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Forecasting the Shock in Economic Data Series using Error Forecast

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Abstract

In this paper, we discussed the Statistical modeling of the original data series and the residuals series. Residual series has been use for the forecasting the shock occurring in the economic data series. Objective and Subjective technique has been used for the modeling.

Keywords: Forecasting, Error forecasting, Box Jenkins method, Objective and subjective approaches.

1. Introduction

Currently, the subjective and objective approach has been widely used for the forecasting purposes. Subjective approach is the Box Jenkins methodology and Objective approach is the new methodology. There are different modeling has been done in the literature regarding to the Foreign Direct Investment.

Sipos et al. (2008) used the autoregressive econometric models to evaluate the impact of the foreign investments in any form whatsoever, on the Romanian economy. Liu X et al. (2002) discussed the impact of foreign direct investment on labor productivity in the Chinese electronics industry. The importance of the Foreign Direct Investment (FDI) in the economic development has been discussed many authors including Fleisher and Chen (1997), Walz (1997), Markusen and Venables (1999) and De Mello (199).

In the objective approach, time series models has been used for the forecasting using the residuals series as an independent variable (explanatory or auxiliary variable

Two main stages for this purpose are as follows:

Stage 1 Build the appropriate models on the original series using Box Jenkins methodology. After selecting the appropriate models and determined the residuals series of that model. (Subjective Approach)

Stage 2 Statistical modeling has been conducting on the error series, for model building there are different methods to adopt the models.

2. Methodology

A different time series model has been used for the data series of FDI. There are different models has been used which are AR(p) MA(q) and ARIMA(p,d,q) using the subjective approach. All the important steps have been followed for the modeling of the FDI and determine the residuals for each model. After determine the residuals, first technique has been used on the residuals series which are given below:

- Apply the same model of the original series on the residuals series
- Apply the appropriate models for the residuals series
- Predict the error using the time period as independent variable.(Regression Model)
- Predict the residual using the regression model with random numbers as an independent variable.

At the end build the model on the original series using the residuals series as an explanatory variable like as the REG-ARIMA modeling.

3. Data Analysis

In the data analysis, followed the following steps: **(**Subjective Approach**)**

- Check the Stationary of the data using ADF
- Determine the order of the ARIMA(p,d,q) model
- Estimate the parameter of the models.
- Residuals testing (AC, PAC, ARCH)
- Forecasting.

After following the above necessary steps for the subjective approach, we noted that first step shows that series is not stationary and it is stationary at 1^{st} difference. There are four models have been used for data series which are given below:

a) AR(1)
b) MA(1)
c) AR(1), AR(2)
d) ARMA(1,2) (using 1^{st} diff. series)

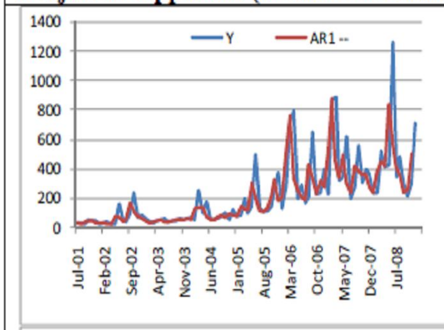
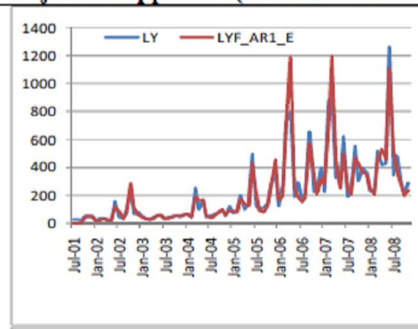
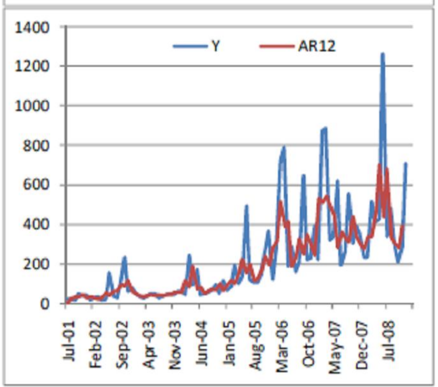
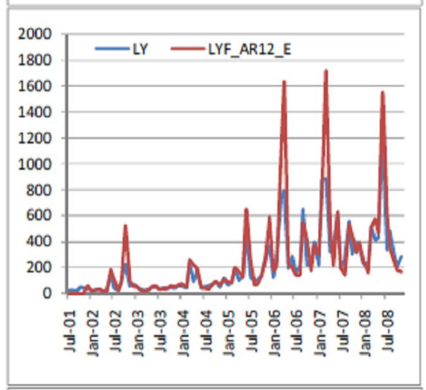
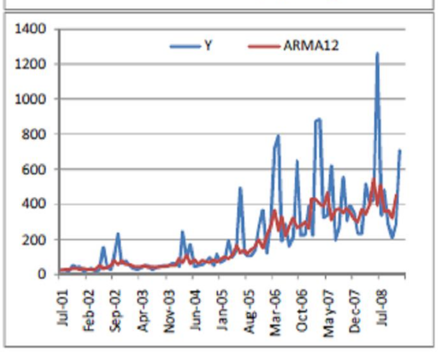
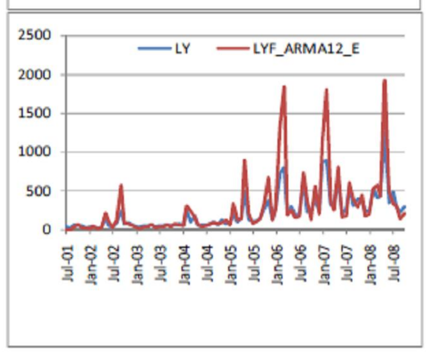
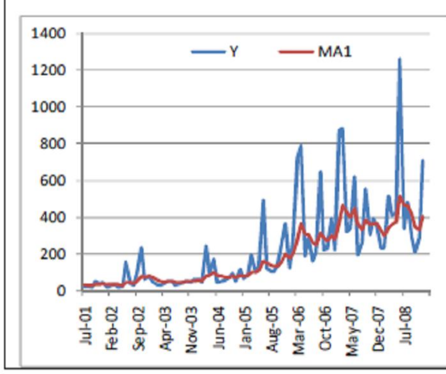
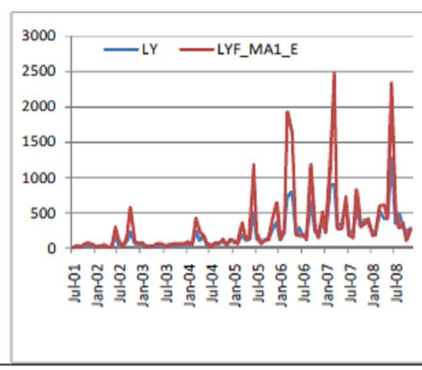
After applying these models, determine the residuals of each model and apply the same model on the residuals and forecast the residuals.

4. Objective Approach

At that stage objective approach has been used and applying the above four models using their residuals series as an independent variable. In the literature VECM (Vector Error Correction Mechanism) and Co-integration techniques are available when the explanatory variables for the forecasting. There are some limitations in these techniques likes “order of co-integration should be same”, “Long Term relations”, “lags of error” etc.

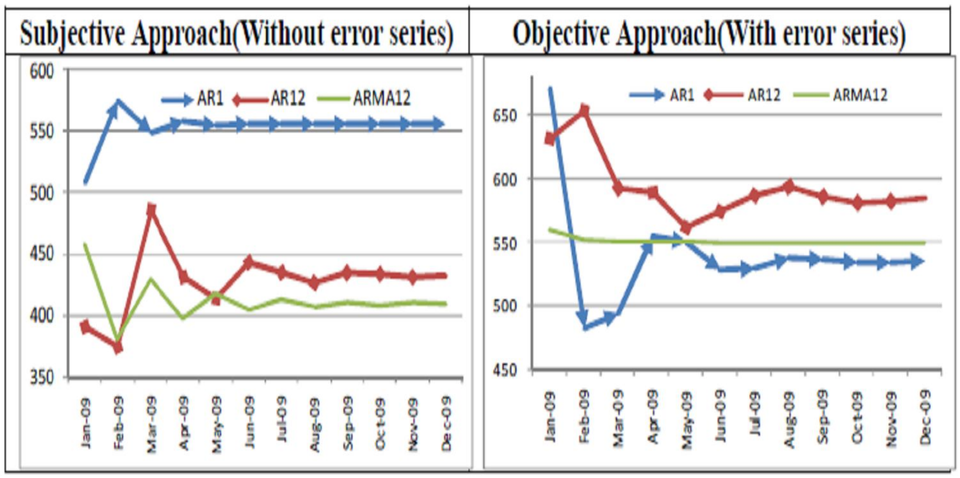
5. Results

Results of Objective and Subjective Approach are as follows:

Subjective Approach (Without error series)	Objective Approach (With error series)
	
	
	
	

6. Discussion

From the above result, objective technique performs better in the situation of shock occurring in the data series. Graphical representation clearly shows the shock occurring in the data. The second important results are that the co-efficient of the residuals series is the significant in each model. On the other hand, objective approach shows that shock will occur in the future from the graph given below. This approach also shows the long term behavior of the data series.



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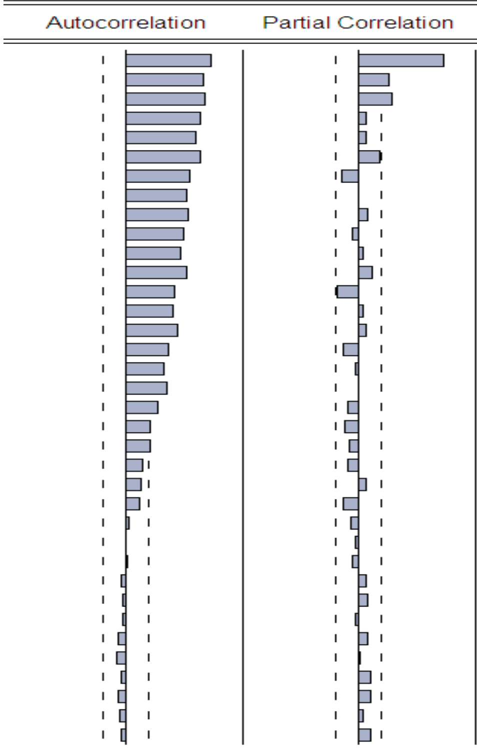
Appendix

Notations	
Y, LY	Foreign Direct Investment (Monthly series)
AR1	Forecast using AR1 Model
AR12	Forecast using AR1& AR2 Model
ARMA12	Forecast using ARMA(1,2) Model
MA1	Forecast using MA1 Model
LYF_AR1_E	Forecast using AR1 Model on (Using AR1 error as independent)
LYF_AR12_E	Forecast using AR1&AR2 Model on (Using AR1 &AR2 models error as independent)
LYF_ARMA12_E	Forecast using ARMA(1,2) Model on (Using ARMA(1,2) error as independent)
LYF_MA1_e	Forecast using MA1 Model on (Using MA1 error as independent)

Correlogram (Actual Data Series)

Sample: 2001M07 2009M12
Included observations: 90



	AC	PAC	Q-Stat	Prob
1	0.759	0.759	53.619	0.000
2	0.691	0.271	98.547	0.000
3	0.706	0.302	146.05	0.000
4	0.659	0.070	187.86	0.000
5	0.626	0.062	226.05	0.000
6	0.660	0.187	268.97	0.000
7	0.567	-0.152	301.04	0.000
8	0.538	0.006	330.21	0.000
9	0.563	0.079	362.62	0.000
10	0.509	-0.050	389.47	0.000
11	0.488	0.033	414.48	0.000
12	0.533	0.123	444.62	0.000
13	0.429	-0.184	464.38	0.000
14	0.419	0.044	483.50	0.000
15	0.456	0.060	506.50	0.000
16	0.374	-0.133	522.16	0.000
17	0.337	-0.032	535.02	0.000
18	0.362	0.003	550.12	0.000
19	0.280	-0.095	559.23	0.000
20	0.221	-0.123	565.03	0.000
21	0.220	-0.077	570.86	0.000
22	0.141	-0.097	573.29	0.000
23	0.138	0.072	575.64	0.000
24	0.115	-0.136	577.30	0.000
25	0.033	-0.057	577.43	0.000
26	0.006	-0.023	577.44	0.000
27	0.010	-0.057	577.45	0.000
28	-0.036	0.062	577.62	0.000
29	-0.026	0.075	577.71	0.000
30	-0.028	-0.020	577.82	0.000
31	-0.072	0.076	578.55	0.000
32	-0.085	0.014	579.59	0.000
33	-0.039	0.113	579.81	0.000
34	-0.066	0.099	580.46	0.000
35	-0.057	0.049	580.95	0.000
36	-0.048	0.100	581.30	0.000

Table 1: ADF

Null Hypothesis: D(LY) has a unit root				
Exogenous: None				
Lag Length: 4 (Automatic based on AIC, MAXLAG=11)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-6.816277	0.0000
Test critical values:	1% level		-2.592782	
	5% level		-1.944713	
	10% level		-1.614233	
*MacKinnon (1996) one-sided p-values.				

Table 2: AR(1) Model

Dependent Variable: D(LY)				
Method: Least Squares				
Sample (adjusted): 2001M09 2008M12				
Included observations: 88 after adjustments				
Convergence achieved after 3 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.373698	0.100471	-3.719475	0.0004
R-squared	0.134819	Mean dependent var		0.037346
Adjusted R-squared	0.134819	S.D. dependent var		0.714974
S.E. of regression	0.665034	Akaike info criterion		2.033342
Sum squared resid	38.47754	Schwarz criterion		2.061494
Log likelihood	-88.46706	Durbin-Watson stat		2.261419
Inverted AR Roots	-.37			

Table 3: AR(1), AR(2) Model

Dependent Variable: D(LY) Method: Least Squares Sample (adjusted): 2001M10 2008M12 Included observations: 87 after adjustments Convergence achieved after 3 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.525821	0.100748	-5.219171	0.0000
AR(2)	-0.401929	0.100852	-3.985338	0.0001
R-squared	0.270455	Mean dependent var		0.042016
Adjusted R-squared	0.261872	S.D. dependent var		0.717768
S.E. of regression	0.616666	Akaike info criterion		1.893741
Sum squared resid	32.32352	Schwarz criterion		1.950429
Log likelihood	-80.37774	Durbin-Watson stat		2.018438
Inverted AR Roots	-.26+.58i	-.26-.58i		

Table 4: ARIMA(1,1,2) Model

Dependent Variable: D(LY) Method: Least Squares Sample (adjusted): 2001M09 2008M12 Included observations: 88 after adjustments Convergence achieved after 7 iterations Backcast: 2001M07 2001M08				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.647365	0.093767	-6.903965	0.0000
MA(2)	-0.600497	0.097532	-6.156955	0.0000
R-squared	0.321910	Mean dependent var		0.037346
Adjusted R-squared	0.314025	S.D. dependent var		0.714974
S.E. of regression	0.592168	Akaike info criterion		1.812411
Sum squared resid	30.15699	Schwarz criterion		1.868714
Log likelihood	-77.74610	Durbin-Watson stat		1.951078
Inverted AR Roots	-.65			
Inverted MA Roots	.77	-.77		

Table 5: MA(1) Model

Dependent Variable: D(LY) Method: Least Squares Sample (adjusted): 2001M08 2008M12 Included observations: 89 after adjustments Convergence achieved after 7 iterations Backcast: 2001M07				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	-0.740036	0.071144	-10.40201	0.0000
R-squared	0.294623	Mean dependent var		0.037864
Adjusted R-squared	0.294623	S.D. dependent var		0.710917
S.E. of regression	0.597076	Akaike info criterion		1.817628
Sum squared resid	31.37198	Schwarz criterion		1.845590
Log likelihood	-79.88443	Durbin-Watson stat		1.824853
Inverted MA Roots	.74			

Table 6: AR(1) Model (Using Objective Technique)

Dependent Variable: D(LY) Method: Least Squares Sample (adjusted): 2001M10 2008M12 Included observations: 87 after adjustments Convergence achieved after 19 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR1_E	0.901233	0.040854	22.05971	0.0000
AR(1)	-0.494609	0.103896	-4.760630	0.0000
R-squared	0.889382	Mean dependent var		0.042016
Adjusted R-squared	0.888081	S.D. dependent var		0.717768
S.E. of regression	0.240125	Akaike info criterion		0.007402
Sum squared resid	4.901081	Schwarz criterion		0.064089
Log likelihood	1.678023	Durbin-Watson stat		2.460630
Inverted AR Roots	-.49			

Table 7: AR(1), AR(2) Model

Dependent Variable: D(LY)
Method: Least Squares
Date: 27/07/09 Time: 17:32
Sample (adjusted): 2001M12 2008M12
Included observations: 85 after adjustments
Convergence achieved after 56 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR12_E	1.115816	0.056406	19.78174	0.0000
AR(1)	0.226065	0.100058	2.259345	0.0265
AR(2)	-0.472399	0.097635	-4.838444	0.0000
R-squared	0.782823	Mean dependent var		0.033230
Adjusted R-squared	0.777526	S.D. dependent var		0.717996
S.E. of regression	0.338658	Akaike info criterion		0.707006
Sum squared resid	9.404535	Schwarz criterion		0.793217
Log likelihood	-27.04776	Durbin-Watson stat		1.841936
Inverted AR Roots	.11-.68i	.11+.68i		

Table 8: ARIMA(1,1,2) Model

Dependent Variable: D(LY)
Method: Least Squares
Sample (adjusted): 2001M10 2008M12
Included observations: 87 after adjustments
Convergence achieved after 16 iterations
Backcast: 2001M08 2001M09

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARMA12_E	1.272966	0.043921	28.98287	0.0000
AR(1)	0.751300	0.085034	8.835257	0.0000
MA(2)	-0.602980	0.095637	-6.304904	0.0000
R-squared	0.739661	Mean dependent var		0.042016
Adjusted R-squared	0.733463	S.D. dependent var		0.717768
S.E. of regression	0.370564	Akaike info criterion		0.886292
Sum squared resid	11.53468	Schwarz criterion		0.971324
Log likelihood	-35.55372	Durbin-Watson stat		2.146812
Inverted AR Roots	.75			
Inverted MA Roots	.78	-.78		

Table 9:MA(1) Model

Dependent Variable: D(LY) Method: Least Squares Sample (adjusted): 2001M08 2008M12 Included observations: 89 after adjustments Convergence achieved after 221 iterations Backcast: 2001M07				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA1_E	1.378694	0.067707	20.36252	0.0000
MA(1)	0.649952	0.081008	8.023354	0.0000
R-squared	0.628406	Mean dependent var		0.037864
Adjusted R-squared	0.624134	S.D. dependent var		0.710917
S.E. of regression	0.435848	Akaike info criterion		1.199171
Sum squared resid	16.52685	Schwarz criterion		1.255095
Log likelihood	-51.36310	Durbin-Watson stat		2.065797
Inverted MA Roots	-.65			

Table 10: Correlation Matrix

Correlation Between LY and Error Terms			
	Pearson Correlation	**Sig. (2-tailed)**	**N**
AR1_e	0.390	0.000	88
AR12_e	0.398	0.000	87
MA1_e	0.452	0.000	89
ARMA12-e	0.457	0.000	88

Data Series (July, 2001 to December, 2008)