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Creating quality portfolios using score-based models: a systematic review

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This paper aims to find out if a score-based investment strategy could be developed using different scales. To achieve this objective several academic sources have been used and it is found that score-based investment not only outperforms the market but also protects the investors from the risks arising out of avoidable poor investments in the market. The project is a summary of bibliographic outcome of several scholars who have attempted to find out the impact of score-based investments in their respective markets. Score-based investments are typically dependent on accounting parameters and changes in these parameters signal that a firm's performance is geared up for a change. The study has been done using a systematic literature review. Several research papers in peer-reviewed journals were referred starting from 1934 to 2021. Various equity-based scores like F-score, G score, L score and C score and debt-based scores like Z score, O score and M score are used for the construction of portfolios. It has been found that across geographies the use of score-based investing is known to give superior returns as compared to the market. Several pieces of literature provide the evidence. Developed countries like USA, UK, Australia, and Canada have a large concentration of literary sources that point to the evidence of score-based investing. At the same time, it is also pertinent to note that the performance of such techniques works relatively better in markets that are not efficient and where asymmetry in information flow is evident.

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Introduction

Investors have always looked to maximize their returns on investment (Graham and Dodd 1934). From fundamental analysis to technical analysis of stock, the investment goal has been to beat the market by a margin as wide as possible while keeping the portfolio risks in check (Graham and Dodd 1934). Whilst fundamental analysis has looked towards buying stocks cheap only to reap the benefits of their rising values later, technical analysis has been more focused on taking advantage of swings in the price, momentum & volume (Bettman et al., (2009)). Fundamental analysis focuses on basic revenue, earnings, and liquidity parameters, while technical analysis tries to gauge the trends in sentiment and undercurrents. So, it can be inferred that while fundamental analysis targets stocks for the medium to long term, technical analysis is a preferred tool for short term investing (AS 2013). Fundamental analysis also finds usage in debt space, while technical analysis is restricted to equity investment in the short and long term. Fundamental analysis uses various methods to uncover the intrinsic value of a stock, one of which is score-based investing, which has been discussed in this paper. It has largely been a niche that considers quality aspects like the change in the numbers of simple accounting measures like revenue, cash flows, leverage, solvency and profitability (Lev and Thiagarajan 1993). For investments, these tenets and changes in them are measured and attributed a score derived from a formula or binary score of "0" or "1" as indicated by the respective variable that measures factors such as revenue, cash flows, financial ratios, and profitability or changes in them. The data may pertain not only to the firm in question but also to its sectoral peers and the economy at large (Ohlson 1980). The result obtained by calculating these scores forms the basis of investment or otherwise. Also, given that a firm's performance can change in various time frames, its score obtained in the above process is also likely to vary accordingly (Abarbanell and Bushee 1998). Therefore, a given score holds good for investment or disinvestment for a period upto two years beyond which the prediction of performance based on scores dilutes and becomes insignificant (Piotroski 2000).

There are two broad types of score-based investment techniques – debt-based and equity-based. Debt-based techniques include Z score (Altman, 1968), O score (Ohlson 1980), and M score (Beneish 1999) while equity-based methods include F score (Piotroski 2000), G score (MohanRam (2005)), C score (Montier 2021) and L score (Dorantes 2013). Debt-based techniques apply to individual corporate while equity-based methods follow a portfolio-based approach. It can be seen that various techniques apply selectively and conditionally to different categories in terms of geography, type of security, size of the company, time and other macro-economic variables (Novy-Marx 2013). Also, none of the techniques guarantees a hundred per cent success every time, yet some fail to provide consistent results (Novy-Marx 2013). So it becomes essential to understand in detail how these techniques have evolved and how they can be leveraged to earn above-market returns and when they should be avoided while creating portfolios.

Thus, score-based investment techniques come across as a high-quality investment strategy that can be used to generate above-market returns across various geographies (MohanRam (2005)). The data needed to formulate scores are readily available from annual reports of the companies, government websites, and databases like CMIE and Bloomberg.

Literature Review

The first attempt at score-based investment technique was directed towards debt instruments. Altman Z score was the first notable debt score that was designed to predict the bankruptcy of manufacturing firms two years in advance. It broadly considered factors internal to a firm's performance like profitability, liquidity, leverage solvency and activity ratios (Altman 1968). Ohlson's O score followed it in 1980, a 9-factor model that included firms accounting data and macroeconomic data (Ohlson 1980). The model was considered superior to the Altman Z score as it could predict default with over 90 per cent accuracy instead of Altman Z scores accuracy ranging from seventy to ninety per cent. Altman Z score was revised to a four-variable Z score in 1993 to improve its predictive ability. Another score, called the M score, was devised by Beneish (Beneish 1999) that uses financial ratios to check if there is a high probability the company's reporting has been manipulated. It was designed to predict bankruptcy for non-financial firms. The M score attempted to measure the manipulation of earnings within firms of a given industry. Beneish, Lee and Nichols (2013) later used these scores to successfully predict comparatively poorer earnings posted by corporates with high M-scores, which indicated higher manipulation of earnings. Both M & Z score is used for the protection of the investors primarily in fixed income securities (Mahama 2015). Campbell proposed the formula for detecting the probability of default in firms in the short-term using firms accounting data and market data (S&P 500) (Campbell et al. 2011).

In equity space, several scholars have attempted to realize the value of change in simple accounting fundamentals encapsulated in scores that ultimately determine how good or bad the stock is likely to be. While the value investment theory proposed by Graham and Dodd dates back to 1934 (Graham and Dodd 1934) notable works in the field of score-based investments following from accounting books was first formulated by Lev and Thiagarajan (Lev and Thiagarajan 1993) who recognized twelve factors from the books of accounts such that a change in them could act as a precursor to stock performance. Abarbanell and Bushee (Abarbanell, J.S and Bushee 1998) used the above signals and developed portfolios that consistently yielded super normal in US markets. These twelve factors were further refined and restructured by Joseph Piotroski into F-score, ranging between numbers 0–9, to test the strength of a firm's revival endeavours. The score could be used only for "distressed stocks" defined as the first twenty percentile of stocks with high book to market value often referred to as "value stocks". The closer the score is to 9 the better the improvement in the financial position of a firm (Piotroski 2000). Every parameter used in the calculation of the F-score is a simple accounting measure & its change is considered to be a signal towards the change in the financial position of the firm which would soon be reflected in the price change. Piotroski (Piotroski 2000) opined that a change in fundamental accounting numbers signals a turnaround that points towards the predictable performance of returns. Several other papers have tried capturing the change in returns using different fundamentals. Noma (2010) has suggested a hedging & shorting strategy of low F score firms to get more returns. Hyde 2018 tested for four alpha generations. However, he finds that stocks with high F-score were not able to generate four alphas. Eremenko (2018) tests the validity of the generation of returns for high F-score firms in the non-US markets i.e. the BRIC & the UK & the Germany markets. Likewise, Tripathy (2017) & Pullen did a study for their respective markets & found that the F-scale analysis was able to give excess returns compared to the market. It was also found that F-score gives rise to good corporate governance as well. Chung et al. (2015) showed institutional governance, in the long run, gives rise to an improved F score. The researchers have in their way tested the score-based investments to see how effectively they stand the test of the market.

Table 1 Z score for Manufacturing Firms.

Component	Derivation
Z(M)	(1.2 × Z1) + (1.4 × Z2) + (3.3 × Z3) + (0.6 × Z4) + (1.0 × Z5)
Z1	Working capital/Total Assets
Z2	Retained earnings/Total Assets
Z3	Earnings before interest taxes (EBIT)/Total Assets
Z4	Market Value of Equity/Total Liabilities
Z5	Sales/Total Assets

On similar lines, the last twenty percentiles of the book to market ratio are referred to as growth stocks for which Partha S Mohanram devised a scale to determine if there are good stocks that provide better returns than peers because low book value stocks are often considered expensive and so fail to provide expected returns (MohanRam (2005)). He named the scale as G score.

Both Piotroski & Mohanram used the book to market (BM) ratio value of stocks in their study. The BM factor used for the initial screening of stocks is well documented in several pieces of financial literature & it has been shown that the ratio bears a strong positive correlation with that of the future stock performance (Fama and French (1996)). High BM stocks earn excess returns in comparison to the others because of their risk. Hence both Piotroski & Mohanram have used BM stocks, to begin with, in the design of their study. Low BM have historically yielded better returns as found by Graham and Dodd when markets were relatively inefficient with information asymmetry and poor participation (Graham and Dodd 1934). The use of Mohanram's G score across diversified portfolio has also been established by Khatwani and Mishra (Khatwani and Mishra 2021). While consistency of F score and M score over different accounting practices over Z score and C score has been established by Nadar and Wadhwa (Nadar and Wadhwa 2020).

Score-based models at a glance. All the above score-based models use quantitative and accounting data to arrive at their respective scores. The final scores obtained are then matched with standard scores to arrive at an investment decision. All the above scores are explained in brief as under:

Z score by Altman. In 1968 Edward Altman devised a score called Z score which was used to measure the financial distress of a manufacturing firm which may lead to eventual bankruptcy within two years (Altman 1968). The formula for Z score for manufacturing Z(M) is given in Table 1

A score of 1.8 and below indicates high bankruptcy risk while a score of 3 and over indicates sound financial health.

Separate Z scores were developed for non-manufacturing firms, Z(NM) as well as for emerging markets, Z(EM) as given in Table 2

A score of 1.1 and below indicates high bankruptcy risk while a score of 2.6 and over indicates sound financial health. Z score is said to provide results with over 72% accuracy with a timeline of 2 years (Eidelman 1995).

O score by Ohlson. O score developed by James Ohlson is a linear combination of nine factors that may be obtained by accounting information and disclosures (Ohlson 1980). O score is calculated as given in Table 3:

Ohlson O score gives the probability of a firms default within 2 years as given as [O score/(1 + O score)] with about 90% accuracy (Altman 1993).

Table 2 Z score for Non-Manufacturing Firm.

Component	Derivation
Z(NM)	(6.56 × Z1) + (3.26 × Z2) + (6.72 × Z3) + (1.05 × Z4)
Z(EM)	3.25 + (6.56 × Z1) + (3.26 × Z2) + (6.72 × Z3) + (1.05 × Z4)
Z1	(Current Assets - Current Liabilities)/Total Assets
Z2	Retained earnings/Total Assets
Z3	Earnings before interest taxes (EBIT)/Total Assets
Z4	Book Value of Equity/Total Liabilities

Table 3 O-Score Description.

Component	Derivation
O-score	$(-1.32) - [0.407 \times \log(TA/GNP)] + (6.03 \times TL/TA) - (1.43 \times WC/TA) + (0.0757 \times CL/CA) - 1.72 \times X - (2.37 \times NI/TA) - 1.83 \times (FFO/TL) + 0.285 \times Y - [0.521 \times (NI - NIL)]/ [\lvert NI \rvert + \lvert NIL \rvert]$
TA	TA denotes Total Assets
TL	TL denotes Total Liabilities
GNP	GNP denotes Gross National Product price index level
WC	WC demotes working Capital
CL	CL denotes current Liabilities
CA	CA denotes current Assets
X	X assumes 1 if Total Liabilities exceeds Total Assets else 0
NI	NI denotes Net Income
NIL	NIL denotes Net Income Last year
FFO	FFO denotes Funds from operations
Y	Y assumes 1 if there is net loss for last two years else 0

M score by Beneish. The M-score by Beneish gauges the extent of manipulation on firms' earnings as well as other fraudulent activities (Mantone 2013). M score corresponds to the magnitude of the probability of manipulation of and financial statement and earnings. M score is derived as shown in Table 4:

It has been proposed by Warshavsky (2012), Mantone (2013), Omar et al. (2014) and other scholars an M-score greater than −2.22 was a signal of a possible high manipulation financial statement and earrings estimated to be over 71%.

F score by Piotroski. F score by Joseph Piotroski measures the extent to which a distressed stock shows a positive turnaround through its accounting information which largely remains ignored by the markets (Piotroski 2000). These stocks are said to be value stocks as they are highly underpriced compared to their peers and the F score picks such stocks while they are underpriced. Specifically, they form the top 20 percentile of the stocks arranged in the descending order of book value divided by market value. As the turnaround reflects in the periodical disclosures of performance the stock gains it's due and brings high returns for the holder for two years beyond which the power of F score becomes insignificant (Aggarwal and Gupta 2009). The calculation of the F score is as Table 5.

F score = Profitability score (F1 + F2 + F3 + F4) + Leverage and Liquidity score (F5 + F6 + F7) + Efficiency score (F8 + F9)

Thus, all the components that add up to the total F score try to measure a positive turnaround for a distressed stock. Thus, a portfolio of stocks with a higher F score ranging from 7 to 9 significantly outperforms the index while a portfolio of lower score F score stocks not only underperform the index but may also witness significant bankruptcies (Agrawal 2015).

G score by Mohanram. Mohanram had devised the G score, which picks up winners among growth stocks. Growth stocks are here

Table 4 M-score Model by Beneish.

Component	Derivation
M-score	−4.84 + 0.92 × M1 + 0.528 × M2 + 0.404 × M3 + 0.892 × M4 + 0.115 × M5 − 0.172 × M6 + 4.679 × M7 − 0.327 × M8
M1	Index of Days sales in Receivables Index
M2	Index of Gross Margin
M3	Asset Quality Index
M4	Index of Sales Growth
M5	Index of Depreciation
M6	Index of Sales, General and Administrative expenses
M7	Index of Leverage
M8	Total Accruals/Total Assets

Table 5 F-Score Model.

Component	Derivation
F-score	F1 + F2 + F3 + F4 + F5 + F6 + F7 + F8 + F9
F1	1 if the return on assets is positive in the current year else 0
F2	1 if operating cash flow is positive in the current year else 0
F3	1 if a change in return on assets is higher than the previous year else 0
F4	1 if (operating cash flow ÷ Total assets) > return on assets else 0
F5	1 if the leverage decreases compared to the previous year else 0
F6	1 if the current ratio improves over the previous year else 0
F7	1 if new shares are not issued last year else 0
F8	1 if the gross margin improves over the previous year else 0
F9	1 if the assets turnover ratio improves over the previous year else 0

Table 6 G-Score Model Description.

Component	Derivation
G-score	G1 + G2 + G3 + G4 + G5 + G6 + G7 + G8
G1	1 if return on assets > Industry median, for current year, else 0
G2	1 if cash flow > Industry median, for the current year else 0
G3	1 cash flow exceeds net income in the current year else 0
G4	1 if the variance of firm's return on assets < Industry median else 0
G5	1 if the variance of firms year on year sales growth < Industry median, else 0
G6	1 if the Research and Development Intensity > Industry median, for the current year else 0
G7	1 if the Capital Expenditure (Capex) Intensity > Industry median, for the current year else 0
G8	1 if the Advertising Intensity > Industry median, for the current year else 0

defined as those 20 percentiles of stocks that have the lowest book to market value ratio (MohanRam (2005)). Thus, with already high valuations it is important to identify the ones with the potential to grow further. G score helps to identify such stocks by measuring their competitive performance within the industry to which the stock belongs (Asness, et al., (2019). The calculation of the G score is as given in Table 6.

G score = Profitability score (G1 + G2 + G3) + Earnings Variability score (G4 + G5) + Spending Conservatism score (G6 + G7 + G8)

It is thus evident that G score tries to encapsulate those signals that place the firm comfortably above its peers in the industry with regards to profitability, earnings variability as well as with regards to expenditure on activities like research and development, Capex, and Advertising which may decrease earnings in the short run but aid in building long term profitability (Asness et al., (2012)).

A portfolio of stocks with a high G score ranging from 6 to 8 is found to significantly outperform the index (MohanRam (2005)).

Table 7 C score model description.

Component	Derivation
C-score	C1 + C2 + C3 + C4 + C5 + C6
C1	1 if the divergence between net income and cash flows exceeds the previous year, else 0
C2	1 if the receivable days exceeds the previous year, else 0
C3	1 if the inventory days exceeds the previous year, else 0
C4	1 if the other current assets previous year, else 0
C5	1 if the ratio of depreciation to gross fixed assets is lower than the previous year, else 0
C6	1 if the total assets grow over 10% in last year 1, else 0

C score by Montier. Montier C score is a score that measures the extent to which a company is manipulating its accounting disclosures. Montier terms it as "Cooking the books" and measures the early signals in advance with C score that ranges from 0 to 6 (Montier 2021). Thus, firms with a high C score may be used to create a negative portfolio of stocks which provides returns as the stocks realize their real value. A portfolio of these stocks when combined with an equal positive portfolio in Index generated a consistent return of over 8% in US markets Table 7. The calculation of C score is as under.

Thus, a high Montier C score of 5–6, captures dubious activities on the part of company management that lead to underperformance within 2 years (Montier, 2021).

L score by Dorantes. L score by Dorantes measures the extent to which a distressed stock shows a positive turnaround through its accounting information which largely remains ignored by the markets (Dorantes 2013). These stocks are said to be value stocks as they are highly underpriced compared to their peers and the L score picks such stocks while they are underpriced. Specifically, they form the top 20 percentile of the stocks arranged in the descending order of book value divided by market value. As the turnaround reflects in the periodical disclosures of performance the stock gains it's due and brings high returns for the holder for two years beyond which the power of L score becomes insignificant (Khatwani et al. (2018)). The calculation of the L score is as shown in Table 8.

Thus, all the components that add up to the total L score try to measure a positive turnaround for a distressed stock. Thus, a portfolio of stocks with a higher L score of ranging from 6 to 8 significantly outperforms the index while a portfolio of stocks with a lower score L score of 0–3 significantly underperforms the index (Dorantes 2013).

Comparison of various score based investment models. Debt-based investment models were introduced much before equity-based models. All of these originated from the studies conducted initially in the US markets and then were successfully replicated in other markets. The comparison of these models on various parameters is provided in the adjoining Table 1.

The most utilized financial parameters across these scores are identified as Total assets, Current Ratio, Sales/Revenue, earnings, margins, cash flows accruals, leverage, working capital and other Industry/Economic factors external to the firm (Table 9).

Evidence of success. The oldest score-based model for predicting distress by Altman (Altman 1968) also happens to be the most cited (over 19000 citations) and popular one. It was successfully developed by Altman using US firms. Altman, Iwanicz-Drozdowska, Laitinen, and Suvas, (Altman et al. (2017)) reviewed and validated the international applicability of Altman Z score by applying on 31 major European countries as well as on the US, China and Columbia. The results were found to be satisfactory. Other researchers were able to establish the utility of the score in various other markets like New Zealand (Chung, Tan and Holdsworth 2008), Kenya (Odipo and Itati 2011), Jordan (Alkhatib, Bzour (2011)), Malaysia (Venkadasalam 2016), Indonesia (Prasetiyani, Sofyan (2020)), India (Chouhan, Chandra and Goswami 2014), UAE (Zaabi 2011), Mexico (Chávez and Hernández 2018) Pakistan (Hussain et al. 2014) Korea (Altman et al. (1995)) Japan (Shirata 1998) Sri Lanka Nanayakkara (Nanayakkara, Azeez (2015)), Hong Kong (Lau 2014) Zimbabwe (Mavengere 2015) Tables 10, 11

Table 8 L score Model Description.

Component	Derivation
L-score	L1 + L2 + L3 + L4 + L5 + L6 + L7 + L8
L1	1 if there is a positive change in the inventory compared to the previous year else 0
L2	1 if there is a positive change in the accounts receivable compared to the previous year else 0
L3	1 if there is a positive change in the gross margins compared to the previous year else 0
L4	1 if there is a positive change in selling and administrative expenses compared to the previous year else 0
L5	1 if there is a positive change in the effective tax rate compared to the previous year else 0
L6	1 if there is a positive change in the Capital expenditure compared to the previous year else 0
L7	1 if there is a positive change in the margin to cost ratio compared to the previous year else 0
L8	1 if there is a positive change in the working capital compared to the previous year else 0

Ohlson's O score (Ohlson 1980) was synthesized using a database of 2000 US firms. Begley, Ming and Watts (Begley, Ming and Watts 1996) were able to establish the superior performance of O score over Z score in terms of producing less type one error and comparable type two error in the US markets. It was later replicated and confirmed by Boritz, Kennedy and Sun (Boritz, Kennedy and Sun 2007) in the Canadian markets. Thereafter it has been successfully applied at various other regions like Thailand (Lawrence, Pongsatat, and Lawrence 2015), China (Wang and Campbell 2010), Japan (Lai et al. (2010)) Hong Kong (Lau 2014), Indonesia (Najib and Cahyaningdyah 2020), India (Ghosh 2017), Iran (Jouzbarkand et al. 2013) and nineteen major countries of Europe (Acheampong and Elshandidy 2021). Keating (Keating et al. (2005)) demonstrated the performance of O score in the US non-profit sector.

Beneish (Beneish 1999) synthesized the M score and successfully tested the same in the US markets wherein he was able to isolate companies that manipulated accounting information to positively impact share and bond valuations. Beneish, Lee, and Nichols, (Beneish, M. D., Lee, C. M., & Nichols, D. C. 2013) established that M score acted as a forensic accounting method which could identify growth firms that engaged in accounting games not grave enough to induce any negative regulatory action but would result in disappointing investors. The result was even more effective for low accrual firms. MacCarthy (MacCarthy, 2017) observes that both M score and Z score when considered together yielded superior results. Kamal, Salleh and Ahmad (Kamal, Salleh, and Ahmad 2016) successfully detected 14 out of 17 Malaysian companies charged with fraudulent financial reporting. Similarly, the efficacy of M score has been established

Table 9 Comparison of Score based investment methods.

Sr	Score	Year	Originator	Target Markets	Approach	Portfolio type	scoring logic	Score Interpretation
1	Z-score	1968	Edward Altman	Debt	Single scrip	Long & Short	Ratio based	3 and over Good 1.8 and lower poor
2	O-score	1980	James Ohlson	Debt	Single scrip	Long & Short	Probabilistic	Low Probability Good, high probability poor
3	M-score	1999	Messod D Beneish	Debt	Single scrip	Long & Short	Ratio based	−2.22 and lower Good, −1.78 and higher poor
4	F-score	2000	Joseph Piotroski	Value stocks	Portfolio	Long & Short	Binary	7–9 Good, 0–3 poor
5	G-score	2005	Partha Mohanram	Growth stocks	Portfolio	Long	Binary	6–8 Good, 0–2 poor
6	C-score	2008	J Montier	Overpriced stocks	Portfolio	Short	Binary	0–2 Good, 5–6 poor
7	L-score	2013	Carlos Alberto Dorantes Dosamantes	Value stocks	Portfolio	Long & Short	Binary	6–8 Good, 0–2 poor

Table 10 Accounting Data for Score based Methods.

Sr	Score	Total Assets	Current Ratio	Sales/ Revenue	Earnings	Leverage	External Factors	Working Capital	Accruals	Cash Flows	Sales/ Admin Expenses	Margins
1	Z-score	Yes	No	Yes	Yes	No	No	Yes	No	No	No	No
2	O-score	Yes	Yes	No	No	Yes	Yes	Yes	No	Yes	No	No
3	M-score	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes
4	F-score	No	Yes	No	No	Yes	No	No	Yes	Yes	No	Yes
5	G-score	No	No	Yes	Yes	No	Yes	No	No	Yes	Yes	No
6	C-score	Yes	No	No	Yes	No	No	No	Yes	No	No	No
7	L-score	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes

Table 11 Base Articles by Global Citation Score (31/07/2021).

Year	Title	Author	Journal	Global Citation Score
1968	Financial ratios, discriminant analysis and the prediction of corporate bankruptcy.	Altman, E. I	The journal of finance	20177
1980	Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy.	Ohlson, J. A	Journal of accounting research	7947
2000	Value investing: The use of historical financial statement information to separate winners from losers.	Piotroski, J. D	Journal of Accounting Research	1365
1999	The detection of earnings manipulation	Beneish, M.D	Financial Analysts Journal	1316
2005	Separating winners from losers among low book-to-market stocks using financial statement analysis. Review of accounting studies	Mohanram P.S	Harvard Business Review	393
2010	Value investing: tools and techniques for intelligent investment	Montier. J	John Wiley & Sons	56
2013	The relevance of using accounting fundamentals in the Mexican stock market.	Dosamantes, Carlos Alberto Dorantes	Journal of Economics Finance and Administrative Science	31

in Greece (Repousis 2016), Vietnam (Anh and Linh 2016), Iraq (Talab, Flayyih and Ali 2017), Zimbabwe (Mavengere 2015), Bosnia and Herzegovina (Halilbegovic et al. (2020)) Iran (Taherinia and Talebi 2019) Ghana (Adu-Gyamfi 2020), Nigeria (Nwoye, Okoye, and Oraka 2013), Malaysia (Arshad, Iqbal, Omar 2015), Turkey (Özcan 2018), Bangladesh (Sakibqs 2019) Romania (Mihalcea 2020), China (Lu, and Zhao 2020), India (Kaur, Sharma, and Khanna 2014) Lebanon (Dbouk, Zaarour 2017) the Slovak Republic and Czech Republic (Valaskova and Fedorko 2021). Within Beneish model it was found in Romania that a company can restore to financial fraud by creating fictious sales, changes in the reevaluation techniques and increases in revenues, correlated with a decrease of depreciation. (Mare, Safta (2021)).

F score (Piotroski 2000) by Piotroski is the oldest and most popular score based fundamental analysis technique of equity investment. It was formulated by Piotroski to identify value stocks in the US markets (Piotroski 2000). It was also successfully tested in several markets like Japan (Noma (2010)), Europe (Tikkanen and Äijö 2018), India (Aggarwal and Gupta, 2009), South Africa (Pullen 2013), Australia (Hyde 2018), Brazil (Lopes & Galdi (2008)), Mexico (Durán-Vázquez et al. (2014)), Thailand (Tantipanichkul and Supattarakul 2015), EAFE (Europe, Asia and Far East) markets (Walkshäusl 2020), Indonesia (Asmadi, Izzaty and Erwan 2021) Piotroski (Piotroski 2013) also established that superior returns earned through F score was not do not imbibe higher portfolio risk. Agrawal (Agrawal 2015) went on to establish that low F scores helped predict bankruptcy. F score was successfully used create superior long portfolios in Germany for as long as three years by Pätäri, E. J., Leivo, T. H., & Ahmed, S. (2021).

G score by Mohanram (MohanRam (2005)) was formulated to identify performers among growth stocks in the index. It was applied in other markets like Eurozone (Amor-Tapia and Tascon 2016), India (Khatwani and Mishra 2021), Brazil (Villaschi et al. (2011), Thailand (Tantipanichkul and Supattarakul 2015) and Taiwan (Shen et al. (2014)). It was also observed in Indian markets that value – growth dispersal is highest during distress in the bear market. As such, value investment should be avoided during high financial crisis and pandemic (Ghosal 2021).

C score by Montier (Montier 2021) was devised to trace dubious activities by companies that would eventually lead to underperformance in the US markets. It was demonstrated in the South African markets by Govender (2013).

L score by Dorantes (2013) was designed to isolate performing and non-performing stocks in Mexican markets. The study was reaffirmed in the Indian markets by Khatwani (Khatwani et al. (2018)).

Limitations. While most score-based methodologies originated decades back and have established their utility in distinguishing between performing and non-performing instruments in equity and debt markets, their application is not universal. Their limitation has been established by several studies carried out in various geographies over different timelines.

The most referred and popular debt score to date remains the Z score by Altman (1968) followed by Ohlson's O score (Ohlson 1980). These debt scores could however not convincingly predict bankruptcy in Serbia (Muminović et al. (2011)), Australia (Ferguson et al. (2011)), Hong Kong (Lau 2014), Canada (Boritz et al. 2007), Pakistan (Ashraf et al., (2019)), Slovakia (Gavurova et al. (2017)), US (Wu et al. 2010), South Africa (Kidane (2004)), Russia (Yarygina, O'Malley (2016)). Other models like the Beneish M score (Beneish, 1999) are still not as prevalent and have been mostly used in conjunction with other major models. It has also failed to produce successful results in the US (MacCarthy, 2017), Iran (Lotfi, Aghaei Chadegani (2018)) Japan (Bhavani and Amponsah 2017), Slovakia (Petrik, 2016) and Russia (Vetoshkina et al. (2020)). Novy-Marx 2013 constructed an equity portfolio using the G score, and further refined the portfolio using the F score. His study found that such a combination diluted the results implying that looking for survival factors in growth stocks was of little avail.

In the equity space F score by Piotroski (Piotroski 2000) remains the most popular one followed by the Mohanram G score (MohanRam (2005)). Novy-Marx 2013 observed that the F score was losing its relevance amid other tools of fundamental analysis. Similarly, Galdi and Lopes (2013) found out that the G score failed to yield any meaningful results in Brazil. C score and L score being relatively new, have not been tested enough for any meaningful significance or critique to be drawn.

Following are the limitations or potential drawbacks of score-based investment strategies. The scoring models may face subjective judgements as the scoring criteria may be selected based on their own biases and interpretations and therefore lack inconsistency. The models are often based on quantitative factors so it may ignore some important qualitative aspects of investment. The scoring model may provide high priority for short term metrics like profitability, revenue growth and ROI and may not provide the proper reflection of long-term potential and sustainability of the investment made. Scoring models may also overlook some of the intangible factors like brand reputation, customer loyalty, intellectual property which may be potential drivers to consider the investment and can impact the investment significantly. Reverse engineering in the scoring system is possible and may lead to maximizing the score while not reflecting the potential risks and true value.

Methodology

Bibliometric analysis as a scientific tool may be useful for both emerging and established scholars which they can utilize to showcase a retrospective of rich and broad areas of business research (Donthu et al. 2021). Bibliometric study is a systematic review that is adopted to get the bibliometric information using various quantitative methods (Broadus 1987). There may be various tools that can be utilized in an organized way which may consist of multiple scientific studies (Rajeb et al. 2020). Search strategy, sample, date of search, period, data sources, document types and language are all essential components of a bibliometric analysis. The search strategy indicates the terms used, the field and filters used. The sample represents the number of papers analyzed, while the date of search is the basis for the analysis. The period is the number of years analyzed, including the start and last year (Cabezas-Clavijo et al. 2023). Bibliometric analysis evaluates research productivity and impact that helps in identifying key themes and topics and the trends and gaps in the field (Lim and Kumar 2023).

The study analyses bibliometric indicators such as number of articles published per year, countrywide number of articles, author wise number of articles and global citation score. Scopus database was selected to perform a literature search for all published articles on the score-based investment methodologies from 1934 to 2021. Scopus is the second largest comprehensive citation database. Scopus also is a good database as it is enriched with many journals having high impact factor, good accessibility and the ability to download and filter the data. Data was retrieved from 97 research articles in the Scopus database.

A search should use accurate terms to access relevant literature, such as key words or concepts, to access any publication related to the relevant literature (Öztürk et al., 2024). Search queries were built up using the keywords - book to market value, fundamental analysis, accounting fundamentals, score-based investments, bankruptcy, portfolio construction, quantitative fundamentals, portfolio performance. The same was applied within Scopus database – Business Management and Accounting, journal as the type and English as the language. This process was followed by filtering the search results to carefully identify the terms as sometimes the database may extract some papers which may be out of the scope Öztürk et al. 2024). The data obtained by the researcher from the Scopus database in a simultaneous manner. Titles and abstracts were reviewed and then modified the search criteria according to research requirements specifically selecting the necessary topic areas. The method yielded 97 prospective articles. In addition, the researcher has selected solely articles as the document type, considering the uniqueness and originality of the research findings. Therefore, researchers omitted other types of materials such as novels, book chapters, and articles that are still being prepared for publication. Only English articles were used for this investigation. The chosen articles were stored in CSV format and subsequently analyses using VOS viewer software. After filtering the initial search final sample was downloaded with a compatible file format with the software tools for further analysis. Further to data download data cleaning process was carried out that involved duplicates and correcting errors, Consistency was maintained in predefined inclusion exclusion criteria and the accuracy were kept at the time of coding. We have tried to address the bias issue by minimizing authors who are citing their own work extensively and tried not to overemphasize the prolific authors and institutions We have also included valuable contributions from less frequently publishing researchers. The period that we have taken is very large, so the temporal bias is also avoided.

We have used Bibliometric and Biblioshiny software for this study. Various network maps have been visualized using VOS viewer (Khanra et al. (2021)). For the selection of documents databases were selected first and then research papers were searched for this domain. Key words were selected then using Scopus database. These were saved then as a BIB file and then merging was done using R studio. The following methods were carried out as suggested by Rafael Queiroz (2022).

- Downloading Of R Studio
- Exporting the BIB file from Scopus
- Merging of BIB file to generate an XLSX file.
- Uploading XLSX file to Biblioshiny.

Systematic domain reviews can be achieved through bibliometric techniques that will facilitate more complete understanding of the existing literature and understanding the important insights (Hulland 2024). To augment the bibliometric analysis with an enrichment toolbox apart from using these traditional tools, network metrices and clustering visualization has also been implemented (Donthu et al. 2021). For, identification and assessment of novel insights these auxiliary assessments are done (Hulland 2024). The word cloud analysis is conducted for the same purpose.

Prominent trends can be identified by scanning the data. This includes growth or decline in publication, citation metrics over the period and the most productive and influential contributions (Lim and Kumar 2023). Thematic analysis has been carried out where themes are analyzed based on the quadrants where they are placed.

Further with the help of citation analysis key authors and important research papers were identified with their significant contributions. Trend analysis was conducted to see the pattern of growth of literature over the selected time span. With the VOS viewer tool analysis of co-occurrences of the key words were carried out to get the mapping of relationship between author keywords.

Findings

In Fig. 1 post 2013 interest in research in these areas also improved and there was a 200% rise in the production of number of articles on scoring based models. Most of the articles got published during the tenure from 2019 to 2021.

Figure 2 *describes that most of the publications were concentrated in USA and China followed by United Kingdom and India.*

Figure 3 describes the authors' concentration of articles and Chan, A.P. C and Zhou, W got maximum publications during the period of the study.

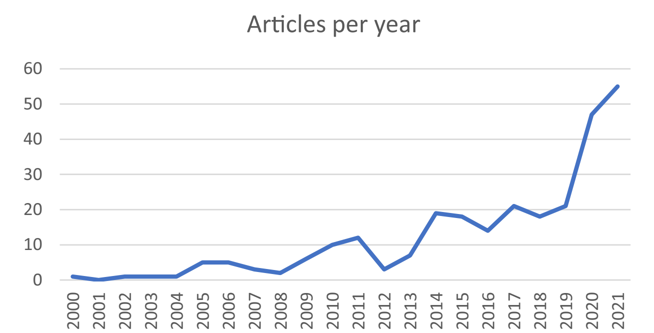

Fig. 1 Number of Articles per Year.

The most influential keywords found are fundamental analysis, data mining, stock performance, bond portfolio, bankruptcy, score-based investments and high returns.

Figure 4 describes the word cloud analysis based on keywords: book to market value and score-based investments obtained from Vos Viewer. The most relevant terms that we can isolate are Value relevance, value premium, capital structure, asset pricing, liquidity.

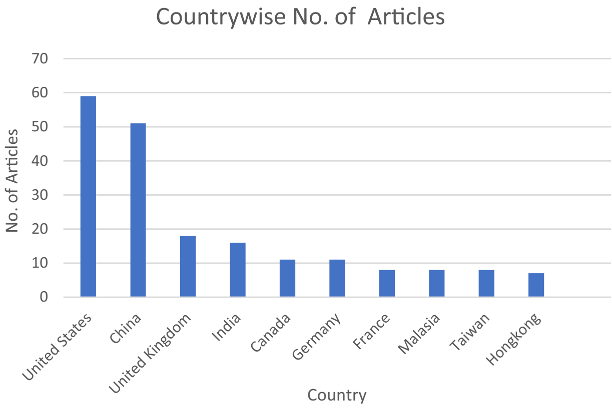

Fig. 2 Country wise number of Articles.

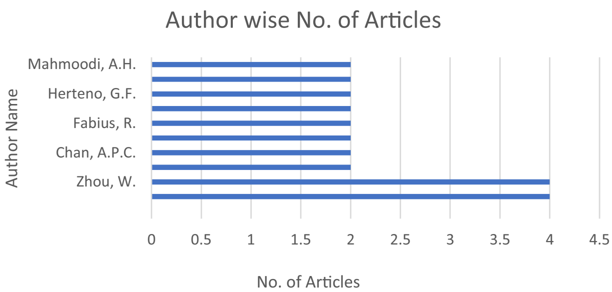

Fig. 3 Author wise Number of Articles.

Discussions

While it has been established that score-based investment strategies worked well for most geographies, the literature points that the same cannot be asserted for varying timelines. It can be deduced that most of the limitations of these techniques have been raised in the last decade, putting a question mark for the future utility. Boritz (Boritz et al. 2007) and Wu (Wu et al. 2010) observe that most of these techniques were developed decades before and cannot predict performance in modern times. Other researchers also propose to make these score-based techniques more robust and applicable by including behavioural finance aspects into the scoring regime, such as CEOs and managers personal credit scores (Kallunki, Pyykkö (2013)). Researchers like Franzen (Franzen et al. (2007)) have stressed the intensity of research and development factors in the scores to make it more contemporary. Piotroski (Piotroski 2000) opined that change in promoters holding could also impact the performance of stocks, especially with lower capitalization. Ashraf, Félix and Serrasqueiro (Ashraf et al., (2019)) caution against the reliance on these techniques in the financial crisis and further propose using signals such as non-payment of dividends and bonus shares to be included in the scoring system.

There is also a visible trend of these score-based methodologies being used in conjecture with each other and other established investment techniques. Z score and O score have been combined several times for the sake of both comparison and confirmation (Najib and Cahyaningdyah 2020) with mixed results. Similarly, the M score has also been combined with the Z score (MacCarthy 2017). Integrating the F score with O score also improved the outcomes for equity investments (Durán-Vázquez et al. (2014)). Some researchers have also successfully combined equity score-based investment methodologies like F score and G score with technical analysis tools to time the market more efficiently (Hong-Yi et al. (2016)). Combining such score-based

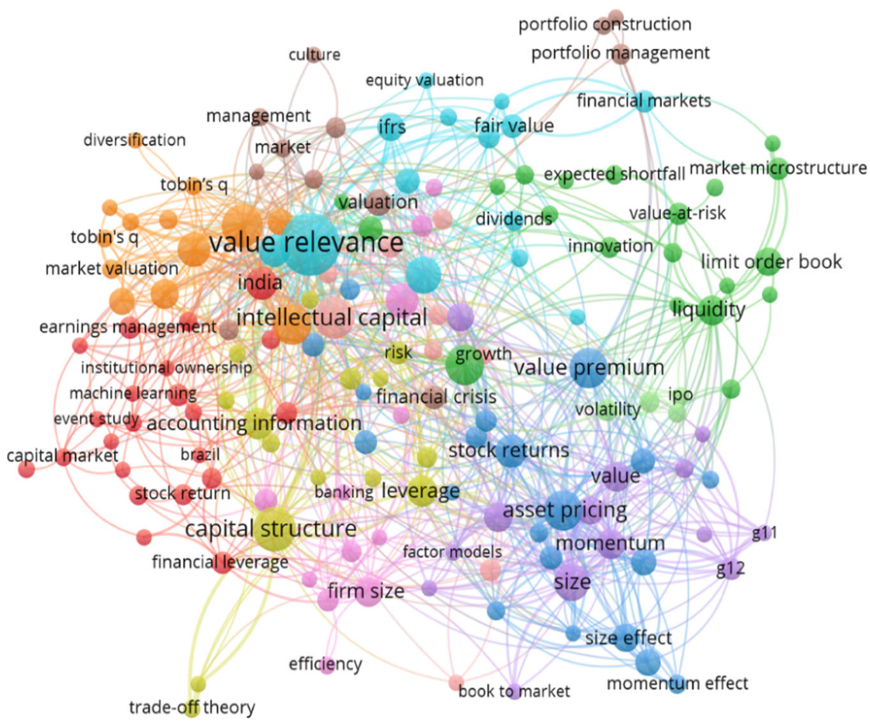

Fig. 4 Word Cloud Analysis.

methodology within themselves and other investment indicators is on the rise.

C score and L score being relatively new, their use and combination with other scores-based methodologies are yet to be tested. As the C score provides those indicators that help isolate manipulative firms with others, their combination with debt-based scores or non-performers of F score may yield beneficial results. L score bears similarity with F score and may deliver valuable results if it is used to replace F score from the past studies. In future, score-based investment methodologies may have to imbibe non-accounting as well as non-financial signals also to encapsulate indications that can have a predictable impact on the stock prices like customer feedback on products (Huang 2018) and change in auditor (Lau 2014), quality, environ protection and product safety (Raonić and Srejović (2008)).

The situation in a market having friction and incomplete information leads to the concept of asymmetric information. This is the information gap between market participants and firm managers. In this imperfect market condition investors react to the available information which may be reflected in the asset prices. Scoring models may play an important role in these scenarios. For example, let us consider the z-score as a measure of risk-taking behavior it is found that investment efficiency is at high for increasing financial stability, but investment scale and financial flexibility may reduce the financial stability of the firms. The relevance of tangible assets will also reduce while the importance of intangible assets will emerge as a better driver for firm stability Duho (2022). Some researchers have linked the Z score to provide incremental information to the "hidden" true credit rating (Elliott, Siu, and Fung 2014). While others have recommended the score to be used at policy level decision making (Shisia et al. (2014)).

Khatwani and Mishra (2021) successfully applied G score across diversified sectors of Indian stock markets to create portfolios with superior performance than the index but with comparable risk. The value "C" in that sense was meant to measure the magnitude of the extent to which the executives in corporates resorted to "cooking the books" in a bid to retain their status of being counted among "high flying stocks". As these misrepresentations get disclosed to the markets, a significant correction in the stock price may be inevitable. Dorantes later devised the L-score for value stocks and successfully demonstrated that stock markets in Mexico gave superior returns based on the signals in the L-score (Dorantes 2013). It was later successfully applied in the Nifty 500 index of the National Stock Exchange of India by Khatwani (Khatwani et al. (2018)).

Following are the potential challenges of implementing score-based investment in different market conditions. The scoring models are historical data driven and based on certain assumptions about the future performance. So, they lack the predictive power in different market conditions or if there are changes in industry dynamics or when there are rapid changes in other external factors. Sometimes black swan events can happen which may not be adequately captured in the scoring models. Again, different scoring models fit into different types of industries which may not be relevant for investments in unconventional business models, emerging industries or in innovative technologies. Thus, using scoring models can put restrictions for evaluating a range of investment opportunities. Scoring models are static in nature so they are less adaptable to changing market conditions and investment strategies. If market dynamics change the models may need some changes in existing criteria. Fixing a scoring model will limit the spirit of adaptability of changes in a changing market condition.

Conclusion

The present paper analyses bibliometric data and a literature review of several journal articles listed in the Scopus database to present a complete score-based investments evolution.

The study finds that the leading five countries considering the total number of publications are the United States, United Kingdom, Australia, Turkey and Mexico. According to the full cited articles, the leading academic institutions include South Florida Tampa, Centers for Disease Control and Prevention, Academy of Educational Development, University of Nicosia, and Emory University. The key publication journals are Journal of Accounting Research, Journal of Finance, Journal of Economics, Finance and Administrative Science, Journal of Finance and Accounting.

The top five seminal article authors include Altman (1968), Ohlson (1980), Beneish (1999), Piotroski (2000), MohanRam (2005) and Dorantes (2013). All the contributions mentioned above have a global citation score of more than 30.

The next research question deals with the commonly used theories, contexts, characteristics, and methodologies of previous studies. The widely used approach in the area is primarily fundamental analysis. The study also finds that imbibing customer and employee engagement models may help to arrive at better results. The context used in the score-based investment is making prudent investment choices in capital markets. The characteristics of the extant literature consider liquidity, leverage, profitability, competitiveness, and macro-economic variables. The antecedents identified are changes in accruals, current ratio, taxes, margins, relative investments in advertisements and research. The outcome of a score-based investment is the creation of a superior portfolio earning above-market returns in the short to medium term of about one to two years. The commonly used methodologies are regression, factor analysis, correlation, and panel data.

Score based investment essentially forms a multifaceted construct. Some topics seem to be more pertinent than others in bibliometric analysis, as they receive relatively more citations. Highly cited articles are valuable and futuristic. However, it is necessary to repeat the citation analysis and descriptive analysis of the bibliometric data at least once in 10 years to examine their development and impact in the area. This paper then addresses different issues related to score-based investments. Thus, future researchers can integrate a comprehensive empirical study, which combines qualitative data with accounting data to arrive at a more meaningful result. Recent studies also reveal that score-based investment methodology may be used only in conjunction with either other scores or with other known techniques of fundamental or technical analysis.

Future scope

In the future new scores may be tested in isolation as well as in combination with other scores and tools to create quality portfolios. Also, new parameters like customer feedback, attrition ratio, auditor change, change in promoters' holdings may be investigated to arrive at a robust score-based model. It may also be contended that some sectors like banking follow a very different accounting pattern and ratio as compared to other manufacturing or services sectors, so it may evolve a completely new set of scores that would be industry specific. Integration with specific technical tools may also be considered for shorter investment horizons. The scores that may be developed and refined in future must also take into consideration the effect of varying accounting practices on net score since scores like F score and M score are resistant to changes in accounting practices while Z score and C score are not (Nadar and Wadhwa 2020). The scores also carry an inherent limitation of capturing the quality and not the magnitude of change. Thus, assigning weights to capture the magnitude of change may also be considered in future which can be seen in non-binary scores like Z score and O score. Also, very few scores like the O score consider the overall macroeconomic scenario which may be very relevant for high beta category stocks like aviation, real estate.

The review of the extant literature on score-based investments reveals future research areas for theory development, context, characteristics, and methodology. The following research questions have remained unanswered in the past and need to be addressed: How can score based investment strategies imbibe qualitative data in the score? How can the score-based investment strategy differ across different sectors and sizes of firms? They can also be studied across regions to find out the generalizability of the results. The empirical relationship between antecedents and outcome could also be analyzed. Lastly, methodologies like Logit, Probit, Arch, Garch and data mining may be used apart from regression, factor analysis, correlation, and panel data.

The scoring-based models after the integration of artificial intelligence (AI) have entered a sophisticated process instead of strict rule-based implementation into credit and investment processes (Mendhe et al. 2024). AI has become a transformative force in credit scoring. The use of AI in scoring models has emerged as a more nuanced evaluation of risk factors and enhanced the spectrum of factors beyond the conventional ones (Kamyab et al. 2023). Decision trees and random forests have become effective to capture the relationships within datasets and provide flexibility in the assessment of risk (Mubarak et al. 2023). Predictive analytics has added a new dimension in reshaping the scoring methodologies because of their precision and capacity to conduct in-depth analysis (Țîrcovnicu and Hategan 2023). Using machine learning tools has added a separate direction to conduct the non-linear analysis for better understanding the intricate relationships within datasets (Zaki et al. 2024). Inclusion of various nontraditional data like rental payment history, utility payments and social media behaviour can also be included in these models to get a comprehensive view (Akagha et al. 2023). With more technological advancement predictive analysis will play a pivotal role in optimizing various credit scoring model for better accuracy and understanding Wirawan (2023).

Data availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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