Box-Jenkins ARIMA approach to predicting net FDI inflows in Zimbabwe

Nyoni, Thabani

University of Zimbabwe

3 July 2018

BOX – JENKINS ARIMA APPROACH TO PREDICTING NET FDI INFLOWS IN ZIMBABWE

Thabani Nyoni

Department of Economics, University of Zimbabwe, Harare, Zimbabwe

Email: nyonithabani35@gmail.com

Abstract

This study attempts to model and forecast net FDI inflows in Zimbabwe over the next 2 decades. Spanning from 1980 – 2017, annual time series data for net FDI inflows in Zimbabwe was used. The ADF test indicates that FDI data is I (1). The study identifies the minimum AIC value and subsequently presents ARIMA (1, 1, 1) model as the optimal model to forecast FDI in Zimbabwe. The ADF test also indicates that the residuals of the ARIMA (1, 1, 1) model are I (0), thus confirming its adequacy. A diagnosis of the inverse roots of AR/MA polynomials confirms that our estimated model is stable. The predicted net FDI inflows over the next 2 decades show a relatively poor and unimpressive growth trend. Amongst the main policy prescriptions, the study recommends that policy makers in Zimbabwe ought to come up with investor – friendly policies in order to attract the much needed FDI.

Key Words: AR, ARIMA, ARMA, Foreign Direct Investment (FDI), Forecasting, MA, Zimbabwe

1. INTRODUCTION & BACKGROUND

Foreign Direct Investment (FDI) is defined as an investment that involves a long term relationship, interest and management influence by a resident of one economy (foreign direct investor / parent enterprise) in an enterprise residing in an economy other than that of the foreign direct investor (Prasanna, 2015). FDI, as defined by Park (2003); is the flow of capital from a foreign country to a host country to control assets, establish production or service facilities and to conduct business activities. FDI, according to Abdul & Al-Samarrai (1998); is defined as an investment that arises when the investor in the mother country invests in another country with an intension to have control on how to manage and run it. FDI is critical in the development of any economy in the sense that it transfers financial resources, technology and innovative & improved management strategies along with raising productivity. Studies such as Firebaugh (1992), Romer (1993), Borensztein *et al* (1998), Mello (1999), Fry (1999), Khan (2007), Quader (2009), Azam (2010) and Pradhan *et al* (2011) amongst others indicate that there is a positive relationship between FDI and economic growth. In Zimbabwe, authors such as Mafusire (2004), Gwenhamo (2009), Chingarande *et al* (2012), Moyo (2013), Sikwila (2014) and Muzurura (2016a & b) confirm that there is a positive relationship between FDI and economic growth. However, studies such as Udomkerdmongkol & Morrissey (2008); argue that there is negative relationship between FDI and economic growth.

In absolute terms FDI inflows to the Sub – Saharan Africa region have increased since the start of 1990s (UNCTAD, 2004). The value of FDI to the region rose from US $36.7 billion in 1990 to a level of US $108.5 billion in 2000, and stood at US $474 billion as at 2013 (World Bank, 2015). However, Zimbabwe has not benefited from the FDI inflows into the region (Muzurura, 2016b). While other Southern African countries such as Mozambique and Zambia attract billions of US dollars in FDI, Zimbabwe struggles to receive only one tenth of a million US dollars in FDI per annum. This study, whose objectives are three – fold, namely: to check the stationarity of the FDI series, to select the best ARIMA model and to forecast net FDI inflows for Zimbabwe over the next 2 decades[1]; actually differs from the previous Zimbabwean studies[2] on FDI simply because it is the first of its kind. No study has been done so far to forecast FDI in Zimbabwe using ARIMA models. In this study, I employ the Box – Jenkins ARIMA approach not only due to its simplicity but also for its appropriateness with regards to my sample size. The best fit model is then used to forecast Zimbabwe's expected annual net FDI inflows for the next 2 decades. The rest of the

[1] 2018 – 2037.

[2] for example Dailami & Walton (1992), Jenkins (1998), Mafusire (2004), Gwenhamo (2009), Chingarande *et al* (2012), Bayai & Nyangara (2013), Moyo (2013), Sikwila (2014) and Muzurura (2016a & b).

paper is organized in chronological order as follows: literature review, materials & methods, results: presentation, interpretation & discussion, recommendations, conclusion and appendix.

2. LITERATURE REVIEW

Theoretical Literature Review[3]

The Hecksher – Ohlin model, postulated by Hecksher & Ohlin (1919); basically argues about international differences in labor, labor skills, physical capital or land that create productive differences that help explain why trade happens. This theory avers that countries will import products that use their limited factors and export these products that use their abundant and cheap factors of production. The Product Life Development theory postulated by Raymond & Vernon (1966); argues about the shift of international trade and international investment. The theory basically avers that a product goes through 4 stages, namely: the innovative, take off, maturity and decline. At the beginning, that is; the initial stage, firms are mainly focused on the domestic market, but as the product matures; firms begin to export to other countries. Innovative firms at this stage enjoy the profits of the sales of their newly invented products until rival firms duplicate and start producing the same product. The Eclectic Paradigm postulated by Dunning (1981); offers the reasons why enterprises decide to go global and these are ownership, locational and internationalization. Ownership advantages allow enterprises to diversify their technologies, brand recognition and unique product qualities. Locational advantages are privileges related to cheap resources, favorable exchange rates and conducive regulations which may not be available in their home countries. The internalization advantages, as noted by Vernon (1966) and Dunning (2001); arise from exploiting imperfections in external markets, and reduction of state – generated imperfections such as tariffs, foreign exchange controls and subsidies. Zimbabwe, as already mentioned in Nyoni & Bonga (2017); is a landlocked country, blessed with natural resources that are in abundance and these include rich mineral deposits, arable tracks of land, flora and fauna, abundant sunlight and water. This is one of the reasons why international enterprises would want to invest in Zimbabwe. However, issues of corruption[4], poor governance and macroeconomic instability keep on hindering the smooth flow of FDI into Zimbabwe.

Empirical Literature Review

Al-Abdulrazag & Bataineh (2007) forecasted FDI inflows into India using ARIMA models, hinged on the Box – Jenkins technique; over the period 1976 – 2003 and found out that there is an expected increase of FDI volumes over the period 2004 – 2025. Biswas (2015) studied net FDI inflows in India using the Box – Jenkins ARIMA model over the period 1992 – 2014 and found out that FDI in India is following an increasing trend over the forecasted period (2015 – 2034). In yet another Indian study, Dhingra *et al* (2015) analyzed foreign institutional investment inflows using the ARIMA models (based on the Box – Jenkins methodology) over the period January 2004 to September 2012 and found out that various AR terms and MA terms influence the current inflow or out flow of foreign institutional investment. Prasanna (2015) modeled and forecasted FDI inflows into SAARC using ARIMA models (based on the Box – Jenkins approach) over the period 1970 – 2012 and found out that the total value of FDI expected for the next 25 years (2013 – 2037) is US $1672895.8 million and average FDI expected for the next 25 years is US $66915.81 million for SAARC. Closer to home and more recently, in Zambia, Jere *et al* (2017) forecasted FDI inflows using ARIMA models (based on the Box – Jenkins technique) over the period 1970 – 2014 and found out that there will be a gradual increase in annual net FDI inflows of about 44.36% by 2024 in Zambia. Our empirical literature review indicates that no similar study has been done in Zimbabwe so far. This study is not the end of the road but the beginning of a series of scientific enquiries into understanding the dynamics of FDI inflows in Zimbabwe.

3. MATERIALS & METHODS

Empirical Model Building & Estimation

The Moving Average Process

Given that μ_t is a purely random process with mean zero and variance σ^2, then a process FDI_t defined by equation one below:

---

[3] These theories let us understand why FDI exists.
[4] already discussed in Nyoni (2017).

$FDI_t = \psi_0\mu_t + \psi_1\mu_{t-1} + \ldots + \psi_z\mu_{t-z}$ ……………………………………………………………………………………… (1)

is operationally known as a Moving Average (MA) process of order z and is technically denoted by MA (z), where FDI_t represents net Foreign Direct Investment inflows at time t, $\psi_0 \ldots \psi_z$ are estimation parameters, μ_t is the current disturbance while $\mu_{t-1} \ldots \mu_{t-z}$ are past disturbances. Equation two below:

$FDI_t = \psi_0\mu_t + \psi_1\mu_{t-1}$ …………………………………………………………………………………………….. (2)

is thus an MA process of order one [MA (1)]. Because the past errors are unobserved variables, we scale them such that $\psi_0 = 1$. Since:

$E\ (\mu_t) = 0$ ……… (3)

for all t, implies that:

$E\ (FDI_t) = 0$ …….. (4)

and:

$Var\ (FDI_t) \approx (\sum_{i=0}^{z}\psi_t^2)\sigma^2$ ………………………………………………………………………………… (5)

Equation five holds water on the basis that μ_t are independent with a common variance σ^2. Therefore, equation one can be re – specified as:

$FDI_t = \mu_t + \psi_1\mu_{t-1} + \ldots + \psi_z\mu_{t-z}$ ………………………………………………………………………………….. (6)

The above equation can be re – written as:

$FDI_t = \sum_{i=1}^{z}\psi_i\mu_{t-i} + \mu_t$ …………………………………………………………………………………………… (7)

Using the lag operator, L; equation seven would be written as:

$FDI_t = \sum_{i=1}^{z}\psi_i L^i\mu_t + \mu_t$ ………………………………………………………………………………………….. (8)

or as:

$FDI_t = \psi(L)\mu_t$ ……………………………………………………………………………………………………….. (9)

where:

$\psi(L) = \emptyset(L)$[5] ………………………………………………………………………………………………….. (10)

An Autoregressive Process

The process FDI_t given by equation eleven below:

$FDI_t = a_1 FDI_{t-1} + a_2 FDI_{t-2} + \ldots + a_r FDI_{t-r} + \mu_t$ ………………………………………………………… (11)

is operationally known as an Autoregressive (AR) process of order r and is technically denoted by AR (r), where $\alpha_1 \ldots \alpha_r$ are estimation parameters, $FDI_{t-1} \ldots FDI_{t-r}$ are previous period values of the FDI series and μ_t is as previously defined. Equation eleven can be written as:

$FDI_t = \sum_{i=1}^{r} a_i FDI_{t-i} + \mu_t$ ……………………………………………………………………………………….. (12)

The above equation may also be represented as:

$FDI_t = \sum_{i=1}^{r} a_i L^i FDI_t + \mu_t$ ………………………………………………………………………………….. (13)

or

$a(L)FDI_t = \mu_t$ ……………………………………………………………………………………………………….. (14)

where:

[5] Defined in equation (22)

$a(L)=\phi(L)$[6] …… (15)

We can also re – write equation eleven as follows:

$FDI_t=(a_1L+a_2L^2+\ldots+a_rL^r)FDI_t+\mu_t$ ……………………………………………………………………………….. (16)

Therefore, equation seventeen below:

$FDI_t=(a_1L)FDI_t+\mu_t$ ……………………………………………………………………………………………….. (17)

is an AR process of order one [AR (1)].

The ARMA process

Box & Jenkins (1976) combined the autoregressive and moving average terms in order to come up with an ARMA model. In this study, rather than simply relying on either MA (z) or AR (r) models; I derive a more advanced model, in the name of an ARMA (r, z) process; which is a combination of AR (r) and MA (z) processes. Hence, combining equations one and eleven; an ARMA (r, z) process can be specified as follows:

$FDI_t=a_1FDI_{t-1}+\ldots+a_rFDI_{t-r}+\mu_t+y_1\mu_{t-1}+\ldots+y_z\mu_{t-z}$ ……………………………………………………………….. (18)

Similarly, by combining equations seven and twelve; equation eighteen can also be represented in form below:

$FDI_t=\sum^r_{i=1}a_iFDI_{t-i}+\sum^z_{i=1}y_i\mu_{t-i}+\mu_t$ …………………………………………………………………………….. (19)

We can as well specify equation eighteen as follows:

$\phi(L)FDI_t=\O(L)\mu_t$ ………………………………………………………………………………………………… (20)

where $\phi(L)$ and $\O(L)$ are polynomials of orders r and z respectively, simply defined as:

$\phi(L)=1-a_1L-a_2L^2\ldots a_rL^r$ ……………………………………………………………………………………… (21)

$\O(L)=1+y_1L+y_2L^2+\ldots+y_zL^z$ ………………………………………………………………………………… (22)

The ARMA (r, z) can only be used for stationary time series data. However, in reality, many time series are non – stationary since they usually contain trends and or seasonal patterns. This implies that, from an application point of view; ARMA models are not appropriate for describing non – stationary time series; and for such reasons, this study proposes an ARIMA model, which is simply a generalization of an ARMA model to account for the case of non – stationarity.

The ARIMA process

Making prediction in time series using a univariate approach is best done by employing the ARIMA models (Alnaa & Ahiakpor, 2011). A stochastic process FDI_t is called an Autoregressive Integrated[7] Moving Average (ARIMA) [r, d, z] process if it is I (d) and the d times differenced process has an ARMA (r, z) representation. ARIMA models, according to Box & Jenkins (1974); are a set of models that describe the process (e.g. FDI_t) as a function of its own lags and white noise process. If the sequence, Δ^dFDI_t satisfies an ARMA (r, z) process; then the sequence of FDI_t also satisfies the ARIMA (r, d, z) process such that:

$\Delta^dFDI_t=\sum^r_{i=1}a_i\Delta^dFDI_{t-i}+\sum^z_{i=1}y_i\mu_{t-i}+\mu_t$ …………………………………………………………………… (23)

which can also be simply represented as:

$\Delta^dFDI_t=\sum^r_{i=1}a_i\Delta^dL^iFDI_t+\sum^z_{i=1}y_iL^i\mu_t+\mu_t$ ……………………………………………………………… (24)

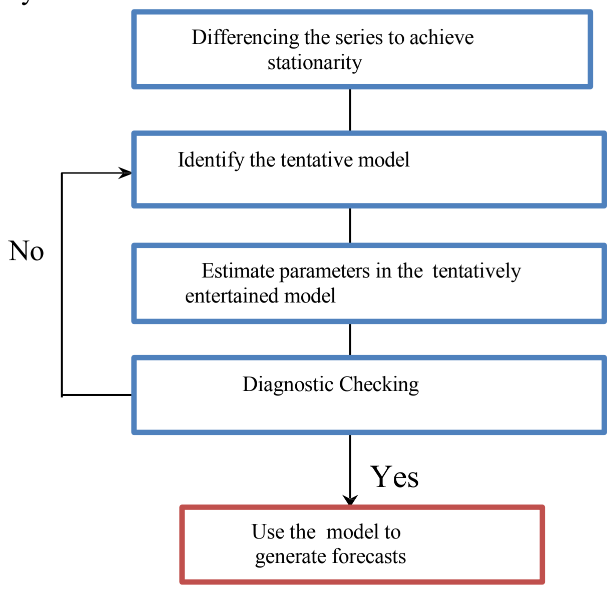
[6] Defined in equation (23)

[7] The family of univariate time series models is not complete without a third element, orders of integration (Wang, 2009).

Where Δ is the difference operator, vector $\alpha \in \mathbb{R}^r$ and $\gamma \in \mathbb{R}^z$, everything else remains as previously defined.

The Box-Jenkins Methodology

Box & Jenkins (1970) developed a practical approach to build ARIMA model, which best fit to a given time series and also satisfy the parsimony principle. Their concept has fundamental importance on the area of time series analysis and forecasting (Lombardo & Flaherty, 2000; Zhang, 2003). The Box – Jenkins approach does not assume any particular pattern in the historical data of the series to be forecasted but rather, it uses a three step iterative approach of model identification, parameter estimation and diagnostic checking to determine the best parsimonious model from a general class of ARIMA models (Box & Jenkins, 1970; Lombardo & Flaherty, 2000; Zhang, 2003). The Box – Jenkins technique is diagrammatically shown below:



The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram to decide on the appropriate orders of the AR and MA components. The researcher will also rely on other widely used (and yet complementary) measures for model identification such as the Akaike Information Criterion (AIC). The AIC is a popular and yet robust method used in estimating parameters of an identified model and is given by:

$$AIC=-2\log \text{Ł}+2m \quad \ldots \quad (25)$$

where Ł is the likelihood and m is the number of parameters estimated in the model such that:

$$m=p+q+P+Q \quad \ldots \quad (26)$$

It is not always feasible to obtain the AIC just because not all computer programs produce the AIC or Ł. Therefore, an important approximation is represented as follows:

$$AIC=n(1+\log(2\Pi))+n\log\sigma^2+2m \quad \ldots \quad (27)$$

However, as an alternative to the AIC, the Schwarz – Bayesian Information Criterion (SBIC) may also be used and is simply given as:

$$SBIC=\log\sigma+(m\log n)/n \quad \ldots \quad (28)$$

It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgment because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic checking shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, then there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an adequate model is identified.

Data Collection

An extensive time series data is required for univariate time series forecasting (Wabomba *et al*, 2016). In fact, Chatfield (1996) and Meyler *et al* (1998) actually recommend more than 50 observations in order to build a reliable ARIMA model. However, recently; a number of studies such as Judi (2007), Al-Abdulrazag (2007), Zhang (2013), Shahini & Haderi (2013), Dritsaki (2015) and Biswas (2015) amongst others; have consistently shown that less than 50 observations can also build a reliable ARIMA model. After all, Abdullah (2012) and Huwiler & Kaufmann (2013) reiterate that ARIMA models are widely used for conducting short – term forecasts of economic time series. In this study, forecasting Zimbabwean net FDI[8] is based on 37 observations of annual time series data for the period 1980 – 2017. All the data used in this study was collected from the World Bank, IMF (International Monetary Fund) and ZimStats (Zimbabwe Statistics Agency).

Diagnostic Tests & Model Evaluation

Stationarity Test (Unit Root Test)

The Augmented Dickey Fuller (ADF) test was used to check the stationarity of the FDI series. The ADF test is generally carried out as follows:

$$\Delta FDI_t = \text{ɒ} + \theta_t + \psi FDI_{t-1} + ɖ_1 \Delta FDI_{t-1} + \ldots + ɖ_{\varphi-1} \Delta FDI_{t-\varphi+1} + \mu_t \quad \ldots\ldots\ldots (29)$$

where ɒ is a constant, θ is the coefficient on the time trend and φ is the lag order on the AR process. The researcher conducted the ADF test under the null hypothesis, ψ=0. The results of the ADF test are shown in the table below:

Levels: intercept

Table 1

Variable	ADF Statistic	Critical Values		Conclusion
FDI	-2.049140	-3.621023	@1%	Not Stationary
		-2.943427	@5%	Not Stationary
		-2.610263	@10%	Not Stationary

Levels: trend & intercept

Table 2

Variable	ADF Statistic	Critical Values		Conclusion
FDI	-2.901234	-4.226815	@1%	Not Stationary
		-3.536601	@5%	Not Stationary
		-3.200320	@10%	Not Stationary

Levels: without intercept and trend & intercept

Table 3

Variable	ADF Statistic	Critical Values		Conclusion
FDI	-1.501015	-2.628961	@1%	Not Stationary
		-1.950117	@5%	Not Stationary
		-1.611339	@10%	Not Stationary

[8] Measured in US Dollars per annum

Tables 1, 2 and 3 indicate that the FDI series is not stationary at levels. Hence the need to check stationarity at first difference as shown below in tables 4, 5 and 6.

1st difference: intercept

Table 4

Variable	ADF Statistic	Critical Values		Conclusion
D(FDI)	-7.022576	-3.626784	@1%	Stationary
		-2.945842	@5%	Stationary
		-2.611531	@10%	Stationary

1st difference: trend & intercept

Table 5

Variable	ADF Statistic	Critical Values		Conclusion
D(FDI)	-6.911900	-4.234972	@1%	Stationary
		-3.540328	@5%	Stationary
		-3.202445	@10%	Stationary

1st difference: without intercept and trend & intercept

Table 6

Variable	ADF Statistic	Critical Values		Conclusion
D(FDI)	-7.098076	-2.630762	@1%	Stationary
		-1.950394	@5%	Stationary
		-1.611202	@10%	Stationary

Tables 4, 5 and 6 show that the FDI series became stationary after first differencing. This implies that the FDI series is integrated of order one, that is; I (1).

Evaluation of various ARIMA[9] models

Table 7

Model	AIC
ARIMA (1, 1, 1)	***1473.612***
ARIMA (1, 1, 2)	1475.636
ARIMA (2, 1, 1)	1475.567
ARIMA (3, 1, 1)	1477.562
ARIMA (1, 1, 3)	1477.577

The table above indicates that the ARIMA (1, 1, 1) model has the lowest AIC value and is therefore chosen.

ADF Test of the Residuals from the ARIMA (1, 1, 1) model

Levels: intercept

Table 8

[9] These models were estimated using Exact Maximum Likelihood. The software packages used in this study are Gretl and E – Views 7.

Variable	ADF Statistic	Critical Values		Conclusion
μ_t	-6.229149	-3.632900	@1%	Stationary
		-2.948404	@5%	Stationary
		-2.612874	@10%	Stationary

Levels: trend & intercept

Table 9

Variable	ADF Statistic	Critical Values		Conclusion
μ_t	-6.3466065	-4.243644	@1%	Stationary
		-3.544284	@5%	Stationary
		-3.204699	@10%	Stationary

Levels: without intercept and trend & intercept

Table 10

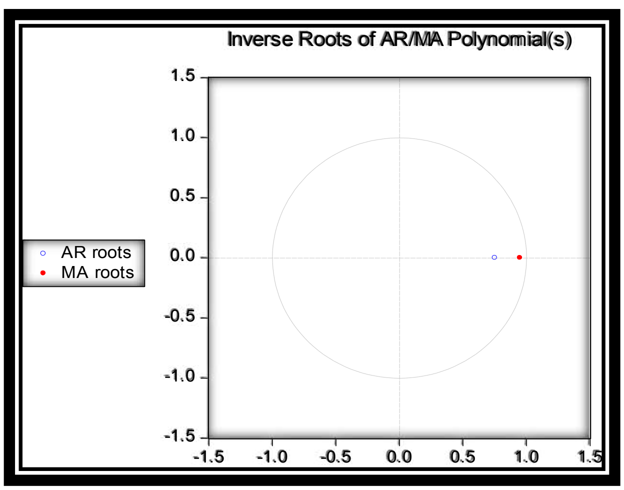
Variable	ADF Statistic	Critical Values		Conclusion
μ_t	-6.129491	-2.632688	@1%	Stationary
		-1.950687	@5%	Stationary
		-1.611059	@10%	Stationary

Tables 8, 9 and 10 indicate that the generated residuals of the chosen ARIMA (1, 1, 1) model satisfy the characteristics of a white noise process since the residuals have been shown to be stationary. Having satisfied this condition, we can conclude that our model is adequate and therefore, we can use the model for forecasting and control.

Stability Test of the ARIMA (1, 1, 1) model

Inverse Roots of AR/MA Polynomial(s)

Figure 1



The diagram above indicates that the chosen ARIMA (1, 1, 1) model is stable because the corresponding inverse roots of the characteristic polynomials are in the unit circle.

4. RESULTS: PRESENTATION, INTERPRETATION & DISCUSSION

Results

Table 11

Variable	Coefficient	Std. Error	z	p – value
AR (1)	0.701109	0.35316	1.9852	0.04712
MA (1)	-0.893065	0.25126	-3.5544	0.00038

The chosen model as summarized in the table above; is ARIMA (1, 1, 1) model and can be presented as follows:

$$DFDI_t=0.701109DFDI_{t-1}-0.893065\mu_{t-1} \quad \text{………………………………………………………………} \quad (30)$$

p – value (0.04712) (0.0038)

Std. Error (0.35316) (0.25126)

Interpretation of the results in table 11 above

The coefficient of the AR (1) component is positive and statistically significant at 5% level of significance. This points to the fact that previous period net FDI inflows are important in determining current values of net FDI. For example, when previous period value of net FDI was relatively high; it is a signal of good investment opportunities in the host country and this may lead to more FDI inflows in the next period; and the opposite is true. In this case our model implies that a 1% increase in the previous period net FDI will lead to approximately 0.7% increase in the current period net FDI inflows. The coefficient of the MA (1) component is negative and statistically significant at 1% level of significance. The implication is that unobserved shocks to net FDI inflows have a strong negative impact on net FDI inflows in Zimbabwe. Such shocks may include unpredictable political events and natural disasters such as earth – quakes and drought. In fact our model indicates that a 1% increase in such shocks will lead to approximately 0.89% decrease in net FDI inflows in Zimbabwe.

Forecasting

Table 12

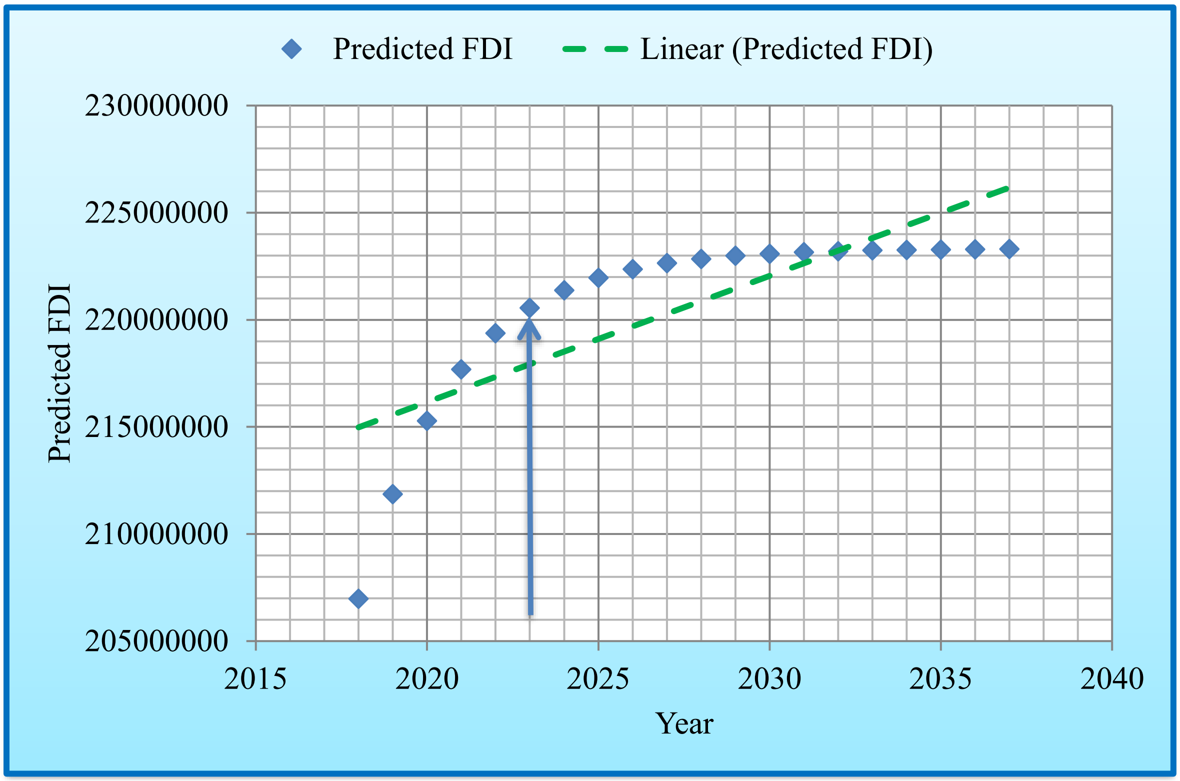
Year	Prediction	Std. Error	95% interval
2018	206967000	98890600	13144600 – 400789000
2019	211851000	127140000	-37339300 – 461041000
2020	215275000	143527000	-66032800 – 496584000
2021	217676000	154531000	-85198100 – 520551000
2022	219360000	162643000	-99415300 – 538134000
2023	220540000	169061000	-110814000 – 551893000
2024	221367000	174425000	-120500000 – 563234000
2025	221947000	179103000	-129089000 – 572984000
2026	222354000	183319000	-136945000 – 581653000
2027	222639000	187212000	-144290000 – 589568000
2028	222839000	190873000	-151265000 – 596943000
2029	222979000	194361000	-157962000 – 603920000
2030	223078000	197718000	-164442000 – 610597000
2031	223147000	200970000	-170747000 – 617040000
2032	223195000	204137000	-176107000 – 623296000
2033	223229000	207233000	-182941000 – 629399000

2034	223252000	210268000	-188866000 – 635371000
2035	223269000	213249000	-194692000 – 641230000
2036	223281000	216182000	-200428000 – 646990000
2037	223289000	219070000	-206080000 – 652658000

The table above summarizes the forecasting results of net FDI inflows over the period 2018 – 2037.

Predicted net FDI inflows over the period 2018 – 2037

Figure 2



The graph above indicates that net FDI inflows in Zimbabwe will increase at an increasing rate from now until 2023, after which it may start increasing at a decreasing rate. The most interesting observation is that our model predicts that annual net FDI inflows may not (or never) exceed half a million US dollars in Zimbabwe, holding other things constant. In fact, the graph indicates that over the next 2 decades, Zimbabwean net FDI shows a relatively lower and unimpressive growth trend. Now, considering the importance of FDI in the growth of the economy and the fact that FDI is also a source of liquidity; we also conclude that Zimbabwe's economy is not likely to grow significantly any time soon, but of course holding other things constant. The poor FDI inflows in Zimbabwe have been necessitated by, among other things; the indigenization policy which has frustrated many foreign investors. Other factors that continue to scare away investors in Zimbabwe include political uncertainty and the general macroeconomic instability. Unless and until the Zimbabwean FDI policy is properly revised, no significant FDI inflows will ever take place. Successive governments should know that the previous political administration (the Mugabe – led) failed to attract FDI mainly because of its failure to come up with investor – friendly policies. Therefore, if FDI inflows are to increase in Zimbabwe, a number of issues have to be addressed first, for example corruption, rule of law, indigenization issues and bureaucracy amongst others. Our results confirm Muzurura (2016b)'s observation that Zimbabwe's dearth of industrial development has been partially related to the challenges of attracting sufficient levels of FDI and that Zimbabwe continues to face diminishing FDI inflows.

Forecast Evaluation

Forecast Evaluation Statistics

Table 13

Name of Forecast Evaluation Statistic	Statistic
Mean Error	17607000
Mean Squared Error	9786700000000000
Root Mean Squared Error	98928000
Mean Absolute Error	57707000
Mean Percentage Error	-10.007
Mean Absolute Percentage Error	89.072
Theil's U	0.91024

Smaller values of the statistics indicated in table 13 would generally indicate that the forecast is quite good. However, our model has a relatively high value of the inequality coefficient of Theil's U, that is approximately 0.91 and this implies that our model may not have the best forecasting ability.

5. RECOMMENDATIONS

i. The main policy implication of this study is that policy makers in Zimbabwe should come up with investor – friendly policies in order to attract the much needed FDI.
ii. The political economy of Zimbabwe cannot be overlooked each time economic policy dynamics are discussed (Nyoni, 2018). A stable political environment is recommended because it is a signal of a favorable investment climate (Nyoni & Bonga, 2017).
iii. A conducive macroeconomic environment should be created and sustained if Zimbabwe is to receive reasonable amounts of FDI.

6. CONCLUSION

It is important to highlight the fact that predicting economic variables such as FDI is not an easy process[10] because the results of such studies are easily affected by structural breaks[11] in the economy. The results of the estimated model remain relevant as long as there are no structural breaks such as change of government or disease outbreak such as the Ebola outbreak [in some parts of Africa]. Therefore, as already noted by Wabomba *et al* (2016), policy makers ought to pay attention to the risk of adjustment in the economic operation and maintain the stability and continuity of microeconomic regulation and control in order to prevent the economy from severe fluctuations and adjust the corresponding target value according to the actual situation. The purpose of the study was to model and forecast Zimbabwean net FDI based on the Box – Jenkins technique. Through collection and analysis of the annual net FDI data for Zimbabwe, determining the order of integration, model identification, diagnostic checking as well as forecasting, the best ARIMA model was chosen as shown in table 7, estimated as shown in table 11 and presented as shown in equation (30). Our analysis of the results indicate that the model performs better in terms of both in – sample and out – of – sample forecasts.

REFERENCES

---

[10] The forecasting result of this model is ONLY a predicted value; the reader should note that the economy is a complex and dynamic system.

[11] In this study, we assume they are not there simply because over the study period Zimbabwe was under the rule of the same president (Mr. Mugabe) and the ruling party (Zanu – PF). For simplicity, we don't consider any other issue as a "significant" structural break.

1. Abdul, H. S & A-Samarrai, H (1998). A seminar on foreign direct investment justification and notification, Baghdad, http://www.ijbms.com/Vol5/3/8-abhijit-biswas.pdf

2. Abdullah, L (2012). ARIMA model for gold bullion prices forecasting, *International Journal of Advances in Applied Sciences*, 1 (4): 153 – 158.

3. Alnaa, S. E & Ahiakpor, F (2011). ARIMA (autoregressive integrated moving average) approach to predicting inflation in Ghana, *Journal of Economics and International Finance*, 3 (5): 328 – 336.

4. Azam, M (2010). An empirical analysis of the impacts of exports and foreign direct investment on economic growth in South Asia, *Interdisciplinary Journal of Contemporary Research in Business*, 2 (7): 249 – 258.

5. Bayai, I & Nyangara, D (2013). An analysis of determinants of private investment in Zimbabwe for the period 2009 – 2011, International Journal of Economics and Management Sciences, 2 (6): 11 – 42.

6. Biswas, A (2015). Forecasting net Foreign Direct Investment inflows in India: Box – Jenkins ARIMA Model, *International of Management and Business Studies*, 5 (3): 49 – 58.

7. Borensztein, E., Gregorio, J. D & Lee, J. W (1998). How does foreign direct investment affect economic growth? *Journal of International Economics*, 45: 115 – 135, https://doi.org/10.1016/S0022-1996(97)00033-0

8. Box, G. E. P & Jenkins, G. M (1970). Time Series Analysis, Forecasting and Control, *Holden Day*.

9. Box, G. E. P & Jenkins, G. M (1974). Time Series Analysis, Forecasting and Control, *Holden Day*.

10. Box, G. E. P & Jenkins, G. M (1976). Time Series Analysis: Forecasting and Control, Revised Edition, Holden Day.

11. Chingarande, A., Maduva, B., Karambakuwa, R. T., Denhere, W., Tafirei, F., Zivanai, O., Muchingami, L & Mudavanhu, V (2012). The impacts of interest rates on foreign direct investment: a case study of the Zimbabwean economy (February 2009 – June 2011), *International Journal of Management Sciences and Business Research*, 1 (5): 1 – 24.

12. Dailami, M & Walton, M (1992). Private investment, government policy and foreign capital: a study of the Zimbabwe experience, *World Bank*, Washington DC.

13. Dhingra, V. S., Bulsara, H. P & Ghandhi, S (2015). Forecasting foreign institutional investment flows towards India using ARIMA modeling, *Management*, 75 (2015): 13 – 26.

14. Dritsaki, C (2015). Forecasting real GDP rate through econometric models: an empirical study from Greece, *Journal of International Business and Economics*, 3 (1): 13 – 19.

15. Dunning, J. H (1981). International production and multinational enterprise, *George Allen & Unwin*, London.

16. Dunning, J. H (2001). Theories of foreign direct investment: multinational enterprises and the global economy, *Cheltenham*, pp: 52 – 76.

17. Firebaugh, G (1992). Growth effects of foreign domestic investment, *American Journal of Sociology*, pp: 105 – 130, http://dx.doi.org/10.1086/229970

18. Fry, M (1999). Some lessons for South Asia from developing country experience with foreign direct investment, *The World Bank*, Washington DC.

19. Gwenhamo, F (2009). Foreign direct investment in Zimbabwe: The role of institutional factors, *University of Cape Town*, Working Paper No. 144.

20. Huwiler, M & Kaufmann, D (2013). Combining disaggregate forecasts for inflation: The SNB's ARIMA model, *Swiss National Bank Economic Studies*, No. 7.

21. Jenkins, C (1998). Private investment, government policy and foreign capital: a study of the Zimbabwe experience, *Journal of African Economies*, 7 (1): 34 – 61.

22. Jere, S., Kasense, B & Chilyabanyama, O (2017). Forecasting foreign direct investment to Zambia: a time series analysis, *Scientific Research Publishing – Open Journal of Statistics*, 7 (2017): 122 – 131.

23. Khan, S (2007). Aid flow to Bangladesh and the question of accountability of CSOs at national level to the people they serve, http://www.unnayan.org/news/files/CSO.pdf

24. Lombardo, R & Flaherty, J (2000). Modeling new private housing starts in Australia, *Pacific – Rim Real Estate Society Conference*, University of Technology Sydney.

25. Mafusire, A (2004). An empirical analysis of the export – FDI growth nexus in Zimbabwe, *Botswana Journal of Economics*, 2: 19 – 102.

26. Mello, D. L. R (1999). Foreign direct investment led growth: evidence from times and panel data, *Oxford Economic Papers*, 51 (1): 133 – 151, http://dx.doi.org/10.1093/oep/51.1.133

27. Meyler, A., Kenny, G & Quin, T (1998). Bayesian VAR models for forecasting Irish inflation, *Central Bank of Ireland*, Technical Paper 4.

28. Moyo, T (2013). The impact of foreign direct investment on economic growth: The case of Zimbabwe (2009 – 2012), *International Journal of Economics, Finance and Management Sciences*, 1 (6): 323 – 329.

29. Muzurura, J (2016a). Determinants of foreign direct investment (FDI) in Zimbabwe: what factors matter? *Research in Business and Economics Journal*, 11 (2016): 1 – 19.

30. Muzurura, J (2016b). Is public corruption the main cause of low foreign direct investment in Zimbabwe? *British Journal of Economics, Finance and Management Sciences*, 13 (1): 1 – 18.

31. Nyoni, T & Bonga, W. G (2017). An Empirical Analysis of the Determinants of Private Investment in Zimbabwe, *Dynamic Research Journals Journal of Economics and Finance (DRJ – JEF)*, 2 (4): 38 – 54.

32. Nyoni, T (2017). The Curse of Corruption in Zimbabwe, *International Journal of Advanced Research and Publications*, 1 (5): 285 – 291.

33. Nyoni, T (2018). A Critical Diagnosis of the Success/Failure of Economic Policies in Zimbabwe During the Banana (1980 – 1987) and the Mugabe (1988 – 2017) Administrations: Learning the Hard Way, *Dynamic Research Journals Journal of Business and Management (DRJ – JBM)*, 1 (2): 27 – 33.

34. Pradhan, R., Saha, D & Gupta, V (2011). Determinants of FDI in SAARC countries: an investigation using panel VAR model, *Information Management and Business Review*, 3 (2): 117 – 126.

35. Prasanna, P. W. L (2015). Modeling and forecasting Foreign Direct Investment (FDI) into SAARC for the period of 2013 – 2037 with ARIMA, *International Journal of Business and Social Science*, 6 (2): 264 – 272.

36. Quader, S. M (2009). Foreign direct investment in Bangladesh: an empirical analysis on its determinants and impacts, *Munich RePEc Archive (MPRA)*, Paper No. 26134.

37. Romer, P (1993). Idea gaps and object gaps in economic development, *Journal of Monetary Economics*, 32 (3): 543 – 573.

38. Shahini, L & Haderi, S (2013). Short – term GDP forecast: One quarter to one year ahead, *European Scientific Journal*, 9 (34): 198 – 208.

39. Sikwila, M. N (2014). Foreign direct investment: does it matter? A case for Zimbabwe, *Research in Business and Economics Journal*, 10 (2014): 1 – 12.

40. UNCTAD (2014). Foreign direct investments in Africa, *United Nations*, New York & Geneva.

41. Vernon, R (1966). International investment and international trade in the Product Cycle, *Quarterly Journal of Economics*, 80: 190 – 207.

42. Wang, P (2009). Financial Econometrics, 2nd Edition, *Routledge – Francis & Taylor Group*, New York.

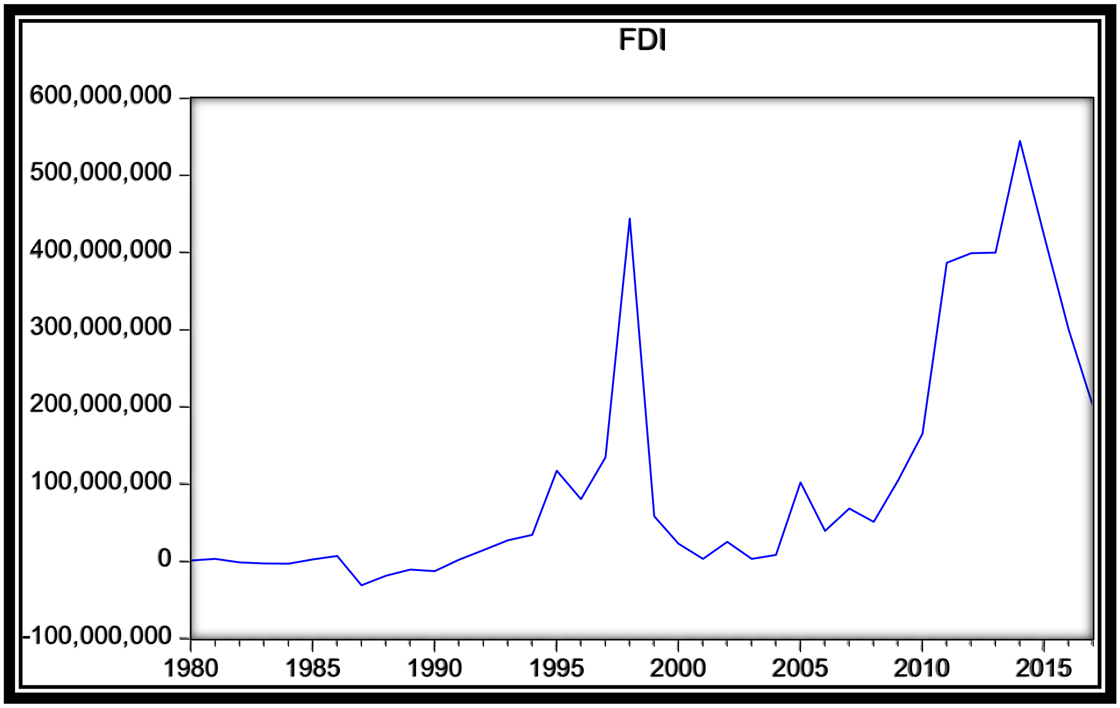
43. World Bank (2015). Foreign direct investment in Africa, *World Bank*, Washington DC.

44. Zhang, G. P (2003). Time Series Forecasting using a hybrid ARIMA and neural network model, *Neurocomputing*, 50 (2003): 159 – 175.

45. Zhang, H (2013). Modeling and forecasting regional GDP in Sweden using autoregressive models, Working Paper, *Hogskolan Dalana University*, Sweden.

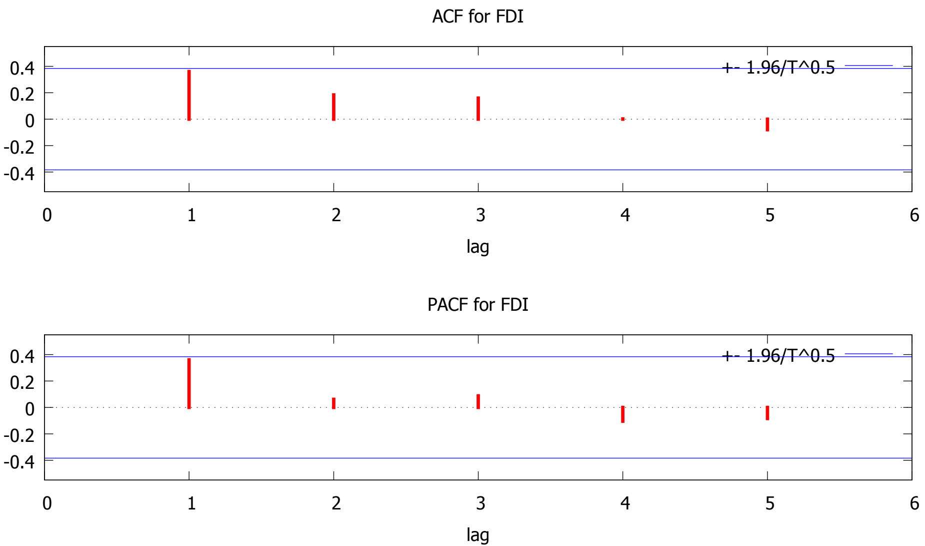
APPENDIX[12]

Time Series Plot

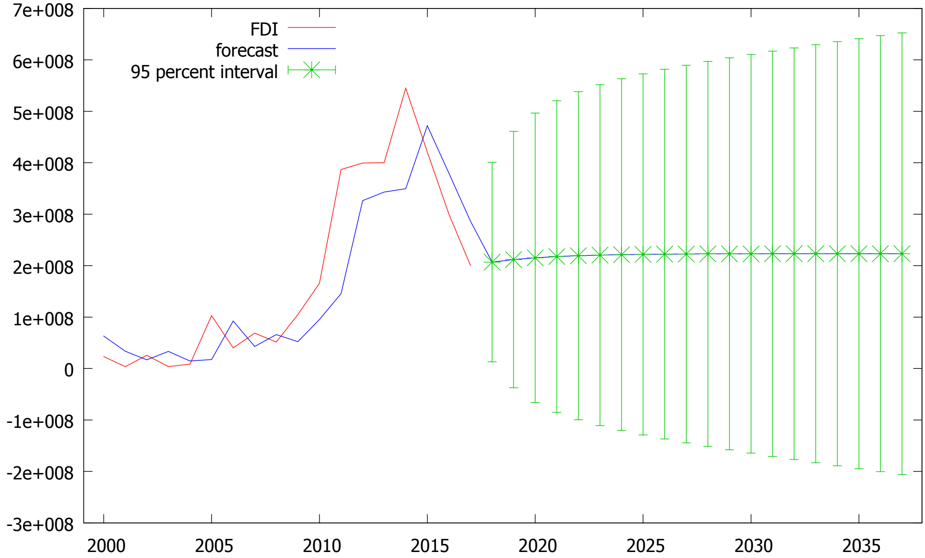


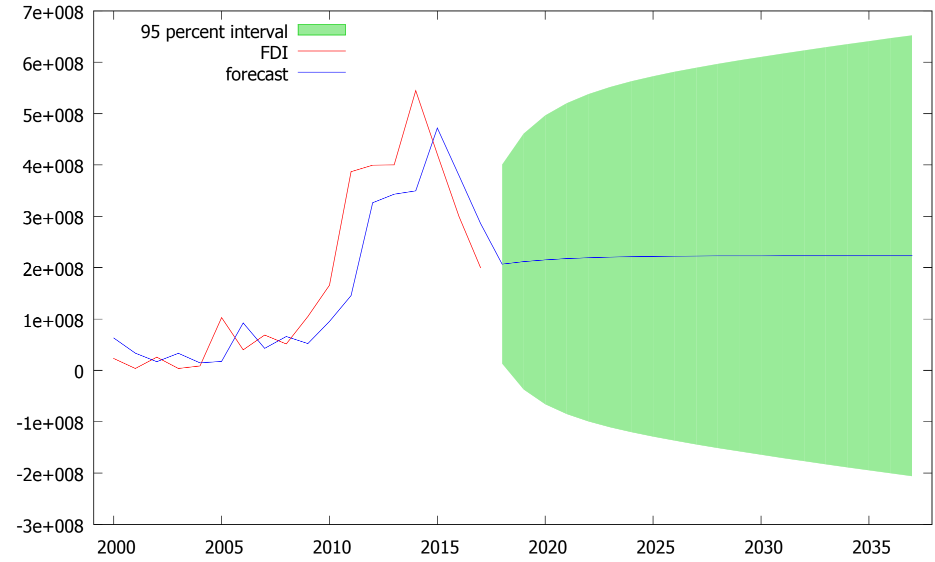
---

[12] The rest of the appendix is merged as follows: correlogram plot for FDI in levels, forecast error bars, shaded area 95% confidence interval, low & high lines and as well as 95% confidence ellipse & 95% marginal intervals. Forecast error bars, the shaded area 95% confidence interval, the low & high lines and the 95% confidence ellipse & 95% marginal intervals reveal that the accuracy of our forecast is satisfactory since it falls within the 95% confidence interval.

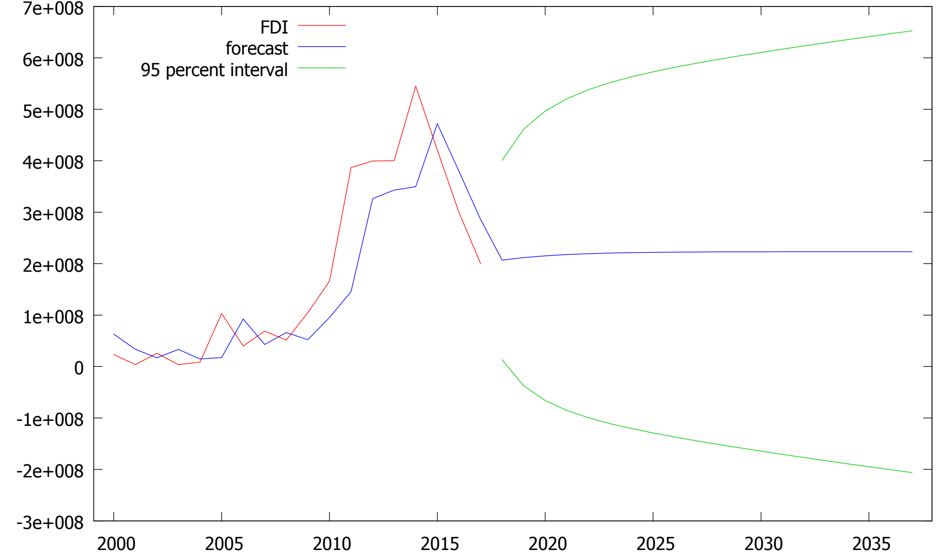


ACF for FDI
+- 1.96/T^0.5
0.4
0.2
0
-0.2
-0.4
0
1
2
3
4
5
6
lag
PACF for FDI
+- 1.96/T^0.5
0.4
0.2
0
-0.2
-0.4
0
1
2
3
4
5
6
lag

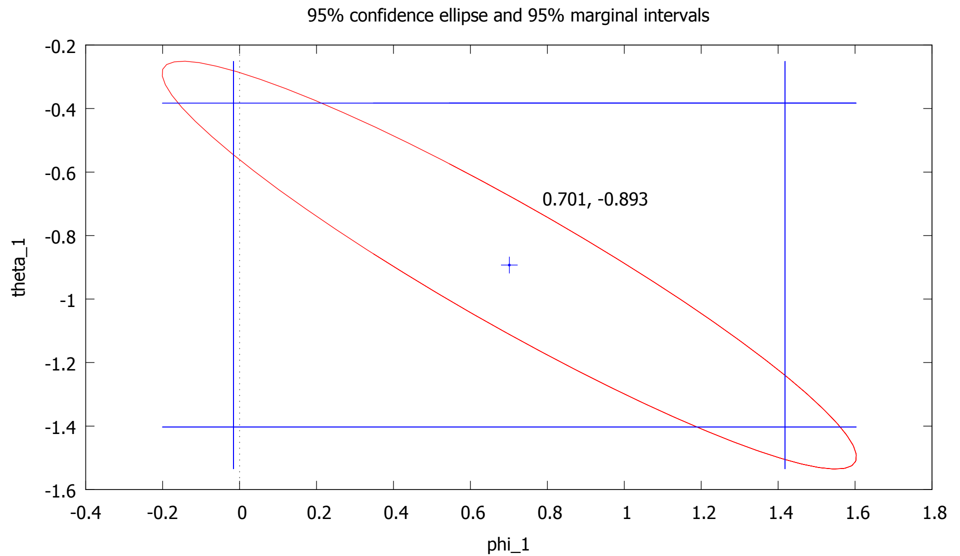

7e+008
6e+008
5e+008
4e+008
3e+008
2e+008
1e+008
0
-1e+008
-2e+008
-3e+008
2000
2005
2010
2015
2020
2025
2030
2035
FDI
forecast
95 percent interval



95 percent interval
FDI
forecast
7e+008
6e+008
5e+008
4e+008
3e+008
2e+008
1e+008
0
-1e+008
-2e+008
-3e+008
2000
2005
2010
2015
2020
2025
2030
2035



FDI
forecast
95 percent interval
7e+008
6e+008
5e+008
4e+008
3e+008
2e+008
1e+008
0
-1e+008
-2e+008
-3e+008
2000
2005
2010
2015
2020
2025
2030
2035


95% confidence ellipse and 95% marginal intervals
0.701, -0.893
theta_1
phi_1
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
-1.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8