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FORECASTING CROATIAN STOCK MARKET INDEX: CROBEX

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Abstract:
Forecasting stock returns is considered one of the hardest tasks for every potential investor. This paper attempts to predict the movement of Croatian stock market index Crobex on Zagreb Stock Exchange. Main aim of this paper was to empirically examine the best univariate Autoregressive Integrated Moving Average model for forecasting. This research examined ARIMA (p;d;q) model on weekly closed prices of Crobex from 01/01/2011 to 01/01/2013. First it was necessary to meet the stationary condition. While checking the conditions of stationarity, data series were observed by ACF, PACF plots and by Ljung– Box Q statistic and Augmented Dickey–Fuller test statistic. After differencing, statistic showed that the data is stationary and the next step was to find the best ARIMA model. The most important criteria that were used are: R-squared, Adjusted R-squared, Akaike information criterion, Schwarz criterion and Hannan–Quinn information criterion. After checking the exceptionally large number of models it was found the model that suits best, according to the criteria.

Keywords: Croatian Stock Market, Crobex, Forecasting, ARIMA.

Jel Classification: G17

INTRODUCTION

Due to the strong impact of the global economic crisis Croatian stock index Crobex showed no signs of recovery since 2008. Pessimism and the possibility of expanding the debt crisis played an important role in the exceptionally low stock turnover and a large decline in the prices of the aforementioned year. In order to gain better perception of the crisis that affected Croatian capital market we have described the historical movement of the Crobex in the past 13 years.

Timeline of movement stock index Crobex since 2001 flowed mainly at levels below 1000 points with occasional testing these levels. At the end of 2001 the index rose at 1000 points which became his new level of support. At these levels, along with testing new resistance level Crobex remained until the third quarter of 2005 when new resistance level was broken and converted into support level. For about one year index

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remained at that level. In the third quarter of 2006 Crobex prospered and climbed at 3000 points. In the first quarter of 2007 Crobex showed a strong desire to continue the progression and the index break 4000 points and within just 6 months of testing he jumped for then huge 25% and climbed at 5000 points. The level of 5000 points was few times tested in this period and finally peak was reached at a level of 5392 points. In January of 2008 bad news for capital market started. Crobex sunk below 5000 points at the level of 4000 points around which fluctuated until the middle of the first quarter 2008 when the price continued its correction and went below 4000 points. As the bottom could not be seen, at the end of the third quarter of 2008, price collapsed below 3000 points. In mid – November of 2008 price declined below 2000 points until the end of the fifth month of 2009 when the index started to fluctuate at a level of around 2000 points to the present day.

Crobex is an official stock index of the Zagreb Stock Exchange. Only those stocks that are traded more than 90% of the total number of trading days in the six-month period may enter into the composition of the index Crobex. Approximately every six months revision on stocks is conducted. Rank of each stock that meets the requirement of trading days shall be determined on the basis of the free float market capitalization and stock turnover.

Each of the above criteria shall be given a weighting of 50%, with a mean or a weighted market share to be calculated. Crobex index included 25 shares with the highest mean. The index is calculated as the ratio of free float market capitalization and the free float of market capitalization on the base date. The share of free float of market capitalization of individual stocks with a total market capitalization of index Crobex may not exceed 15%. The index is calculated according to the formula that follows:

$$I_t^j = \frac{\sum_{i=1}^{n} p i,t^j \cdot q_{i,T} \cdot f_{i,T}}{K_T \cdot \sum_{i=1}^{n} p_{i,T} \cdot g_{i,T} \cdot f_{i,T}} \cdot B \tag{1}$$

I_t^j Crobex index value on day t at time j

$I_{i,t}^j$ last price of share i on day t at time j

$q_{i,T}$ number of shares i in the issue of their portion on revision day T

$f_{i,T}$ free float factor of share i on the last day of the month preceding revision day T

B index base value, set at 1000 on 01 July 1997

$p_{i,T}$ last price of share i on base date or the day preceding its inclusion in the Crobex index (in case of subsequent inclusion)

K_T index base adjustment coefficient on revision day T

The base date which is taken to calculate the equity index is 01 July1997. The base value amounts to 1000 points. Audit is carried out every six months, or every third Friday in March and September.

BOX–JENKINS METHODOLOGY

To predict future trend or prices there are two basic ways that we can use; causal methods and calculate influence of fundamental indicators on trend and prices or we can forecast using technical analysis and historical patterns. ARIMA belongs to the use of technical analysis. According Orsag (2003) technical analysis focuses on conditions in the capital markets, studying the changes in price and volume of trades, supply and demand, etc. Here are used indicator series from capital markets such as are indices and averages. More about technical analysis see in (Ivanovic 1997; Orsag and Dedi 2011). There are several different methods of analyzing and forecasting time series — naive models, moving averages, exponential smoothing methods, single-equation regression models, Autoregressive Integrated Moving Average models. Box–Jenkins technique, credited to George Box and Gwilym Jenkins, used an iterative approach of identifying a potentially useful model from a general class of models. Box–Jenkins methodology uses both the autoregressive and the moving average techniques for forecasting and tries to find best combination of two methods. Word „best" is associated with model that most accurately predicts future trend. A time series Y_t is said to follow an integrated autoregressive moving average model if the d^{th} – difference $W_t = \Delta^d Y_t$ is a stationary ARMA process. If W_t follows an ARMA (p;d) model, it can be said that Y_t is an ARIMA (p;d;q) process. The current value Y_t is autoregressed on the past p observations: Y_{t-1}, Y_{t-2}…, Y_{t-p}.

ARIMA model therefore have three model parameters, one for the AR—(p) process which present number of autoregressive terms, one for the I—(d) process which present the number of seasonal differences and one for the MA—(q) process which present number of lagged forecast errors in the prediction equation. An autoregressive model generates, a new predictor variable using the Y variable lagged one or more periods.

The general form for the autoregressive class of models in the Box–Jenkins methodology is show in equation that follows.

$$Y_T=\beta_0+\beta_1 Y_{T-1}+\beta_2 Y_{T-2}\ldots\ldots\ldots\ldots+\beta_p Y_{T-p}+\varepsilon_T \tag{2}$$

Y_T = Forecast Y value for the time period T

Y_{T-1}, Y_{T-p} = Y values for time period T lagged 1,2,……p periods.

$\beta_0, \beta_1, \beta_2$ = Regression coefficients

ε_T = Random error component at time T

β_0= Constant (if the data are differenced, the constant can be left out of the equation)

Box–Jenkins methodology, consist of several procedures: 1st phase—identification; 2nd phase—assessment; 3rd phase—diagnostics; and 4th phase—forecasting. Limitations of ARIMA models can only deal with time series that are stationary in the means and variances. If the data isn't stationary then differencing must be used to achieve stationarity.

LITERATURE OVERVIEW

Kalu (2010) investigated forecasting of the Nigerian Stock Exchange by ARIMA (p;d;q) model and his model failed to match market performance between January 2009 and December 2009. U–statistics indicated that ARIMA (1;1;1) forecast of the NSE index outperformed the naive model. Kalu concluded that economic crisis destroyed the correlation between the NSE index and its past. Kalezic, Cerovic and Bozovic (2007) used ARIMA models for estimating inflation rate. They concluded that ARIMA is very effective model in assessing future course of the inflation. Al-Shiab (2006) examined univariate ARIMA forecasting model for predicting Amman Stock Exchange (ASE). Jiban, Hoque and Rahman (2013) successfully examined the best ARIMA model for forecasting daily share price of Square Pharmaceuticals Limited (SPL). Jarrett and Kyper (2011) used ARIMA for predicting Chinese Stock Market. They concluded that daily prices of Chinese stock equity securities have an autoregressive component, and they indicated that the use of intervention analysis is very useful in explaining the dynamics of the impact of serious interruptions in an economy and the changes in the time series of a price index. Bonini et al. (2007) forecasted Italian monthly stock prices by ARMA model. Their resulting model showed both a robust fitting capability when tested in the in-sample period and a good predictive capability when applied to an out of sample period of monthly Italian stock market returns. Junaidi (2011) empirically examined predictability of time series of earnings and stock patterns by means of Autoregressive Integrated Moving Average model. His first hypothesis stated that there is ability in predicting earnings income, and it's statistically supported. Second hypothesis stated that there is the ability of earnings in predicting price pattern that hypothesis was also statistically supported. Zhang (2009) compared ARCH and ARIMA model in stock price forecasting. He concluded that ARCH model has smaller relative error, so ARCH model fitted better than ARIMA.

METHODOLOGY AND DATA

Aim of this paper was to predict Crobex price movement using only the available information which are contained in the historical movements so the time series could be generated. Time series that will be used for forecasting represented weekly closing prices from January 2011 till January 2013. As described at the beginning, major growth on capital market started in 2004 and it lasted to 2008 when a large drop happened. In order to calculate as accurately forecasting as possible, there are chosen time series from 2011 where is no high market volatility recorded and 2011 together with 2012 provides actual data that will be used in prediction of 2013. This research used total of 105 weekly data, 52 weeks in 2011 and 53 weeks in 2012.

Table 1. Crobex descriptive statistics in period: 01/01/2011–01/01/2013

Mean	Median	Max.	Min.	Std. Dev.	Observations
1907.34	1803.90	2311.50	1623.08	226.29	105

Two years were taken in sum 105 observations. To select the best ARIMa model data are split into two periods: estimation period and validation period.

The process of making ARIMA model involves the following steps:

1) Collection of input data that would be used for prediction.
2) Displaying data graphically and by correlogram in order to determine their stationarity, and conducting certain tests that will confirm stationarity [autocorrelation, partial autocorrelation, Ljung–Box Q-test, Augmented Dickey–Fuller test (ADF-test) ….]. If the data are not stationary it is necessary to implement certain procedures to ensure that information will become stationary.
3) The ARIMA models are in the third step assessed by using the Ordinary Least Squares (OLS) method. In order to choose the best ARIMA model there are used following criteria: The Akaike Information Criteria (AIC), Schwartz Information Criteria (SIC), Hannan–Quinn Information Criterion.

First the data were shown graphically to check stationarity. If the data is not stationary there must be suitable transformation steps conducted. In graph that follows it were generated 105 weekly values which are realization of stochastic process.

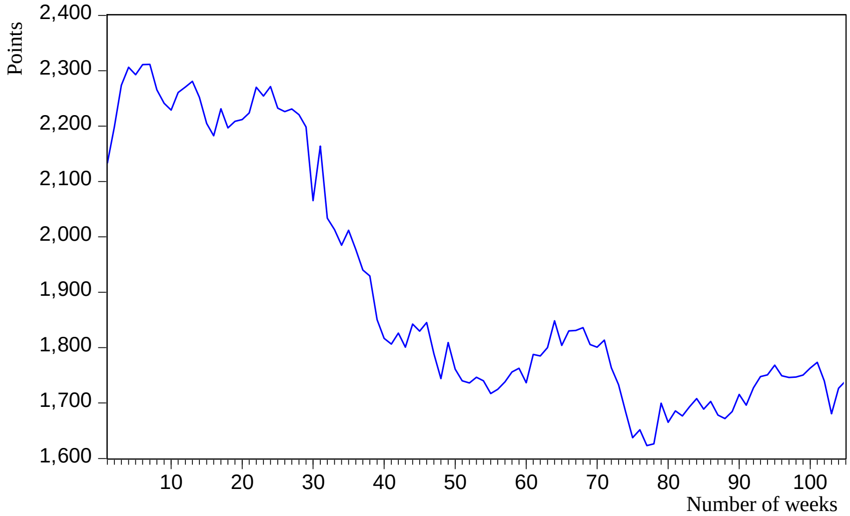


Figure 1. Weekly prices of stock index Crobex

From Figure 1, it can be noticed that observed time series is nonstationary, but it is certainly necessary to conduct a formal statistical control. In this purpose, the test of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were used.

Table 2. Correlogram of original data of weekly Crobex time series

Sample: 1/01/2011– 31/12/2012
Included observations: 105

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|*******	.|*******	1	0.980	0.980	103.66	0.000
.|*******	.|. |	2	0.960	0.004	204.12	0.000
.|*******	**|. |	3	0.931	-0.232	299.56	0.000
.|******|	.|. |	4	0.901	-0.046	389.87	0.000
.|******|	.|. |	5	0.872	0.041	475.22	0.000
.|******|	*|. |	6	0.839	-0.081	555.13	0.000
.|******|	.|. |	7	0.809	0.040	630.24	0.000
.|******|	*|. |	8	0.777	-0.066	700.11	0.000
.|***** |	.|. |	9	0.747	0.033	765.41	0.000
.|***** |	.|. |	10	0.715	-0.052	825.87	0.000
.|***** |	.|. |	11	0.683	-0.036	881.64	0.000
.|***** |	*|. |	12	0.649	-0.066	932.56	0.000

The correlogram indicates high and slowly declining values of empirical Autocorrelation Function and Partial Autocorrelation Function. All values of Autocorrelation Function are positive, and after observed 12 weeks relatively high, for k=12 is 0.649. Higher—order autocorrelation was tested by Ljung–Box Statistics. The value of Q—statistics for k=1 is 103.66, which also indicates autocorrelation. Finally, the analysis of p—value at each unit lag (k=1) indicate the existence of autocorrelation, which confirms that the observed time series is nonstationary.

One of the basic characteristics of the stationary process is rapidly declining values of Sample Autocorrelation Function (SACF). However, in addition to previously mentioned, formal statistical tests have to be conducted in order to determine whether the time series of Crobex weekly closing prices is stationary or not. For this purposes the Dickey–Fuller test statistics was conducted.

Table 3. Unit root testing of original weekly Crobex data

Null Hypothesis: Crobex has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic—based on SIC, maxlag = 12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.057914	0.7299
Test critical values:	1% level	-3.495021	
	5% level	-2.889753	
	10% level	-2.581890	

*MacKinnon (1996) one-sided p–values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(Crobex)
Method: Least Squares
Sample (adjusted): 17/01/2011– 31/12/2012
Included observations: 103 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CRO(-1)	-0.016553	0.015647	-1.057914	0.2926
D(CRO(-1))	-0.152550	0.096736	-1.576981	0.1180
C	26.51611	30.07147	0.881770	0.3800

R-squared	0.037183	Mean dependent var	-4.445049
Adjusted R-squared	0.017926	S.D. dependent var	36.07521
S.E. of regression	35.75040	Akaike info criterion	10.01969
Sum squared resid	127809.1	Schwarz criterion	10.09643
Log likelihood	-513.0142	Hannan–Quinn criter.	10.05078
F-statistic	1.930938	Durbin–Watson stat	1.991599
Prob(F-statistic)	0.150381		

Augmented Dickey–Fuller test is a test for unit root in time series analysis. It was a negative number; the more negative it is, the stronger the rejection of the hypothesis is. In the previous table, values of Dickey–Fuller test values are given (ADF = -1.057914). Comparing to the critical values of ADF test, at the significance level of 1%, 5% and 10%, it's clear that empirical ADF is greater than critical, which confirms null hypothesis that the time series shown on the table 3. was not stationary.

In order to remove nonstationarity, the weekly Crobex prices are differenced. According to Jiban, Hoque and Rahman (2013) differencing is comparatively simple operation that involves calculating consecutive changes in the values of the data series. Differencing is used when the mean of a series is changing over time to time.

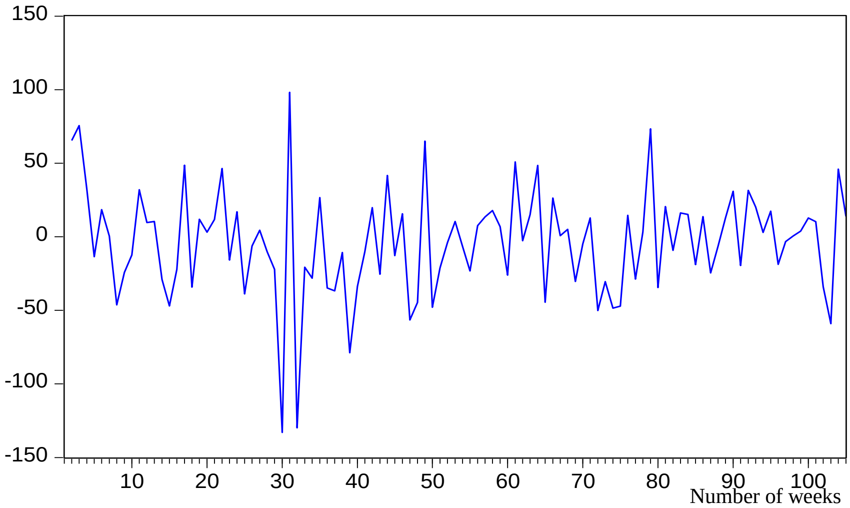


Figure 2. Differenced weekly prices of stock index Crobex

Differencing is simple operation that involves calculating consecutive changes in the values of the data series. Figure 2. showed differenced weekly prices of stock index Crobex. Chart indicates that the values of series fluctuate randomly around zero (average level). The following correlogram is correlogram of 1st differenced values of the observed time series. The next step also confirms that statistically.

Table 4. Correlogram of differenced data of weekly Crobex time series

Sample: 01/01/2011– 31/12/2012
Included observations: 104

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	1	-0.159	-0.159	2.7178	0.099
.|* |	.|* |	2	0.151	0.129	5.1843	0.075
.|. |	.|* |	3	0.039	0.084	5.3506	0.148
.|. |	.|. |	4	0.038	0.038	5.5091	0.239
.|. |	.|. |	5	0.057	0.053	5.8740	0.319
*|. |	*|. |	6	-0.142	-0.147	8.1285	0.229
.|* |	.|* |	7	0.177	0.123	11.679	0.112
*|. |	.|. |	8	-0.093	-0.021	12.665	0.124
.|* |	.|. |	9	0.096	0.059	13.743	0.132
.|. |	.|. |	10	-0.047	-0.024	14.005	0.173
.|. |	.|. |	11	0.025	0.000	14.077	0.229
*|. |	*|. |	12	-0.106	-0.140	15.434	0.219

The value of empirical Autocorrelation function vanished in the first lags (as opposed to the values shown on correlogram shown on the Figure 2), which indicated stationary of differenced time series. This conclusion was confirmed by Ljung–Box values (Q-test Statistics for k=1 is 2.7178) which were on this correlogram extremely small. The stationary was also tested through Dickey–Fuller test.

Table 5. Unit root testing of differenced weekly Crobex data

Null Hypothesis: DCRO has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.01252	0.0000
Test critical values:	1% level	-3.495021	
	5% level	-2.889753	
	10% level	-2.581890	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DCRO)
Method: Least Squares
Sample (adjusted): 3 105
Included observations: 103 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DCRO(-1)	-1.159802	0.096549	-12.01252	0.0000
C	-5.075320	3.545180	-1.431612	0.1553

R-squared	0.588260	Mean dependent var	-0.500971
Adjusted R-squared	0.584184	S.D. dependent var	55.47359
S.E. of regression	35.77148	Akaike info criterion	10.01141
Sum squared resid	129239.5	Schwarz criterion	10.06257
Log likelihood	-513.5874	Hannan–Quinn criter.	10.03213
F-statistic	144.3007	Durbin–Watson stat	1.986748
Prob(F-statistic)	0.000000		

ADF value (ADF statistics = -11.98825), which was less than critical values at all levels of significance indicated that differenced data of Crobex time series was stationary. For processes which are nonstationary, and need to be differenced to become stationary, it can be said that they have integrated order d, because it's necessary to differentiate d—times to achieve stationary. Nonstationary values of Crobex weekly prices have integrated order d=1.

The table below shows the parameters estimated by Ordinary Least Square Method (OLS) and other statistical analytical values for multiple models. After the estimation, the model which best reflects the pattern data series was chosen.

Table 6. Crobex first difference weekly ARIMA (p;d;q) statistic

Variable	R^2	Adj. R^2	AIC	SIC	HQC
AR(1)	0.007	0.007	10.012	10.038	10.022
AR(2)	0.009	0.009	9.970	9.996	9.980
AR(3)	-0.022	-0.022	9.999	10.025	10.010

Table 6. (*continued*)

Variable	R^2	Adj. R^2	AIC	SIC	HQC
AR(4)	-0.021	-0.021	10.008	10.034	10.019
AR(5)	-0.020	-0.020	10.013	10.039	10.023
MA(1)	0.006	0.006	10.038	10.064	10.049
MA(2)	0.018	0.018	10.026	10.052	10.036
MA(3)	-0.005	-0.005	10.050	10.075	10.060
MA(4)	-0.007	-0.007	10.051	10.077	10.061
MA(5)	-0.003	-0.003	10.048	10.073	10.058
AR(1) MA(1)	0.030	0.020	10.008	10.059	10.029
AR(2) MA(2)	0.009	-0.001	9.990	10.041	10.011
AR(3) MA(3)	-0.021	-0.032	10.018	10.070	10.039
AR(4) MA(4)	0.068	0.059	9.937	9.989	9.958
AR(5) MA(5)	0.158	0.149	9.841	9.894	9.863
AR(10) MA(10)	0.214	0.205	9.798	9.852	9.820
AR(15) MA(15)	0.276	0.267	9.747	9.803	9.770
AR(16) MA(16)	0.482	0.476	9.399	9.456	9.422
AR(17) MA(17)	0.317	0.308	9.681	9.737	9.703
AR(18) MA(18)	0.436	0.429	9.498	9.555	9.521
AR(20) MA(20)	0.477	0.470	9.445	9.502	9.468

From the series of models which have been assessed, as the best model was chosen model ARIMA (16;1;16). Namely, the ARIMA (16;1;16) model has the highest value of R square, and the smallest values of the Akaike info criterion (AIC=9.399), Schwarz info criterion (SIC=9.456) and Hannan–Quinn criterion (HQC=9.422).

Once the correct model is selected, it is possible to show actual, fitted and residual form of Crobex weekly closing prices.

Table 7. Correlogram of residuals of weekly Crobex time series

Sample: 05/05/2011–31/12/2012
Included observations: 88
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	0.020	0.020	0.0354	
. | . |	. | . |	2	0.065	0.065	0.4275	
. |*. |	. |*. |	3	0.116	0.114	1.6868	0.194
. | . |	. | . |	4	0.024	0.016	1.7394	0.419
. | . |	. | . |	5	0.045	0.030	1.9334	0.586
.*| . |	.*| . |	6	-0.114	-0.133	3.1837	0.528
.*| . |	.*| . |	7	-0.102	-0.113	4.2054	0.520
.*| . |	.*| . |	8	-0.102	-0.101	5.2420	0.513
.*| . |	.*| . |	9	-0.127	-0.093	6.8572	0.444
.*| . |	. | . |	10	-0.095	-0.059	7.7808	0.455
. | . |	. | . |	11	-0.046	0.005	7.9994	0.534
. | . |	. | . |	12	-0.020	0.017	8.0419	0.625

The correlogram of residuals shows that the values of Autocorrelation function, as well as Partial Autocorrelation functions, are relatively small. In addition, there are small values of Ljung–Box test values, as well as p—values. From this correlogram can be concluded that there is no autocorrelations of residual, which is further evidence of series stationary.

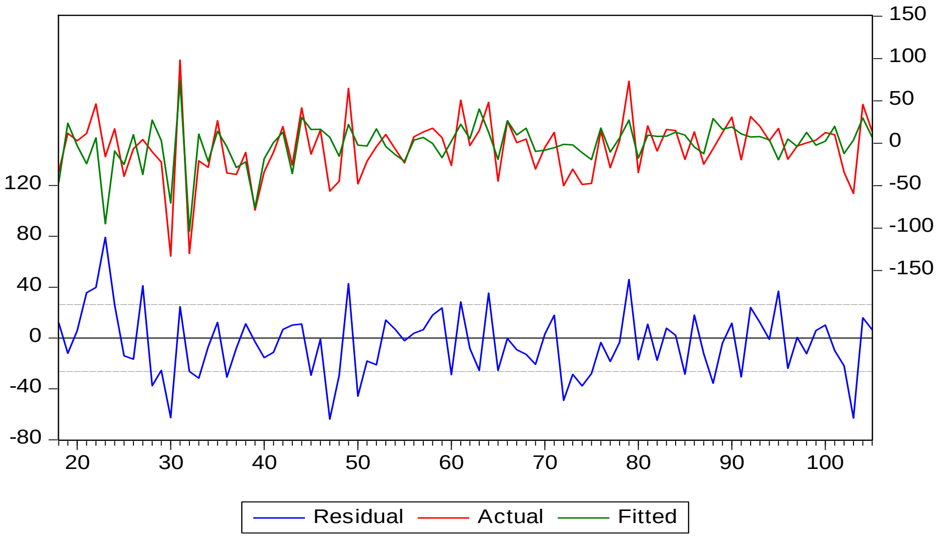


Figure 3. Actual, fitted and residual form of ARIMA (16;1;16) model of forecasting Crobex weekly prices

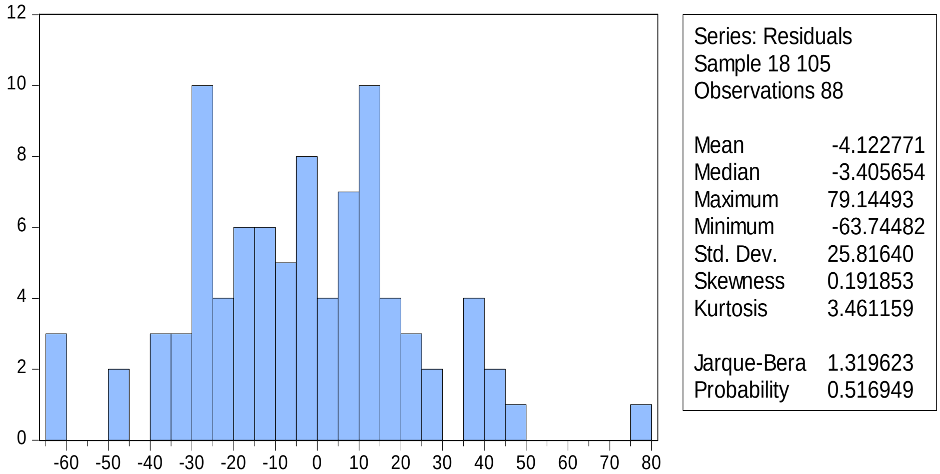
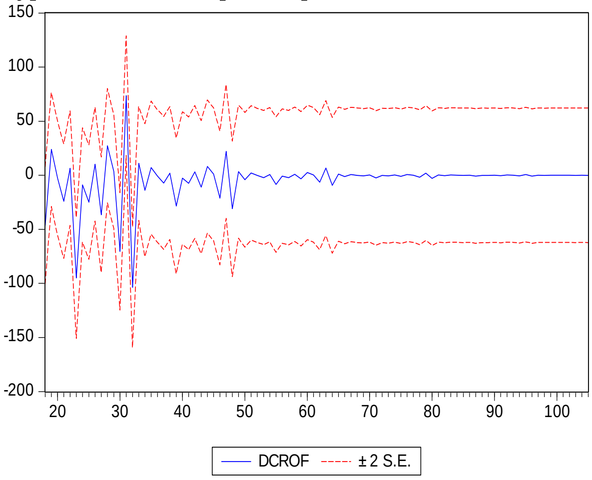


Figure 4. Histogram of residuals Jarque–Bera testing

Figure above presented histogram that showed residuals and Jarque–Bera test. Jarque–Bera test uses the coefficient of skewness and kurtosis of the residuals estimated using the least squares method. It is testing whether the estimated size differ significantly from the values of these measures for normal distribution. Hypothesis H_0 says that "error of relations are normally distributed" it rejects as false if $JB > \chi^2_\alpha$ or alternatively if the empirical significance level of p is less than the theoretical level of significance *α*. As it can be seen from the figure above probability 0.516>α, null hypothesis was accepted as possible.



Forecast: DCROF	
Actual: DCRO	
Forecast sample: 1 105	
Adjusted sample: 18 105	
Included observations: 88	
Root Mean Squared Error	30.60146
Mean Absolute Error	24.67681
Mean Abs. Percent Error	118.3242
Theil Inequality Coefficient	0.528699
Bias Proportion	0.002167
Variance Proportion	0.245990
Covariance Proportion	0.751844

Figure 5. Forecast of Crobex weekly prices, Theil Inequality Coefficient

Figure 5 above shows Thiel's inequality coefficient. Theil's U presents measure how good are time series estimated in comparison to a corresponding time series of observed values. As more Theil's U tends to zero, the better forecasting method is. Our Theil Inequality Coefficient was equal to 0.528699 <1 and confirmed that ARIMA model outperformed naive model.

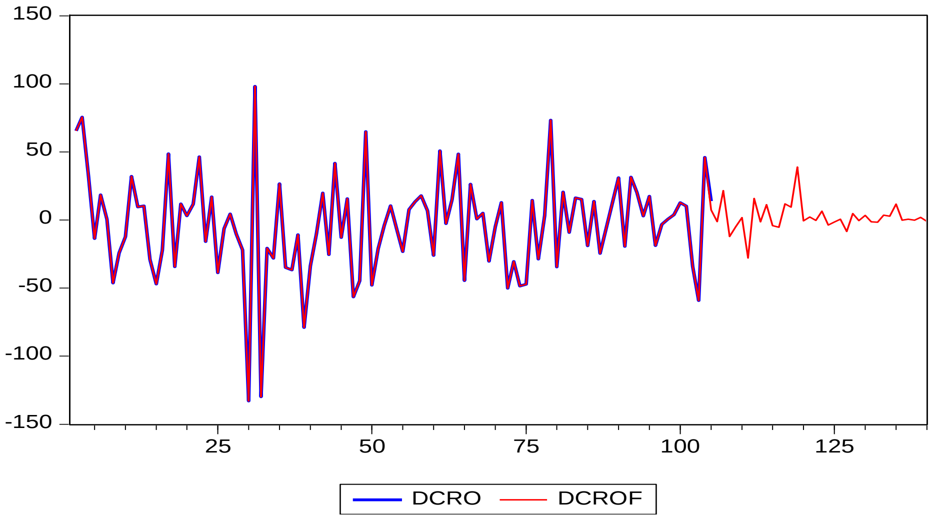


Figure 6. Forecasting with ARIMA (16;1;16)

On the previous figure it can be noticed that bold line presents actual data in sum 105 weeks, thin line presents forecasted period of 35 additional weeks. These values are also presented in the table below.

Table 8. Actual and predicted values from ARIMA model

No. of week	DCRO	DCROF	No. of week	DCRO	DCROF
101	10.2100	10.2100	121	N/A	1.3424
102	-33.9600	-33.9600	122	N/A	-0.3603
103	-59.1100	-59.1100	123	N/A	6.4792
104	45.9900	45.9900	124	N/A	-3.6530
105	13.8500	4.4815	125	N/A	-1.4874
106	N/A	-1.2028	126	N/A	0.5409
107	N/A	21.6296	127	N/A	-8.3713
108	N/A	-12.1951	128	N/A	4.7528
109	N/A	-4.9655	129	N/A	-0.4046
110	N/A	1.8058	130	N/A	3.3854
111	N/A	-27.9460	131	N/A	-1.2575
112	N/A	15.8665	132	N/A	-1.5935
113	N/A	-1.3506	133	N/A	3.5534
114	N/A	11.3018	134	N/A	2.8427
115	N/A	-4.1981	135	N/A	11.6600
116	N/A	-5.3197	136	N/A	-0.1829
117	N/A	11.8624	137	N/A	0.4021
118	N/A	9.4900	138	N/A	-0.1079
119	N/A	38.9248	139	N/A	1.9408
120	N/A	-0.6106	140	N/A	-1.0943

Tabel above showed DCRO which presents differenced actual Crobex data and DRCOF which presents forecasted values for next 35 weeks.

CONCLUSION

Box–Jenkins method or in other words ARIMA doesn't assume there is any particular pattern in the historical data of the series to be forecast, this method uses both past values of Y and past error terms in the forecasting process to produce the model. This research was conducted to find ARIMA model that best fits to forecast of given time series. In this paper weekly data were used from January 2011 till January 2013. While testing the original time series with AC, PAC, Q-stat, ADF, it was concluded that the time series is not stationary. First requirement of ARIMA model was to work with stationary data. It was very important to meet first condition, so the time series was differentiated. After rechecking the stationarity of obtained data next step was to find suitable ARIMA model. Using iterative process, over 200 models were tested. According to criteria R^2, Adj. R^2, AIC, SIC, HQC best model was chosen, it was model (16;1;16). This model was tested by Jarque–Bera whether the tested sample have skewness and kurtosis which matches to normal distribution, and the answer was positive. Statistically speaking > α, null hypothesis was accepted as possible. Theil Inequality Coefficient was equal to 0.528699 which is less than 1 and that confirms that ARIMA model outperformed naive model.

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