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The Predictability of the Amman Stock Exchange using the Univariate Autoregressive Integrated Moving Average (ARIMA) Model

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Abstract

This study examines the univariate ARIMA forecasting model, using the Amman Stock Exchange (ASE) general daily index between 4/1/2004 and 10/8/2004; with out-of-sample testing undertaken on the following seven days. Different diagnostic tests were performed to find the best model describing the data. The selected model predicted that the ASE would continue to grow by 0.195% for seven days starting on 11/8/2004. This forecast, however, was not consistent with actual performance during the period of the prediction (11/8/2004 – 19/8/2004) since ASE declined by –0.003% assuring the fact that ASE followed most closely the EMH in its weak form.

I. Introduction

Increased economic activity brings an increased demand for capital. Historically, the best means of meeting this demand is through a stock exchange. In March, 1999 the Amman Stock Exchange (ASE) was transformed into a non-profit, private institution with administrative and financial autonomy. It is authorized to function as an exchange for the trading of securities. The ASE is committed to the principles of fairness, transparency, efficiency, and liquidity.

In Jordan everything connected with stock market operations has had an unfavorable public image. This is because the Jordan stock exchange began almost as a private club, catering to a handful of members; not as a public institution functioning for the public good. As a result, the stock exchange still remains an institution in which only a microscopic section of the country is interested. Inadequate disclosure practices by Jordanian companies listed in the stock market and, consequently, more speculative activities in the securities market help explain the lack of public trust.

As a consequence, the Jordanian government adopted a comprehensive capital market reform policy in order to: 1) boost the private sector; 2) expand and diversify the national economy and; 3) improve regulation of the securities market to meet international standards. Among the most important changes to the capital markets were: 1) use of international electronic trading, settlement and clearance systems; 2) elimination of obstacles to investment and; 3) strengthening capital market supervision. The goal of capital market supervision was to establish transparency in operation and safe trading in securities, in keeping with international standards.

The Temporary Securities Law, No. 23, of 1997 was a turning point for the Amman Stock Exchange. Its aim was to restructure and regulate the Jordanian capital market in conformity with international standards. The Amman Stock Exchange observes international standards of fair practice in the orderly conduct of the market.

To comply with international standards and best practices since 1998, the ASE has worked closely with the Jordan Securities Commission (JSC) on surveillance matters and maintains strong relationships with other exchanges, associations, and international organizations. The ASE is an active member of the Union of Arab Stock Exchanges, Federation of Euro-Asian Stock Exchanges (FEAS), an affiliate member of the World Federation of Exchanges (WFE), and an affiliate member of the International Organization for Securities Commissions (IOSCO).

The above significant changes in the way of running the capital market compared to past history where the market suffered from severe operational and informational problems has raised up the issue whether such improvements will be reflected on the capital market future performance.

Forecasting is an important part of econometric analysis, especially when talking about capital markets and their performance. In this respect the Autoregressive Integrated Moving Average (ARIMA), popularly known as the Box-Jenkins methodology, is one of the most popular forecasting methods.

However, research in the forecasting field has largely centered on three alternative approaches. The first is based around vacancy rates (Wheaton 1987; Wheaton and

Torto 1988). The second has tended to use supply and demand variables in reduced form models. The third uses forecast models based on rental forecasting (Brooks and Tsolacos 2000; Brooks and Tsolacos 2001; MacGarth 2003; Tsolacos 2002; Tsolacos et al. 1998). In the last decade there has been an increasing amount of empirical research on property markets (Chandrashekaran and Young 2000; Geltner and Mei 1995; Karakozova 2004; Siviatanides 1998; Siviatanides et al. 2001; Siviatanidou and Siviatanides 1999; Viezer 1999). So far, studies of emerging capital markets have been limited to describing them. As far as this researcher knows, this is the first study to deal with forecasting the future performance of the ASE.

The rest of the paper is organized as follows: Section II presents the literature, Section III describes the methodology of the study, Section IV presents the empirical results and discusses them, Section V provides concluding comments.

II. Review of the Literature

A search of the literature found very few studies using the Univariate ARMIMA model. One of the few papers was written by Wilson et al. (2000). This study, "*Comparing Univariate Forecasting Techniques in Property Markets*," focused on predicting turning points in a securitized real estate return series in the US, the UK and Australia. These authors employ ARIMA and exponential smoothing models to identify turning points and compare the performance of these models with a spectral technique. The former two models study the behavior of returns and forecast turning points from the time domain, whereas the latter provides a view of the frequency domain. In this way, the authors attempted through spectral analysis to identify hidden cycles of differing lengths and amplitudes in the return series. The findings of this study show that the spectral analysis, which assumes a four-year cycle in the data, performs well in capturing turning points in all quarterly series of real estate returns. Moreover, the study found that spectral analysis identified more clearly turning points than ARIMA and outperformed the exponential smoothing models which, as expected, did not predict the turning points. The Study demonstrated the ability of different models to predict turning points. The study further showed the need to do use frequency domains to study the cyclical behavior of real estate returns.

Leong and Maki (2000) considered the long-run neutrality hypothesis using Australian data. A reduced form autoregressive integrated moving average (ARIMA) model was used with both quarterly seasonally unadjusted and adjusted Australian real GDP and nominal money supply to test the neutrality hypothesis. Using two measures of money stock, M1 and M3, it was shown that the hypothesis was supported using M1 as a measure of money supply, that is, changes in M1 had no effects on changes in real output. However, the long-run neutrality hypothesis was rejected using M3, in that changes in M3 significantly affect changes in real output. These results, when the real Australian GDP was applied to the long-run neutrality hypothesis, indicate that the type of money supply used greatly effects the outcome.

Brooks and Tsolacos (2001b) studied a single real estate return series in the UK, examining the forecasting performance of three different methodologies. The first forecasting methodology took the unconditional mean from a trailing sample of 200 observations of real estate returns. Such a model is identical to a random walk with drift in the log of the prices. The other forecasting methodologies are the ARMA model and vector autoregressive model (VAR). Along with real estate returns, two other variables are included in the VAR system, namely; the term structure of interest rates and the gilt-equity yield ratio. Brooks and Tsolacos used these methodologies to produce 160 out-of-sample forecasts for horizons of up to six months. The forecast evaluation criteria demonstrated that the long-term mean and the ARMA specification are more appropriate for forecasting in the short-term (i.e. one month ahead) than the more complex VAR model. However, the latter model produces the highest proportion of the correct return sign predictions. For the six months forecast, the long-term means return produces the most accurate forecasts under all evaluation measures.

Another study conducted by Brooks and Tsolacos (2003) explored the issue of forecasting real estate returns for five European countries: the UK, Belgium, the Netherlands, France and Italy. Using the VAR mathematical system it was demonstrated that the gilt-equity yield ratio was, in most cases a better predictor of securitized returns, then the term structure or the dividend yield. In particular, investors should consider, when using real estate return models, the accuracy of prediction of the gilt-equity ratio in Belgium, the Netherlands, and France, and the term structure of interest rates in France.

When predictions obtained from the VAR and univariate time-series models were compared with the predictions of an artificial neural network models; it was found no single model was universally superior in all series Accuracy and horizons considered, the neural network model is generally able to offer the most accurate predictions over one month horizons. For quarterly and biannual forecasts, the random walk with a drift is the most successful for the UK, Belgium and Dutch returns and the neural network for French and Italian returns. Although this study underscores market context and forecast horizon as parameters relevant to the choice of the forecast model, it also demonstrates that analysis should exploit the potential of neural networks and assess more fully their forecast performance as opposed to more traditional models.

Forecasting accuracy was tested for five models: the ARMIA model, the Bayesian Vector Autoregression approach, the OLS based single equation model and the simultaneous equation model by Stevenson and MacGarth (2003). These models were estimated using the CB Hiller Pasrker London Office index between the years of 1977-1996, with out-of-sample testing with data gathered over three years. Diagnostic testing is also conducted on the alternative models. The findings reveal that the Bayesian VAR model produces the best forecasts, while the ARIMA model fails to account for the large uptake in rental values during the testing period.

Karakozova (2004) conducted an econometric study of office returns determination in the Helsinki area, a small European market, over a 30-year period from 1971 to 2001. This study investigates variations in office capital growth, which is the most volatile component of total office returns, in the Helsinki market using three alternative models. These models are: a regression model, an error correction model (ECM), and the ARIMA model with an exogenous explanatory variable (i.e. ARIMAX). Karakozova also evaluates the forecasting performance of the alternative specifications. These results indicate that the ARIMAX models, incorporating past values of capital growth and growth in service sector employment and in the gross domestic product, are able to account for extreme fluctuation in the data, and thus provide the best forecasting tool for office returns in Helsinki. The ECM models, which incorporate long-run information, can not satisfactorily account for the irregularities in the Helsinki office market, such as the boom-bust cycle of the 1980s and 1990s, and thus are suitable for modeling and forecasting only part of the Helsinki market. Karakozova predicted that office capital returns will continue to grow in real terms by an average of 0.1% between 2002 and 2005. This study demonstrates that real office total returns will grow at an average rate of 5.7% over the same time period.

III. Methodology and Data Selection

There are five approaches to economic forecasting based on time series data. These are: exponential smoothing methods, single-equation regression models, simultaneous-equation regression models, autoregressive integrated moving average models (ARIMA), and vector auto-regression (VAR).

The ARIMA model is unique, because it does not construct either a single-equation or simultaneous-equation model; but instead analyzes the probabilistic, or stochastic, properties of an economic time series, then lets the data speak for itself. Unlike the regression models, in which Y_t is explained by the K explanatory variable, the Box-Jenkins methodology allows Y_t to be explained by past or lagged values of Y itself and stochastic error terms. For this reason, ARIMA models are sometimes called *atheoretic* models, because they are not derived from any economic theory that is based on simultaneous-equations models.

Y_t follows a first-order autoregressive or AR(1), stochastic process, if the following equation is true:

$$(Y_t - \delta) = \alpha_1 (Y_{t-1} - \delta) + u_t \qquad (1)$$

where δ is the mean of Y and where u_t is the uncorrelated random error term with zero mean and constant variance σ^2 (i.e. it is *white noise*). The above model demonstrates that the value of Y at time t depends on its value in the previous time period and a random term, where the Y values are expressed as deviations from their mean value. In other words, the model indicates that the forecast value of Y at time t is simply some proportion of its value at time $(t-1)$ equal α_1 plus a random shock or disturbance at time t. If the value of Y at time t depends on its value in the previous two time periods, it can be said that Y_t follows a second-order autoregressive or AR(2). One way of expressing the model is:

$$(Y_t - \delta) = \alpha_1 (Y_{t-1} - \delta) + \alpha_2 (Y_{t-2} - \delta) + \ldots.. + \alpha_p (Y_{t-p} - \delta) + u_t \qquad (2)$$

Equation (2) is a pth-order autoregressive or AR(p) process.

It should be understood that the AR(p) process is not the only mechanism that could have generated Y. If Y at time t is equal to a constant plus moving average of the current and past white noise error terms, it is said that Y follows a first-order moving average or MA(1) process expressed as:

$$Y_t = \mu + \beta_0 u_t + \beta_1 u_{t-1} \qquad (3)$$

In general, The model may be expressed as:

$$Y_t = \mu + \beta_0 u_t + \beta_0 u_{t-1} + \beta_0 u_{t-2} + \ldots + \beta_0 u_{t-q} \qquad (4)$$

Equation (4) is said to be a pth-order moving average or MA(q) process.

It is quite likely that *Y* has the characteristics of both AR and MA, which is called ARMA and *Y*, it therefore, follows an ARMA(q, p) process written as:

$$Y_t = \theta + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \beta_0 u_t + \beta_0 u_{t-1} + \beta_0 u_{t-2} + \ldots + \beta_0 u_{t-q} \qquad (5)$$

Where θ represents a constant.

The time series models we have discussed all assume that the time series is stationary. In other words, the mean and variance for the series are constant and its covariance is time invariant. The logic behind the stationary assumption is that, if the estimated model used for forecasting is stationary, then it must be assumed that the features of this model are constant through time, and particularly over future time periods. The reason for requiring stationary data is that any model, which is inferred from these data, can itself be interpreted as stationary or stable, therefore, providing valid basis for forecasting.

It could be argued that many financial and economic data series are non-stationary, but are integrated instead. For example, if a time series is integrated of the first order (i.e. it is I(1)), its first differences are I(0), that is stationary. Generally speaking, if a time series is I(d) after differencing it *d* times, I(0) can be obtained. If we have to difference a time series *d* times to make it stationary and then apply the ARMA(q, p) model, we say that the original time series is ARIMA(q, d, p), that is, it is an autoregressive integrated moving average time series. The stationary issue can be checked by adopting the Dickey-Fuller, Augmented Dickey-Fuller, and Phillips-Perron unit root tests.

In order to adopt the proper model, the *q*, *d*, and *p* values should be determined.

Correlogram and partial correlogram will be used in this paper to find these values. Consequently, the model to be tested can be rewritten as:

$$Y^*_t = \theta + \alpha_1 Y^*_{t-1} + \alpha_2 Y^*_{t-2} + \ldots + \alpha_p Y^*_{t-p} + \beta_0 u_t + \beta_1 u_{t-1} + \ldots + \beta_1 u_{t-q} \qquad (6)$$

Where Y^* denote the *d* difference of a time series.

Having identified the appropriate *q* and *p* values, we now need to estimate the parameters of the autoregressive moving average terms included in the model using the E-views. The chosen model needs to be tested, to be certain it fits the data, because another ARIMA model could perform better or at least as well. That is why adopting Box-Jenkins ARIMA modeling needs considerable skill to choose the proper ARIMA model. Some of those tests required are: R-squared, Adjusted R-squared, Akaike info criterion (AIC), Shwarz criterion (SIC), Durbin-Watson (D-W), and Jarque-Bera for the residuals. The model chosen should have the lowest AIC and SIC on one hand and the highest R-squared and Adjusted R-squared on the other and its D-W more close to (2).

Econometricians argue that volatility clustering is one of the special problems involved in forecasting the fluctuation of prices of financial assets (Gujariti 2003). This argument can be verified by adopting the Autoregressive Conditional Heteroscedasticity (ARCH LM) model for the residuals.

Having met our standards and after selecting the model that best fits the data, MINITAB was used to forecast the ASE daily general index for the coming seven days from 11/8/2004 till 19/8/2004.

IV.The Empirical Results and Discussion

Following the methodology presented in Section III, Table 1 shows the correlogram and partial correlogram of the ASE daily general index and first difference daily general index. It can be argued that the ACF of the ASE daily general index declines gradually. It is up to 23 lags are individually statistically significantly different from zero, for they all are outside the 95% confidence pounds. But at all other lags, they are not statistically different from zero. The same rule could be used for the PACF, which drops dramatically after the first lag from 0.92 to -0.192, and all its values after the first lag are statistically insignificant.

Table 1: Correlogram and Partial Correlogram
4/1/2004 – 10/8/2004

ASE First Difference Daily General Index		**ASE Daily General Index**		
PACF	**ACF**	**PACF**	**ACF**	
0.204	0.204	0.920	0.920	1
-0.206	-0.156	-0.192	0.818	2
-0.022	-0.100	0.114	0.737	3
-0.059	-0.052	0.024	0.674	4
-0.039	-0.038	0.074	0.628	5
0.047	0.046	0.058	0.597	6
0.000	0.042	-0.095	0.554	7
-0.237	-0.215	-0.019	0.502	8
0.007	-0.108	0.141	0.474	9
-0.067	-0.009	0.017	0.460	10
-0.053	-0.019	0.34	0.449	11
-0.062	-0.037	0.018	0.441	12
-0.152	-0.104	-0.001	0.428	13
0.046	0.010	0.109	0.423	14
0.052	0.092	0.004	0.423	15
0.041	0.132	-0.053	0.414	16
0.205	0.214	-0.073	0.388	17
-0.045	0.032	-0.141	0.339	18
-0.057	-0.126	-0.008	0.285	19
-0.042	-0.112	0.037	0.248	20
0.102	0.125	0.059	0.235	21
-0.102	-0.005	-0.082	0.217	22
0.062	-0.012	0.069	0.203	23
-0.078	-0.039	-0.045	0.184	24
-0.025	-0.134	0.046	0.166	25
0.065	-0.017	-0.008	0.158	26
0.050	0.093	-0.026	0.156	27
-0.042	0.016	-0.081	0.140	28
0.031	-0.070	0.015	0.120	29
0.081	0.060	-0.005	0.104	30
0.053	0.090	-0.119	0.075	31
0.007	0.053	-0.021	0.043	32
0.091	0.133	-0.085	0.006	33
-0.028	0.011	-0.136	-0.054	34
-0.021	-0.104	-0.033	-0.117	35
-0.090	-0.129	0.019	-0.157	36

Table 1 highlights the fact that the ASE daily general index time series is not stationary and it must be converted to a stationary situation before we can apply the Box-Jenkins methodology. Such a transformation can be seen in the ACF and PACF of the ASE first difference daily general index time series presented in Table 1. Since no observed trend in this series can be seen, it is an indication that the first difference of the time series is stationary. Following the robustness approach, Dickey-Fuller, Augmented Dickey-Fuller, and Phillips-Perron unit root test were employed and its results are presented in Table 2.

Table 2: ASE Daily General Index Stationary Test

Critical Value at 1% level	Computed Value	Unit Root Test
-3.4749	-2.428876	Dickey-Fuller
-3.4752	-2.919549	Augmented Dickey-Fuller
-3.4749	-2.642382	Phillips-Perron

Since the computed values for all unit root tests, in absolute values, are less than the critical values at 1% level of significance, it can be concluded that ASE daily general index time series is not stationary confirming the results presented in Table 1. Running the same tests for the ASE first difference daily general index, it is seen that the series become a stationary one as reported in Table 3.

Table 3: ASE First Difference Daily General Index Stationary Test

Critical Value at 1% level	Computed Value	Unit Root Test
-3.4752	-9.823964	Dickey-Fuller
-3.4755	-9.419886	Augmented Dickey-Fuller
-3.4752	-9.867652	Phillips-Perron

The next step is to find the *p* and *q* that best fits the series. One way to accomplish this is to consider the ACF and PACF and the associated correlograms of a selected number of ARIMA processes. Since each of these stochastic processes exhibit typical patterns of ACF and PACF, we can identify the time series with that process if the time series fits one of these patterns. Since the ACF and PACF of the ASE first difference daily general index do not show any typical pattern to reach *p* and *q* values, the researcher decided to choose a collection of ARIMA (p,d,q) models for different values of *p* and *q*. Following the procedures explained in the methodology, four standards were used for determining the most accurate ARIMA model from the collection exercised, namely; R-square, Adjusted R-square, Akaike info criterion (AIC), and Shwarz criterion (SIC). Appendix 1 presents these tests ranked according to the selected *p* and *q* values.

Appendix 1 demonstrates that model number 30 is the most accurate one where p = 4, d = 1, and q = 5, according to the four standards used. The results of the univariate ARIMA(4,1,5) model are shown in Table 4.

Table 4: Univariate ARIMA(4,1,5) model Estimators:
ASE First Difference Daily General Index is the Dependent Variable

Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.4884	0.694728	1.610363	1.118764	C
0.0000	5.175849	0.100598	0.520680	AR(1)
0.0000	-9.236705	0.078818	-0.728015	AR(2)
0.0000	8.259701	0.088661	0.732310	AR(3)
0.0038	-2.940961	0.124839	-0.367145	AR(4)
0.0565	-1.923785	0.121806	-0.234329	MA(1)
0.0000	5.241128	0.110389	0.578561	MA(2)
0.0000	-6.847218	0.125385	-0.858537	MA(3)
0.4763	0.714263	0.155356	0.110965	MA(4)
0.1041	1.636220	0.111753	0.182852	MA(5)

R- square	34.28%	AIC	8.962
Adjusted R- square	30.44%	SIC	9.146
D-W	2.003	F-Statistic	8.125
		Prob.(F-Statistic)	0.000

It can be seen from Table 4 that the coefficient of AR(1), AR(2), AR(3), AR(4), MA(2), and MA(3) are highly significant. The fact that R- square and Adjusted R- square are not high enough, could be explained by the loss of information from the long-run relationships among the variables (Pindyck and Rubinfeld 1991). The value of Durbin-Watson, moreover, strongly supports the view that there is no positive or negative first order serial correlation. In addition, the F-Statistic value is high enough to be significant indicating that ARIMA(4, 1,5) comfortably explains the date and is suitable for accurate forecasting.

A very strict assumption, in choosing the most accurate model, is that the error terms are assumed to have white noise (i.e. zero mean and constant variance), uncorrelated, and normally distributed. The Jarque-Barra test demonstrated (see Appendix 1), along with its probability showing, that the residuals were normally distributed. After the ARCH LM test for autocorrelation in the error variance of the selected model was completed, it demonstrated that the error terms were not serially correlated. Since $\chi^2 = 2.463423$, its probability was higher than a 10% level of confidence (Prob. 0.116525), consequently, the residuals did not contain ARCH effects.

It should be said that D-W statistic tests only for the first order autocorrelation and it requires both an intercept in the regression and no lagged dependent variables among the regressors. While it is an important and widely used test for the autocorrelation, it is still only a partial test. A more general approach to testing for serial autocorrelation is to compute the autocorrelations and partial autocorrelations of the residuals up to any specified number of lags. The ljung-Box Q statistic tests for serial autocorrelation by computing the autocorrelations to see if they are zero; that is, whether or not the series is white noise. If the series is the residuals from ARIMA estimation, the number of degrees of freedom is equal to the number of autocorrelations less the number of autoregressive and moving average terms previously estimated. Using SPSS software, Table 5 shows that residuals autocorrelations are equal to zero at different chosen number of lags, since the p-values are greater than 10%. This confirms our model as the most appropriate one among those tested.

Table 5: ASE Forecasted Daily General Index
11/8/2004 – 19/8/2004

P-Value	Degrees of Freedom	Ljung-Box (χ^2)	Lags
0.959	1	2.023	6
0.217	2	10.786	7
0.282	3	10.904	8
0.225	5	14.154	10
0.280	3	14.336	12
0.134	9	21.079	14
0.136	7	22.214	16
0.118	13	26.436	18
0.134	25	39.784	30
0.132	23	41.026	32

Thus our model would take the following form:

$$Y^*t = 1.118764 + 0.520680Y^*t\text{-}1 - 0.728015Y^*t\text{-}2 + 0.732310Y^*t\text{-}3 - 0.367145Y^*t\text{-}4 + \varepsilon t$$

$$- 0.234329\varepsilon t\text{-}1 + 0.578561\varepsilon t\text{-}2 - 0.858537\varepsilon t\text{-}3 + 0.110965\ \varepsilon t\text{-}4 + 0.182852\ \varepsilon t\text{-}5 \qquad (7)$$

Now that we have found a successful model, we can forecast the original time series using *p* and *q*. Our k-period forecast of *f Yt* would be given by:

$$fYT\,(K) = fYT + fY^*T(1) + fY^*T(2) + \dots + fY^*T(K) \qquad (8)$$

where *fYT* is the forecast of Y and *fY** is the forecast of ΔY. The resulting forecast of Y for the next seven days covers the period 11/8/2004 – 19/8/2004 (See Appendix 3).

Appendix 3 forecasts that the ASE would continue to grow by 0.195% for the next seven days starting on 11/8/2004 as the ARIMA model predicted highlighting the potential for slow growth of the capital market. However, looking at the actual data over the same forecasted period, it seems that the ASE performance declined on average by –0.003%. These conflicting results support the Efficient Market Hypothesis and its existence.

The Efficient Market Hypothesis states there are three kinds of efficiency: *Operation Efficiency*, *Allocation Efficiency*, and *Informational Efficiency*. Information Efficiency is when information on traded securities is instantly reflected in their price. Therefore, stock prices at time (*t*) should react only to relevant information I_t, which, in theory, is available to everyone. In an Efficient Market, past information (I_{t-i}) has already been reflected in the share prices, and these prices at time *t* should not respond to such information. If the market at time *t-i* anticipates some information, which is released at time *t*, then the market at time *t* should react only if the information released was better or worse than that anticipated.

An implication of the Efficient Market Hypothesis is that, since news reaches the market randomly prices will react to that news in a random way. Thus it is impossible to forecast price changes and thus profit from these forecasts. It is at this point that the Efficient Market Hypothesis becomes a testable hypothesis.

Several versions of the EMH have been widely discussed and tested in the literature. The differences revolve around the definition of the information set θ_t used in those tests. There are three broad categories of hypothese: weak form, semi-strong form, and strong form In the Weak-form of efficient market hypothesis, θ_t is information only from the past price history of the market during time *t*. In the semi-strong form of EMH, θ_t refers to all publicly available information at time *t*, including the past history of prices. In the strong form of the EMH, θ_t is all information known at time *t*.

Since the ARIMA model forecasts were significantly different from the actual growth rate between 11/8/2004 and 27/3/2005, according to the ASE database (See Appendix 3), the ASE followed most closely the EMH in its weak form.

V. Conclusion

This study has investigated predictions of ASE performance over a period of seven days. The ASE daily general index was used by a time series technique, the Univariate Autoregressive Integrated Moving Average (ARIMA) model. Different diagnostic test were preformed to find the model that best fitted the data. It was found that ASE would continue to grow by 0.195% for the next seven days starting on 11/8/2004 as the ARIMA model predicted. However, looking at the actual data over the same forecasted period, it seems that the ASE performance declined on average by –0.003%. Therefore, the prediction failed to match market performance between 11/8/2004 and 17/4/2004, the time studied. In brief, the ASE preformed most closely to the EMH weak form.

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