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Box–Jenkins Modeling of Greek Stock Prices Data

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ABSTRACT

Recent econometric procedures are employed in this paper to investigate the behavioral properties of Athens Stock Exchange (ASE) indices. The results of serial correlation showed that the hypothesis of weak-form efficiency of ASE should be rejected. The augmented Dickey–Fuller tests and Phillips–Perron tests confirm the existence of unit root on levels of stock prices. The random walk hypothesis matches with auto regressive integrated moving average (0,1,2) model where the future values of stock prices cannot be defined from past values. Afterwards, the results of Theil inequality coefficient indices showed that the forecasting ability of the model is not satisfactory.

Keywords: Market Efficiency, Auto Regressive Integrated Moving Average Models, Stationary and Random Walk Tests, Stock Prices, Forecasting, Greece
JEL Classifications: C53, E27

1. INTRODUCTION

French mathematician Bachelier on his doctoral thesis entitled "Speculation Theory" in 1900 introduced for the first time the meaning of efficient market. On his doctoral thesis he supports that "past, present and even future facts are reflected on market price but often present an unclear relationship on price variations." If markets are competitive, thus efficient, investors will not collect successive gains from investments on these markets. Until now the meaning of efficient capital market has been developed, studied but also doubted from many researchers.

Bachelier's paper, in a large extent, has been ignored until 1930. From 1930, a small number of research showed that stock prices and other financial time series follow the model of random walk (RW) (Cowles, 1933; 1934; Cowles and Jones 1937; Kendall, 1953). From the decade of 1950 and afterwards, economists analyze the macroeconomic time series using computers investigating extensively the issue of efficient markets. Samuelson in 1965 has expanded on Bachelier's theory and supported that "if the market is efficient, prices will show the behavior of RW."

The efficient market hypothesis has been developed from Fama in the beginning of 1965 when he published his doctoral thesis with the title "The Behavior of Stock Market Prices." Fama on his doctoral thesis concludes that stock market fluctuation on prices is unexpected and follows a RW. Even if the hypothesis of efficient market of Fama from empirical analyses showed many problems, Beechey et al. (2000) consider Fama's hypothesis an important starting point from scientific studies.

2. EFFICIENT MARKET HYPOTHESIS

Efficient market hypothesis was emerged as the most important theory in the mid 1960's. Fama is regarded as the "Father" of efficient market hypothesis where he began in 1960 with his doctoral thesis. After in the 1970's he published an article entitled "Efficient Capital Markets: A Review of Theory and Empirical Work" where he suggests two basic meanings. The first consists of three forms of efficiency on stock markets, the weak form, semi-strong and strong form. The second meaning supports that market efficiency can be rejected only when the equilibrium model of the market can be rejected, in other words the mechanism which determines market prices. The present paper examines the three forms of efficiency of financial markets, where each one has different consequences on markets' function. Thus,

- Weak form efficiency argues that future stock prices cannot be predicted with the prices from the past
- Semi-strong form efficiency argues that information for stock prices is available to the public from companies' announcements as well as from the annual stock returns
- Strong form efficiency argues that stock prices use all information (public and private) so nobody cannot win from a monopolistic information for excessive returns.

The prerequisite for the three forms of efficiency is information cost. But because this doesn't happen, Fama (1991) reconsidered the definition of markets efficiency hypothesis. Thus, he supported that "*prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed marginal costs.*" Later, Fama (1998) made a modification on the definition on efficient market hypothesis where he argued that "*the expected value of abnormal returns is zero, but chance generates deviations from zero (anomalies) in both directions.*"

Because the efficient market hypothesis from Fama is regarded as one of the most important proposal on finance, however, there is no consensus from scientists about when the markets are efficient. So, there are many techniques which have been applied from economists and they can accept or doubt about the efficient market hypothesis. In the following paragraph we report some of the papers that have studied the efficient market hypothesis.

3. LITERATURE REVIEW

For efficient market hypothesis many scientists have studied and suggested various models using various econometric techniques and forecasting. Some of them are reported below:

The paper of Moberek and Keasey (2000) show that there is no weak form efficiency in the stock market of Bangladesh. Using daily data for the period 1988-1997 from Dhaka Stock Exchange and techniques from parametric (autocorrelation test, auto regressive integrated moving average [ARIMA] model) and non-parametric tests (Kolmogorov–Smirnov normality test) concluded on the no weak form efficiency.

Pandey (2003) for the analysis of efficient market hypothesis of Indian Stock Market (ISM) used three well-known stock market indices for the period January 1996 until June 2002. Employing autocorrelation techniques and runs tests he concluded that ISM doesn't follow the RW hypothesis.

Worthington and Higgs (2004) examine the efficient market hypothesis for 16 developed European countries. Using daily data and serial correlation techniques and runs test as well as unit root tests and multiple variance ratio (MVR), concluded that from emerging markets (Czech Republic, Hungary, Poland and Russia) only Hungary is characterized from RW so it has a weak form efficiency. From developed countries only Germany, Ireland, Portugal, Sweden and the United Kingdom fulfill the RW hypothesis.

The RW hypothesis is examined also from Tas and Dursonoglu (2005) for the stock market of Istanbul. Using daily data from 1995 to 2004 for Istanbul Stock Exchange National-30 index (ISE-30) and runs tests techniques and Dickey–Fuller unit root test concluded that ISE-30 index does not follow the RW theory.

Hassan et al. (2006) examine seven European Stock Markets which are regarded as emerging as well as their correlations in relation with stock markets of USA and Great Britain. Using weekly data for the period December 1988 until August 2002 and Ljung–Box *Q*-statistic, runs test, and variance ratio tests concluded that the markets of Greece, Slovakia and Turkey are unstable and those of Czech Republic, Hungary, Poland and Russis are unpredictable.

Dragotă et al. (2009) analyze the return of Bucharest Stock Exchange index using Cowels–Jones test, runs test and the MVR. The conclusions of their paper showed that RW hypothesis cannot be rejected for the stock market of Bucharest, thus the weak form efficiency is valid.

RW hypothesis is examined for emerging Visegrad countries (Poland, Czech Republic, Hungary and Slovakia) from Dritsaki (2011). Using techniques of autocorrelation analysis and unit root tests, concluded that for the examined period Visegrad countries follow the RW procedure meaning that on the stock markets of these countries the weak form efficiency is valid. Afterwards, with cointegration tests and causality, Dritsaki examines the short and long-run relationships among the four emerging markets.

Finally, Sekreter and Gursoy (2014) using daily data for the period January 2006 and November 2012 of ISE-100 examined stock market forecasting using quantitative methods with ARIMA models as well as with generalized autoregressive conditional heteroskedastic (GARCH) and exponential GARCH models. The conclusions of the paper present that ARIMA models are best for the forecasting on this paper.

4. STATIONARY AND RW TESTS

According to Greene (2002), many and various econometric problems can arise from non-stationary time series that are examined before using regression analysis. Therefore, economic variables such as stock prices should be examined as far as their stationarity is concerned.

Fama's hypotheses for market efficiency are accepted from the academic world. Many scientists have proposed various techniques for these hypotheses testing. Campbell et al. (1997. p. 32) for the weak form efficiency of the market suggest three different hypotheses: The rationale expectations, the Martingale process and the RW hypothesis. These three forms for RW hypothesis are contained in the RW1, RW2 and RW3 models:

- The RW hypothesis (RW1) is the simplest type of RW and assumes that increments are independently and identically distributed (IID.). It is defined as:

$$P_t = \mu + P_{t-1} + \varepsilon_t \quad \varepsilon_t \rightarrow \mathrm{IID}\left(0, \sigma^2\right) \tag{1}$$

  Where, P_t is the price, μ is the drift term, and ε_t is the error term, with mean 0 and variance σ^2 (Campbell et al., 1997. p. 32)

- The RW hypothesis (RW2) relaxes the probability distribution assumption of RW1 and defines a RW process one where the increments are still independent but not identically distributed (Campbell et al., 1997. p. 32)
- Due to the characteristics of real asset returns, it is virtually impossible to find a real price process who respects the strict assumptions of RW1 or even RW2. Therefore, in the majority of the cases, empirical studies rely on a more general form of RW which drops also the assumption of independence in the increments to include processes that satisfy only the non-correlation requirement (Campbell et al., 1997. p. 32).

The RW3 is the most often empirically tested hypothesis of RW.

Elbarghouthi et al. (2012) report that the weak form efficiency (except for serial correlation tests and runs tests) is based on the RW hypothesis which is connected with stationarity. Thus, the unit root test should be done in order to examine for the stationarity of time series.

If we use the natural logarithm in time series, then we can regard that error term follows a normal distribution.

Using,

$$R_t = \ln\frac{P_t}{P_{t-1}} = \ln P_t - \ln P_{t-1} \quad (2)$$

The weak EMH implies that the log of the price is generated by the following process:

$$\ln\left(P_t\right) = \mu + \ln\left(P_{t-1}\right) + \varepsilon_t \qquad \varepsilon_t \rightarrow IID\left(0,\sigma^2\right) \quad (3)$$

Where, P_t and P_{t-1} are prices of the indices at time t and $t-1$, μ is the possible expected price change or the drift term and ε_t is the error term.

The above function (3) is a RW procedure with drift. So the time series $\ln(P_t)$ has unit root.

5. METHODOLOGY AND DATA

The ability, a researcher has to predict the stock price to meet the fundamental objectives of investors and operators of stock market for gaining more benefits, is priceless. A successful forecasting apart from the earnings it can also limit the hazard and prevent from stock price change in the future. Stock markets are affected from many factors, so the contribution of forecasting methodology is important, as it happens in this paper.

According to function (3) the weak form hypothesis in the market implies that successive stock price changes are independent and identically distributed, so the past movements or trend of a stock price or market cannot be used to predict its future movements. In most empirical studies the weak form efficiency is examined mostly with two tests. The serial correlation test of time series and the unit root test.

Autocorrelation is used to measure the dependence of a variable on its past values. With this test we aim to determine whether the serial correlation coefficients are statistical significant (different from zero). The hypothesis of weak efficiency should be rejected if stock returns are serially correlated. The Ljung–Box (1978) Q-statistics is used, based on autocorrelation coefficients. Autocorrelation coefficients define the linear correlation between two observations of the returns time series. The Q-statistic is asymptotically distributed as a χ^2 variable with degrees of freedom equal to the number of autocorrelations. Under this test, the null and alternative hypotheses are:

H_0: No autocorrelation exist in the data (weak efficient)

H_1: Autocorrelation exist in the data (AR[p] or MA[q] or ARMA[p,q]).

The unit root test is used to test for the hypothesis of weak form efficiency. If returns present unit root then price returns follow a RW procedure, validating the hypothesis of weak form efficiency. Augmented Dickey–Fuller (1979) test and Phillips–Perron (1988) test are used for unit root in Athens Stock Exchange (ASE) returns.

Many methods and approaches for formulating forecasting models are available in the literature. This study deals with time series forecasting model, in particular, the ARIMA models. These models are described by Box and Jenkins (1976).

Box–Jenkins modeling has been successfully applied in various stock markets activities. These models allow investors who have data only from past years such as price shares, to forecast future prices once without having to search for other related time series data which are related with the time series that they study.

Box and Jenkins (1976) were the first who tried to answer in a systematic way if various time series can be depicted on a ARIMA (p,d,q) model. The ARIMA (p,d,q) can be depicted as:

$$\beta(L)\Delta^d y_t = \delta + \alpha(L)\varepsilon_t \quad (4)$$

Where, $\beta(L) = 1 - \beta_1 L - \beta_2 L - \ldots - \beta_p L^p$ is the operator of autocorrelation and $\alpha(L) = 1 - \alpha_1 L - \alpha_2 L - \ldots - \alpha_p L^p$ is the operator of moving average and afterwards forecasts can be done for their future development.

The sample data used in this study consists of daily prices of Athens Stock Market index, for the period from 25 June 1999 until 9 May 2014. The total number of observations of the sample is 3711 and the data are collected from Thessaloniki Stock Exchange Center.

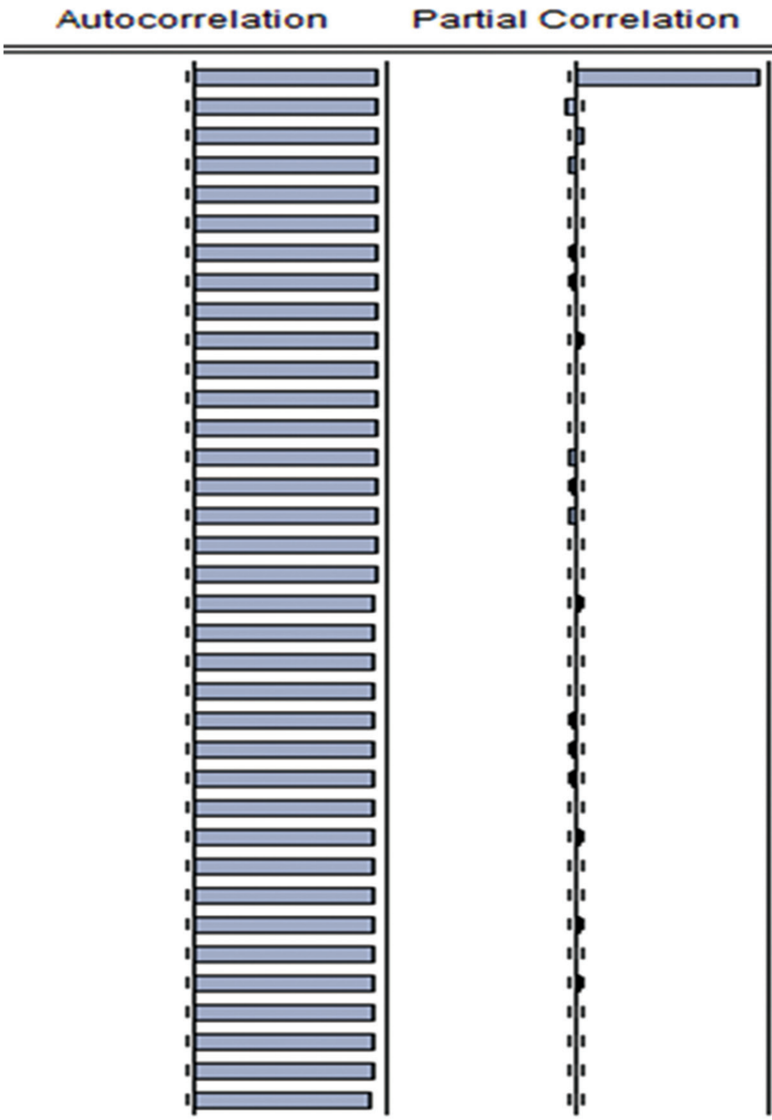
6. EMPIRICAL RESULTS

6.1. Serial Correlation

The results for the tests on serial correlation, Ljung–Box statistics are presented in Tables 1 and 2.

The results on Tables 1 and 2 show that there is autocorrelation in the levels so we reject the null hypothesis for the weak form efficiency of Athens Stock Market prices. Therefore, there will be a form of autocorrelation such as AR(p) or MA(q) or ARMA(p,q). So, we should find which form suits best in the data that we

Table 1: Autocorrelation coefficients and Ljung–Box *Q*-statistics in level of stock price indices



	AC	PAC	Q-Stat	Prob
1	0.999	0.999	3708.4	0.000
2	0.998	-0.052	7411.5	0.000
3	0.998	0.030	11110.	0.000
4	0.997	-0.025	14803.	0.000
5	0.996	-0.007	18491.	0.000
6	0.995	-0.004	22173.	0.000
7	0.994	-0.011	25851.	0.000
8	0.993	-0.023	29522.	0.000
9	0.992	-0.004	33188.	0.000
10	0.992	0.013	36848.	0.000
11	0.991	0.007	40503.	0.000
12	0.990	-0.003	44153.	0.000
13	0.989	0.004	47796.	0.000
14	0.988	-0.032	51435.	0.000
15	0.987	-0.020	55067.	0.000
16	0.986	-0.034	58692.	0.000
17	0.985	0.002	62311.	0.000
18	0.984	0.003	65924.	0.000
19	0.983	0.014	69531.	0.000
20	0.982	0.008	73132.	0.000
21	0.981	0.001	76726.	0.000
22	0.980	0.008	80314.	0.000
23	0.979	-0.012	83897.	0.000
24	0.978	-0.013	87472.	0.000
25	0.977	-0.009	91042.	0.000
26	0.976	-0.008	94605.	0.000
27	0.975	0.010	98162.	0.000
28	0.974	-0.006	101712	0.000
29	0.973	0.001	105256	0.000
30	0.972	0.014	108794	0.000
31	0.971	-0.003	112325	0.000
32	0.970	0.010	115850	0.000
33	0.969	0.001	119369	0.000
34	0.968	0.000	122882	0.000
35	0.967	-0.006	126389	0.000
36	0.966	-0.008	129889	0.000

examine. In order to find the form of model for Athens stock prices the methodology of Box–Jenkins is applied.

The Box–Jenkins methodology consists of the following phases:

6.2. Testing for Non-stationarity

The detection of stationarity of time-series. If time series is non-stationary in the levels, then we gradually get first or second differences for achieving stationarity. Augmented Dickey–Fuller (1979) and Phillips–Perron (1988) tests are used for testing stationarity of time series.

The results of Table 3 show that time series of ASE index is stationary in first differences. Therefore, on ARIMA (p,d,q) model, d equals 1 ($d = 1$).

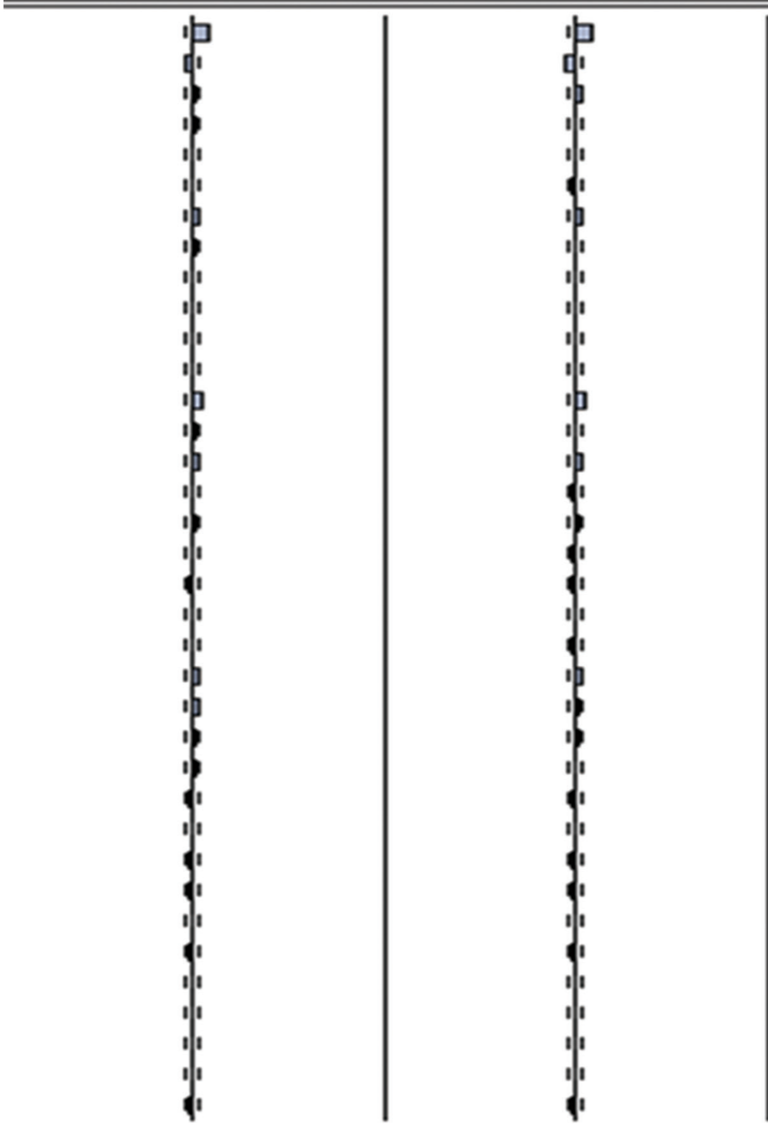
6.3. Identification of the Model ARMA(p,q)

From the behavior of coefficient values of autocorrelation ρ_k and the coefficients of partial autocorrelation φ_{kk} of Table 2 we can determine the form of the model ARMA(p,q). The p parameter of autoregressive operator $\beta(L)$ on function (4) is determined from the coefficient of partial autocorrelation where $\varphi_{kk} = 0$ for $k > p$. Another simple way to determine the significance of partial autocorrelation is to compare its value with the critical value $\pm\frac{2}{\sqrt{n}}$.

The q parameter of operator from moving averages $\alpha(L)$ on function (4) is determined from autocorrelation coefficient ρ_k where $\rho_k = 0$ for $k > p$. Another simple way to determine the significance of coefficient autocorrelation $\hat{\phi}_{kk}$ is to compare its value with the critical value $\pm\frac{2}{\sqrt{n}}$.

Afterwards, I find the critical value from $\pm\frac{2}{\sqrt{n}}$ which is $\pm\frac{2}{\sqrt{3711}} = \pm 0.033$. From the column of autocorrelation coefficients of Table 2 we observe that only the values of coefficients ρ_1 and ρ_2 are larger than the value ±0.033, while from

Table 2: Autocorrelation coefficients and Ljung–Box *Q* statistics in first differences of stock price indices



Lag	AC	PAC	Q-Stat	Prob
1	0.093	0.093	32.238	0.000
2	-0.043	-0.052	39.073	0.000
3	0.022	0.031	40.813	0.000
4	0.012	0.005	41.350	0.000
5	0.005	0.006	41.437	0.000
6	-0.008	-0.009	41.685	0.000
7	0.025	0.027	44.015	0.000
8	0.011	0.005	44.459	0.000
9	-0.005	-0.004	44.555	0.000
10	-0.008	-0.007	44.765	0.000
11	0.001	0.002	44.771	0.000
12	0.008	0.007	45.017	0.000
13	0.043	0.043	51.929	0.000
14	0.016	0.008	52.894	0.000
15	0.028	0.030	55.818	0.000
16	-0.002	-0.009	55.841	0.000
17	0.015	0.019	56.722	0.000
18	-0.005	-0.011	56.802	0.000
19	-0.015	-0.012	57.694	0.000
20	0.004	0.003	57.757	0.000
21	-0.007	-0.010	57.953	0.000
22	0.028	0.030	60.928	0.000
23	0.027	0.022	63.649	0.000
24	0.025	0.023	65.901	0.000
25	0.009	0.005	66.186	0.000
26	-0.013	-0.015	66.824	0.000
27	0.005	0.005	66.902	0.000
28	-0.008	-0.014	67.162	0.000
29	-0.014	-0.013	67.900	0.000
30	-0.001	-0.003	67.904	0.000
31	-0.023	-0.024	69.891	0.000
32	-0.004	0.002	69.948	0.000
33	-0.005	-0.005	70.029	0.000
34	-0.003	0.000	70.064	0.000
35	0.000	-0.002	70.064	0.000
36	-0.014	-0.015	70.832	0.000

Table 3: Unit root tests of stock price indices

ASE indices	ADF		PP	
	C	C, T	C	C, T
Level	−0.923 (2)	−1.341 (2)	−0.957 [12]	−1.398 [12]
First difference	−43.163 (1)*	−43157 (1)*	−55.387 [9]*	−55.379 [9]*

*,**,***Imply significance at the 1%, 5%, 10% level, respectively, The numbers within parentheses for the ADF, represents the lag length of the dependent variable used to obtain white noise residuals, The lag length for the ADF equation was selected using AIC, The numbers within brackets for the PP statistics represent the bandwidth selected based on Newey–West (1994) method using Bartlett Kernel. MacKinnon critical value for rejection of null hypothesis of a unit root a significant at the 1% level. AIC: Akaike information criterion, PP: Phillips-Perron, ADF: Augmented Dickey-Fuller

Table 4: Choice of ARMA models with AIC, SIC and (HQ) criteria

p	*q*	AIC	SIC	HQ
0	1	−5.194	−5.191	−5.193
0	2	−5.196	−5.191	−5.194
1	0	−5.193	−5.188	−5.192
1	1	−5.195	−5.190	−5.193
1	2	−5.195	−5.188	−5.193
2	0	−5.195	−5.190	−5.193
2	1	−5.195	−5.188	−5.193
2	2	−5.196	−5.188	−5.193

HQ: Hannan-Quinn, AIC: Akaike information criterion, SIC: Schwartz information criterion, ARMA: Autoregressive-moving-average

the column of partial autocorrelation the values $\hat{\phi}_1$ and $\hat{\phi}_2$ are larger that critical value ±0.033. So we get that value of p between $0 \le p \le 2$ (because parameter p is determined from the coefficient of partial autocorrelation) and the value of q between $0 \le q \le 2$ (because parameter q is determined from autocorrelation coefficient). In the meantime a table is created with the values of p and q (Table 4).

The results of Table 4 show that according to Akaike information criterion, Schwartz information criterion and Hannan–Quinn the ARMA model is of the form ARMA (0,2) because we get the smallest values of these criteria. Due to the fact that the model is stationary in first differences which means that ($d = 1$), the ARIMA model will be ARIMA (0,1,2). Afterwards, we continue with the next phase, estimating this model.

6.4. Estimation of the Model ARIMA (0,1,2)

The estimation of ARIMA model (0,1,2) is presented on Table 5.

From the estimation of ARIMA (0,1,2) we can see that the coefficients are statistically significant in 1% level of significance. So, we can use this model. Its form is presented below:

DLP = −0.0003 + 0.1007e_{t-1} – 0.0488e_{t-2} + e_t
t-statistics = (−1.037), (6.141)… (−2.843)
P = [0.299] [0.000]… [0.004]
Standard error = {0.0003}, {0.016}… {0.016}

6.5. Diagnostic Checking of the Model ARIMA (0,1,2)

On Table 6 the residuals testing if given, from the results of Table 6 we can see that *Q*-statistics Ljung–Box test which follows χ^2 distribution with $v = k-p-q$ degrees of freedom gives probability values larger than 5% which means that the residuals are not autocorrelated. Therefore, this model can be used for forecasting.

6.6. Prediction Validity for the Models

Theil's inequality coefficient (*U*) measures the prediction accuracy of a model ARIMA (0,1,2). Theil's inequality coefficient (*U*) can be calculated from the following equation (Theil, 1961):

$$U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{Y}_t - Y_t\right)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{Y}_t\right)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t\right)^2}} \qquad 0 \le U \le 1 \qquad (5)$$

Where,

Y_t: Actual value of endogenous variable at time *t*.

$\hat{Y}_t$: Redacted value of endogenous variable at time *t*.

T: Number of observations in the simulations (of the sample).

If Theil's inequality coefficient equals zero $U = 0$, then actual values of the series are equal to estimated $Y_t = \hat{Y}_t$ for all *t*, so in this case there is a "perfect fit" between actual and predicted data. On the other hand, if inequality coefficient equals one $U = 1$, there is no proper forecasting for the examined model. We present the indices of Theil's called as "proportions of inequality" and are the following:

- Bias proportion: Indicates the systematic differences in actual and forecasted values

$$UM = \frac{\left(\bar{\hat{Y}} - \bar{Y}\right)^2}{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{Y}_t - Y_t\right)^2} \qquad (6)$$

Where, $\bar{\hat{Y}}$ and $\bar{Y}$ are the means of the series of $\hat{Y}_t$ and Y_t respectively. The bias proportion measures the distance between the mean of simulated series from the mean of actual series

- Variance proportion: Indicates unequal variances of actual and forecasted values

$$US = \frac{\left(s_{\hat{Y}} - s_Y\right)^2}{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{Y}_t - Y_t\right)^2} \qquad (7)$$

Where, $s_{\hat{Y}}$ and s_Y are the standard deviations of the series $\hat{Y}_t$ of and Y_t respectively. The proportion of variance measures the distance between the variance of simulated series from the variance of actual series

- Covariance proportion: Indicates the correlation between the actual and forecasted values (zero = perfect correlation between actual and forecasted values)

$$UC = \frac{2(1-\rho)\, s_{\hat{Y}}\, s_Y}{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{Y}_t - Y_t\right)^2} \qquad (8)$$

Where, ρ is the correlation coefficient between $\hat{Y}_t$ and Y_t. The proportion of covariance measures the non-systematic error of simulation.

Table 5: Estimation of ARIMA (0,1,2) model

Dependent variable: DLP
Method: Least squares
Date: 01/16/15 Time: 09:44
Sample (adjusted): 23711
Included observations: 3710 after adjustments
Convergence achieved after 5 iterations
MA Backast: 0 1

Variable	Coefficient	Standard error	*t*-statistics	*P*
C	−0.000323	0.000312	−1.037385	0.2996
MA (1)	0.100791	0.016411	6.141744	0.0000
MA (2)	−0.046668	0.016411	−2.843674	0.0045
R^2	0.011843	Mean dependent variable	−0.00323	
Adjusted R^2	0.011310	SD dependent variable	0.018103	
SE of regression	0.018000	AIC	−5.196076	
Sum squared resid	1.201074	SC	−5.191048	
Log likelihood	9641.722	HQ criterion	−5.194287	
F-statistic	22.21462	Durbin-Watson statistics	2.001344	
P (*F*-statistic)	0.000000			
Inverted MA roots	0.17	−0.27		

Autoregressive-moving-average, HQ: Hannan-Quinn, AIC: Akaike information criterion, SIC: Schwartz information criterion, SD: Standard deviation, SE: Standard error

Table 6: Diagnostic residual test of ARIMA(0,1,2) model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.001	-0.001	0.0035	
		2	0.002	0.002	0.0145	
		3	0.021	0.021	1.6328	0.201
		4	0.009	0.009	1.9339	0.380
		5	0.007	0.007	2.1209	0.548
		6	-0.010	-0.011	2.5291	0.639
		7	0.025	0.025	4.9188	0.426
		8	0.008	0.008	5.1627	0.523
		9	-0.004	-0.004	5.2172	0.633
		10	-0.007	-0.008	5.3956	0.715
		11	0.003	0.003	5.4374	0.795
		12	0.004	0.003	5.4923	0.856
		13	0.043	0.044	12.499	0.327
		14	0.009	0.009	12.794	0.384
		15	0.031	0.030	16.275	0.235
		16	-0.007	-0.009	16.446	0.287
		17	0.017	0.017	17.549	0.287
		18	-0.005	-0.007	17.634	0.346
		19	-0.015	-0.015	18.522	0.357
		20	0.008	0.004	18.739	0.408
		21	-0.010	-0.011	19.140	0.448
		22	0.028	0.028	22.169	0.331
		23	0.022	0.023	23.996	0.293
		24	0.022	0.022	25.850	0.258
		25	0.009	0.008	26.167	0.293
		26	-0.014	-0.016	26.889	0.310
		27	0.006	0.004	27.043	0.354
		28	-0.008	-0.011	27.290	0.394
		29	-0.014	-0.015	28.052	0.408
		30	0.002	-0.001	28.072	0.461
		31	-0.024	-0.024	30.234	0.402
		32	-0.001	-0.000	30.239	0.453
		33	-0.005	-0.003	30.339	0.500
		34	-0.004	-0.001	30.393	0.548
		35	0.003	0.001	30.436	0.595
		36	-0.019	-0.019	31.736	0.579

The relationship between the previous percentages is $UM + US + UC = 1$

On the Figure 1 the actual and fitted values of ASE are presented as well as the residuals from the estimation function of ARIMA (0,1,2) model. Also, Theil's index is estimated as well as the other indices for the forecasting ability of the model.

The results of the forecasting of the ARIMA (0,1,2) model show that Theil inequality coefficient is very close to 1 and the proportion of variance is very high (US = 0.9522). So, we can say that with ARIMA (0,1,2) model we don't get a good forecasting for the variations of the stock prices of ASE.

7. CONCLUSION

This paper has investigated empirically the efficiency of ASE. The efficient market hypothesis has been assessed using recent econometric procedures such as serial correlation and unit root test.

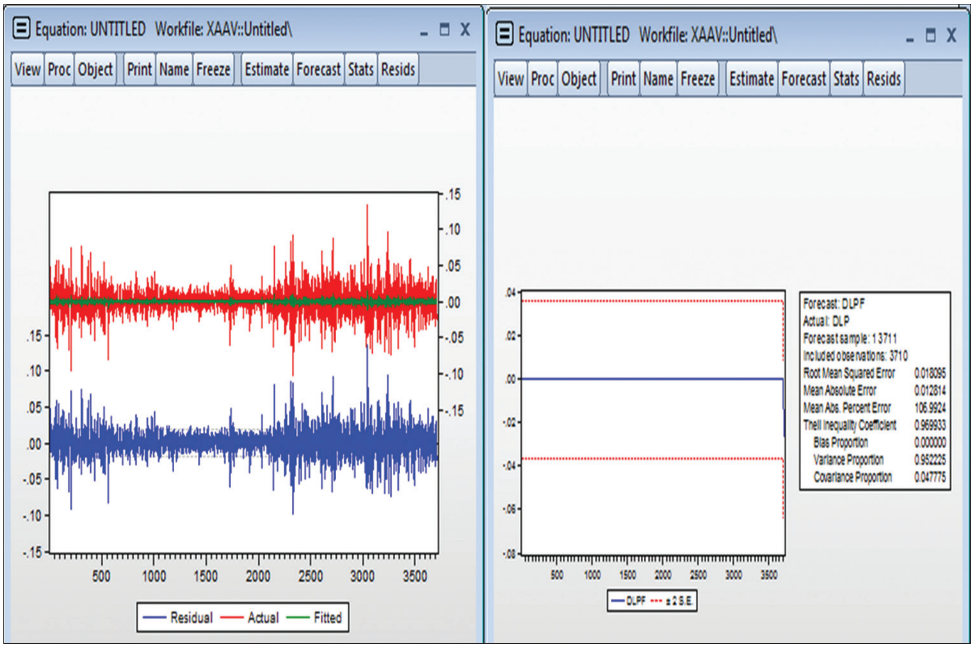
The results of serial correlation showed that the hypothesis of weak form efficiency of ASE should be rejected due to serial correlation. On the other hand, stock market index present a unit root both with constant and constant and trend on the same time lags.

Whilst the price indices series showed deterministic or stochastic trends, nevertheless, the presence of a unit root (non-stationarity) in stock prices is only a necessary (but not sufficient) condition for a random-walk process.

Moreover, the RW model fits the ARIMA (0,1,2) model where the future value of share prices cannot be determined on the basis of past information.

Finally, Theil inequality coefficient showed that on this model we cannot have correct forecasting for ASE stocks.

Figure 1: Actual, fitted values and residuals



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