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REGRESSION MODELS OF PRICE OF EQUITY ON PROFIT OF EQUITY–CASE STUDY, MARKETS OF EQUITIES IN KSA

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ABSTRACT

This paper aims at studying the regression models that represent the relationship between the average profit of equity and the average price of equity. The study was conducted at 60 companies in the KSA, it includes cross-sectional data. The data which was used in the research covered the period 2012-2015. The Linear, Polynomial [Quadratic, Cubic, Logarithmic, Inverse, Exponential, and Logistic Regressions were used to analyze the data. The important result was, there is a significant relationship between the average profit of equity and the average price per equity. The best models are the simple linear regression model $\widehat{PRICE} = \underset{(4.56)}{23.605} + \underset{(1.919)}{11.174}\,PROFIT$ and the exponential model $\ln(PRICEadjusted) = \underset{(0.142)}{2.723} + \underset{(0.046)}{0.269}\,PROFITadjusted$, because their data is nearly normally

Keywords: Profit, Price, Equity, OIU, Sudan, Shaqra Uni., KSA

1. INTRODUCTION

This paper deals with fitting models that should be used to estimate the average price of equity in markets of equities in the KSA.

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The problem of the study is that, the researchers do not find previous study that, was used several fitted regression models to estimate the average price of equity in markets of equities in KSA; therefore they conducted this study.

The main objective of this paper is to fit a mathematical model used to estimate average price of equity in markets of equities in the KSA.

The importance of the paper is that, it will determine the best model that passes all the tests of the significance and the assumptions.

The market in which shares are issued and traded, either through exchanges or over-the-counter markets. Also known as the stock market, it is one of the most vital areas of a market economy because it gives companies access to capital and investors a slice of ownership in a company with the potential to realize gains based on its future performance (Investopedia, 2017).

Equity markets are the meeting point for buyers and sellers of stocks. The securities traded in the equity market can be either public stocks, which are those listed on the stock exchange, or privately traded stocks. Often, private stocks are traded through dealers, which is the definition of an over-the-counter market (Investopedia, 2017).

A market that gives companies a way to raise needed capital and gives investors an opportunity for gain by allowing those companies' stock shares to be traded. Also called stock market, (Business dictionary, 2017).

In fact, regression analysis is a statistical process for estimating the relationships among variables. It includes many techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables. More specifically, regression analysis helps one understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. Most commonly, regression analysis estimates the conditional expectation of the dependent variable given the independent variables – that is, the average value of the dependent variable when the independent variables are fixed.

Less commonly, the focus is on a quantize, or other location parameter of the conditional distribution of the dependent variable given the independent variables. In all cases, the estimation target is a function of the independent variables called the regression function. In regression analysis, it is also of interest to characterize the variation of the dependent variable around the regression function which can be described by a probability distribution.

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Really regression analysis is widely used for prediction and forecasting, where its use has substantial overlap with the field of machine learning. Regression analysis is also used to understand which, among the independent variables relate to the dependent variable, and to explore the forms of these relationships. In restricted circumstances, regression analysis can be used to infer causal relationships between the independent and dependent variables. However, this can lead to illusions or false relationships, so caution is advisable; (Armstrong; 2012), for example, correlation does not imply causation.

Many techniques for carrying out regression analysis have been developed. Familiar methods such as linear regression and ordinary least squares regression are parametric, in that the regression function is defined in terms of a finite number of unknown parameters that are estimated from the data. A nonparametric regression refers to techniques that allow the regression function to lie in a specified set of functions, which may be infinite-dimensional.

The execution of regression analysis methods in practice depends upon the form of the data generating process, and how it relates to the regression approach being used. Since the true form of the data-generating process is generally not known, regression analysis often depends to some extent on making assumptions about this process. These assumptions are sometimes testable if a sufficient quantity of data is available. Regression models for prediction are often useful even when the assumptions are moderately violated, although they may not perform optimally. However, in many applications, especially with small effects or questions of causality based on observational data, regression methods can give misleading results (Freedman; 2005) and (Cook; 1982).

Usually regression models involve the following variables:

The unknown parameters, denoted as β, which may represent a scalar or a vector.
The independent variables, X.
The dependent variable, Y.

In various fields of application, different terminologies are used in place of dependent and independent variables.

A regression model relates Y to a function of X and β is $Y= f(X, \beta)$.

The approximation is usually formalized as $E(Y \mid X) = f(X, \beta)$. To carry out regression analysis, the form of the function f must be specified. Sometimes the form of this function is based on knowledge about the relationship between Y and X that does not rely on the data. If no such knowledge is available, a flexible or convenient form for f is chosen.

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Assume now that the vector of unknown parameters β is of length k. In order to perform a regression analysis the user must provide information about the dependent variable Y:

If N data points of the form (X, Y) are observed, the most common situation is $N > k$ data points are observed. In this case, there is enough information in the data to estimate a unique value for β that best fits the data in some sense, and the regression model when applied to the data can be viewed as an over determined system in β.

In the last case, the regression analysis provides the tools for:

Finding a solution for unknown parameters β that will, for example, minimize the distance between the measured and predicted values of the dependent variable Y (also known as the method of least squares). Under certain statistical assumptions, the regression analysis uses the surplus of information to provide statistical information about the unknown parameters β and predicted values of the dependent variable Y.

1.1 Necessary number of independent measurements:

Consider a regression model which has two unknown parameters, β_0, β_1. If we have 10 pairs of (X,Y), the best one can do is to estimate the average value and the standard deviation of the dependent variable Y. Similarly, measuring at two different values of X would give enough data for a regression with the two unknowns, but not for three or more unknowns.

If the experimenter had performed measurements at three different values of the independent variable vector X, then regression analysis would provide a unique set of estimates for the three unknown parameters in β.

In the case of general linear regression, the above statement is equivalent to the requirement that the matrix $(X^T.X)$ is invertible.

1.2 Statistical assumptions:

When the number of measurements, N, is larger than the number of unknown parameters, k, and the measurement errors εi are normally distributed, then the excess of information contained in $(N - k)$ measurements is used to make statistical predictions about the unknown parameters. This excess of information is referred to as the degrees of freedom of the regression.

1.3 Classical assumptions for regression analysis include:

- The sample is representative of the population for the inference prediction.
- The error is a random variable with a mean of zero conditional on the explanatory variables.

- The independent variables are measured with no error. (Note: If this is not so, modeling may be done instead using errors-in-variables model techniques).
- The predictors are linearly independent, i.e. it is not possible to express any predictor as a linear combination of the others.
- The errors are uncorrelated, that is, the variance–covariance matrix of the errors is diagonal and each non-zero element is the variance of the error.
- The variance of the error is constant across observations (homoscedasticity). If not, weighted least squares or other methods might instead be used.

These are sufficient conditions for the least-squares estimator to possess desirable properties; in particular, these assumptions imply that the parameter estimates will be unbiased, consistent, and efficient in the class of linear unbiased estimators. It is important to note that actual data rarely satisfies the assumptions. That is, the method is used even though the assumptions are not true. Variation from the assumptions can sometimes be used as a measure of how far the model is from being useful. Many of these assumptions may be relaxed in more advanced treatments. Reports of statistical analyses usually include analyses of tests on the sample data and methodology for the fit and usefulness of the model.

Assumptions include the geometrical support of the variables, Cressie (1996).Independent and dependent variables often refer to values measured at point locations. There may be spatial trends and spatial autocorrelation in the variables that violate statistical assumptions of regression. Geographic weighted regression is one technique to deal with such data, Fotheringham; 2002. Also, variables may include values aggregated by areas. With aggregated data the modifiable areal unit problem can cause extreme variation in regression parameters, Fotheringham; 1991. When analyzing data aggregated by political boundaries, postal codes or census areas results may be very distinct with a different choice of units.

1.4 Linear regression:

In linear regression, the model specification is that the dependent variable, $\mathbf{y_i}$ is a linear combination of the parameters (but need not be linear in the independent variables). For example, in simple linear regression for modeling "n" data points there is one independent variable: $\mathbf{x_i}$, and two parameters, $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_1}$:

straight line:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i ....(1)$$

$$i = 1,2,...,n$$

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In multiple linear regression, there are several independent variables or functions of independent variables.

Adding a term in x_i^2 to the preceding regression gives a parabola as in equation 2:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \varepsilon_i ....(2)$$
$$i = 1,2,...,n$$

This is still linear regression; although the expression on the right hand side is quadratic in the independent variable $\mathbf{x_i}$, it is linear in the parameters $\boldsymbol{\beta_0}$, $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$.

In both cases, ε_i is an error term and the subscript "i" indexes a particular observation.

Given a random sample from the population with respect to equation 1, we estimate the population parameters and obtain the sample linear regression model 3:

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i ....(3)$$
$$i = 1,2,...,n$$

The residual, , $e_i = y_i - y_i^{\wedge}$, is the difference between the value of the dependent variable predicted by the model, $\mathbf{y_i}$, and the true value of the dependent variable, $\mathbf{y_i}$. One method of estimation is ordinary least squares. This method obtains parameter estimates that minimize the sum of squared residuals, SSE, Kutner, et al; 2004 and Ravishankar and Dey; 2002. Similarly with respect to model or equation 2, we estimate the population parameters and obtain the sample linear regression model 4:

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i + \hat{\beta}_2 X_i^2 ....(4)$$
$$i = 1,2,...,n \quad and \quad \hat{\beta}_2 \neq 0$$

Equation 4 has the form of a linear regression model as in model 5, (where I have added an error term ε):

$$y = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \varepsilon .....(5)$$

$$where, \quad x_1 = x \text{ and } x_2 = x^2$$

The residual, , $e_i = y_i - y_i^{\wedge}$, is the difference between the value of the dependent variable predicted by the model, $\mathbf{y_i}$, and the true value of the dependent variable, $\mathbf{y_i}$. One method of estimation is ordinary least squares.

Also, sometimes denoted RSS:

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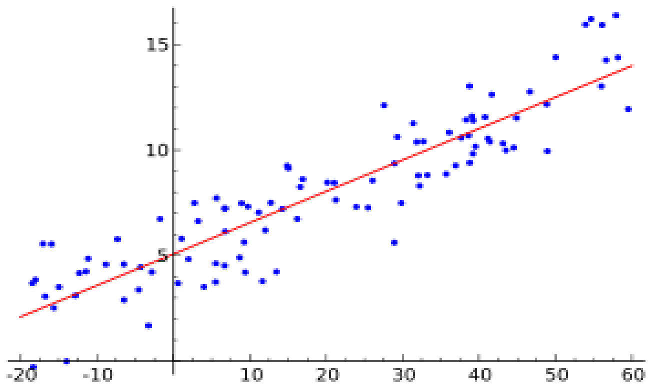
$$SSE = \sum_{i=1}^{n} e_i^2$$

Minimization of this function results in a set of normal equations, a set of simultaneous linear equations in the parameters, which are solved to yield the parameter estimates, $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_1}$. Figure 1, shows the fitted line of the simple linear regression.

Figure 1: Illustration of linear regression on a data set.



In the case of simple regression, the formulas for the least squares estimates are

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}, \quad and \quad \hat{\beta}_0 = \bar{y} - \hat{\beta}_0 \bar{x}$$

where $\bar{x}$ is the mean (average) of the x values and $\bar{y}$ is the mean of the y values.

Under the assumption that the population error term has a constant variance, the estimate of that variance is given by:

$$\hat{\sigma}_\varepsilon^2 = \frac{SSE}{n-2} = \frac{\sum_{i=1}^{n} e_i^2}{n-2}$$

This is called the mean square error (MSE) of the regression. The denominator is the sample size reduced by the number of model parameters estimated from the same data, (n-p) for p regression or (n-p-1) if an intercept is used. In this case, p=1 so the denominator is n-2.

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The standard errors of the parameter estimates are given by

$$\hat{\sigma}_{\hat{\beta}_0} = \hat{\sigma}_{\varepsilon}\sqrt{\frac{1}{n} + \frac{\bar{x}^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}}, \quad and \quad \hat{\sigma}_{\hat{\beta}_1} = \hat{\sigma}_{\varepsilon}\sqrt{\frac{1}{\sum_{i=1}^{n}(x_i - \bar{x})^2}}$$

Under the further assumption that the population error term is normally distributed, the researcher can use these estimated standard errors to create confidence intervals and conduct hypothesis tests about the population parameters.

1.5 Polynomial regression:

In statistics, polynomial regression is a form of linear regression in which the relationship between the independent variable x and the dependent variable y is modeled as an nth degree polynomial in x. Polynomial regression fits a nonlinear relationship between the value of x and the corresponding conditional mean of y, denoted E(y |x), and has been used to describe nonlinear phenomena such as the growth rate of tissues, [Shaw, P; et al. ;2006] the distribution of carbon isotopes in lake sediments, [Barker, PA; et al, 2001] and the progression of disease epidemics, [Greenland, Sander, 1995]. Although polynomial regression fits a nonlinear model to the data, as a statistical estimation problem it is linear, in the sense that the regression function E(y | x) is linear in the unknown parameters that are estimated from the data. For this reason, polynomial regression is considered to be a special case of multiple linear regression.

The predictors resulting from the polynomial expansion of the "baseline" predictors are known as interaction features. Such predictors/features are also used in classification settings, [Yin-Wen Chang; 2010]. Quadratic and cubic regression can be taken as special cases of polynomial regression.

1.6 Quadratic regression:

In algebra, a quadratic function, a quadratic polynomial, a polynomial of degree 2, or simply a quadratic, is a polynomial function in one or more variables in which the highest-degree term is of the second degree. In statistics, a quadratic function in two variables *x* and y is obtained by formula 2 which given above.

1.7 Cubic regression

In algebra, a cubic function, a cubic polynomial, a polynomial of degree 3, or simply a cubic, is a polynomial function in one or more variables in which the highest-degree term is of the third degree. In statistics, a cubic function in two variables *x*(independent variable) and y (dependent variable) is obtained by formula 6 which given below:

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$$y = \beta_0 + \beta_0 x + \beta_2 x^2 + \beta_3 x^3 + \varepsilon \text{..........}(6)$$
$$\beta_3 \neq 0$$

Given a random sample from the population with respect to equation 6, we estimate the population parameters and obtain the sample linear regression model 7:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_0 x + \hat{\beta}_2 x^2 + \hat{\beta}_3 x^3 \text{...........}(7)$$

Equation 7 has the form of a linear regression model as in model 8, (where we have added an error term ε):

$$y = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_3 + \varepsilon \text{.....}(8)$$

$where,\quad x_1 = x,\quad x_2 = x^2 and\ x_3 = x^3$

1.8 Exponential Regression using a Linear Model

Sometimes linear regression can be used with relationships which are not inherently linear, but can be made to be linear after a transformation. In particular, we consider the following exponential model9:

$$y = \alpha e^{\beta x} \text{........}(9)$$

Taking the natural log of both sides of the equation 9, we have the following equivalent equation10:

$$\ln(y) = \ln \alpha + \beta x \text{........}(10)$$

This equation has the form of a linear regression model as in model 11, (where we have added an error term ε):

$$y' = \alpha' + \beta x + \varepsilon \text{......}(11)$$

Observation: Since $\alpha e^{\beta(x+1)} = \alpha e^{\beta x} e^{\beta}$, we note that an increase in x of 1 unit results in y being multiplied by e^{β}

Observation: A model of the form ln y = βx + δ is referred to as a log-level regression model. Clearly any such model can be expressed as an exponential regression model of form (9), by setting $\alpha = e^{\delta}$.

1.9 Power regression:

A power regression is a function of the form 12:

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$$Y = \beta_0 . X^{\beta_1} .... (12)$$

where y is a dependent variable, x is an independent variable and β_0 and β_1 are constants.

Taking the natural log of both sides of the equation 12, we have the following equivalent equation 13:

$$\ln(y) = \ln \beta_0 + \beta_1 \ln(x) .... (13)$$

The equation 13 has the form of a linear regression model as in model 14, (where we have added an error term ε):

$$y' = \beta_0' + \beta_1 x' + \varepsilon ...... (14)$$

1.10 Inverse regression:

An inverse regression is a function of the form 15:

$$Y = \beta_0 + \frac{\beta_1}{X} ..... (15)$$

where y is a dependent variable, x is an independent variable (x≠0) and β_0 and β_1 are constants.

The equation15 has the form of a linear regression model as in model 16, (where we have added an error term ε):

$$y = \beta_0 + \beta x' + \varepsilon ...... (16)$$

Where $x' = \dfrac{1}{x}$

β_0 and β_1 can be estimated as same as in the linear model 3.

1.11 Logarithmic regression:

A logarithmic regression is a function of the form 17:

$$Y = \beta_0 + \beta_1 . Ln(X) .... (17)$$

Given a random sample from the population with respect to equation 17, we estimate the population parameters and obtain the sample linear regression model 18,(where we have added an error term ε):

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$$Y_i = \hat{\beta}_0 + \hat{\beta}_1 X_i' + \varepsilon_i \text{........}(18)$$

$$where, \quad X' = \ln X \quad and \quad x > 0$$

β_0 and β_1 can be estimated as same as in the linear model 3.

In the more general multiple regression model, there are p independent variables can be written as in equation 19:

$$y_i = \sum_{j=1}^{p} \beta_j x_{ij} + \varepsilon_i \text{......}(19)$$

$$i = 1,2,\ldots,n$$

where x_{ij} is the i^{th} observation on the j^{th} independent variable, and where the first independent variable takes the value 1 for all i (so $\boldsymbol{\beta_1}$ is the regression intercept).

The least squares parameter estimates are obtained from p normal equations. The residual can be written as in equation 20:

$$\varepsilon_i = (y_i - \sum_{i=1}^{p} \hat{\beta}_j x_{ij}) \text{......}20$$

The normal equations areas in equation 21:

$$\sum_{i=1}^{n} \sum_{j=1}^{p} X_{ij} X_{ik} \hat{\beta}_j = \sum_{i=1}^{n} X_{ik} y_i \text{........}21$$

$$k = 1,2,.., p$$

In matrix notation, the normal equations are written as in equation 22:

$$(X^T X)\hat{\beta} = X^T Y \text{........}22$$

where the ij element of X is x_{ij}, the i element of the column vector Y is y_i, and the j element of $\hat{\beta}$ is $\hat{\beta}_j$. Thus X is n×p, Y is n×1, and $\hat{\beta}$ is p×1. The solution is in equation 23:

$$\hat{\beta} = (X^T X)^{-1} X^T Y \text{........}23$$

Once a regression model has been constructed, it may be important to confirm the goodness of fit of the model and the statistical significance of the estimated parameters. Commonly used checks of goodness of fit includes the R-squared, analyses of the pattern of residuals and hypothesis testing. Statistical significance can be checked with an F-test of the overall fit, followed by t-tests of individual parameters.

Interpretations of these diagnostic tests rest heavily on the model assumptions. Although examination of the residuals can be used to invalidate a model, the results of a t-test or F-test are sometimes more difficult to interpret if the model's assumptions are violated. For example, if the error term does not have a normal distribution, in small samples the estimated parameters will not follow normal distributions and complicate inference. With relatively large samples, however, a central limit theorem can be invoked such that hypothesis testing may proceed using asymptotic approximations, Steel, et al; 1960 and Chiang; 2003.

2. MATERIAL AND METHODS

The main objective of this paper is to fit a mathematical model used to estimate average price of equity (dependent variable) by using average profit of equity as independent variable in markets of equities in the KSA.

A cross-sectional survey was carried out of reports of the Saudi stock market. Average of data of four years -2012to 2015-was used in the data analysis. The data covered 60 companies in KSA stock market.

The important reasons for using the data for the years 2012to 2015 are:

- The mentioned period was quite recent.
- There were zero values in profit of some companies, therefore, the average of profit of these years was obtained to avoid division by zero in the analysis of the data.

The models were used in this paper are given below:

Firstly: For the average of the data of price of equity and profit of equity, equations 1 and 2 are used in fitting regression model of price of equity on profit of equity.

where: Y is the mean of the price of equity.

X is the mean of the profit of equity.

$\boldsymbol{\beta_0}$ is the mean of the price of equity when mean of the profit of equity is zero.

$\boldsymbol{\beta_1}$ is the rate of change of mean of the price of equity when mean of the profit of equity changes by one unit.

$\boldsymbol{\varepsilon_i}$ is the error term ~NID(0, σ^2).

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To avoid division by zero for the inverse function and logarithm of zero for the functions that contain logarithm in their formulas, a constant 1 was added to each mean of the dependent and the independent variables for the all studied companies.

2.1 Analysis of simple linear regression:

Table 1 shows models summary consists of R, R^2, Adjusted R^2 and Durbin –Watson Statistics for the data of the price of the equity.

Table (1): Models Summary of the price of the equity, including R, R^2, Adjusted R^2 and Durbin –Watson Statistics, with respect to Analysis of simple linear regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.607[a]	.369	.358	27.5882176	1.606

a. Predictors: (Constant), PROFIT (x)

b. Dependent Variable: PRICE (y)

Table 2 shows analysis of variance of the data of the price of the equity under simple linear regression. The table consists of Components of Sum of Squares, Degrees of Freedom, Mean Squares, Calculated F and P-value (sig).

Table (2): Analysis of Variance (ANOVAa) of the Fitted Models of price of equity under simple linear regression

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25809.659	1	25809.659	33.911	.000[b]

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	Residual	44144.365	58	761.110		
	Total	69954.025	59			

a. Dependent Variable: PRICE

b. Predictors: (Constant), PROFIT

Table 3 shows Estimating and Testing the Significance of the Coefficients of the Fitted Models of the data of the price of the equity under simple linear regression. The table contains Unstandardized Coefficients**,** Standardized Coefficients, Std. Error, t-statistic and P-values.

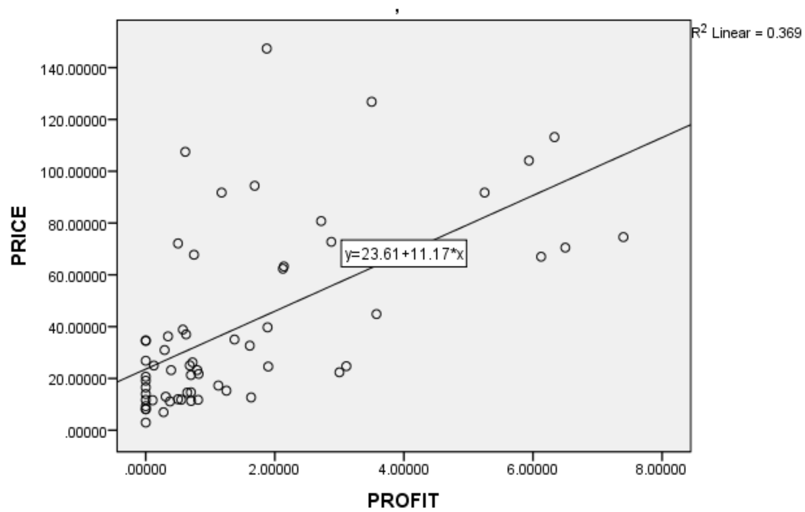
Table (3): Estimating and Testing the Significance of the Coefficients of the Fitted Model of the data of the price of the equity under simple linear regression

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	Constant	23.605	4.560		5.177	.000
	PROFIT	11.174	1.919	.607	5.823	.000

a. Dependent Variable: PRICE

b. Predictors: (Constant), PROFIT

Figure 2: Fiting of Simple Linear Regression of Equity Price on Equit Profit



y = PRICE (Price of Equity).

x = PROFIT = PROFIT (Profit of Equity).

2.2 Analysis of quadratic regression:

Table 4 shows models summary consists of R, R^2, Adjusted R^2 and Durbin –Watson Statistics for the data of the price of the equity of the analysis of quadratic regression

Table (4): Models Summary of the price of the equity, including R, R^2, Adjusted R^2 and Durbin –Watson Statistics, with respect to Analysis of quadratic regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.641[a]	.411	.391	26.8803102	1.402
a. Predictors: (Constant), PROFITSQU, PROFIT					
b. Dependent Variable: PRICE					

Table 5 shows analysis of variance of the data of the price of the equity under quadratic regression. The table consists of Components of Sum of Squares, Degrees of Freedom, Mean Squares, Calculated F and P-value (sig).

Table (5): Analysis of Variance (ANOVAa) of the Fitted Models of price of equity under quadratic regression

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	28768.614	2	14384.307	19.908	.000[b]
	Residual	41185.411	57	722.551		
	Total	69954.025	59			

a. Dependent Variable: PRICE

b. Predictors: (Constant), PROFITSQU, PROFIT

Table 6 shows Estimating and Testing the Significance of the Coefficients of the Fitted Models of the data of the price of the equity under quadratic regression. The table contains Unstandardized Coefficients**,** Standardized Coefficients, Std. Error, t-statistic and P-values.

Table (6): Estimating and Testing the Significance of the Coefficients of the Fitted Model of the data of the price of the equity under quadratic regression

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	16.965	5.523		3.072	.003
	PROFIT	22.931	6.103	1.246	3.757	.000
	PROFITSQU	-1.913-	.945	-.671-	-2.024-	.048
a. Dependent Variable: PRICE						

2.3 Analysis of cubic regression:

Table 7 shows models summary consists of R, R^2, Adjusted R^2 and Durbin –Watson Statistics for the data of the price of the equity of the analysis of cubic regression.

Table (7): Models Summary of the price of the equity, including R, R^2, Adjusted R^2 and Durbin –Watson Statistics, with respect to Analysis of cubic regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.641[a]	.411	.380	27.11412815	1.406

a. Predictors: (Constant), PROFIT.CUBE, PROFIT, PROFITSQU

b. Dependent Variable: PRICE

Table 8 shows analysis of variance of the data of the price of the equity under cubic regression. The table consists of Components of Sum of Squares, Degrees of Freedom, Mean Squares, Calculated F and P-value (sig).

Table (8): Analysis of Variance (ANOVAa) of the Fitted Models of price of equity under cubic regression

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	28784.172	3	9594.724	13.051	.000[b]
	Residual	41169.853	56	735.176		
	Total	69954.025	59			

a. Dependent Variable: PRICE

b. Predictors: (Constant), PROFIT.CUBE, PROFIT, PROFITSQU

Table 9 shows Estimating and Testing the Significance of the Coefficients of the Fitted Models of the data of the price of the equity under cubic regression. The table contains Unstandardized Coefficients, Standardized Coefficients, Std. Error, t-statistic and P-values.

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Table (9): Estimating and Testing the Significance of the Coefficients of the Fitted Model of the data of the price of the equity under cubic regression

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	17.399	6.321		2.753	.008
	PROFIT	21.400	12.190	1.163	1.756	.085
	PROFITSQU	-1.183-	5.111	-.415-	-.231-	.818
	PROFIT.CUBE	-.077-	.532	-.180-	-.145-	.885

a. Dependent Variable: PRICE

2.4 Analysis of Exponential Regression:

Table 10 shows models summary consists of R, R^2, Adjusted R^2 and Durbin –Watson Statistics for the data of the price of the equity of the analysis of the exponential regression.

Table (10): Models Summary of the price of the equity, including R, R^2, Adjusted R^2 and Durbin –Watson Statistics, with respect to the analysis of the exponential regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.612[a]	.375	.364	.65707040	1.555

a. Predictors: (Constant), PROFIT.ADJ (x)

b. Dependent Variable: LN.PRICE.ADJ (y)

Table 11 shows analysis of variance of the data of the price of the equity under exponential regression. The table consists of Components of Sum of Squares, Degrees of Freedom, Mean Squares, Calculated F and P-value (sig).

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Table (11): Analysis of Variance (ANOVAa) of the Fitted Models of price of equity under exponential regression

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	15.007	1	15.007	34.758	.000[b]
	Residual	25.041	58	.432		
	Total	40.048	59			

a. Dependent Variable: LN.PRICE.ADJ (y)

b. Predictors: (Constant), PROFIT.ADJ (x)

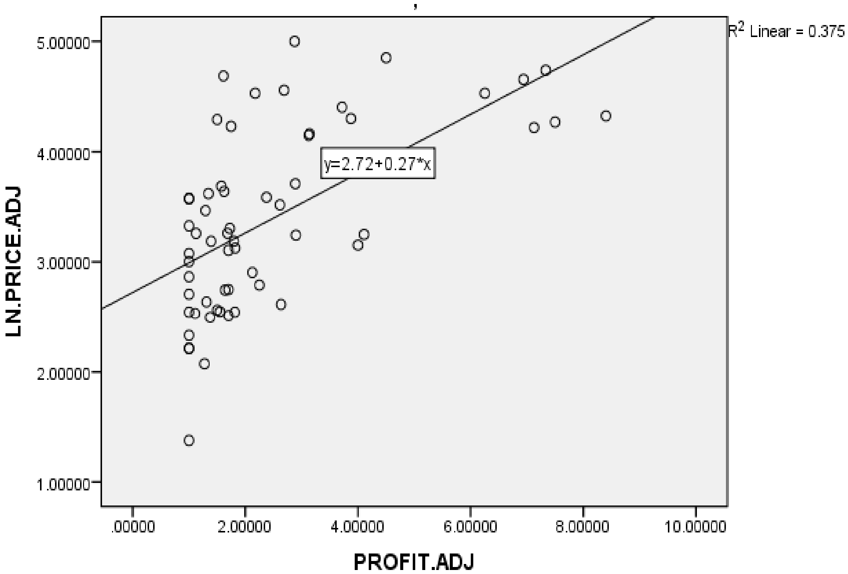
Table 12 shows Estimating and Testing the Significance of the Coefficients of the Fitted Models of the data of the price of the equity under exponential regression. The table contains Unstandardized Coefficients**,** Standardized Coefficients, Std. Error, t-statistic and P-values.

Table (12): Estimating and Testing the Significance of the Coefficients of the Fitted Model of the data of the price of the equity under exponential regression

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.723	.142		19.213	.000
	PROFIT.ADJ	.269	.046	.612	5.896	.000

a. Dependent Variable: LN.PRICE.ADJ (y)

Figure 3: Fiting of Exponential Regression of Equity Price on Equit Profit



y = LNPRICEADJ = Logarithm of the adjusted price(price+1)

x = PROFITADJ = Adjusted profit (profit+1)

2.5 Analysis of Power Regression

Table 13 shows models summary consists of R, R^2, Adjusted R^2 and Durbin –Watson Statistics for the data of the price of the equity of the analysis of the power regression.

Table (13): Models Summary of the price of the equity, including R, R^2, Adjusted R^2 and Durbin –Watson Statistics, with respect to the analysis of the power regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.661[a]	.437	.427	.62375808	1.431

a. Predictors: (Constant), LN.PROFIT.ADJ

b. Dependent Variable: LN.PRICE.ADJ

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Table 14 shows analysis of variance of the data of the price of the equity under powerregression. The table consists of Components of Sum of Squares, Degrees of Freedom, Mean Squares, Calculated F and P-value (sig).

Table (14): Analysis of Variance (ANOVAa) of the Fitted Models of price of equity under power regression

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17.481	1	17.481	44.931	.000[b]
	Residual	22.566	58	.389		
	Total	40.048	59			

a. Dependent Variable: LN.PRICE.ADJ

b. Predictors: (Constant), LN.PROFIT.ADJ

Table 15 shows Estimating and Testing the Significance of the Coefficients of the Fitted Models of the data of the price of the equity under power regression. The table contains Unstandardized Coefficients, Standardized Coefficients, Std. Error, t-statistic and P-values.

Table (15): Estimating and Testing the Significance of the Coefficients of the Fitted Model of the data of the price of the equity under power regression

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.771	.123		22.570	.000
	LN.PROFIT.ADJ	.886	.132	.661	6.703	.000

a. Dependent Variable: LN.PRICE.ADJ

2.6 Analysis of Inverse Regression:

Table 16 shows models summary consists of R, R^2, Adjusted R^2 and Durbin –Watson Statistics for the data of the price of the equity of the analysis of the inverse regression.

Table (16): Models Summary of the price of the equity, including R, R^2, Adjusted R^2 and Durbin –Watson Statistics, with respect to the analysis of the inverse regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.607[a]	.368	.357	27.60813557	1.393

a. Predictors: (Constant), INVERSEPROFITADJ

b. Dependent Variable: PRICE.ADJ

Table 17 shows analysis of variance of the data of the price of the equity under inverse regression. The table consists of Components of Sum of Squares, Degrees of Freedom, Mean Squares, Calculated F and P-value (sig).

Table (17): Analysis of Variance (ANOVAa) of the Fitted Models of price of equity under inverse regression

Model		Sum of Squares	df	Mean quare	F	Sig.
1	Regression	25745.894	1	25745.894	33.778	.000[b]
	Residual	44208.131	58	762.209		
	Total	69954.025	59			

a. Dependent Variable: PRICE.ADJ

b. Predictors: (Constant), INVERSEPROFITADJ

Table 18 shows Estimating and Testing the Significance of the Coefficients of the Fitted Models of the data of the price of the equity under inverse regression. The table contains Unstandardized Coefficients**,** Standardized Coefficients, Std. Error, t-statistic and P-values.

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Table (18): Estimating and Testing the Significance of the Coefficients of the Fitted Model of the data of the price of the equity under inverse regression.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	83.404	8.092		10.307	.000
	INVERSE. PROFIT. ADJ	-72.731-	12.514	-.607-	-5.812-	.000

a. Dependent Variable: PRICE.ADJ

2.7 Analysis of Logarithmic Regression:

Table 19 shows models summary consists of R, R^2, Adjusted R^2 and Durbin –Watson Statistics for the data of the price of the equity of the analysis of the logarithmic regression.

Table (19): Models Summary of the price of the equity, including R, R^2, Adjusted R^2 and Durbin –Watson Statistics, with respect to the analysis of the logarithmic regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.638[a]	.407	.396	26.75463302	1.412

a. Predictors: (Constant), LN.PROFIT.ADJ

b. Dependent Variable: PRICE.ADJ

Table 20 shows analysis of variance of the data of the price of the equity under logarithmic regression. The table consists of Components of Sum of Squares, Degrees of Freedom, Mean Squares, Calculated F and P-value (sig).

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Table (20): Analysis of Variance (ANOVAa) of the Fitted Models of price of equity under logarithmic regression

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	28437.022	1	28437.022	39.727	.000[b]
	Residual	41517.002	58	715.810		
	Total	69954.025	59			

a. Dependent Variable: PRICE.ADJ

b. Predictors: (Constant), LN.PROFIT.ADJ

Table 21 shows Estimating and Testing the Significance of the Coefficients of the Fitted Models of the data of the price of the equity under logarithmic regression. The table contains Unstandardized Coefficients**,** Standardized Coefficients, Std. Error, t-statistic and P-values.

Table (21): Estimating and Testing the Significance of the Coefficients of the Fitted Model of the data of the price of the equity under logarithmic regression.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	16.133	5.266		3.064	.003
	LN.PROFIT.ADJ	35.751	5.672	.638	6.303	.000

a. Dependent Variable: PRICE.ADJ

3. RESULTS

According to the skewness and kurtosis coefficients, which are shown in Appendix 1, the best models are the simple linear regression model $\hat{PRICE} = \underset{(4.56)}{23.605} + \underset{(1.919)}{11.174} PROFIT$ and the exponential model $\ln(PRICEadjusted) = \underset{(0.142)}{2.723} + \underset{(0.046)}{0.269} PROFITadjusted$, because their data is nearly normally distributed. From the summary that was shown in tables 1 and 10, the simple linear and the exponential models has Durbin-Watson values approximately equal to 2, therefore

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there are no autocorrelations. From the summary that was shown in tables 4, 7, 13, 16 and 19, the other models have Durbin-Watson values less than 2, so there are positive autocorrelations in these models.

3.1 Interpretation of results of simple linear model:

From table 1, the coefficient of correlation is 0.607, that means there is positive medium correlation between the price and the profit of the equity. The adjusted R-square approximately equal to 0.36, that means 36 % of the change of the price of the equity refers to the change of the profit of the equity. From table 2, the calculated vale of F is 33.91 with p-value (Sig=0.000), that means the fitted model is highly significant. Table 3 shows that, all coefficients of the model are highly significant, because the constant (23.605) has calculated t- value (5.177) with p-value (Sig=0.000). Also the coefficient of the profit (11.174) has calculated t- value (5.823) with p-value (Sig=0.000).). According to the linear model, the initial value of the price of the equity (when profit is zero) is equal to24.72 and if the profit of the equity changes by 1 unit, the price of the equity changes by 11.174 units.

3.2 Interpretation of results of exponential model:

From table 10, the coefficient of correlation is 0.612, that means there is positive medium correlation between the price and the profit of the equity. The adjusted R-square approximately equal to 0.364, that means 36.4 % of the change of the logarithm of the adjusted price (y) of the equity refers to the change of the adjusted profit (x) of the equity. From table 11, the calculated vale of F is 34.758 with p-value (Sig=0.000), that means the fitted model is highly significant. Table 12 shows that, all coefficients of the model are highly significant, because the constant (2.723) has calculated t- value (19.213) with p-value (Sig=0.000). Also the coefficient of the profit (0.269) has calculated t- value (5.896) with p-value (Sig=0.000).. According to the exponential model, the initial value of the price of the equity (when profit is zero) is equal to $e^{2.723} =$ 15.22593 and if the profit of the equity changes by 1 unit, the price of the equity changes by $e^{0.269} =$ 1.30866 units.

4. DISCUSSIONS

In consequence of the above mentioned results, the following points discussed:

To conduct similar studies compared by other stock markets.

To conduct similar studies by using time series data to fit models.

To take the advantages of this study in the planning.

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APPENDIX:

Appendix (1): Descriptive statistics of price of equity, profit of equity and their transformations.

		PROFIT	PRICE	PROFIT.ADJ	PRICE.ADJ	LN.PROFIT.ADJ	LN.PRICE.ADJ	PROFITSQU	PROFIT.CUBE	INVERSEPROFITADJ
N	Valid	60	60	60	60	60	60	60	60	60
	Missing	0	0	0	0	0	0	0	0	0
Std. Error of Mean		.24164	4.44534	.24164	4.44534	.07928	.10636	1.5599	10.3089	.03708
Std. Deviation		1.87173	34.43343	1.87173	34.43343	.61409	.82388	12.0831	79.852	.28722
Skewness		1.756	1.284	1.756	1.284	.773	.092	2.702	3.213	.092
Std. Error of Skewness		.309	.309	0.309	.309	.309	.309	.309	.309	.309
Kurtosis		2.357	.858	2.357	.858	-.308-	-.698-	6.605	10.188	-1.146-
Std. Error of Kurtosis		.608	.608	0.608	.608	.608	.608	.608	.608	.608
Range		7.40000	144.400	7.400	144.400	2.12823	3.61972	54.760	405.22	.881
Minimum		.00000	2.975	1.000	3.97500	.00000	1.38002	.000	.00	.1191
Maximum		7.40000	147.375	8.400	148.37500	2.12823	4.99974	54.760	405.22	1.000

