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ASSESSING STOCK PERFORMANCE USING PANEL LOGISTIC REGRESSION: EVIDENCE FROM KSA STOCK MARKET

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Abstract. Assessing stock performance is very important for investors to act in future. KSA stock market is evolving rapidly; so the objective of our paper is to analyze the stock performance using panel logistics regression. Logistic model is a variety of probabilistic statistical classification model. It is also used to predict a binary response from a binary predictor. The model has used the preprocessed data set of closing value, fundamental and technical data of 18 firm listed in KSA stock market. The data set encompassed the trading days from 7th January, 2007 to 18th May, 2015. The method gives us estimation with up to 90.59% accuracy.

Keywords: stock performance; panel logistic regression; fundamental ratios; technical analysis.
2010 AMS Subject Classification: 91G80.

Introduction

Recently measuring stock performance is gaining more and more consideration, perhaps because of the fact that if the trend of the market is successfully forecasted the traders may be well directed. The profitability of trading in the stock market to a large extent rest on the predictability stock performance.

The data accessible to investors, regardless of its source (fundamental, technical or behavioral) represents a fundamental basis in taking decisions on a capital market. Due to the diversity of existing information specific to the stock market and to the presence of information asymmetry, investors must demonstrate they are able to explain and examine the information delivered when taking decisions.

Forecasting stock performance is surely so challenging and complex. In literature, no complete, precise model has been recommended for expecting stock performance. A stock's performance

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can be studied founded on financial ratios obtainable from the company's annual report. Earlier literature proposes that financial indicators are vital tools for evaluating future stock performance for researchers, analysts and investors. Ratio analysis has been developed, so, as one of the main parameters employed by investors and fund managers to fix the intrinsic value of shares; therefore, financial ratios are used extensively for the assessment of stock.

Due to increasing importance; the aim of this study is to forecast the stock market performance trends by using logistic regression. Our contribution is twice, the first concern the assessment of stock performance where we use not only financial ratios but we introduce technical indicators. The second is at the level of statistical model where we use panel logistic data to measure and predict the stock market for several sectors and for the overall market. Logistic model is a type of probabilistic statistical classification model. It is also used to predict a binary response from a binary predictor, used for predicting the outcome of a categorical dependent variable(i.e., a class label) based on one or more predictor variables (features). The model has used the preprocessed data set of 17 stocks from seven different sectors of Saudi stock market. The data set encompassed the weekly data from 7th January, 2007 to 18th May, 2015.

This paper contains four sections. The first one introduce the study, in the second we review literature linked to our paper, then we explain methodology of research and present results, the forth section concludes the paper.

1- Literature review

The link between the information delivered by the financial statements and stock price was demonstrated ever since 1968 by Ball and Brown (1968). As regards to the effect of a rate detrimental to another, Chen and Dodd (1997) indicated that, even though ratios concerning value creation offer more information than traditional ratios in explaining the overall performance of a stock, they must not replace traditional ratios such as Earnings Per Share (EPS), Return On Assets (ROA) or Return On Equity (ROE). Maditions et al. (2009) targeted in their study the same connection between stock return and ratios concerning creating value, respectively traditional ratios such as Return On Investments (ROI), ROE and EPS for the Athens Stock Exchange. ArabSalehi and Mahmoodi (2011) have analyzed the link between the Economic Value Added (EVA), as a ratio concerning value creation for shareholders, traditional accounting ratios and their capacity to explain stock return.

Further studies have extended the research area to Market to Book Ratio (M/B Ratio), Price-Earnings Ratio (P/E Ratio), Dividend Yield. Because each one of these ratios uses the price as numerator, the connection with the capital gains yield should be positive (Lewellen, 2004). The importance of P/E Ratio was analyzed by Basu (1977) who showed that firms with low P/E presented higher returns than firms with great P/E ratios. The M/B Ratio is considered to be one of the main determinants of stock performance for a company and, based on numerous studies, has proven to have a significant explanatory power on the stock return (Ruthenberg et al., 2011). Rosenberg et al. (1985) and Chan et al. (1991) used in their studies the inverse of this ratio (Book to Market Ratio - B/M Ratio) showing the existence of a direct and positive relationship with stock returns.

Logistic Regression is a multivariate analysis model (Lee, 2004) very useful for prediction. The applications of this model in the area of finance is growing rapidly. Many researchers employed the multivariate discriminant analysis prediction model. Altman is the pioneer in the year 1968 while logistic regression was used by the Ohlson in 1980. The first study on prediction focuses on classifying companies as either non-defaulters or defaulters.

In forecasting bankruptcy and financial distress, logistic regression was applied by Ohlson (1980) and then by Zavgren (1985) and other researchers. Logistic regression technique yields coefficients for each independent variable based on a sample of data (Huang, Chai and Peng, 2007). Logistic regression models with more than one explanatory variable are applied in practice (Haines and Others, 2007, Pardo, Pardo and Pardo, 2005). The benefit of logistic regression is that variables may be either discrete or continuous, they do not necessarily have normal distributions (Lee, 2004).

2- Data, methodology and results

3-1- Data and variables

The data consists of weekly stock returns of 18 firms from different sectors cited in the Saudi stock market (TASA). The period under consideration is from 07/01/2007 to 18/05/2015. The data set consists of 2091 data points for each firm. The data has been obtained from the official web site of Saudi stock market that provides weekly stock market data.

Table 1: Description of sample data

Sector	Symbol	Name
Banks & Financial Services	1060	Saudi British Bank
	1120	Al Rajhi Bank
	1090	Samba Financial Group
Petrochemical Industries	2010	Saudi Basic Industries Corp.
	2330	Advanced Petrochemical Co.
	2250	Saudi Industrial Investment Group
Cement	3010	Arabian Cement Co.
	3040	Qassim Cement Co.
Agriculture & Food Industries	6050	Saudi Fisheries Co.
	2280	Almarai Co.
	6010	National Agricultural Development Co.
Energy & Utilities	5110	Saudi Electricity Co.
	2080	National Gas and Industrialization Co
Telecommunication & Information Technology	7020	Etihad Etisalat Co.
	7010	Saudi Telecom Co.
Real Estate Development	4020	Saudi Real Estate Co.
	4100	Makkah Construction and Development Co.
	4090	Taiba Holding Co.

The study variables are classified into two categories: Fundamental variables based on financial ratios and technical variables. These variables are summarized in table 2.

Table 2: Description of independent variables

Type	Name	Formulae
Fundamental data	EPS - Earnings Per Share	Net Profit / Number of Shares
	P/E - Price-Earnings Ratio	Stock Price / Earnings Per Share
	P/B - Price to Book Ratio	Stock Price / Book Value Per Share
Technical data	MOM - Momentum (12)	Stock price (t) - Stock price (t-12)
	RSI – Relative Strength Index	100 - 100/(1 + RS*) *Where RS = Average of x days' up closes / Average of x days' down closes.
	ADW - Accumulation distribution of Williams	Acc/Dist = ((Close – Low) – (High – Close)) / (High – Low) * Period's volume

The data needed of the proposed variables were taken from the financial statements of the sample firms and stock market data , found on the website www.tadawul.com.sa.

To carry out the logistic regression, first a method is needed for classifying a company as a “good” or “poor” investment choice for a given time. In this study we use a method that is simple, if the value of a company’s stock over a given time rose above market return, it is classified as a “good” investment option; otherwise, it is classified as a “poor” investment option. Here, the TASI (Tadawul All Share Index) return has been taken as proxy for market return. The return was calculated using the following formula:

$$return = \frac{p_j - p_{j-1}}{p_{j-1}} \times 100$$

Where:

p_j is the closing price for week j

p_{j-1} is the closing price for week j-1

3-2- Application of Panel logistic regression

Logistic regression is used in our study because we assume that the relation between variables is non-linear. Also this type of regression is preferred when the response variable is binary which means that can take only two values 1 or 0.

Logistic regression could forecast the likelihood, or the odds ratio, of the outcome based on the predictor variables, or covariates. The significance of logistic regression can be evaluated by the log likelihood test, given as the model chi-square test, evaluated at the $p < 0.05$ level, or the Wald statistic. Logistic regression has the advantage of being less affected than discriminant analysis when the normality of the variable cannot be assumed.

It has the capacity to analyze a mix of all types of predictors [Hair, 1995]. Logistic regression, which assumes the errors are drawn from a binomial distribution, is formulated to predict and explain a binary categorical variable instead of a metric measure. In logistic regression, the dependent variable is a log odd or logit, which is the natural log of the odds.

In the logistic regression model, the relationship between Z and the probability of the event of interest is described by this link function.

$$p_{ij} = \frac{e^{zij}}{1+e^{zij}} = \frac{1}{1+e^{-zij}}$$

$z_{ij} = log\left(p_{ij}/1 - p_{ij}\right)$

Where

p_{ij} is the probability the j^h case experiences the event of interest at time i

z_{ij} is the value of the unobserved continuous variable for the j^{th} case at time t

The z value is the odds ratio. It is expressed by

$z_{ij} = c + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip}$

Where

x_{ij} is the ratio of the j^{th} firm at time i^{th}

β_j is the j^{th} coefficient

P is the number of firms

i is time

βj are the regression coefficients that are estimated through an iterative maximum likelihood method. However, because of the subjectivity of the choice of these misclassification costs in practice, most researchers minimize the total error rate and, hence, implicitly assume equal costs of type I and type II errors [Ohlson, 1980; Zavgren, 1985].

In order to carry out logistic regression analysis, first a method is needed for classifying returns as a “1” or “0” for a given day. In this study we use a method that is simple and objective, if the value of a return in week j is above the market return, it is noted as a “good” (mentioned "1"); otherwise, it is classified as a “poor” (mentioned "0").

As mentioned, the study contains 2091 data where 1394 are used for estimating and 697 used for validating the model. For variables, we have the market return as dependent variable and six independent variables. Three of them is financial ratios and the others are technical indicators.

We conduct the logistic regression in two steps. The first called general model where we introduced all our independent variables. The second is called the reduced model where we use only the significant variables of the general model.

The estimation is done using the software Stata12 and the results are summarized in the following table:

Table 3: Full model results

Variables	Coefficient	Std. error	z-statistic	Prob.
Constant	0.0710642	0.0467251	2.52	0.010
EPS	0.002037	0.0006601	3.09	0.002
P/E	0.0001635	0.0001275	1.28*	0.200
P/B	0.0003166	0.0001194	2.65	0.008
MOM	33.54473	0.807452	41.54	0.000
RSI	-0.003231	0.0008663	-3.73	0.000
ADW	-0.5908938	0.0309335	-19.10	0.000

(*): is significantly non-significant at 5% level

The final panel logistic regression equation is estimated in general model by using the maximum likelihood estimation:

Zij = 0.0710642 + 0.002037***EPS** + 0.0001635***P/E** + 0.0003166***P/B** + 33.54473***MOM** - 0.003231* **RSI** - 0.5908938***ADW**

We note that the statistic Log likelihood is equal to -23595.832. This statistic suppose in the null hypothesis that all coefficients are equal to zero except the constant. Here we reject this hypothesis with zero probability to be wrong. This means that our model is globally significant. To enforce the results, we make the wald test which study the same hypothesis. We found Wald chi2(6) equal to 3564.87 (prob =0). So we reject the null hypothesis.

Regarding the results of this model, the variable momentum has the higher influence on the stock performance and is more important in prediction among the technical and fundamental variables chose in our estimation. while the variable P/E is significantly non-significant so it will be removed in the next step which is the reduced model. For technical indicators, they show negative coefficient so they have negative impact on stock performance.

Now we will speak about the marginal effect of variables. The marginal effect for jth explicative variable $x_i^{[j]}$ is defined as :

$$\frac{\partial p_i}{\partial x_i^{[j]}} = f(x_i\beta).\beta_j = \frac{e^{x_i\beta}}{(1+e^{x_i\beta})^2}\beta_j$$

Because of the sign of $f(x_i\beta)$ is always positive, so the sign of this derivate is the same of the coefficient. So the positive sign indicate an increase in the probability of y to be equal to 1 which is the case for variables: higher price, lower price,and oil. While a negative sign reflect a decrease in this probability which the case for the variable open price.

For more explanation we calculate the elasticity $\varepsilon_{p_i/x_i^{[j]}}$ as the variation in percentage of the probability p_i that $y_i = 1$ occurs due to a variation of 1% of the jth explicative variable $x_i^{[j]}$. Elasticity is defined as:

$$\forall i \in [1, N] \qquad \varepsilon_{p_i/x_i^{[j]}} = \frac{x_i^{[j]}\beta_j}{1+exp^{x_i\beta}}$$

Table 4: elasticity of variables in complete model

Variables	EPS	P/E	P/B	MOM	RSI	ADW
dy/ex	0.0151894	0.0045098	0.0183969	0.0122018	-0.1665735	-0.0040409
Std. Err	0.004922	0.003517	0.0069409	0.0002937	0.04466	0.0002115
z	3.09	1.28	2.65	41.54	3.73	-19.10
P>|z|	0.002	0.200	0.008	0.000	0.000	0.000

With a 95% degree of confidence a 1% increase of EPS, P/E, P/B and MOM determines an increase in the probability of good performance of 1.5%, 0.4%, 1.8%, and 1.2% successively. The 1% increase of RSI and ADW determines an increase in the probability of bad performance of 16.6% and 4% successively.

Because of the ratio P/E was non-significant, we will perform the reduced model by eliminating this variable.

Table 5: reduced model results

Variables	Coefficient	Std. error	z-statistic	Prob.
Constant	0.0673188	0.0466281	2.44	0.010
EPS	0.0020257	0.000659	3.07	0.002
P/B	0.0003016	0.0001187	2.54	0.011
MOM	33.49904	0.806433	41.54	0.000
RSI	-.0032522	0.0008661	-3.76	0.000
ADW	-0.5892745	0.0308989	-19.07	0.000

The final logistic regression equation is estimated in a reduced model by using the maximum likelihood estimation:

Zij = 0.0673188 + 0.0020257***EPS** + 0.0003016***P/B** + 33.49904* **MOM** -0. 0032522* **RSI** -0.5892745***ADW**

In this estimation the momentum has more influence on the stock performance.

We note that the statistic log likelihood is equal to -23596.642. This statistic suppose in the null hypothesis that all coefficients are equal to zero except the constant. Here we reject this hypothesis with zero probability to be wrong. This means that our model is globally significant. To enforce the results we make the wald test which study the same hypothesis. We found chi-square(5) equal to 3564.06 (prob=0). So we reject the null hypothesis.

To measure the quality of our model we calculate LR test. Results show that LR test is equal to 1.62 with Prob > chi2 = 0.2032. this means that the reduced model will not improve the results of our estimation regarding the performance of stocks.

Using this result we will estimate the value of our dependent variable for the left 697 data in order to test the performance of our model. The result are shown in the following table::

Table 6: Expectation-Prediction Evaluation

Measure	Full model		Reduced model	
	Correct (%)	Wrong (%)	Correct (%)	Wrong (%)
Y=1	91.50	8.50	92.01	7.99
Y=0	89.68	10.32	90.1	9.9
Total	**90.59**	**9.41**	**91.05**	**8.94**

Here we validate the results of the LR Test that the reduced model will not improve the results and we can still use the results of the full model for estimation with accuracy of our model is of 91.5 % which is very important and can help investor to implement the best investment strategy.

3-3- Results according sectors

Now we use the panel logistic regression for each sector to detect the pertinent variable according to sector.

Table 7: Banks & Financial Services

Variables	Coefficient	Std. error	z-statistic	Prob.
Constant	-0.0422022	0.0825116	-2.51	0.009
EPS	0.0026581	0.0032496	0.82*	0.413
P/E	0.0040021	0.0071056	0.56*	0.573
P/B	0.0023271	0.0021499	1.98	0.079
MOM	52.88689	2.438997	21.68	0.000
RSI	-0.0001454	0.001345	-0.11*	0.914
ADW	-0.2433182	0.0781569	-3.11	0.002

(*): is significantly non-significant at 5% level

The final panel logistic regression equation is for Banks & Financial Services sector:

Zij = -0.0422022 + 0.0026581***EPS** + 0.0040021***P/E** + 0.0023271***P/B** + 52.88689***MOM** - 0.0001454 * **RSI** - 0.2433182***ADW**

For this sector only technical indicators are significant (MOM and ADW). This is because of banks operate and generate profit in such a fundamentally different way than most other businesses. While other industries create or manufacture products for sale, the primary product a bank sells is money. The financial statements of banks are typically much more complicated than those of companies engaged in virtually any other type of business. While investors considering bank stocks look at such traditional equity evaluation measures as price-to-book (P/B) ratio or price-to-earnings (P/E) ratio, they also examine industry-specific metrics to more accurately evaluate the investment potential of individual banks.

Table 8: Petrochemical Industries

Variables	Coefficient	Std. error	z-statistic	Prob.
Constant	-0.145911	0.089037	-1.94	0.091
EPS	0.001517	0.0049438	0.31*	0.759
P/E	0.0081671	0.0038153	2.14	0.032
P/B	0.0019517	0.0024816	0.79*	0.432
MOM	15.28646	1.318951	11.59	0.000
RSI	-0.0027916	0.0013032	-2.14	0.032
ADW	-0.577478	0.0589467	-9.80	0.000

(*): is significantly non-significant at 5% level

The final panel logistic regression equation is for Petrochemical Industries Services sector:

Zij = -0.145911+ 0.001517***EPS** + 0.0081671***P/E** + 0.0019517***P/B** + 15.28646***MOM** - 0.0027916* **RSI** - 0.577478***ADW**

For financial ratios, only P/E is significant while all technical indicators are significant. This can be interpreted by the fact that petrochemical companies are unique from a valuation standpoint. Because of this, investors need to focus on a different subset of ratios to analyze the growth and profitability of these companies.

Table 9: Cement

Variables	Coefficient	Std. error	z-statistic	Prob.
Constant	-0.0661099	0.10782	-2.61	0.040
EPS	0.0085987	0.0036623	2.35	0.019
P/E	0.0036276	0.0045415	0.80*	0.424
P/B	0.0014913	0.0025114	0.59*	0.553
MOM	40.99056	3.289145	12.46	0.000
RSI	-0.0002697	0.0017103	-0.16*	0.875
ADW	-0.2805249	0.0904628	-3.10	0.002

(*): is significantly non-significant at 5% level

The final panel logistic regression equation is for Cement sector:

Zij = -0.0661099 + 0.0085987***EPS** + 0.0036276***P/E** + 0.0014913***P/B** +40.99056 ***MOM** - 0.0002697* **RSI** - 0.2805249***ADW**

Only EPS, MOM and ADW are significant. In the nature of manufacturing processing (burning and grinding), energy consumption is high. So, the portion of electricity and fuel costs for burning and grinding is higher than cost burden that arises from purchases of raw materials, compared with other industries. For this reason the stock performance cannot be assessed by financial ratios.

Table 10: Agriculture & Food Industries

Variables	Coefficient	Std. error	z-statistic	Prob.
Constant	-0.051061	0.0674485	-2.76	0.049
EPS	0.0079417	0.005861	1.36*	0.175
P/E	0.0041325	0.0021409	1.98	0.054
P/B	0.0004325	0.0027576	0.16*	0.875
MOM	17.85488	1.464216	12.19	0.000
RSI	-0.0000182	0.0013535	-0.01*	0.989
ADW	-0.5355184	0.0820166	-6.53	0.000

(*): is significantly non-significant at 5% level

The final panel logistic regression equation is for Agriculture & Food Industries sector:

Zij = -0.051061+ 0.0079417***EPS** + 0.0041325***P/E** + 0.0004325***P/B** + 17.85488***MOM** - 0.0000182* **RSI** - 0.5355184***ADW**

Only P/E, MOMO and ADW is significant. This is due to the characteristics of this sector linked to environment, weather and technology.

Table 11: Energy and Utilities

Variables	Coefficient	Std. error	z-statistic	Prob.
Constant	-0.0652408	0.1273665	-2.51	0.038
EPS	0.0135143	0.0163561	0.83 *	0.409
P/E	0.0023846	0.0035206	0.68 *	0.498
P/B	0.0027098	0.0029693	0.91 *	0.361
MOM	38.23043	3.20363	11.93	0.000
RSI	0.0036392	0.0016872	2.16	0.031
ADW	-1.842595	0.3100435	-5.94	0.000

(*): is significantly non-significant at 5% level

The final panel logistic regression equation is for Energy and Utilities sector:

Zij = -0.0652408 + 0.0135143***EPS** + 0.0023846***P/E** + 0.0027098***P/B** + 38.23043***MOM** - 0.0036392* **RSI** - 1.842595***ADW**

Only technical indicators are significant this is because stocks have greater volatility when compared to other businesses. energy prices see large price swings in the face of good or bad economic news for this reason stock performance is not explained by financial ratios.

Table 12: Telecommunication & Information Technology

Variables	Coefficient	Std. error	z-statistic	Prob.
Constant	-0.2228236	0.1007434	-2.21	0.027
EPS	0.0052234	0.0024541	2.13	0.033
P/E	0.0013422	0.0046756	0.29*	0.774
P/B	0.0046038	0.0026929	1.99	0.067
MOM	47.94377	3.667935	13.07	0.000
RSI	0.000171	0.0018001	0.09*	0.924
ADW	-0.3706529	0.1055895	-3.51	0.000

(*): is significantly non-significant at 5% level

The final panel logistic regression equation is for Telecommunication & Information Technology sector:

Zij = -0.2228236+ 0.0052234***EPS** + 0.0013422***P/E** +0.0046038***P/B** + 47.94377 ***MOM** - 0.000171 * **RSI** - 0.3706529 ***ADW**

Almost indicators are significant this can be explained by the opportunities of this sector that are: Potential high earnings growth, earnings are resilient during economic downturn, high, profit margins, trade below historical average.

Table 13: Real Estate Development

Variables	Coefficient	Std. error	z-statistic	Prob.
Constant	-0.1985419	0.0934765	-2.12	0.034
EPS	0.0015543	0.0034817	0.45*	0.655
P/E	0.0016281	0.0025451	2.64	0.022
P/B	0.0025647	0.0022427	2.14	0.053
MOM	30.09493	2.104844	14.30	0.000
RSI	0.0008597	0.0013832	0.62*	0.534
ADW	-0.2027982	0.0892433	-2.27	0.023

(*): is significantly non-significant at 5% level

The final panel logistic regression equation is for Real Estate Development sector:

Zij = -0.1985419 + 0.0015543***EPS** + 0.0016281***P/E** + 0.0025647***P/B** + 30.09493 ***MOM** + 0.0008597 * **RSI** - 0.2027982 ***ADW**

The results for log likelihood test and wald test are summarized in table 14 and show that our model for all sectors is significant.

Table 14: log likelihood and wald test

Sectors	Log likelihood	Wald chi2	Prob.
Banks & Financial Services	-3829.1297	679.44	0.0000
Petrochemical Industries	-4103.9644	406.15	0.0000
Cement	-2505.3928	216.78	0.0000
Agriculture & Food Industries	-3924.4227	262.40	0.0000
Energy & Utilities	-2478.0259	233.62	0.0000
Telecommunication & Information Technology	-2336.3526	240.23	0.0000
Real Estate Development	-3775.2113	249.58	0.0000

3- Conclusion

In this paper, an attempt is made to explore the use of panel logistic regression to determine the factors which significantly affect the stock performance. Panel logistic regression method helps the investor to form an opinion about the time to invest. It may be observed that six variables i.e. EPS, P/E, P/B, MOM, RSI and ADW can classify up to 90,95% into two categories good and bad. This prediction rate is very good, so it can be used for prediction with higher accuracy.

This study was also be performed on seven sectors: Banks & Financial Services, Petrochemical Industries, Cement, Agriculture & Food Industries, Energy & Utilities, Telecommunication & Information Technology and Real Estate Development. In all sectors, technical indicators were more significant than financial ratios and can be more helpful in predicting stock performance.

We can deduce from this study that the use of panel logistic regression give us very pertinent prediction with high accuracy using a mixture of fundamental and technical variables.

Conflict of Interests

The author declares that there is no conflict of interests.

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