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BANKRUPTCY PREDICTION MODELS: A COMPARATIVE ANALYSIS

Master's thesis

INTERNATIONAL BUSINESS ADMINISTRATION, finance

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Tallinn 2019

I declare that I have compiled the paper independently
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The document length is 12623 words from the introduction to the end of conclusion.

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ABSTRACT

Prediction of bankruptcy for companies is very important in the life of a business. It is paramount for the management of the company to know the health and the risk level of the company. Several bankruptcy models has been developed by various researchers but there has not been any general agreement on which model is the best. The objective of this master's thesis is to do comparative analysis of Altman's (1993) revised Z-score model and Ohlson's O-score model for UK companies. The author used E-view and IBM SPSS (Statistical Package for Social Sciences) to analyse the gathered data for testing of the two models.

The research hypothesis formulated was to determine is Altman's (1993) revised Z-score model more accurate in predicting bankruptcy for UK companies than Ohlson's O-score model? The result of the analysis tested that Altman's (1993) Z-score model has a very strong positive coefficient of correlation among the observed years for this thesis. The conclusion was that Altman's (1993) Z-score model is more accurate in predicting bankruptcy for UK companies than the Ohlson's O-score model.

Keywords: Bankruptcy prediction, Altman's Z-score, Ohlson's O-score, Financial ratio and Manufacturing companies.

INTRODUCTION

A company is insolvent when it is unable to meet up with its financial obligations as they fall due. It is important for a company to always check its credit rating. Credit management organizations should ensure from time to time that the credit rating of all the companies that are serviced by the credit management organization is within the acceptable level. This will serve as a way of mitigating against company bankruptcy.

The author selected this topic due to different bankruptcy prediction models that have been developed in which some researchers claimed that Altman's Z-score model is more accurate than Ohlson's O-score model. Karamzadeh (2013) agreed that Altman's Z-Score bankruptcy prediction model is significant compared to that of Ohlson's O-Score model. It is necessary for the management of companies to checkmate the company status using a bankruptcy prediction model. Accurate bankruptcy prediction model needs to be applied by company managers, current/potential shareholders and other stakeholders to check the status of the company.

The research problem for this study: even though some companies do report profit year-in-year-out, the companies still end up been bankrupt as a result of financial distress. It is important for the managers of companies to pay attention to the liquidity and solvency level of the company. As mention by Altman (1968) that five financial ratios are relevant for businesses and these ratios are activity, solvency, profitability, liquidity and leverage. It is necessary that these ratios are paid attention to by the managers to avoid being bankrupt.

The objective of this thesis is comparative analysis of two (2) different bankruptcy prediction models that have been formulated by researchers in different parts of the world. The models include Altman's (1968) Multivariate model and Ohlson's (1980) O-score model. The components of each model are classified and analyzed with their differences. The financial ratios that are mostly used by researchers in building up the bankruptcy prediction models and their relevance are considered. Analysis of related special literature is applied. This thesis tends to answer the question of whether Altman's (1993) revised Z-score model is more accurate in predicting bankruptcy for UK companies when compare to Ohlson's O-score model. Therefore, two hypotheses have been developed for this research paper as follows:

H_1: Altman's (1993) revised Z-score model is not more accurate in predicting bankruptcy for UK companies than Ohlson's O-score model.

The related literature used for this thesis were extracted from Science direct databases, TalTech graduate theses library and Google Scholar databases. The research paper adopted quantitative analysis approach for analysing accounting data that were extracted from UK manufacturing companies annual report listed on the London Stock Exchange database.

This thesis is structured in the following sequence. The first chapter discusses definitions of bankruptcy, related literature on the topic by selected authors and their conclusions, theories of bankruptcy and the two bankruptcy prediction models. The second chapter discusses the research methodology which includes the research design, population of the study, sampling procedure and size, data collection instrument reliability, validation, method of data analysis and limitation of the methodology. The third chapter includes the data analysis, comparison of the two different models, while the fourth chapter discusses the summary of findings, conclusions, and recommendations.

1. THEORETICAL BACKGROUND

1.1. Definition of Bankruptcy

The force of new businesses and their competitive powers brought into an existing market can make non-profitable companies go bankrupt. The insolvent company must leave the market leading to liquidation. This will create more opportunities for companies that are able to withstand the competition and manage their scarce resources judiciously and efficiently. Stakeholders of the insolvent company such as creditors/suppliers of funds and materials, customers, community, partners etc. will be negatively affected either losing part or the whole of their investments.

It is important to carry out a bankruptcy prediction test on companies to discover early symptoms of insolvency that can lead to liquidation. The test result will assist to take the right steps or measures to mitigate a future occurrence of bankruptcy in companies.

According to Beaver (1966) bankruptcy is referred to a failure of a company. He defined failure as *"the inability of a firm to pay its financial obligations as they mature"*. Altman (1968) wrote that *"bankruptcy is used in its most general sense, meaning simply business failure"*. He further said that *"a firm with poor profitability and/or solvency record may be regarded as a potential bankrupt"*.

The author observed from the above definitions that both Altman and Beaver referred to bankruptcy as company failure due to business inability to meet its financial obligation as they fall due. That is, both authors view the bankruptcy of a company in the same way. Ohlson's (1980) mention in his work that he does not *"concerned"* himself with the definition of bankruptcy or how it *"ought to be defined".* Therefore, there is no specific definition of bankruptcy from Ohlson.

Odibi, Basit, and Hassan (2015) refer to bankruptcy as a legal proceeding specifying the inability of an individual or a corporate company to fulfil its financial obligations as at when due. It is a

legal process in which a debtor either individual or corporate company is relief of the total debt to make a part payment of the debt in settlement of the total debt through court approval.
Estonia's Bankruptcy Act 1996 Chapter 1, General Provisions defines bankruptcy in the following way:
"*Bankruptcy means the insolvency of a debtor declared by a court ruling. A debtor is insolvent if the debtor is unable to satisfy the claims of the creditors and such inability, due to the debtor's financial situation, is not temporary". "A debtor who is a legal person is insolvent also if the assets of the debtor are insufficient for covering the obligations thereof and, due to the debtor's financial situation, such insufficiency is not temporary".*

UK Bankruptcy Act of 1914 defines bankruptcy as:
"If execution against him has been levied by seizure of his goods under process in an action in any court, or in any civil proceeding in the High Court, and the goods have been either sold or held by the sheriff for twenty-one days:… or If the debtor gives notice to any of his creditors that he has suspended, or that he is about to suspend, payment of his debts".

Canada Bankruptcy and Insolvency Act R.S.C., 1985, c. B-3, bankrupt and bankruptcy are defined as follows:
"Bankrupt means a person who has made an assignment or against whom a bankruptcy order has been made or the legal status of that person"; (failli).
"Bankruptcy means the state of being bankrupt or the fact of becoming bankrupt"; (faillite).

The Law of Federation of Nigeria (2004) Bankruptcy Act Chapter B2 defines bankruptcy as:
"A debtor commits an act of bankruptcy, if a creditor – has obtained a final judgment or final order against him for any amount, and execution thereon not having been stayed, has a bankruptcy notice served on him, and does not, within fourteen days after service of the notice… or if he files in the court a declaration of his inability to pay his debts or presents a bankruptcy petition against himself".

According to Agarwal and Taffler (2007) bankruptcy refers to the recreation of a new type of capital which may include devaluation of some loans, conversion of some debenture stocks to equity capital. It also refers to government intervention or when the creditors/suppliers decide to checkmate business operations and transactions of companies. All these may serve as symptoms of predicting a company failure which tend to lead to corrective measure for companies.

Boratynska and Grzegorzewska (2018) referred to company bankruptcy as a process that takes a long period of time for the affected companies to file a bankruptcy proceeding. It may not be immediately when the companies discover the indications of insolvency. One of the symptoms of a bankrupt company as specified by the author is when the financial status/strength of the company is weak and depreciating. The frequent downsizing of the company is an indication that the company is in a financial crisis which may likely lead to liquidation in the nearest future.

Table 1.1 below depicts the comparison of bankruptcy definitions as defined legally and by different authors. It is compared in terms of the characteristics that are embedded in each definition, symptoms that could be the cause of the bankruptcy situation and the outcome after been declared bankrupt.

Table 1.1. Comparison of bankruptcy definitions

Authors	Year	Characteristics Of Bankruptcy Definitions	Symptoms		Outcome
Boratynska and Grzegorzewska	2018	As a process of a long period of time	Weak financial status	Frequent downsizing	Ends in liquidation
Odibi, Basit and Hassan	2015	Legal proceeding	Unable to pay up financial obligations when they fall due	Relief of debt	Make part payment of debt
Agarwal and Taffler	2007	Recreation of new capital	Involved devaluation of debts	Conversion of debt to equity	Involved government intervention
Nigeria	2004	Creditor obtained a final judgement against the debtor of any amount	The inability of the debtor to pay it debt	Served with a bankrupt notice	Declared bankrupt
Estonia Bankruptcy Act	1996	The court ruling, temporal financial situation	Unable to satisfy creditors claim	Insufficient assets	Declared insolvent by court
Canada Bankruptcy and Insolvency Act	1985	State of being bankrupt	An order has been made against the debtor		Declared bankrupt by the court
Altman E. I.	1968	Business failure	Poor profitability	Poor solvency	Potential bankrupt
Beaver W. H.	1966	Company failure	Unable to pay its debt		Become bankrupt
United Kingdom	1914	Seizure of good	Suspend payment of debt		Court declaration

Source: author’s table

- ☞ In the opinion of the author of this thesis, bankruptcy is a declaration by the court upon an individual or a company due to the inability to meet up with its financial obligations as at when due. Bankruptcy should not be likened as a process that takes a long period of time or recreation of new capital. A company may be going through financial difficulties, that does not mean that the company is bankrupt. The company might have a liquidity problem for a period of time probably due to low sales revenue. Also, a company can decide to do capital re-engineering or reorganization which involved the conversion of debenture stock to equity capital, raising new equity capital or seek for government support during financial distress. This does not warrant that the company is bankrupt. In light of the above point, a company is said to be bankrupt after it must have been declared by the court as a bankrupt company.

1.2. Related Literature

This sub-chapter review selected kinds of literature that are relevant to this research paper and theories of bankruptcy. The author selected the below kinds of literature because it helps to shed more light and give a better understanding of the topic. The literature included the opinions of each author and their conclusion. The purpose of filling bankruptcy proceeding is to settle all debts and at the same time reduce the cost of filing bankruptcy procedure (Mizdrakovic and Bokic, 2016).

Nouri and Soltani (2016) make use of 103 companies that are listed in the Cyprus stock market for five years period with the relevant set of variables through the logistic regression model. They concluded that the macroeconomic variable does not have any significant relationship with the bankruptcy of a company. Chan, Chou, Lin and Liu (2016) concluded that government authorities who are in charge of making laws do consider bankruptcy prediction model before deciding on which law to adopt. Business owners use the models to predict their financial strength and status to ensure they are not a victim of liquidation and to improve their operational policy and business structure. Existing or potential investors use the models to evaluate which business they should continue to invest in and which is to be removed.

Beaver (1966) predicted a univariate model which is one of the prominent research that has been done on bankruptcy prediction. He mentions that financial ratios are not the only way of predicting bankruptcy, but it served as one of the important tools used in the prediction. Another prominent researcher Altman (1968) made research on bankruptcy prediction and used multiple discriminant analysis (MDA). He used five standard ratios based on their potential relevance and popularity in the study which includes activity, solvency, profitability, liquidity and leverage ratios.
According to Odibi, Basit and Hassan (2015) bankruptcy has become one of the most basic and important issues in the business world, as it relates to monetary well-being of corporate businesses. Investors have developed a keen interest in the reliability of corporate companies when trying to

invest their money in the business. Investors check out for the credit rating of corporate companies they are interested in investing their money before making the final decision. There has been several types of researches for predicting bankruptcy models in different parts of the world by various researchers. The business model can be influenced by culture, economic situation, politics and government policy.

Odibi et al. (2015) through stratified random sampling techniques selected 34 manufacturing companies in Malaysia and tested them with the aid of sample t-test using five financial ratios. It was concluded that out of the five financial ratios that were tested under the Z-score model four were significantly related to corporate bankruptcy prediction. Beaver et al. study (as cited in Wu, Gaunt and Gray, 2010) the likelihood of bigger companies to be bankrupt is very slim when compared to smaller companies. Bigger companies operate in several business units and environments. Bigger companies are open to business opportunities or business diversification, the larger the company the better it can anticipate bankruptcy in the nearest future.

Hillegeist et al. study (as cited in Wu, Gaunt and Gray, 2010) made a comparative analysis between the Black-Scholes-Merton Probability (BSM-Prob) of bankruptcy, Altman and Ohlson models. They concluded that their BSM-Prob model performs better than Altman and Ohlson's models using both available and predicted data as samples during the comparison. Sinarti and Sembiring (2015) used the Z-Score, Springate, and Zmijewski model to predict bankruptcy for listed manufacturing companies in Indonesia. They used linear regression and t-test to prove the hypothesis for 11 metals and manufacturing companies from the basic industry. The conclusion was that there is a significant difference when they use Z-score with Zmijewski, and Springate with Zmijewski. While there is no significant difference using Z-score with Springate.

Fedorova, Gilenko and Dovzhenko (2013) applied various algorithms which are multivariate discriminant analysis (MDA), classification and regression tree (CRT), artificial neural network (ANN), logit-regression (LR) and AdaBoost methodology to predict bankruptcy for Russian companies. The outcome was that twelve out of thirteen financial predictors that were recommended by two Russian legislative acts for bankruptcy analysis proved to be insignificant during the bankruptcy analysis.

Boratynska and Grzegorzewska (2018) implement the theory of fussy-set Quality Comparative Analysis (fsQCA) using Multivariate model and Logit model to predict bankruptcy in agribusiness in comparison with quantitative methods. They concluded that existing models for bankruptcy prediction should be carefully selected by managers and it should be adjusted to reflect the current situation of business activity. Tobback, Bellotti, Moeyersoms, Stankova and Martens (2017) used relational data to predict bankruptcy for SMEs concluded that when detecting a risky company, the relational model gives a better prediction than the financial model.

Imelda and Alodia (2017) examined 40 manufacturing companies in Indonesia to test Altman and Ohlson model. The outcome was that "*Ohlson Model and the Logit Analysis are more accurate than the Altman Model and the Multiple Discriminant Analysis in predicting bankruptcy of manufacturing firms in the Indonesian Stock Exchange (BEI) in 2010-2014"*. Delen Kuzey & Uyar (2016) employed CHAID, C5.0, QUEST AND C&RT to test the performance of company with the aid of financial ratios and concluded that CHAID and C5.0 gives a better prediction accuracy than others.

Dichev (1998) carried out a test to know if bankruptcy risk is systematic or not. He said that bankruptcy risk is one of the ways that companies do measure distress and concluded that "*bankruptcy is not rewarded by higher returnd"*. Karas and Reznakova (2015) created their own bankruptcy prediction model known as BI (Bankruptcy Index Model). The model was tested for stability and accuracy and the conclusion was that BI accuracy is "significantly lower'' when compared to other bankruptcy prediction model. Liang, Lu, Tsai and Shih (2016) included corporate governance indicators (CGI) to seven financial ratios for bankruptcy prediction and to assess performance of both. The conclusion was that only two variables (board and owner structure) from the CGI and the seven financial ratios are the most important for bankruptcy prediction.

Tian and Yu (2017) used hazard model to predict bankruptcy for international market with the aid of Compustat Global database. The outcome was that, for japan market retained earnings/total assets, total debt/total assets and current liabilities/sales are selected by adaptive LASO method. Sung, Chang and Lee (2015) used data miningto developed bankruptcy prediction model that can be applicable during stable and bad economic situation and concluded that *"the bankruptcy prediction model revealed that the major variables in predicting bankruptcy were "cash flow to total assets" and "productivity of capital" under normal conditions and "cash flow to liabilities," "productivity of capital," and "fixed assets to stockholders equity and long-term liabilities" under crisis conditions. The accuracy rates of final prediction models in normal conditions and in crisis conditions were found to be 83.3 percent and 81.0 percent, respectively"*.

Marcinkevičius and Kanapickienė (2014) carried out a research to know if the conventional model for bankruptcy prediction applicable for Lithuania construction companies that became bankrupt during the financial crisis. The outcome was that Chesser model, Springate model and the Altman model are the most accurate bankruptcy models among others for predicting bankruptcy. Onakoya and Olotu (2017) argued that distribution of bankruptcy wealth is supported by five theories except value-based theory. The value-based theory does not give any solution to the financial problem of bankrupt companies out of six that were reviewed. It shows that theoretical knowledge is not enough for companies to survive.

Andres, Landajo, and Lorca (2012) conducted research with the help of alternative accounting ratios to predict bankruptcy based on the multinorm analysis. The outcome state that the method produced a major improvement in bankruptcy prediction on the linear and non-linear classifier. Terminal failure processes were used to determine bankruptcy and the result shows that "better prediction accuracy" using 3 years data was achieved than the common models (Jardin 2015). Lu, Yang and Huang (2015) discovered that Bayesian Binary quantile regression is the most useful model. It predicts bankruptcy accurately to its optimum level for air carrier including U.S. healthy and non-healthy air carriers, using data related to a financial report from 1990 to 2011.

Iturriaga and Sanz (2015) developed a neural network model to predict bankruptcy in U.S. bank. The result shows that real estate loans with provisions were the major cause for failed banks during the financial crisis using 2002-2012 data collected from the Federal Deposit Insurance Corporation.

- 🕮 In the author's opinion bankruptcy prediction model is a useful tool in the hands of a company manager. It is observed that most of the selected literatures that was reviewed made use of multivariate and logistic regression model for their analysis. All the outcomes tend toward paying attention to the financial ratios of the company. It is important for the manager of a company to be awared of the most suitable model to apply to check the risk level of the company. The author observed that a company can be influenced by its insolvency level, low profitability, inappropriate diversification, high gearing, and penetration of importation, decrease in net working capital and overtrading. The financial indicators of companies should be paid more attention to because these could be a possible sign of bankruptcy prediction for companies.

1.2.1. Bankruptcy Theories

The importance of bankruptcy theories cannot be left out when treating issues relating to bankruptcy. It is important for stakeholders that are involved in the bankruptcy issue to be aware of the best way to deal with it. This will lead to a win-win situation for each party. A good overview of bankruptcy theories can be found in the paper by Onakoya and Olotu (2017).

These bankruptcy theories include Bankruptcy Jurisprudence theory, Creditors Bargaining theory, Risk Sharing theory, Value-Based theory, Absolute Priority theory, Bankruptcy Policy theory, and Team Production theory. Figure 1.1 shows all the bankruptcy theories and are explained accordingly.

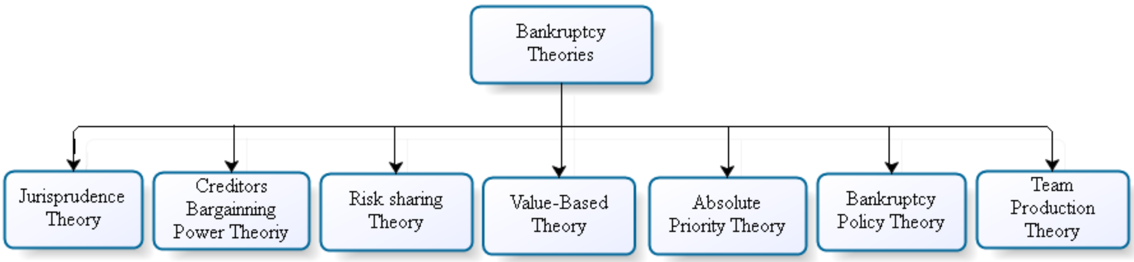

Figure 1. 1 Bankruptcy Theories
Source: Onakoya and Olotu, 2017

Jurisprudence Theory. According to Onakoya and Olotu (2017), is divided into two part. First, use the bankruptcy law to maximize debtor's wealth while the second ensures the protection of creditor and debtor economic assets.

Creditors Bargaining Power Theory. This theory was founded by Jackson in 1982 while in 1989 Jackson and Scott modify the theory to reflect what bankruptcy law ought to be (Onakoya and Olotu, 2017). The theory enables creditors to make a better bargain with the indebted company immediately creditors predict that the company may become bankrupt in the future. In the event of disagreement between the creditors and the company, the individual creditor must strategically pursue his own interest on how to collect his claim from the company before any other creditors.

Risk Sharing Theory. This theory was founded by Jackson and Scott in 1989 to modify the creditor's bargain theory because of its shortcoming of an unequal settlement of creditor’s claims Onakoya and Olotu (2017). It ensures that all the creditors are involved in sharing the risk of the debtors. Some creditors may be experienced in global market problems or specific industry problems. In the situation where all or some of the creditors are risk averse, the common risk will be shared based on individual knowledge about the risk. Therefore, the risk will be evenly distributed among all creditors to minimize their loss.

Value-Based Theory. According to Onakoya and Olotu (2017), the theory was propounded by Korobkin D. R. in 1991. the theory sees the debtor as a natural person who has the ambition to succeed. Debtor assets are not only considered as a means of settling all the creditors, but the value of the debtor is also put into consideration.

Absolute Priority Theory. According to Onakoya and Olotu (2017), this theory states that creditors should be settled in the order they are created. Secured creditors should be settled first before others. The rule can be violated by the court.

Bankruptcy Policy Theory. This theory was propounded by Warren in 1993 (Onakoya and Olotu, 2017). It state that other stakeholders like the staff of the indebted company that does not have any right to the company assets should also be protected.

Team Production Theory. Board members of the bankrupt company remain and maintain the same level of authority to decide and coordinate how all the affected creditors will be settled.

1.3. Bankruptcy Prediction Models

This sub-chapter discusses the two bankruptcy prediction models that are important to this study. The two models are Altman's Z-score model and Ohlson's O-score model. These models are seen to be accounting based because the models are built with the aid of financial ratios. Figure 1.2 depicts the two important model for this study.

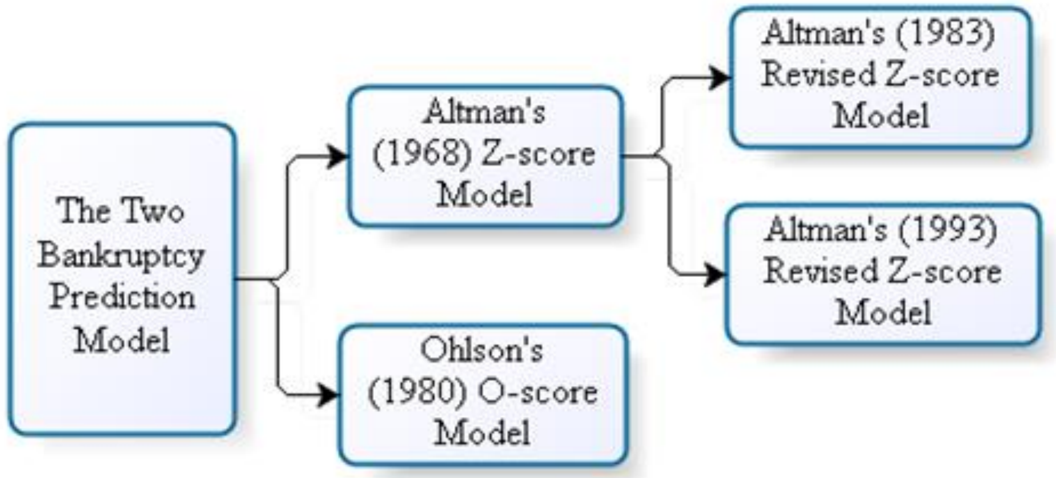

Figure 1. 2 Bankruptcy Prediction Model
Source: author’s diagram

1.3.1. Altman’s (1968) Z-score Model

This is a multivariate bankruptcy prediction model that was propounded by Altman E. I. in 1968 to determine the likelihood that a company may go bankrupt within two years. The model is a classic financial matrix commonly used by financial developers, financial analysts, creditors, banks and auditors. It is used to predict the riskiness of a company or the likelihood that a business will go into bankruptcy. The model is based on the company income statement and statement of financial position. The model has five main financial components that when put together will give a better idea of predicting the bankruptcy of a company. These main financial components are ratios which are presented in table 1.3 and are classified into financial categories:

Working Capital to Total Assets. This ratio measures the usage of the assets of a company. It helps companies to measure the coverage of its short-term debts through the use of comparative analysis between the company current assets and its total assets. This ratio gives a piece of information regarding the liquidity of the company as it's open up the leftover of company assets after all the short-term liabilities have been taken care of.

A high working capital to total assets ratio indicates that the company is improving in terms of liquidity and is able to meet up with all its short-term obligations. While a low ratio indicates that the company is insolvent and may not be able to pay up all it short-term financial obligation as at when due which may result in bankruptcy. A ratio can be said to be low when is less than one while a ratio of 1.5 to two can be said to be high.

Return on Assets (ROA). This ratio indicates how the company assets are used to generate profit. It informs the investors, owners, creditors, analysts and managers of how efficiently the assets of the company are used by the management to generate the revenues. Company assets equal debts plus equity capital provided by the shareholders and these assets are used to finance the operations of the company.

Retained Earnings to Assets. Retained earnings are the portion of the net earning that is set aside to be reinvested or used for payment of a debt. This ratio measures the solvency of a company, it indicates the extent to which a company relied on debt to finance its business operation. High retention of company earnings helps a company to fund its assets more with its own capital than borrowing. The higher the borrowing of a company the higher the risk to go bankrupt.

Equity to Total Liabilities. This ratio is used to measure the financial leverage of a company. It shows the ability of a company to finance its business operations through the use of its own cash rather than debt. This ratio also indicates the ability of the shareholders' equity to settle all debts that may arise due to the bankruptcy situation.

Assets Turnover. This ratio measures the efficient usage of a company asset in generating revenue or income. A higher ratio indicates that the company is performing better and otherwise is the case. A higher revenue generated per dollar indicates that the company is making full use of its assets.

Table 1.2 depicts the main financial ratio that is comprised in the Altman's bankruptcy model, the table also shows the weight, formula and components category of each ratio.

$$\mathrm{Z} - \mathrm{score} = \mathrm{X}_1\mathrm{b}_1 + \mathrm{X}_2\mathrm{b}_2 + \mathrm{X}_3\mathrm{b}_3 + \mathrm{X}_4\mathrm{b}_4 + \mathrm{X}_5\mathrm{b}_5$$

Where b_1, b_2, …… b_5 are the weight for each component which is the discriminant coefficient. X_1, X_2, ……X_5, are the main five financial components which are known as the independent variables.

X_1 = Working capital to total assets

X_2 = Retained earnings to total assets

X_3 = Return on Assets (ROA)

X_4 = Equity to total liabilities

X_5 = Assets turnover

Table 1.2. The main financial components

Main Components	Weight	Components Formula	Components Category
Working capital to Total assets	1.2	Working capital/Total Assets	Assets usage: measures the amount of liquid assets
Retained earnings to Total assets	1.4	Retained earnings/Total assets	Investment profitability: determines the combined profit.
Return on Assets (ROA)	3.3	EBIT/Total assets	Investment profitability: determines the level of change in earnings, excluding tax and interest.
Equity to Total liabilities	0.6	Market value of equity/Total liabilities	It assesses the change in the market value of the company shares.
Assets turnover	0.999	Sales/Total assets	Assets Usage: determine the change in turnover of company assets.

Source: author’s table

The discriminant coefficients are determined by indicating various corporations that have been declared bankrupt. Identical samples of corporations or companies were picked that have remained the match between commercial enterprises and the relative size of assets. In addition to all of the above components is the Z-score and the idea behind it is to see the likelihood that a company will go bankrupt. The Z-score rating is as follows:

If Z-score > 2.99, it indicates that the company is doing well and is not likely to go bankrupt.

If Z-score < 1.81, it indicates that the company is doing badly and has a high risk to go bankrupt.

If 1.81 < Z > 2.99, it indicates uncertainty and cannot be easily predicted if the company will go bankrupt or not, it also raised concern for the affected companies.

Altman designed this model specifically for manufacturing companies with assets based on $1 million and above. Although, some modifications have been done on the model for it to be applicable to other types of industry. Altman Z-score model for bankruptcy prediction has been widely used by financial analysts and creditors to determine the riskiness of the company they are about to provide a fund to. The Z-score model incorporates major items in the statement of financial position and the income statement.

1.3.2. Altman's (1968) Revised Z-score Model

Altman developed a new model in 1983 which is known as the second generation model. This model was revised by the author (Altman) to accommodate other private manufacturing companies not listed on the stock exchange market. This model is exceptionally published for the help of the private manufacturing companies to predict bankruptcy. Due to this development, the market value of equity in X_4 as used in the original Z-score model changes to book value of equity for a better comparison with different metrics. Due to changes in the revised model, the weight of the components also changes.

The revised Z-score is as follows:

$$Z - \text{score} = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5$$

Where:

X_1= Working Capital / Total Assets

X_2= Retained Earnings / Total Assets

X_3= Earnings before Interest and Taxes / Total Assets

X_4= Book Value of Equity / Book Value of Total Liabilities

X_5= Sales / Total Assets

The revised Z-score rating is as follows:

If Z-score > 2.99, it indicates that the company is doing well and is not likely to go bankrupt.

If 1.23 < Z > 2.99, it indicates uncertainty and cannot be easily predicted if the company will go bankrupt or not which is also known as the Grey Zone, it also raised concern for the affected companies.

If Z-score < 1.23, it indicates that the company is doing badly and has a high risk to go bankrupt.

1.3.3. Altman's (1993) Revised Z-score Model

This Z-score model covers more bankrupt companies and is relatively useful for both small and big companies. This revised model was an improvement on the 1983 Z-score modified model. The model is also useful for industrial companies such as non-manufacturing companies and emerging market companies. The components of this revised model changes to four from the initial five different components, that is, excluding the X_5 which is sales to total assets.

Also, the market value of equity in X_4 was replaced by the book value of equity in order to accommodate companies that are not listed on the stock exchange market. A company that is not listed on the stock exchange market cannot have a market value of its equity which is one of the limitations of the original Z-score model. As a result of this, the weight of each component in the revised model changes. Figure 1.3 depicts the revised Z-score model which shows the four ratios and their individual weight.

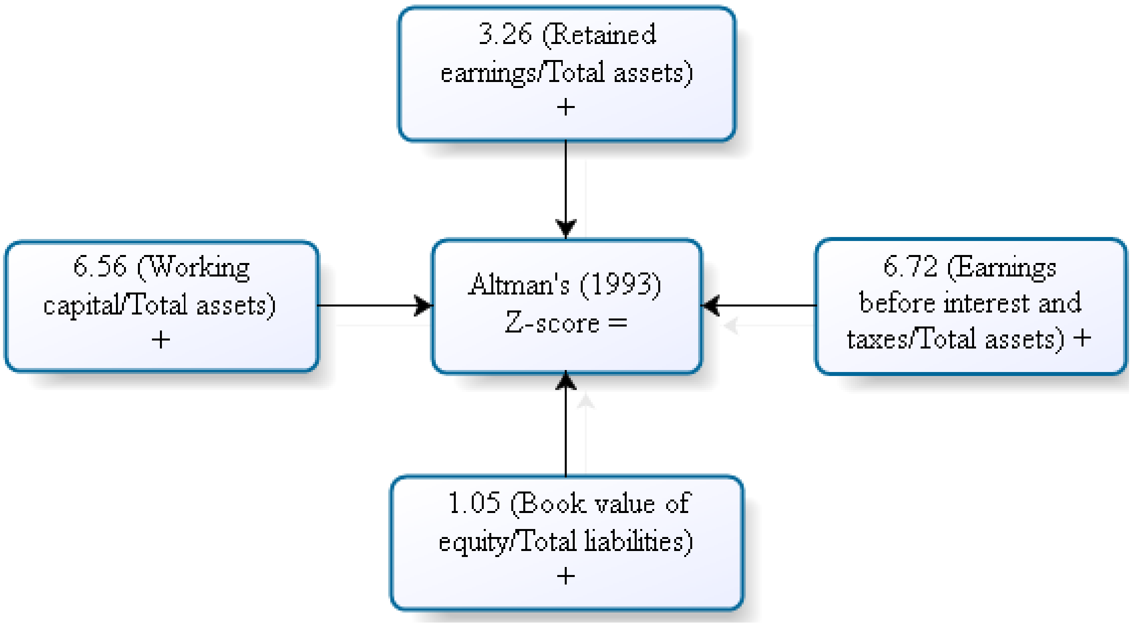

Figure 1. 3 Altman's (1993) revised Z-score model
Source: author's diagram

For better understanding, figure 1.3 is further explained below with the Z-score model.

$$Z = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4,$$

where:

X_1= Working capital / total assets

X_2= Retained earnings / total assets

X_3= Earnings before interest and taxes / total assets

X_4= Book value of equity / total liabilities.

The revised Z-score rating is as follows:

If Z-score > 2.60, it indicates that the company is doing well and is not likely to go bankrupt.

If 1.10 < Z > 2.60, it indicates uncertainty and cannot be easily predicted if the company will go bankrupt or not which is also known as the Grey Zone, it also raised concern for the affected companies.

If Z-score < 1.10, it indicates that the company is doing badly and has a high risk to go bankrupt.

Criticism

The model has some criticism despite its wide acceptance and usage. Altman's bankruptcy prediction model has been in usage for more than 50 years, the accuracy of predicting bankruptcy may change due to the passage of time. The model does not indicate specifically the liquidity position of the company since a company cannot pay its debt obligations by profit declared in the books of account but by cash. The model would have incorporated the quick ratio of a corporation which measures the readiness of a company to meet up with its financial obligations when they fall due.

The model only described the company ratios than comparing the probability of a company going bankrupt. The model can be used as a warning signal than predicting the bankruptcy of a company (Teodori, 1989). The model does not consider the future impact of interest and inflation rate on the operation of the business because it relies on past information in the financial statement to predict bankruptcy.

- ☞ The author's opinion regarding this model is that other industrial companies that are either listed or non-listed on the stock exchange can use this model to predict bankruptcy. It can also be used to compare what the impact may look like if a listed and a non-listed company are place side by side for comparison purposes. The model has been seen to be useful because it accommodates all kind of sectors. Therefore, a company that operate in more than one sector like manufacturing, services and trading can applied this model for bankruptcy prediction. It will be more complicated for such a company to use several models or the Altman's (1968) model for predicting bankruptcy since it engages in more than one business line.

1.3.4. Ohlson's (1980) O-score Model

Ohlson was the first to introduce logit regression to predict the likelihood that a company may become bankrupt soon or sooner than expected. Ohlson developed this bankruptcy prediction model in 1980 after criticizing the Altman's Z-score model. Ohlson uses logistic regression statistical method to formulate the O-score model to avoid some problems that are associated with MDA. The Ohlson model estimates the risk that is associated with a distressed company. Ohlson applied financial information of companies that are publicly available to develop the bankruptcy prediction model.

Ohlson applied nine financial ratios to set up the model. The financial ratios are the variables which have weight and constant element that is static regardless of any changes in one of the variables used to set up the model. Two out of the nine variables used are classified as dummy factors because their impact on the model is typically zero. Generally, the model is seen as a safer method of predicting the bankruptcy of companies than other models. The price index level of the GNP that was included in the Ohlson bankruptcy prediction model cannot be derived from the financial statements of a company. Other components/variables of the model can be found in the publicly traded company financial statement. The GNP price index level was used to modify the total assets of the company and to determine the changes in the price index which may result in inflation.

Table 1.3 describes the components of Ohlson's O-score model, it shows the weight, the formula for each ratio and the category of the ratios. The table gives a better understanding of the model and how the ratios are categorized either as liquidity, solvency, assets usage, investment and leverage.

Ohlson's O-score model:

$$\mathrm{O-score} = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + \ldots + B_9X_9$$

B_0 is a constant that takes a negative value of -1.32.

$$\text{Probability of Failure} = \mathrm{P} = \frac{\exp(\mathrm{O-score})}{1} + \exp(\mathrm{O-score})$$

With the aid of logistic function, the O-score is converted into probability whereby P>0.5 and P<0.5 indicates a risky and a safe company respectively.

Table 1.3. Main nine financial ratios

Main Components	Weight (B)	Components Formula	Components Category
X_1: Adjusted Size	-0.407	Log (Total assets/GNP price-level index)	It determines the size of a company by adjusting the total assets for inflation.
X_2: Leverage	6.03	Total Liabilities/Total assets	Solvency: It determines the level of indebtedness. The higher the debt, the higher the risk of bankruptcy.
X_3: Working capital measure	-1.43	Net Working capital/Total Assets	Assets Usage: Measures the percentage of liquid assets in a company
X_4. Inverse current ratio	0.0757	Current liabilities /Current assets	Liquidity: It shows the level of liquidity of a company
X_5: Discontinuity correction for leverage measure (Dummy Variable 1)	-1.72	1 if total liabilities exceed total assets, 0 otherwise	Leverage: It helps to correct the extreme leverage level of a company.
X_6: Return on assets (ROA)	-2.37	Net income/Total Assets	Investment profitability: Determines the profit level of a company which is assumed to be negative because of default.
X_7: Fund to debt ratio	-1.83	Operating income before depreciation/Total liabilities	Liquidity: Measures the ability of a company to finance its debt using operating cash flow alone.
X_8: Discontinuity correction for ROA (Dummy Variable 2)	0.285	1 if a net loss for the last two years, 0 otherwise	Liquidity: It helps to correct the two-year losses effect of a company.
X_9: Change in Net Income	-0.521	(Net income(t) - Net income(t-1)) / (Net income(t) + Net income(t-1))	Profitability. It measures possible continuous losses for two consecutive years in the history of company life.

Source: author's table

According to Ohlson (1980), the sample size used to build up the bankruptcy prediction model comprised of 105 bankrupt companies and over 2000 non-bankrupt companies. While Altman made use of only 66 companies that include both bankrupt and non-bankrupt companies to establish the bankruptcy prediction model. Altman's model discriminates between the bankrupt and the non-bankrupt companies. The data observed by Ohlson from the bankrupt and non-bankrupt companies were used to develop the O-score model. The O-score model is said to be more accurate for predicting bankruptcy of a company than the Altman model considering a 2-year time frame. The sample used by Ohlson resulted in over 90% accuracy which is far better than the Altman's model of over 70% accuracy.

The liquidity position, size, performance and financial structure of companies play a vital role in bankruptcy prediction using the O-score model. Ohlson also considered the timing of the data that are used to build up the model. Ohlson mentioned in his work that the timing when the data were available to the public determines whether the company entered bankruptcy before or after the data was released. Unlike the previous studies that do not consider the timing of the information.

- 🕮 Ohlson (1980) concluded that: *"the predictive power of any model depends upon when the information (financial report) is assumed to be available and the predictive powers of linear transforms of a vector of ratios seem to be robust across (large sample) estimation procedures. Hence, more than anything else, significant improvement probably requires additional predictors"*.

Based on the discussion in this chapter, it is important for managers of companies to think of the best model to adopt to check the riskiness of their company. Altman's Z-score model has been widely used all over the world, this could be that the model is not complicated like the Ohlson's O-score model. The models can predict the health status and risk level of a company respectively.

- ☞ A manager that would like to know how risky its company is at some period may want to use the Ohlson's O-score model which could be appropriate for such a company. The timing of the information use to determine the risk level of the company must be taken into consideration for accurate prediction. Also, a manager that would like to know the health status of his company may want to apply the Alman's Z-score model most especially the 1993 revised Z-score model which can be used for all kind of companies. Altman's (1993) revised Z-score model has made it easier for all companies to be able to predict the health status at any given time.

Companies no longer operate in only one kind of business or sector due to the economic situation and that is why it is very important for all the companies to be able to predict the status of the company. The bankruptcy prediction result may help the company to think of diversifying into a different kind of business operation that may be profitable. Therefore, if the accurate bankruptcy prediction model is used by the manager of a company to predict future bankruptcy it will assist them in taking the right decision.

2. RESEARCH METHODOLOGY

This chapter focuses on the methodology adopted to determine is Altman's (1993) Z-score model is more accurate in predicting bankruptcy for UK companies than the Ohlson's O-score model. The chapter is basically divided into various sub-chapters such as the research design, the population of the study, sampling, procedure and sample size, data collection instrument and validation, the method of data analysis, and limitation of the methodology adopted in the study.

2.1. Research Design

This study comprised a body of methods adopted to achieve its stated objectives. This research design adopts a quantitative and descriptive approach which according to Kothari (2004) *"is based on the measurement of quantity or amount. It is applicable to phenomena that can be expressed in terms of quantity".* Kothari also mentions that the mind and the insight of the researcher determine the outcomes of the research work. The adoption of a bankruptcy prediction model entails having to rely on financial statements of selected companies based on a secondary source of data gathered.

The research is designed to adopt the use of a secondary source of data gathering and using the financial statements of 30 selected companies from the United Kingdom. The research sets out to compare the two bankruptcy prediction models used by the various companies selected for scientific observations. A comparative analysis of the two models was carried out as they are widely used in the country adopted for this research study. The two bankruptcy models are Altman's (1993) revised Z-score model and Ohlson's (1980) O-score model.

The models are adopted to test the best possible predictor of bankruptcy based on the country. The use of the Altman's Z-score seems dominant in the UK than the Ohlson's O-score predictor. The research is designed to apply the two models to the selected manufacturing companies in the UK while taking a comparative approach in deciding how these predictors work. The predictors do explain or give more information about the probability of financial distress in the firms present in the UK for this research study.

2.2. Population of the Study

The population of the research study which is also termed as the universal set consists of all companies in the UK that engage in consumer goods and industrial goods and services. The companies are quoted on the London Stock Exchange from 2013 to 2017 as well as in World Bank economic indicator data for a five-year operational period. There are over 390 companies that are operating in consumer goods and industrial goods and services. This data can be seen from the London Stock Exchange database and the database link is listed on the reference page of this research paper.

2.3. Sampling, Procedure and Sample Size

A sample remains a subset of the universal set (i.e. the population). It is taken from the population to make an inference or a conclusion on the whole. The sampling that was adopted in this study is the use of convenience or purposive sampling which according to Kothari (2004), involves the selection of elements from a population for inclusion in the sample based on the ease of access. The subjects are companies that engage in consumer goods and industrial goods and services in the UK.

Thirty (30) companies are selected with the use of convenience sampling technique. This selection is based on the availability of the selected companies annual report on the London Stock Exchange database for the five (5) years period under review. Not all companies that are listed on the London Stock Exchange have their annual reports for the 5 years. The selected companies five (5) years of financial and market-based information are gathered for examination from which a conclusion was reached. The sample size shows a total number of 30 publicly quoted companies in the UK from which inference was made.

2.4. Data Collection Instrument Reliability and Validation

The use of a secondary source of data collection and gathering was adopted for this research study. The gathering of data using a secondary source involves examining financial report, stock market report of the various organizations as well as economic data from the World Bank database for the five-year period. The variables required in the models to be compared involve the use of financial data such as data for working-capital, leverage, equity and retained earnings etc. which can only be derived from the financial report.

The collected annual report of the selected companies are examined from which the variables required to reach a conclusion are derived. According to Kothari (2004), secondary data *''are those data which have already been collected''*. The data involve those already collected by the corporate bodies as well as the corporate institutions used in this study which has been presented to the stock market and can be relied upon. Kothari (2004) said that *''reliability has to do with the accuracy and precision of a measurement procedure … Practically is concerned with a wide range of factors of economy, convenience, and interpretability''.*

(Kothari, 2004) the test of validity remains an important *''critical criterion''* and it indicates the level of ''*which an instrument measures what it is supposed to measure*. *In other words, validity is the extent to which differences found with a measuring instrument reflect the true differences among those being tested''*. Most importantly, the secondary data can be relied upon and remain valid because its contents are done and handled by professionals. The input of a professional supervisor was also included in ensuring that the instruments are valid and can easily be relied upon for further analysis.

2.5. Method of Data Analysis

Different researchers have employed several bankruptcy prediction models to predict if a company will go bankrupt, although there is still no consensus or general agreement on which one is the most appropriate. Some researchers claimed that Altman's model is more accurate while others claimed that Ohlson's is better and more accurate than Altman's model. The choice is driven by several factors including among others, the time horizon considered with respect to whether the study is for the short-run or long run, hence, as a test of robustness. The components of the models also played a strong role in determining which of the model is more accurate.

The financial reports of the selected companies from the UK are also adopted. To analyse the data, the two models of Altman's (1993) Z-score model and Ohlson's (1980) O-score model are used. Each model serves as a predictor of likely bankruptcy of the selected organizations. The models are in linear regression form while considering both dependent and independent variables.

A coefficient of correlation as well as regression analysis was carried out to determine the relationship that does exist among the selected variables. The use of both descriptive and inferential statistical analysis tools was adopted to the research for effective analysis using a five-year period time series from 2013 to 2017. The use of E-view 9 and SPSS v. 20 was considered for the analysis of data gathered respectively for an effective comparative analysis as well as to test for the effectiveness of the models.

2.6. Limitation of Methodology

The research methodology is limited to the sample size adopted. The research only considered two bankruptcy prediction models while also adopting a five-year time series based on the variables highlighted in the various models. What this means is that not all variables in a financial report are considered except for that described as being a part of the model. Also, the use of convenience sampling gives the researcher the privilege to pick items that best suit his research study which prove more purposive compared to the use of random and stratified sampling technique.

3. DATA PRESENTATION AND ANALYSIS

This chapter focused on the presentation of data gathered from secondary sources such as financial data gathered from London Stock Exchange database. The data gathered are for 30 selected companies that engage in consumer goods and industrial goods and services in the UK. Purposive sampling technique was used to determine the sampling size to that was adopted for the research paper. This sampling technique according to Kothari (2004) *"is a deliberate or non-probability sampling which involves deliberate selection of particular units of the universe for constituting a sample which represents the universe."* The data gathered is for a five five-years period from 2013 to 2017.

The data gathered consist of financial reports of the selected companies for the years 2013–2014, 2014–2015, 2015–2016 and 2016–2017. Ratio analysis was used to compute the figures arrived at in line with the regression equations as contained in the Altman's and Ohlson's models. The models include working capital, current assets to current liabilities, retained earnings to total assets, working capital to total assets of the business, book value of equity to total liabilities etc.

3.1. Frequency Distribution of Data

The balance sheet size of each selected company varies from one to another as at the year ended 2017. Table 3.1 depicts the value of the balance sheet size of each selected manufacturing company in UK. The author used 2017 balance sheet size because its the most recent and available annual report on the London Stock Exchange database for all the selected companies.

According to Table 3.1, British American Tobacco has the largest balance sheet size of more than 141 billion pounds. Followed by Diageo Plc with over 28.8 billion pounds in size compared to Associated British Foods which has more than 12.8 billion pounds balance sheet size. This is an indication that the consumer goods and industrial goods and services companies are large in size and they are highly exposed to risks.

Table 3.1. Balance sheet size as at year ended 2017 for the UK companies

S/N	**Companies**	**Balance Sheet Size as at Year Ended 2017**
		£
1	British American Tobacco	141,038,000,000
2	Diageo Plc	28,848,000,000
3	Associated British Foods Plc	12,810,000,000
4	GKN Plc	8,862,000,000
5	Arla Foods UK Plc	6,422,000,000
6	Smiths Group	5,157,000,000
7	RPC Group Plc	4,751,800,000
8	DS Smith Plc	4,493,000,000
9	Imperial Brands Plc	3,099,000,000
10	Tate & Lyle	2,771,000,000
11	Burberry Group Plc	2,413,400,000
12	Greencore Group Plc	2,038,400,000
13	Britvic Plc	1,613,000,000
14	Elementis Plc	1,339,700,000
15	Essentra Plc	1,239,700,000
16	Laird Plc	1,119,500,000
17	Topps Tiles Plc	993,700,000
18	Howden Joinery Group Plc	808,500,000
19	Costain	661,100,000
20	Cranswick Plc	651,300,000
21	Renishaw Plc	643,800,000
22	De La Rue Plc	557,100,000
23	Base Resources	495,420,000
24	Ted Baker Plc	424,300,000
25	Mcbride Plc	419,900,000
26	TT Electronics Plc	364,600,000
27	Eurocell	114,630,000
28	TP Group	54,020,000
29	Chamberlin Plc	23,040,000
30	Octagonal	7,310,000

Source: author's calculations

According to Table 3.1, British American Tobacco has the largest balance sheet size of more than 141 billion pounds. Followed by Diageo Plc with over 28.8 billion pounds in size compared to Associated British Foods which has more than 12.8 billion pounds balance sheet size. This is an indication that the consumer goods and industrial goods and services companies are large in size and they are highly exposed to risks.

Also, the 2017 balance sheet size is significant to this study because apart from its availability, its also the 10 years annual report after the 2007–2008 global economic crisis. Some of the companies have been in operation before 2007 or 2008 and are still able to remain in business up till now.

3.2. Analysis and Interpretation of Data.

Companies in the UK

The selected companies are all listed on the London Stock Exchange. The UK economy has a GNP value for the five-year period based on the World Bank data as, over 1.724 trillion GBP in 2013, 1.806 trillion GBP in 2014, 1.852 trillion GBP in 2015, 1.920 trillion GBP in 2016 and 2.011 trillion GBP in 2017. This indicates an increase in the Gross National Product at market price for the five-year period being the subject of focus for the companies being examined in the UK. This is depicted on Figure 3.1.

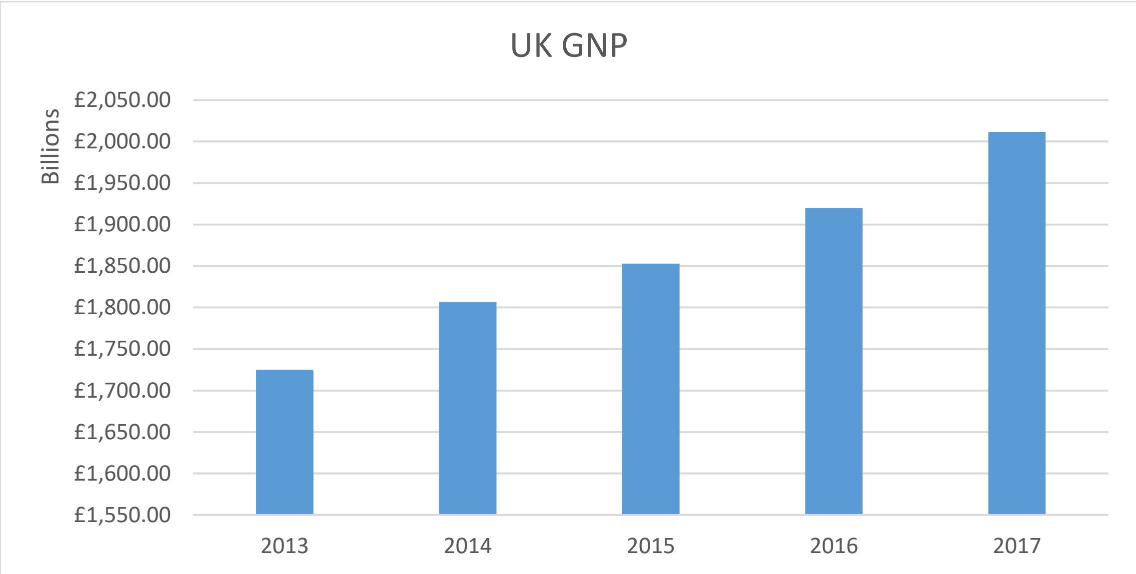

Figure 3. 1. Five Years GNP

Source**:** author's calculations

It can be seen from Figure 3.1 that 10 years after the global economic crisis, UK still recorded regular growth on their GNP value for the 5 years that was examined.

The analysis carried out based on tests conducted using both Altman's and Ohlson's bankruptcy prediction model for all companies is being interpreted below. It is based on the models used for various coefficients in line with the various accounting ratios mostly focused on the liquidity, profitability and stability ratios of the selected companies.

The Altman's Test Result

The Altman's bankruptcy prediction model adopted for the UK companies tend to identify healthy, unhealthy and unpredictable companies based on the linear model given as:

$$Z = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4.$$

The decision criteria for the model adopts the result where; Z is greater than 2.60 it is an indication that the company is healthy when Z is less than 1.10 it is an indication that the company is unhealthy and where 1.10 is less than Z-score and Z-score is less than 2.60 then the company's financial health can be said to be unpredictable (grey zone).

Table 3.2 shows the health status of the selected companies in the UK. The health status for the year 2017 was considered as the current health status of the companies. This is because 2017 data has been the most recent available annual report that was used for the analysis 10 years after the global economic crisis.

Altman's Z-score model was used to determine the current health status of each of the company. The numbers and percentage of companies with its current health status can be seen on the Table 3.2.

Table 3.2. Health status of the companies based on 2017 financial year (Altman Z-score)

Summary of Findings	No. of Companies	%
Healthy	17	57%
Unhealthy	6	20%
Unpredictable	7	23%
Total	30	100%

Source: author's computation

According to the analysis carried out, 17 (57%) companies are healthy and 6 (20%) are unhealthy and another 7 (23%) companies are observed to be unpredictable as depicted on Table 3.2 for the observed companies in the United Kingdom. The analysis was based on the result computed using Altman's (1993) Z-score model.

The Ohlson's Test Result

The Ohlson's Bankruptcy Test adopts nine complex variables with a probability to measure the risky or safe nature of the various companies using the regression model. The coefficients are included with the various ratio analysis for profitability, liquidity and stability ratios respectively to test for the solvency of the various companies with the aid of the model depicted below:

$$\mathrm{O-score} = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + \ldots + B_9X_9$$

The basis of the decision on the risky and safety nature of the business is determined by the probability equation:

$$Probability\ of\ Failure = P = \frac{\exp(\mathrm{O-score})}{1} + \exp(\mathrm{O-score})$$

Where the P>0.5 the business is said to be RISKY and where the P<0.5 the business is said to be SAFE.

Ohlson's O-score model was used to determine the risk status of each of the company. The numbers and percentage of companies with its status either risky or safe can been seen in Table 3.3.

Table 3.3. Health status of the companies based on 2017 financial year (Ohlson's O-score)

Summary of Findings	No. of Companies	%
Safe	4	13%
Risky	26	87%
Total	30	100%

Source: author's computation

According to the analysis carried out, 26 (86.67%) companies are "Risky" while 4 (13.33%) are "Safe" as depicted on Table 3.3 for the observed companies in the United Kingdom based on Ohlson's model for the year 2017.

3.3. Descriptive Statistics of the Mean, Standard Deviation and Variance for the UK Companies

The statistics describes the mean, standard deviation and the variance for each of the selected companies. It shows how the data were distributed, deviate from one another and the disparity among the set of data. The index used for this statistics is the average Altman's (1993) Z-score value for the 5 years period that is being reviewed.

The descriptive statistical values of all companies for the years being examined based on the Altman's (1993) Z-score model computed are depicted on Table 3.4. The highest mean value of the distribution is within 8.47 and 12.89 while the highest standard deviation computed is at 4.11

for Octagonal. The variance of the distribution which shows the rate of disparity among the set of data being examined is high at a value of 16.93 for Octagonal.

- The author's observed from Table 3.4 that the highest mean depicts the average performance of the companies that falls within the range of 8.47 and 12.89. This shows that companies within that range might be doing very good based on the available data. Octagonal has the highest standard deviation mention above which shows that the company has the highest risk among the selected companies.

Table 3.4. Mean, standard deviation and variance for the UK companies using Altman's (1993) Z-score values for the 5 years under review

S/N	Companies	Mean	SD Deviation	Variance
1	Arla Foods UK Plc	1.23	0.16	0.03
2	Associated British Foods Plc	5.26	0.26	0.07
3	Base Resources	1.26	0.64	0.41
4	British American Tobacco	1.65	0.21	0.05
5	Britvic Plc	1.08	0.50	0.25
6	Burberry Group Plc	7.41	0.74	0.54
7	Chamberlin Plc	0.82	0.61	0.37
8	Costain	1.01	0.20	0.04
9	Cranswick Plc	5.10	0.51	0.26
10	Diageo Plc	2.29	0.12	0.01
11	De La Rue Plc	2.17	0.83	0.69
12	DS Smith Plc	0.82	0.13	0.02
13	Elementis Plc	5.57	1.22	1.49
14	Essentra Plc	2.88	1.10	1.22
15	Eurocell	4.08	1.21	1.45
16	GKN Plc	1.91	0.53	0.28
17	Greencore Group Plc	0.25	0.16	0.03
18	Howden Joinery Group Plc	7.40	0.77	0.59
19	Imperial Brands Plc	0.19	0.35	0.12
20	Laird Plc	1.99	0.64	0.41
21	McBride Plc	-0.08	0.38	0.14
22	Renishaw Plc	8.47	1.47	2.15
23	RPC Group Plc	1.33	0.22	0.05
24	Ted Baker Plc	5.78	0.88	0.77
25	Topps Tiles Plc	1.51	0.33	0.11
26	TT Electronics Plc	4.21	1.57	2.45
27	TP Group	1.63	2.61	6.81
28	Smiths Group	3.19	0.57	0.33
29	Octagonal	12.89	4.11	16.93
30	Tate & Lyle	2.70	0.69	0.47

Source: author's computation

Table 3.5 shows how the data were distributed, deviate from one another and the disparity among the set of data. The index used for this statistic is the average Ohlson's O-score value for the 5 years period that have been reviewed.

Table 3.5. Mean, standard deviation and variance for the UK companies using Ohlson's O-score values for the 5 years under review

S/N	Companies	Mean	SD Deviation	Variance
1	Arla Foods UK Plc	0.83	0.01	0.00
2	Associated British Foods Plc	0.67	0.03	0.00
3	Base Resources	0.80	0.14	0.02
4	British American Tobacco	0.82	0.01	0.00
5	Britvic Plc	0.86	0.00	0.00
6	Burberry Group Plc	-2.28	6.99	48.89
7	Chamberlin Plc	0.81	0.02	0.00
8	Costain	0.76	0.02	0.00
9	Cranswick Plc	0.63	0.04	0.00
10	Diageo Plc	0.63	0.36	0.13
11	De La Rue Plc	0.83	0.02	0.00
12	DS Smith Plc	0.83	0.00	0.00
13	Elementis Plc	2.01	4.49	20.12
14	Essentra Plc	0.79	0.05	0.00
15	Eurocell	-0.65	3.20	10.23
16	GKN Plc	0.83	0.01	0.00
17	Greencore Group Plc	0.80	0.10	0.01
18	Howden Joinery Group Plc	0.61	0.05	0.00
19	Imperial Brands Plc	0.84	0.01	0.00
20	Laird Plc	0.82	0.05	0.00
21	McBride Plc	0.86	0.01	0.00
22	Renishaw Plc	0.83	0.01	0.00
23	RPC Group Plc	0.24	0.54	0.29
24	Ted Baker Plc	0.74	0.04	0.00
25	Topps Tiles Plc	0.86	0.01	0.00
26	TT Electronics Plc	0.82	0.16	0.03
27	TP Group	0.57	0.18	0.03
28	Smiths Group	0.60	0.05	0.00
29	Octagonal	0.97	1.66	2.75
30	Tate & Lyle	0.60	0.05	0.00

Source: author's computation

Table 3.5 describe the statistical values of all companies for the years being examined based on the Ohlson's O-score model computed. The highest mean value of the distribution is within 0.97 and 2.01 while the highest standard deviation computed is at 6.99 for Burberry Group Plc. The variance of the distribution which shows the rate of disparity among the set of data being examined is high at a value of 48.89 for Burberry Group Plc.

- ☞ A high standard deviation depicts a high level of risk for a business. It can be seen that Burberry Group Plc have the highest standard deviation based on Ohlson's O-score value. This shows that Burberry Group Plc has the highest risk among all the selected companies.

3.4. Inferential Analysis

IBM SPSS (Statistical Package for Social Sciences) v.20 was used to analyse and compare the significance of the two bankruptcy models in predicting bankruptcy. The Altman's and Ohlson's model were tested based on the findings made from the United Kingdom. Altman's prediction model rests on three yardsticks. That is a company is healthy if the Z-score is higher than 2.60 and if the Z score is lower than 1.10 then it is unhealthy, but where 1.10 is lower than the z-score and the z score is less than 2.60 then the company is said to be unhealthy.

The Ohlson's model makes use of nine variables and coefficients with a probability for measuring the "risky" and "safe" organizations. The use of Pearson's coefficient as an inferential statistical tool was adopted to observe the level of significance of the models. It was used to compare between the two models (Altman and Ohlson) to know which is to predict bankruptcy. The following analyses were carried out using IBM SPSS.

3.5. Analysis of Pearson's Coefficient of Correlation for Altman's Z-score Computation for the UK Companies

The SPSS v.20 was used to analyse the financial data that was extracted from the London Stock Exchange database. Table 3.6 shows the descriptive statistics that were generated from the use of SPSS with it mean and standard deviation of the Altman's Z-score value.

Table 3.6. Descriptive statistics

Year	Mean	SD Deviation	N
2013-2014	3.127	3.1913	30
2014-2015	3.027	2.6907	30
2015-2016	3.107	3.2519	30
2016-2017	3.547	3.2566	30

IBM SPSS v.20
Source: author's calculation

According to the Table 3.6, the mean distribution for the companies for the years being examined shows mean values from 3.02 to 3.54. This is the average of the distribution based on the test conducted for the companies. This is an indication of values above the 2.60 thresholds for measuring healthy companies based on the Altman's standards. The rate of deviation of the values computed is from 2.69 to 3.25 by which the data deviate from one another for a total number (n) of 30 selected companies in the United Kingdom.

A high standard deviation depicts high level of risk for businesses. Based on Altman's Z-score values for 2016–2017 there is just 0.0047 increase in the standard deviation from 2015–2016. It can be said that the risk of the companies still remains the same both years.

Pearson's coefficient of correlation helps to determine the level of correlation between the data for the years under review using the Alman's Z-scores. Table 3.7 depicts the relationship between the observed years and shows how positively or negatively the data are correlated with each other.

Table 3.7. Correlations

Year		2013-2014	2014-2015	2015-2016	2016-2017
2013–2014	Pearson Correlation	1	.874**	.937**	.882**
	Sig. (1-tailed)		.000	.000	.000
	N	30	30	30	30
2014–2015	Pearson Correlation	.874**	1	.821**	.754**
	Sig. (1-tailed)	.000		.000	.000
	N	30	30	30	30
2015–2016	Pearson Correlation	.937**	.821**	1	.958**
	Sig. (1-tailed)	.000	.000		.000
	N	30	30	30	30
2016–2017	Pearson Correlation	.882**	.754**	.958**	1
	Sig. (1-tailed)	.000	.000	.000	
	N	30	30	30	30

**. Correlation is significant at the 0.01 level (1-tailed).
Source: author's computation

According to the Table 3.7, there is a very strong correlation among the results conducted using Altman's model for the companies observed and listed on the London Stock Exchange. The 2013–2014 year shows a positively high coefficient of correlation at 0.874 (87.4%) with that of 2014–2015, 0.937 (93.7%) with that of 2015–2016 and a highly positive coefficient of correlation at 0.882 (88.2%) for 2016–2017. Also, the 2014–2015 year is positively correlated with that of 2015–2016 at 0.821 (82.1%) and at a very positive high correlation with 2016–2017 at 0.754 (75.4%) while that of 2016-2017 is highly positively correlated with that of 2015–2016 at 0.958 (95.8%).

- ☞ This is an indication that the Altman's prediction model is quite effective for all the years being examined as well as for the companies being reviewed. The analysis was done at a 1% significant level and at a confidence level of 99% at a one-tailed test with the P-values computed at 0.000 respectively for all the years.

In the opinion of the author with regards to the result above generated from the correlation Table 3.7, it can be said that the financial situation of a company for the previous year has an impact or effect on the following year's financial results. The result shows a positive and very strong correlation between each year for all the selected companies. It means that if a company should record some losses in the previous year, such losses will need to be recouped in the following year's profit. Losses can be accumulated for some period pending when the company is able to recover all the losses.

Decision Criteria

When the P-value is higher than the Alpha value at 0.01 we accept the null hypothesis else we reject the null hypothesis when the P-value is lower to the Alpha value. Therefore, in this case, the P-value is lower than the alpha value then we reject the null hypothesis that Altman's (1993) Bankruptcy prediction model is not more accurate in predicting bankruptcy for UK companies than Ohlson's O-score model.

Therefore, the Altman's (1993) revised Z-score model is more accurate in predicting bankruptcy for UK companies than Ohlson's O-score model.

The result agrees with other authors who have carried out a comparative test using Altman's and Ohlson's model. It shows that bankruptcy can be better predicted using Altman's Z-score model for UK companies that engage in consumer goods and industrial goods and services.

3.6. Analysis of Pearson’s Coefficient of Correlation for Ohlson's O-score Computation for the UK companies

Ohlson’s O-score model was also analysed with the use of SPSS which gives the below result. Table 3.8 shows the descriptive statistics that were generated from the use of SPSS with it mean and standard deviation of the Ohlson’s O-score values.

Table 3.8. Descriptive Statistics

Year	Mean	Std. Deviation	N
2013–2014	.563	2.9110	30
2014–2015	.597	.4767	30
2015–2016	.853	.5661	30
2016–2017	.540	1.1309	30

IBM SPSS v.20 (Source: author’s calculation)

According to the Table 3.8, the mean distribution for the companies for the years being examined shows mean values from 0.540 to 0.853. This is the average of the distribution based on the test conducted for the companies for the period. This is an indication of values above the 0.5 thresholds for measuring Risky and Safe companies based on the Ohlson's standards while all the averages point at RISKY for the years examined. The rate of deviation of the values computed is from 0.47 to 2.91 by which the data deviate from one another for a total number (n) of 30 selected companies in the United Kingdom.

Based on Ohlson’s O-score values the highest risk level for all the companies was observed during year 2013–2014 as determined by the satndard deviation. Due to passage of time the risk reduced in year 2014–2015 and 2015–2016 but later increased by 0.5648 which is about double of the previous year.

Table 3.9 depicts the relationship between the observed years and shows how positively or negatively the data are correlated with each other. According to Table 3.9, there is a very low correlation among the results conducted using Ohlson's model for the companies observed and listed on the London Stock Exchange.

Table 3.9. Correlations

Year		2013-2014	2014-2015	2015-2016	2016-2017
2013–2014	Pearson Correlation	1	.116	-.734**	-.229
	Sig. (1-tailed)		.270	.000	.112
	N	30	30	30	30
2014–2015	Pearson Correlation	.116	1	-.035	.131
	Sig. (1-tailed)	.270		.427	.246
	N	30	30	30	30
2015–2016	Pearson Correlation	-.734**	-.035	1	.301
	Sig. (1-tailed)	.000	.427		.053
	N	30	30	30	30
2016–2017	Pearson Correlation	-.229	.131	.301	1
	Sig. (1-tailed)	.112	.246	.053	
	N	30	30	30	30

**. Correlation is significant at the 0.01 level (1-tailed).
Source: author's computation

The 2013–2014 year shows a positively low coefficient of correlation at 0.116 (11.6%) with that of 2014–2015, -0.734 (-73.4%) with that of 2015–2016 and a low negative coefficient of correlation at -0.229 (-22.9%) for 2016–2017. Also, the 2014–2015 year is low negatively correlated with that of 2015–2016 at -0.35 (-35%) and at a very low positive correlation with 2016–2017 at 0.131 (13.1%). While that of 2016–2017 is low positively correlated with that of 2015–2016 at 0.301 (30.1%).

- ☞ This is an indication that the Altman's prediction model is quite effective for all the years being examined as well as for the companies being reviewed.

The analysis was done at a 1% significant level and at a confidence level of 99% at a one-tailed test with the P-values mostly above the significant level of 0.01 at 1-tailed test respectively for all the years.

The author observed from the result above generated from the SPSS that the relationship between each year under review are more of low positively and high negatively correlated. This shows that the financial situation of the previous year does not have any effect or impact on the current year.

Decision Criteria

When the P-value is higher than the Alpha value at 0.01 we accept the null hypothesis else we reject the null hypothesis when the P-value is lower to the Alpha value. Therefore, in this case, the

P-value is higher than the Alpha value then we accept the null hypothesis that Ohlson's O-score model is not more accurate in predicting bankruptcy for UK companies than Altman's (1993) Z-score model.

Therefore, the Altman's (1993) Z-score model is more accurate in predicting bankruptcy for UK companies than Ohlson's O-score model.

3.7. Findings

From the analysis carried out above, the following findings were deduced:

i. The Altman's (1993) Z-score model is more accurate in predicting bankruptcy for UK companies that engage in consumer goods and industrial goods and services than Ohlson's O-score model.
ii. The Altman's bankruptcy prediction model is not as complex as the Ohlson's models with so many variables that are quite misleading and prone to errors.
iii. Some of the Ohlson's variables are just inverse of the ratio analysis computations which are attached to coefficient that help to drive the values of the equation variables.
iv. The result generated from the use of SPSS for Ohlson's O-score shows that there is no good correlation between the years under review. This can be referred to as each year can be treated on a stand-alone basis, meaning that the financial situation of the previous year cannot affect that of the current year.

From the analysis carried out it can be concluded that the Altman's (1993) Z-score model is more accurate in testing for bankruptcy compared to the Ohlson's O-score model which is quite complex in computing. This finding is in line with the findings of Karamzadeh (2013), who agreed that Altman's Z-Score bankruptcy prediction model is more accurate compared to that of Ohlson's O-Score model.

4. SUMMARY, CONCLUSION AND RECOMMENDATION

This chapter focuses on the research summary of findings and the conclusions as well as the recommendations made on the bases of the tests conducted. As stated in the introduction, the research paper aims to compare the two bankruptcy prediction models to determine which is more accurate in predicting bankruptcy for UK companies that engage in consumer goods and industrial goods and services.

4.1. Summary of Findings

The findings revealed that the 30 selected companies in the UK were best tested using Altman's (1993) revised Z-score model. With the help of Pearson's coefficient of correlation at a confidence level of 99%, Altman's (1993) revised Z-score model shows more accurate result. The Altman's (1993) revised Z-score model remains a model with very unique variables and coefficients. The findings shows that the revised model can be adopted for companies that engage in consumer goods and industrial goods and services in predicting bankruptcy in the UK.

Ohlson's model is complex in nature for analysis. One of the shortcomings being the adoption of GNP (Gross National Product) at market price which remains a macro-economic factor unlike individual organizations saddled with micro-economic problems. Also, the predictors are based on too many assumptions of having to assign 1 for companies if net income for the past two years is negative. And assigning 0 to companies with positive net income for the past two years one which made other variables for computation useless and of no use. It was observed that most of the ratio analysis are inverse of the normal liquidity and solvency ratios, for example, the current assets ratio was transposed from CA/CL to CL/CA likewise the ratio of TA/TL being transposed to TL/TA.

4.2. Conclusions

A small or big company can become bankrupt within one or two years when the economic situation of the country changes and become unfavourable one. The company location does not matter, a company can reside in a developed country and still goes bankrupt. This is one of the crucial reasons why bankruptcy prediction has become an important topic for company management, researchers' investors and academic professionals,

Companies go bankrupt due to many reasons in which some of the reasons are within the control powers of management of the company like debt management and solvency. While some are beyond the control of the company management like the economic situation of the country, the business environment etc. Therefore, the purpose of this research paper is to compare Altman's (1993) revised Z-score model to that of Ohlson's O-score model to determine which is more accurate to predict bankruptcy for companies that engage in consumer goods and industrial goods and services in the UK in the period 2013–2017 using 30 selected companies.

The result of the analysis shows that there are much strong and very high positive correlations between the observed years using Altman's (1993) Z-score model compared to Ohlson's model which is an indication of a strong relationship among variables being tested. This can be seen on the correlations Table 3.7 and 3.9. The conclusion was that the Altman's (1993) Z-score model is more accurate in predicting bankruptcy for the UK companies than the Ohlson's O-score model. The Altman's (1993) revised Z-score model is accurate for all the companies irrespective of sectors, unlike the 1968 model which has its shortcomings of only being suitable to predict for manufacturing companies.

4.3. Recommendation

This master's thesis is limited to the selected companies in the UK that engage in consumer goods and industrial goods and services. Since Altman's Z-score model is not limited to only manufacturing companies, it can be recommended that future researchers should test the Altman's (1993) Z-score model and Ohlson's O-score model on other sectors to determine which is more accurate.

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APPENDICES

Appendix 1. Altman's Z-score for the selected companies

Atlman's Z-Scores Zones of Discrimination Z-Score>2.60 "Healthy" Z-Score<1.10 "Unhealthy" 1.10< Z <2.60 "Unpredictable"						
Country	Companies	2013-2014	2014-2015	2015-2016	2016-2017	Current Status
UK						
1	Arla Foods UK Plc	1.02	1.21	1.31	1.39	
		Unhealthy	Healthy	Healthy	Healthy	Healthy
2	Associated British Foods Plc	5.04	5.04	5.45	5.53	
		Healthy	Healthy	Healthy	Healthy	Healthy
3	Base Resources	0.68	1.03	1.16	2.17	
		Unhealthy	Unhealthy	Healthy	Healthy	Healthy
4	British American Tobacco	1.75	1.52	1.42	1.89	
		Unpredictable	Unpredictable	Unpredictable	Unpredictable	Unpredictable
5	Britvic Plc	1.12	1.76	0.62	0.83	
		Unpredictable	Unpredictable	Unhealthy	Unhealthy	Unhealthy
6	Burberry Group Plc	6.45	7.23	7.92	8.06	
		Healthy	Healthy	Healthy	Healthy	Healthy
7	Chamberlin Plc	0.95	1.43	0.92	- 0.03	
		Unhealthy	Unpredictable	Unhealthy	Unhealthy	Unhealthy
8	Costain	1.05	1.06	0.73	1.19	
		Unhealthy	Unhealthy	Unhealthy	Unpredictable	Unpredictable
9	Cranswick Plc	5.14	4.56	4.90	5.78	
		Healthy	Healthy	Healthy	Healthy	Healthy
10	Diageo Plc	2.24	2.29	2.18	2.46	
		Unpredictable	Unpredictable	Unpredictable	Unpredictable	Unpredictable
11	De La Rue Plc	2.86	2.92	1.42	1.49	
		Healthy	Healthy	Unpredictable	Unpredictable	Unpredictable
12	DS Smith Plc	0.92	0.87	0.62	0.87	
		Unhealthy	Unhealthy	Unhealthy	Unhealthy	Unhealthy
13	Elementis Plc	5.96	6.62	5.90	3.81	
		Healthy	Healthy	Healthy	Healthy	Healthy
14	Essentra Plc	4.35	2.80	1.68	2.69	
		Healthy	Healthy	Unpredictable	Healthy	Healthy
15	Eurocell	2.39	4.10	4.69	5.14	
		Unpredictable	Healthy	Healthy	Healthy	Healthy
16	GKN Plc	1.73	1.66	1.56	2.69	
		Unpredictable	Unpredictable	Unpredictable	Healthy	Healthy
17	Greencore Group Plc	0.07	0.38	0.16	0.39	
		Unhealthy	Unhealthy	Unhealthy	Unhealthy	Unhealthy
18	Howden Joinery Group Plc	6.43	8.29	7.34	7.56	
		Healthy	Healthy	Healthy	Healthy	Healthy
19	Imperial Brands Plc	0.59	0.36	0.01	(0.19)	
		Unhealthy	Unhealthy	Unhealthy	Unhealthy	Unhealthy
20	Laird Plc	2.51	1.91	1.12	2.41	
		Unpredictable	Unpredictable	Unpredictable	Unpredictable	Unpredictable
21	McBride Plc	(0.45)	(0.35)	0.34	0.12	
		Unhealthy	Unhealthy	Unhealthy	Unhealthy	Unhealthy
22	Renishaw Plc	9.53	9.83	6.74	7.76	
		Healthy	Healthy	Healthy	Healthy	Healthy
23	RPC Group Plc	1.51	1.31	1.03	1.47	
		Unpredictable	Unpredictable	Unhealthy	Unpredictable	Unpredictable
24	Ted Baker Plc	6.21	6.68	5.56	4.66	
		Healthy	Healthy	Healthy	Healthy	Healthy
25	Topps Tiles Plc	1.08	1.49	1.63	1.86	
		Unhealthy	Unpredictable	Unpredictable	Unpredictable	Unpredictable
26	TT Electronics Plc	3.07	3.45	3.81	6.52	
		Healthy	Healthy	Healthy	Healthy	Healthy
27	TP Group	- 0.27	- 0.46	2.13	5.12	
		Unhealthy	Unhealthy	Unpredictable	Healthy	Healthy
28	Smiths Group	2.49	3.25	3.15	3.88	
		Unpredictable	Healthy	Healthy	Healthy	Healthy
29	Octagonal	14.31	6.76	15.27	15.24	
		Healthy	Healthy	Healthy	Healthy	Healthy
30	Tate & Lyle	2.97	1.82	2.57	3.44	
		Healthy	Unpredictable	Unpredictable	Healthy	Healthy

Appendix 2. Ohlson's O-score for the selected companies

Ohlson's O-score Model Where P<0.5 "Safe" P>0.5 "Risky"						
Country	Companies	2013-2014	2014-2015	2015-2016	2016-2017	Current Status
UK						
1	Arla Foods UK Plc	0.83	0.83	0.82	0.82	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
2	Associated British Foods Plc	0.67	0.70	0.67	0.63	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
3	Base Resources	1.01	0.73	0.74	0.70	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
4	British American Tobacco	0.82	0.82	0.84	0.80	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
5	Britvic Plc	0.87	0.86	0.86	0.86	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
6	Burberry Group Plc	-12.56	-0.68	2.64	1.49	
	Ohlson's Probability	Safe	Safe	Risky	Risky	Risky
7	Chamberlin Plc	0.79	0.82	0.79	0.83	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
8	Costain	0.73	0.77	0.79	0.75	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
9	Cranswick Plc	0.60	0.65	0.67	0.59	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
10	Diageo Plc	0.81	0.81	0.80	0.09	
	Ohlson's Probability	Risky	Risky	Risky	Safe	Safe
11	De La Rue Plc	0.80	0.83	0.82	0.85	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
12	DS Smith Plc	0.83	0.83	0.84	0.84	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
13	Elementis Plc	8.67	-1.04	-0.07	0.49	
	Ohlson's Probability	Risky	Safe	Safe	Safe	Safe
14	Essentra Plc	0.78	0.75	0.86	0.75	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
15	Eurocell	2.14	0.17	0.36	-5.26	
	Ohlson's Probability	Risky	Safe	Safe	Safe	Safe
16	GKN Plc	0.84	0.84	0.84	0.82	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
17	Greencore Group Plc	0.85	0.84	0.64	0.86	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
18	Howden Joinery Group Plc	0.66	0.63	0.54	0.63	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
19	Imperial Brands Plc	0.84	0.84	0.85	0.84	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
20	Laird Plc	0.77	0.83	0.81	0.88	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
21	McBride Plc	0.84	0.87	0.86	0.86	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
22	Renishaw Plc	0.84	0.84	0.83	0.82	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
23	RPC Group Plc	0.26	-0.52	0.64	0.59	
	Ohlson's Probability	Safe	Safe	Risky	Risky	Risky
24	Ted Baker Plc	0.73	0.68	0.76	0.77	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
25	Topps Tiles Plc	0.87	0.86	0.85	0.84	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
26	TT Electronics Plc	0.89	0.99	0.79	0.61	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
27	TP Group	0.64	0.67	0.67	0.30	
	Ohlson's Probability	Risky	Risky	Risky	Safe	Safe
28	Smiths Group	0.58	0.64	0.65	0.54	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky
29	Octagonal	-1.03	0.68	3.00	1.22	
	Ohlson's Probability	Safe	Risky	Risky	Risky	Risky
30	Tate & Lyle	0.58	0.64	0.65	0.54	
	Ohlson's Probability	Risky	Risky	Risky	Risky	Risky

Appendix 3. Altman's *Z*-score computed for each year

ALTMAN'S REVISED ZERO-SCORE MODEL (1993) Z-SCORE=6.56X1+3.26X2+6.72X3+1.05X4							
	UK		VARIABLES				
S/N	Companies	Year	X1 (6.56*WC/TA	X2 (3.26*RE/TA)	X3 (6.72*EBIT/TA	X4 (1.05*BvE/TL	Z-score
1	Arla Foods UK Plc	2013	0.49	0	0.46	0.40	1.36
		2014	0.23	0	0.37	0.42	1.02
		2014	0.32	0	0.40	0.49	1.21
		2016	0.22	0	0.53	0.55	1.31
		2017	0.38	0	0.40	0.61	1.39
2	Associated British Foods Plc	2013	0.56	1.73	0.63	1.77	4.69
		2014	0.58	1.85	0.69	1.91	5.04
		2014	0.70	1.98	0.51	1.85	5.04
		2016	0.84	2.20	0.64	1.76	5.45
		2017	1.03	1.63	0.85	2.01	5.53
3	Base Resources	2013					
		2014	0.21	- 0.19	- 0.14	0.80	0.68
		2015	0.43	- 0.25	0.16	0.68	1.03
		2016	0.65	- 0.37	0.17	0.72	1.16
		2017	0.67	- 0.26	0.81	0.95	2.17
4	British American Tobacco	2013	0.26	0.67	0.24	0.37	1.53
		2014	0.09	0.20	1.17	0.30	1.75
		2014	0.17	0.18	0.97	0.20	1.52
		2016	0.08	0.27	0.79	0.28	1.42
		2017	(0.07)	0.85	0.31	0.80	1.89
5	Britvic Plc	2013	(0.25)	(0.46)	0.69	0.04	0.02
		2014	0.45	(0.30)	0.89	0.09	1.12
		2014	0.86	(0.12)	0.81	0.20	1.76
		2016	(0.23)	(0.10)	0.73	0.22	0.62
		2017	(0.18)	0.05	0.68	0.28	0.83
6	Burberry Group Plc	2013	1.50	1.15	1.33	1.59	5.57
		2014	1.91	1.34	1.52	1.67	6.45
		2014	2.25	1.50	1.36	2.11	7.23
		2016	2.68	1.61	1.17	2.45	7.92
		2017	2.89	1.58	1.10	2.49	8.06
7	Chamberlin Plc	2013					
		2014	0.49	0.54	- 0.61	0.52	0.95
		2015	0.49	0.39	0.13	0.42	1.43
		2016	0.15	0.36	0.03	0.39	0.92
		2017	- 0.43	0.08	0.11	0.21	- 0.03
8	Costain	2013					-
		2014	0.68	0.37	0.35	0.34	1.05
		2014	0.60	0.38	0.37	0.31	1.06
		2016	0.72	0.17	0.36	0.19	0.73
		2017	1.15	0.42	0.45	0.32	1.19
9	Cranswick Plc	2013	0.55	1.53	0.00	2.52	4.60
		2014	0.78	1.60	0.00	2.75	5.14
		2014	0.74	1.66	0.00	2.17	4.56
		2016	0.84	1.73	0.00	2.33	4.90
		2017	0.98	1.86	0.00	2.94	5.78
10	Diageo Plc	2013	0.78	0.23	0.61	0.50	2.11
		2014	0.74	0.35	0.64	0.52	2.24
		2014	0.60	0.46	0.64	0.59	2.29
		2016	0.61	0.43	0.56	0.58	2.18
		2017	0.45	0.62	0.65	0.75	2.46

Appendix 3. (Continuing)

11	Diary Crest Group Plc	2013	1.29	0.48	0.14	0.48	2.38
		2014	1.23	0.51	0.54	0.59	2.86
		2014	1.40	0.51	0.40	0.61	2.92
		2016	0.78	(0.17)	0.55	0.27	1.42
		2017	1.31	(0.57)	0.59	0.16	1.49
12	DS Smith Plc	2013	(0.19)	0.26	0.24	0.45	0.75
		2014	(0.29)	0.30	0.41	0.49	0.92
		2014	(0.31)	0.21	0.51	0.47	0.87
		2016	(0.46)	0.26	0.41	0.41	0.62
		2017	(0.45)	0.38	0.49	0.45	0.87
13	Elementis Plc	2013					-
		2014	1.28	1.55	1.08	2.05	5.96
		2014	1.46	1.76	0.81	2.59	6.62
		2016	1.27	1.73	0.62	2.28	5.90
		2017	0.89	1.31	0.46	1.16	3.81
14	Essentra Plc	2013	0.62	1.25	0.72	0.85	3.43
		2014	0.75	1.22	0.75	1.64	4.35
		2014	0.59	0.92	0.48	0.81	2.80
		2016	0.46	0.68	-0.24	0.78	1.68
		2017	0.65	0.95	0.03	1.05	2.69
15	Eurocell	2013					-
		2014	(0.02)	0.48	1.75	0.18	2.39
		2015	1.09	0.91	1.63	0.47	4.10
		2016	1.24	1.16	1.64	0.65	4.69
		2017	1.60	1.33	1.42	0.79	5.14
16	GKN Plc	2013	0.62	0.73	0.60	0.42	2.38
		2014	0.61	0.52	0.29	0.30	1.73
		2015	0.49	0.53	0.29	0.35	1.66
		2016	0.62	0.36	0.25	0.33	1.56
		2017	0.76	0.57	0.53	0.83	2.69
17	Greencore Group Plc	2013	(1.34)	0.22	0.40	0.35	(0.38)
		2014	(1.01)	0.29	0.39	0.40	0.07
		2014	(0.12)	0.04	0.05	0.42	0.38
		2016	(0.76)	0.20	0.40	0.31	0.16
		2017	(0.39)	0.08	0.14	0.56	0.39
18	Howden Joinery Group Plc	2013	2.66	0.56	1.82	1.11	6.16
		2014	3.02	0.57	1.96	0.88	6.43
		2014	3.13	1.31	2.17	1.68	8.29
		2016	2.71	1.30	2.13	1.19	7.34
		2017	2.85	1.41	1.95	1.35	7.56
19	Imperial Tobacco Group	2013	(0.62)	(0.09)	0.46	0.26	0.02
		2014	(0.13)	(0.09)	0.53	0.28	0.59
		2014	(0.36)	0.03	0.44	0.24	0.36
		2016	(0.51)	(0.15)	0.46	0.22	0.01
		2017	(0.84)	(0.11)	0.49	0.26	(0.19)
20	Laird Plc	2013	0.49	0.03	0.53	1.17	2.22
		2014	0.91	0.10	0.53	0.97	2.51
		2014	0.51	(0.05)	0.69	0.76	1.91
		2016	0.67	(0.46)	0.44	0.46	1.12
		2017	1.04	(0.25)	0.50	1.12	2.41

Appendix 3. (Continuing)

21	Mcbride Plc	2013	(0.22)	(0.40)	0.14	0.33	(0.15)
		2014	0.24	(0.67)	-0.22	0.20	(0.45)
		2014	0.12	(0.82)	0.16	0.18	(0.35)
		2016	0.32	(0.71)	0.53	0.21	0.34
		2017	0.05	(0.76)	0.64	0.19	0.12
22	Renishaw Plc	2013	2.35	2.16	1.17	2.47	8.16
		2014	2.60	2.25	1.26	3.42	9.53
		2014	2.78	2.32	1.44	3.29	9.83
		2016	2.17	2.19	0.54	1.84	6.74
		2017	2.22	2.28	0.93	2.33	7.76
23	RPC Group Plc	2013	0.34	0.53	0.40	0.46	1.73
		2014	0.17	0.47	0.49	0.39	1.51
		2014	0.27	0.23	0.31	0.49	1.31
		2016	0.12	0.18	0.23	0.49	1.03
		2017	0.40	0.15	0.27	0.65	1.47
24	Ted Baker Plc	2013					-
		2014	1.87	1.71	1.32	1.32	6.21
		2014	1.89	1.76	1.41	1.62	6.68
		2016	1.57	1.50	1.17	1.32	5.56
		2017	1.41	1.41	0.99	0.85	4.66
25	Topps Tiles Plc	2013					-
		2014	0.77	(0.99)	1.29	0.01	1.08
		2014	0.73	(0.64)	1.27	0.13	1.49
		2016	0.28	(0.39)	1.50	0.24	1.63
		2017	0.49	(0.16)	1.21	0.33	1.86
26	TT Electronics Plc	2013					-
		2014	0.43	1.09	0.52	1.04	3.07
		2014	1.34	0.92	0.35	0.85	3.45
		2016	1.55	0.94	0.29	1.04	3.81
		2017	1.50	1.62	0.45	2.95	6.52
27	TP Group	2013					-
		2014	1.89	- 3.47	- 0.80	2.11	- 0.27
		2015	1.81	- 4.20	- 0.54	2.47	- 0.46
		2016	1.80	- 1.61	- 0.06	2.00	2.13
		2017	3.01	- 0.85	- 0.07	3.03	5.12
28	Smiths Group	2013					-
		2014	1.21	0.51	0.71	0.06	2.49
		2015	1.39	0.61	0.67	0.58	3.25
		2016	1.08	0.88	0.58	0.61	3.15
		2017	1.48	1.03	0.65	0.71	3.88
29	Octagonal	2013					-
		2014	5.49	- 1.30	-	10.12	14.31
		2015	1.97	- 4.09	-	8.88	6.76
		2016	2.75	- 0.04	0.90	11.66	15.27
		2017	3.22	0.51	1.77	9.73	15.24
30	Tate & Lyle	2013					-
		2014	0.94	0.61	0.68	0.74	2.97
		2014	0.61	0.46	0.09	0.66	1.82
		2016	1.05	0.47	0.33	0.71	2.57
		2017	1.26	0.64	0.57	0.97	3.44

Appendix 4. Ohlson's O-score computed for each year

S/N	COMPANY		X1 (-0.407*(Log(TA/GNP price-level index))	X2 (6.03*TL/TA)	X3 (-1.43*NWC/TA)	X4 (0.0757*CL/CA)	X5 (-1.72*{1, if TL>TA, 0 otherwise})	X6 (-2.37*NI/TA)	X7 (-1.83*EBITDA/TL)	X8 (0.285(1, if NL for last 2 yrs, 0 otherwise)	X9 (-0.521*{NIt-NLt-1}/{NIt+NIt-1})	**O-Score**	**P=(exp(0-score)/1+(exp (0-score)**
1	Arla Foods UK Plc	2013	1.00	-	-0.11	0.06	-	-0.11	-0.30	-	-	0.53	0.35
		2014	0.99	4.37	-0.05	0.07	-	-0.11	-0.26	-	-0.02	4.98	0.83
		2014	0.99	4.32	-0.07	0.07	-	-0.10	-0.30	-	0.02	4.93	0.83
		2016	1.01	4.11	-0.05	0.07	-	-0.10	-0.37	-	0.04	4.71	0.82
		2017	1.02	3.96	-0.08	0.07	-	-0.11	-0.33	-	-0.04	4.47	0.82
													-
2	Associated British Foods Plc	2013	0.90	-	-0.12	0.06	-	-0.15	-0.71	-	-	-0.02	-0.02
		2014	0.91	2.24	-0.13	0.06	-	-0.18	-0.77	-	-0.05	2.07	0.67
		2014	0.92	2.14	-0.15	0.05	-	-0.12	-0.62	-	0.10	2.32	0.70
		2016	0.91	2.18	-0.19	0.05	-	-0.17	-0.68	-	-0.12	1.99	0.67
		2017	0.89	2.25	-0.23	0.05	-	-0.22	-0.92	-	-0.10	1.73	0.63
													-
3	Base Resources	2013											-
		2014	-0.98	3.17	-0.15	0.06	-	-0.10	-0.42	0.29	-195.14	-193.28	1.01
		2014	-1.01	3.59	-0.14	0.05	-	0.09	-0.08	0.29	-0.07	2.73	0.73
		2016	-1.00	3.65	-0.09	0.05	-	0.07	-0.07	0.29	-0.03	2.86	0.74
		2017	-0.97	3.43	-0.05	0.05	-	0.07	0.07	0.29	-0.52	2.37	0.70
													-
4	British American Tobacco	2013	0.74	-	-0.06	0.07	-	-0.37	-0.10	-	-	0.27	0.22
		2014	0.75	4.47	-0.02	0.07	-	-0.31	-0.41	-	0.06	4.61	0.82
		2014	0.72	4.69	-0.04	0.07	-	-0.34	-0.34	-	-0.07	4.68	0.82
		2016	0.69	5.07	-0.02	0.07	-	-0.29	-0.31	-	-0.02	5.19	0.84
		2017	0.47	4.76	0.02	0.08	-	-0.63	-0.17	-	-0.40	4.12	0.80
													-
5	Britvic Plc	2013	1.31	-	0.05	0.08	-	-0.14	-0.27	-	-	1.03	0.51
		2014	1.31	5.80	-0.10	0.06	-	-0.19	-0.34	-	-0.10	6.45	0.87
		2014	1.28	5.58	-0.19	0.06	-	-0.19	-0.33	-	-0.04	6.17	0.86
		2016	1.25	5.05	0.05	0.08	-	-0.17	-0.31	-	-0.03	5.93	0.86
		2017	1.26	4.99	0.04	0.08	-	-0.16	-0.32	-	0.01	5.90	0.86
													-
6	Burberry Group Plc	2013	1.22		-0.33	0.04	-	-0.35	-3.46	-	-	-2.88	1.53
		2014	1.21	2.39	-0.42	0.04	-	-0.40	-3.68	-	-0.06	-0.93	-12.56
		2014	1.19	2.32	-0.50	0.03	-	-0.37	-3.08	-	-0.01	-0.41	-0.68
		2016	1.19	2.00	-0.59	0.03	-	-0.32	-3.94	-	0.02	-1.61	2.64
		2017	1.19	1.81	-0.64	0.03	-	-0.28	-5.17	-	0.02	-3.05	1.49
													-
7	Chamberlin Plc	2013											-
		2014	-0.43	4.02	-0.11	0.07	-	0.18	0.25	0.29	-0.52	3.74	0.79
		2014	-0.43	4.32	-0.11	0.07	-	-0.00	-0.05	0.29	0.53	4.61	0.82
		2016	-0.40	4.41	-0.03	0.07	-	0.03	-0.01	0.29	-0.59	3.76	0.79
		2017	-0.43	5.02	0.09	0.09	-	0.10	-0.04	0.29	-0.30	4.81	0.83
													-
8	Costain	2013											-
		2014	-0.98	4.57	-0.15	0.07	-	-0.11	-0.12	-	-0.52	2.75	0.73
		2014	-1.00	4.66	-0.13	0.07	-	-0.10	-0.13	-	-0.01	3.35	0.77
		2016	-1.03	5.10	-0.16	0.07	-	-0.10	-0.12	-	-0.05	3.72	0.79
		2017	-1.02	4.63	-0.25	0.06	-	-0.12	-0.16	-	-0.05	3.08	0.75
													-
9	Cranswick Plc	2013	1.47		-0.12	0.06	-	-0.20	-1.03	-	-	0.18	0.15
		2014	1.46	1.61	-0.17	0.05	-	-0.22	-1.17	-	-0.05	1.51	0.60
		2014	1.45	1.52	-0.16	0.05	-	-0.20	-0.82	-	0.01	1.85	0.65
		2016	1.42	1.97	-0.18	0.05	-	-0.18	-1.04	-	-0.03	2.02	0.67
		2017	1.42	1.87	-0.21	0.05	-	-0.24	-1.35	-	-0.10	1.43	0.59
													-
10	Diageo Plc	2013	0.75		-0.17	0.05	-	-0.24	-0.29	-	-	0.10	0.09
		2014	0.77	4.08	-0.16	0.05	-	-0.23	-0.33	-	0.04	4.22	0.81
		2014	0.76	4.04	-0.13	0.05	-	-0.23	-0.32	-	-0.03	4.13	0.81
		2016	0.74	3.87	-0.13	0.05	-	-0.20	-0.28	-	0.01	4.06	0.80
		2017	0.75	3.88	-0.10	0.06	-	-0.23	-0.34	-	-0.04	3.98	0.80

Appendix 4. (Continuing)

11	Diary Crest Group Plc	2013	1.32	-	-0.28	0.05	-	0.02	-0.14	-	-	0.97	0.49
		2014	1.36	4.15	-0.27	0.05	-	-0.14	-0.34	-	-0.72	4.08	0.80
		2014	1.37	3.86	-0.31	0.04	-	-0.09	-0.23	-	0.13	4.78	0.83
		2016	1.41	3.82	-0.17	0.06	-	-0.14	-0.25	-	-0.07	4.65	0.82
		2017	1.45	4.81	-0.29	0.03	-	-0.14	-0.24	-	0.04	5.66	0.85
													-
12	DS Smith Plc	2013	1.09	-	0.04	0.08	-	-0.05	-0.26	-	-	0.91	0.48
		2014	1.10	4.22	0.06	0.09	-	-0.10	-0.30	-	-0.18	4.89	0.83
		2014	1.12	4.10	0.07	0.09	-	-0.11	-0.34	-	-0.02	4.91	0.83
		2016	1.09	4.17	0.10	0.09	-	-0.10	-0.26	-	-0.02	5.08	0.84
		2017	1.08	4.34	0.10	0.09	-	-0.11	-0.31	-	-0.06	5.14	0.84
													-
13	Elementis Plc	2013											-
		2014	-1.11	2.04	-0.28	0.03	-	-0.43	-0.87	-	-0.52	-1.13	8.67
		2014	-1.10	1.74	-0.32	0.02	-	-0.24	-0.76	-	0.15	-0.51	-1.04
		2016	-1.09	1.90	-0.28	0.03	-	-0.18	-0.53	-	0.09	-0.06	-0.07
		2017	-1.15	2.87	-0.20	0.03	-	-0.21	-0.26	-	-0.14	0.95	0.49
													-
14	Essentra Plc	2013	1.34	-	-0.14	0.05		-0.16	-0.57		-	0.52	0.34
		2014	1.33	3.34	-0.17	0.05		-0.17	-0.81		-0.05	3.52	0.78
		2014	1.27	2.36	-0.13	0.05		-0.11	-0.46		0.01	2.98	0.75
		2016	1.28	3.41	-0.10	0.06		0.07	-0.32		1.94	6.33	0.86
		2017	1.31	3.46	-0.14	0.05		-0.22	-0.35		-1.06	3.03	0.75
													-
15	Eurocell	2013											-
		2014	-0.66	5.14	0.01	0.08	-	-5.35	-0.56	-	-0.52	-1.88	2.14
		2014	-0.68	4.18	-0.24	0.05	-	-2.62	-0.64	-	0.15	0.20	0.17
		2016	-0.70	3.73	-0.27	0.05	-	-1.61	-0.72	-	0.09	0.56	0.36
		2017	-0.71	3.43	-0.35	0.04	-	-2.43	-0.68	-	-0.14	-0.84	-5.26
													-
													-
16	GKN Plc	2013	0.99		-0.14	0.06		-0.15	-0.33		-	0.43	0.30
		2014	0.99	4.30	-0.14	0.06		-0.06	-0.18		0.21	5.18	0.84
		2014	0.97	4.68	-0.11	0.06		-0.06	-0.18		-0.04	5.32	0.84
		2016	0.95	4.52	-0.14	0.06		-0.06	-0.16		-0.05	5.11	0.84
		2017	0.96	4.58	-0.17	0.05		-0.14	-0.56		-0.18	4.54	0.82
													-
17	Greencore Group Plc	2013	1.32		0.30	0.17		-0.06	-0.24		-	1.47	0.60
		2014	1.32	4.53	0.22	0.14		-0.11	-0.23		-0.15	5.71	0.85
		2014	0.90	4.36	0.03	0.15		-0.01	-0.26		-0.05	5.12	0.84
		2016	1.30	0.43	0.17	0.12		-0.09	-0.18		0.05	1.79	0.64
		2017	1.22	4.66	0.09	0.10		-0.02	-0.18		0.29	6.16	0.86
													-
18	Howden Joinery Group Plc	2013	1.44		-0.59	0.03		-0.46	-1.16		-	-0.74	-2.83
		2014	1.40	2.93	-0.66	0.03		-0.58	-1.09		-0.12	1.91	0.66
		2014	1.40	3.27	-0.69	0.03		-0.61	-1.69		-0.03	1.69	0.63
		2016	1.39	2.32	-0.60	0.03		-0.59	-1.36		-0.01	1.18	0.54
		2017	1.38	2.83	-0.63	0.03		-0.54	-1.36		0.00	1.72	0.63
													-
19	Imperial Tobacco Group	2013	0.73	-	0.14	0.10		-0.08	-0.26		-	0.63	0.39
		2014	0.75	4.83	0.03	0.08		-0.13	-0.27		-0.11	5.18	0.84
		2014	0.73	4.76	0.08	0.09		-0.14	-0.22		-0.04	5.26	0.84
		2016	0.72	4.89	0.11	0.10		-0.05	-0.24		0.23	5.77	0.85
		2017	0.74	4.97	0.18	0.12		-0.11	-0.27		-0.19	5.44	0.84
													-
20	Laird Plc	2013	1.35	-	-0.11	0.06		-0.09	-0.37	-	-	0.83	0.46
		2014	1.34	2.85	-0.20	0.04		-0.13	-0.34	-	-0.12	3.43	0.77
		2014	1.33	3.13	-0.11	0.05		0.02	-0.38	-	0.71	4.75	0.83
		2016	1.31	3.49	-0.15	0.05		0.23	-0.23	-	-0.45	4.25	0.81
		2017	1.32	4.19	-0.23	0.04		-0.15	-0.36	0.29	2.44	7.54	0.88

Appendix 4. (Continuing)

21	Mcbride Plc	2013	1.46		0.05	0.08		-0.03	-0.18	-	-	1.37	0.58
		2014	1.47	4.60	-0.05	0.07		0.11	0.20	-	-0.99	5.41	0.84
		2014	1.49	5.07	-0.03	0.07		0.00	-0.16	-	0.48	6.93	0.87
		2016	1.49	5.16	-0.07	0.07		-0.10	-0.28	0.29	-0.57	5.98	0.86
		2017	1.50	5.03	-0.01	0.07		-0.05	-0.31	-	0.16	6.40	0.86
													-
22	Renishaw Plc	2013	1.34		-0.07	0.07		-0.07	-0.30		-	0.96	0.49
		2014	1.32	4.19	-0.04	0.07		-0.07	-0.29		-0.02	5.17	0.84
		2014	1.22	4.41	-0.06	0.07		-0.05	-0.21		-0.10	5.27	0.84
		2016	1.15	4.10	-0.03	0.07		-0.05	-0.17		-0.07	5.01	0.83
		2017	1.07	4.10	-0.09	0.06		-0.07	-0.20		-0.21	4.66	0.82
													-
23	RPC Group Plc	2013	1.48		-0.52	0.02		-0.41	-1.40		-	-0.83	-4.81
		2014	1.46	1.80	-0.57	0.01		-0.44	-1.85		-0.06	0.36	0.26
		2014	1.43	1.42	-0.61	0.02		-0.51	-2.00		-0.09	-0.34	-0.52
		2016	1.43	1.46	-0.48	0.02		-0.19	-0.65		0.23	1.81	0.64
		2017	1.42	2.19	-0.49	0.02		-0.33	-1.23		-0.16	1.43	0.59
													-
24	Ted Baker Plc	2013										-	-
		2014	1.61	2.68	-0.41	0.05		-0.34	-0.81		-0.07	2.69	0.73
		2014	1.58	2.32	-0.42	0.04		-0.36	-0.97		-0.06	2.14	0.68
		2016	1.53	2.97	-0.34	0.04		-0.31	-0.64		-0.05	3.19	0.76
		2017	1.50	3.04	-0.31	0.05		-0.26	-0.58		-0.01	3.42	0.77
													-
25	Topps Tiles Plc	2013											-
		2014	1.74	5.98	-0.17	0.06		-0.31	-0.44		-0.08	6.77	0.87
		2014	1.74	5.38	-0.16	0.06		-0.31	-0.50		-0.01	6.19	0.86
		2016	1.75	4.91	-0.06	0.07		-0.39	-0.64		-0.04	5.60	0.85
		2017	1.75	4.60	-0.11	0.06		-0.32	-0.59		0.04	5.44	0.84
													-
26	TT Electronics Plc	2013											-
		2014	1.50	3.03	-0.09	0.07		0.07	-0.50		3.84	7.91	0.89
		2014	1.48	3.33	-0.29	0.04		-0.06	-0.33		108.89	113.06	0.99
		2016	1.47	3.03	-0.34	0.04		-0.08	-0.25		-0.12	3.74	0.79
		2017	1.52	1.58	-0.33	0.04		-0.31	-0.71		-0.25	1.55	0.61
													-
27	TP Group	2013											-
		2014	-0.51	2.00	-0.41	0.03	-	0.27	0.66	0.29	-0.52	1.80	0.64
		2014	-0.48	1.80	-0.40	0.03	-	0.16	0.49	0.29	0.17	2.05	0.67
		2016	-0.49	2.08	-0.39	0.04	-	0.02	0.05	0.29	0.42	2.01	0.67
		2017	-0.58	1.55	-0.66	0.02	-	0.03	0.07	0.29	-0.30	0.43	0.30
													-
28	Smiths Group	2013											-
		2014	- 1.34	3.94	- 0.26	0.04	-	- 0.16	- 0.30	-	- 0.52	1.40	0.58
		2014	- 1.36	3.88	- 0.30	0.04	-	- 0.15	- 0.28	-	- 0.01	1.81	0.64
		2016	- 1.37	3.81	- 0.24	0.04	-	- 0.14	- 0.25	-	- 0.01	1.85	0.65
		2017	- 1.39	3.59	- 0.32	0.03	-	- 0.26	- 0.30	-	- 0.19	1.16	0.54
													-
29	Octagonal	2013											-
		2014	0.04	0.57	-1.20	0.01	-	0.31	-	0.29	-0.52	-0.51	-1.03
		2014	0.06	0.64	-0.43	0.02	-	1.98	-	0.29	-0.37	2.17	0.68
		2016	-0.20	0.50	-0.60	0.01	-	-0.24	-2.97	0.29	1.72	-1.50	3.00
		2017	-0.23	0.59	-0.70	0.01	-	-0.32	-4.95	0.29	-0.13	-5.45	1.22
													-
30	Tate & Lyle	2013											-
		2014	-1.34	3.94	-0.26	0.04	-	-0.16	-0.30	-	-0.52	1.40	0.58
		2014	-1.36	3.88	-0.30	0.04	-	-0.15	-0.28	-	-0.01	1.81	0.64
		2016	-1.37	3.81	-0.24	0.04	-	-0.14	-0.25	-	-0.01	1.85	0.65
		2017	-1.39	3.59	-0.32	0.03	-	-0.26	-0.30	-	-0.19	1.16	0.54