Forecasting earnings of firm's listed in ASE using ARIMA model

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Abstract. The study aims to estimate and forecast earnings of the firms listed in Amman Stock exchange (ASE) using a time series data of earning per share (EPS) for the period from 1978 till 2016. The data has been extracted from firms' annual reports. A wavelet Transform (WT) decomposes the data and detects the fluctuations and outlay values. The parameters p, d, and q are estimated using the ARIMA model, the results show that the ARIMA models accuracy criteria MASE and RSME have the lowest values (0.7089 and 0.0709) respectively, thus the forecasting accuracy is high. It is concluded that firms' earnings show slow increasing trend for the upcoming 38 financial years.

Keywords: forecasting, WT, ARIMA model, earning per share, Jordan.

1. Introduction

Earning refers to after-tax net income, sometimes called the bottom line, or a profit, it's a crucial aspect that affect the firm's share price, also it indicates whether the business will be profitable and successful in the long run or not, so it measured a firm performance which is formed based on the accrual basis of accounting. Earning is an important figure that it's used extensively as measure of firm performance by users of financial information like investors, management, creditors, customers and all other stakeholders to make decision for future actions, therefore the need to forecast firms' future performance is

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highly importance for them. The main goal of financial reporting is to provide useful information to make informed financial decisions. Thus, the evaluation of accounting information in forecasting future profitability has been always studied and presented in financial accounting studies (Oskouei and Zadeh, 2017; Alsinglawi and Aladwan, 2018).

The aim of this research is to forecast the future firm's earning based on past earnings' pattern by using Earning per Share (EPS) as a single figure that summarize the firm's' performance, EPS is generally considered as the most important factor to determine the share price and the firms' value (Islam et al., 2014). This study is supposed to offer a valuable understanding for the firm's expected financial performance. Therefore, a more accurate forecasting would be helpful for decision makers to make a data-driven decision.

Financial data generally are a type of time series data that often show trending and seasonality that presenting a challenge to develop an effective forecasting model. The issue of how effectively modeling financial series data and how to increase the superiority of forecasting is still unresolved in literatures. Plenty of previous studies used different types of models in forecasting like; Autoregressive Integrated Moving Average (ARIMA) model; ARIMA is considered as most widely used approaches in time series forecasting and able to describe the autocorrelations in the data. The ARIMA framework to forecasting is formerly developed by (Box et al., 2015).

The primary objective of this study is to explore whether the use of earnings' time series based on Earning per share (EPS) would help to forecast the future direction and movement of firms' earnings? Therefore, to be able to capture the future earnings of firms, we will try to achieve the following objectives that are: 1) detect the earning's trend of firms listed in ASE;2) select the best ARIMA model firms; 3) forecast earning's trend for firms and finally develop ARIMA model that is able to predict future earnings of the firms.

The rest of the paper is organized as follows. Section 2 describes the literature review. Section 3 introduces the methodology and framework. Sections 4 describe the data descriptions and analytical results. Finally, Section 5 presents our conclusions.

2. Literature review

Many investors depend on earnings to understand firms' performance to make their investment decisions; the basic measurement of earnings is earnings per share (EPS). This metric is considered as a summary indicator for performance (Schroeder et al., 2009). Most of the time the earnings forecasts are based on analysts' prospecting of firms' growth and profitability; to forecast earnings, stock analysts shape financial models that estimate prospective revenues and costs, and incorporate other factors like economic growth, currencies and other macroeconomic factors that influence firms' growth (Ramezani et al., 2002).

The analysts use market research reports to get a sense of firms' growth trends in order to understand the dynamics of the firms under consideration.

Many researchers employed mathematical modeling like ARIMA model to forecast financial series data like (Mills et al., 2011; Steel, 2014; Uko and Nkoro 2012; Devi et al., 2013; Jaya and Sundar, 2012), but still nobody used series data of EPS as a proxy to forecast earnings.

2.1 Time series forecasting

The time series is defined as data points indexed in time order, it is a series taken at consecutive similarly spaced points in time. Therefore, it is ordered and the requirement to maintain this ordering imposes certain restrictions on its processing. Furthermore, the time series data usually ordered by factors such as distance but naturally the time factor is the main ordering encounter. Thus, some groups are referred to as time series. Time series analysis has widely applications in many fields like; Sales, accounting, economic and stock market forecasting. Time series analysis is used to recognize the relationship between the attributes of current value to that of its previous or later values (Mills et al., 2011). Based on this for financial data like earnings we are interested in identifying previous values to see how current values get affected, also we are interested to forecast the future values (Steel, 2014). ARIMA model is widely used to analyze time series data and to understand the impact of past values in forecasting future values. Wrathful to say It was rarely to find in literatures studies that used ARIMA model to forecast future earning based on time data series of earning per share (EPS), most research work focused on forecasting stock market indices, like Junior et al (2014) who assessed the performance of ARIMA model for time series forecasting of IBOVESPA, they concluded that the ARIMA model can be used for financial time series data forecasting. A study by Uko and Nkoro (2012) that analytically compared the influence of ECM, VAR, and ARIMA models in forecasting inflation of Nigeria, it revealed that ARIMA is a superior forecaster of inflation at Nigeria.

Devi et al (2013) has used ARIMA model with its parameters to forecast the NSE Nifty Midcap50 companies among them top 4 companies the results were implemented using criterions like AIC & BIC. Paul et al (2013) empirically found that the best ARIMA (2, 1, 2) model for forecasting based on AIC, SIC AME, RMSE, MAPE in content of SPL data series. Jaya and Sundar (2012) used ARIMA model for 19 IT firms and analyzed the market capitalization of the firms. Authors found that firms are categorized into three trends i.e. companies on an upward, linear and downward trends. Shrimal and Prasad (2016) found the best ARIMA model for predicting market capitalization using some of mathematical criteria such as RMSE and MAPE; they applied this model on 21companies.

2.2 Why earning per share (EPS)?

The term earnings per share (EPS) summarize a firm's earnings that are a net income after taxes and preferred stock dividends. The EPS is evaluated by dividing net income earned in a specific annually reporting period, by the entire number of shares remaining during the same period, EPS is most important variable that affect the share's price, it is a key driver of share prices, and it is a main component to compute the price-earnings valuation ratio. EPS is used as an indicator to capture a firm's profitability per each unit of shareholder ownership called per share, furthermore profitability can be assessed by prior earnings, current earnings or future projected earnings, therefore earning per share is widely considered to be the most popular method of quantifying a firm's profitability, EPS is generally viewed as a more accurate measure and is more commonly cited (Besley and Brigham, 2007).

3. Methodology

This section consists of the research framework include the mathematical model that is used to achieve the purpose of this research and mathematical criteria used.

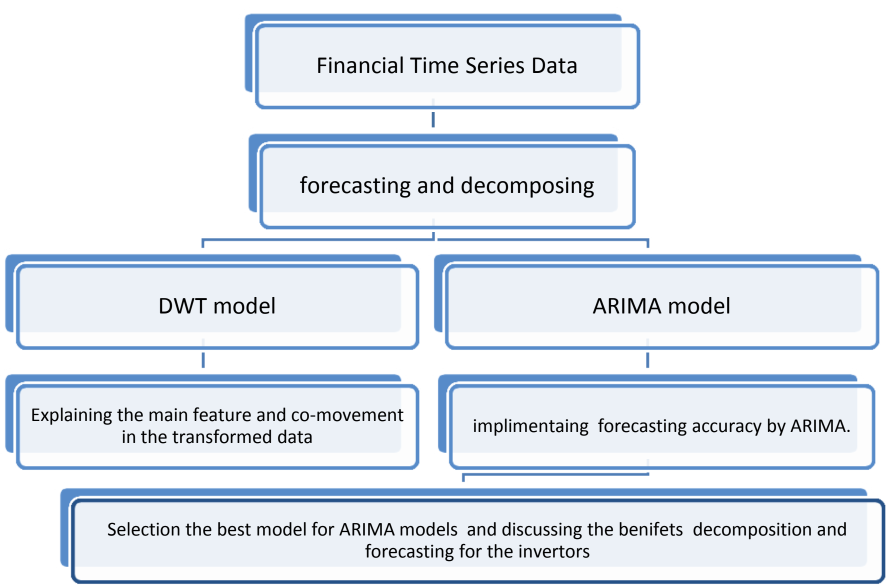

Figure 1: research framework

3.1 ARIMA model

An Auto regressive (AR) process is a series depends on its lagged values. The AR (p) model is a regression model which defined as:

$$Yt = \alpha_0 + \alpha_1 Yt - 1 + \alpha_2 Yt - 2 + ... + \alpha_p Yt - p. \tag{1}$$

Moving average (MA) model is related if the AR process is not the only mechanism that generates Y, but it contains past values with its error terms. MA (q) process is defined as:

$$\epsilon t = \beta_1 \epsilon t + \beta_2 \epsilon t - 2 + \beta_3 \epsilon t - 3 + ... + \beta q Y \epsilon t - q. \tag{2}$$

That contains the white noise errors. When Y has the equations 1 and 2 it is called by ARMA (p, q) model. Since the financial time series data are type of non-stationary, therefore differencing the series will yield a stationary time series (Gujarathi et al., 2012; Box et al., 2015).

If the financial data becomes stationary when differenced d times, we name the series as I (d). Consequently, if ARMA (p,q) is applied to a series financial data which is I(d), then the original time series is ARIMA(p, d, q). The ARIMA methodology proposed that finding the values of p and q for AR and MA respectively by referring to the correlogram.

3.2 Wavelet transform formula

WT is a mathematical model employed to convert the original observations into a time-scale domain. The model is very appropriate with the non-stationary data since most of the financial data are non-stationary. WT can be divided into Discrete Wavelet transform (DWT) and continuous wavelet transforms (CWT). DWT consists of many functions such as Haar, Daubechies, and Maximum overlapping Wavelet transform (MODWT) and others. All of these functions have the same properties with different applications. In this article, the WT will be presented with its equation for all functions. For more details please refer to (Daubechies, 1992; Chiann and Morettin, 1998; Genay et al., 2002; Al Wadi, 2011).

WT is based on Fourier analysis (FT), which represents any function as the sum of the sine and cosine functions. WT is simply a function of time t that obeys a basic rule, known as the wavelet admissibility condition (Genay et al., 2002):

$$C_\varphi = \int_0^\infty \left(\frac{|\varphi f|}{f}\right) df < \infty. \tag{3}$$

Where is the FT, it was introduced to solve problems associated with the FT with non-stationary signals and the signals that are localized Time-Domain dimensions.

Father wavelets describe low-frequency parts of a signal where the mother wavelets describe high-frequency components. Equation (4) represents the father and mother wavelets respectively, with j=1,2,3,..., J in the J-level wavelet decomposition(Gencay, et, al., 2002):

$$\Phi j, k = 2^{-\frac{j}{2}} \phi(t - \frac{2^j k}{2^j}). \tag{4}$$

Father and mother wavelets and satisfy the following function:

$$\int \phi(t)dt = 1 and \int \varphi(t)td = 0. \tag{5}$$

The WT approximation to $f(t)$ is defined by:

$$F(t) = \sum S_{J,K}\Phi_{J,K}(t) + \sum d_{J,K}\varphi_{J,K}(t) + \sum d_{J-1,K}\varphi_{J-1,K}(t) + ... + \sum d_{1,K}\varphi_{1,K}(t), \tag{6}$$

$$S_J(t) = \sum S_{J,K}\Phi_{J,K}(t), \tag{7}$$

$$D_J(t) = \sum d_{J,K}\Phi_{J,K}(t). \tag{8}$$

Where S_J (t), and D_J(t) are introducing the smooth and details coefficients respectively. The smooth coefficients dives the most important features of the data set and the details coefficients are used to detect the main features in the dataset. For more details about the WT and its functions please refer to (Wadi, 2015; Al-Khazaleh et al., 2015).

3.2.1 Accuracy criteria

In this section the researchers will present the criteria which have been used to make a fair comparison, and then present the framework comparison with more details. The researches have been adopted to compare the performance of the models within two types of accuracy criteria which are Mean absolute square error (MSE), Root mean squared error (RMSE), and Mean absolute error (MAE). For more details about the mathematical model refer to (Aggarwal et al., 2008; Al Wadi et al., 2011).

4. Results

4.1 Data description

In this research, the statistical population includes firms listed in ASE over the time period of 1978-2016, a complete 38 years of time series data for 266 firms listed firms in ASE; because of variations in the number of listed companies from a year to year, we have used average earning per share(EPS) as a proxy to the firms' earning, EPS is considered as summary indicator that explain the firms' performance in term of profitability (Schroeder et al., 2009; Aladwan et al., 2018). The time series data were accessed from the ASE and extracted from firms' annual financial reports. The MATLAB and MINTAB software were used to analyze the data.

Figure 2 represents the model of the study.

Research hypothesis	**Independent Variable**	**Dependent Variable**	**Statistics**
Modeling and forecasting EPS	Time	EPS	Histogram, accumulated histogram and descriptive statistics, WT, ARIMA

Figure 2: Data analysis matrix

Histogram, accumulated histogram and descriptive statistics of the time series are shown in figure 3, which shows a linear path with positive slope; therefore, it is none stationary homogenous type, characterized by constant changes from one period to another.

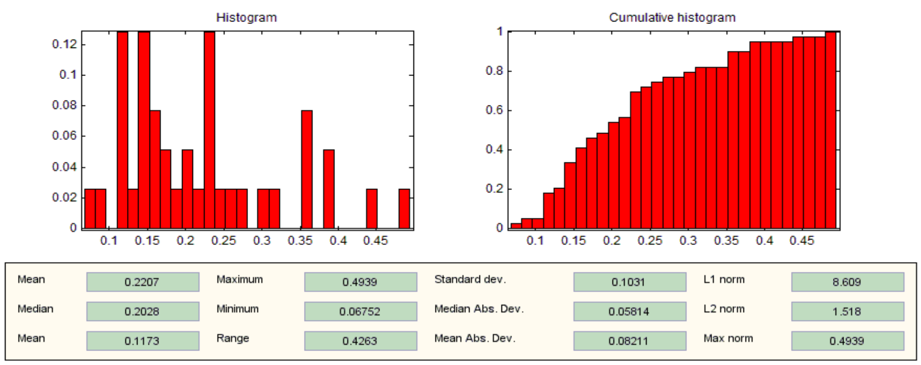

Figure 3: Statistical Analysis

4.1.1 Decomposing time series

Usually, the time series data has three components that are a trend, noise and seasonal components. Decomposition of the time series means separating original time series into these components. Therefore, Fig (4) shows the decomposition of based on WT. The decomposition consists of a1, which are the approximated coefficients used for the proper forecasting and d1 that show the fluctuations of data. Mathematically, the equation can be represented as S= a1+d1 where S is the original data.

Refer to the Fig (4) a visual inspection of the time plots shows that EPS data time series has a trend of random fluctuations this means the data are

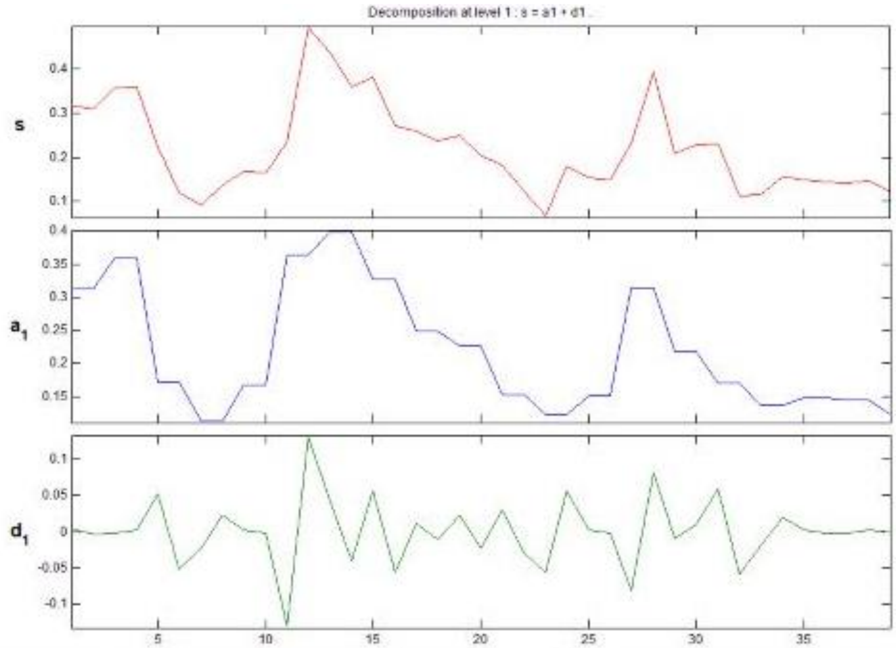

Figure 4: EPS 1978-2016 using WT

non-stationary and it is not constant around mean and variance. This type of non-stationary time series data contains a seasonal trend can be carried out by spectral Analysis function which is WT. Yield, random trend can be transformed into a linear trend. Before conducting additional analysis using ARIMA model then the data has to be discussed with its behaviors. Therefore, d1 is used to clarify the main features and fluctuations of the time series data, it has been clear that there was much fluctuation we descript that there is many events that ASE faced during the period under study which summarized in table 1

Table 1: events that effect EPS

obs	Year	Event that affect the EPS
4	1981	high earnings from exports to Iraq due to Iraq-Iranian Ware
11	1988	shrinking in liquidity because of Releasing ties with Palestine
13	1990	Iraq Kuwait conflict that enhanced demand and support earnings
17	1994	pull back in demand of products because of sanctions on Iraq
28	2005	Enhanced liquidity because of foreign investment from Gulf investors
31	2008	International financial crisis
34	2011	Syrian conflict

After we have done the decomposing process of time series data, we applied the ARIMA forecasting process.

The fitted ARIMA models were diagnosed using MASE and RMSE. Parameter estimation for the ARIMA models was done using the Gaussian MLE

Table 2: Average of EPS Earnings

	ARIMA Average EPS. Jordanian Dinar
Model	(2,2,1)
MASE	0.7089
RMSE	0.0709

criterion. The ARIMA models fitted based on the lowest value of MASE (0.7089) and RMSE (0.0709) as appear in table 2, with a fit ARIMA is ARIMA (2,2,1).

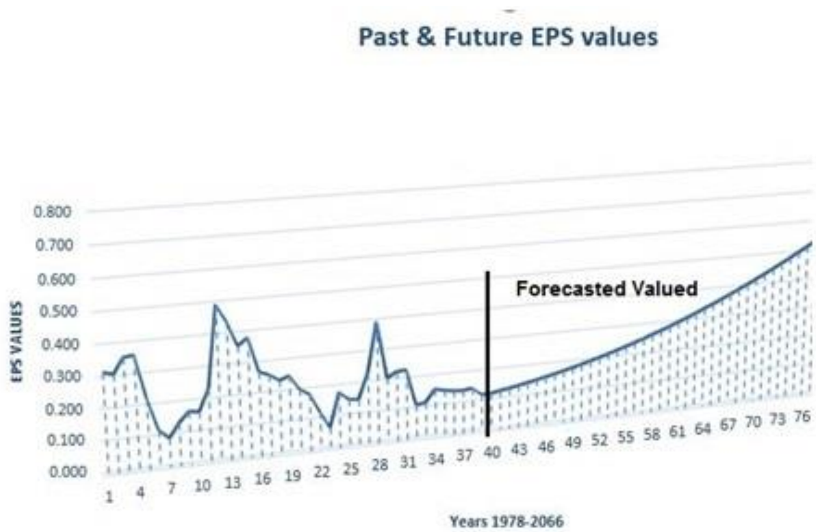

Figure 5: past and future EPS values

Figure 3 shows the EPS original time data series from (1978 till 2016) and the forecasted data of the EPS for the coming forty years (2017 till 2066), this suggests that the EPS long term trend is up ward slopping, which gives an indication that ASE firms' long-term profitability is growing. Furthermore, the EPS as experienced high fluctuation in the past 38 years, in the year of 1991, we are expecting the EPS value will reach its high past level in the year of 2044.

5. Conclusion

In this paper we deployed a WT model to decompose the data to detect the fluctuation and outlier values, then we utilized ARIMA model in forecasting firms' future earnings using earning per share (EPS) time series of firms' listed ASE of the years 1978 to 2016. It is clear that ARIMA model offers an excellent technique for forecasting any variable like EPS. It is strength lies in its fitting varieties of different types of time series with any pattern of change. In the process of model building, the original data is found none stationary then converted to be stationary. An ARIMA (2, 2, 1) model is developed for analyzing and forecasting EPS for ASE firms among all of various tentative ARIMA models as it has lowest BIC values. From the results, it can be observed that influence R Square value is (95%) high and Mean Absolute Percentage Error is very small for the fitted model. Therefore, the forecasting accuracy is high. It is concluded that firms' earnings show slow fluctuations and increasing trend for upcoming seventy-six financial years.

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