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Research Article

Forecasting ARIMA model for foreign trade statistics

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Abstract

Time series models are applied with time series data of variables measured over time. The study focuses on examining the forecasting performance of the autoregressive Moving Average (ARMA). The study investigates the statistical properties of the series, the residuals of the ARIMA model. The model attempts to identify the trend and statistical properties. The question studied was whether information from the proposed model gave a better trade forecast. The "forecasting" situation examined really involved added useful information. The analysis of the data demonstrates that the model applied here may be useful to understand the properties of the time series model of Saudi-US foreign trade statistics.

Keywords: ARIMA Models, Autocorrelation, Box-Jenkins Models, Correlograms, Identification.

introduction

Time series analysis accounts for the fact that data points taken over time may have an internal structure (such as autocorrelation, trend or seasonal variation) that should be account for. Time series models are used to obtain an understanding of the underlying forces and structure that produced the observed data as well as fitting a model and proceed to forecast. The purpose of this article is to provide an analysis of time series model for foreign trade statistics. In the following sections, the techniques those are useful for analyzing and identifying patterns in time series data will be introduced. As in most other analysis, in time series analysis it is assumed that the data consist of a certain pattern (usually a set of identifiable components and random noise (error), which makes the pattern difficult to identify. Some recommendations based on the results obtainable from foreign trade data are to be introduced. Early detailed discussion of the methods described in this topic can be found in Box and Jenkins (1976), Box et al.(1970), Brockwell and Davis(1996). Other related issues on time series models ,such as multivariate and univariate time series analysis ,pooling and residual analysis were found in Journal of Time Series Analysis (see Ginger et al. (2007), Jean-Marc et al. (2007), Massimiliano (2007), Elena (2007). Recently Robert et al. (2011) has covered time series analysis and its applications presents a balanced and comprehensive treatment of both time and frequency domain methods with accompanying theory. In addition to coverage of classical methods of time series regression, ARIMA (autoregressive integrated moving averages) models, spectral analysis and state-space models. In his page, Robert (2014) has presented linear regression and time series forecasting models with focus on ARIMA models. Testing for trends in ARIMA models was also found in Rob (2014).

The Model

The original Box-Jenkins modeling procedure involved an iterative process of model selection, parameter estimation and model checking. According to *Rob J (2001)*, recent explanations of the process (e.g., *Makridakis et al., 1998)* often add a preliminary stage of data preparation and a final stage of model application or forecasting. Consider the simple time series model, then each observation would be consisting of a constant (*b*) and an error component ε (epsilon), that is:

$X_t = b + \varepsilon_t$.
When applied recursively to each successive observation in the series, each new smoothed value (forecast) is computed as the weighted average of the current observation and the previous smoothed observation; the previous smoothed observation was computed in turn from the previous observed value and the smoothed value before the previous observation, and so on. The series equation can be expressed in the following form:

$$xt = \xi + \phi 1*x(t-1) + \phi 2*x(t-2) + \phi 3*x(t-3) + ... + \varepsilon$$

Where:

ξ is a constant (intercept), and

ϕ_1, ϕ_2, ϕ_3 are the autoregressive model parameters.

is a random error or random shock and ε.

An autoregressive process will only be stable if the parameters are within a certain range; for example, if there is only one autoregressive parameter then is must fall within the interval of $-1 < \phi < 1$. Otherwise, the series would not be stationery. However, each element in the series can also be affected by the past error ***(****see Copyright StatSoft, Inc., 1984-2003)* that cannot be accounted for by the autoregressive component, that is:

$$x_t = \mu + \varepsilon_t - \theta_1*\varepsilon_{(t-1)} - \theta_2*\varepsilon_{(t-2)} - \theta_3*\varepsilon_{(t-3)} - ...$$

Where:

μ is a constant, and: $_1\theta$, θ_2, θ_3 are the moving average model parameters.

In a multiple regression model, the variable of interest can be forecasted using a linear combination of predictors. In an autoregression model, we forecast the variable of interest using a linear combination of past values of the variable. The term *auto*regression indicates that it is a regression of the variable against itself. Thus an autoregressive model of order *p* can be written as: Rob and George (2014).

$$yt=c+\phi 1yt-1+\phi 2yt-2+\cdots+\phi pyt-p+et,$$

where *c* is a constant and *et* is white noise. This is like a multiple regression but with *lagged values* of *yt* as predictors. We refer to this as an AR(*p*) model.

Time series patterns can be described in terms of two components: trend and seasonality .The former represents a general systematic linear or nonlinear component that changes over time. If there is considerable error in the time series data, then the first step in the process of trend identification is smoothing. The most common technique is moving average smoothing which replaces each element of the series by either the simple or weighted average of *n* surrounding elements. A logarithmic, exponential, or polynomial function can be used to remove the nonlinearity to approximate the data by a linear function. Seasonal patterns of time series can be examined via correlograms which displays the autocorrelation function (*ACF*), that is, serial correlation coefficients (and their standard errors) for consecutive lags in a specified range of lags.

Exponential smoothing and ARIMA models are the two most widely-used approaches to time series forecasting problem. While exponential smoothing models were based on a description of trend and seasonality in the data, ARIMA models aim to describe the autocorrelations in the data Rob and George(2014).

Forecasting based on ARIMA models, commonly known as the Box–Jenkins approach, comprises following stages:

i.) Model identification ii.) Parameter estimation iii.) Diagnostic checking. These stages are repeated until a “suitable” model for the given data has been identified.

The (Autoregressive Moving Average model, ARMA), introduced by Box and Jenkins (1976) includes autoregressive as well as moving average parameters, specifically, the three types of parameters in the model are: (*p*), (*d*), and (*q*). In the notation models are summarized as ARIMA (*p, d, q*); so, for example, a model described as (0, 1, 2) means that it contains 0 (zero) autoregressive (*p*) parameters and 2 moving average (*q*) parameters.

Given a time series of data X_t, the ARMA model consists of two parts, an autoregressive (AR) part and a moving average (MA) part. Following *Elena Pesavento, (*2007), the AR(*p*) model can be written as:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t.$$

where $\varphi_1, \ldots, \varphi_p$ are the parameters of the model, *c* is a constant and ε_t is an error term. Omitting the constant (c),the notation MA(*q*) refers to the moving average model of order *q*:

$$X_t = \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

Where the $\theta_1, ..., \theta_q$ are the parameters of the model and the $\varepsilon_t, \varepsilon_{t-1}$,... are again, the error terms.

The notation ARIMA (*p*, *q*) refers to the model with *p* autoregressive terms and *q* moving average terms. This model contains the AR (*p*) and MA(*q*) models,

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}.$$

The error terms ε_t are assumed to be independent identically-distributed random variables with zero mean: $\varepsilon_t \sim N(0,\sigma^2)$ where σ^2 is the variance.

Usually the series first needs to be differenced until it is stationary. In order to determine the necessary level of differencing, one should examine the plot of the data and autocorrelogram**.** Significant changes in level (strong upward or downward changes) usually require first order non seasonal (lag=1) differencing; strong changes of slope usually require second order non seasonal differencing. If the estimated autocorrelation coefficients decline slowly at longer lags, first order differencing is usually needed.

At the stage of(identification) , we need to decide how many autoregressive (*p*) and moving average (*q*) parameters are necessary to yield an effective model of the process ,model that fits the data.ARMA models can, after choosing p and q, be fitted by least squares regression to find the values of the parameters which minimize the error term. It is generally considered good practice to find the smallest values of p and q which provide an acceptable fit to the data. Elena Pesavento (2007)**.**

At the (estimation) step, the estimates of the parameters are used in the last stage (Forecasting) to calculate new values of the series and confidence intervals for those predicted values. The estimation process is performed on transformed (differenced) data; before the forecasts are generated, the series needs to be integrated (integration is the inverse of differencing) so that the forecasts are expressed in values compatible with the input data. This methodology is named as (ARIMA), Auto-Regressive Integrated Moving Average). Robert et al. (2011) introduced autocorrelation and cross-correlation functions (ACFs and CCFs) as tools for clarifying relations that may occur within and between time series at various lags. In addition, they explained how to build linear models based on classical regression theory for exploiting the associations indicated by large values of the ACF or CCF. In statistics, the autocorrelation function (ACF) of a random process describes the correlation between the processes at different points in time. Let X_t be the value of process at the time t. If X_t has mean μ and variance $\boldsymbol{\sigma^2}$then following Elena Pesavento (2007**)** the definition of the ACF is:

$$R(t,s) = \frac{E[(X_t - \mu)(X_s - \mu)]}{\sigma^2},$$

Where E is the expected value operator and R, the correlation function, ranges between [1,-1], but for the second order stationary, the ACF can be obtained by:

$$R(k) = \frac{E[(X_i - \mu)(X_{i+k} - \mu)]}{\sigma^2},$$

Where k is the lag [**t-s**]

However, for a discrete time series of length n with known mean and variance, the ACF can be estimated by:

$$\hat{R}(k) = \frac{1}{(n-k)\sigma^2} \sum_{t=1}^{n-k} [X_t - \mu][X_{t+k} - \mu]$$

For any positive integer k < n
In time series analysis regression, Durbin-Watson test (D.W) can be used for detection of first order autocorrelation or Durbin's H statistic when lagged dependent variable is used as explanatory variable Elena Pesavento (2007).
The major tools used in the identification phase, before the estimation step are plots of the series, correlograms of auto correlation (ACF), and partial autocorrelation (PACF**).** A correlogram is graph of the autocorrelation ρ_l versus l (the time lags). If cross-correlation is used, it is called a cross-correlogram. *Elena Pesavento (2007***)***.*In the same graph one can draw upper and lower bounds for autocorrelation with significance level α:

$B = \pm t_{1-\alpha/2} SE(\hat{\rho}_l)$ With $\hat{\rho}_l$ as the estimated autocorrelation in period l.

If the autocorrelation is higher (lower) than this upper (lower) bound, the null hypothesis of no autocorrelation is rejected at the confidence level α. Thus, positive (negative) autocorrelation is given; t is the quantile of the t-distribution; SE is the standard error, which can be computed by the formula for MA (l) processes, thus:

$SE(\hat{\rho}_1) = \frac{1}{T}$ bzw. $SE(\hat{\rho}_l) = \sqrt{\frac{1 + 2\sum_{i=1}^{l-1} \hat{\rho}_i^2}{T}}$ for $l > 1$

We can reject the null that there is no autocorrelation between periods that are close to each other.

DATA ANALYSIS

Introduction

Saudi oil production and investment policies have assumed important to the industrialized and the developing world, particularly to the United States which have been more clearly in1990, after the Gulf War (1991) because it was the major oil-producing country and thereby has strong influence on international oil supplies and prices. Saudi Arabia is second in the world to Canada in proven reserves of petroleum (24% of the proved total), ranks as the largest exporter of petroleum, and plays a leading role in OPEC. Saudi Arabia has an oil-based economy where the petroleum sector accounts for roughly 75% of budget revenues, 40% of GDP, and 90% of export earnings. Saudi oil reserves are the largest in the world, and Saudi Arabia is the world's leading oil producer and exporter. Oil accounts for more than 90% of the country's exports and nearly 75% of government revenues (see Country Analysis Briefs home page (2005), The World Fact Book (2006), Arab Countries, Special Arab Files, Saudi Arabia(2006). (Source: Country Analysis Briefs home page (2005)).

Model Results

In this section, the data of foreign trade statistics of USA and Saudi Arabia, which include exports and imports in million dollars for the period (1985-2005), for Saudi Arabia, is the main supplier of oil to USA. In this section, techniques to identify trend components in the time series data will be of interest. If the time series data contain considerable error, then the first step in the process of trend identification is smoothing by using the moving average smoothing which replaces each element of the series by either the simple or weighted average of *n* surrounding elements.
In this analysis of foreign trade data, a summary of three models for exports (Exp) and imports (Imp) is given in table(1),where ANOVA Summary for the same models is shown in table (2) and the coefficients are presented in table(3). Significant tests are also summarized for the models (2) and (3). Time series data have been adequately approximated by a linear function; since there is a clear monotonous nonlinear component, thus data first need to be transformed to remove the nonlinearity. Logarithmic, exponential, and logistic function have been used to satisfy the

required analysis. The curve fit for each of exports and imports is shown in different transformations, in table (4) which shows significant F at 0.05, table (6) where insignificant F is seen and figures (1),(2) successively. A first step in analyzing the underlying model is to examine the autocorrelations (ACF) and partial autocorrelations. Seasonal patterns of time series can be examined via correlograms. The correlogram (autocorrelogram) displays graphically and numerically the autocorrelation function (*ACF*), that is, serial correlation coefficients (and their standard errors) for consecutive lags in a specified range of lags (1 through 20). While examining correlograms one should keep in mind that autocorrelations for consecutive lags are formally dependent. While examining correlograms we keep in mind that autocorrelations for consecutive lags are formally dependent. For instance, If the first element is closely related to the second, and the second to the third, then the first element must also be somewhat related to the third one, etc. If so, then the pattern of serial dependencies can change considerably after removing the first order auto correlation (i.e., after differencing the series with a lag of 1). The numerical autocorrelation function for exports was displayed in figure (4). The serial correlation coefficients and their standard errors for consecutive lags were taken. Ranges of two standard errors for each lag are marked in correlograms. It should be noted that only very strong and highly significant autocorrelations are to be interested in. A first step in diagnostic checking of fitted models is to analyze the residuals from the fit for any signs of non– randomness. The analysis contains a plot of the residuals, the autocorrelation of the residuals and the p-values of the Ljung–Box statistic. The test examines the Null of independently distributed residuals. If the residuals are not, then they come from a miss–specified model. Partial autocorrelations is a useful method to examine serial dependencies is to examine the partial autocorrelation function (*PACF*) - an extension of autocorrelation, where the dependence on the intermediate elements (those within the lag) is removed. Partial autocorrelation is similar to autocorrelation, except that when calculating it, the (auto) correlations with all the elements within the lag are partial out (see figure (4-5)). If a lag of 1 is specified, then the partial autocorrelation is equivalent to auto correlation. The autocorrelation plot can provide answers to whether or not the data are random, an observation related to an adjacent observation, the observed time series autoregressive, what is the appropriate model for the observed time series, and if the underlying model is valid and sufficient. To check for randomness in the data set, autocorrelation plots are used (see figure(6). This randomness is ascertained by computing autocorrelations for data values at varying time lags .If random, such autocorrelations should be near zero for any and all the lag separations .If non –random, then one or more of the autocorrelations will be significantly non-zero. Autocorrelations should be near- zero for randomness, otherwise the randomness assumption fails. The autocorrelation plot shows that the time series is not random, but rather has a high degree of autocorrelation between adjacent and near-adjacent observations. Autocorrelations and partial autocorrelations for exports and imports are displayed through figures (4-7) to (4-10) and 20 first lags are computed with two standard errors. Serial dependency for a particular number of lag can be removed by differencing (converting) the series and make the series stationary which is necessary for ARIMA and other techniques. For autoregressive process time series may consist of elements that are serially dependent in the sense that one can estimate a coefficient or a set of coefficients that describe consecutive elements of the series from specific, time-lagged (previous) elements. An autoregressive process will only be stable if the parameters are within a certain range; for example, if there is only one autoregressive parameter then is must fall within the interval of $-1 < \phi < 1$. Otherwise, past effects would accumulate and the values of successive x_t' s would move towards infinity, that is, the series would not be stationary. If there is more than one autoregressive parameter, similar (general) restrictions on the parameter values can be defined. Autoregressive as well as moving average parameters, and explicitly include differencing in the formulation of the model. Specifically, the three types of parameters in the model are: the autoregressive parameters (*p*), the number of differencing passes (*d*), and moving average parameters (*q)* were computed for the series after it was differenced once as seen in (Figure 4-11). At the estimation step**,** the parameters are estimated using function minimization procedures; so that the sum of squared residuals is minimized. The estimates of the parameters are used in the last stage (*Forecasting*) to calculate new values of the series (beyond those included in the input data set) and confidence intervals for those predicted values. The estimation process is performed on transformed (differenced) data; before the forecasts are generated, the series needs to be *integrated* (integration is the inverse of differencing) so that the forecasts are expressed in values compatible with the input data. This automatic integration feature is represented by the letter I in the name of the methodology (ARIMA = Auto-Regressive Integrated Moving Average). Approximate *t* values are reported, computed from the parameter standard errors to evaluate the model. If not significant, the respective parameter can in most cases be dropped from the model without affecting substantially the overall fit of the model. The major concern here is that the residuals are systematically distributed across the series (e.g., they could be negative in the first part of the series and approach zero in the second part) or that they contain some serial dependency which may suggest that the ARIMA model is inadequate. The analysis of ARIMA residuals constitutes an important test of the model. The estimation procedure assumes that the residual are not (auto-) correlated and that they are normally distributed.

Table 1. Models summary for Foreign Trade Data

model	R	R square	R square adjusted	Std. Error of the Estimate
Mod (1): Predictors:(Constant),imp	0.139	0.019	-0.032	1881.6610
Mod(2): Predictors,(Constant),yr	0.445	0.198	0.155	1702.0773
Mod(3): Predictors,(Constant),yr	0.826	0.683	0.666	3454.6957

Table 2. ANOVA for Foreign Trade

Model	Sum of squares	Df.	Mean square	F	Sig
Model(1):					
Dependent Variable: Exp					0.547
Regression	1334088	1	1334087.562	0.377	
Residual	67272315	19	3540648.141		
Total	68606402	20			
Model(2):					
Predictors(Constant),yr					0.043
Dependent Variable: exp					
Regression	13562126	1	13562125.94	4.681	
Residual	55044276	19	2897067.174		
Total	68606402	20			
Model(3):	4.87E+08	1	487452983.4	40.843	0.000
Predictors(Constant),yr	2.27E+08	19	11934922.34		
Dependent Variable: imp	7.14E+08	20			

Table 3. Coefficients for Model s of Foreign Trade Statistics

Model	Unstandardized coefficients		Standardized Coefficients	t	Sig
	B	Std.Error	Beta		
Model(1):Dependent variable exp	5410.1830	841.752	0.139	6.427	0.000
C(constant) imp	4.322E-02	0.070			0.547
Model(2):Dependent variable exp					
(Constant)yr	-258904	122371,1	0.445	-2.116	0.048
	132.715	61.339		2.164	0.043
Model (3):Dependent variable imp	-1576882	248375.8	0.826	-6.349	0.000
(Constant) yr	795.648	124.499		6.391	0.000

Table 4. Curve fit for exports

Upper Dependent	Mth	Rsq	d.f.	F	Sig f	bound	b0	b1
EXPORTS	LIN	.198	19	4.68	.043	-258904	132	.715
EXPORTS	LOG	.198	19	4.70	.043	-2.E+06	265	207
EXPORTS	EXP	.257	19	6.56	.019	2.0E-19	.025	9
EXPORTS	LGS	.257	19	6.56	.019 .	4.9E+18	.	

Table 5. Curve fit for Imports

Upper	Dependent	Mth	Rsq	d.f.	F Sigf	bound	b0 b1
IMPORT	LIN	.683	19	40.84	.000	-2.E+06	795.648
IMPORT	LOG	.682	19	40.73	.000	-1.E+07	1586584
IMPORT	EXP	.716	19	47.80	.000	7.4E-68	.0820
IMPORT	LGS	.716	19	47.80	.000 .	1.4E+67	.9212

Table 6. Curve fit for exports and import

Independent: EXPORTS

Dependent	Mth	Rsq	d.f.	F	Sigf	Upper bound	b0	b1
IMPORT	LIN	.019	19	.38	.547		7799.20	.4499
IMPORT	LOG	.050	19	1.00	.331		-25825	4202.39
IMPORT	EXP	.061	19	1.23	.281		5575.60	8.0E-05
IMPORT	LGS	.061	19	1.23	.281		.0002	.9999

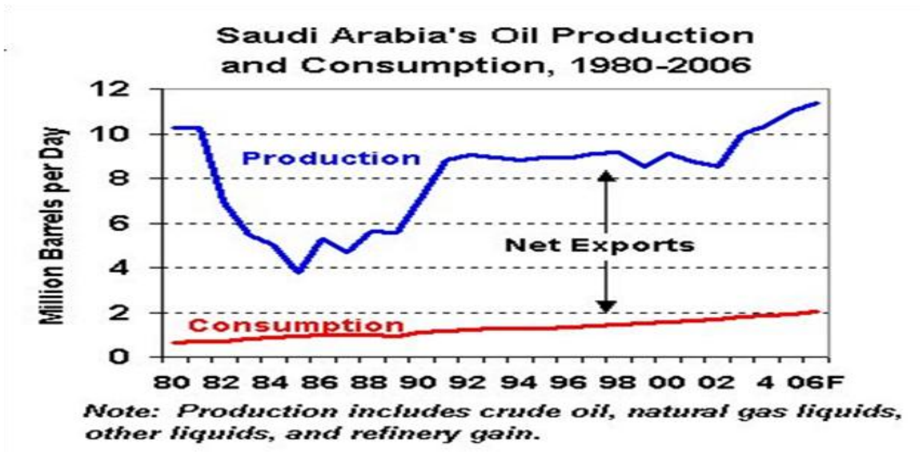

Figure 1. Sudi Arabia Oil Production and Consumption(1980-2006)

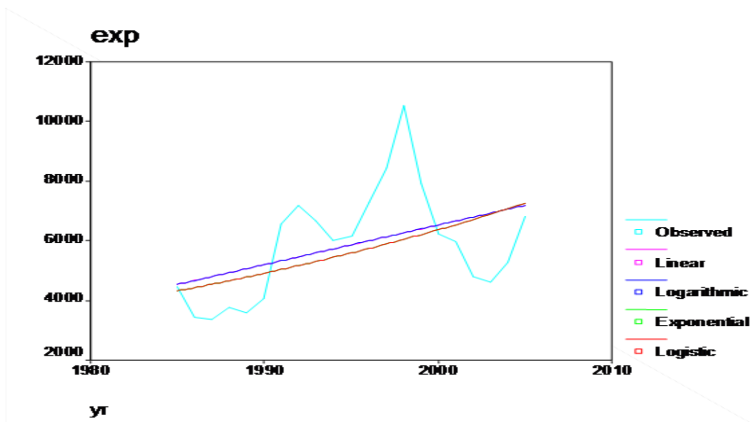

Figure 2. Curve Fit for Exports

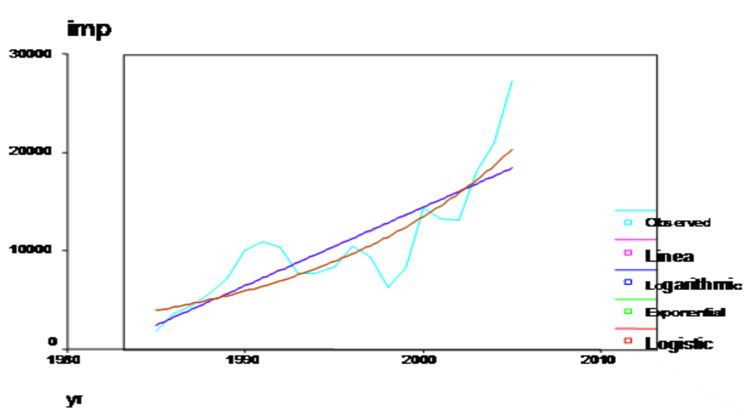

Figure 3. Curve Fit for Imports

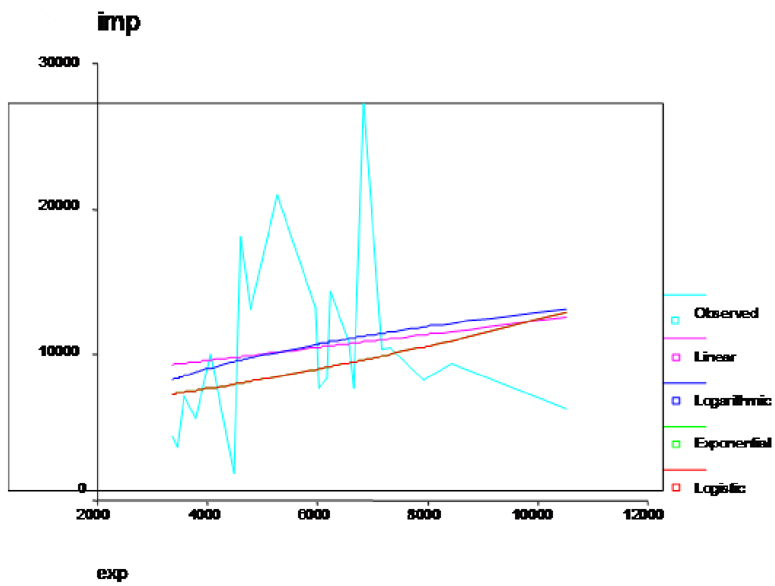

Figure 4. Curve Fit for Imports and Exports

Autocorrelations: EXPORTS exp

```
 Auto- Stand.
Lag  Corr.  Err. -1  -.75  -.5 -.25   0   .25  .5   .75   1  Box-Ljung  Prob.
□ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □
□ *******.*******             14.019  .000    .       203.  762.  1
  2  .420  .198                  □ ********          18.509  .000
  3  .161  .193                  □ ***               19.203  .000
  4 -.008  .188                  *                   19.205  .001
  5 -.085  .182                **□                   19.425  .002
  6 -.084  .176                **□                   19.653  .003
  7 -.083  .170                **□                   19.890  .006
  8 -.240  .164              *****□                  22.037  .005
  9 -.346  .158             ******□                  26.847  .001
 10 -.402  .151             *******□                 33.933  .000
 11 -.406  .144             *******□                 41.898  .000
 12 -.289  .137              *****□                  46.391  .000
 13 -.101  .129                 **□                  47.007  000
 14  .043  .120                   □ *                47.133  .000
 15  .061  .111                    □ *               47.435  .000
 16  .068  .102                   □ *                47882  .000
```

Plot Symbols: Autocorrelations * Two Standard Error Limits.

Total cases: 21 Computable first lags: 20

Figure 5. Exports Autocorrelations

```
Partial Autocorrelations:   EXPORTS   exp
   Pr-Aut- Stand.
Lag  Corr.   Err. -1  -.75  -.5 -.25   0   .25  .5   .75   1
□ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ □
□ ********.******                218.   762.   1
  2  -.382   .218           ********□
  3   .026   .218                □ *
  4  -.073   .218               *□
  5   .015   .218                *
  6   .033   .218                □ *
  7  -.097   .218              **□
  8  -.438   .218          *********□
  9   .191   .218                □ ****
 10  -.284   .218             ******□
 11   .024   .218                 *
 12   .130   .218                 □ ***
 13  -.007   .218                 *
 14  -.057   .218                *□
 15   .016   .218                 *
 16  -.102   .218               **□
```

Plot Symbols: Autocorrelations *   Two Standard Error Limits

Total cases: 21   Computable first lags: 20

Figure 6. Exports Partial Autocorrelations

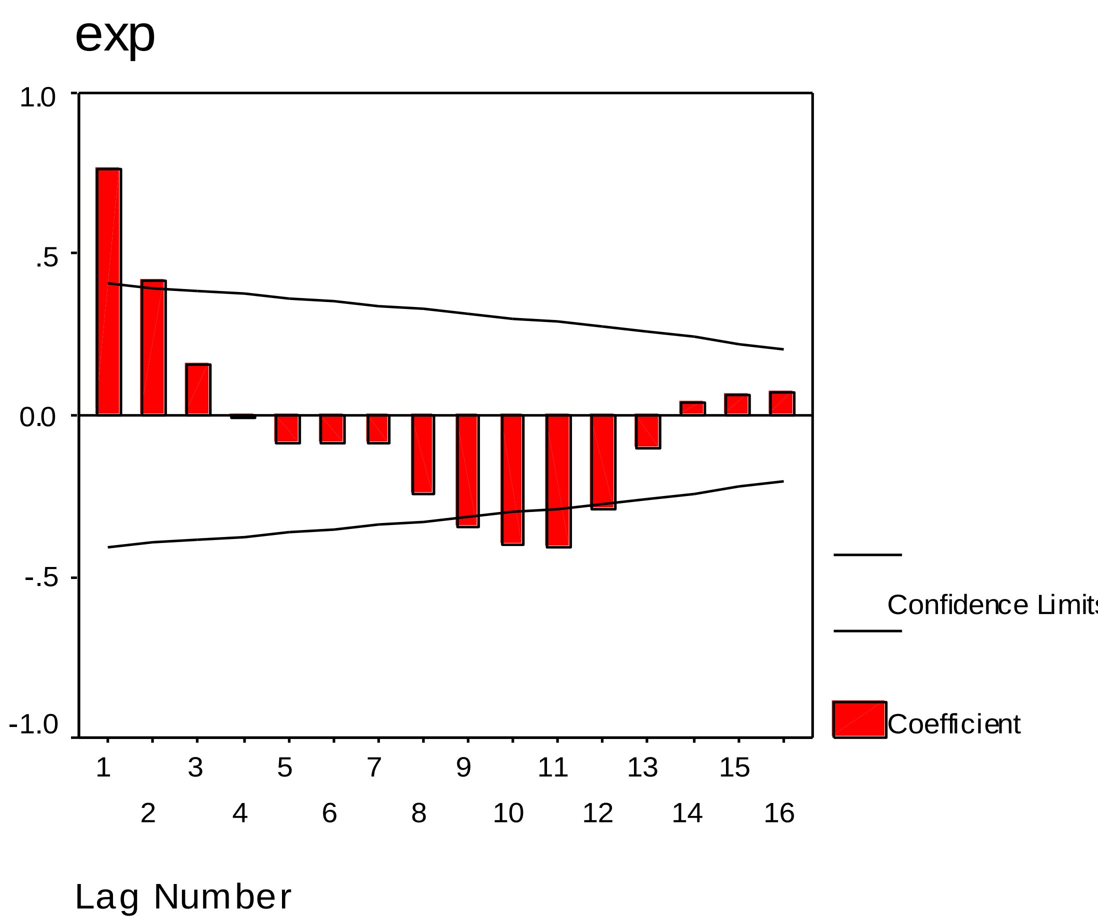

Figure 7. Exports Autocorrelation function

```
Autocorrelations:   EXPORTS   exp
Auto- Stand
Lag  Corr.   Err. -1   -.75  -.5 -.25   0   .25  .5   .75   1   Box-Ljung  Prob.
                            ▫⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩▫
⇔*******.*******          14.019   .000                       203.   762.   1
  2   .420   .198                 ⇔********                    18.509   .000
  3   .161   .193                 ⇔***                        19.203   .000
  4  -.008   .188                  *                          19.205   .001
  5  -.085   .182               **⇔                           19.425   .002
  6  -.084   .176               **⇔                            19.653   .003
  7  -.083   .170                  **⇔                         19.890   .006
  8  -.240   .164               *****⇔                        22.037   .005
  9  -.346   .158              ******⇔                        26.847   .001
 10  -.402   .151             *******⇔                        33.933   .000
 11  -.406   .144             *******⇔                        41.898   .000
 12  -.289   .137               *****⇔                        46.391   .000
 13  -.101   .129              **⇔                            47.007   .000
 14   .043   .120                ⇔*                           47.133   .000
 15   .061   .111                     ⇔*                      47.435   .000
 16   .068   .102                   ⇔*                        47.882   .000
```

Plot Symbols: Autocorrelations * Two Standard Error Limits
Total cases: 21 Computable first lags: 20

Figure 8. Exports Autocorrelations

```
Pr-Aut- Stand
Lag  Corr.   Err. -1   -.75  -.5 -.25   0   .25  .5   .75   1
▫⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩▫
⇔********.******            218.   762.       1
  2  -.382   .218            ********⇔         .
  3   .026   .218            .        ⇔*        .
  4  -.073   .218            .       *⇔         .
  5   .015   .218            .        *        .
  6   .033   .218            .        ⇔*        .
  7  -.097   .218            .      **⇔         .
  8  -.438   .218            *********⇔         .
  9   .191   .218            .        ⇔****     .
 10  -.284   .218            .  ******⇔         .
 11   .024   .218            .        *        .
 12   .130   .218            .        ⇔***      .
 13  -.007   .218            .        *        .
 14  -.057   .218            .       *⇔         .
 15   .016   .218            .        *        .
 16  -.102   .218            .      **⇔         .
```

Plot Symbols: Autocorrelations * Two Standard Error Limits
Total cases: 21 Computable first lags: 20

Figure 9. Partial Autocorrelations: Exports

```
Auto- Stand.
Lag  Corr.   Err. -1 -.75 -.5 -.25   0   .25 .5   .75   1   Box-Ljung Prob.
¤⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩¤
⇔*******.*****             10.013   .002        .            203.   644.   1
  2   .391   .198                .        ⇔********              13.905   .001
  3   .222   .193                .        ⇔****    .             15.230   .002
  4   .160   .188                .        ⇔***     .             15.959   .003
  5   .058   .182                 .       ⇔*      .              16.060   .007
  6  -.094   .176                 .     **⇔       .              16.343   .012
  7  -.086   .170                 .     **⇔       .              16.599   .020
  8   .014   .164                 .       *      .              16.606   .034
  9   .013   .158                  .      *     .               16.612   .055
 10  -.047   .151                  .     *⇔      .               16.710   .081
 11  -.064   .144                  .     *⇔      .               16.905   .111
 12  -.030   .137                   .    *⇔     .                16.953   .151
 13   .007   .129                   .     *    .                16.957   .201
 14  -.084   .120                   .  **⇔     .                 17.442   .233
 15  -.206   .111                    ****⇔    .                  20.870   .141
 16  -.272   .102                   *.***⇔    .                  28.017   .031
```

Plot Symbols: Autocorrelations * Two Standard Error Limits.

Total cases: 21 Computable first lags: 20

Figure 10. Autocorrelations: IMPORT

```
Partial Autocorrelations:   IMPORT   imp
Pr-Aut- Stand.
Lag  Corr. Err. -1 -.75 -.5 -.25 0  .25  .5  .75   1
¤⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩⇧⇩⇩⇩⇩¤
⇔********.****        .           218.   644.   1
  2  -.040   .218           .       *⇔         .
  3  -.024   .218           .        *        .
  4   .062   .218           .        ⇔*        .
  5  -.101   .218           .      **⇔         .
  6  -.172   .218           .     ***⇔         .
  7   .118   .218           .        ⇔**       .
  8   .133   .218           .        ⇔***      .
  9  -.102   .218           .      **⇔         .
 10  -.067   .218           .       *⇔         .
 11   .025   .218           .        ⇔*        .
 12  -.017   .218           .        *        .
 13   .027   .218           .        ⇔*        .
 14  -.115   .218           .      **⇔         .
 15  -.177   .218           .    ****⇔         .
 16  -.122   .218           .      **⇔         .
```

Plot Symbols: Autocorrelations * Two Standard Error Limits.

Total cases: 21 Computable first lags: 20

Figure 11. Partial Autocorrelations: IMPORRTS

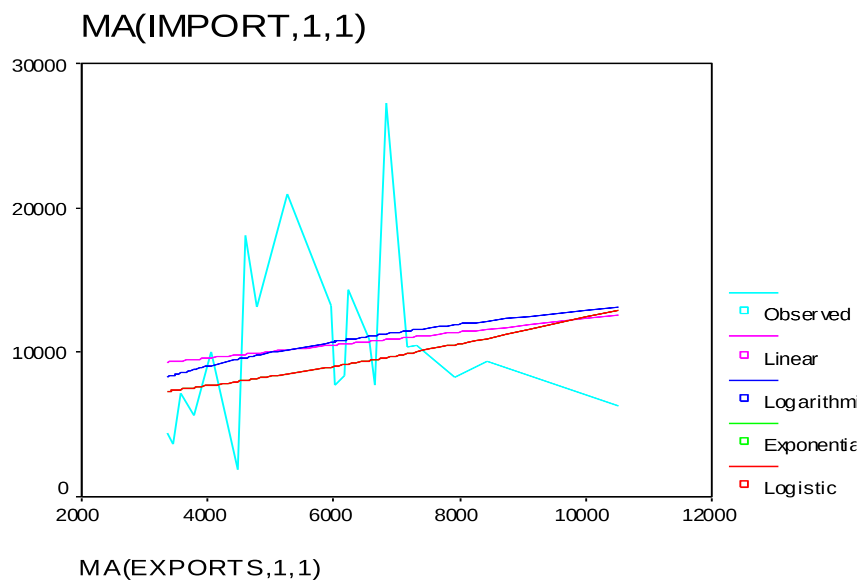

Figure 12. M A for Imports and Exports

However, the model from the figure seemed provided an acceptable fit to the analysis data of foreign trade statistics.

DISCUSSION

The ARIMA methodology, a technique of time series analysis, that has gained enormous popularity in many areas and research practice, confirms its power and flexibility. However, because of its power and flexibility, ARIMA is a complex technique; it is not easy to use, it requires a great deal of experience, and although it often produces satisfactory results, those results depend on the researcher's level of expertise.

A common measure of the reliability of the model is the accuracy of its forecasts generated based on partial data so that the forecasts can be compared with known (original) observations. However, a good model should not only provide sufficiently accurate forecasts, it should also be parsimonious and produce statistically independent residuals that contain only noise and no systematic components. A good test of the model is (a) to plot the residuals and inspect them for any systematic trends, and (b) to examine the autocorrelogram of residuals (there should be no serial dependency between residuals).

It should be noted that the input series for ARIMA needs to be stationary, that is, it should have a constant mean, variance, and autocorrelation through time. Therefore, usually the series first needs to be differenced until it is stationary However, it should be kept in mind that some time series may not require differencing.

ARIMA models may also include a constant beside the standard autoregressive and moving average parameters. The interpretation of a (statistically significant) constant depends on the model that is fit.

A common research questions in time series analysis is whether an outside event affected subsequent observations. For example, did the implementation of a new economic policy improve economic performance? .In general, we would like to evaluate the impact of one or more discrete events on the values in the time series.

CONCLUDING REMARKS

This article has discussed the analysis of a time series model for foreign trade statistics .The ARIMA method used here may be appropriate only for a time series that is stationery and it is recommended that there are at least 50 observations in the input data (the underlying model has 21 observations). It is also assumed that the values of the estimated parameters are constant throughout the series .The article has discussed changes in the foreign trade for the period (1980-2010). The results for the analysis, indicated model, provide useful information for identifying trade trend. An important policy consideration rises from the study is that there is increasing trend for the model of the data. The use of the time series model for forecasts estimates parameters for developing a model to predict changes in trade over time.

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