P-ISSN: 2709-6254 | Journal of Development and Social Sciences | Nov-December 2026, Vol. 7, No. 6
O-ISSN:2709-6262 | https://doi.org/10.47205/jdss.2026(7-VI)03 | [33-47]

JDSS Journal of Development and Social Sciences
www.jdss.org.pk

RESEARCH PAPER

Z-Score Development for Amman Stock Exchange Index Constituents

[1]Ahmad Abdallah Ahmed Alswalmeh and [2]Nuradli Ridzwan Shah Mohd Dali

1. PhD, Faculty of Economics and Muamalat, Islamic Science University of Malaysia, Malaysia.
2. Professor, Faculty of Economics and Muamalat, Islamic Science University of Malaysia, Malaysia.

Corresponding Author: aalswalmeh89@raudah.usim.edu.my

ABSTRACT

This study aims to develop a Z-score discriminant function to distinguish between performing and underperforming companies listed on the Amman Stock Exchange (ASE) and rank constituent companies based on their 2018 performance. Low trading volumes in the ASE highlight the need for reliable performance assessment tools. Accounting and market indicators provide valuable insights for evaluating corporate performance and supporting investment decisions. A quantitative research approach was employed using Jensen's alpha model and multiple discriminant analysis. The study population comprised companies listed on the ASE, with a sample of 63 companies. Monthly share prices and relevant accounting and market indicators were collected for 2018. Twelve financial and market indicators were examined to identify their discriminatory power. The findings identified three significant discriminating indicators: Stock Turnover Ratio (STR), Earnings Per Share (EPS), and Turnover of Assets (TOA). The study successfully developed a performance measurement scale and ranked the sampled companies. These indicators effectively distinguished performing from underperforming companies. ASE companies should be evaluated and ranked annually using the proposed discriminant function. Investors and traders should consider STR, EPS, and TOA when making investment decisions.

KEYWORDS ASE Index, Company Performance, Z-Score, Multiple Discriminant Analyses, Jensen's Alpha, Accounting and Market Indicators

Introduction

Financial markets around the world have witnessed a significant development in the measurement of company performance following Harry Markowitz's formulation of the formal portfolio selection model in 1952. It has also led to the emergence of several models to measure stock performance and its investment risks. The Capital Asset Pricing Model (CAPM) is one of the most important instruments that measure stock performance in global financial markets. It was developed by Sharpe (1964), Lintner (1965), and Mossin (1966) with a series of predictions about equilibrium expected returns on risky assets. In 1968, Michael Jensen developed Jensen's alpha model as a tool to identify skilled portfolio managers in an absolute, rather than a relative, manner. It was originally based on CAPM, which calculates the expected one-period return of any stock or portfolio. On the other hand, the financial statements of a business enterprise minimise information asymmetry and improve contract efficiency by including financial statement information in contracts between the company and other parties. Besides, financial statements provide data to assist in estimating the expected rate of return on investment using accounting and market indicators (Revsine, Collins, Johnson, & Mittelstaedt, 2012). Accounting and market indicators are some of the most important fundamental elements of company performance analysis. They are used to identify the company's efficiency, risks, growth, and value. Analysts have widely used these indicators as measures of a company's strengths and weaknesses in the financial markets (Chuang, 2011; Innocent, Mary, & Matthew, 2013). Furthermore, investors often rely on accounting and market indicators to invest in the

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market. These are publicly available in the financial statements and annual reports of the listed companies.

Indeed, the logical concerns of owners, investors, business partners, and creditors about the financial position of a company call for appropriate assessment tools (Alireza, Parviz, & Mina, 2012; A. Alswalmeh & Dali, 2020b). Predictive models that use financial indicators are one of the accepted tools, but they may not entirely meet investors' needs, since accounting and market indicators may have weak predictive strength in the short run and some predictive power in the long run (Jiang & Lee, 2012). Furthermore, the predictive ability of the indicators on stock prices and returns seems to suffer from structural instability over time (Lettau & Van Nieuwerburgh, 2008). Fama and French (2002) found that the average return on equity was much higher than expected and continued to rise (at that time), while the financial indicators in the 1990s were low. An alternative view, one that has received little attention in the literature, is that these predictive models can be developed better through the combination of the theories of financial statement analysis, which are commonly applied in financial studies, with asset pricing theory.

Over the last decade, the number of constituents of the Amman Stock Exchange General Index (ASE Index) has continually changed, and the number of listed companies has been decreasing. Some of them are performing, while others are underperforming. However, since the trading volume of these companies is still low, there is a lack of research in determining the factors that discriminate between performing and underperforming ASE Index constituents. Because the performances of these companies differ, it is necessary to develop a model that can discriminate and rank them according to their performance to get better investment opportunities, through accounting and market indicators with asset pricing theory. In addition, there is an urgent need to construct a robust ranking method to distinguish investment opportunities. This is especially true for constituents of the ASE index, which are considered the main references for investors' information.

Towards this end, this study is intended to achieve three main objectives. Firstly, to distinguish between performing and underperforming companies. Secondly, to develop a Z-score discriminant function to identify the indicators that can differentiate between performing and underperforming companies. Thirdly, to rank ASE Index companies in 2018 according to the discriminant scores.

Although previous research has discriminated between companies, this study stems from the lack of empirical studies that have assessed and discriminated company performance using Jensen's alpha model and accounting and market indicators. Additionally, the study provides a new contextual benchmark for company performance in Jordan and adopts a new mechanism to distinguish between companies' performance in the ASE. All of this will give investors and market users a greater possibility to make rational decisions.

The remaining part of this study is organized as follows. The following section provides a review of related literature and hypothesis development. Section 3 describes the research methodology, sample, and variables' measurement. Section 4 presents the analysis and findings of the study. The conclusion and implications will be presented in Section 5.

Literature Review

The investment theory in financial markets introduced formal portfolio selection, which grew to be the basis of the modern portfolio theory (MPT). The theory shows how to diversify assets to produce an efficient portfolio. Accordingly, this study uses the theory to identify an efficient company. Specifically, this study is based on two main theories. First, the capital asset pricing model (CAPM) is used to measure the historical performance of the individual company through the Jensen alpha model. Second, the theories of financial

statement analysis, which are commonly applied in financial studies. The study expands the existing theories in the asset pricing model (APM) and financial statement analysis to discriminate companies by the explanatory variables. This contributes new knowledge to the literature by using indicators that are expected to discriminate between performing and underperforming companies.

Discussions on the financial indicators that may be useful in evaluating the companies' performance and risk of bankruptcy have been ongoing for a long time. Beaver (1966) suggested six ratios that can predict company failure, and no-credit interval. Altman (1968) and Altman, Haldeman, & Narayanan (1977) put forward a model of financial ratios that can effectively forecast bankruptcy. Similar research has been carried out to predict bond ratings and yields. Ederington (1986) further found ratios to be effective in evaluating a company's bond ratings. Ederington, Yawitz, & Roberts (1987) found some ratios were able to explain bond yields.

Theoretically, Alswalmeh & Dali (2019) summarised the dimensions affecting the companies' performance using a systematic literature review conducted in four databases: Scopus, ProQuest Central, EBSCOhost, and Google Scholar, from 2008 to 2018. The study identified 10 dimensions of company performance. In addition, the search results revealed that many previous studies examined the companies' performance using accounting and market indicators. Several methods have been used, such as questionnaires, multiple regression, multiple discriminant analysis, and fundamental analysis. Nevertheless, return on total assets was found to be the most important variable to measure the performance of companies.

Recently, the Z-Score (MDA) is frequently used to evaluate companies' performance. Studies under this model employed MDA to distinguish between companies: good or bad, insolvent or solvent, over- or underperforming, and so on. To illustrate, Halteh, Kumar, Gepp, & Gepp (2018) attempted to predict financial distress in 101 publicly listed Islamic banks using cutting-edge stochastic models. A total of 18 accounting ratios were included in the Altman Z-score and Altman Z-score for services models. According to both models, the working capital per total assets ratio was the most important variable for predicting financial distress.

Azar & Nasr (2016) examined whether the solvency and insolvency of SMEs can be predicted using financial ratios and binary logistic regression. The study concluded that Altman Z-scores had modest accuracy, as they were able to reasonably predict solvent SMEs but not insolvent ones. Foo & Pathak (2016) assessed the relationship between financial health and the performance of companies listed in the Chinese and Indian financial markets from 2000 to 2013. The Altman Z-score was used to measure financial health, while ROE was used as a measure of company performance. There was a statistically significant and positive correlation between Z-Score and ROE for both markets.

Odibi, Basit, & Hassan (2015) examined whether Altman's Z-score correctly predicts bankruptcy on a sample of 17 healthy and 17 distressed Malaysian-listed manufacturing companies from 2010 to 2014. Four out of five financial ratios in the Z-score model significantly predicted company failure. Meanwhile, Tyagi (2014) measured the financial performance and the efficiency of the financial operations of Indian logistics companies from 2005 to 2011. Using the Z-score model, the study revealed that the sample was healthy.

Likewise, Venkataramana, Azash, & Ramakrishnaiah (2012) predicted the bankruptcy of companies in India from 2011 to 2010 using a set of financial ratios and Altman's Z-score. Ng, Wong, & Zhang (2011) applied a Z-score model to differentiate solvent and insolvent companies in China. The determinants of the model were seven financial ratios. The study found that the current asset to turnover ratio and working capital to total

asset ratio had the highest discriminatory capacity. Two profitability indicators, namely total profit to turnover and ROA, were also necessary for long-term solvency.

In Jordan, Alswalmeh & Dali (2019b) and Alswalmeh & Qaqish (2021) developed a model to predict the banking sector index using financial indicators. The findings revealed that the financial indicators used could predict the banking sector index in ASE. Alswalmeh & Dali (2020a) classified the financial indicators' capability for Islamic banks and non-Islamic Banks to predict the banking sector index in ASE. The findings discriminated between the indicators that can forecast the banking sector index for Islamic banks and indicators that can forecast non-Islamic Banks. Moreover, the results identified which indicators can forecast all banks in ASE. The study concluded that the indicators used are essential to predict the banking sector index in ASE. Using Z-score, Al-manaseer & Al-oshaibat (2018) investigated the validity of the Altman Z-score model to predict financial failure in insurance companies listed on ASE over the period 2011-2016. The study revealed that the high predictive power of the Z-score model could be a valuable instrument for many users of financial statements to make rational decisions in the face of financial distress. Newly, Qasim (2020) examine the trend performance and predict bankruptcy among three Islamic banks from 2010 to 2016 through the Altman model of Z-score. Moreover, it also introduced the Z-score model as a beneficial diagnostic technique for possible causes behind the bank's performance weakness.

The studies above distinguished between companies that are likely or unlikely to be bankrupt. It seems that the Z-score score, which was first applied in 1968 by Altman, is a useful model to measure financial performance. Mainly, it has 70%-80% effectiveness of the Z-score reliability, and it is identified as a robust technique (Taffler, 2011; Thynne, 2006). Similarly, this study attempts to build an effective model to discriminate between performing and underperforming companies using Jensen's alpha and multiple discriminant analysis, a subject that has received little attention in the literature. It followed the methods and conclusions of Mohd Dali, Mudasir, & AbdulHamid (2008), that inventory turnover and credit turnover/day ratios could discriminate between performing and non-performing *Shariah*-compliant companies in the plantation industry, which recommended the development of the model to different markets and sectors. Thus, based on the literature results, a hypothesis was developed:

H_1: There are differences between performing and underperforming companies.

H_2: Indicators can discriminate between performing and underperforming companies.

Material and Methods

Jensen's alpha is used to measure the previous performance of a portfolio by distinguishing between realized return and expected return. The alpha coefficient (α) is differentiated from the estimated β of CAPM. By regressing stock return (R_i) on market return (R_m) (Reilly & Brown, 2012):

$$R_i = \alpha + \beta R_m \qquad (1)$$

where α is the intercept and β is the slope, that is, $Cov(R_i, R_m) / \sigma_m^2$. The slope of the regression shows the beta (risk) value of that stock. CAPM formula:

$$R_i = R_f + \beta(R_m - R_f) \qquad (2)$$

The intercept from the regression is used along with a modified version of the CAPM Equation (2):

$$R_i = R_f\,(1-\beta) + \beta R_m \qquad (3)$$

This shows that Jensen's alpha coefficient (α) and β are similar to $R_f\,(1-\beta)$ from the CAPM model. The difference between α and $R_f\,(1-\beta)$ can be used to calculate stock performance. This measure is used to see whether the company's stock is either performing or underperforming. Then, for the alpha, we have:

1) $\alpha > R_f\,(1-\beta)$ means that the stock is performing

2) $\alpha = R_f\,(1-\beta)$ means that the stock is performing as expected.

3) $\alpha < R_f\,(1-\beta)$ means that the stock is underperforming.

The MDA technique intends to differentiate the companies into either performing or underperforming. The sample was differentiated using specific accounting and market indicators. Using Jensen's alpha model, market return was regressed to stock return to obtain α and β. If $\alpha > R_f\,(1-\beta)$, the company was categorised as performing (1); if $\alpha < R_f\,(1-\beta)$, it would be categorised as underperforming (0). The accounting and market indicators were selected based on theoretical models and previous research to ensure their validity and suitability for the discriminant analysis. The linear combination for the discrimination function will be differentiated in the form:

$$Z_{jk} = \alpha + W_1X_{1k} + W_2X_{2k} + W_3X_{3k} + \ldots + W_nX_{nk} \qquad (4)$$

Z_{jk} = discriminant Z-score function; W_i = discriminant weight for IVi; X_{ik} = independent variable i for object k

The sample size was also determined to ensure the validity of the discriminant analysis. Most studies suggested a ratio of 20 observations for each predictor variable (Hair, Black, Babin, & Anderson, 2014). In this regard, this study considered the sample size for analyses at the aggregate and group levels. After that, it will be verified that the observations were consistent with the assumptions of the discriminant analysis. Box's M test was used to assess whether the covariance matrices were significantly different across groups. If the assumptions were violated and the potential remedies were unacceptable, the study would consider alternative methods, e.g. logistic regression.

The next step was deriving the discriminant function through a stepwise procedure. The accounting and market indicators were inputted into the discriminant function to determine the extent to which each indicator (and the overall model) contributes to the variances between companies. At each step, the variables with the largest t-values were added to the subsequent model, and the process was repeated until all independent variables were exhausted. Variables that did not contribute to the predictive accuracy of the model were deleted. Wilks' lambda was used to determine the differences between groups. Significant differences in the value of Wilks' lambda were derived from the addition or deletion of any independent variables to the model. If $p < 0.05$, the groups are statistically different, which means that the independent variable(s) are significant discriminators.

Finally, subject to the statistically significant discriminant function and acceptable classification accuracy, the results were further analysed. The discriminant functions were examined to determine the relative importance of each independent variable in discriminating between the groups. The companies were also ranked according to their discriminant scores in descending order.

The study mainly used secondary data sources, such as annual reports, reports and trading data published by the ASE, statistics published by the Central Bank of Jordan (CBJ), and printed and digital articles, books and publications. The monthly data of the sample

from 1 January 2008 to 31 December 2018 were gathered primarily from the ASE database. To ensure the validity of findings and soundness of analysis, it is necessary that there are no missing data. For this reason, 37 companies were removed from the original sample of 100 firms, leaving a final sample of 63 companies. The companies were classified as performing and underperforming using 2018 accounting and market indicators, as they are the most recent dataset available in the annual report. Thus, the study uses non-probability purposive sampling. Means that the population of this study was all companies listed on the Amman Stock Exchange from 1 January 2008 to 31 December 2018. The final sample comprised 63 companies that constitute the stock market's general index, that is, the ASE Index, as at 1 January 2019. The market Index only constitutes companies with large trading volumes. The selection of those companies as they reasonably represent the overall market.

The dependent variable in this study is company (or companies') performance. It was measured as the stock price P_i, the return R_i, and the monthly stock return R_i. The final measure was computed using the following formula (Strong, 2008):

$$R_{i,t} = (P_{i,t} - Pi_{,t-1}) / P_{i,t-1} \quad (5)$$

where $P_{i,t}$ is the monthly price in period *t,* and *Pi, t-1* is the monthly price in period *t-1*. The market return, R_m, is measured using the ASE monthly index. The formula is:

$$R_{mt} = (ASE_{mt} - ASE_{mt-1}) / ASEmt\text{-}1 \quad (6)$$

where ASE_{mt} = ASE index at period t; ASE_{mt-1} = KLSE index at period *t-1*.

The risk-free rate R_f is based on the yield of the Jordanian Government Bond. Then, we have to regress the market return to individual return to get α and β. If Jensen's $\alpha > R_f (1-\beta)$, we categorize it as performing (1), and if Jensen's $\alpha < R_f (1-\beta)$, we categorize it as underperforming (1). Indicators were used to measure the performance of the sample. The indicators measured the annual data of each company. Table 1 displays the indicators assigned as the independent variables, as well as their categories and measurements. The categorisation was based on the surveyed literature.

Table 1
List of Independent Variables

#	Variables	Category	Measurement*
1	Return on Assets (ROA)	Accounting	Net Profit / Average Asset
2	Return on Equity (ROE)	Accounting	Net Income / Average Shareholders' Equity
3	Net Profit Margin (NPM)	Accounting	Net Income / Total Income
4	Current Ratio (CR)	Accounting	Current Asset / Current Liabilities
5	Debt Ratio (DR)	Accounting	Total Liabilities / Shareholders Equity
6	Total Assets Turnover (TOA)	Accounting	Total Revenue / Average Asset
7	Market Capitalisation (MC)	Market	Price Share * Number of Shares Outstanding
8	Stock Turnover Ratio (STR)	Market	Shares Traded / Number of Shares Outstanding
9	Earnings Per Share (EPS)	Market	Net income / Average Common Shares
10	Book Value Per Share (BPS)	Market	Reported Book Value
11	Price-to-Earnings Ratio (PER)	Market	Share Market Price / Earnings Per Share
12	Price-to-book Value (PBV)	Market	Share Market Price / Book Value Per Share

*Source:(Brealey, Myers,& Allen, 2011; Robinson, Greuning, Henry,& Broihahn, 2009; Subramanyam & Wild, 2009)

Results and Discussion

The study reports in Table 2 below the values of accounting and market indicators that used as independent variables to discriminant the performance of the sample. In addition, the study measures Jensen's alpha to estimate the beta (β) and alpha (α) coefficients for each company. The results are shown also in Table 2. The performing

companies were categorised as (1), while the underperforming companies as (0). Based on the results, 24 companies were considered performing and 39 underperforming. Performing companies constituted approximately 38.1 percent of the total sample, while underperforming firms 61.9 percent.

Table 2
Indicators Values and Jensen's Alpha Regression Results

Company	ROA	ROE	NPM	CR	DR	TO/	MC*	STR	EPS	BPS	PER	PBV	α	β	R_f^* (1-	Categor
ARBK	1.70	11.8	33.01	0.3	85.63	5.1	3979.	7.71	0.6	5.7	9.1	1.0	-0.00	0.98	0.001	0
THBK	1.14	8.8	27.10	0.2	86.99	4.2	2636.	0.56	0.2	3.2	29.1	2.5	0.000	0.10	0.089	0
EXFB	1.55	10.7	37.78	0.2	82.86	4.0	184.0	13.95	0.1	1.4	5.9	0.6	-0.00	0.45	0.054	0
BOJX	1.58	10.0	29.10	0.3	84.06	5.4	490.0	44.39	0.2	2.0	11.8	1.1	0.002	0.45	0.054	0
AHLI	0.76	7.0	18.97	0.2	89.18	4.0	208.3	4.82	0.1	1.5	9.7	0.6	-0.00	0.66	0.033	0
CABK	1.01	8.9	22.22	0.2	88.20	4.5	239.4	5.71	0.1	1.8	7.9	0.7	-0.00	0.7	0.027	0
JOIB	1.20	12.6	33.87	34.	86.36	3.5	518.4	3.55	0.2	2.1	10.4	1.3	0.002	0.94	0.005	0
UBSI	1.06	9.4	26.08	0.1	87.92	4.0	256.0	1.75	0.2	2.3	7.1	0.6	-0.00	0.81	0.018	0
JCBK	0.37	3.7	11.29	0.1	90.10	3.2	102.0	0.25	0.0	1.1	20.2	0.7	-0.00	0.42	0.057	0
ABCO	0.85	6.0	23.08	0.2	86.02	3.6	103.4	1.11	0.0	1.4	10.6	0.6	-0.00	0.63	0.036	0
INVB	1.39	8.8	31.97	0.2	84.48	4.3	132.0	1.81	0.1	1.7	8.5	0.7	-0.00	0.50	0.049	0
JOKB	1.55	9.4	33.73	0.2	83.63	4.5	290.0	0.80	0.4	4.4	6.8	0.6	-0.00	0.64	0.035	0
JIJC	0.29	0.3	-0.03	3.1	32.21	0.1	6.7	4.23	0.0	1.2	78.9	0.3	-0.00	0.58	0.041	0
TIIC	2.76	5.6	-0.01	2.0	48.68	0.8	16.9	4.24	0.0	1.3	15.2	0.8	0.006	1.28	-0.028	1
FRST	-7.99	-9.2	-881.84	4.7	13.22	0.0	24.7	4.76	-0.0	0.8	-4.4	0.4	0.008	1.66	-0.066	1
UINV	-1.38	-4.0	-17.28	1.0	49.59	0.0	55.0	73.12	-0.0	0.6	-44.0	1.7	0.019	1.91	-0.09	1
FUTR	-3.77	-4.8	-42.83	2.4	26.95	0.0	7.9	6.11	-0.0	0.9	-7.1	0.3	-0.00	0.92	0.007	0
SANA	-4.41	-4.7	-3318.0	0.7	6.93	0.0	10.0	27.50	-0.0	0.7	-14.1	0.6	0.004	0.85	0.014	0
JEIH	4.71	3.5	39.43	23.	2.77	0.0	8.0	23.62	0.0	1.2	11.6	0.4	0.002	1.32	-0.03	1
AMAL	2.18	2.4	22.64	9.2	9.71	0.1	7.5	84.65	0.0	0.9	22.4	0.5	0.003	1.17	-0.01	1
AAFI	-5.59	-5.7	-132.45	26.	2.62	0.0	5.6	13.84	-0.0	1.2	-7.8	0.4	0.00	1.80	-0.080	1
UCFI	4.93	5.6	29.07	6.7	12.82	0.1	4.1	112.9	0.0	1.1	7.9	0.4	0.000	1.28	-0.028	1
SABK	-0.86	-0.8	-15.78	40.	1.92	0.0	2.9	239.3	-0.0	0.7	-56.6	0.5	0.000	1.08	-0.008	1
ULDC	4.91	6.6	0.62	4.2	25.99	0.0	66.8	57.41	0.0	1.2	19.1	1.2	0.015	1.64	-0.064	1
JRCD	1.18	1.2	0.47	10.	7.89	0.0	13.4	5.12	0.0	1.0	30.5	0.3	-0.00	0.78	0.021	0
IDMC	1.84	2.2	0.40	0.5	18.30	0.0	8.1	79.14	0.0	1.8	9.3	0.2	0.015	2.12	-0.112	1
EMAR	-2.79	-3.6	-1.57	1.2	22.95	0.0	4.0	51.90	-0.0	0.6	-8.3	0.3	-0.01	0.84	0.015	0
ATTA	-0.93	-1.0	-0.46	2.0	7.35	0.0	6.1	78.49	-0.0	0.9	-63.4	0.6	0.00	1.04	-0.004	1
COHO	0.46	0.5	0.02	10.	8.06	0.1	3.3	4.29	0.0	1.1	97.8	0.4	-0.00	0.56	0.043	0
AQAR	1.17	1.2	0.34	2.7	5.44	0.0	5.0	7.74	0.0	1.1	57.7	0.7	0.00	0.93	0.006	1
JNTH	1.31	1.3	0.04	4.2	5.24	0.3	2.7	234.2	0.0	0.8	23.0	0.3	0.009	1.50	-0.050	1
PHNX	-3.29	-5.4	-0.74	0.6	39.38	0.0	16.5	22.77	-0.0	0.5	-6.0	0.3	-0.00	1.10	-0.010	1
REDV	-1.49	-2.7	-4.64	2.2	27.27	0.0	21.3	14.83	-0.0	0.5	-31.0	0.8	0.003	1.33	-0.033	1
DADI	-3.74	-11	-7.41	0.9	66.60	0.5	22.2	6.38	-0.	1.4	-5.5	0.6	-0.00	0.37	0.062	0
MBED	9.15	10.0	14.80	5.3	14.89	0.6	17.7	11.51	0.1	1.6	8.8	0.8	0.005	0.55	0.044	0
UMIC	5.76	6.5	5.39	7.8	11.45	1.0	9.8	8.76	0.1	1.7	14.6	0.9	0.007	0.59	0.040	0
EICO	12.48	35.5	27.39	1.6	64.94	0.4	780.0	36.92	0.8	2.4	15.1	5.3	0.020	0.88	0.011	1
APOT	12.36	14.7	25.87	5.2	16.38	0.4	1334.	26.00	1.5	10	10.6	1.5	0.005	1.53	-0.053	1
JOPH	4.24	7.0	7.05	1.2	39.18	0.6	234.3	57.61	0.5	8.1	4.9	0.3	0.006	2.24	-0.12	1
JOCM	-22.0	192	-56.07	0.5	98.31	0.3	37.4	3.35	-0.	-0.0	-1.0	-20	-0.01	0.61	0.038	0
JOST	-3.14	-5.6	-5.03	0.7	44.17	0.6	14.7	35.91	-0.0	0.9	-7.5	0.4	-0.00	1.75	-0.075	1
AALU	-0.07	-0.1	-0.10	2.4	26.21	0.7	14.9	7.34	0.0	1.6	-131	1.3	0.005	0.05	0.094	0
ASPMM	2.34	2.9	5.71	3.6	20.74	0.4	8.3	12.79	0.0	1.4	21.4	0.6	0.000	0.3	0.061	0
UCIC	-3.52	-5.1	-4.64	2.2	31.91	0.7	11.5	52.35	-0.0	0.9	-6.5	0.3	-0.00	0.54	0.045	0
WIRE	-4.27	-7.5	-8.95	1.5	43.62	0.4	4.2	43.74	-0.0	0.8	-3.4	0.2	-0.00	0.95	0.004	0
JOWM	5.48	5.4	64.51	8.2	4.35	0.0	45.0	1.63	0.2	4.2	13.0	0.7	-0.00	0.46	0.053	0
CEIG	-0.09	-0.1	-0.01	1.6	39.67	0.0	23.9	121.1	0.0	1.0	-146	2.2	0.008	0.33	0.066	0
ABMS	0.45	0.6	1.36	1.1	30.29	0.3	27.0	1.34	0.0	0.8	162.	1.0	0.000	0.23	0.076	0
AIEI	6.62	7.9	27.28	0.4	16.32	0.2	102.0	1.12	0.1	1.8	16.9	1.3	-0.00	0.26	0.073	0
ZEIC	1.68	2.6	4.07	1.1	37.67	0.4	23.9	2.54	0.0	1.9	28.1	0.7	-0.00	0.07	0.091	0
MALL	0.60	0.6	3.37	0.2	12.65	0.1	28.9	2.53	0.0	1.2	76.3	0.5	-0.00	0.62	0.037	0
MSFT	1.89	3.0	3.04	0.7	38.88	0.6	5.9	28.53	0.0	1.1	8.8	0.2	-0.00	0.57	0.042	0
SHIP	7.45	11.4	50.08	1.1	29.00	0.1	24.9	5.07	0.1	1.5	9.1	1.0	0.002	0.54	0.045	0
JETT	7.92	9.5	6.90	2.2	18.07	1.1	21.9	10.92	0.1	1.8	11.3	1.0	0.002	0.37	0.062	0
JTEL	3.41	7.7	6.57	0.5	56.12	0.5	260.6	3.54	0.1	1.4	12.2	0.9	-0.00	0.83	0.016	0
JOPT	2.56	16.7	2.13	1.0	84.04	1.2	227.0	17.72	0.3	2.1	6.2	1.0	0.001	1.37	-0.037	1
JOEP	0.78	7.6	0.96	0.9	89.69	0.8	102.4	12.44	0.1	1.4	10.8	0.8	-0.00	1.06	-0.006	1
OFTC	1.76	2.05	4.62	1.36	26.02	0.38	16.27	16.91	0.02	1.11	17.97	0.37	0.001	1.045	-0.0045	1

ATCO	1.15	3.37	1.73	0.9	73.39	0.6	33.57	3.98	0.0	1.21	21.90	0.7	0.0062	0.761	0.0238	0
MANE	2.27	7.28	1.07	0.5	68.57	2.1	207.9	7.28	0.1	1.31	19.90	1.4	0.0121	1.08	-0.008	1
NAQL	-18.8	-22.6	-52.36	2.1	17.05	0.3	3.06	58.27	-0.2	0.87	-1.12	0.2	-0.004	1.415	-0.0415	1
RICS	-1.78	-2.00	-10.05	0.3	10.94	0.1	4.38	25.90	-0.0	0.91	-19.1	0.3	-0.000	0.545	0.0453	0
SITT	1.04	4.69	7.00	0.8	27.85	0.1	7.02	16.80	0.0	0.97	8.61	0.4	-0.011	0.222	0.0777	0

* MC is in Million (JD).

* R_f at that time based on the yield of the Jordanian Government Bond equal (0.09).

Discriminant Indicators

The function tests the null hypothesis of equal population covariance matrices. Box's M test was used to determine the homogeneity of population covariances. The results in Table 3 showed that the alternative hypothesis was accepted, indicating the heterogeneity of the population covariances. This means that the assumption of discriminant analysis was violated. Nonetheless, since it is a robust analysis, this violation can be ignored.

Table 3
Estimation of Discriminant Function

Box's M		**89.574**
F	**Approx.**	14.060
	df1	6
	df2	15680.342
	Sig.	0.000

Using stepwise method, the variables that discriminate between performing and underperforming companies were identified. The canonical discriminant functions are summarised in Table 4.

Table 4
Summary of Canonical Discriminant Functions (Stepwise statistic)

ASE-Index companies	Eigen value	Variance Percentage%	Canonical Correlation	Wilks' lambda	χ^2	p
	0.433	100	0.550	0.698	21.423	0.000

The Wilks' lambda of the discriminant function was below 1. Lambda ranges between 0 and 1, where 0 signifies major differences and 1 signifies no differences. The lambda indicated that the function has the ability to distinguish between two groups, $\chi^2 = 21.423$, $p < 0.05$. The results suggested that the function was able to significantly discriminate both groups. The canonical correlation for the sample companies was 0.550. Squaring this coefficient means that the discriminant functions explain 30.3 percent of the variance in the dependent variables. This rather low correlation was due to the exclusion of the other nine indicators, which were unable to significantly discriminate between the two groups.

Discriminant analysis aims to develop discriminant functions, that is, the linear combination of independent variables, that can discriminate between groups of the dependent variable. The discrimination criterion is based on Wilks' lambda. In this study, the analysis pertains to the discrimination of the dependent variable into two groups, (1) (Jensen's alpha > 0) and (0) (Jensen's alpha < 0). The null and alternative hypotheses were as follows:

H_0: There is no average vector difference between groups (1) and (0).

H_1: There is an average vector difference between groups (1) and (0).

The Wilks' lambda and chi-square for the sample companies were 0.698 and 21.423. Because $p < 0.05$, H_1 was accepted, suggesting that there were average vector differences between groups (1) and (0).

Table 5 shows the canonical discriminant function coefficients. EPS had the most influence, followed by STR and TOA. EPS and STR had positive coefficients, while TOA had a negative coefficient, which means that the discriminant function of companies was based on higher EPS and STR and lower TOA. Therefore, the discriminant function can be expressed as: Z = - 0.166 + 0.016 (STR) + 1.924 (EPS) - 0.467 (TOA)

Table 5
Canonical Discriminant Function Coefficients

Variable Chosen	function
	1
Stock Turnover Ratio (STR)	0.016
Earnings per Share (EPS)	1.924
Total Asset Turnover (TOA)	-0.467
(Constant	-0.166

Unstandardized coefficients

Table 6 shows the function at group centroid values. They are the means of the above function for each group (i.e., performing and underperforming). These values are used to assess the overall model fit.

Table 6
Functions at Group Centroids

Category	Function
	1
1	0.826
0	-0.508

Unstandardized canonical discriminant functions evaluated at group means

(76.2%) of original grouped cases correctly classified

Based on those values, it is possible to calculate the cut-off point to discriminate between groups (1) and (0):

$$\boldsymbol{cu = \frac{N1Z1 + N0Z0}{N1 + N2}}$$

where: N = total sample; Z1 = centroid of group (1); Z2 = centroid of group (0). Thus:

$$\boldsymbol{Zcu = \frac{11(0.826) + 37(-0.508)}{11 + 37} = -0.202292}$$

The result shows that the cut-off point was -0.202. Companies with a Z-score of less than this value were grouped as underperforming, and those otherwise as performing. In addition, the overall model accuracy was satisfactory, as it was able to correctly classify 76.2 percent of the original grouped cases.

The canonical discriminant function was based on three of 12 accounting and market indicators: EPS, STR, and TOA. These three were found to discriminate between performing and underperforming companies. Therefore, H_2 was accepted. Consequently, companies with Z-scores above the cut-off point are ranked higher and vice versa. By ranking the companies according to their discriminant scores in 2018, it is possible to identify which of them are performing and underperforming (Table 7). The results showed that SABK had the highest rank with a score of 3.68, followed by JNTH with 3.49. This indicates that SABK was the best-performing company in the ASE Index.

Table 7
Company Ranking Based on Z-score

Rank	Company	Z score	Rank	Company	Z score	Rank	Company	Z score
1	**SABK**	3.67727	**22**	**RICS**	0.13632	**43**	**FRST**	-0.23516
2	**JNTH**	3.49242	**23**	**PHNX**	0.13011	**44**	**ABMS**	-0.28865
3	**APOT**	2.91628	**24**	**SITT**	0.12435	**45**	**UMIC**	-0.3061
4	**EICO**	1.87658	**25**	**MSFT**	0.0765	**46**	**ATCO**	-0.33413
5	**CEIG**	1.75429	**26**	**MBED**	0.05545	**47**	**TIIC**	-0.34974
6	**UCFI**	1.71112	**27**	**REDV**	0.04652	**48**	**AALU**	-0.40275
7	**JOPH**	1.59059	**28**	**AIEI**	0.02578	**49**	**DADI**	-0.60792
8	**AMAL**	1.20534	**29**	**JOST**	0.01839	**50**	**MANE**	-0.85932
9	**IDMC**	1.17665	**30**	**AQAR**	-0.01855	**51**	**ARBK**	-1.13805
10	**ATTA**	1.08144	**31**	**OFTC**	-0.0249	**52**	**JOIB**	-1.22515
11	**UINV**	0.94791	**32**	**JRCD**	-0.06425	**53**	**JOCM**	-1.42949
12	**ULDC**	0.90694	**33**	**ASPMM**	-0.06547	**54**	**JOKB**	-1.48451
13	**EMAR**	0.62485	**34**	**AAFI**	-0.09821	**55**	**EXFB**	-1.55118
14	**JOPT**	0.26476	**35**	**JOEP**	-0.13229	**56**	**THBK**	-1.56622
15	**JOWM**	0.26414	**36**	**JTEL**	-0.1323	**57**	**BOJX**	-1.5717
16	**JEIH**	0.26015	**37**	**COHO**	-0.17525	**58**	**UBSI**	-1.60851
17	**NAQL**	0.23424	**38**	**JIJC**	-0.17782	**59**	**JCBK**	-1.61757
18	**UCIC**	0.23355	**39**	**JETT**	-0.17866	**60**	**ABCO**	-1.6923
19	**SANA**	0.21164	**40**	**MALL**	-0.19091	**61**	**AHLI**	-1.75575
20	**WIRE**	0.19757	**41**	**FUTR**	-0.19116	**62**	**INVB**	-1.86701
21	**SHIP**	0.19436	**42**	**ZEIC**	-0.21794	**63**	**CABK**	-1.8766

Graphically, Figure 1 explains that the Z-score zones of 63 companies that constitute the ASE general index range between 3.68 and -1.88.

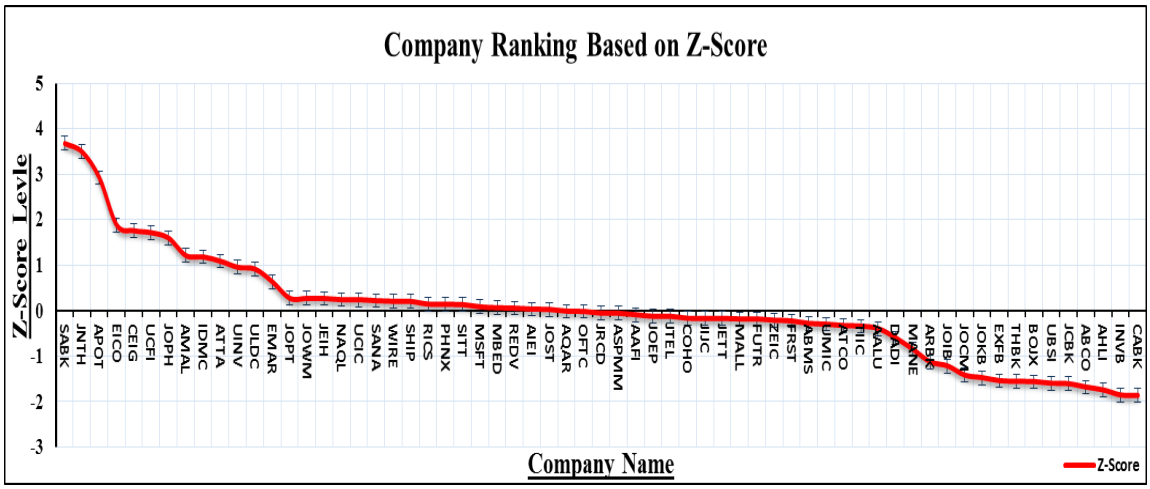

Figure 1. Z-score zones of companies

Conclusion

The logical concerns of owners, investors, business partners, and creditors about the financial position of a company call for appropriate assessment tools. Since the trading volume of the Amman Stock Exchange General Index constituents is still low, there is a lack of research in determining the factors that discriminate between performing and underperforming companies. Thus, this study aims to develop a Z-score discriminant function to identify the indicators that could discriminate between performing and underperforming companies and to rank ASE Index companies in 2018 according to the discriminant scores. Jensen's alpha and multiple discriminant analyses were employed to accomplish this objective. Monthly share price data were collected from ASE's website to

determine Jensen's alpha for the 63 sample companies. Likewise, relevant indicators were also collected from the annual reports of those companies. Accounting and market indicators were used for this study. Out of the 12 indicators, only three indicators significantly discriminated between performing and underperforming companies: STR, EPS, and TOA. This finding showed the efficiency of using accounting and market indicators to evaluate the performance of ASE Index companies. Furthermore, these three indicators were able to be significant discriminators between performing and underperforming companies in the ASE Index.

This study introduces a simple model using multivariate analysis. The uniqueness of this approach is that it does not depend on a single variable. Another aspect that should be considered is model accuracy. The model was fairly accurate, as the three determinants of STR, EPS, and TOA were able to correctly classify 76.2 percent of the original group. Then, the findings identified indicators that investors can use to discriminate between performing and underperforming companies in the ASE.

This study has successfully developed a measurement scale to measure the performance of constituents of the Amman Stock Exchange General Index. The developed scale can be attributed to several studies that have attempted to measure company performance using Z-score (Altman 1968; Altman, Haldeman, & Narayanan 1977; Ederington 1986; Ederington, Yawitz, & Roberts 1987; and recently Mohd Dali, Mudasir, & AbdulHamid, 2008). The results of this study indicate that the "performing companies" group has a different perception of performance, as shown by the computed Z-score. This is the first study to use accounting and market indicators to discriminate between performing and underperforming ASE Index companies. With the introduction of the new context, market users could use the technique on different indices or companies to make appropriate financial decisions.

Recommendations

This study could be duplicated and expanded using comprehensive data from companies of different industries and sectors listed on the ASE or other emerging markets. Moreover, applying the study to developed markets may provide an opportunity to expand and generalise the results, as well as build new knowledge on company performance in financial markets. The companies listed on the Amman Stock Exchange could also be ranked annually based on their performance measured using the method employed in this study. Finally, investors and traders could focus more on these indicators when making investment decisions in the Amman Stock Exchange.

Declarations

Authors' Contribution

Both authors contributed to the development of the research. The first author was responsible for conceptualization, methodology, data collection, and analysis.

Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Ethical Considerations

This study relied on secondary data relating to companies listed on the Amman Stock Exchange. No human participants or personal data were involved.

AI Use Statement

No artificial intelligence (AI) tools were used in the preparation, analysis, writing, or editing of this research manuscript. All research activities and manuscript preparation were conducted by the authors.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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