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Corporate Failure Risk Assessment for Knowledge-Intensive Services Using the Evidential Reasoning Approach

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Abstract: In this study, a new risk assessment model is developed and the evidence reasoning (ER) approach is applied to assess failure risk of knowledge-intensive services (KIS) corporates in the UK. General quantitative financial indicators alone (e.g., operational capability or profitability) cannot comprehensively evaluate the probability of company bankruptcy in the KIS sector. This new model combines quantitative financial indicators with macroeconomic variables, industrial factors and company non-financial criteria for robust and balanced risk analysis. It is based on the theory of enterprise risk management (ERM) and can be used to analyze company failure possibility as an important aspect of risk management. This study provides new insight into the selection of macro and industry factors based on statistical analysis. Another innovation is related to how marginal utility functions of variables are constructed and imperfect data can be handled in a distributed assessment framework. It is the first study to convert observed data into probability distributions using the likelihood analysis method instead of subjective judgement for data-driven risk analysis of company bankruptcy in the KIS sector within the ER framework, which makes the model more interpretable and informative. The model can be used to provide an early warning mechanism to assist stakeholders to make investment and other decisions.

Keywords: bankruptcy assessment; firm failure possibility; enterprise risk management (ERM); multiple criteria decision analysis (MCDA); evidence reasoning (ER); knowledge-intensive services (KIS)

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1. Introduction

The issue of company failure prediction has received considerable critical attention since many firms have been bankrupt due to their suffering from financial risks, which has brought adverse impacts on their investors, creditors, governments and other stakeholders. The narrow definition of financial risk is the possibility that a company may default on its debts, and its essence is the evaluation of companies' debt control capabilities or financial leverage management (Valaskova et al. 2018). This may be the reason why there has been plenty of bankruptcy research in the field of debt default. Despite the extensive research that has been conducted in firm bankruptcy prediction, many appraisal models have been criticized due to the absence of a theoretical basis (Jackson and Wood 2013). This study was based on the enterprise risk management (ERM) theory. ERM is an integrated approach that covers all business risks and helps management understand and manage uncertainty (Bromiley et al. 2015). From the perspective of the ERM theory, the survival and prosperity of a company depends on its abilities to not only deal with risks in internal operations but also properly handle possible losses caused by uncertainties in external environments (Da Silva Etges and Cortimiglia 2019). These risks come from various aspects, such as finance, operation, natural disasters, policies and technology innovation (Sadgrove 2016). It is therefore necessary to take into account macro and industry factors on top of those considered in existing risk assessment models that only include corporate internal information (Khoja et al. 2019; Chapman 2011). Nevertheless, any type of risk can result in financial losses, which is reflected in accounting data. This is consistent with the broader sense of financial risks. That is, risk exists in every part of business management and is affected by various uncontrollable factors, which may result in poor financial status, credit default or even bankruptcy.

Business risks cannot be completely avoided, unless a company stops innovation and expansion, which will inevitably lead to failure. The purpose of ERM is to help stakeholders truly understand risks faced by companies. After risk is identified and assessed, it can be controlled, diversified or reduced with clear objectives (Chapman 2011). This paper focuses on risk assessment and defines the corporate failure risk as the possibility of the company going bankrupt. It can aggregate various consequences or causal factors to assess company failure when only limited data are available. The aim is to observe alert information before company dissolution due to insolvency or bankruptcy and help companies to reduce costs by taking timely actions. On one hand, failure predictive models may provide an early warning mechanism to assist company managers to avoid bankruptcy or minimize costs. On the other hand, these models can help financial institutions select companies which they should invest in or support other relevant companies to choose partnerships.

Different techniques have been proposed to classify failure or non-failure companies. Based on the papers found in the literature, prediction models can be divided into three categories: statistical models, intelligent models and theoretical models (Alaka et al. 2018; Jackson and Wood 2013). Nevertheless, traditional statistical methods, such as multivariate discriminant analysis (MDA), the Logit and Probit model, have some demerits, including assumption of linear correlation and intolerance of missing data (Jayasekera 2018). With the advancement of computer technology, artificial intelligence (AI) algorithms began to be applied to estimate firm failure likelihoods in the 1990s, including neural networks, support vector machines, genetic algorithms, clustering, decision tree, bagging, hybrid approaches, etc. (Ansari et al. 2020; Huang and Yen 2019). Many researchers have argued that AI tools may be more appropriate for predicting company failure than statistical methods (Barboza et al. 2017; Gepp and Kumar 2015). However, there are still arguments against non-parameter methods (Zhao et al. 2015; Ravi Kumar and Ravi 2007). Despite extensive research in firm bankruptcy assessment, many models have been criticized due to the absence of a theoretical basis. Theoretical models have thus been developed, such as cash management theory and the contingent claims models (Jackson and Wood 2013).

Thus far, there is no general model that is the most appropriate for predicting bankruptcy and can be widely used for stakeholders. Corporate failure risk assessment refers to comprehensive evaluation using multiple variables. Since variables may conflict with each other and have different measurement units, corporate failure risk assessment is in essence a multiple criteria decision analysis (MCDA) problem. This discernment has prompted many researchers to apply MCDA methods to financial decision-making issues such as failure risk prediction, credit rating and portfolio selection. (Oliveira et al. 2017; Yurdakul and İç 2004). MCDA uses decision information, such as attribute value and weight, to evaluate alternatives or select the best one through information aggregation. There are families of methods for solving MCDA problems, such as multiple attribute value (utility) function methods (MAVF/MAUF), distance-based preference methods, pairwise comparison methods (e.g., AHP), the evidential reasoning (ER) approach, etc. (Belton and Stewart 2002). However, Von Neumann and Morgenstern's expected utility theory assumes that decision-makers are rational actors, and may not always be applicable in practice since people may not always be rational as defined in the classical utility theory, and decision-making is affected by people's behaviors. Multiple attribute value (utility) function methods (MAVF/MAUF) are the simplest and most widely used methods in MCDA (Belton and Stewart 2002). When a MCDA problem contains sizeable attributes and alternatives, it is tedious, if not impossible, to estimate the utility of every alternative on each attribute (Winston 1994). Pairwise comparison methods (e.g., AHP) applied to evaluate alternatives may lead to rank reversal problems (Yang and Xu 2013; Velasquez and Hester 2013). Due to uncertainty or lack of information, and because decision-makers have different cognitive abilities and risk preferences, most MCDA problems are uncertain, including uncertainty in attribute values and attribute weights. Dealing with uncertain and incomplete information effectively is inevitable when appraising firm failure, for example grasping as much data and information as possible accurately and selecting reliable aggregation methods to integrate incomplete qualitative and quantitative information. This study uses the ER approach, which is an evidence-based MCDA method and can be integrated with data-driven machine learning algorithms, to estimate the possibility of corporate failure using both quantitative and qualitative information. It is based on an inferential evaluation analysis model and Dempster–Shafer theory but overcomes the weakness of the theory that can lead to counterintuitive aggregation results when used to combine conflicting evidence (Yang and Xu 2013). The ER approach has been applied to analyze MCDA problems in a range of fields, such as engineering design, supply chain management, healthcare, performance evaluation, project selection and sustainable development. Risk occurs with uncertain outcomes, which often leads to adverse consequences. The uncertainty of financial risk is reflected in many forms, including credit, investment and operational risk (Holton 2004), and thus the model is built with multiple variables. The ER approach has a theory-based probabilistic reasoning process that is evidence based meaning that the process can be either knowledge-driven or data-driven, or both, so it is well-suited for developing an interpretable model to address bankruptcy assessment issues.

Although a large volume of published studies have investigated company bankruptcy evaluation, few researchers have paid appropriate attention to systematic research into the technology industry or knowledge-intensive services (KIS). In this study, a new model will be developed to assess corporate failure risk by applying the evidence reasoning (ER) approach. The research samples are UK registered private limited failure and non-failure KIS companies from 2007 to 2020 and company data are collected from one year prior to the bankruptcy time covering the period 2006–2019. It is clearly indicated that KIS companies are mainly concerned about innovation and technology. Unlike traditional industries, the operation of KIS has greater risk, such as larger investment in R&D, more rapid technology updates, and higher uncertainty in capital recovery periods, profit models and market demand forecast. It is imperative to build a warning model to evaluate and predict the financial distress of KIS companies. The ER approach can aggregate qualitative and quantitative variables with uncertain or imperfect data and evaluate firm failure risk in the form of probability distribution, which do not require pre-aggregation of various data into a unified scale or unit, and rule- or utility-based transformation techniques can be used to preserve characteristics of original assessments. The research questions are as follows: how to evaluate the probability of a company's bankruptcy in the knowledge-intensive industry? How to combine various variables in an assessment model? Whether external information affects the firm's performance in the UK? How should the evaluation model be applied in practice easily? The contributions of this study are three-fold. (1) By taking into account the probabilistic features of the ER approach, the new model can enable data-driven risk analysis with multiple internal and external attributes considered simultaneously. (2) The model can be used to build an early warning system to assist KIS companies to identify problems in financial management and to improve managers' risk awareness and the ability to manage risk. It can also be used to help creditors, investors and other stakeholders make informative investment decisions. (3) By applying the ER approach, the marginal utility functions of attributes can be constructed to convert observed data into probability distributions using data-driven analysis methods instead of subjective judgment, which makes the model interpretable and informative.

2. Research Methods

2.1. Data Collection

The failure assessment model for private limited KIS companies can help stakeholders better understand the performances of companies and reduce the possibility of missed opportunities and the risk of investment failure caused by information asymmetry. This model can be used to remind the management of current problems in an enterprise and assist the enterprise to implement the early warning analysis of internal risk. Compared with listed companies, it is more difficult for non-listed companies to obtain funds. There is no mandatory requirement to disclose detailed financial data in many countries. The data for non-listed companies are limited. Therefore, from the perspective of investors or creditors, such companies have relatively higher risks. In the UK, however, figures for private limited companies can be considered relatively reliable since they must be registered at Companies House and submit accounts annually, such as a balance sheet and a profit or loss account, which is relevant to corporation tax payment and tax returns. In this model, industry and firm-internal information were collected from the Fame database which contains information on companies throughout the UK and Republic of Ireland. In addition, macroeconomic data were collected from three databases: Companies House, Statista and the Office for National Statistics (UK) during the period of 2006 to 2020. This time range was chosen to assess companies' performance before and after the last financial crisis which happened in 2008. For this study, company failure refers to bankrupted firms, and legally in the UK company bankruptcy is equivalent to the status 'in liquidation'. In this study, we label active companies as low-risk and in liquidation firms as high-risk. Compared with those that have gone bankrupt, operating companies are considered to be low-risk. The registration status is used to classify companies (active or in liquidation) in this paper.

The factors that cause the bankruptcy of a firm are not formed in a short time, and companies may face business dilemma much earlier than reaching eventual bankruptcy. It is vital to perceive any failure warning signals before the actual bankruptcy happens (Lee and Choi 2013). The timing of legal bankruptcy may be much later than the real moment of failure. Therefore, in this study, we define bankruptcy time as the year of last available accounts and use company internal data from one year prior to the bankruptcy day, which involve quantitative and qualitative variables. A sample of 31,710 active companies was chosen for this analysis and this final low-risk group provides 103,892 firm-years of panel data during the sample period; in addition, we collected 388 failed companies and this type of high-risk company should at least have data from two year before the time of failure. It is not necessary that each failed and non-failed sample be matched exactly in common characteristics, e.g., the same size, and a large number of firms may help improve the assessment accuracy of any model (Jackson and Wood 2013). Most papers found in the literature created general unified models for all industries, whilst some concentrated their research on manufacturing analysis. It is more appropriate to design a specific model for an industry than to use a general model (Peres and Antão 2017). In this study, the sample selection followed the definition of Eurostat high-tech KIS (NACE Rev. 2 codes) and four sub-industries were included: 61—telecommunications, 62—computer programming, consultancy and related activities, 63—information service activities and 72—scientific research and development (Eurostat 2016).

2.2. The Hierarchical Model of Failure Risk Assessment for KIS

There has been a lot of literature suggesting that only financial quantitative variables should be used (Nyitrai 2019; Valaskova et al. 2018; Ravi Kumar and Ravi 2007). Financial variables or attributes in this area are considered in five aspects, including profitability, leverage, liquidity, activity and cash flow. The most popular ratios are the ROA (net income/total asset), Debt Ratio (total debt or total liabilities/total assets), Current Ratio (current assets/current liabilities), Total Asset Turnover (sales/total assets) and Cash Flow on Total liabilities (cash flow/total liabilities). Some researchers argue that the main purpose of financial statements is to measure past performance and present historical data, which may not provide sufficient information for the future, and accounting policies can also cause accounting measurement to be subjectively manipulated (Habib et al. 2020). When a company operates normally, financial statements are formulated under the assumption of the going-concern rule. This principle assumes that the company will not go bankrupt in the foreseeable future, which limits its ability to predict bankruptcy accurately. If only static financial statement indicators are used in a bankruptcy model, it is impossible to measure the volatility of assets. If market data are added, such as stock returns and dividend yields, financial distress prediction models can become more accurate than account-based models (Jayasekera 2018). However, Agarwal and Taffler (2008) demonstrated that financial data can reflect a company's performance, so it helps to partially explain the probability of bankruptcy risk. As a company moves closer to bankruptcy, differences in its financial ratios become more pronounced. This is the reason why financial ratios in the recent year are mainly used in the bankruptcy prediction model (Nyitrai 2019).

In addition to differences in financial ratios, several studies support the increased accuracy of bankruptcy models to classify successful and non-successful firms when the effects of market value data and other non-financial firm information are added, for example market value of equity/total liabilities, stock price, firm age, director characteristics and board structure (Huang and Yen 2019; Barboza et al. 2017; Altman et al. 2010). However, market price contains expectations for the future and is only available for listed companies. Only a few authors have explored non-financial indicators alone to assess company failure (Wilson and Altanlar 2014; Lussier and Pfeifer 2001). A few surveys have shown that macroeconomic and (or) industrial factors combined with firm internal data may create a stronger financial distress model, for example using business cycle, industry insolvency, etc. (Khoja et al. 2019; Bhattacharjee and Han 2014; Tinoco and Wilson 2013).

In the existing review papers, hundreds of variables have been found to be related to firm bankruptcy prediction (Ravi Kumar and Ravi 2007; Bellovary et al. 2007). We have summarized 218 variables from 46 previous papers. After comparison with variables mentioned in other review articles, the initial set of variables was selected. Moreover, based on ERM, internal and external factors should be introduced simultaneously to estimate firm risk. The first step of variable selection in the new model is shown as follows. Macroeconomic indicators can be used to evaluate the health conditions of different economies to a certain extent. Countries with different economic status bring different levels of external risk to enterprises, and some macro-factors are chosen in the model since they may have an effect on insolvency, such as GDP annual growth, unemployment yearly rate and CPI inflation rate.

Industry attributes present the performance of a specific industry in detail. There are big differences among various industries in the development stage and survival mode. It is necessary to add industry information to an assessment model since the business bankruptcy rate varies among different industries. In this new model, three industry rates are introduced at the first stage, including industry asset growth, revenue growth and liquidation rate. Industry information is derived from the median of all companies data in the industry.

A company's internal data in this study are considered in five aspects. Profitability is the ability of a company to increase its capital, which is usually reflected in the size of a company's income. The stronger the profitability, the better a company's development and the lower the risk. Profit is the main source of funds for investors to obtain dividends and creditors to receive principal and interest. It is the key issue of most concern to all parties inside and outside a company. It is a direct indicator of company management efficiency and operating performance. When a company has higher profitability, the value of these indicators is larger, including gross margin and return on assets. Operating Efficiency refers to asset management capabilities and properties utilization efficiency. It is analyzed by calculating some relevant indicators of capital turnover. Poor operating efficiency directly affects a company's profitability and solvency. The ratios of account receivable turnover and total asset turnover are used to measure it. Solvency or financial default refers to the ability of a company to use its assets to repay short-term and long-term debt. The debt-paying capacity is a major feature for a company's healthy survival and long-term development. Short-term solvency, also known as liquidity ratio, is always measured in current ratio, and long-term solvency can be expressed as equity ratio or debt ratio. Growth ability means the capacity to increase profits, improve sales, and expand company size. The greater a company's development ability, the lower the failure risk. The indicators used to measure a company's development capability in this study include total asset growth rate and revenue growth. Some basic information of high-risk firms may also differ from that of low-risk companies. For example, young companies are more likely to be found in the set of failed companies.

As shown in the first step, potential attributes are selected from the most popular indicators found in previous studies. The second step is that all attributes used to build the new model are determined on the basis of the results of data analysis. The choice of macro and industry indicators relies on observing indicators and corresponding changes in bankruptcy rate (see Schemes 1–3). In addition, the selection principles of a company's internal indicators are that on one hand its data analysis results should be in line with financial common sense and any variables with counter-intuitive phenomena should be deleted, and on the other hand, by observing the data distribution of each attribute that which has an obvious frequency difference between failure and non-failure companies should be retained (e.g., Scheme 4). Variable selection in previous studies is mostly based on subjective judgments. By contrast, using the data-driven attribute selection method in this model can help improve the reliability and interpretability of the model. The three-level hierarchy of selected attributes for the new corporate failure risk assessment model is displayed in Figure 1.

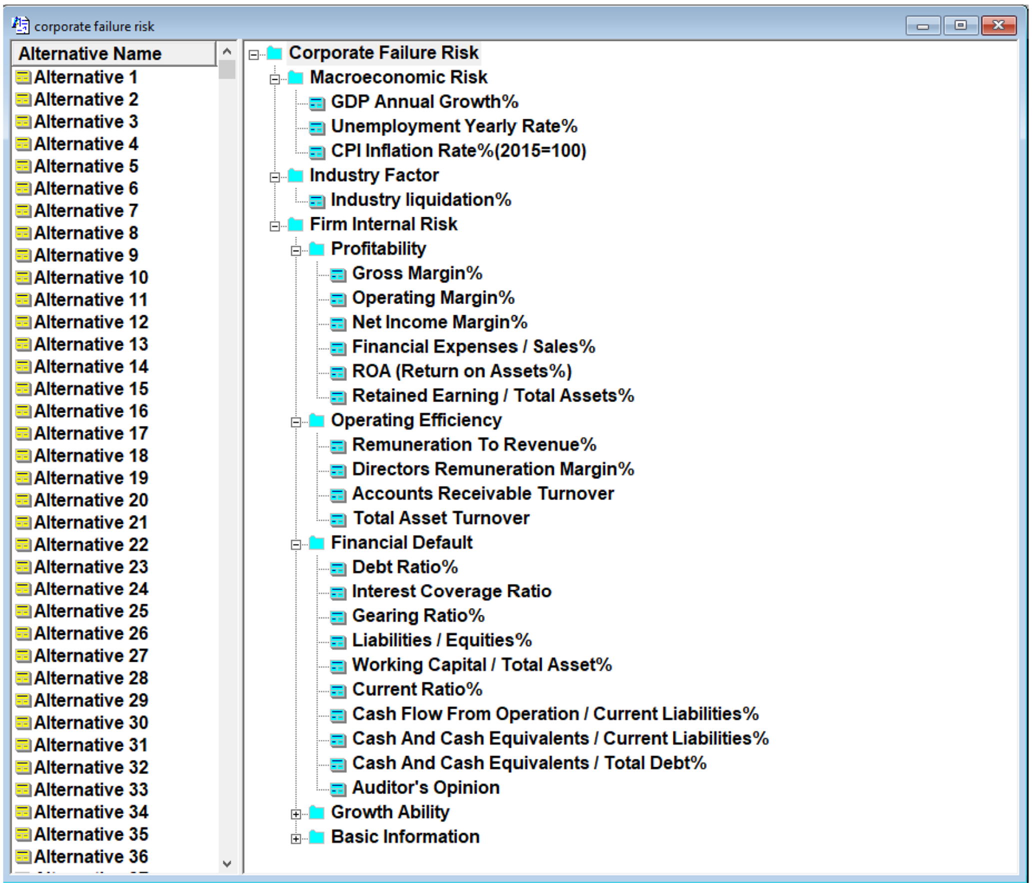


Figure 1. The hierarchical model of corporate failure risk assessment.

2.3. The ER Approach and IDS Software

The individual attributes of the above hierarchical model may measure a company's performance individually. There is a need to combine these attributes to evaluate bankruptcy probability. Since the attributes are related to each other, it is not appropriate to use an additive function to generate the overall assessment (e.g., score) of a company's risk level. The ER approach is a process of nonlinear aggregation that allows attributes to be related to each other but requires that the assessment standard of one attribute is independent of that of another attribute (Yang and Xu 2013). These features make it appropriate to use the ER approach for aggregation of the attributes in the hierarchy. When evaluating qualitative attributes, we define different sets of evaluation levels for data collection, whereas quantitative attributes can be evaluated using numbers. Rule- and utility-based techniques are used to deal with quantitative and qualitative attributes (Yang 2001). In the ER approach, a belief decision matrix is used to represent risk assessments on individual attributes for a firm in the form of probability distribution or belief distribution in general. The ER rule (Yang and Xu 2013) is then used for attribute aggregation.

The main steps of ER are as follows. First, a hierarchy of attributes (criteria) is created with a list of alternatives (firms), as in Figure 1, and the weights and measurement methods of the attributes are decided, and belief decision matrices are then used to model the assessments of each alternative on the hierarchy of attributes in form of probability distribution. Secondly, information transformation techniques can be used to convert assessments on individual attributes under various scales or frames of discernment to assessments under a common scale. Next, the ER algorithm is used for combination of assessments, resulting in an overall assessment for each alternative (Yang and Xu 2013; Yang 2001).

A general frame of discernment can be expressed as $\Theta = \{H_1, H_2, \ldots, H_n\}$, where H_n is an assessment grade or system state, with all grades being mutually exclusive and collectively exhaustive. In this research, the overall frame of discernment for corporate failure assessment is given by Θ = {high risk, low risk}. The sets of evaluation grades for each attribute can be different, which eventually correspond to the overall assessment grades by using the rule and utility-based information transformation techniques (Yang 2001).

For a two-level attribute hierarchy, suppose y is the top-level attribute and L represents the number of lower-level attributes. Then, the assessment of alternative a_l on attribute e_i is represented by probability distribution $S(e_i\ (a_l))$

$$S(e_i\ (a_l)) = \{(H_n, \beta_{n,i}\ (a_l)),\ n = 1, \ldots, N\}$$

where $\beta_{n,i}\ (a_l)$ is the probability (belief) that the risk of firm a_l on attribute e_i is assessed to grade H_n with $0 \leq \beta_{n,i}\ (a_l) \leq 1$ (Yang 2001). A belief decision matrix for firm a_l is composed of all $S(e_i\ (a_l))$ for $i = 1, \ldots, L$.

Let β_n be the probability that firm a_l is assessed to grade H_n on top attribute y, ω_i is the weight on attribute e_i. Then, β_n is calculated by applying the following nonlinear ER algorithm, given that all assessments $S(e_i\ (a_l))$ are independent of each other (Yang and Xu 2013):

$$\beta_n = k\left[\prod_{i=1}^{L}(\omega_i\beta_{n,i} + 1 - \omega_i) - \prod_{i=1}^{L}(1 - \omega_i)\right] \quad (1)$$

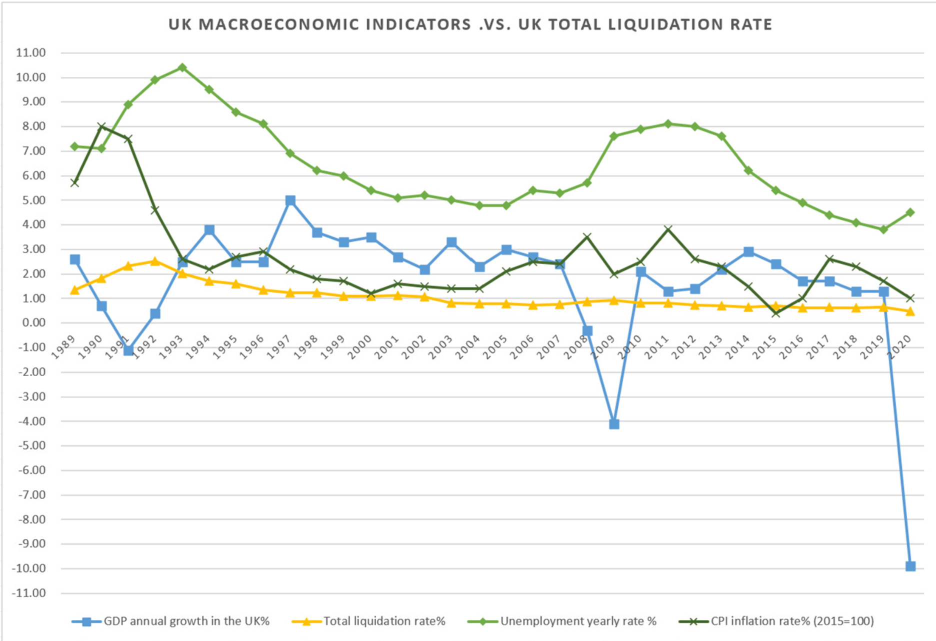
$$k = \left[\sum_{n=1}^{N}\prod_{i=1}^{L}(\omega_i\beta_{n,i} + 1 - \omega_i) - \prod_{i=1}^{L}(1 - \omega_i)\right]^{-1} \quad (2)$$

For a multiple-level hierarchy of attributes, the ER process starts working from the lowest level by combining all probabilistic assessments associated with the same higher-level attribute. The combined assessment is then used as evidence for this high-level attribute and can be combined with other assessments in the same level of hierarchy to generate combined assessments at the next levels, until the combined assessment for the top-level attribute is generated.

Parametric models that cannot handle missing data may lead to bias if we delete samples or replace missing data with the mean values (Peres and Antão 2017; Barreda et al. 2016; Hazak and Männasoo 2007). The ER approach can analyze samples with missing data, or imperfect data in general. Moreover, we do not have to normalize units and scales of attributes to make sure they are in the same data range before aggregation. Although there are many methods and models to predict company failures, they are difficult to apply in practice. The IDS software makes it easy to operate the risk assessment model for problems of practical size.

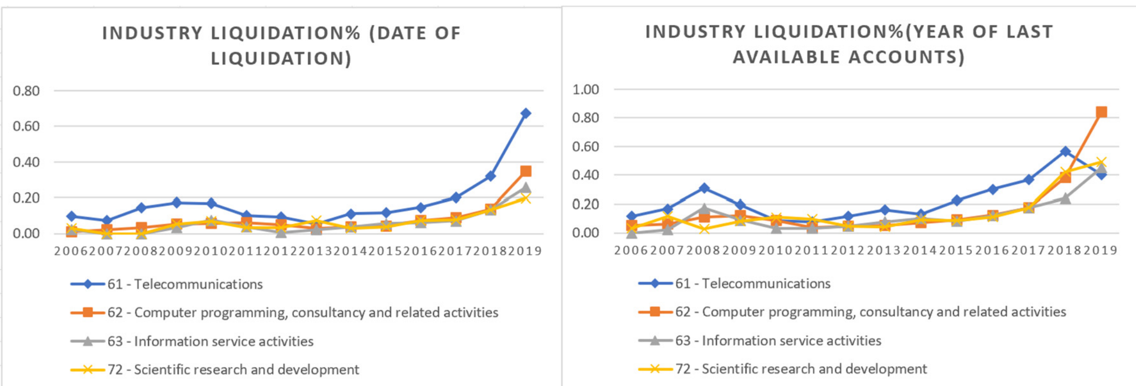
2.4. The Measurement and Weight of Attributes

To assess failure risk of KIS, this model combines company internal attributes with macroeconomic variables and industrial indicators. Additionally, weights should be assigned to attributes to indicate their relative importance. In this study, macroeconomic and industry indicators are selected as attributes for the new corporate risk assessment model through data analysis, instead of using economic knowledge as in previous articles (e.g., Khoja et al. 2019). To investigate the influence of the macroeconomic environment on corporate failure, we collected data on GDP annual growth, unemployment yearly rate, CPI inflation rate and total annual liquidation rate. Scheme 1 shows that the fluctuation of the bankruptcy rate indicator over many years is much smaller than the other three macro factors. The most likely causes of this phenomenon are enterprise exit protection mechanisms adopted by the government and the rescue intervention implemented during the economic recession. Even in periods of poor economic conditions (e.g., the 2008 global financial crisis caused by the US subprime mortgage crisis), the rate of corporate bankruptcy was not as high as assumed. Consequently, the weight of macro attributes in the model is small since it is not highly relevant to company failure risk. The utility function of macro attributes can be constructed as follows. When the economic environment is good, GPD change is positive, unemployment rate falls, and inflation rate is low. Correspondingly, liquidation rate drops slightly; for example, the trend of changes in all attributes from 2011 to 2016 is shown in Scheme 1. In contrast, when the economy is in recession, GPD growth rate is negative for two consecutive quarters or more, unemployment rate increases, and the inflation ratio rises. A slight increase in the rate of corporate bankruptcy can be observed (e.g., 2007–2010 in Scheme 1). The data in 2020 are not accurate due to the impact of the epidemic, and the number of bankruptcies has since dropped sharply (Company Insolvencies 2021). Therefore, this part of the data cannot be used until it has been updated.



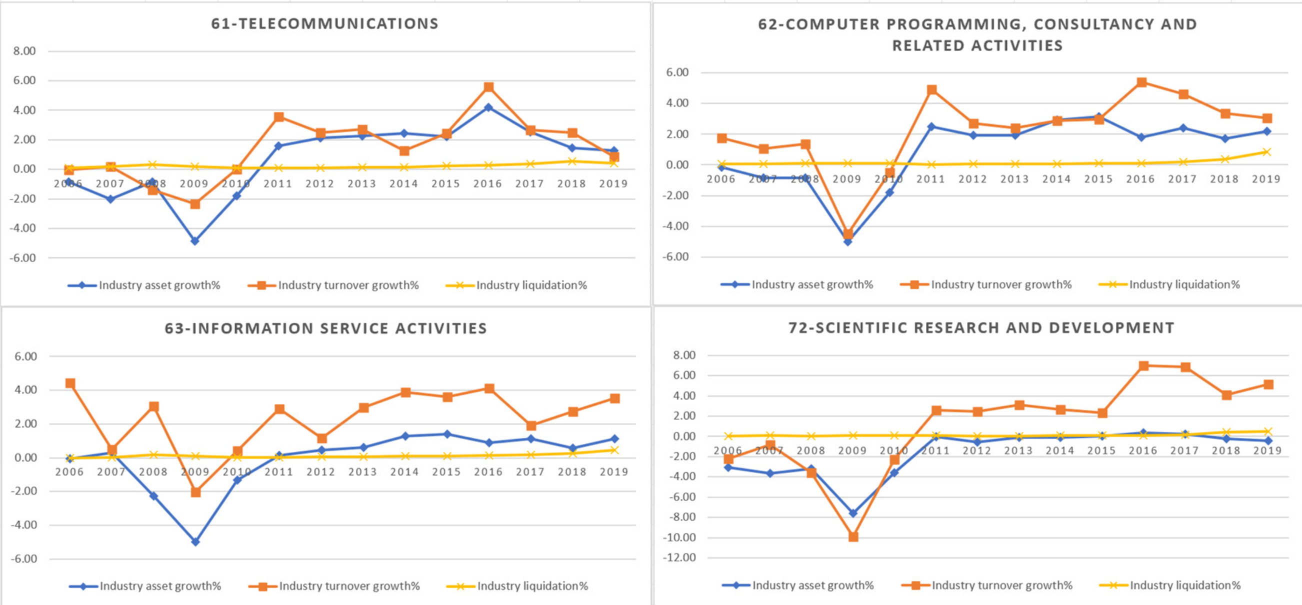
Scheme 1. Macroeconomic indicators analysis. Note that the data sources are Statista for GDP annual growth, the UK Office for National Statistics for the unemployment yearly rate and CPI inflation rate, and Companies House for the total annual liquidations rate.

The three criteria, including industry asset growth, revenue growth and liquidation rate are tested in this study. It can be seen from Scheme 2 that the bankruptcy rate trends of the four sub-industries under the knowledge-intensive industry are similar from 2006 to 2019, and it does not fluctuate much. Industry liquidation rate is calculated according to the number of companies included in the Fame database. The frequently updated database leads to minor changes in the index, which reduces the reliability of the data. Therefore, the weight of industry ratio is small. In Scheme 2, the left graph shows the data collected by the time of bankruptcy registration, and the right one shows the industry bankruptcy rate calculated on the year of last available accounts. It can be observed that during the financial crisis in 2007–2008, there is a time lag in collecting companies' bankruptcy rates in the left graph, and the peak of the bankruptcy rate is in 2009, whilst the actual bankruptcy rate in 2008 is already higher due to the impact of the macro-economy. Hence, this study uses the data shown on the right chart. To define the time of corporate bankruptcy, using the year of last available accounts is more consistent with the facts.



Scheme 2. Knowledge-intensive industry annual liquidation rate. Note that in the Fame data source, industry liquidation rate is the No. of liquidated firms as the percentage of total companies in the industry.

In Scheme 3, based on observation of the four sub-industries, the result can be obtained. From 2007 to 2010, when the value of industry asset growth rate and industry turnover (revenue) growth rate fell to negative values, industry liquidation rate slightly increased. However, during the period of 2016–2019, the bankruptcy rate rose and the indicators of industry asset and turnover growth did not fall sharply. Considering the above contradictory results, these two growth indicators are not retained in the model. Only industry liquidation rate was applied in the model and the utility function of this variable is constructed on the rule that the higher the industry liquidation rate, the greater the probability of company bankruptcy.



Scheme 3. Sub-industries indicators. Note that in the Fame data source, the values of industry asset growth and industry turnover (revenue) growth refer to the median of all companies in the industry.

Most company internal data are collected for quantitative attributes. For construction of marginal utility functions, continuous variables are required to be discretized. In order to achieve this goal, referential points should be identified. Firstly, we have sorted data into bins according to frequency of occurrence. Secondly, histograms of each attribute have been drawn. For example, Operating Margin (%) is shown in Scheme 4. At this stage, we still have too many bins for likelihood analysis, so fewer reference points should be chosen. The principle is that these points can simulate the probability distribution of each variable, including the minimum points, inflection points and Maximum points; at the same time, we have to consider the point with the least overlap between high-risk and low-risk companies, so that the two types of companies can be better distinguished. Once the referential points are determined for one attribute, any observed values χ_j can be transformed into a belief distribution of two adjacent reference values ($\chi_{n,i}$ and $\chi_{n+1,i}$) using Equation (3) (Yang 2001):

$$S(\chi_j) = \{(\chi_{n,i}, \gamma_{n,j}),\ n = 1, \ldots, N\},$$

where

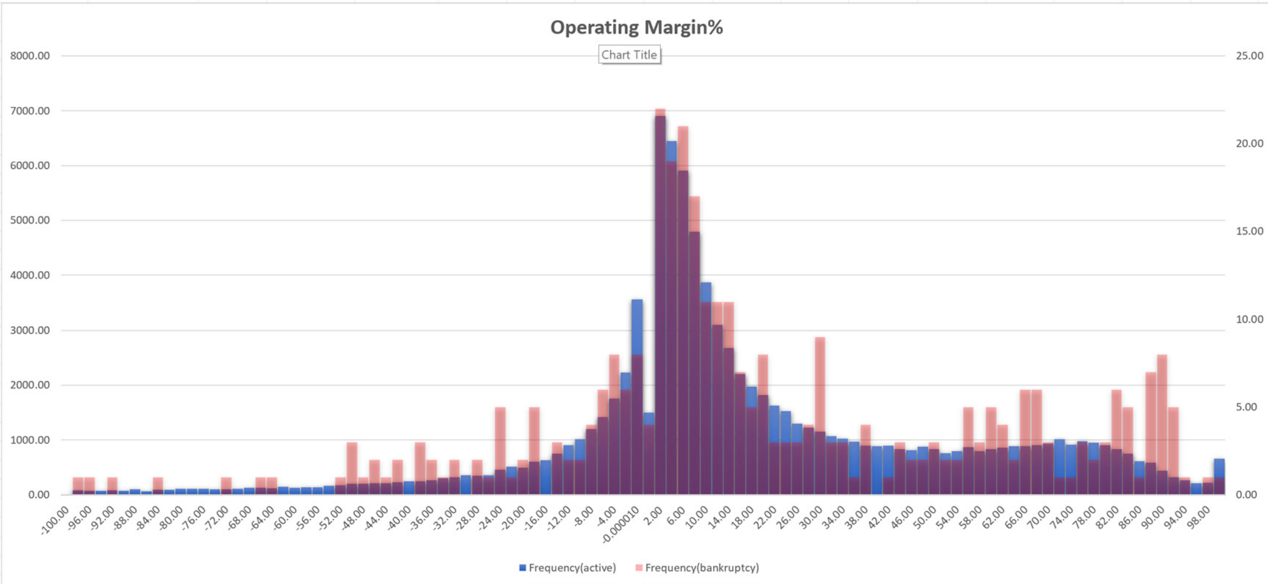
$$\gamma_{n,j} = \frac{\chi_{n+1,i} - \chi_j}{\chi_{n+1,i} - \chi_{n,i}}, \gamma_{n+1,j} = 1 - \gamma_{n,j},\ if\ \chi_{n,i} \le \chi_j \le \chi_{n+1,i} \quad (3)$$

Take a basic attribute Operating Margin (%) ($\chi_1 = 60.02$) of alternative 1 for example. Since $\chi_{5,1} = 52\ and\ \chi_{6,1} = 72$, we can calculate $S(\chi_1)$ as follows:

$$\gamma_{6,1} = \frac{\chi_{5,1} - \chi_1}{\chi_{5,1} - \chi_{6,1}} = \frac{52 - 60.02}{52 - 72} = 0.401,\ \ \gamma_{5,1} = 1 - \gamma_{6,1} = 0.599$$

$$S(\chi_1) = \{(52,\ 0.599), (72,\ 0.401)\}$$

The set of grades for top qualitative attribute is H = {high risk, low risk}. Therefore, it is necessary to provide rules linking numerical values to top grades H_n. In the next step, likelihood analysis is applied to convert child grades to parent grades in the assessment hierarchy.



Scheme 4. Histogram of Operating Margin (%) rate for low-risk and high-risk companies.

The maximum likelihood evidential reasoning (MAKER) framework was introduced by Yang and Xu (2017) to unify different types of uncertainty for data-driven inferential modelling. This study converts observed values into probability distributions in various referential points by calculating the basic probability of each piece of evidence related to different levels of corporate risk n, which is given by $P_{n,j,i} = P_i\ (e_{j,i}\ (n))$. A piece of evidence $e_{j,i}$ is the jth value of sub-attribute x_i. Suppose $C_{n,j,i}$ is the likelihood of observing $e_{j,i}\ (n)$ given corporate risk n. Basic probability $P_{n,j,i}$ is then given as normalized likelihood by the following equation (Yang and Xu 2017):

$$P_{n,j,i} = C_{n,j,i} \ / \sum_{A \subseteq \Theta} C_{A,j,i} \qquad \forall n \subseteq \Theta \tag{4}$$

A basic probability distribution (or belief distribution) for $e_{j,i}$ is thus given by

$$e_{j,i} = \left\{ (e_{j,i}\ (n),\ \ P_{n,j,i}\ ),\ \forall n \subseteq \Theta \ \ and \sum_{n \subseteq \Theta} P_{n,j,i} = 1 \right\} \tag{5}$$

Evidence from original data is acquired using the above likelihood analysis method, which can be summarized as two steps. The first step is to create a frequency table for each company's internal sub-attribute in different referential points from its original data. The frequencies of all attributes in many referential points for low- and high-risk firms are calculated in Python 3.9 by applying Equation (3). For instance, Table 1 presents the frequency of Operating Margin for successful and unsuccessful firms. The second step is to calculate the likelihoods of the Operating Margin rates of low-risk and high-risk companies in different referential points by using Equation (4) (see Table 2).

Table 1. Frequency of Operating Margin (%) rate in many referential points for low- and high-risk companies.

Frequency		−100	−24	4	22	52	72	96	100	Unknown	Total
Company Status	low-risk	2310.27	11,584.44	38,399.06	18,806.35	10,935.93	9343.78	3204.71	645.46	8662	103,892
	high-risk	10.14	46.96	124.18	58.43	37.26	38.29	22.60	1.14	49	388

Table 2. Likelihoods of Operating Margin (%) rate for low-risk and high-risk companies.

Likelihood		−100		−24		4		22		52		72		96		100	
		$C_{n,1,1}$	$P_{n,1,1}$	$C_{n,2,1}$	$P_{n,2,1}$	$C_{n,3,1}$	$P_{n,3,1}$	$C_{n,4,1}$	$P_{n,4,1}$	$C_{n,5,1}$	$P_{n,5,1}$	$C_{n,6,1}$	$P_{n,6,1}$	$C_{n,7,1}$	$P_{n,7,1}$	$C_{n,8,1}$	$P_{n,8,1}$
Company Status	low-risk	0.022	0.460	0.112	0.480	0.370	0.536	0.181	0.546	0.105	0.523	0.090	0.477	0.031	0.346	0.006	0.679
	high-risk	0.026	0.540	0.121	0.520	0.320	0.464	0.151	0.454	0.096	0.477	0.099	0.523	0.058	0.654	0.003	0.321

As can be seen from Table 2, if OM% = −100, the probability distribution or evidence acquired from the data is that 46% of companies are at low risk and 54% are at high risk; when OM% = −24, the evidence is 48% at low risk companies and 52% at high risk; when OM% = 100, the evidence is 67.9% of firms are at low risk and 32.1% are at high risk, etc. The details of all the descriptions and measurements are presented in Table A1 in Appendix A. Two aspects need to be considered for assigning weights: the degree of correlation between this indicator and the corporate bankruptcy risk, and the reliability of the distribution of this indicator acquired from the data. Once the sets of evidence for all attributes are generated by the likelihood analysis, the IDS software, which implements the ER approach, can be used to aggregate the pieces of evidence for all attributes at each firm.

3. The Application of the Corporate Risk Assessment Model and Results

3.1. IDS Application

Due to the large number of attributes that a model needs to take into account, it is often difficult to apply the model in practice (Bellovary et al. 2007). However, the IDS software makes it easy to implement the proposed new model despite the large number of attributes included in the model. IDS has been developed and updated as a software tool to implement the ER approach for large scale applications over many years. The IDS software allows the transformation of complex models and lengthy analysis processes through Windows-based graphical interfaces that make it simple to build hierarchical assessment models, conduct various decision analysis and sensitivity analysis. In Figure 1, the attribute hierarchy and a list of firms for assessment are shown in the IDS main window, where all the functions of the IDS software are accessible through menus and quick access bars. Assessment grades and attribute utilities can be defined for all quantitative and qualitative attributes in the IDS software. An example of a bottom-level attribute is Operating Margin rate as shown in Figures 2 and 3, and the referential points or corresponding probability data are given in Table 2. The Analytical Hierarchy Process method (AHP) in IDS was used to calculate attribute weights. For example, Macroeconomic risk is regarded equally as important as Industry factor and 1/8 times compared to Firm internal risk. Without loss of generality, the three macroeconomic sub-indicators are taken to be of equal importance. Regarding Firm internal factors, financial default is twice as significant as the others. To design the weight of the corporate internal sub-attributes, both reliability and relevance need to be considered. Take profitability for example, as shown in Figure 4. Since there are more missing data for the financial expenses rate, it is assigned the lowest weight. ROA is assigned a higher weight since it is more relevant to corporate profitability. Note that, in this study, pairwise comparisons and other information about attribute weights are assigned by the researchers. In the future research, they should be generated by wider surveys or through machine learning methods. Figure 5 shows the data input window and the step to add alternatives (all sample companies) to the alternative list. It should be noted that one only needs to input data for the bottom-level attributes.

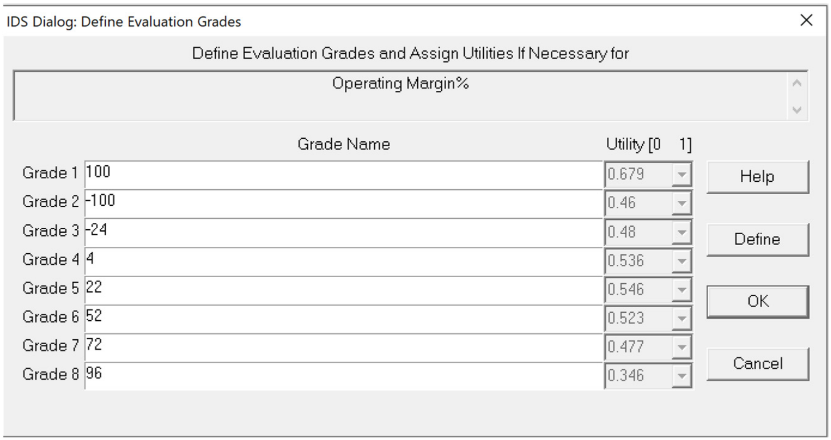


Figure 2. The discrete attribute grades definition.

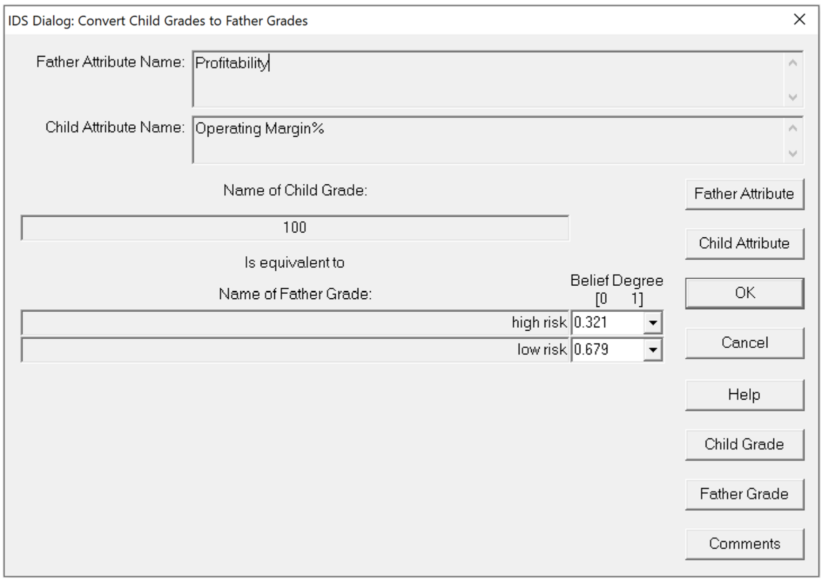


Figure 3. Converting child grades to father grades by rule-based approach.

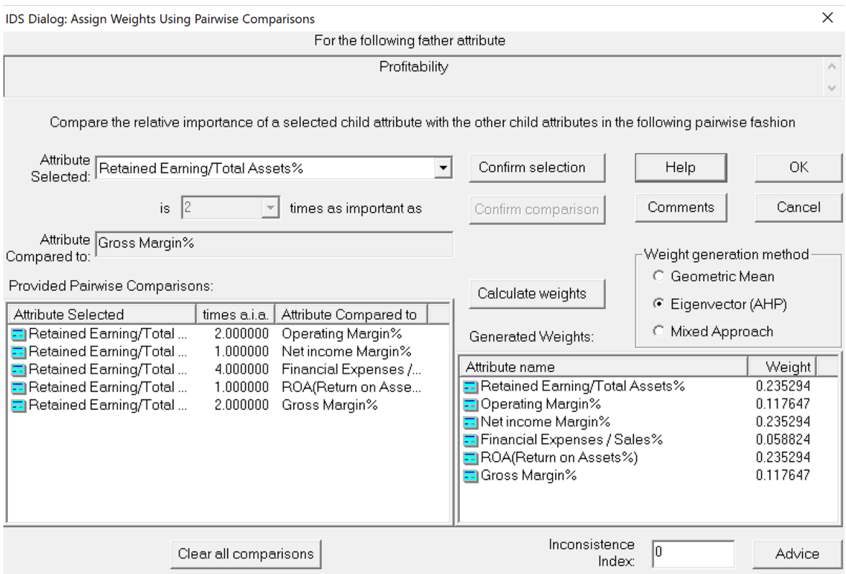


Figure 4. Assigning weights to attributes.

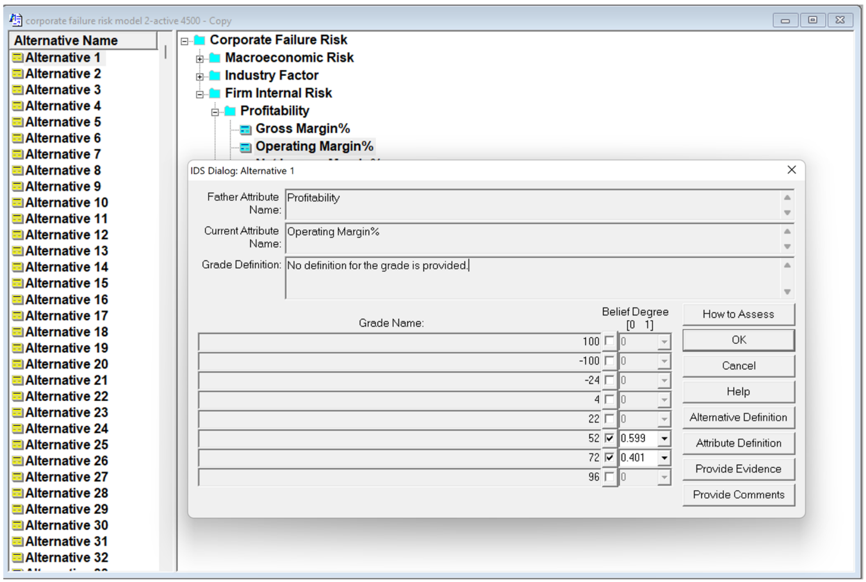


Figure 5. Collecting data for alternatives.

3.2. Result Discussion

The utilities of the top-level attribute are assigned as follows,

$$u(H_1) = u(high\ risk) = 0$$

$$u(H_2) = u(low\ risk) = 1$$

The assessment result is a probability distribution and can also be an average score generated by multiplying the utilities of grades by the product of normalized weight and the degree of belief. Figure 6 shows an example of the assessment result for alternative FAIR, which is an active company. The probability distribution is $S(A) = \{(high\ risk, 41.97\%),\ (low\ risk, 58.03\%)\ \}$ which means its probability of survival is greater than the bankruptcy. The mean utility value of this probability distribution is given by $u(A) = 0 \times 0.4197 + 1 \times 0.5803 = 0.5803$. The higher the score, the lower the probability of bankruptcy.

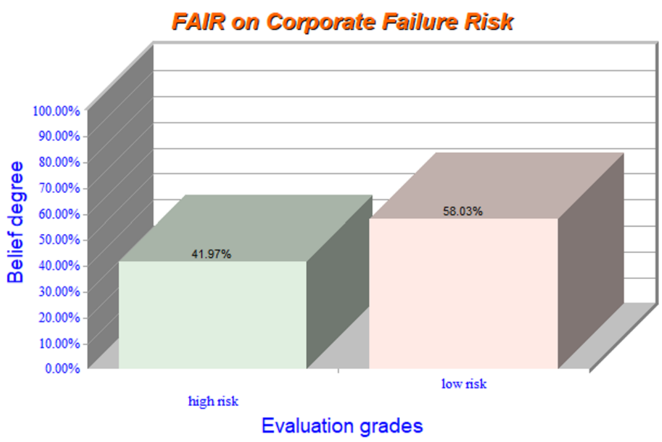


Figure 6. The assessment of a company.

In addition, investors and creditors can compare the overall failure risks of many companies on any selected attributes as shown in Figure 7. If there is not much difference between any firms' overall bankruptcy probability, they can make investment decisions by comparing the company's financial default rates or growth capabilities, etc. Corporate failure risk assessment result for one alternative is displayed in Figure 8 in more details, which may be used to assist managers to analyse the company's strong areas and weak areas and provide warning information about the company's operational risks. The overall evaluation results for some of the companies analysed in this study are shown in Figure 9. Each bar in Figure 9 represents the overall score of a company. If the top part of a bar is grey, it means that there are missing data for the company. In IDS, this can be used to assist in checking whether some original data are missing or the operator forgets to record data.

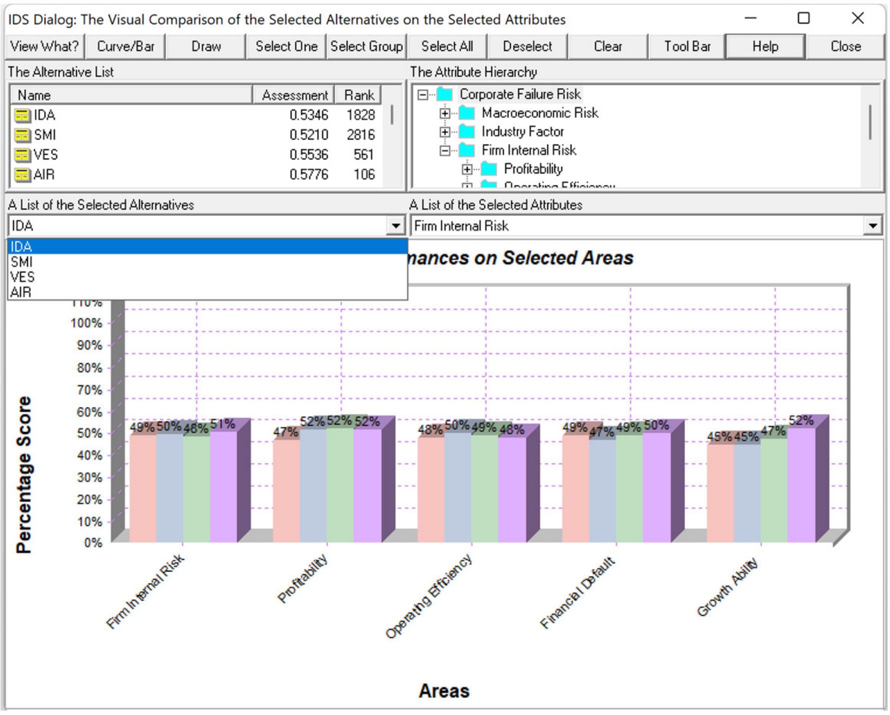


Figure 7. The assessment of selected companies on selected attributes.

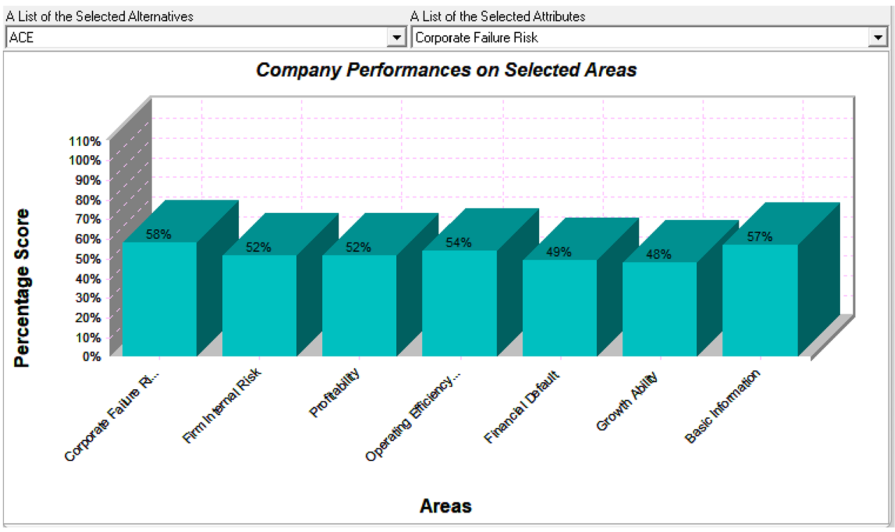


Figure 8. The assessment of one company in detail.

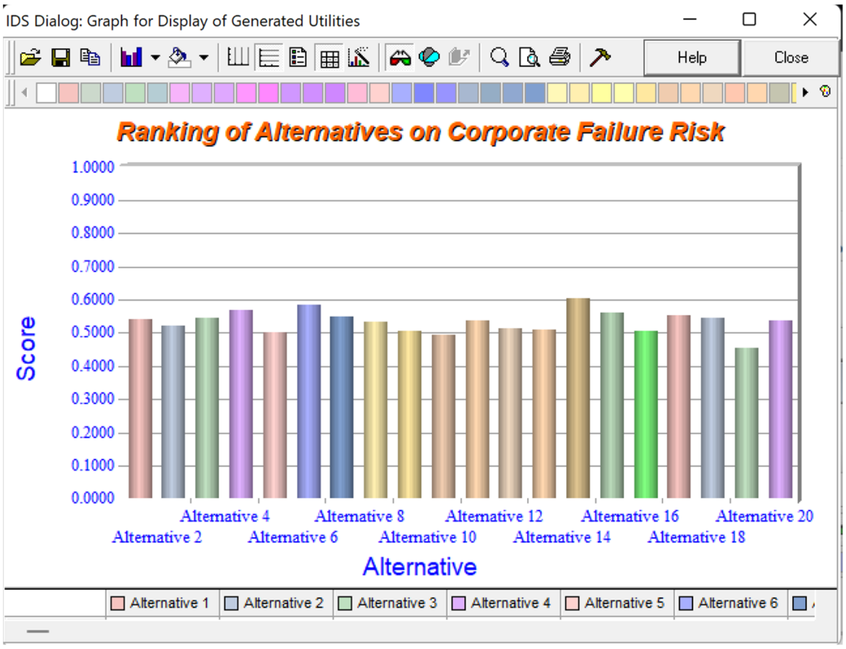


Figure 9. Risk ranking of the assessed firms.

4. Conclusions

It is imperative to build a warning model to assess the probability of corporate failure. A company in financial crisis has a significant impact on other companies in the supply chain. When the number of failed companies reaches a certain number, it triggers a domino effect and even threatens the entire economic environment (Jackson and Wood 2013). In this study, a new hierarchical model was built and the ER approach was applied to evaluate bankruptcy risk for the knowledge-intensive industry in the UK. Furthermore, the likelihood analysis method was used for data-driven risk analysis based on a hierarchy of attributes. Since the development of KIS industry relies on technology and knowledge (e.g., patents, R&D), in this model some specific variables are applied, such as an intangible asset ratio. If this model is generalized to evaluate the failure risk of other industries, a few variables can be replaced. For example, we may consider whether variables related to tangible assets can be used to evaluate the risk of corporate bankruptcy for traditional industries, including inventory turnover or depreciation of owned equipment. Once a different sample set is selected, parameters in the model will be changed, such as referential points and weights. The preliminary analysis results generated using the proposed model showed that the risk distributions and scores provide informative and useful information for corporate failure risk analysis.

This model is based on the ERM theory, which means that from a long-term perspective, external factors will affect the development of the company. The company should also consider the external economic condition and adjust strategies to meet internal and external challenges. The model is developed by applying an ER approach that can deal with both quantitative and qualitative values with imperfect data. The IDS software is easy to operate. The managers of a company can use the model to evaluate which aspects of the company are not performing well, and then further investigate the related issues to help reduce operational risks. Investors and creditors can use the model to assess the risk of the company and make decisions based on their investment preferences (for example, risk-averse investors may avoid investing in high-risk companies).

However, one limitation is that weights are assigned under subjective judgment, therefore, the model needs to be improved by having its parameters optimally trained to reduce misclassification. The current post-epidemic data are not accurate, and more reliable data for 2020–2021 should be collected later for future research. The newly collected data could be used to validate the model for the period in which the global economy is hugely affected by the epidemic. Such validation should be appropriate as the time span selected for collection of the data in this study covers 2008. The purpose includes evaluating the impact of global economy fluctuations on company bankruptcy. Moreover, criticisms in the literature that some financial indicators are unsuitable for start-ups or private companies, since much corporate financial information is missing or unreliable and that a large amount of qualitative data are currently not available. Future studies should consider using more non-financial data, such as human capital, directors' previous relevant management experience, etc. since such qualitative indicators may also be critical to a company's risk prediction.

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Appendix A

Table A1. Descriptions and measurements for all attributes.

Level 2 Attributes	Level 3 Attributes	Level 4 Attributes	Defination	Measurement
Macroeconomic Risk(ω = 0.1)	GDP Annual Growth% (gross domestic product growth) (ω = 0.33)		The greater the GDP growth rate, the better the country's economic development. The two consecutive quarters or more of negative GDP growth means that the economy is in recession (Year on Year growth).	GDPG $\leq$ 0 economic decline GDPG > 0 economic growth
	Unemployment Yearly Rate% (ω = 0.33)		It equals to the No. of people who are without work/labour force of an economy. An increase in the unemployment rate is a signal of economic weakness, which can cause the government to loosen its monetary policy in order to stimulate economic growth; on the contrary, a fall in the unemployment rate will lead to inflation, causing the central bank to tighten its monetary policy and reduce money supply.	Minimum value = 3 Maximum value = 12 During a economic recession, the unemployment rate is higher.
	CPI Inflation Rate% (2015 = 100) (consumer price index change) (ω = 0.33)		CPI refers to the current cost of market basket compared with the base period. The CPI Inflation Rate means the value change over 12 months, which is used to measure the level of national inflation.	Minimum value = 0.4 Maximun value = 8.0 A high CPI inflation rate bad for economy.
Industry Factor (ω = 0.1)	Industry liquidation% (ω = 1)		It means the No. of liquidated firms as a percentage of total companies in the industry. (The median values of the four sub-industries are used in the model)	Best value = 0 Worst value = 1 The higher the industry liquidation rate, the greater the probability of company bankruptcy.

Table A1. *Cont.*

Level 2 Attributes	Level 3 Attributes	Level 4 Attributes	Defination	Measurement	
Firm Internal Risk (ω = 0.8)	Profitability (ω = 0.167)	Gross Margin% (ω = 0.118)	Gross Profit/Turnover*100 (Fame: Turnover = Revenue) It reflects the initial profitability of the main business product or service. Gross Profit is equal to total sales or revenue minus cost of sales, If the company does not have enough gross profit, it may not be able to make up for the subsequent period expenses (e.g., administration expenses, distribution expenses) and then suffer losses.	GPM% = −100 GPM% = −10 GPM% = 12 GPM% = 48 GPM% = 62 GPM% = 88 GPM% = 100	47% low risk, 53% high risk; 38.1% low risk, 61.9% high risk; 43.5% low risk, 56.5% high risk; 47.8% low risk, 52.2% high risk; 54.4% low risk, 45.6% high risk; 50% low risk, 50% high risk; 46.6% low risk, 53.4% high risk.
Firm Internal Risk (ω = 0.8)	Profitability (ω = 0.167)	Operating Margin% (ω = 0.118)	Operating Profit/Turnover*100 Operating profit is equal to gross profit minus all subsequent period expense. When consider expense, e.g., administration expense, many companies have a negative value of profit.	OPM% = −100 OPM% = −24 OPM% = 4 OPM% = 22 OPM% = 52 OPM% = 72 OPM% = 96 OPM% = 100	46% low risk, 54% high risk; 48% low risk, 52% high risk; 53.6% low risk, 46.4% high risk; 54.6% low risk, 45.4% high risk; 52.3% low risk, 47.7% high risk; 47.7% low risk, 52.3% high risk; 34.6% low risk, 65.4% high risk; 67.9% low risk, 32.1% high risk.
		Net Income Margin% (ω = 0.235)	Net income/turnover*100 The net income is the balance of the company's total income minus all costs and expenses. The larger the index, the higher the profitability of the company's business activities. Comparing gross margin and net income margin, we can find out the risks in the business management, such as if the product pricing is reasonable, or whether the main business cost and other various expenses are too high.	NIM% ∈(−∞, −800] NIM% = −100 NIM% = −44 NIM% = 4 NIM% = 36 NIM% = 60 NIM% = 84 NIM% ∈ [200, +∞)	37.4% low risk, 62.6% high risk; 46.3% low risk, 53.7% high risk; 46% low risk, 54% high risk; 54% low risk, 46% high risk; 53.4% low risk, 46.6% high risk; 44.8% low risk, 55.2% high risk; 36.1% low risk, 63.9% high risk; 33.2% low risk, 66.8% high risk.

Table A1. *Cont.*

Level 2 Attributes	Level 3 Attributes	Level 4 Attributes	Defination	Measurement	
		Financial Expenses/Sales% (ω = 0.059)	interest paid/turnover*100	FES% = 0.01 FES% = 0.08 FES% = 0.3 FES% = 1 FES% = 5 FES% = 50 FES% $\in$ [300, +∞)	49.3% low risk, 50.7% high risk; 50.7% low risk, 49.3% high risk; 44.4% low risk, 55.6% high risk; 37.6% low risk, 62.4% high risk; 43.5% low risk, 56.5% high risk; 44.8% low risk, 55.2% high risk; 20.5% low risk, 79.5% high risk.
		Roa(Return On Assets%) (ω = 0.235)	Net Income/Total Asset*100 The return on total assets index assesses the efficiency of asset utilization. In the case of a certain amount of corporate assets, it can be used to analyse the stability of corporate profitability and determine the risks faced by the company. It may also reflect the level of comprehensive management of the enterprise. The higher value of ROA, the better the efficiency of corporate capital utilization and the stronger the profitability.	ROA% $\in$ ($-\infty$, -750] ROA% = -200 ROA% = -38 ROA% = -16 ROA% = 4 ROA% = 40 ROA% = 150 ROA% = 300 ROA% $\in$ [1000, +∞)	38.5% low risk, 61.5% high risk; 37.3% low risk, 62.7% high risk; 39.1% low risk, 60.9% high risk; 53.9% low risk, 46.1% high risk; 54.5% low risk, 45.5% high risk; 46.2% low risk, 53.8% high risk; 48.3% low risk, 51.7% high risk; 64% low risk, 36% high risk; 61.2% low risk, 38.8% high risk.
Firm Internal Risk (ω = 0.8)	Profitability (ω = 0.167)	Retained Earning/Total Assets% (ω = 0.235)	Retained earning/Total assets*100 (Fame: Retained earning = Profit (Loss) Account)	REA $\in$ ($-\infty$, -4000] REA = -300 REA = -120 REA = -16 REA = 4 REA = 56 REA = 90 REA $\in$ [100, +∞)	32.2% low risk, 67.8% high risk; 35.7% low risk, 64.3% high risk; 42.4% low risk, 57.6% high risk; 49% low risk, 51% high risk; 50.7% low risk, 49.3% high risk; 56.2% low risk, 43.8% high risk; 47.9% low risk, 52.1% high risk 55.9% low risk, 44.1% high risk.

Table A1. *Cont.*

Level 2 Attributes	Level 3 Attributes	Level 4 Attributes	Defination	Measurement
	Operating Efficiency (ω = 0.167)	Remuneration To Revenue% (ω = 0.286)	Remuneration/Turnover*100	RER% = 2 43.4% low risk, 56.6% high risk; RER% = 20 55.4% low risk, 44.6% high risk; RER% = 50 52.6% low risk, 47.4% high risk; RER% = 84 49.2% low risk, 50.8% high risk; RER% = 96 38.2% low risk, 61.8% high risk; RER% = 200 34.6% low risk, 65.4% high risk; RER% ∈ [1000, +∞) 26.5% low risk, 73.5% high risk.
		Directors Remuneration Margin% (ω = 0.142)	Directors remuneration/remuneration%	DRR% = 1 55.8% low risk, 44.2% high risk; DRR% = 9 53.7% low risk, 46.3% high risk; DRR% = 16 47% low risk, 53% high risk; DRR% = 25 41.4% low risk, 58.6% high risk; DRR% = 80 48.5% low risk, 51.5% high risk; DRR% = 100 45.6% low risk, 54.4% high risk; DRR% ∈ [200, +∞) 100% low risk, 0% high risk.
		Accounts Receivable Turnover (ω = 0.286)	Turnover/Trade Debtors It measures the realization speed of the company's accounts receivable. The higher the index, the stronger liquidity of assets and the lower bad debt losses. However, too high accounts receivable turnover rate limits the company's sales scale.	ART = 1 57.4% low risk, 42.6% high risk; ART = 3 50% low risk, 50% high risk; ART = 5.5 50.8% low risk, 49.2% high risk; ART = 9.5 52.5% low risk, 47.5% high risk; ART = 12 42.6% low risk, 57.4% high risk; ART = 20 48.1% low risk, 51.9% high risk; ART = 40 42.7% low risk, 57.3% high risk; ART = 90 43.7% low risk, 56.3% high risk; ART ∈ [200, +∞) 56.7% low risk, 43.3% high risk.
Firm Internal Risk (ω = 0.8)	Operating Efficiency (ω = 0.167)	Total Asset Turnover (ω = 0.286)	turnover/total assets It can be applied to evaluate the use efficiency of all assets of the enterprise. The utilization of the enterprise assets could be improved by increasing income or reducing assets. The larger the better.	TAT = 0.1 48.2% low risk, 51.8% high risk; TAT = 1.8 50.7% low risk, 49.3% high risk; TAT = 4.5 49.9% low risk, 50.1% high risk; TAT = 8 49.5% low risk, 50.5% high risk; TAT = 20 53% low risk, 47% high risk; TAT = 80 55.4% low risk, 44.6% high risk; TAT ∈ [100, +∞) 55.5% low risk, 44.5% high risk.

Table A1. *Cont.*

Level 2 Attributes	Level 3 Attributes	Level 4 Attributes	Defination	Measurement	
	Financial Default (ω = 0.333)	Debt Ratio% (ω = 0.143)	Total liabilities/Total Assets It indicates the proportion of funds provided by creditors in total assets. The scale of corporate debt should be kept within a reasonable range. When the debt ratio is greater than 100, it shows that the company is insolvent and the owner's equity is negative.	DR% = 2 DR% = 8 DR% = 42 DR% = 86 DR% = 100 DR% = 230 DR% = 500 DR% = 3000 DR% ∈ [15,000, +∞)	61.1% low risk, 38.9% high risk; 43.5% low risk, 56.5% high risk; 55.1% low risk, 44.9% high risk; 53.1% low risk, 46.9% high risk; 45.3% low risk, 54.7% high risk; 40.3% low risk, 59.7% high risk; 44.8% low risk, 55.2high risk; 39.9% low risk, 60.1% high risk; 33.1% low risk, 66.9% high risk;
		Interest Coverage Ratio (ω = 0.036)	Profit (Loss) before Interest paid/Interest Paid It is used to assess the company's ability to pay interest expenses. A low value means that the company's profits can only be barely used to pay interest on liabilities, which further shows that the company's solvency is weak.	ICR = −50 ICR = −10 ICR = −4 ICR = 2 ICR = 17 ICR = 40 ICR ∈ (200, +∞)	35.6% low risk, 64.4% high risk; 29.1% low risk, 70.9% high risk; 43.1% low risk, 56.9% high risk; 49.4% low risk, 50.6% high risk; 43.4% low risk, 56.6% high risk; 43.1% low risk, 56.9% high risk; 55.3% low risk, 44.7% high risk.
		Gearing Ratio% (ω = 0.143)	(Short Term Loans & Overdrafts + Long Term Liabilities)/Shareholders Funds *100 It is an indicator used to evaluate the rationality of capital structure and the company's long-term solvency. Low debt means that the company does not make full use of the leverage effect, thereby limiting the expansion of the company. However, high debt brings higher risks to creditors and investors.	GR% = 1 GR% = 10 GR% = 14 GR% = 34 GR% = 90 GR% = 250 GR% ∈ [800, +∞)	50.7% low risk, 49.3% high risk; 50.7% low risk, 49.3% high risk; 51.1% low risk, 48.9% high risk; 55.2% low risk, 44.8% high risk; 51.4% low risk, 48.6% high risk; 52.5% low risk, 47.5% high risk; 50.3% low risk, 49.7% high risk.

Table A1. *Cont.*

Level 2 Attributes	Level 3 Attributes	Level 4 Attributes	Defination	Measurement	
Firm Internal Risk (ω = 0.8)	Financial Default (ω = 0.333)	Liabilities/Euqities% (ω = 0.071)	liabilities/euqities*100	LE% $\in (-\infty, -1000)$ LE% = −550 LE% = −100 LE% = 5 LE% = 90 LE% = 150 LE% = 550 LE% = 1000 LE% $\in [5000, +\infty)$	50.3% low risk, 49.7% high risk; 41% low risk, 59% high risk; 42.1% low risk, 57.9% high risk; 47.1% low risk, 52.9% high risk; 55.9% low risk, 44.1% high risk; 56% low risk, 44% high risk; 49.3% low risk, 50.7% high risk; 54.7% low risk, 45.3% high risk; 41.6% low risk, 58.4% high risk.
		Working Capital/Total Asset% (ω = 0.143)	Working capital/total asset*100 OR (Current Assets-Current Liabilities)/total assets*100	WCA% = −2000 WCA% = −750 WCA% = −100 WCA% = −15 WCA% = 5 WCA% = 10 WCA% = 60 WCA% = 90 WCA% = 100	32.7% low risk, 67.3% high risk; 45.6% low risk, 54.4% high risk; 45.1% low risk, 54.9% high risk; 45.6% low risk, 54.4% high risk; 51.5% low risk, 48.5% high risk; 53.6% low risk, 46.4% high risk; 51.7% low risk, 48.3% high risk; 43.8% low risk, 56.2% high risk; 59.2% low risk, 40.8% high risk.
		Current Ratio% (ω = 0.143)	Current Assets/Current Liabilities It means how much current assets can be used to repay each unit of current liabilities. The higher the ratio, the stronger the company's short-term debt repayment ability, and the less likely that the company will default on their debt.	CR% = 0.1 CR% = 0.4 CR% = 1 CR% = 2 CR% = 3 CR% = 20 CR% = 100	42.6% low risk, 57.4% high risk; 45.9% low risk, 54.1% high risk; 49.7% low risk, 50.3% high risk; 53.1% low risk, 46.9% high risk; 47.1% low risk, 52.9% high risk; 48.3% low risk, 51.7% high risk; 51.1% low risk, 48.9% high risk.

Table A1. *Cont.*

Level 2 Attributes	Level 3 Attributes	Level 4 Attributes	Defination	Measurement
		Cash Flow From Operation/ Current Liabilities% (ω = 0.071)	cash flow from operation/current liabilities*100 It evaluates the company's ability to repay short-term liabilities from the perspective of cash flow. When the value of this indicator is large, it indicates that the company has sufficient cash flow, which can guarantee the timely repayment of debts. However, if the value is too large, it means that the company has not fully utilized assets and the management efficiency is low.	CAL% ∈ (−∞, −300] 32.1% low risk, 67.9% high risk; CAL% = −30 35.5% low risk, 64.5% high risk; CAL% = 10 59.5% low risk, 40.5% high risk; CAL% = 70 53.4% low risk, 46.6% high risk; CAL% = 150 40.2% low risk, 59.8% high risk; CAL% ∈ [500, +∞) 44% low risk, 56% high risk.
Firm Internal Risk (ω = 0.8)	Financial Default (ω = 0.333)	Cash And Cash Equivalents/ Current Liabilities% (ω = 0.143)	cash and cash equivalents/current liabilities*100	CCL% = 1 34.2% low risk, 65.8% high risk; CCL% = 4 38.1% low risk, 61.9% high risk; CCL% = 10 48.9% low risk, 51.1% high risk; CCL% = 78 55% low risk, 45% high risk; CCL% = 120 60.1% low risk, 39.9% high risk; CCL% = 400 54.2% low risk, 45.8% high risk; CCL% ∈ (5000, +∞) 48.8% low risk, 51.2% high risk.
		Cash And Cash Equivalents/ Total Debt% (ω = 0.036)	increased cash and cash equivalents/total debt*100	CCD% ∈ (−∞, −100] 60.7% low risk, 39.3% high risk; CCD% = −30 38.6% low risk, 61.4% high risk; CCD% = 5 46.1% low risk, 53.9% high risk; CCD% = 25 59.1% low risk, 40.9% high risk; CCD% = 85 47.6% low risk, 52.4% high risk; CCD% ∈ [200, +∞) 49.1% low risk, 50.9% high risk.
		Auditor'S Opinion (ω = 0.071)	It is an opinion expressed by an independent auditor on whether the company's financial statements meet the standards.	AO = Qualified 16% low risk, 84% high risk; AO = Not audited/unknown 55% low risk, 45% high risk; AO = Unqualified 46% low risk, 54% high risk.

Table A1. *Cont.*

Level 2 Attributes	Level 3 Attributes	Level 4 Attributes	Defination	Measurement
	Growth Ability (ω = 0.167)	Revenue Growth% (ω = 0.308)	Revenue growth-1 year%	RG% = −100 40.6% low risk, 59.4% high risk; RG% = −20 42.2% low risk, 57.8% high risk; RG% = −14 50.8% low risk, 49.2% high risk; RG% = 5 54.8% low risk, 45.2% high risk; RG% = 20 58.3% low risk, 41.7% high risk; RG% = 30 61% low risk, 39% high risk; RG% = 80 51.5% low risk, 48.5% high risk; RG% ∈ [200, +∞) 50.3% low risk, 49.7% high risk.
		Asset Growth% (ω = 0.154)	Asset growth-1 year%	AG% = −100 45.4% low risk, 54.6% high risk; AG% = −20 47.1% low risk, 52.9% high risk; AG% = −14 53.5% low risk, 46.5% high risk; AG% = 2 56.3% low risk, 43.7% high risk; AG% = 20 54.3% low risk, 45.7% high risk; AG% = 30 46.3% low risk, 53.7% high risk; AG% ∈ [200, +∞) 46.8% low risk, 53.2% high risk.
Firm Internal Risk (ω = 0.8)	Growth Ability (ω = 0.167)	Intangible Assets/ Total Assets% (ω = 0.076)	intangible assets/total assets*100	ITA% = −1 57.4% low risk, 42.6% high risk; ITA% = 1 59.6% low risk, 40.4% high risk; ITA% = 5 52.1% low risk, 47.9% high risk; ITA% = 10 40.3% low risk, 59.7% high risk; ITA% = 45 47.8% low risk, 52.2% high risk; ITA% = 100 43.3% low risk, 56.7% high risk.
		Cash Flow From Operations/Sales% (ω = 0.154)	Cash Flow From Operations/Sales *100 It represents the net cash flow from operating activities per unit of sales revenue.	CAS% ∈ (−∞, −100] 28.7% low risk, 71.3% high risk; CAS% = −10 39.1% low risk, 60.9% high risk; CAS% = 5 59.9% low risk, 40.1% high risk; CAS% = 15 59.6% low risk, 40.4% high risk; CAS% = 50 38% low risk, 62% high risk; CAS% ∈ [250, +∞) 54.1% low risk, 45.9% high risk.
		Cash And Cash Equivalents/Current Asset% (ω = 0.308)	cash and cash equivalents/current asset*100 It examines the proportion of cash to current asset. The larger the value the more stable the development and the lower the operating risk.	CCA% = 1 37.1% low risk, 62.9% high risk; CCA% = 4 40.8% low risk, 59.2% high risk; CCA% = 32 49.9% low risk, 50.1% high risk; CCA% = 54 56.2% low risk, 43.8% high risk; CCA% = 96 54.7% low risk, 45.3% high risk; CCA% = 100 61.1% low risk, 38.9% high risk.

Table A1. *Cont.*

Level 2 Attributes	Level 3 Attributes	Level 4 Attributes	Defination	Measurement	
	Basic Information (ω = 0.167)	Average Age Of Directors% (ω = 0.111)		DA% = 18 DA% = 45 DA% = 52 DA% = 57 DA% = 66 DA% = 93	54.8% low risk, 45.2% high risk; 51.2% low risk, 48.8% high risk; 43.5% low risk, 56.5% high risk; 48.1% low risk, 51.9% high risk; 57.7% low risk, 42.3% high risk; 62.4% low risk, 37.6% high risk.
		Women On Board% (ω = 0.111)		WOB% = 1 WOB% = 10 WOB% = 20 WOB% = 40 WOB% = 50 WOB% =67 WOB% = 100	47.8% low risk, 52.2% high risk; 47% low risk, 53% high risk; 51.6% low risk, 48.4% high risk; 57.4% low risk, 42.6% high risk; 61.6% low risk, 38.4% high risk; 53.1% low risk, 46.9% high risk; 48.6% low risk, 51.4% high risk.
Firm Internal Risk (ω = 0.8)	Basic Information (ω = 0.167)	Firm Size(No. Of Employee) (ω = 0.222)		NEM = 1 NEM = 3 NEM = 10 NEM = 50 NEM = 55 NEM = 200 NEM = 250 NEM = 900 NEM = 3000	40.6% low risk, 59.4% high risk; 46.8% low risk, 53.2% high risk; 43.7% low risk, 56.3% high risk; 43.1% low risk, 56.9% high risk; 54.7% low risk, 45.3% high risk; 55.8% low risk, 44.2% high risk; 57.1% low risk, 42.9% high risk; 61.9% low risk, 38.1% high risk; 96.3% low risk, 3.7% high risk.
		Company Age (ω = 0.222)		CA% = 1 CA% = 6 CA% = 10 CA% = 26 CA% = 40 CA% = 120	23.1% low risk, 76.9% high risk; 34.6% low risk, 65.4% high risk; 55.5% low risk, 44.5% high risk; 63.5% low risk, 36.5% high risk; 80.7% low risk, 19.3% high risk; 68.7% low risk, 31.3% high risk.

Table A1. *Cont.*

Level 2 Attributes	Level 3 Attributes	Level 4 Attributes	Defination	Measurement
		Firm Size (Ln Assets) (ω = 0.222)		LNA% = 1 77.9% low risk, 22.1% high risk; LNA% = 8 74% low risk, 26% high risk; LNA% = 11 47.6% low risk, 52.4% high risk; LNA% = 14 38.6% low risk, 61.4% high risk; LNA% = 16 50.2% low risk, 49.8% high risk; LNA% = 20 59.7% low risk, 40.3% high risk; LNA% = 26 44.9% low risk, 55.1% high risk.
		No. Of Subsidiaries (ω = 0.111)		NSB% = 1 59.8% low risk, 40.2% high risk; NSB% = 2 59.8% low risk, 40.2% high risk; NSB% = 4 94.1% low risk, 5.9% high risk; NSB% = 10 87.4% low risk, 12.6% high risk; NSB% = 60 69.8% low risk, 30.2% high risk; NSB% = 250 100% low risk, 0% high risk.

Note: In Fame, 'Bank and Deposits' is equal to 'cash and cash equivalents', 'Profit (Loss) Account' is 'retained earnings/accumulated profits' and 'Turnover' is 'revenue' actually.

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