.

In (1.6), $f_0(R)$, $f_1(R)$, ..., $f_{m-1}(R)$ are functions of the lead

time R and in general they include polynomials, exponentials, sines and cosines, and products of these functions. For a given origin t , the coefficients $b_j^{(t)}$ are constants applying for all lead time R but they change from one origin to the next, adapting themselves to the particular part of the series being considered. It is important to point out that it is the general autoregressive operator $\psi(B)$ defined above, which determines the mathematical form of the forecasts function, i.e., the nature of the f 's. In other words, it determines whether the forecasting function is to be a polynomial, a mixture of sines and cosines, a mixture of exponentials or some combinations of these functions.

2. EMPIRICAL INVESTIGATION

To begin the empirical investigation of the ARIMA modelling and forecasting, we choose the Gross Domestic Product (GDP) in seasonally adjusted form. The choice of GDP is based on its importance for micro-economic decision makers such as firms and macro-economic agents like governments and labour unions.

For governments a higher level of growth in GDP implies a strong economy, and hence tighter fiscal or monetary policy may be advisable in order to halt the economy from "over-heating". Firms, on the other hand, will be concerned about higher inflation rates if the GDP growth is more than anticipated. Labour unions also have keen interest about the level of GDP, especially if they are

going to negotiate wage contracts in the near future.

The gross domestic product is published every quarter by Statistics Canada both in real (constant 1981 prices) or nominal (market prices) terms. For the type of policy evaluations mentioned above real GDP is often consulted and it is a much preferred indicator of economic growth than the nominal GDP (obviously, nominal GDP movements are "contaminated" by price level developments). However, for illustrative purposes both the nominal and real GDP are discussed here.

2.2 THE MODELLING PROCEDURE

2.2.A. NOMINAL GDP

As mentioned earlier the time series under consideration are the GDP at market and constant prices for the period 1976 first quarter to 1988 fourth quarter, a total of 52 observations. From the plot of the data (see figure 1) the variance of this series (GDP at market price) appears to be roughly constant through time while the mean seems to increase. This may imply an estimated autocorrelation function (acf) that decays slowly to zero indicating a non-stationary mean and the need for differencing.

Identification I: To start the identification procedure the acf and partial autocorrelation function (pacf) of the undifferenced data (see figure 1a, 1b) are analyzed. The estimated

THE PLOT OF NOMINAL GDP
IN MILLIONS OF CURRENT DOLLARS

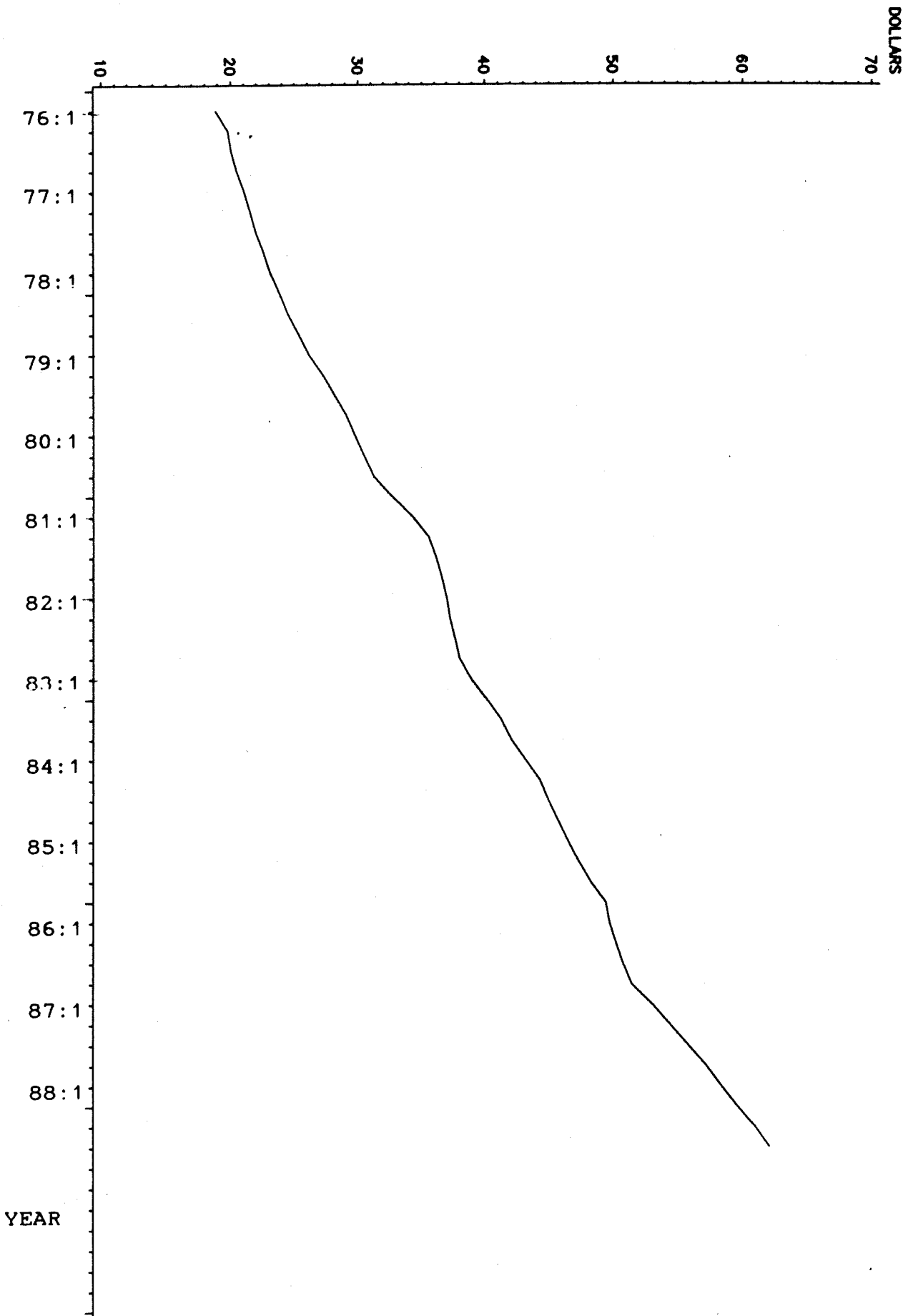


Figure 1

ARIMA PROCEDURE *

NAME OF VARIABLE = GDPS
 MEAN OF WORKING SERIES= 381442
 STANDARD DEVIATION = 125338
 NUMBER OF OBSERVATIONS= 52
 AUTOCORRELATIONS

LAG	COVARIANCE	CORRELATION	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	STD
0	1.571E+10	1.00000												*****										0
1	1.476E+10	0.93982												*****										0.138675
2	1.383E+10	0.88039												*****										0.230657
3	1.290E+10	0.82085												*****										0.288121
4	1.196E+10	0.76159												*****										0.330044
5	1.104E+10	0.70306												*****										0.362267
6	1.015E+10	0.64592												*****										0.38762
7	9270559144	0.59012												*****										0.407794
8	8421900880	0.53610												*****										0.423898
9	7608813681	0.48434												*****										0.436742
10	6795257881	0.43255												*****										0.446952
11	5977807049	0.38052												*****										0.454931
12	5160075673	0.32847												*****										0.461011
13	4331418447	0.27572												*****										0.46549
14	3548770772	0.22590												*****										0.46862
15	2790693435	0.17764												****										0.47071
16	2052686375	0.13066												***										0.471997
17	1327454245	0.08450												**										0.472692
18	616127903	0.03922												*										0.472983
19	-85317522	-0.00543																						0.473045
20	-728138303	-0.04635											*											0.473046
21	-1.300E+09	-0.08275										**												0.473134
22	-1.825E+09	-0.11617										**												0.473412
23	-2.312E+09	-0.14714										***												0.47396
24	-2.756E+09	-0.17543										****												0.474838

MARKS TWO STANDARD ERRORS

FIGURE 1a

* Nominal GDP identification

PARTIAL AUTOCORRELATIONS *

LAG	CORRELATION	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
1	0.93982												*****										
2	-0.02467											*											
3	-0.03243											*											
4	-0.03033											*											
5	-0.02734											*											
6	-0.02236											*											
7	-0.02313											*											
8	-0.01968											*											
9	-0.01558											*											
10	-0.03503											*											
11	-0.03829											*											
12	-0.03763											*											
13	-0.04476											*											
14	-0.01545											*											
15	-0.02658											*											
16	-0.02990											*											
17	-0.03486											*											
18	-0.03569											*											
19	-0.03872											*											
20	-0.01294											*											
21	-0.00437											*											
22	-0.01541											*											
23	-0.01992											*											
24	-0.01784											*											

ARIMA IDENTIFICATION PROCEDURE

9:58 THURSDAY,

AUTOCORRELATION CHECK FOR WHITE NOISE

TO	CHI	AUTOCORRELATIONS																				
LAG	SQUARE	DF	PROB	0.940	0.880	0.821	0.762	0.703	0.646	0.590	0.536	0.484	0.433	0.381	0.328	0.276	0.226	0.178	0.131	0.084	0.039	
6	219.70	6	0.000																			
12	305.10	12	0.000																			
18	318.77	18	0.000																			
24	326.02	24	0.000	-0.005	-0.046	-0.083	-0.116	-0.147	-0.175													

FIGURE 1b

* pacf of Nominal GDP

acf falls to zero slowly, indicating that the mean of the data is non-stationary and that non-seasonal differencing is required. (It is important to mention, at this point, that a decaying acf implies that the estimated autocorrelations at longer lags are still statistically significant, based on a t-test. According to figure 1a the autocorrelations at lag 1 through 5 are significantly different from zero at the 5% significance level, this level is indicated by the dot ".", the remaining lags are also significant although at a higher significance level).

At this point one can proceed with the differencing of the series to attain stationarity. For more illustrative purposes, however, one can also confirm this finding by going through the estimation stage. Suppose differencing is not required, then according to the pacf (figure 1b) the model for estimation is an AR(1) since this is consistent with the combination of a decaying pattern in the estimated acf and the cutoff to zero after lag 1 in the estimated pacf. For a pure MA model the process would be just the opposite: spikes followed by a cutoff in the acf, and a tailing off of the pacf. An AR(1) is called for rather than a higher order AR model because the pacf has a spike at lag 1 only. Therefore the model is

$(1-\phi B)Q_t = a_t$ where Q_t denotes GDP at time t and a_t denotes a purely random (white noise) process.

Estimation and Diagnostic Checks: Output 1 and 1a show the estimated results and the corresponding residual acf and pacf. According to the estimation result ϕ is equal to 0.998925 with a

THE UNDIFFERENCED NOMINAL GDP
ESTIMATION RESULT

Maximum Likelihood Estimation

Parameter	Estimate	Approx. Std Error	T Ratio	Lag
MU	35.60961	115.16660	0.31	0
AR1,1	0.99892	0.0091773	108.63	1

Constant Estimate = 0.03822467

Variance Estimate = 0.85362877

Std Error Estimate = 0.9400153

AIC = 149.239493

SBC = 153.14198

Number of Residuals = 52

Correlations of the Estimates

Parameter	MU	AR1,1
MU	1.000	0.987
AR1,1	0.987	1.000

Autocorrelation Check of Residuals

To Lag	Chi Square	DF	Prob	Autocorrelations					
6	211.51	5	0.000	0.889	0.840	0.789	0.739	0.715	0.704
12	375.56	11	0.000	0.672	0.655	0.633	0.636	0.619	0.622
18	526.46	17	0.000	0.589	0.591	0.573	0.575	0.557	0.550
24	625.51	23	0.000	0.498	0.442	0.408	0.400	0.391	0.399

OUTPUT 1

THE UNDIFFERENCED NOMINAL GDP

Autocorrelation Plot of Residuals

lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
0	0.983639	1.00000												*****										
1	0.785430	0.88887												*****										
2	0.742117	0.83985												*****										
3	0.696787	0.78855												*****										
4	0.652653	0.73883												*****										
5	0.632257	0.71552												*****										
6	0.621900	0.70380												*****										
7	0.594030	0.67226												*****										
8	0.578934	0.65518												*****										
9	0.577068	0.65307												*****										
10	0.563595	0.63782												*****										
11	0.547072	0.61912												*****										
12	0.549578	0.62196												*****										
13	0.526565	0.58912												*****										
14	0.513374	0.58098												*****										
15	0.510753	0.57802												*****										
16	0.507984	0.57488												*****										
17	0.492039	0.55684												*****										
18	0.485785	0.54976												*****										
19	0.440181	0.49815												*****										
20	0.390402	0.44182												*****										
21	0.360341	0.40780												*****										
22	0.353289	0.39982												*****										
23	0.345480	0.39098												*****										
24	0.352660	0.39910												*****										

Partial Autocorrelations

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
1	0.88887												*****										
2	0.23706												*****										
3	0.04183												*										
4	-0.00284																						
5	0.11370												**										
6	0.12201												**										
7	-0.04263											*											
8	0.03213												*										
9	0.12227												**										
10	0.01769																						
11	-0.03973												*										
12	0.10171												**										
13	-0.07957											**											
14	0.04393												*										
15	0.05532												*										
16	0.06123												*										
17	-0.05603											*											
18	0.00232																						
19	-0.17606											****											
20	-0.17009											****											
21	-0.02305																						
22	0.15235												***										
23	0.04574												*										
24	0.02664												*										

high t-statistic. The estimate is almost 1.0, which contradicts the stationarity condition for an AR(1) model. Furthermore, the estimated mean is highly correlated with the parameter ($r = 0.987$), which indicates inappropriate differencing. This conclusion is reinforced by estimates that are unstable as indicated in output 1. A practical rule is to difference when we have serious doubts about whether the mean of a series is stationary which is the case under question. Now we proceed with the modelling of the differenced series.

Identification II: Figure 2 shows the plot of the first differences of the original data. This series seems to fluctuate around a constant mean and does not show upward movement as the original series in figure 1. The estimated acf for the first differences in figure 2a indicates no further differencing is required since after two lags all the autocorrelations are not significant at the 5% level. The pacf (see figure 2b) has one spike at lag one and the rest are insignificant. The autocorrelation check for white noise shows a chi-square value 41.94 indicating the series is not white noise. (See figure 2a, 2b). Based on this information an AR(1) model seems to be an adequate model to estimate.

Estimation and Diagnostic Checks: The estimation results and the residuals appear in output 2 and 2a. All the pertinent statistics indicate that the model is adequate. The estimated AR coefficient is significant according to the value of the t-

THE FIRST DIFFERENCES OF NOMINAL GDP
IN MILLIONS OF CURRENT DOLLARS

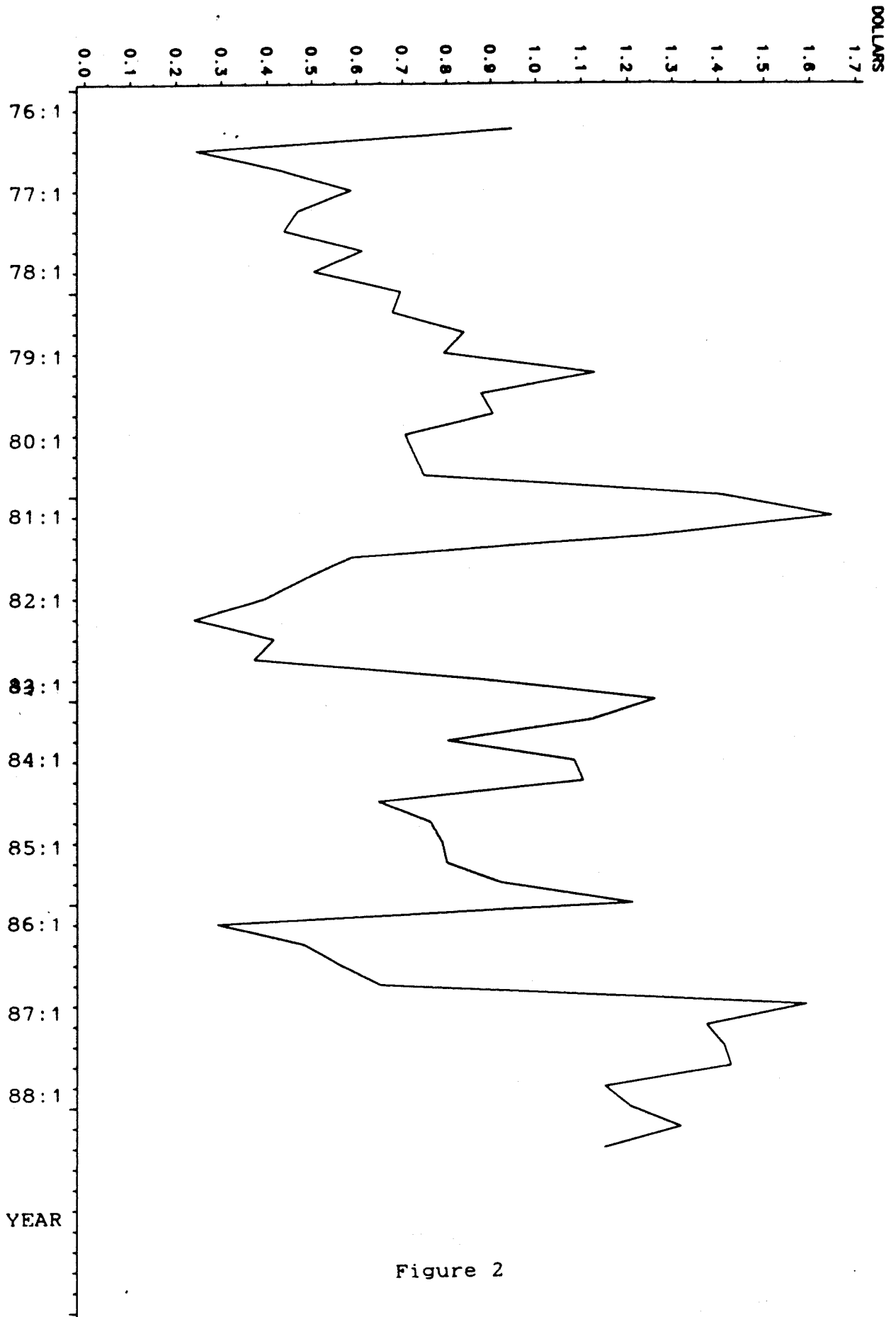


Figure 2

ARIMA PROCEDURE *

NAME OF VARIABLE = GDPS
 PERIOD(S) OF DIFFERENCING=1.
 MEAN OF WORKING SERIES= 8455.14
 STANDARD DEVIATION = 3627.36
 NUMBER OF OBSERVATIONS= 51
 AUTOCORRELATIONS

LAG	COVARIANCE	CORRELATION	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	STD
0	13157734	1.00000												*****										0
1	8228334	0.62536												*****										0.140028
2	4158759	0.31607												*****										0.186934
3	1366791	0.10388												**										0.197134
4	-1187570	-0.09026										**												0.198204
5	-1585225	-0.12048									**													0.199009
6	-918784	-0.06983									*													0.200434
7	-1446720	-0.10995									**													0.20091
8	-945612	-0.07187									*													0.202087
9	7904.51	0.00060										*												0.202587
10	-676488	-0.05141										*												0.202587
11	-1265874	-0.09621									**													0.202843
12	-706199	-0.05367									*													0.203736
13	-532688	-0.04048									*													0.204013
14	-12196.4	-0.00093										*												0.20417
15	1208866	0.09187											**											0.20417
16	1733614	0.13176											***											0.204979
17	1292129	0.09820											**											0.206633
18	1634827	0.12425											**											0.207546
19	939343	0.07139											*											0.209
20	-449599	-0.03417									*													0.209477
21	-2020028	-0.15352									***													0.209586
22	-2236380	-0.16997									***													0.21178
23	-1608396	-0.12224									**													0.214438
24	-305058	-0.02318																						0.2158

* MARKS TWO STANDARD ERRORS

FIGURE 2a

* First differences of Nominal GDP

PARTIAL AUTOCORRELATIONS *

LAG	CORRELATION	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
1	0.62536												*****										
2	-0.12318									**													
3	-0.06853									*													
4	-0.16045									***													
5	0.06365											*											
6	0.04351										*												
7	-0.14590									***													
8	0.04851										*												
9	0.06023										*												
10	-0.13072									***													
11	-0.07847									**													
12	0.08387										**												
13	0.01354																						
14	-0.00950																						
15	0.07940										**												
16	0.07610										**												
17	-0.06599									*													
18	0.07021										*												
19	-0.01339																						
20	-0.08051									**													
21	-0.19075									****													
22	0.08878										**												
23	0.08343										**												
24	-0.00790												**										

ARIMA IDENTIFICATION PROCEDURE

9:58 THURSDAY

AUTOCORRELATION CHECK FOR WHITE NOISE

TO LAG	CHI SQUARE	DF	PROB	AUTOCORRELATIONS					
6	28.87	6	0.000	0.625	0.316	0.104	-0.090	-0.120	-0.070
12	30.94	12	0.002	-0.110	-0.072	0.001	-0.051	-0.096	-0.054
18	35.06	18	0.009	-0.040	-0.001	0.092	0.132	0.098	0.124
24	41.91	24	0.013	0.071	-0.034	-0.154	-0.170	-0.122	-0.023

FIGURE 2b

* PACF OF THE FIRST DIFFERENCES OF NOMINAL GDP

ARIMA:PRELIMINARY ESTIMATION *

INITIAL AUTOREGRESSIVE ESTIMATES

1 0.62536

CONSTANT TERM ESTIMATE= 3167.62
 WHITE NOISE VARIANCE EST= 8012055
 ARIMA IDENTIFICATION PROCEDURE

12:45 FRID/

ARIMA: CONDITIONAL LEAST SQUARES ESTIMATION

ITERATION	SSE	MU	AR1,1	CONSTANT	LAMBDA
0	405027051	8455.14	0.625361	3167.62	1.0E-05
1	404739630	8624.85	0.63432	3153.93	1.0E-06
2	404739071	8631.45	0.634919	3151.18	1.0E-07

PARAMETER	ESTIMATE	APPROX. STD ERROR	T RATIO	LAG
MU	8631.45	1038.46	8.31	0
AR1,1	0.634919	0.111699	5.68	1

CONSTANT ESTIMATE = 3151.18

VARIANCE ESTIMATE = 8259981
 STD ERROR ESTIMATE = 2874.02
 AIC = 958.965*
 SBC = 962.829*
 NUMBER OF RESIDUALS= 51

* DOES NOT INCLUDE LOG DETERMINANT

CORRELATIONS OF THE ESTIMATES

	MU	AR1,1
MU	1.000	0.059
AR1,1	0.059	1.000

AUTOCORRELATION CHECK OF RESIDUALS

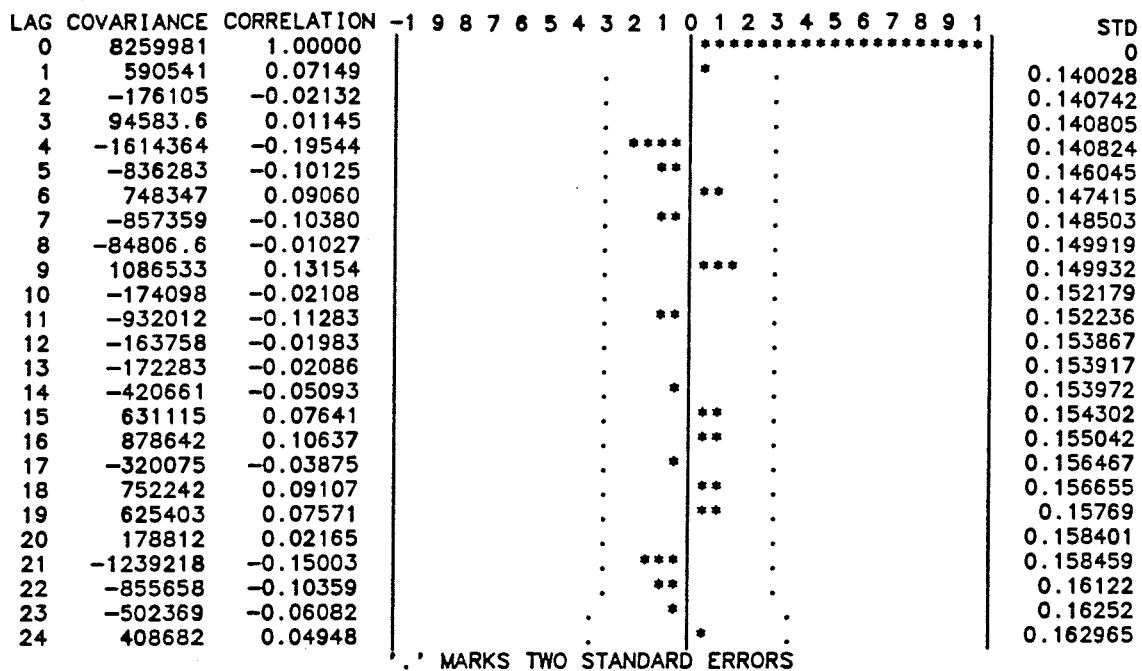
TO LAG	CHI SQUARE	DF	PROB	AUTOCORRELATIONS						
6	3.60	4	0.463	0.071	-0.021	0.011	-0.195	-0.101	0.091	
12	6.30	10	0.789	-0.104	-0.010	0.132	-0.021	-0.113	-0.020	
18	8.63	16	0.928	-0.021	-0.051	0.076	0.106	-0.039	0.091	
24	12.79	22	0.939	0.076	0.022	-0.150	-0.104	-0.061	0.049	

OUTPUT 2

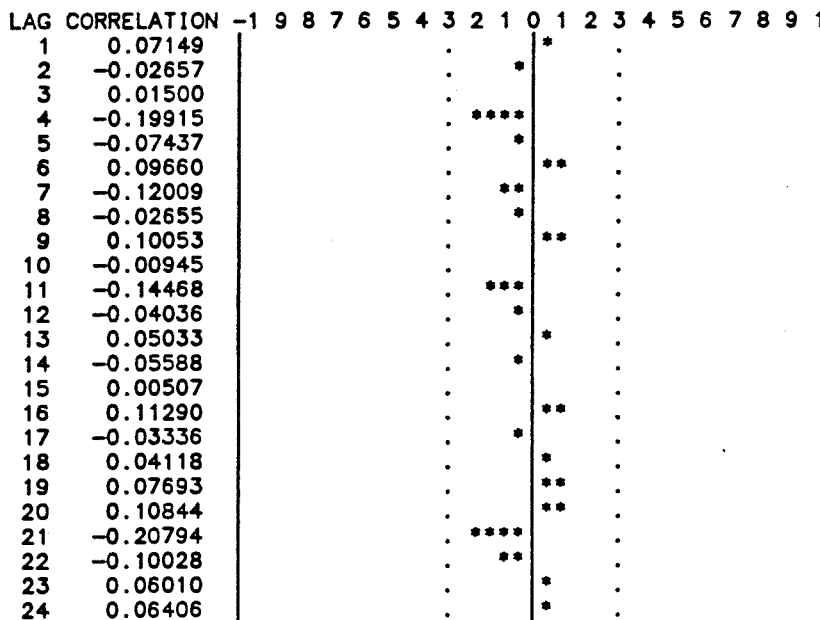
OUTPUT 2

* Estimation result of the first differences of Nominal GDP

*
AUTOCORRELATION PLOT OF RESIDUALS



PARTIAL AUTOCORRELATIONS



OUTPUT 2A

* ACF AND PACF OF THE RESIDUALS
OF THE FIRST DIFFERENCES OF
NOMINAL GDP

statistic. The invertibility (stationary) condition is also satisfied since ϕ is less than 1.

According to the residual act and pacf in output 2a, we accept the null hypothesis that the innovations of the model are not correlated. At 5% level of significance the p-value for the first 24 lags is 0.939 (the p-value is the probability of obtaining a sample chi-square value as large as the calculated chi-square).

2.2.A.1 Alternative Models: From the acf and pacf of the first differenced series we may assume an MA (2) or an ARMA (1,1) model as possible candidates. However, earlier estimates rendered the models inadequate (either due to insignificant parameters or high chi-square statistics for the residuals).

The plot of the first difference suggests, as pointed out earlier, that the mean of the series is stationary. However, there seems to be some instability of the variance given the rather high oscillation in the late periods compared to the earlier quarters. To verify this observation, we used the Box-Cox sum of squares test to determine the optimal lambda (see appendix) value for the identified model.

The appropriate transformation according to the Box-Cox test is the square root of the original series. As can be seen from the plot of the transformed series (figure 4), the variance has relatively stabilized. The identification and estimation of the transformed model gave us an autoregressive process of order one.

Adding this extra step in the identification and estimation stage, as illustrated in table 1, gives better forecast values and

THE SQUARE ROOT OF NOMINAL GDP
IN MILLIONS OF CURRENT DOLLARS

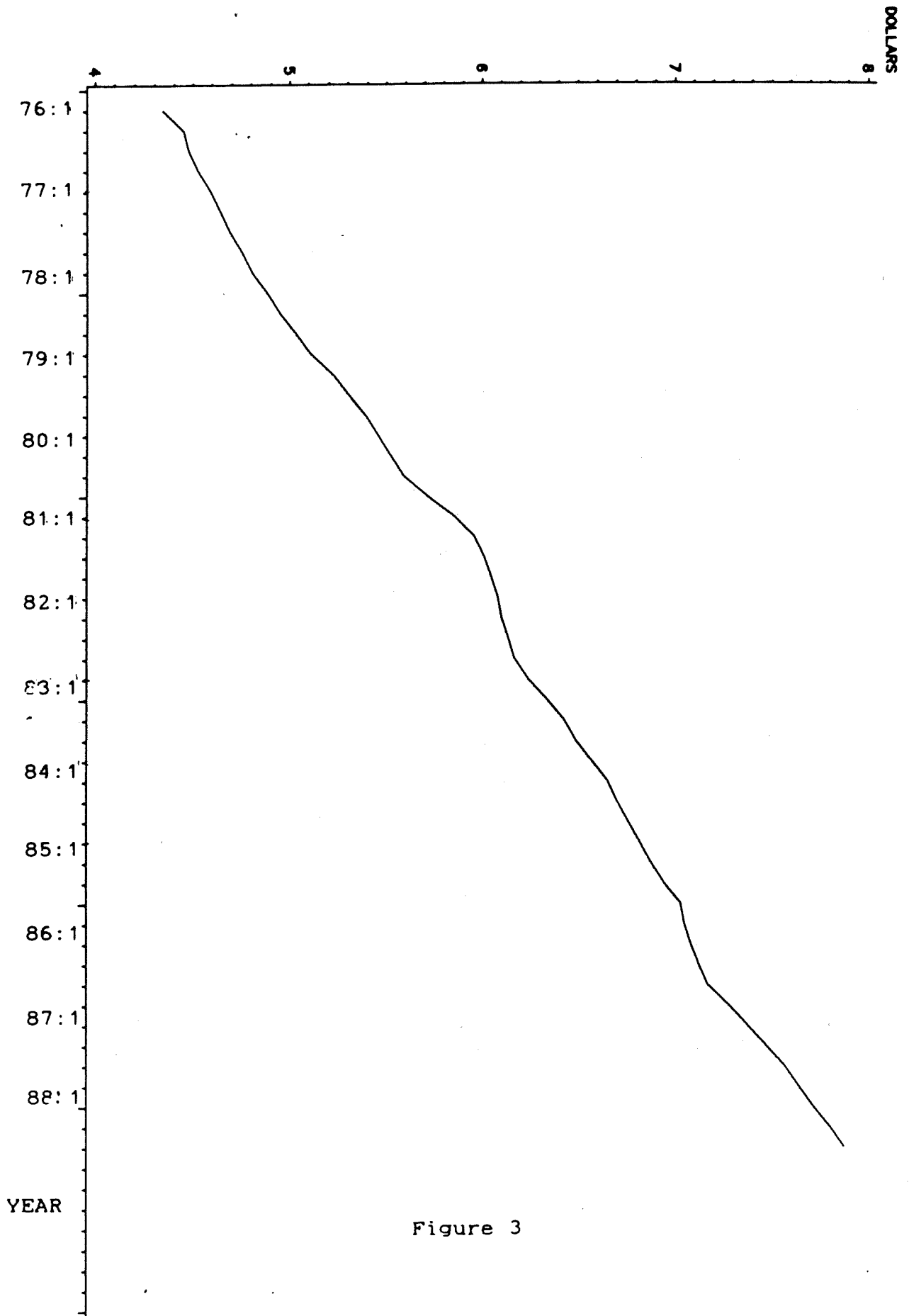


Figure 3

THE FIRST DIFFERENCES OF NOMINAL GDP (SQRT)*
 IN MILLIONS OF CURRENT DOLLARS

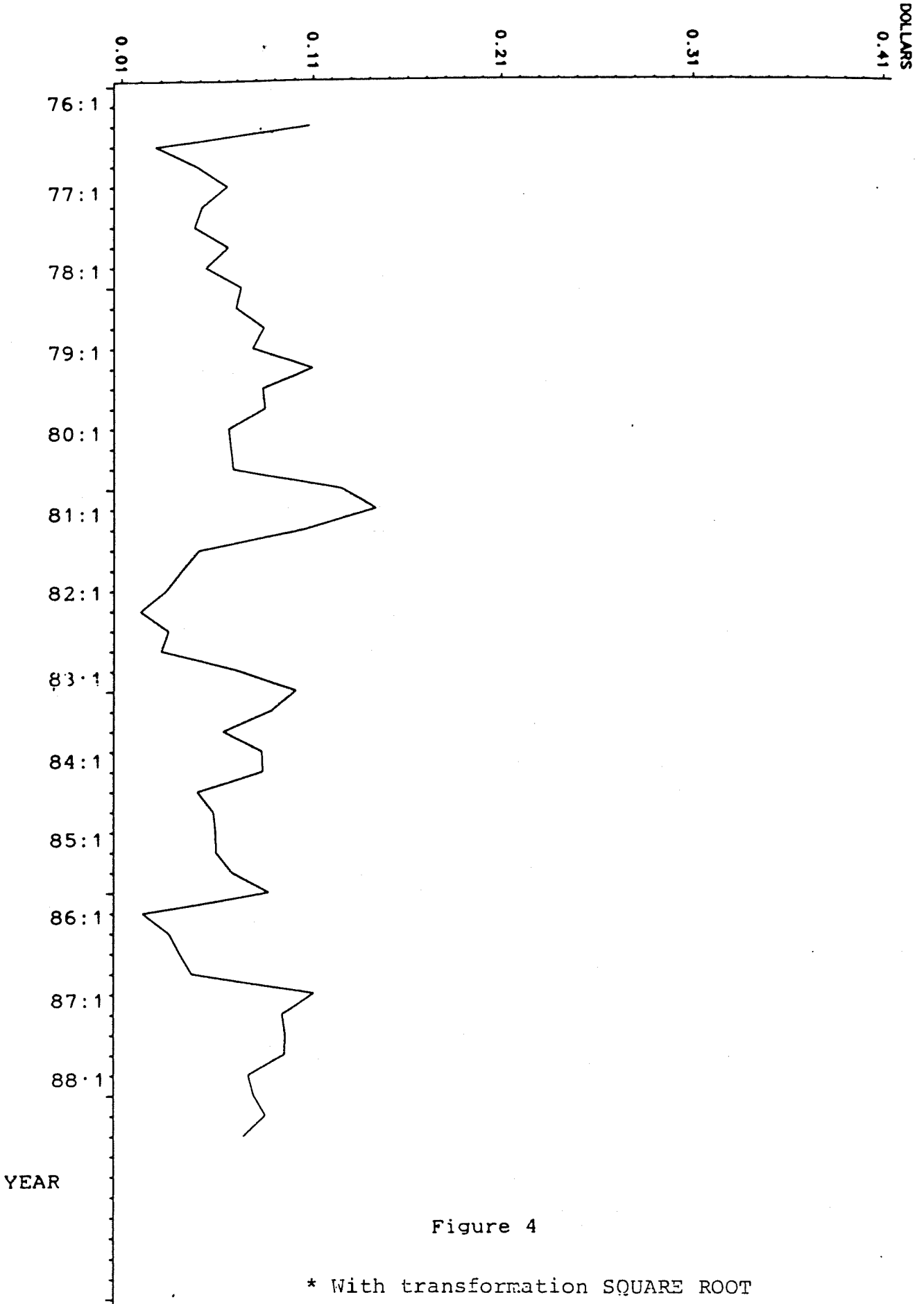


Figure 4

* With transformation SQUARE ROOT

TABLE 1

FORECAST COMPARISONS BETWEEN TENTATIVELY
IDENTIFIED AND ESTIMATED ARIMA MODELS
FOR NOMINAL GDP LEVELS

ERROR MEASURES	FORECAST MODEL	
	ARIMA (TRAN)	ARIMA
% ERROR		
1989:1	-0.55	-0.67
1989:2	-0.27	-0.51
1989:3	0.38	-0.18
1989:4	0.19	-0.66
MSPE*	0.14	0.29
RMSPE**	0.37	0.54

NOTE:

ARIMA (TRAN) => (1,1,0) TRANSFORMATION (SQUARE ROOT)

ARIMA => (1,1,0) NO TRANSFORMATION

* Mean Square Percentage Error (see page 48)

** Root Mean Square Percentage Error (see page 48)

emphasises the point that a simple eye-balling of a plot of a series is not sufficient.

Seasonality:

According to the residual acf and pacf (output 2a or 4a,b), there is no significant autocorrelation for all lags. However, the plot shows some "relatively" high spikes at the seasonal lags (lags 4,8,12...) as compared to the other lags. This seems to indicate that there still may be some residual seasonality left in the already seasonally adjusted GDP.

One possible explanation for the presence of residual seasonality is that GDP is an aggregate economic variable, the seasonal adjustment of which is made through the seasonal adjustment of several components. Such aggregation by itself could create autocorrelation at the seasonal and other lags. Furthermore, some of the variables that make up the GDP, for one reason or another, may enter into the aggregate, as not seasonally adjusted. Finally, another possible explanation is that the seasonal adjustment method may have inadequately adjusted the series. However, the results from the X11ARIMA (Dagum,1988) (see appendix) indicate that there is no significant stable or moving seasonality in the seasonally adjusted series.

We have also fitted a seasonal autoregressive and moving average components to our tentatively identified model and the parameter were statistically insignificant. The final estimated model based on our modelling process is the first differences of the square root of GDP with an autoregressive component at lag 1

OUTPUT FROM THE IDENTIFICATION
& ESTIMATION OF THE SQUARE ROOT
OF GDP *

NAME OF VARIABLE = SQGDP
PERIOD(S) OF DIFFERENCING=1.
MEAN OF WORKING SERIES= 0.0692251
STANDARD DEVIATION = 0.0268283
NUMBER OF OBSERVATIONS= 51
AUTOCORRELATIONS

LAG	COVARIANCE	CORRELATION	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	STD
0	.000719759	1.00000												*****										0
1	.000369117	0.51283												*****										0.140028
2	.000134563	0.18696												****										0.172978
3	-2.702E-05	-0.03754																						0.176896
4	-.00016469	-0.22881												*****										0.177052
5	-.00018705	-0.25988												*****										0.182758
6	-0.0001025	-0.14241												***										0.189866
7	-.00011656	-0.16194												***										0.191949
8	-4.243E-05	-0.05895												*										0.194609
9	.000012426	0.01726																						0.194959
10	-3.059E-05	-0.04250												*										0.194989
11	-.00010719	-0.14892												***										0.195171
12	-7.786E-05	-0.10818												**										0.197386
13	-7.360E-05	-0.10226												**										0.198545
14	-4.317E-05	-0.05998												*										0.199575
15	.000028084	0.03902												*										0.199929
16	0.00007254	0.10078												**										0.200078
17	.000040577	0.05638												*										0.201071
18	.000082725	0.11493												**										0.20138
19	.000068027	0.09451												**										0.202663
20	-2.990E-05	-0.04155												*										0.203525
21	-.00015975	-0.22194												****										0.203691
22	-.00015816	-0.21974												****										0.208379
23	-.00010428	-0.14488												***										0.212874
24	-1.958E-05	-0.02720												*										0.214799

MARKS TWO STANDARD ERRORS

OUTPUT 4a

* (NOMINAL GDP)

OUTPUT FROM THE IDENTIFICATION
& ESTIMATION OF THE SQUARE ROOT
OF GDP *

12:47 SUND

PARTIAL AUTOCORRELATIONS

LAG	CORRELATION	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
1	0.51283												*****										
2	-0.10318									.		**											
3	-0.12397									.		**											
4	-0.19263									.	****												
5	-0.05533									.	*												
6	0.05985									.		*											
7	-0.17533									.	****												
8	0.04388									.		*											
9	-0.00960									.													
10	-0.12737									.	***												
11	-0.18757									.	****												
12	0.01750									.		*											
13	-0.03637									.		*											
14	-0.06858									.		*											
15	0.00659									.													
16	0.02941									.		*											
17	-0.09071									.	**												
18	0.04927									.		*											
19	0.02167									.													
20	-0.13478									.	***												
21	-0.28573									.	*****												
22	-0.01229									.		*											
23	0.06453									.		*											
24	-0.07349									.		*											

SAS

12:47 SUND.

AUTOCORRELATION CHECK FOR WHITE NOISE

TO	CHI	AUTOCORRELATIONS									
LAG	SQUARE	DF	PROB								
6	24.42	6	0.000	0.513	0.187	-0.038	-0.229	-0.260	-0.142		
12	28.70	12	0.004	-0.162	-0.059	0.017	-0.043	-0.149	-0.108		
18	31.94	18	0.022	-0.102	-0.060	0.039	0.101	0.056	0.115		
24	43.88	24	0.008	0.095	-0.042	-0.222	-0.220	-0.145	-0.027		

OUTPUT 4b

* (NOMINAL GDP)

OUTPUT FROM THE IDENTIFICATION
& ESTIMATION OF THE SQUARE ROOT
OF GDP*

12:47 SUND

ARIMA: MAXIMUM LIKELIHOOD ESTIMATION

PARAMETER	ESTIMATE	APPROX. STD ERROR	T RATIO	LAG
MU	0.0701098	0.00670152	10.46	0
AR1,1	0.524553	0.120379	4.36	1

CONSTANT ESTIMATE = 0.0333335

VARIANCE ESTIMATE = .000543563

STD ERROR ESTIMATE = 0.0233144

AIC = -236.372

SBC = -232.509

NUMBER OF RESIDUALS= 51

CORRELATIONS OF THE ESTIMATES

	MU	AR1,1
MU	1.000	0.005
AR1,1	0.005	1.000

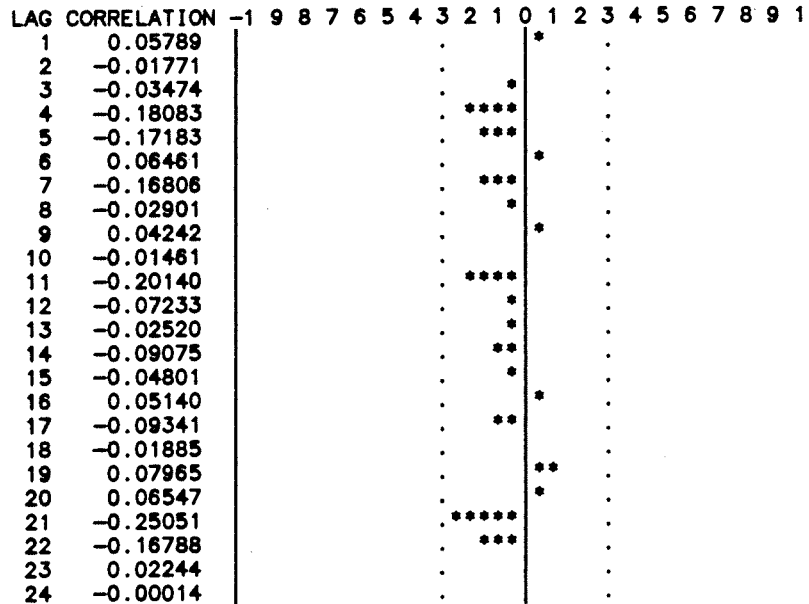
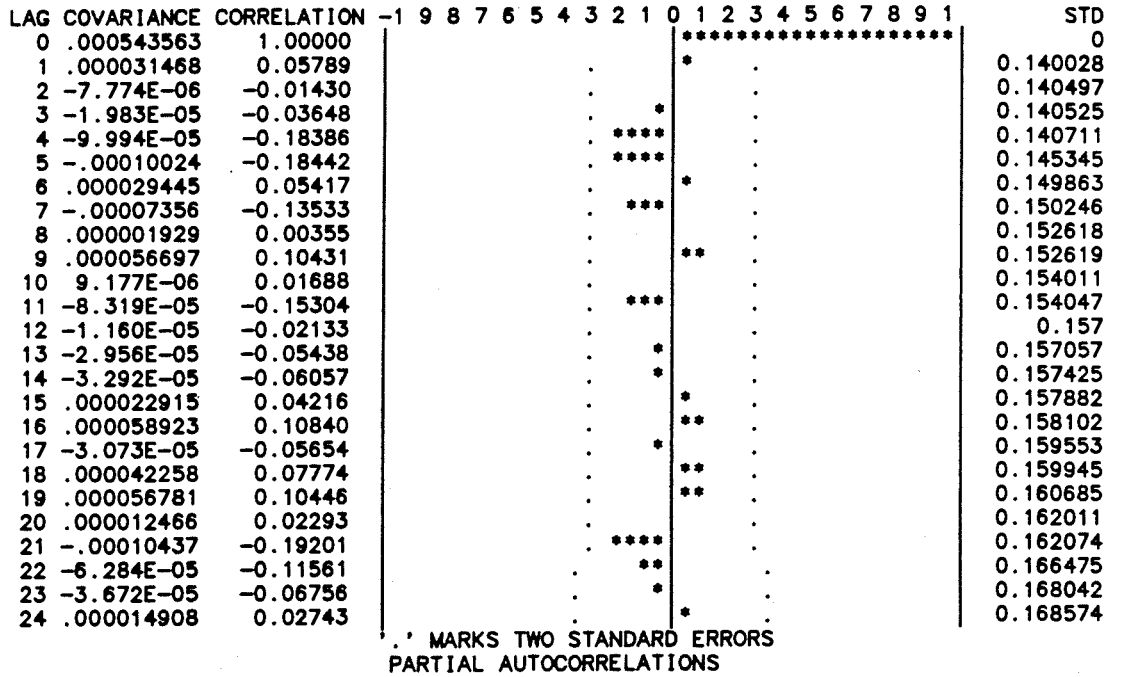
AUTOCORRELATION CHECK OF RESIDUALS

TO LAG	CHI SQUARE	DF	PROB	AUTOCORRELATIONS						
6	4.39	4	0.356	0.058	-0.014	-0.036	-0.184	-0.184	0.054	
12	7.85	10	0.644	-0.135	0.004	0.104	0.017	-0.153	-0.021	
18	10.11	16	0.861	-0.054	-0.061	0.042	0.108	-0.057	0.078	
24	16.16	22	0.808	0.104	0.023	-0.192	-0.116	-0.068	0.027	

OUTPUT 4c

* (NOMINAL GDP)

AUTOCORRELATION PLOT OF RESIDUALS



OUTPUT 4d

* (NOMINAL GDP)

and a deterministic trend.

2.2.B. REAL GDP

We begin our identification process of seasonally adjusted real GDP by examining the plot (figure 5). The mean of the series is not stationary since there is a persistent upward trend. However, the trend is not as dominant as the one from the nominal GDP we saw earlier. Recall also from figure 1 that the nominal GDP does not show the recession of 1981-82 at all. In fact due to the high inflation and interest rate of the period the national output increased slightly!

Identification I According to the estimated acf (output 5a,5b) the autocorrelations drop to zero after four lags (at 5% significance level). While this may imply a stationarity mean, fitting an AR(1) model (based on a decaying acf a spike at lag one in the pacf) gave us a non-invertible parameter which is an indication of under-differencing. Therefore, we difference the series once to attain stationarity.

Figure 6 shows the plot of the first differences of real GDP (1981 dollars) and output 6a and 6b show the plot of the estimated acf and pacf of the first differences. After lag one all the autocorrelations and partial autocorrelations are insignificant; this indicates the mean to be stationarity and also an AR(1) or MA(1) to be possible models to estimate. Since the pattern in the pacf seem to resemble a damped sine wave pattern we choose an MA(1)

PLOT OF REAL GDP
IN MILLIONS OF (1981) DOLLARS

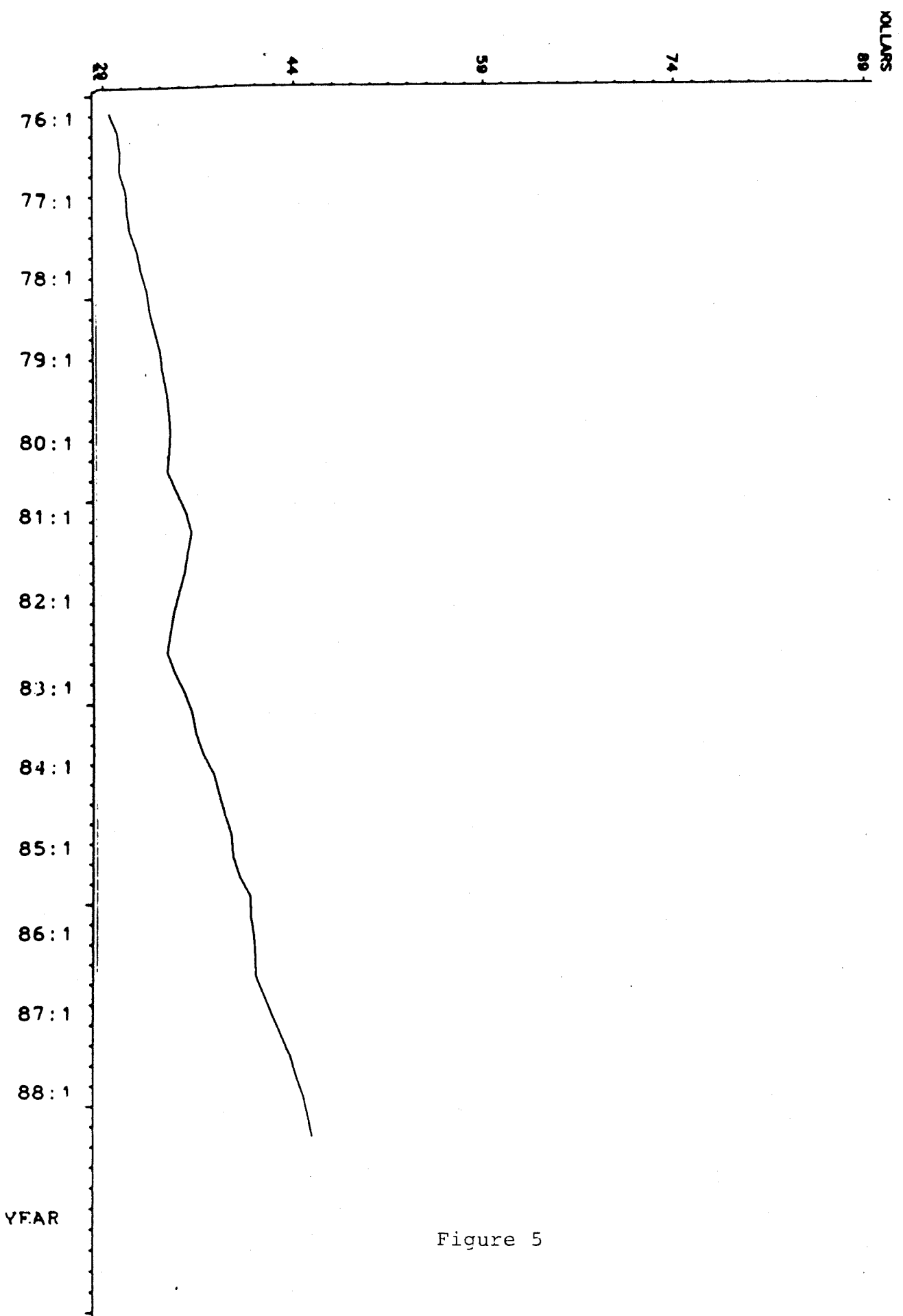


Figure 5

NAME OF VARIABLE = GDP81
 MEAN OF WORKING SERIES= 36.3977
 STANDARD DEVIATION = 4.31162
 NUMBER OF OBSERVATIONS= 52
 AUTOCORRELATIONS

LAG	COVARIANCE	CORRELATION	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	STD
0	18.5901	1.00000												*****										0
1	17.2551	0.92819												*****										0.138675
2	15.9209	0.85642												*****										0.228838
3	14.5669	0.78358												*****										0.28386
4	13.2162	0.71093												*****										0.322788
5	11.9346	0.64199												*****										0.351612
6	10.7001	0.57558												*****										0.373474
7	9.54708	0.51356												*****										0.39016
8	8.51945	0.45828												*****										0.402951
9	7.58498	0.40801												*****										0.412852
10	6.6487	0.35765												*****										0.420535
11	5.6863	0.30588												*****										0.426344
12	4.75824	0.25596												*****										0.430544
13	3.82736	0.20588												****										0.43346
14	3.01416	0.16214												***										0.435337
15	2.27591	0.12243												**										0.436496
16	1.52982	0.08229												**										0.437156
17	0.823561	0.04430												*										0.437454
18	0.134353	0.00723																						0.43754
19	-0.561249	-0.03019											*											0.437543
20	-1.07248	-0.05769											*											0.437583
21	-1.42501	-0.07665											**											0.437729
22	-1.6913	-0.09098											**											0.437987
23	-1.91959	-0.10326											**											0.43835
24	-2.06162	-0.11090											**											0.438818

MARKS TWO STANDARD ERRORS

OUTPUT FROM THE IDENTIFICATION
& ESTIMATION OF GDP(1981)

PARTIAL AUTOCORRELATIONS

LAG	CORRELATION	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
1	0.92819												*****										
2	-0.03691											*											
3	-0.04642											*											
4	-0.03953											*											
5	-0.01541																						
6	-0.02367																						
7	-0.01078																						
8	0.00739																						
9	-0.00231																						
10	-0.03796											*											
11	-0.04789											*											
12	-0.02448																						
13	-0.03832											*											
14	0.00673																						
15	-0.00719																						
16	-0.03940											*											
17	-0.02476																						
18	-0.03228											*											
19	-0.04125											*											
20	0.03349												*										
21	0.03147												*										
22	0.00601																						
23	-0.01424																						
24	0.00661																						

SAS

14:45 SATURD

AUTOCORRELATION CHECK FOR WHITE NOISE

TO	CHI	AUTOCORRELATIONS								
LAG	SQUARE	DF	PROB							
6	198.23	6	0.000	0.928	0.856	0.784	0.711	0.642	0.576	
12	258.52	12	0.000	0.514	0.458	0.408	0.358	0.306	0.256	
18	265.34	18	0.000	0.206	0.162	0.122	0.082	0.044	0.007	
24	269.28	24	0.000	-0.030	-0.058	-0.077	-0.091	-0.103	-0.111	

PLOT OF THE FIRST DIFFERENCES OF REAL GDP
IN MILLIONS OF (1981) DOLLARS

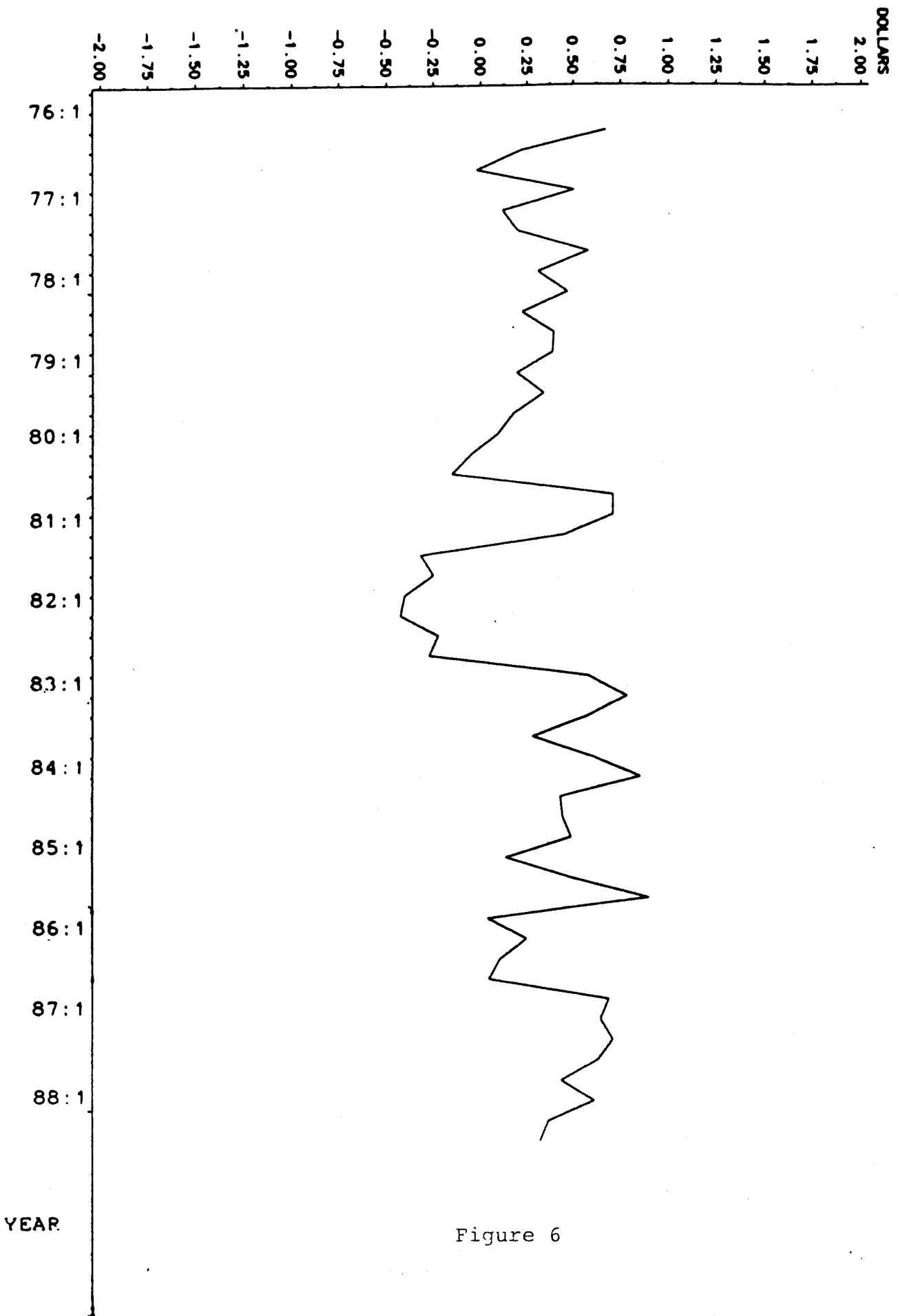


Figure 6

OUTPUT FROM THE IDENTIFICATION
& ESTIMATION OF FIRST DIFFERENCE OF
GDP(1981)

NAME OF VARIABLE = GDP81
 PERIOD(S) OF DIFFERENCING=1.
 MEAN OF WORKING SERIES= 0.311553
 STANDARD DEVIATION = 0.331897
 NUMBER OF OBSERVATIONS= 51
 AUTOCORRELATIONS

LAG	COVARIANCE	CORRELATION	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	STD
0	0.110156	1.00000												*****										0
1	0.0535509	0.48614												*****										0.140028
2	0.0212392	0.19281												****										0.169928
3	0.0104193	0.09459												**										0.174165
4	-0.011891	-0.10795										**												0.17517
5	-0.0050625	-0.04596									*													0.176469
6	-0.0117609	-0.10677									**													0.176704
7	-0.0105205	-0.09551									**													0.177964
8	-.00261669	-0.02375											*											0.178966
9	0.00464206	0.04214											*											0.179028
10	0.00636418	0.05777											*											0.179222
11	-.00557378	-0.05060									*													0.179587
12	-.00423314	-0.03843									*													0.179867
13	0.00144066	0.01308									*													0.180027
14	-.00410689	-0.03728									*													0.180046
15	-.00281978	-0.02560									*													0.180197
16	.000621421	0.00564									*													0.180269
17	-.00348002	-0.03159									*													0.180272
18	0.00376661	0.03419									*													0.180381
19	0.00841511	0.07639									**													0.180508
20	-.00357804	-0.03248									*													0.181141
21	-0.0181372	-0.16465									***													0.181255
22	-0.0229536	-0.20837									****													0.184164
23	-0.0245721	-0.22307									****													0.18873
24	-0.010769	-0.09776									**													0.193831

. MARKS TWO STANDARD ERRORS

OUTPUT FROM THE IDENTIFICATION
& ESTIMATION OF FIRST DIFFERENCE OF
GDP(1981)

PARTIAL AUTOCORRELATIONS

LAG	CORRELATION	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
1	0.48614												*****										
2	-0.05699									.		*											
3	0.03050									.		*											
4	-0.20715									.	****												
5	0.12764									.			***										
6	-0.16235									.	***												
7	0.05976									.		*											
8	-0.03189									.		*											
9	0.13124									.			***										
10	-0.07431									.		*											
11	-0.08786									.	**												
12	0.01532									.													
13	0.07158									.		*											
14	-0.08480									.	**												
15	0.00723									.													
16	0.03898									.		*											
17	-0.05042									.		*											
18	0.05392									.		*											
19	0.03960									.		*											
20	-0.09870									.	**												
21	-0.19341									.	****												
22	-0.05694									.	*												
23	-0.07838									.	**												
24	0.12684									.			***										

SAS

14:45 SATURD

AUTOCORRELATION CHECK FOR WHITE NOISE

TO LAG	CHI SQUARE	DF	PROB	AUTOCORRELATIONS						
6	16.81	6	0.010	0.486	0.193	0.095	-0.108	-0.046	-0.107	
12	18.02	12	0.115	-0.096	-0.024	0.042	0.058	-0.051	-0.038	
18	18.36	18	0.432	0.013	-0.037	-0.026	0.006	-0.032	0.034	
24	31.19	24	0.148	0.076	-0.032	-0.165	-0.208	-0.223	-0.098	

OUTPUT 6b

model for estimation.

Estimation and Diagnostic Checks: The estimation results indicate (output 6c,6d) that an MA(1) with a deterministic constant is an adequate model. The estimated MA coefficient is invertible and statistically significant, the residuals are non-correlated (the p-value for the chi-square statistics is .937) and the constant term is also statistically significant. Preliminary Box-Cox test on the original series did not show a need for transforming and the first differences on the original series is still the appropriate model.

However, the pacf of the residuals (output 6d) now show a high autocorrelation at lag 4 (seasonal lag). Thus, we include a seasonal moving average parameter to the estimated model.

Identification II: The inclusion of the seasonal moving average (output 6e,6f) parameter improves the residual autocorrelations and, though not shown here, gives better forecast values than the MA(1) model. One reason why this residual seasonality was not observed for the nominal series may be the fact that the trend is very dominant in the latter and consequently obscures the identification of the small amount of seasonality left in. The final estimated model, therefore, is the first differences of real GDP with a moving average components at lag 1 and 4 plus a deterministic constant. Using the Box-Jenkins notation, it results in an

OUTPUT FROM THE IDENTIFICATION
& ESTIMATION OF FIRST DIFFERENCE OF
GDP(1981)

ARIMA: MAXIMUM LIKELIHOOD ESTIMATION

PARAMETER	ESTIMATE	APPROX. STD ERROR	T RATIO	LAG
MU	0.315229	0.0637052	4.95	0
MA1,1	-0.562176	0.120244	-4.68	1

CONSTANT ESTIMATE = 0.315229

VARIANCE ESTIMATE = 0.0866444

STD ERROR ESTIMATE = 0.294354

AIC = 22.3282

SBC = 26.1918

NUMBER OF RESIDUALS= 51

CORRELATIONS OF THE ESTIMATES

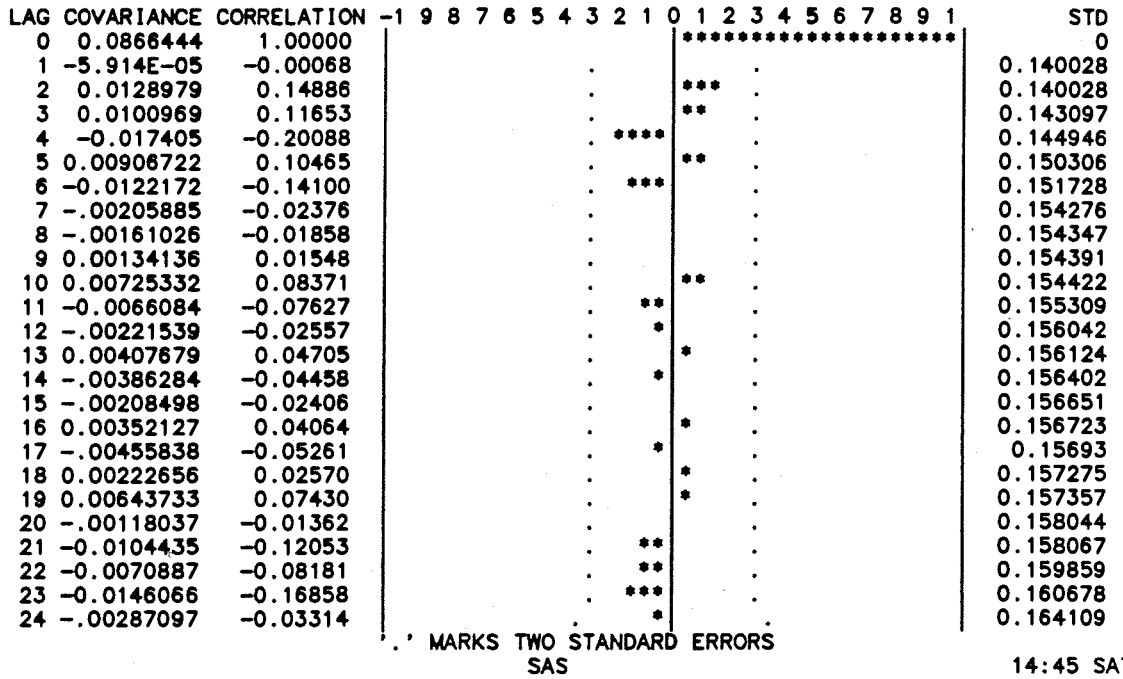
	MU	MA1,1
MU	1.000	-0.008
MA1,1	-0.008	1.000

AUTOCORRELATION CHECK OF RESIDUALS

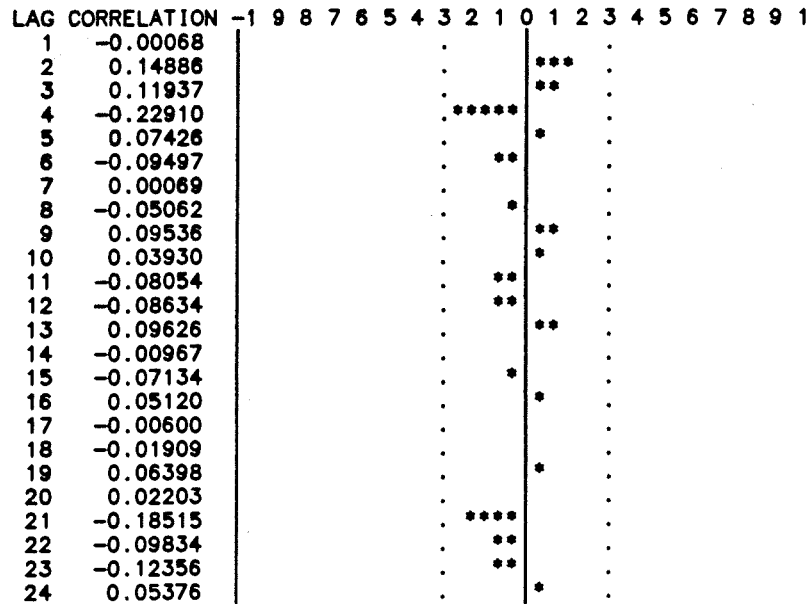
TO LAG	CHI SQUARE	DF	PROB	AUTOCORRELATIONS						
6	6.15	4	0.189	-0.001	0.149	0.117	-0.201	0.105	-0.141	
12	7.12	10	0.714	-0.024	-0.019	0.015	0.084	-0.076	-0.026	
18	7.87	16	0.953	0.047	-0.045	-0.024	0.041	-0.053	0.026	
24	13.13	22	0.929	0.074	-0.014	-0.121	-0.082	-0.169	-0.033	

OUTPUT FROM THE IDENTIFICATION
& ESTIMATION OF FIRST DIFFERENCE OF
GDP(1981)

AUTOCORRELATION PLOT OF RESIDUALS



PARTIAL AUTOCORRELATIONS



ARIMA: MAXIMUM LIKELIHOOD ESTIMATION

PARAMETER	ESTIMATE	APPROX. STD ERROR	T RATIO	LAG
MU	0.311267	0.0509748	6.11	0
MA1,1	-0.565995	0.122303	-4.63	1
MA2,1	0.208595	0.144525	1.44	4

CONSTANT ESTIMATE = 0.311267

VARIANCE ESTIMATE = 0.0846775

STD ERROR ESTIMATE = 0.290994

AIC = 22.3331

SBC = 28.1286

NUMBER OF RESIDUALS= 51

CORRELATIONS OF THE ESTIMATES

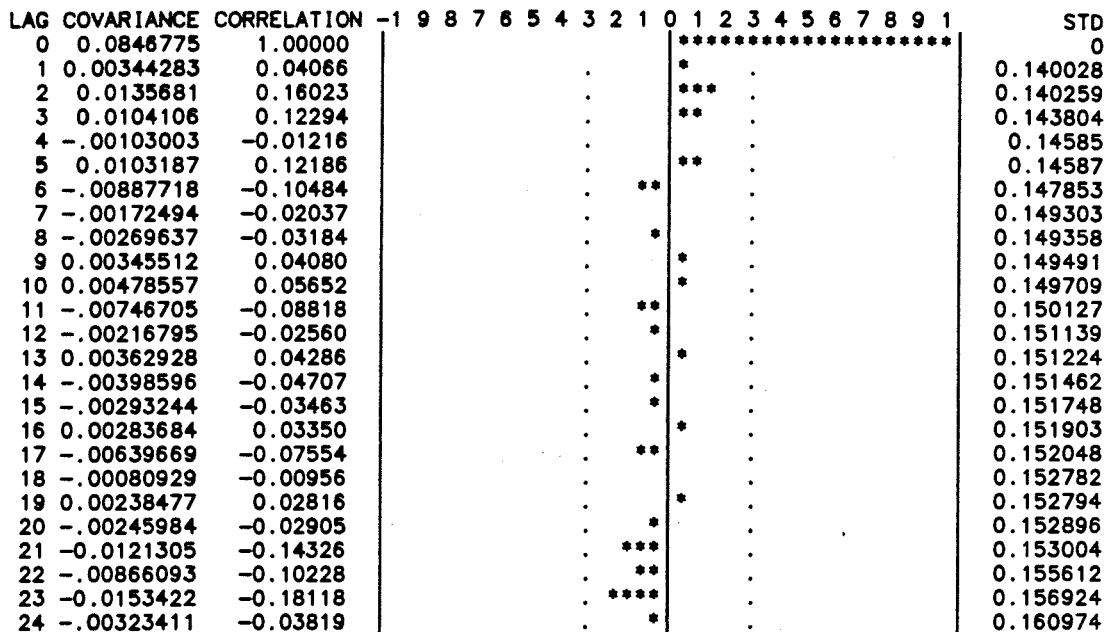
	MU	MA1,1	MA2,1
MU	1.000	-0.013	-0.055
MA1,1	-0.013	1.000	0.103
MA2,1	-0.055	0.103	1.000

AUTOCORRELATION CHECK OF RESIDUALS

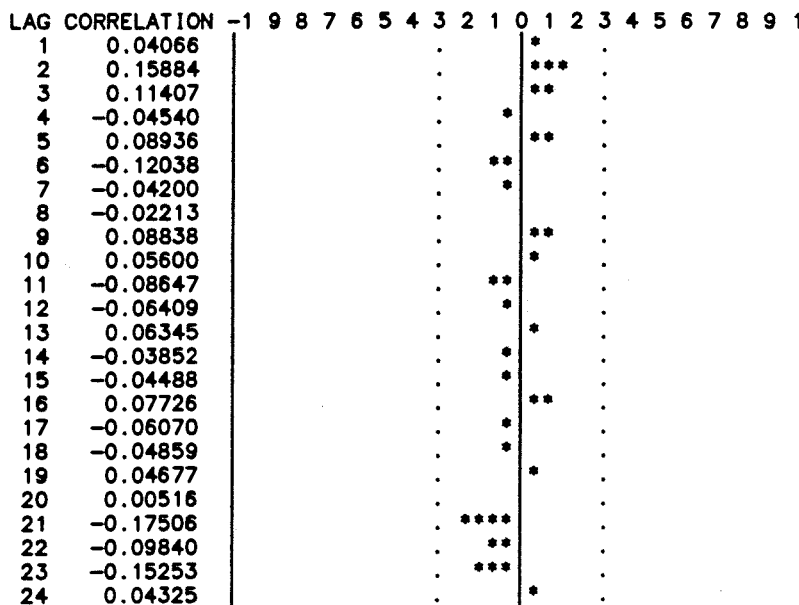
TO	CHI	AUTOCORRELATIONS							
LAG	SQUARE	DF	PROB						
6	3.90	3	0.273	0.041	0.160	0.123	-0.012	0.122	-0.105
12	4.88	9	0.845	-0.020	-0.032	0.041	0.057	-0.088	-0.026
18	5.81	15	0.983	0.043	-0.047	-0.035	0.034	-0.076	-0.010
24	12.09	21	0.937	0.028	-0.029	-0.143	-0.102	-0.181	-0.038

OUTPUT 6e

AUTOCORRELATION PLOT OF RESIDUALS



MARKS TWO STANDARD ERRORS
PARTIAL AUTOCORRELATIONS



$(0,1,1) (0,0,1)_4$ model.

3. FORECAST COMPARISONS

This section compares the forecast performance of ARIMA models for real and nominal GDP with two other forecasting methods, namely, the naive forecast model and a macro-econometric model from the Conference Board of Canada.

3.1 Naive Forecast Model:

The "naive" forecast model implies that the forecasts for time $t+1$ is equal to the value observed at time t . The naive forecast is often used as a point of reference in the sense that, given its simplicity, any other forecasting method has to produce superior results. The naive forecasting method is then defined by:

$$(3.1.1) \quad Z_t = Z_{t-1}$$

$$\Rightarrow Z_{t+1} = Z_t$$

$$(3.1.2) \quad Z_{t+1} = Z_{t-1}$$

3.2 Econometric Models

The Econometric model chosen for this study is the quarterly macro-econometric model of the Conference Board of Canada (CBC). This model consists of 849 equations including disaggregated sectors of consumption, investment, exports, imports, etc. The method of estimation is ordinary least squares (OLS) on each

equation. The exogenous variables are generated from the U.S. Warton Econometric model, population and demographics, energy investment, oil prices, tax rates, and government spending. The GDP is estimated from the aggregates of the following sectors of the Keynesian identity:

$$Q = C + I + G + X - M \quad (3.2.1)$$

Further details about the model are not provided for the public.

Even though the information on the Econometric model is limited the following observations can be made:

- a) The choice of OLS estimation versus 2SLS (two stage least squares) may be a source of serious concern from a theoretical point of view since 2SLS is unbiased asymptotically (for large sample size). From the practical point of view, however, it is quite impossible to have a large sample size to begin with and thus for the small sample size the practitioner is justified in using OLS. It is appropriate to mention at this stage that preliminary studies done on other quarterly macro-econometric models seem to suggest 2SLS to be a better estimator (Bodkin, 1989).
- b) At the forecasting stage of an econometric model, forecasts of the exogenous variables are required. These forecasts are usually obtained, as mentioned above, from other econometric models (Warton) or equations estimated outside of the systems of equations under study. In cases like this, the large econometric model may introduce errors from other models or equations that can seriously distort the forecasts. At the same time, there is clearly a delay in generating forecasts if the future values of the exogenous variables are unavailable.

Forecasts from a simultaneous equation model are obtained from the following structural form equations:

$$(3.2.2) \quad BY_i + \Gamma X_i = e_i$$

where Y_i denotes the vector of G endogenous variable at the i th observation, B denotes the parameters of endogenous variables. (a non-singular matrix), X_i denotes the exogenous or lagged endogenous variables at the i th observation, Γ denotes the parameters of predetermined variable and e_i denotes a vector of G stochastic disturbance term at the i th observation. Thus the estimates will have the following form:

$$(3.2.3) \quad Y_i = -B^{-1}\Gamma X_i + B^{-1}e_i$$

$$Y_i = \pi X_i + U_i$$

(3.2.4) $Y_{i+h}^e = \pi^e X_{i+h}^e + U_{i+h}^e$ where Y^e , π^e , X^e and U^e denote estimated values.

Equation (3.2.3) is the reduced form equation where π denotes a matrix of reduced form coefficients and U_i denotes the reduced form stochastic disturbance term.

3.3 Forecast Error Measures

Four types of error measures are used to indicate the forecasting performance of the three models used to extrapolate the two series analyzed here.

percentage (standardized) difference between the actual and the forecasted value for each quarter, and is defined by:

$$(3.3.1) \quad \frac{(X_t^f - X_t)}{(X_t)} * 100$$

Where X_t denotes actual and X_t^f denotes forecast value.

ii) Mean Square Percentage Error (MSPE): The mean square percentage error is the sum of the square of the percentage error (3.3.1) divided by the number of forecasts calculated, symbolically:

$$(3.3.2) \quad MSPE = 1/n \sum_{t=1}^n ((X_t^f - X_t) / (X_t)) * 100)^2$$

iii) Root Mean Square Percentage Error (RMSPE): Same as (ii) but the square root of equation 3.3.2 is used.

iv) Theil's Inequality Coefficient: If $X_t\%$ denotes the percentage growth and $X_t^f\%$ denote the predicted percentage growth, then

Theil's inequality coefficient (Theil, 1966) U_t is defined as:

$$(3.3.3) \quad U_t^2 = \frac{1/n \sum_{t=1}^n (X_t\% - X_t^f\%)^2}{1/n \sum_{t=1}^n (X_t\%)^2}$$

$$U_t = [U_t^2]^{1/2}$$

3.4 Analysis of the Results

Table 2a and table 2b show the results of the three measures for the level forecasts of the nominal and real GDP respectively, while table 3a and 3b show the results of the four measures for the growth rates of the nominal and real GDP. Both the ARIMA and the econometric models use information up to and including the fourth quarter of 1988 to forecast one year ahead (the forecasts are not reinitialized).

In forecasting the level of nominal GDP (see table 2a) the ARIMA model performed better than the econometric model. This is also true for Real GDP (table 2b). In tracking the growth rate of nominal GDP, the CBC econometric model does a better job (table 3a) but for Real GDP (table 3b) the forecast from the ARIMA model are closer.

Since GDP is a slow changing variable, a fairly large simultaneous equation model like the CBC model (which is built with many purposes in mind, including the studies of the many possible economic effects of changes in government policies and exogenous variables), the short term forecasting may be affected.

Summarizing the information provided in the tables above, we can conclude that both the econometric and the ARIMA models provide superior results than does the naive forecast model as one would expect. Furthermore, in forecasting the levels of nominal and real GDP, the ARIMA model is superior to the CBC econometric model, while in forecasting the growth rate of nominal GDP, the econometric model does a better job.

TABLE 2a

FORECAST ERRORS OF NOMINAL GDP LEVELS

ERROR MEASURE	FORECAST MODEL		
	CBC	ARIMA	NAIVE
% ERROR			
1989:1	-0.91	-0.55	2.3
1989:2	-0.86	-0.27	3.7
1989:3	-0.81	0.38	4.7
1989:4	-0.75	0.19	6.5
MSPE	0.7	0.14	20.8
RMSPE	0.84	0.37	4.56

NOTE:

CBC => CONFERENCE BOARD OF CANADA

ARIMA => (1,1,0)TRAN(SQUARE ROOT)

TABLE 2b

FORECAST ERRORS OF REAL GDP LEVELS

ERROR MEASURE	FORECAST MODEL		
	CBC	ARIMA	NAIVE
% ERROR			
1989:1	-0.85	0.11	-0.6
1989:2	-0.77	0.2	-1
1989:3	-1.27	0.26	-1.55
1989:4	-1.2	0.13	-2.31
MSPE	1.09	0.03	5.1
RMSPE	1.04	0.18	2.26

NOTE:

CBC => CONFERENCE BOARD OF CANADA

ARIMA => (0,1,1)(0,0,1)₄

TABLE 3a

FORECAST ERRORS OF NOMINAL GDP GROWTH RATES

ERROR MEASURE	FORECAST MODEL		
	CBC	ARIMA	NAIVE
% ERROR			
1989:1	0.12	-0.57	-2.37
1989:2	0.04	0.29	-1.46
1989:3	0.05	0.65	-1.06
1989:4	0.07	-0.19	-1.89
MSPE	0.01	0.22	3.1
RMSPE	0.08	0.47	1.76
U _t	0.04	0.26	1

NOTE:

CBC => CONFERENCE BOARD OF CANADA

ARIMA => (1,1,0)TRAN(SQUARE ROOT)

TABLE 3b

FORECAST ERRORS OF REAL GDP GROWTH RATES

ERROR MEASURE	FORECAST MODEL		
	CBC	ARIMA	NAIVE
% ERROR			
1989:1	0.7	0.11	-0.6
1989:2	0.09	0.09	-0.41
1989:3	-0.51	0.06	-0.56
1989:4	0.07	-0.13	-0.77
MSPE	0.19	0.01	0.36
RMSPE	0.43	0.1	0.6
Ut	0.37	0.09	1

NOTE:

CBC => CONFERENCE BOARD OF CANADA

ARIMA => (0,1,1)(0,0,1)₄

3.5 Limitations of ARIMA Forecasting Models.

i) The most identifiable shortcoming of univariate time series models is their limitation in providing information beyond a forecast value. These models, for example, cannot provide us with information regarding the effect of government expenditure or the impact of free trade on the forecasts provided for 1989.

ii) Given the type of identification, estimation and forecasting technique used in this paper, the time series models cannot indicate or predict sudden movements away from the historical path (e.g. turning points) of a series under study. This is a serious limitation if a recession of some depth is expected to hit the economy, and some information regarding the timing and/or severity is required to foretell.

iii) Although the ARIMA class of models are quite broad, they are restricted to stationary time series or those series that exhibit stationarity after differencing. Since the prediction of future values are constrained to be linear functions of the observations, we also have to assume linearity of the models. Such restriction, often sufficient approximation of reality, does not cover every aspect of real life situation and thus a broader class of models should be entertained.

It should also be pointed out here that the assumption of linearity was somewhat relaxed in our case study earlier by applying the Box-Cox transformation to our model. According to

table 1, using the square root of the original series has provided us with a better forecast.

iv) Since stationarity is an important factor in ARIMA modelling, increasing trends are usually differenced. Such trends may be caused by systematic components that consequently should be explained appropriately through some explicit economic theory.

v) Whereas, the statistical tools such as the acf and pacf help the researcher in choosing a tentative model for estimation and forecasting, most of the time he or she has to rely on personal (subjective) judgements. Unless the researcher has extensive knowledge and experience in time series modelling, such judgements can be inaccurate and may lead to inferior forecast values.

It is desirable, therefore, for the researcher to seek expert opinion from other researchers who have done more work on that particular time series or related data. Furthermore, fitting a series of simple ARIMA and seasonal ARIMA models and selecting the one with desirable statistics is a good starting point if the identification stage gives inadequate information.

Fortunately, as indicated by authors such as Wecker (1981), Newbold (1983), and Priestley (1988), current developments in time series analysis show that some of the limitations may be overcome by new sets of time series models. One interesting contribution is that of Harvey and Todd (1983) which introduces "structural time series models" as alternatives to ARIMA models.

In their article, the above authors point out that structural time series models are formulated in terms of the usual time series decomposition of trend, seasonal, irregular and other underlying components and thus facilitate alternative model selection strategy. Furthermore, according to their empirical findings, the structural time series models perform as well as, and in some cases (especially in cases where sudden changes occur in the data), better than univariate ARIMA models.

As verified by this study, time series models produce relatively superior forecast values than competing models. Subsequently applications of time series models have extended into econometric modelling realms as substitutes for large econometric models (such as Vector Autoregressive models) or as a complement to regression models through the modelling of the stochastic term (Pindyck and Rubinfeld, 1981). Both of these applications require extensive theoretical exposition and empirical verification to include in this paper, and thus, interested readers are referred to Pindyck and Rubinfeld (1981) and Litterman (1986) for a detailed discussion.

4. CONCLUSIONS:

This investigation has shown that the univariate ARIMA model forecast of nominal and Real GDP for the period first quarter 1989 to the fourth quarter 1989 has performed better than the macro-econometric model of the Conference Board of Canada (CBC) for three of the four cases discussed. The process leading to an ARIMA

forecasting stage, however, was shown to be rather complex and at times subjective. It was suggested, therefore, to exercise caution and on occasion to re-estimate the models and compare the forecasting performance of each model to acquire an adequate model.

While current research in time series is expected to introduce better models that can improve some of the drawbacks of ARIMA modelling, existing models were found to be limited in providing prediction of turning points and in decomposing components of time series adequately or efficiently. Furthermore, the restriction of stationarity and linearity are an inadequate approximation of reality and a broader class of models (including non-linear models as well) should be considered.

Since in most business firms and government agencies quick and reliable information regarding macro-economics time series is needed, time series models are justifiably useful.

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APPENDIX

Invertibility:

As mentioned earlier the invertibility condition is satisfied if the roots of the characteristic equation are outside the unit circle (Proof in B-J 1970). To illustrate consider the following examples:

$$i) \quad \phi_1 = 0.8 \quad \phi_2 = -0.15$$

$$(1 - 0.8B + 0.15B^2) = (1 - .5B)(1 - .3B) = 0$$

The characteristic roots in this case are all greater than one (i.e, they are outside the unit circle) and thus the stationarity condition is satisfied.

$$ii) \quad \phi_1 = 1.5 \quad \phi_2 = -.5$$

$$(1 - 1.5B + 0.5B^2) = (1 - B)(1 - 0.5B)$$

This example has one root at 1 and consequently the stationarity condition is not satisfied.

Box-Cox Transformation:

Box-Cox transformations for forecasting purposes have two uses (Box-Cox, 1964). The first is to make a series variance stationary while the other is to assist in determining the relationship between two or more variables (for example, between dependent and explanatory variables).

$$Z_t = \frac{(z_{t+m})^\lambda - 1}{\lambda} \quad \text{suppose } m=0$$

ii

case a: $\lambda=0 \Rightarrow \frac{(Z_t)^0 - 1}{0}$ indeterminate

by L'ho^pital's rule:

$$\lim_{\lambda \rightarrow 0} \frac{\partial [(Z_t)^\lambda - 1]}{\partial \lambda}$$

$$\lim_{\lambda \rightarrow 0} \frac{Z_t^\lambda \ln Z_t}{1} = \ln Z_t$$

case b: $\lambda=1 \quad \frac{(Z_t)^1 - 1}{1} = Z_t - 1$

case c: $\lambda=-1 \quad \frac{(Z_t)^{-1} - 1}{-1} = -(Z_t)^{-1} + 1$

Portmanteau (Q) Statistics:

Recall that $\rho_k = \gamma_k / \gamma_0 \quad \forall k 0, 1, 2, \dots$

For an ARMA (p,q) process:

$$(\phi)Z_t = (\theta)n_t \text{ thus,}$$

$$[1 + \alpha_1\phi + \alpha_2\phi^2 + \dots + \alpha_p\phi^p]Z_t = [1 + \beta_1\theta + \beta_2\theta^2 + \dots + \beta_q\theta^q]n_t$$

If this process is invertible and the estimates are significant, then the residuals are estimated for white noise property:

$$\hat{n}_t \text{ from } [\hat{(\phi)} / \hat{(\theta)}]$$

$$r_k = \frac{(\sum_{t=k+1}^T \hat{n}_t \hat{n}_{t-k})}{(\sum_{t=1}^T \hat{n}_t^2)^2} \quad \forall k 1, 2, \dots$$

According to Box and Pierce (1970):

$$T \sum_{k=1}^n r_k^2 \sim X_{m-p-q}^2$$

Ho: r_k is white noise when n_t is $n \sim (0, \sigma^2)$

Autocorrelation Function (ACF):

An estimate of the theoretical autocorrelation function is given by:

$$r_k = \frac{\sum_{t=k+1}^n (x_t - \bar{x})(x_{t-k} - \bar{x})}{\sum_{t=1}^n (x_t - \bar{x})^2} \quad \text{where } \bar{x} \text{ is the sample mean}$$

For uncorrelated observations, the variance of r_k is approximately:

$$V(r_k) \approx 1/n \quad \text{where } n \text{ is number of observations}$$

For the general case, however, the Bartlett (Box-jenkins, 1970; 34-35) approximation is used to calculate the standard deviation:

$$s(r_k) = (1 + 2 \sum_{j=1}^{k-1} r_j)^{1/2} n^{-1/2} \quad \forall r_j > k-1$$

The theoretical autocorrelation is also calculated as the ratio of the covariance and variance of the time series at specific lags. The following are three simple ARMA models and their theoretical acf.

CASE 1 AR(1)

$$e_t = \phi e_{t-1} + n_t$$

where n_t is white noise

$$E(n_t) = 0$$

$$E(n_t)^2 = \sigma^2$$

$$E(n_{t-i} n_{t-j}) = 0 \quad \forall i \neq j$$

$$e_t = \phi(\phi e_{t-2} + n_{t-1}) + n_t$$

$$= \phi^2(\phi e_{t-3} + n_{t-2}) + \phi n_{t-1} + n_t$$

$$= \phi^3(\phi e_{t-4} + n_{t-3}) + \phi^2 n_{t-2} + \phi n_{t-1} + n_t$$

$$= \dots$$

$$= \dots$$

$$= \dots$$

$$= \phi^j e_{t-j} + n_t + \phi n_{t-1} + \phi^2 n_{t-2} + \dots + \phi^{j-1} n_{t-j+1}$$

and for $j \rightarrow \infty$,

$$e_t = n_t + \phi n_{t-1} + \phi^2 n_{t-2} + \dots$$

$$E(e_t) = E(n_t + \phi n_{t-1} + \phi^2 n_{t-2} + \dots) = 0$$

$$\begin{aligned} E(e_t)^2 &= E(n_t + \phi n_{t-1} + \phi^2 n_{t-2} + \dots)^2 \\ &= E(n_t)^2 + \phi^2 E(n_{t-1})^2 + \phi^4 E(n_{t-2})^2 + \dots \\ &= \sigma^2 + \phi^2 \sigma^2 + \dots \end{aligned}$$

since $E(n_{t-i} n_{t-j}) = 0$
all cross terms are
ignored.

$$= \sigma^2 (1 + \phi^2 + \phi^4 + \dots)$$

$$E(e_t)^2 = \frac{\sigma^2}{1 - \phi^2} \quad (\text{A1.1})$$

$$\begin{aligned} E(e_t e_{t-1}) &= E(n_t + \phi n_{t-1} + \phi^2 n_{t-2} + \dots)(n_{t-1} + \phi n_{t-2} + \phi^2 n_{t-3} + \dots) \\ &= \phi \sigma^2 + \phi^3 \sigma^2 + \phi^5 \sigma^2 + \dots \\ &= \phi \sigma^2 (1 + \phi^2 + \phi^4 + \dots) \\ &= \frac{\phi \sigma^2}{1 - \phi^2} \quad (\text{A1.2}) \end{aligned}$$

$$\rho_1 = \frac{E(e_t e_{t-1})}{E(e_t)^2} = \frac{\phi \sigma^2 / 1 - \phi^2}{\sigma^2 / 1 - \phi^2} = \phi \quad (\text{A1.3})$$

$$\begin{aligned} E(e_t e_{t-k}) &= E(n_t + \phi n_{t-1} + \dots + \phi^k n_{t-k} + \phi^{k+1} n_{t-k+1} + \dots)(n_{t-k} + \phi n_{t-k+1} + \dots) \\ &= (\phi^k \sigma^2 + \phi^{k+1} \phi \sigma^2 + \phi^{k+2} \phi^2 \sigma^2 + \dots) \\ &= \phi^k \sigma^2 (1 + \phi^2 + \phi^4 + \dots) \\ &= \frac{\phi^k \sigma^2}{1 - \phi^2} \quad (\text{A1.4}) \end{aligned}$$

$$\rho_k = \frac{E(e_t e_{t-k})}{E(e_t)^2} = \frac{\phi^k \sigma^2 / 1 - \phi^2}{\sigma^2 / 1 - \phi^2} = \phi^k \quad (\text{A1.5})$$

CASE 2 MA(1)

$$e_t = n_t + \theta n_{t-1} \quad (\text{again } n_t \text{ is white noise})$$

$$E(e_t) = 0$$

$$\begin{aligned} E(e_t)^2 &= E(n_t + \theta n_{t-1})^2 \\ &= \sigma^2 + \theta^2 \sigma^2 \quad (\text{all cross terms are zero}) \\ &= \sigma^2 (1 + \theta^2) \end{aligned} \quad (\text{A2.1})$$

$$\begin{aligned} E(e_t e_{t-1}) &= E(n_t + \theta n_{t-1})(n_{t-1} + \theta n_{t-2}) \\ &= \theta \sigma^2 \end{aligned} \quad (\text{A2.2})$$

$$\rho_1 = \frac{(e_t e_{t-1})}{(e_t)^2} = \frac{\theta \sigma^2}{\sigma^2 (1 + \theta^2)}$$

$$\rho_1 = \frac{\theta}{(1 + \theta^2)} \quad (\text{A2.3})$$

$$\begin{aligned} E(e_t e_{t-k}) &= E(n_t + \theta n_{t-1})(n_{t-k} + \theta n_{t-k+1}) \\ &= 0 \end{aligned}$$

$$\rho_k = 0$$

CASE 3 ARMA(1,1)

$$\begin{aligned} e_t &= \phi e_{t-1} + n_t + \theta n_{t-1} \\ &= \phi(e_{t-2} + n_{t-1}) + n_t + \theta n_{t-1} \\ &= \phi^2(e_{t-3} + n_{t-2}) + n_t + (\phi + \theta)n_{t-1} \\ &\quad \dots \\ &\quad \dots \\ &= \phi^j e_{t-j} + n_t + (\theta + \phi)n_{t-1} + \phi(\theta + \phi)n_{t-2} + \phi^2(\theta + \phi)n_{t-3} + \dots + \phi^{j-2}n_{t-j+1}, \end{aligned}$$

again for $j \rightarrow \infty$,

$$e_t = n_t + (\theta + \phi)n_{t-1} + \phi(\theta + \phi)n_{t-2} + \phi^2(\theta + \phi)n_{t-3} + \dots$$

$$E(e_t) = 0$$

$$\begin{aligned} E(e_t)^2 &= E(n_t + (\theta + \phi)n_{t-1} + \phi(\theta + \phi)n_{t-2} + \dots)^2 \\ &= \sigma^2 [1 + (\theta + \phi)^2 + \phi^2(\theta + \phi)^2 + \phi^4(\theta + \phi)^2 + \dots] \\ &= \sigma^2 \{ 1 + (\theta + \phi)^2 [1 + \phi^2 + \phi^4 + \phi^6 + \dots] \} \\ &= \sigma^2 \{ 1 + [(\theta + \phi)^2 / (1 - \phi^2)] \} \end{aligned}$$

$$E(e_t)^2 = \frac{(1 + \theta^2 + 2\phi\theta)\sigma^2}{1 - \phi^2} \quad (\text{A3.1})$$

$$\begin{aligned} E(e_t e_{t-1}) &= E(n_t + (\theta + \phi)n_{t-1} + \phi(\theta + \phi)n_{t-2} + \dots)(n_{t-1} + (\theta + \phi)n_{t-2} + \dots) \\ &= [(\theta + \phi)\sigma^2 + \phi(\theta + \phi)^2\sigma^2 + \phi^3(\theta + \phi)^2\sigma^2 + \dots] \\ &= \sigma^2(\theta + \phi) [1 + \phi(\theta + \phi) + \phi^3(\theta + \phi) + \dots] \\ &= \sigma^2(\theta + \phi) \{ 1 + \phi(\theta + \phi) [1 + \phi^2 + \phi^4 + \dots] \} \\ &= \sigma^2(\theta + \phi) \{ 1 + [\phi(\theta + \phi) / (1 - \phi^2)] \} \\ &= \frac{(1 + \phi\theta)(\phi + \theta)\sigma^2}{1 - \phi^2} \quad (\text{A3.2}) \end{aligned}$$

$$\begin{aligned} \rho_1 &= \frac{(1 + \phi\theta)(\phi + \theta)\sigma^2}{1 - \phi^2} \cdot \frac{(1 - \phi^2)}{(1 + \theta^2 + 2\phi\theta)\sigma^2} \\ &= \frac{(1 + \phi\theta)(\phi + \theta)}{(1 + \theta^2 + 2\phi\theta)} \quad (\text{A3.3}) \end{aligned}$$

$$\begin{aligned} E(e_t e_{t-k}) &= (\dots + \phi^{k-1}(\theta + \phi)n_{t-k} + \phi^k(\theta + \phi)n_{t-k+1} \dots)(\dots + n_{t-k} \\ &\quad + (\phi + \theta)n_{t-k+1} + \phi(\phi + \theta)n_{t-k+2} \dots) \\ &= \phi^{k-1}(\theta + \phi)\sigma^2 + \phi^k(\theta + \phi)^2\sigma^2 + \phi^{k+2}(\theta + \phi)^2 + \dots \\ &= \phi^{k-1}(\theta + \phi)\sigma^2 [1 + \phi(\phi + \theta) + \phi^3(\theta + \phi)^2 + \dots] \end{aligned}$$

$$\begin{aligned}
&= \phi^{k-1}(\theta+\phi)\sigma^2 \{ 1 + \phi(\phi+\theta) [1 + \phi^2 + \phi^4 + \dots] \} \\
&= \phi^{k-1}(\theta+\phi)\sigma^2 \{ 1 + [\phi(\phi+\theta) / (1-\phi^2)] \} \\
&= \frac{\sigma^2 (\phi^{k-1})(1+\theta\phi)(\theta+\phi)}{1-\phi^2} \qquad \qquad \qquad (A3.4)
\end{aligned}$$

$$\begin{aligned}
\rho_k &= \frac{\sigma^2 (\phi^{k-1})(1+\theta\phi)(\theta+\phi)}{1-\phi^2} \cdot \frac{1-\phi^2}{(1+\theta^2+2\phi\theta)\sigma^2} \\
&= \frac{(\phi^{k-1})(1+\theta\phi)(\theta+\phi)}{(1+\theta^2+2\phi\theta)}
\end{aligned}$$

Partial Autocorrelation Function:

The correlation between two random variables, in some cases, is due to the correlation of these two variables to the same third variable. To adjust for this correlation the partial autocorrelation function is used. The pacf essentially measures the additional correlations between two lags after adjusting for the intermediate lags.

To calculate the sample pacf one can fit autoregressive models of increasing order; the estimate of the last coefficient of each model is the sample pacf.

$$\phi_{kk} = \frac{r_k - \sum_{j=1}^{k-1} \phi_{k-1,j}^{\wedge} r_{k-j}}{1 - \sum_{j=1}^{k-1} \phi_{k-1,j}^{\wedge} r_j}$$

INTEGRATION

The original variable Z_t and a differenced variable W_t are linked deterministically by the differencing operator $(1-B)^d$.

$$W_t = (1-B)^d Z_t$$

This relationship between Z_t and W_t is very important because, after building an ARIMA model for the stationary series W_t , we often want to forecast the original nonstationary series Z_t .

Suppose $d=1$ then,

$$Z_t = (1-B)^{-1} W_t$$

$(1-B)^{-1}$ can be written as infinite series:

$$(1+B+B^2+B^3+\dots)$$

$$\begin{aligned} Z_t &= (1+B+B^2+B^3+\dots) W_t \\ &= W_t + W_{t-1} + W_{t-2} + \dots \\ &= \sum_{i=0}^t W_i \end{aligned}$$

Since the Z 's are sums of the W 's, we can get to Z by integrating.

REFERENCES (For Appendix)

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TEST FOR THE PRESENCE OF SEASONALITY ASSUMING STABILITY

	SUM OF SQUARES	DGRS. OF FREEDOM	MEAN SQUARE	F-VALUE
BETWEEN QUARTERS	6202894.0444	3	2067631.34814	1.792
RESIDUAL	55393658.8271	48	1154034.55890	
TOTAL	61596552.8715	51		

NO EVIDENCE OF STABLE SEASONALITY AT THE 0.1 PER CENT LEVEL

NONPARAMETRIC TEST FOR THE PRESENCE OF SEASONALITY ASSUMING STABILITY

KRUSKAL-WALLIS STATISTIC 7.8055

DEGREES OF FREEDOM 3

PROBABILITY LEVEL 5.021%

NO EVIDENCE OF SEASONALITY AT THE ONE PERCENT LEVEL

MOVING SEASONALITY TEST

	SUM OF SQUARES	DGRS. OF FREEDOM	MEAN SQUARE	F-VALUE
BETWEEN YEARS	8919456.1667	12	743288.013888	1.012
ERROR	26432910.7019	36	734247.519498	

NO EVIDENCE OF MOVING SEASONALITY AT THE FIVE PERCENT LEVEL

COMBINED TEST FOR THE PRESENCE OF IDENTIFIABLE SEASONALITY

IDENTIFIABLE SEASONALITY NOT PRESENT

X

Test for the Presence of stable and moving seasonality of the GDP series

TEST FOR THE PRESENCE OF SEASONALITY