Forecasting Stock Market Returns Via Monte Carlo Simulation: The Case of Amman Stock Exchange

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ABSTRACT

This study investigates the ability of Monte Carlo simulation (MCs) to predict stock market returns in Amman Stock Exchange (ASE). Specifically, we compare the in-sample forecasting ability of MCs with the Simple and Exponential Moving average techniques. The data of the study consists of the daily general float index of ASE over the period (2003-2012). Forecasting accuracy is measured by four proxies: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil Inequality Coefficient (U). The results indicate that MCs is the most accurate forecasting technique among the others investigated. Moreover, ASE seems to be inefficient at the weak level, given that technical analysis approaches enable investors to predict stock market returns.

Keywords: Efficient Market Hypothesis, Random variables, In-Sample Forecasting, Monte Carlo Simulation, Simple Moving Average, Exponential Moving Average, Geometric Brownian Motion, Amman Stock Exchange.

INTRODUCTION

Over the past 50 years, many financial analysts implement multi kinds of squeaky research on the stock market, in the hope of achieving one goal: to beat the market. The concept of beating the market refers to realizing continuous and higher rates of return than market return and at the same level of risk (Zhang, 2004). Therefore, accurate prediction of stock prices presents a challenging function for traders and investors. Pluralities of factors including economical, social, political and psychological ones; interact in a complex way to form stock movement patterns (Assaleh *et al.*,

2011). Although, the efficient market hypothesis asserts that none of any techniques is effective to predict the market. Forecasting market prices may be done following one or a set of two approaches, fundamental analysis approach and technical analysis approach. Each approach has its own advantages as well as its limitations (Malkiel, 1999). Bodie *et al.* (2013) defines fundamental analysis as the analysis of the firm which uses earnings, expected dividends, expected interest rates, and risk evaluation to determine the fair or the fundamental value of the stock. In fact, fundamental analysts study the past earnings and examine the company financial statements: Balance sheet, Cash flow statement and Income statement, in order to measure its intrinsic value. They state that the market price of the stock equals its fundamental value, when the required rate of return equals the expected holding period return, and for overpriced stock; the required rate of return is greater than the anticipated rate of return.

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Technical analysis is essentially defined as using and interpreting the historical trend of the stock, in order to predict its future price. Thus, it is concerned with the study of past trading information to make a price forecast such as the movements of common stock prices and the volume of trading. The logic behind the technical approach stems from the belief that prices have certain movements' patterns, in which they are not totally random and history can repeat itself.

This study uses the technical analysis approach in order to make the best forecast of the stock return. In specific, we use Monte Carlo simulation (MCs) to predict the returns of the free float stock market index of Amman Stock Exchange (ASE) over the period (2003-2012). Forecasting stock market returns is a very essential topic to both academicians and practitioners. It may have insightful indications for the determinants of stock prices, and for the efficient market hypothesis. Therefore, if stock market returns are predictable then investors may depend on technical analysis approaches to formulate their investment strategies. Decision makers can also base their future economic plans on their forecasts of the stock market index returns.

The importance of this study comes from the lack of similar ones that use technical analysis approaches to forecast stock returns in ASE as an emerging market. To the best of the researcher's knowledge this is the first study that uses MCs to predict stock market returns in ASE. Thus, the motivation of this research is to introduce the concept of MCs into the Jordanian sector and utilize it in forecasting the Jordanian stock market prices. In other words, it appears worthy to provide researches with a technical technique that can be used to accurately predict stock market returns in ASE. The reason behind using MCs in specific rather than other techniques is that its power in data extrapolation (forecasting beyond the known data points), it randomly

generates thousands of series representing potential outcomes for possible returns. Thus, the random simulation increases its reliability and accuracy as a forecasting method. Section 2 introduces MCs. Section 3 reviews the related literature. Section 4 describes data and methodology. Section 5 presents the empirical results. Section 6 concludes.

Monte Carlo Simulation

Generally speaking, Monte Carlo technique can be defined as any technique which uses random numbers to solve a problem. It can deal with either probabilistic or statistical problems (James, 1980). Halton (1970) has defined Monte Carlo as a method that represents the explanation of a problem as a parameter of a hypothetical population and using a random sequence of numbers to create a sample of the population, from which statistical estimates of the parameter can be obtained. Therefore, simulation in general is known as a numerical technique for conducting experiments in the computer, involving random sampling from probability distributions.

Essentially, the concept of MCs is based on the Law of Large Numbers and the Central Limit Theorem. More precisely, the Law of Large Numbers assumes that as the sample size increases, the sample mean is forced to be closer and closer to the population mean (BelginSert, 2011). The Central Limit Theorem states that we can assume a normal distribution of data as the sample size increases.

Monte Carlo methods are statistical techniques which are sufficient to solve a complex mathematical or statistical problem. The logic behind MCs is creating sequences of random numbers to perform statistical simulation with generating new configurations of a system of interest over long periods of real time (Rollett&Manohar, 2004).

Moreover, the primary function of MCs is to minimize the variance by averaging the results of large numbers of samples, even when the Convergence is slow (Lafortune, 1996). Simulation facilitates solving many problems in financial engineering, which focus on estimating a certain value such as: pricing derivative securities, computing price sensitivities, and evaluating portfolio risks. Consequently, MCs is a stochastic method that is often applied to approximate expectations. In fact, MCs is applied by three essential steps: generating sample paths randomly, evaluating the payoff along each path, and calculating an average to attain estimation (Chen & Hong, 2007).

Advantages of Monte Carlo Simulation

MCs has several advantages compared to other numerical methods. Thus, applying MCs is easy and flexible to solve a complex financial problem (Boyle *et al.*, 1997). Moreover, MCs is often being attractive to deal with problems that have many dimensions, because its rate of convergence does not depend on the dimensionality of the problem (Chen & Hong, 2007). The execution of MCs does not consume a lot of time because of the increasing speed of computer programming (Whiteside II PE, 2008).

Finally, MCs is free from the restrictions of solving Newton's equations of motion. This freedom allows generating trial configurations within the statistical mechanics ensemble of choice (Earl & Deem, 2008).

Limitations of Monte Carlo Simulation

On the other hand, the limitations of MCs include the following: First, Inappropriate inputs such as standard deviations and correlations, can lead to wrong simulation results. Second, there are a number of unknown factors that simulation can't truly account for during an investor's lifetime. Third, MCs is troubled from its

ability to model serial correlation between what comes out and what was just drawn, because there is no way to control variables. So that, the user should be prepared to make the necessary adjustments if the results that are generated seem out of line (Ibbotson Associates, 2005). Fourth, because Newton's equations of motion don't solve therefore, no dynamical information can be gathered from a traditional MCs (Earl & Deem, 2008). Finally, MCs may hold some statistical and systematic errors (Umrigar, 2010).

Literature Review

Numerous studies find significant signs of the ability of predicting stock prices in different stock markets with different techniques. Some researchers use fundamental analysis approaches to do the job (see for example, Lewellen, 2004; Belke and Polleit, 2004; Elleuch and Trabelsi, 2009; Kheradyar and Ibrahim, 2011; Al-khatib and Al-Horani, 2012; Shubita, 2013), however, others use technical methods to predict stock prices. We will focus on the later studies given that our study utilizes a technical approach.

Kim (2003) applies support vector machines methods (SVMs), to predict the daily Korean composite stock price index (KOSPI) over January 1989 to December 1998. This method uses a risk function consisting of the empirical error and a regularized term which is derived from the structural risk minimization principle. They compare it with back-propagation neural networks and case-based reasoning. Their empirical results show that SVM provides a promising alternative to stock market prediction.

Atmeh and Dobbs (2006) investigate the performance of fourteen moving average trading rules in forecasting future prices of the daily general index of Amman Stock Exchange over the period 1992 to 2001.The study utilizes bootstrap methodologies such

as: the random walk model, AR (1)[1], and GARCH-M. The results suggest that technical trading rules can assist to forecast market movements, with evidence that the short run rules may be profitable even after allowing for transactions costs. In addition, the returns that were generated by the bootstrap reveal that the actual trading profits are not consistent with those that might be generated by the random walk or AR(1) methods.

Döpke *et al*. (2008) provide an evidence of the ex-ante predictability of monthly excess stock returns in Germany, based on real -time macroeconomic data from 1994 to 2005. Recursive modeling approach has been applied in order to forecast stock returns in real time while Sharp, Treynor, and Jenson's ratios have been applied to measure the performance of stock returns. They have found that the return which is predicted based on real - time macroeconomic data is the same as the return based on revised macroeconomic data. Furthermore, the performance of portfolio switching strategies based on the preceding real – time macroeconomic data is the same as the performance based on revised macroeconomic data.

Tsao Pan (2010) proposes a hybrid model to enhance prediction ability. The model merges the principal component regression (PCR) model and the general regression neural network (GRNN) to resolve both multicollinearity problems and non-linearity problems at the same time. The study sample includes the daily stock information of Taiwanese and Chinese companies from 3 August 2004 to 26 March 2008. The study uses ten financial ratios: turnover of receivables, inventory turnover, fixed assets turnover, current ratio, acid-test ratio, debt ratio, net profit ratio, return on asset ratio, long-term capital to fixed asset ratio and sales/shares. For the testing results, the researcher has calculated five

indices: the root mean square error, revision theil inequality coefficient, mean absolute error, mean absolute percentage error and coefficient of efficiency. The empirical results show that the prediction power of the hybrid model is more powerful than each method separately.

Ali *et al*. (2011) use the artificial neural network in modeling the stock prices of seven Jordanian service and industrial companies listed in Amman Stock Exchange. The model was evaluated by stock market brokers through the use of a questionnaire that was distributed in Amman Stock Exchange. For each company, a full year was used for training the network, and another for validation of results. The results show that the network is able to produce the output within a mean squared error of $0.0023*10^{-8}$ from the target. The network output (forecasted prices) is very close to the actual data (price) except for the last month where the actual price has a small drop. The majority of the respondents stated that they may depend on the artificial neural network technique and that they believe that the technique is applicable to all categories of companies.

Assaleh *et al*. (2011) utilize two prediction models for forecasting securities' prices of two leading stocks in Dubai Financial Market (DFM). These stocks are: Emaar Properties (EMAAR) and Dubai Islamic Bank (DIB). EMAAR is the leading real estate developer in the Middle East and DIB is the world's first fully fledged Islamic bank. These stocks were chosen because they have sufficient historical data, actively traded, and each represents a different sector in the UAE economy. The study uses daily closing prices over the period from April 2000 to March 2006 (a total of 2176 data points). They use Artificial Neural Networks (ANN) and Polynomial Classifiers (PC) as modeling techniques to predict stock prices from historical price data. This was the first time to apply PC to be used in stock prices

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[1] The autoregressive model

prediction. Both models use the same inputs and the data for both models is identical. Results indicate, in general, that both models are effective. Very good results are found in terms of mean absolute error percentage. Both models reveal an average error around 1.5% when predicting the next day price, an average error of 2.5% when predicting the second day price, and an average error of 4% when predicting the third day price.

Giovanis (2011) examines the performance of several investment strategies based on four different prediction approaches of stock returns: the moving average (MA), the Moving Average Convergence-Divergence (MACD), a random walk autoregressive model, and the model that he has proposed; Generalized Autoregressive Conditional Heteroskedasticity (GARCH) regression with Wavelet decomposition and Monte Carlo simulations algorithm developed in MATLAB. He uses five major stock market indices (S&P 500 for U.S.A., FTSE-100 index for UK, DAX index for Germany, CAC-40 for France and NIKKEI-225 for Japan),based on daily data of closing price returns. The period of estimation starts from 3, January 1950 for S&P 500, 2, April 1984 for FTSE-100, 26, November 1990 for DAX, 1, March 1990 for CAC-40 and 4, January 1984 for NIKKEI-225. The ending time period for the estimation is similar for all estimations and it is 30, October 2009. The remaining period from 2, November through 13, November 2009 is obtained as the forecasting test period, which is actually 10 trading days. The empirical results reveal that the procedures MA and MACD might lead to net profits, but not in all cases. In contrast, random walk autoregressive model leads in all cases to net losses. Finally, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) regression with Wavelet decomposition and Monte Carlo simulations model lead always to net profits and give significantly higher profits in three stock

indices than the other techniques.

Kara *et al.* (2011) investigate the predictability of financial movement direction with artificial neural networks (ANN) and support vector machines (SVMs) by predicting the daily closing price movement of Istanbul Stock Exchange (ISE) National 100 Index. The period from January 2, 1997 to December 31, 2007 has been covered. The experimental results show that both techniques have given significant performance in predicting stock price movements, but ANN model gives better performance than SVM.

Although of the few studies that use MCs to predict stock prices, researchers find it consistent and precise (see for example, Boyle *et al.*, 1997; Chen & Hong, 2007; Whiteside II PE, 2008). Its large number of random forecasts gives it its power in prediction. This study applies MCs to forecast stock market returns in ASE. We focus on ASE as a highly volatile emerging market that may manifest an anomalous deviation from the efficient market hypothesis compared to the developed stock exchanges. Such deviation makes the forecasting approaches much effective in predicting stock returns.

Data and Methodology

The data of this study consists of the daily values of the free float market index of ASE over the period (2003 – 2012). This index reflects the stock prices of the firms that are traded and excludes the non – traded stocks.

Forecasting Techniques

The forecasting techniques that we use in this study are: simple moving average (SMA), exponential moving average (EMA) and Monte Carlo simulation (MCs).

Simple Moving Average

Moving average method is one of the most popular methods of technical analysis. A moving average is

calculated as an average of observations from a number of subsequent time periods. It smoothes out the irregularities in the data series. A SMA is the average of price series over a selected time period which gives an equal weight to each period price. The mechanism of SMA includes the market movement forward in time; the oldest price is removed from the average calculation and replaced by the most recent price (Mendelsohn, 2000).

The SMA is expressed as follows (Giovanis, 2011):

$$ f = \frac{1}{n} \sum_{i=0}^{n-1} A(n-i) \qquad (1) $$

Where n is the time interval over which the average is computed. f is the forecasted value. A is the actual value. We calculate the SMA over 2, 3, 5 and 10 days.

Exponential Moving Average

The exponential moving average (EMA) solves the equal-weight problem of the simple moving average (SMA). In specific, the SMA gives the same weight for every data point. On the other hand, the EMA gives greater weights to more recent data; thus the weight of the past data declines exponentially (Brooks, 2006).

The following equation defines the general expression of EMA (Cargal, 1988):

$$ f_{t+1} = (1-\alpha) A_t + \alpha f_t \qquad (2) $$

Where f : is the forecasted value, α is the smoothing constant ($0 < \alpha < 1$), the larger the α, the more weight is given to recent observation (damping factor), and A is the actual value. We apply the EMA with two values of damping factor (α), 20% and 30% (These values are standardized by statistical packages such as e-views).

Monte Carlo Simulation

To predict the stock price via MCs, the following steps are done: First we calculate the average daily return and the standard deviation of returns for a certain period of time repeatedly (we assume it one month for the purposes of this study). Second, we estimate random numbers on a daily basis over the study period. . Third, we follow a geometric Brownian motion (stochastic process) in which we sum the average return with a random shock of return calculated by multiplying the standard deviation by the random value estimated in the second step. Finally, in order to calculate the forecasted price in day t+1, we multiply the actual price on day t by the exponential value of the sum calculated in the third step. The forecasted returns are calculated following the formula (Choong, 2012):

$$ \ln(P_t / P_{t-1}) = \mu + z\sigma \qquad (3) $$

Where

μ : is the constant (deterministic component) daily mean of return which is calculated on month- by- month basis (drift).

Z: is the pseudorandom number (stochastic component).

σ : is the monthly volatility; it expresses the stochastic random shock.

The Brownian motion process assumes that the forecasted return is a function of the historical mean return (drift) plus a random stochastic shock in returns (volatility). For simulation process; we apply the previous process 1000 times, and then the averages of these iterations are found.

Comparison Techniques of Forecasting Accuracy

The measures of forecasting accuracy that are used in this study are: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil Inequality Coefficient (U). In each of the forthcoming definitions, A_t is the actual value, f_t is the forecasted value, $e_t = A_t - f_t$ is the forecast

error and n is the number of observations.

The RMSE is a measure of the average squared deviation of the forecasted values from the actual ones. It is given by the following equation:

$$RMSE = \sqrt{\sum \frac{e_t^2}{n}} \qquad (4)$$

The MAE is an error statistic that averages the absolute deviation of the forecasted values from the original ones. It is given by the following formula:

$$MAE = \frac{\sum |e_t|}{n} \qquad (5)$$

MAPE represents the percentage of average absolute error occurred; which is tended to reinforce the perception of inaccurate forecasts. The properties of MAPE are similar to those of MAE properties. It is given by the following equation:

$$MAPE = \frac{1}{n} \cdot \sum \frac{|e_t|}{A_t} \qquad (6)$$

Finally, Thiel's Inequality Coefficient is known as Thiel's U. It is the ratios of the root mean squared errors to the root mean of the squared forecasted values plus the root mean of the squared actual values. It is given as:

$$U = \frac{\sqrt{\frac{1}{n} \cdot \sum (A_t - f_t)^2}}{\sqrt{\frac{1}{n} \cdot \sum f_t^2} + \sqrt{\frac{1}{n} \cdot \sum A_t^2}} \qquad (7)$$

The closer the four error measures to zero the better is the forecast.

Empirical Results

Table 1 presents a summary descriptive statistics of the daily market index value, actual stock market returns and forecasted stock market returns estimated via the three forecasting techniques. The descriptive statistics cover the period (2003-2012). The actual mean return is 0.0002 and it is same under all forecasting techniques. The median values are close to each others. However, the standard deviation of returns estimated via MCs is the closest to the one of the actual returns.

Table 1. Summary of Descriptive Statistics

Variables	Mean	Median	Max	Min	SD
Index	2378.061	2571.10	5043.70	1034.0	925.99
Actual return	0.0002	0.0005	0.0469	-0.0453	0.0103
SMA 2 days	0.0002	0.0004	0.0445	-0.0416	0.0081
SMA 3 days	0.0002	0.0003	0.0426	-0.0410	0.0067
SMA 5 days	0.0002	0.0003	0.0245	-0.0309	0.0053
SMA 10 days	0.0002	0.0002	0.0139	-0.0244	0.0039
EMA 20%	0.0002	0.0005	0.0421	-0.0427	0.0088
EMA 30%	0.0002	0.0004	0.0407	-0.0405	0.0080
MCs	0.0002	0.0004	0.0512	-0.0530	0.0107

Table 1 shows a summary descriptive statistics of the daily market index value, actual stock market returns and forecasted stock market returns estimated via the three forecasting techniques. SMA denotes simple moving average, EMA denotes exponential moving average and MCs denotes Monte Carlo simulation.

Table 2 reports the four accuracy measures (RMSE, MAE, MAPE, U) for all the forecasting techniques (SMA of 2-days, SMA of 3-days, SMA of 5-days, SMA of 10-days, EMA of 20% damping factor, EMA of 30% damping factor, and MCs). In the four accuracy measures (RMSE, MAE, MAPE, U), the closer the measure to zero, the more accurate is the technique. It can be noted from the Table 2 that MCs technique has relatively the best prediction accuracy comparing to the other six techniques.

MCs technique shows the lowest values of RMSE, MAE, MAPE, and U comparing to all six forecasting techniques. Thus, MCs is the most accurate in predicting stock market returns of ASE over the period (2003-2012) comparing to the SMA and EMA techniques. Furthermore, the techniques are arranged in a descending order from the lowest RMSE to those with the highest RMSE as follows: MCs, SMA of 2-days, SMA of 3-days, SMA of 5-days SMA of 10-days, EMA of damping factor 30%, and finally EMA of damping factor 20%. The values of their corresponding RMSE are respectively, 0.0031, 0.0064, 0.0082, 0.0090, 0.0097, 0.0117, and 0.0120. The results are consistent based on the MAE measure, but with different values as follows: 0.0022, 0.0043, 0.0055, 0.0061, 0.0066, 0.0079, and 0.0081.

In contrast, MAPE gives slightly different results. The techniques are arranged in a descending order from the lowest MAPE to those with the highest MAPE as follows: MCs, SMA of 10-days, SMA of 5-days SMA of 2-days, SMA of 3-days, EMA of damping factor 30%, and EMA of damping factor 20%. The values of their corresponding MAPE are respectively, 1.4551, 1.8978,

2.3521, 2.5549, 2.8845, 4.1405, and 4.4935.

Likewise, Theil Inequality Coefficient (U) provides different results from the previous measures. The techniques are arranged in a descending order from the lowest U to those with the highest U as follows: MCs, SMA of 2-days, SMA of 3-days, SMA of 5- days, EMA of damping factor 20%, EMA of damping factor 30%, and SMA of 10-days. The values of their corresponding U are respectively, 0.1494, 0.3483, 0.4800, 0.05774, 0.06321, 0.06404, and 0.06878. But, all in all it seems that all the forecasting accuracy results are closed to each other's. Figure 1 confirms our results. MCs shows the lowest value of RMSE, MAE, MAPE, and U. Indicating that, it is the most accurate forecasting technique.

Table 2.Summary Results of the Four Accuracy Measures

Variables	RMSE	MAE	MAPE	U
SMA 2	0.0064	0.0043	2.5549	0.3483
SMA 3	0.0082	0.0055	2.8845	0.4800
SMA 5	0.0090	0.0061	2.3521	0.5774
SMA 10	0.0097	0.0066	1.8978	0.6878
EMA 20%	0.0120	0.0081	4.4935	0.6321
EMA 30%	0.0117	0.0079	4.1405	0.6404
MCs	0.0031	0.0022	1.4551	0.1494

Table 2 shows the four accuracy measures (RMSE, MAE, MAPE, U) for all the forecasting techniques (SMA of 2-days, SMA of 3-days, SMA of 5-days, SMA of 10-days, EMA of 20% damping factor, EMA of 30% damping factor, and MCs). RMSE denotes Root Mean Squared Error, MAE denotes Mean Absolute Error, MAPE denotes Mean Absolute Percentage Error and U denotes Theil Inequality Coefficient.
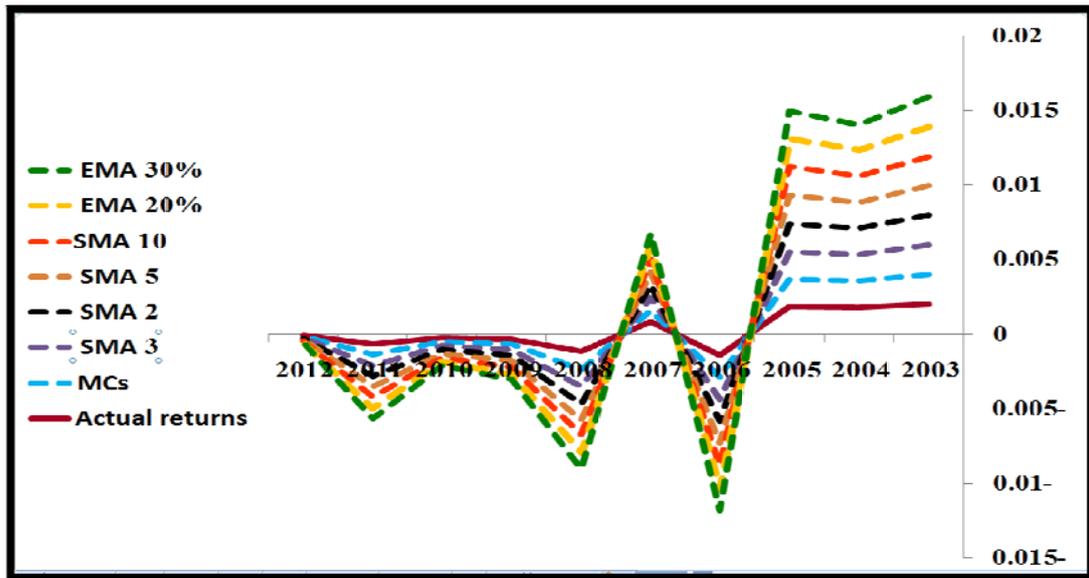
Figure 1. Yearly Forecasted Returns vs. Actual Returns

Conclusion

This study investigates the forecasting ability of three forecasting techniques in predicting the stock market returns of ASE over the period (2003- 2012). In fact, the techniques which are used include four simple moving average techniques, two exponential moving average techniques, and Monte Carlo simulation. The forecasting ability is estimated via four accuracy measures based on the error term (the difference between the actual and forecasted returns). The results can be summarized as follows: First, technical analysis techniques were useful to predict stock returns by utilizing time series data. Second, the results indicate that Monte Carlo technique has a superior ability to predict stock market returns. Third, according to forecasting accuracy measures: RMSE, MAE, MAPE, and U; the forecasting techniques are arranged from the most accurate to the least as: MCs,

MA, and finally EMA. Lastly, Amman Stock Exchange seems to be inefficient at the weak level, because the market can be predicted using technical analysis techniques. Therefore, investment strategies can be utilized and investors are able to choose when to buy or sell according to these strategies.

In conclusion, predicting future returns is a very critical subject to academicians, investors, policy makers and for all other parties who are interested in ASE. This study has introduced MCs as a technical approach that could help all these parts in forecasting stock prices which in turn will be vital in the calculations of the cost of capital, portfolio management, setting economic plans and many other financial decisions. Future research could investigate the applicability of other technical approaches such as neural networks.

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التنبؤ بعوائد سوق الأسهم بواسطة محاكاة مونتي كارلو: حالة بورصة عمان للأوراق المالية

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ملخص

تختبر هذه الدراسة قدرة محاكاة مونتي كارلو على التنبؤ بعوائد سوق الأسهم في بورصة عمان للأوراق المالية. وبالتحديد فإننا نقارن قدرة التنبؤ داخل العينة لمونتي كارلو مع طرق المعدل المتحرك البسيط والأسي . تكونت بيانات الدراسة من القيم اليومية للمؤشر العام للأسهم الحرة لبورصة عمان للأوراق المالية في الفترة (2003 – 2012). تقاس دقة التنبؤ من خلال أربعة مقاييس هي:الجذر التربيعي لمعدل مربع الخطأ، والمعدل المطلق لمعامل الخطأ، والمعدل المطلق النسبي لمعامل الخطأ، ومعامل ثايل لعدم المساواة. تشير النتائج إلى أن محاكاة مونتي كارلو هي أدق طريقة تنبؤ من بين الطرق المدروسة. إضافةً إلى ذلك فإنه يبدو بأن بورصة عمان للأوراق المالية غير كفؤة على المستوى الضعيف ويُعزى هذا إلى قدرة المستثمرين على التنبؤ بعوائد الأسهم بإستخدام طرق التحليل الفني.

الكلمات الدالة: فرضية كفاءة السوق، المتغيرات العشوائية،التنبؤ داخل العينة، مُحاكاة مونتي كارلو ،المتوسط المتحرك البسيط، المتوسط المتحرك الأسي، هندسية الحركة البروانية، بورصة عمان للأوراق المالية.