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RESEARCH ARTICLE

A TRANSFER FUNCTION TECHNIQUE FOR MOELING SUDANESE AGRICULTURAL EXPORTS

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ABSTRACT

Nowadays, a lot of statistical techniques for determining dynamic models aiming at defining and controlling most appropriate variables of a system has been used. One of the most used is transfer function model (ARIMAX) discussed by Box and Tiao. In this paper Transfer function technique was applied to data representing agricultural exports and exchange rate in the Sudan for the period (1956 – 2018). Augmented Dickey-Fuller (ADF) tests confirmed both series level are non stationary however, their first difference is stationary. Both ADF as well as ACF test confirmed that ARIMA(1,1,0) is appropriate model for modeling both agricultural exports and exchange rate in the Sudan. According to the application of transfer function approach proposed by Box and Tiao as well as models selection criteria, ARIMAX - TF Model *(3, 0, 1)* model shown smallest values of models selection criteria. Hence it is chosen as an appropriate and parsimonious transfer function model for forecasting agricultural exports data in the Sudan.

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INTRODUCTION

Agriculture is the main economic sector in the Sudan economy contributing 27% to the GDP and employing about 80% of the work force (Bank of Sudan, 2015). Agriculture also provides raw materials for the manufacturing sector, which is mainly agro-industries like sugar and food industries. Most importantly, since the independence, the agricultural exports represent about 90% of total exports and have been considered as the main source for the country's foreign exchange reserves. Therefore, most of development plans in Sudan during the next half of last century have focused primarily on the promotion of the agricultural exports however, the exploitation of oil in1999 has resulted in changing the country's production structure, and hence affected the exports performance of the other sectors (African Development Bank2012). Primary resources are agricultural, including sorghum, millet, wheat, maize, rice sesame, groundnuts, sunflower, cotton and tomato. The main cropping systems are irrigated farming schemes and rain-fed farming. Major agricultural exports are cotton, sesame, Arabic gum and livestock. Grain sorghum is the principal food crop, and wheat is grown for domestic consumption. Since the independence, the agricultural exports represent about 90% of total exports and have been considered as the main source for the country's foreign exchange reserves. Regarding the trend of agricultural exports, the statistics show that the outflow of Sudanese agricultural exports has decreased sharply during the period followed oil exploitation (i.e. 1999-2011). Accordingly, the Sudan in the past few years suffered from a decline of 80% of its foreign currency earnings and a 35.6% reduction in budget revenue as well as high inflation rates and devaluation of exchange rate. Therefore, understanding the performance of Sudanese agricultural exports and its potential in foreign markets would be necessary to guide effective export promotion strategy. Nowadays the exchange rate becomes one of the most heavily and interesting research areas in the discipline. Exchange rate movements are perhaps the most important factors affecting agricultural exports, changes in exchange rates have a significant impact on the world's political and economic stability and the welfare of individual countries. It is also acknowledged that parallel exchange rate has a negative impact on the macroeconomic performance, since parallel premium indicates a market distortion, hence reduces trade and growth (Kiguel and O'Connel, 1995). In addition, the spread between black market and official rate may enforce the speculative activities in foreign currencies and illegal trade, and result in capital flight and deviation of remittances flows from the formal channels (Kiguel and O'Connel, 1995; Elbadawi, 1994).

Exchange rate is one of the determinants used in assessing the performance of an economy. A very strong exchange rate is a reflection of a strong and viable economy. On the other hand, a very weak currency is a reflection of a very vulnerable and weak economy. The development and application of time series analysis in econometric casting has occurred rapidly during the past two decades. In recent years, focus in this area has shifted from univariate or single equation to multivariate and simultaneous equation models. In particular, there has been deal of study on dynamic equation systems (Zellner and Palm (1974)), rational structural form models (Wall (1976)), and vector autoregressive-moving models (Tiao and Box (1981), Jenkins and alavi).[1] Modeling and forecasting agricultural exports in the Sudan requires finding a model that reasonably represents it. In the literature many academics and practitioners suggest a number of approaches for building a time series models are discussed however, the suitability of any of these methods to a given time – series data has to be judged on the basis of its fit to that data. In this study transfer function model (ARIMAX) discussed by Box and Tiao will applied to data representing agricultural exports and exchange rate with the objective of identifying an appropriate model that provides an accurate predictions for agricultural exports in the Sudan.

MATERIALS AND METHODS

There are some cases where we have more than one time series; this case is described by multiple time series. For example, if we have two time series, one is called the input series and the other is called the output series, if we symbolize to the input series by X_t and the output series by Y_t, then the effect of the input series X_t to the output series Y_t can be studied through a relationship or function which known as the transfer function.

Transfer function is a multivariate time series analysis technique describes the dynamic relationship between input and output series, it is also use to study the impact of input series X_t on the output series Y_t.[2-3]

Consider two time series denoted by y_t and x_t which are both stationary. Then, the transfer function model (TFM) can be written as follows:

$$y_t = \mu_j + \sum_{j=1}^{k} \frac{w(B)}{\delta(B)} x_{jt-b} + \frac{\theta(B)}{\phi(B)} \varepsilon_t \quad (1)$$

where:

y_t is the dependent variable (output series).
x_{jt} is the independent variable (input series).
μ_j is constant term,
ε_t is the noise series of the system that is independent of the input series (the stochastic disturbance).

$$w(B) = w_0 + w_1 B + w_2 B^2 + \cdots + w_h B^h \; ; \; \delta(B) = 1 - \delta_1 B - \delta_2 B^2 - \cdots - \delta_r B^r \quad (2)$$

The parameters r, b, h represent the order of the numerator polynomial , the delay parameter that indicates the time lag until input affects the output also called dead-time or delay time, and order of the denominator polynomial respectively.

It's assume that the roots of all the polynomials $w(B), \delta(B), \theta(B), \phi(B)$ lie outside the unit circle as well as differencing may be required to produce stationary for both input and output series.

$$\frac{\theta(B)}{\phi(B)} \varepsilon_t = noise\ ARMA$$

The construction of transfer function model (TFM) is likewise ARIMA modelling, it can be done through the stages of identification, estimation and diagnostic checking.[4-6] In identification state the researcher must be finding out the orders (*b, r, h*) of a rational form transfer function, and then nonlinear least square method can be used to estimate parameters, after estimation of the model, researcher must have to check for randomness of disturbance term series of identified and estimated model. Figure (1) bellow illustrate the The Transfer Function Model Diagram.

Figure (1) The Transfer Function Model Diagram. The cross-correlation function between two time series Y_t and X_t is expressed as follows:

$$r_{x,y}(k) = \frac{C_{x,y}(k)}{S_x S_y} \quad (3)$$

where:

$$C_{x,y}(k) = \begin{cases} \frac{1}{n} \sum_{t=1}^{n-k} (x_t - \bar{x})(y_{t+k} - \bar{y}) & k \geq 0 \\ \frac{1}{n} \sum_{t=1}^{n+k} (x_{t-k} - \bar{x})(y_t - \bar{y}) & k \leq 0 \end{cases} \quad (4)$$

$$S_x = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(x_t - \bar{x})^2} \quad (5)$$

$$S_y = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \bar{y})^2} \quad (6)$$

The cross correlation function is not symmetric at $k = 0$.[6]

The objective of the identification stage is to obtain some idea of the order r and s of the transfer function model and to derive initial guesses for the parameter ll, wand the delay parameter b. In the same way that the auto-correlation function is used to identify p, d, q parameters of the univariate model, the r, s and b parameters for the transfer function models are identified by the cross correlation between the input and the output. Following Box-Jenkins the whole process of identification, estimation and diagnostic and forecasting can be outlined as follows:

The basic steps of transfer function modeling are as follows (Wei, 2006; Box et al, 1994): 1- Prewritten the input series. Transfer function models require both the input and the output series to be stationary. This step includes the traditional way of modeling time series: inspect the autocorrelation functions (ACF) and partial autocorrelation functions (PACF) for possible differencing and determining the order of the ARIMA model, then investigating the behavior of the noise series as diagnostic checking. The prewhitened input series is denoted by the following model:

$$\alpha_t = \frac{\phi_x(B)}{\theta_x(B)} x_t \quad (7)$$

Where:

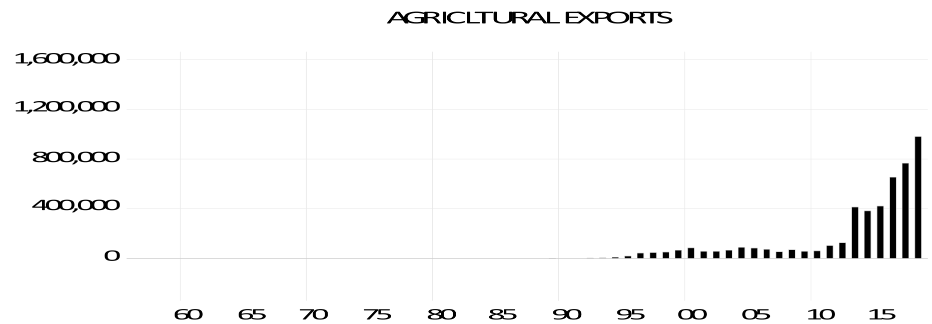
α_t is a white noise process with mean zero and variance σ_α^2.
2- Prewritten the output series. The output series will then be filtered using the prewhitened input series defined in step 1. The transformed output series is denoted by the following model:

$$\beta_t = \frac{\phi_x(B)}{\theta_x(B)} y_t \quad (8)$$

3- Calculate the sample cross correlation function (CCF) between α_t and β_t and estimate the transfer function. The CCF, via significant correlations between the input and the output series determines which lags of the input series are significantly. Influencing the current output value. The sample CCF therefore is vital in estimating the impulse responses and consequently, the transfer function. It is important to note that both input and output series must be prewhitened in order to have meaningful interpretations of the CCF. If the input and output series have a rigid dependence structure, then when the output series is filtered through the estimated model of the input, then it is also prewhitened. 4- Estimate the noise series and combine it with the function in step 4 to have the estimated transfer function model. In transfer function modeling, the noise process is not limited to a white noise process.

RESULTS AND DISCUSSION

This section provides empirical analysis results of applying transfer function modeling and forecasting technique to study the dynamic relationship between agricultural exports as an in endogenous variable as well as exchange rate as an exogenous variable through transfer function methodology. Secondary time series data representing agricultural exports and exchange rate in the Sudan for the period (1956 – 2018), the data are obtained from Central Bureau of Statistics and central Bank of Sudan reports. This study assumes that changes in exchange rate affect agricultural exports which lead to a significant change in the national economy. Figure (2) illustrates the multi bar charts of agricultural exports and exchange rate in the Sudan for the period (1956 – 2018).



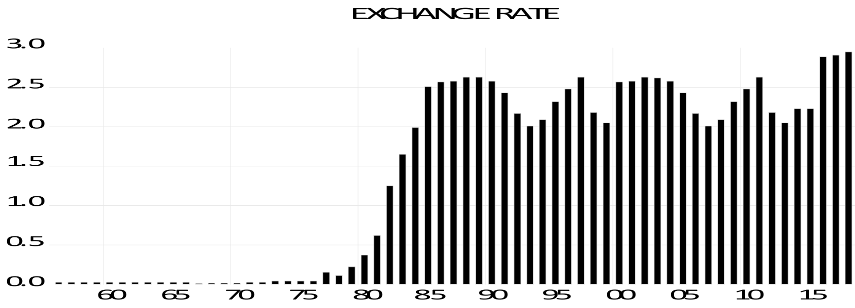


Figure 2. The Multi graph of agricultural exports and exchange rate in the Sudan for the period (1956 – 2018)

It can be seen that agricultural exports in the Sudan fluctuate around constant level till the beginning of 1995 and then vary from year to another increasing or decreasing till the end of 2010 and then shows a significant global upward trend till the end of study. Exchange rate was also fluctuates around constant level till beginning of 1980 and then shown high volatility till the end of 2018 and also shows a global upward trend. The application of the ADF test with trend and intercept results to data representing agricultural exports and exchange rate in the Sudan for the period (1956 – 2018) in table (1) reports that both agricultural exports and exchange rate series are stationary at first difference.

Table (1) ADF test results

	Level	*First Difference*
Variables	*Trend and Intercept*	*Trend and Intercept*
Agricultural exports	*6.818490*	*-4.049676**
Exchange Rate	*-0.949424*	*-5.367654**

** means rejection of the null hypothesis (the series has a unit root) at 5% significance level*

According to Box-Tiao (1975) building a transfer function model for describing the dynamic relationship among agricultural exports and exchange rate in the Sudan requires identifying the ranks ***(b, r, h)*** of ARIMAX- TF model, estimation and finally diagnostic checking. Following the construction of prewritten both input and output series for building a transfer function model it is found that both time series under consideration exports and exchange rate in the Sudan followed an ARIMA(1,1,0) process.

From the correlogram of agricultural exports in the Sudan for the period (1956 – 2018) in Figure (3), it can be seen that the ACF shows large positive significant peaks decays exponentially to zero after log of 5, while the PACF shows large positive significant peak at lag 1, this results confirm that the agricultural exports data in the Sudan is not stationary. Moreover the agricultural exports series is subject to an autoregressive model. After a tentative agricultural exports model has been identified, its parameters will then estimates.

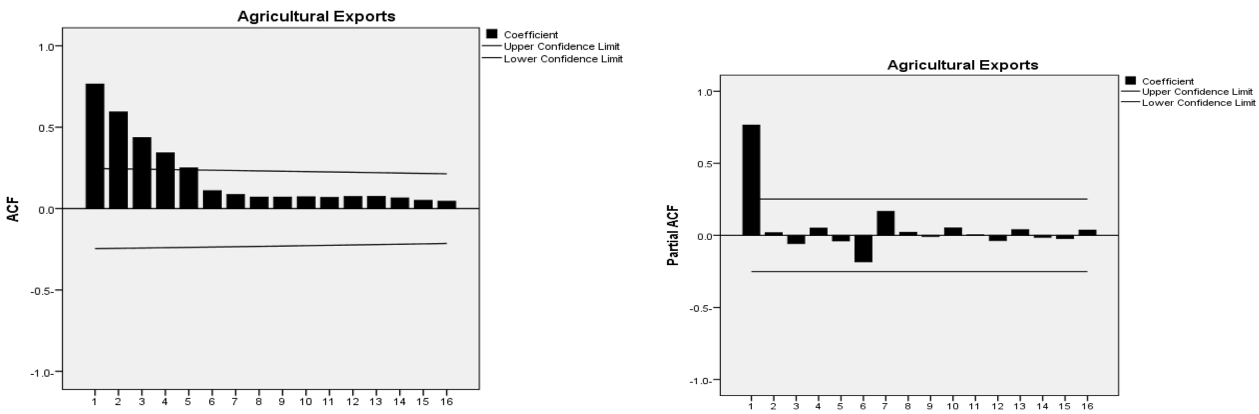


Figure (3) The correlogram of agricultural exports in the Sudan for the period (1956 – 2018)

From the correlogram of exchange rate in the Sudan for the period (1956 – 2018) in Figure (4), it can be seen that the ACF shows large positive significant peaks decays gradually to zero while the PACF shows large positive significant peak at lag 1, this results confirm that the agricultural exports data in the Sudan is not stationary.

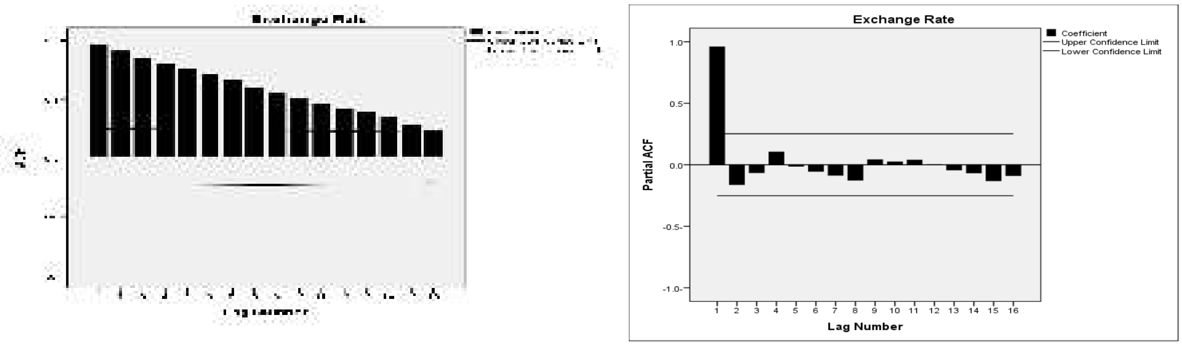


Figure (4) The correlogram of exchange rate in the Sudan for the period (1956 – 2018)

Table (2) illustrates the parameters estimation of an ARIMA(1,1,0) model using ordinary least square method the estimated equation model is stated as follows:

$$\mathrm{D}(agricultural\ exports_{\mathrm{t}}) = 17059.707 + 0.297 agricultural\ exports_{\mathrm{t-1}} + e_{\mathrm{t}}$$

Table 2. ARIMA Model Parameters

ARIMA Model Parameters								
					Estimate	SE	t	Sig.
Agricultural Exports-Model_1	Agricultural Exports	No Transformation	Constant		17059.707	9723.470	1.754	.084
			AR	Lag 1	.297	.140	2.113	.019
			Difference		1			

It can be seen that the autoregressive part of the model was seen significantly different from zero. From correlogram of exchange rate in the Sudan for the period (1956 – 2018) in Figure (2) above, it can be seen that the ACF shows large positive significant peaks decays exponentially to zero, while the PACF shows large positive significant peak at lag 1, this results confirm that the exchange rate data in the Sudan is not stationary. Moreover the exchange rate series is subject to an autoregressive model. After the identified of exchange rate model, its parameters will then estimates. Table (3) illustrates the parameters estimation of an ARIMA(1,1,0) model using ordinary least square method, the estimated equation model is stated as follows:

$$\mathrm{D}(\text{exchange rate}_{\mathrm{t}}) = 0.047 + 0.339\text{exchange rate}_{\mathrm{t-1}} + e_{\mathrm{t}}$$

Table (3) ARIMA Model Parameters

ARIMA Model Parameters								
					Estimate	SE	t	Sig.
Exchange Rate-Model_1	Exchange Rate	No Transformation	Constant		.047	.037	1.267	.210
			AR	Lag 1	.339	.121	2.798	.007
			Difference		1			

It can be seen that the autoregressive part of the model was seen significantly different from zero. The cross- correlation both prewritten agricultural exports series and exchange rate series in the Sudan for the period (1956 – 2018) as well as their prewritten series shown that the dead time *b* is equal to *3* which is the last significant lag number in the right tail of cross-correlation function.

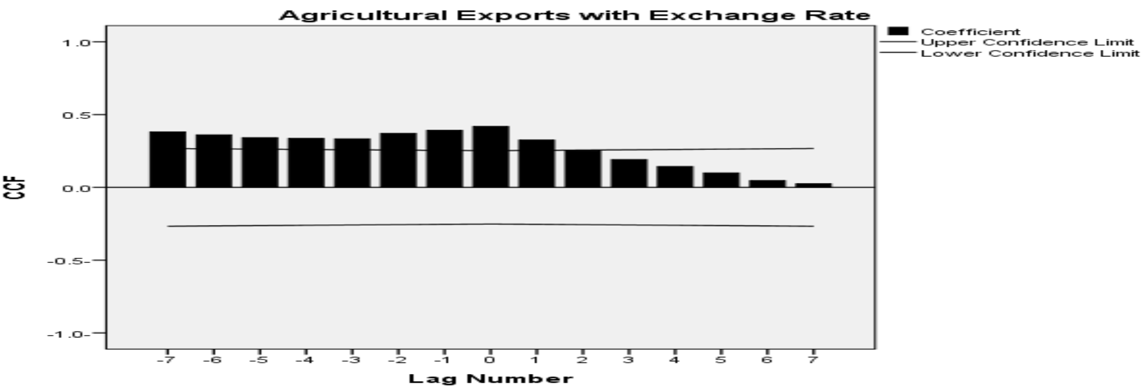


Figure (5) Cross- correlation of prewritten agricultural exports and prewritten exchange rate in the Sudan for the period (1956 – 2018)

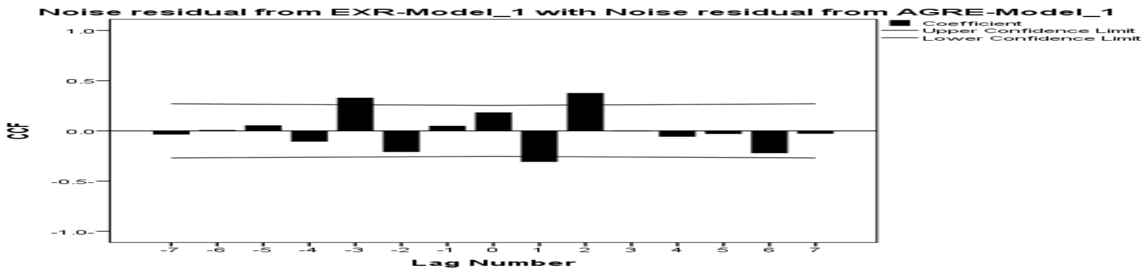


Figure (6) Cross- correlation of agricultural exports and exchange rate in the Sudan for the period (1956 – 2018)

Numerous ARIMAX - TF Model *(b, r, h)* models for modeling agricultural exports data in the Sudan are being suggested, table (4) demonstrates the suggested models and their corresponding RMSE, MAPE, MAE and Normalized BIC for models comparison criteria.

Table (4) **ARIMAX - TF Model *(b, r, h)***

ARIMAX - TF Model *(b, r, h)*	**RMSE**	**MAPE**	**MAE**	**Normalized BIC**
ARIMAX - TF Model *(3, 0, 1)*	192381.236	433304.340	109802.407	24.544
ARIMAX - TF Model *(3, 1, 1)*	193799.859	436431.868	110259.793	24.629
ARIMAX - TF Model *(3, 1, 0)*	197238.598	349815.138	110577.781	24.594
ARIMAX - TF Model *(3, 2, 1)*	196170.071	423932.304	111836.007	24.728
ARIMAX - TF Model *(3, 1, 2)*	196610.887	418061.129	110627.763	24.732
ARIMAX - TF Model *(3, 2, 2)*	192067.741	328666.012	120002.527	24.756

A closer look to table (4) it can be shown that ARIMAX - TF Model *(3, 0, 1)* model have smallest values of models selection criteria, this model will be select as an appropriate transfer function model for forecasting agricultural exports data in the Sudan. Table (5) illustrate the ARIMAX - TF Model *(3, 0, 1)* model parameters for agricultural exports data in the Sudan during the period(1956 – 2018), the estimated equation of the TF Model *(3, 0, 1)* model is expressed as follows:

$$Agricultural\ Exports_t = 109968.225 + \left(\frac{-91752.654}{1-.867B}\right) Exchange\ rate_{\ t-3} + \varepsilon_t$$

Table (5) ARIMA Model Parameters

ARIMA Model Parameters							
				Estimate	SE	t	Sig.
	Agricultural Exports	Constant		109968.225	33834.827	3.250	.002
	Exchange Rate	Delay		3			
		Numerator	Lag 0	-91752.654	61122.609	-1.501-	.139
		Difference		1			
		Denominator	Lag 1	.867	.137	6.320	.000

It can be seen that the constant level as well as denominator lag 1 parameters are seen statistically significantly different from zero at 5% significant level. After a tentative appropriate transfer function model has been identified and its parameters been estimated, diagnostic checking is then applied to the fitted model. It is necessary to supplement this approach by less specific checks applied to the residuals for the fitted model. The application of correlogram test on the residuals of ARIMAX - TF Model *(3, 0, 1)* model confirmed that the residuals series of the model are random.

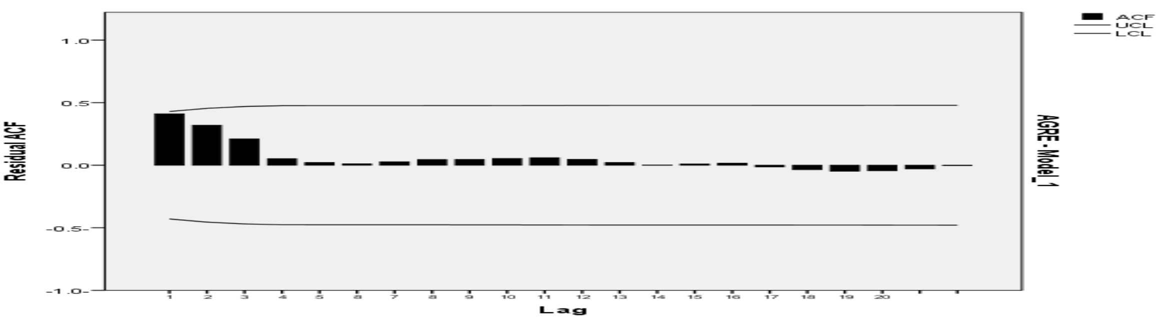


Figure (7) Residuals autocorrelations function of TFM

Figure (8) bellow shows the observable and fitted values of agricultural exports data as well as their 95% confidence intervals

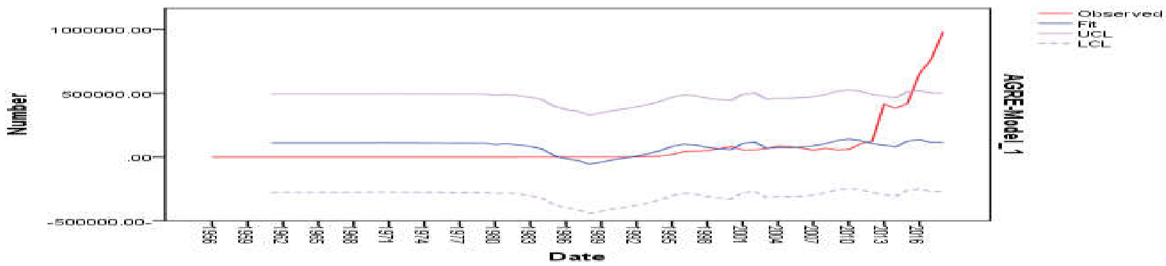


Figure (8) Observable and fitted values of agricultural exports data

4- Conclusion

In this paper Transfer function technique (ARIMAX) models discussed by Box and Tiao was applied to data representing agricultural exports and exchange rate in the Sudan for the period (1956 – 2018). Augmented Dickey-Fuller (ADF) tests confirmed both series level are non stationary however, their first difference is stationary. Both ACF and PACF confirmed that ARIMA(1,1,0) is appropriate model for modeling both agricultural exports and exchange rate in the Sudan. Based on Transfer function technique ARIMAX - TF Model *(3, 0, 1)* model shown smallest values of models selection criteria. Hence it is chosen as an appropriate and parsimonious transfer function model for forecasting agricultural exports data in the Sudan, therefore for this particular type of data ARIMAX - TF Models are highly recommended.

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