Distribution properties of contractors’ financial ratios

This item was submitted to Loughborough University's Institutional Repository by the/an author.


Additional Information:

• This is a conference paper. The original paper was first published by ARCOM as part of the Conference Proceedings.

Metadata Record: https://dspace.lboro.ac.uk/2134/33504

Version: Published

Publisher: ARCOM

Rights: This work is made available according to the conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0) licence. Full details of this licence are available at: https://creativecommons.org/licenses/by-nc-nd/4.0/

Please cite the published version.
DISTRIBUTIONAL PROPERTIES OF CONTRACTORS' FINANCIAL RATIOS

F.T. Edum-Fotwe1, A.D.F. Price2 and A. Thorpe3
Department of Civil and Building Engineering,
Loughborough University, Loughborough, Leicestershire,
LE11 3TU, UK

Abstract
The application of financial ratios for evaluating the performance of construction contractors has received some considerable attention in academic research. This has led to the development of financial ratio models for identifying contractors with potential failure characteristics. The ratio models are mathematical expressions which linearly combine several weighted financial ratios to provide a single score, usually described as a Z-score, which can be employed in the evaluation.

Practically all previous researchers in ratio modelling for predicting contractor failure either assumed, or attempted to fit their empirical data to the normal distribution. Previous work done by the authors of this paper, on improving the performance of financial ratio models, indicated the prevalence of outliers for a significant proportion of the data. To reduce the effect of the outliers, some of the ratio model developers resorted to improvements, such as outlier removal and transformation, to get their data to conform to a normal distribution. The central theme of this paper is that, although this approach may be correct mathematically, it only goes to support the view that financial ratios are essentially not characterised by normal distributions. Identifying the underlying distributions that characterise these financial ratios should lead to a more rational approach for developing efficient ratio models. To do this, the paper presents an approach for investigating the distributional properties of the ratios, with the view to utilising the identified distributions for estimating failure prediction models.

Keywords: Ratio models, normality, failure mode, phases of financial performance, distribution

Introduction
Contractor evaluation and corporate risk assessment in the construction industry often incorporates financial-based analysis. The application of such financial evaluation has been described by Edum-Fotwe (1995) to be either from a normative or positive perspective. The normative approach compares a contractor's ratios with some standard value, usually some industry benchmark. In the positive approach, ratios are employed for prediction, and this has, in recent times, led to the development of models for that purpose. Analysis involved in financial evaluation usually relies on the application of the ratios from a company's financial accounts, to provide a profile of that company. The different ratios employed in such evaluation can, however, produce contradictory indications. The development of ratio models, to replace the separate single ratios for such an evaluation, overcomes this setback of contradictory indications. The application of the models for corporate evaluation should lead to useful information on the financial standing of a company for strategic planning purposes. It can equally be utilised to evaluate the financial stability of contractors in order to assist the decision of client bodies, in conjunction with project-oriented criteria that are in current use.

E-mail:
1F.T.Edum-fotwe@lboro.ac.uk
2A.D.F.Price@lboro.ac.uk
3A.Thorpe@lboro.ac.uk
The growth in popularity of these models for corporate evaluations derives from their advantage in providing a quick and overall objective assessment of a company's performance. If these models are to become sufficiently reliable as a common evaluation tool for the construction industry, then they need to be reasonably accurate. Inman (1991) for instance outlined six cases in which evaluation with both the models of Altman (1983), and Taffler (1983) produced contradictory results. Langford et al. (1993), in a similar exercise showed that for the construction industry, the model of Mason and Harris (1979) was very much susceptible to mis-classification. Karels and Prakash (1987) argued that the reliability of the models employed for such evaluation relate to the quality of the data employed in their modelling, as well as the theoretical assumptions which forms the basis of their application.

Previous work done by Edum-Fotwe et al. (1995), on improving the performance of financial ratio models, indicated the prevalence of outliers for a significant proportion of the data. To reduce the effect of the outliers, some of the ratio model developers resorted to improvements, such as outlier removal and transformation, to get their data to conform to a normal distribution. We are of the view that, although this approach may be correct mathematically, it only goes to support the point that financial ratios are essentially not characterised by normal distributions. Identifying the underlying distributions that characterise these financial ratios should ensure a more rational approach for developing efficient ratio models. The paper reviews some the developments in ratio modelling, and the underlying criteria for the statistical techniques that are employed in their estimation. It also presents an approach for investigating the distributional properties of the ratios, with the view to utilising the identified distributions for estimating failure prediction models for construction contractors.

**Nature of financial ratios**

Although financial evaluation encompasses several analyses; for example, ratios, sources and application of funds, and break-even investigations; ratio analysis enjoys the greatest popularity. Edum-Fotwe et al. (1996) have outlined the three main approaches in which financial ratio measures are usually employed for corporate evaluations. They also provide several examples of ratio models developed for both general and construction specific application.

A financial ratio is composed of two variables and it is the behaviour of these and their relationship with one another that governs the behaviour of the financial ratio which they make up. The critical assumption when using financial ratios is proportionality. It implies that the relationship between the two variables is linear and the constant is zero (Whittington, 1980). The violation of these assumptions accounts for non-normal distributions (Barnes, 1982).

Consider for example, the statistical relationship between two sets of variables \( X_{ij} \) and \( Y_{ij} \), which represent cross-sectional accounting numbers. There are \( n \) members of the population that defines such relevant accounting numbers for the construction industry or any strategic group within that industry. Then \( X \) and \( Y \) are defined respectively by

\[
X_{ij} : X_{i1}, X_{i2}, X_{i3}, ..., X_{in}; \quad \text{and} \\
Y_{ij} : Y_{i1}, Y_{i2}, Y_{i3}, ..., Y_{in}.
\]

Where \( i \) represents different cases of the same cross-sectional accounting numbers defined by \( j \). A financial ratio is established by the combination of \( X_{ij} \) and \( Y_{ij} \) in a form which is expressed as follows:

\[
R_{ij} = \frac{X_{ij}}{Y_{ij}} \quad \text{Eq-1}
\]
The distributional characteristics of $R_{ij}$ is influenced therefore by both $X_{ij}$ and $Y_{ij}$, and may take an entirely different form from that of $X_{ij}$ and $Y_{ij}$.

**Financial ratio models**

Ratio models are mathematical expressions that linearly combine several weighted financial ratios to provide a single score, described as a Z-score, which is employed in positive evaluation. The output of the model is a forecast of the potential for a contractor's organisation to continue in business as a going concern. The input of the model is historical financial data. Ratio models in existence were developed by the multivariate statistical technique of logistic regression or discriminant analysis. There is as yet no clear empirical evidence indicating that any one of the methods is superior to the other. Efron (1975) argued that discriminant models were more efficient for classification than those employing logistic regression. Researchers in both general business (Edmister, 1972; Altman, 1983; Taffler, 1983; Keasey and Watson, 1986), and the construction sector (Mason and Harris, 1979; Kangari, 1988; Abidali, 1990; Russell and Jaselski, 1992; Langford et al., 1993; Ramsey-Dawber, 1993; Edum-Fotwe, 1995), have directed considerable effort toward the development and application of the ratio models for assessing companies. Ratio models have been developed to address a variety of performance evaluation, and decision-making contexts. These include analysis of securities, audit evaluation, bond rating, and commercial credit scoring. So far, ratio models developed for the construction industry have directed attention only at the early identification of potential bankrupt companies to minimise stakeholders' risk. These developments have followed the pioneering work of Altman (1983) which utilised the discriminant technique to establish a five parameter model for predicting the potential for bankruptcy. Altman's approach was subsequently employed by other ratio model developers including Taffler (1983), Abidali (1990), and Robertson (1984). The next section examines a fundamental assumption on which the development of the ratio models are based.

**Distribution assumptions for ratio modelling**

Ratio models are generally constructed by the technique of multi-discriminant analysis. The fundamental assumption of this technique is that the independent variables or attributes employed in estimating the models are characterised by a normal distribution. Significant violation of this assumption can result in an inefficient model. There is no evidence from previous model developers regarding the condition of normality for their data. As such, it would appear that ratio models have been constructed on the basis that financial ratio data were both univariate and multivariate normally distributed. This assumption has been shown to be unreliable (Karels and Prakash 1987, Frecka and Hopwood 1983, Watson 1990). In particular, Deakin (1976) analysed eleven financial ratios for univariate normality, and concluded that only one could be described as exhibiting some acceptable degree of normality. The condition of normality is essential for the consistent application of the multi-discriminant technique. The assumption of normality, without empirical validation, may be an important contribution in explaining the inefficiency of existing ratio models. Thus, the normality of the attributes needs to be investigated to ensure that the models are constructed with normal or reasonably near-normal variables.

**Improving ratio models**

Although various attempts have been made at improving the predictive ability of ratio models, none of these have given particular consideration to identifying the nature of distributional properties of the financial ratios, from which empirical data these models are estimated. For instance, Argenti (1980), elected to use other managerial factors, (which he described as A-scores) in combination with financial ratio models. Others, including Mason and Harris (1979) and Abidali (1990) adopted the incorporation of trends, as part of the independent variables for their ratio model. Also, data quality
improvement techniques, such as the removal of outliers and transformations, have been suggested by some investigators as a way of ensuring a reduction in the effects of non-normality, and thereby, enhance the statistical validity of the models (Frecka and Hopwood 1983).

Investigating normality of financial ratios
Investigation of the normality of cross-sectional financial ratios was previously undertaken by Edum-Fotwe et al. (1995a). The investigation adopted the Shapiro-Wilk (W) test for analysing the financial ratio attributes. This test has been shown to be an effective procedure for evaluating the assumption of normality against a wide spectrum of non-normal alternatives (Shapiro et al., 1968). The chi-square which is the most popular test for assessing the normality of empirical data, was not employed for the simple reason that, the chi-square procedure relies on knowing the population parameters. The usual practice is to use the sample mean and variance as the 'true' estimates of their population counterparts. The possibility of mis-specification due to such estimation of the population parameters, from a sample which does not give the most likely estimates, can influence the outcome of the investigation, and hence any subsequent analysis. Financial data, the population from which the samples are drawn for the analysis, can be described as continuous or infinite. Hence, its population parameters are 'unknown', and the chi-square test can, therefore, produce test results that could be mis-leading. The W-test does not depend on the population parameters being known, and is therefore considered more suitable. Additionally, the W-test is scale and origin invariant, and so eliminates the problem of accepting a biased sample. Based on the distribution of the sample, the W procedure tests the null hypothesis

\[ H_0 : \text{the parent population is normal, against the alternative} \]
\[ H_1 : \text{the parent population is not normal.} \]

A detailed description of the test has been provided by Hahn and Shapiro (1994), and reproduced by Edum-Fotwe (1995). Edum-Fotwe et al. (1995a) also provided an outline of the various treatments to improve the normality and quality for their data, in addition to the data source employed. Figure 1 presents the comparative improvement in normality for the ratio samples after subjecting them to various forms of treatments. This shows a considerable increase in normality for the samples of financial ratios, after they had been subjected to data improvements. Notwithstanding this improvement, some of the samples still exhibited non-normality after treatment.

![Figure 1: Proportion of ratios exhibiting normality after treatment (Edum-Fotwe et al. 1995a)](image-url)
The improved ratio samples were employed in developing a ratio model for identifying potentially bankrupt contracting organisations. This was based on a concept of different phases for a contractors' financial profile, instead of the simplistic bankrupt/not bankrupt approach adopted by many of the models. A four phase profile was adopted for the model as follows: financially sound phase; starting phase of failure; intervening phase of failure; and final phase of failure. The resulting model based on this four phase profile, and which utilised the improved ratios was designated as sequential ratio model. Its name reflects the approach in which the model is applied. Evaluating a contractor with it required the application of three linear discriminant equations in sequence. The three equations employed input variables of annual ratio differences ($Z_d$), three-year averages ($Z_a$), and the basic ratios ($Z_b$), in the form shown below.

\[
Z_d = C_{d0} + \sum_{i=1}^{n} C_{di} X_i \\
Z_a = C_{a0} + \sum_{i=1}^{n} C_{ai} X_i \\
Z_b = C_{b0} + \sum_{i=1}^{n} C_{bi} X_i
\]

Where $Z_d$, $Z_a$, $Z_b$, are dimensionless measures for classification; $C_{jo}$, $C_{ji}$, ($j = d, a, b$), represent the discriminant coefficients for each function; and $X_i$ refers to ratio variables. Equation 2 represents the discriminant function of annual ratio differences. This classifies between a financially sound phase and the starting phase of failure. Equation 3 represents the discriminant function of three-year averages ratios, to classify between the initial distress phase and the intervening phase; and Equation 4, the discriminant equation of basic ratios, to classify between the intervening phase and the potential imminent phase of failure (final phase).

The classification criteria and examples of corporate evaluations with the sequential model can be found in Edum-Fotwe (1995). Table 1 presents comparative evaluations

<table>
<thead>
<tr>
<th>COMPANY</th>
<th>Z-value</th>
<th>Z-value</th>
<th>ABDALI</th>
<th>SEQUENTIAL MODEL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zd</td>
<td>Za</td>
<td>Zb</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>-2489.52</td>
<td>31591.58</td>
<td>Failed</td>
<td>GLTP 1.66 1.24 0.86 Failed</td>
</tr>
<tr>
<td>B</td>
<td>-1193.86</td>
<td>-2067.33</td>
<td>Failed</td>
<td>Failed 2.37 1.88 1.81 Intermediate</td>
</tr>
<tr>
<td>C</td>
<td>-1537.91</td>
<td>-874.09</td>
<td>Failed</td>
<td>1.93 1.29 1.64 Intermediate</td>
</tr>
<tr>
<td>D</td>
<td>-1502.58</td>
<td>35.53</td>
<td>Failed</td>
<td>GLTP 1.91 1.49 0.75 Intermediate</td>
</tr>
<tr>
<td>E</td>
<td>-1581.56</td>
<td>-720.30</td>
<td>Failed</td>
<td>2.12 2.72 2.49 Intermediate</td>
</tr>
<tr>
<td>F</td>
<td>-984.26</td>
<td>-8610.74</td>
<td>Failed</td>
<td>2.05 1.87 1.41 Intermediate</td>
</tr>
<tr>
<td>G</td>
<td>-454.32</td>
<td>-299.60</td>
<td>Failed</td>
<td>2.25 2.36 2.21 Intermediate</td>
</tr>
<tr>
<td>H</td>
<td>-3171.33</td>
<td>-307.38</td>
<td>Failed</td>
<td>2.14 1.84 1.26 Intermediate</td>
</tr>
<tr>
<td>I</td>
<td>-2151.53</td>
<td>-612.97</td>
<td>Failed</td>
<td>2.15 2.34 1.86 Intermediate</td>
</tr>
<tr>
<td>J</td>
<td>-1996.99</td>
<td>-5144.14</td>
<td>Failed</td>
<td>1.66 1.07 0.81 Failed</td>
</tr>
</tbody>
</table>

251
two other models developed for the construction industry, with the sequential model. This was based on the 1992 financial reports of ten large construction contracting organisations. Eight of the ten companies were evaluated as intermediate, and two companies as showing potential for failure, by the sequential model. By the end of 1994 nine of the ten companies were still trading, reflecting largely the evaluation of the sequential model. The Abidali model correctly evaluated one company as having *Good long term prospects* (GLTP). However, it also classified as having good long term prospects, the only company in the test sample that experienced severe financial crises two years later. Otherwise all the other companies in the sample were inaccurately evaluated as failed by the Abidali model. The Mason and Harris model presented the greatest inaccuracy. It evaluated all the ten companies in the sample as exhibiting characteristics of failed companies. The fact that one company was mis-classified by the sequential model, perhaps reflects the need to appreciate the underlying distributions that characterise financial ratios for the purposes of modelling.

**Fitting of natural distributions to financial ratios**

The fitting of distributions to data has a long history, and many different procedures have been advocated. The most common and widely employed of the different procedures is the normal distribution. Hahn and Shapiro (1994) account for the popularity of the normal distribution by outlining that the central limit theorem leads one to expect this distribution to provide a reasonable representation for many, but not all, phenomena which is measurable in numerical terms.

The statistical distribution of financial ratios is important when undertaking cross-sectional analysis. Primarily, if the mean and standard deviation of a particular distribution are known, and that the distribution approximates to normality, then it is possible to determine the relative position of a specific company ratio within the industry distribution.

Practically all earlier developers of cross-sectional ratio models therefore, attempted to fit their empirical data to one single theoretical distribution; the normal distribution, for the reason outlined above. These include the works of Altman (1983), Taffler (1983), Mason and Harris (1979), Abidali (1990), and Edum-Fotwe (1995).

Edum-Fotwe et al. (1995a) also reported the prevalence of outliers in empirical distributions of construction contractors' financial ratios. Following the guidelines of Frecka and Hopwood (1983), the method of outlier removal was adopted to enhance the normality of the empirical data which was subsequently employed in sequential ratio modelling by Edum-Fotwe et al. (1995b). Knowledge of the existence of extreme outliers in a distribution allows the determination of their impact upon the mean of a ratio. For example, if a certain ratio is characterised by a number of extreme outliers, either positive or negative, then a comparison of a company's ratio against the classification criteria developed for such a ratio might be potentially misleading, since this benchmark might have suffered some distortion. Indeed it is important to appreciate the implications for inter-firm comparisons for an industry, when the distribution for a ratio exhibits non-normality and is characterised by extreme outliers. In such a situation, it would seem inappropriate to use the mean value as a benchmark for evaluation (Bougen and Drury 1980). The decision regarding which classification criteria should be the benchmark for the industry depends crucially on identifying the natural distributions of the financial ratios employed for the models.

In addition to the importance of ratio distributions for the classification criteria, one should also appreciate the significance of non-normality in the choice of statistical tools for empirical analysis. There is considerable impact of the effect of non-normality for univariate least squares regression analysis and the subsequent t-distribution significance tests. When employed for multivariate models, to which most contemporary financial ratio models for corporate evaluations conform, the effects
become even more amplified. The non-transformed use of financial ratios in most multivariate models is dependent upon the distributions of the ratios being normal, and since this requirement is often not met, alternative techniques need to be found in order to ensure better accuracy for the resulting prediction models (Bougen and Drury 1980).

Other distributions that have been known to characterise real life data include the gamma, log-normal, and beta distributions. These examples and other such statistical formulations lead to a wide diversity of distribution shapes which provide a desirable generality for investigating the properties of financial ratios. For all the different distributions, it is possible to define a plane \((\beta_1, \beta_2)\) such that \(\beta_1\) and \(\beta_2\) respectively represent the square of the standardised measure of skewness, and the standardised measure of peakedness, for a particular distribution. Figure 2 shows the regions in the \((\beta_1, \beta_2)\) plane for the different distributions.

These are the normal, beta (for which the uniform distribution is a special case), gamma (for which the exponential distribution provides a special case), and the log-normal distributions. The t-distribution which is symmetric, is also indicated, and shows that it approaches the normal distribution as its degrees of freedom becomes arbitrary large. For all normal distributions, \(\beta_1=0\), and \(\beta_2=3\). Therefore the normal distribution is represented as a single point in the plane. Exponential and uniform distributions also, are characterised by single point parameters, and are similarly represented in the plane.

Figure 2: Regions in \((\beta_1, \beta_2)\) plane for various distributions (Richard Shapiro 1994)
The gamma, log-normal and t-distributions are defined by curves. Thus, gamma distributions can be fitted for all values of \( \beta_1 \) and \( \beta_2 \) that have co-ordinates located on the curve. The curve for the gamma distribution is close to that for the log-normal, especially for small values of \( \beta_1 \). According to Hahn and Shapiro (1994), this explains the fact that empirical data can frequently be fitted equally well, or poorly, by either the gamma or log-normal distributions. The beta distribution, which has two shape parameters, occupies a region, and provides greater generality than any of the other distributions. In addition, there is a large region of values of \( \beta_1 \) and \( \beta_2 \) that is not covered by any of the above distributions, which is described by Hahn and Shapiro (1994) as the impossible region. Empirical data with parameters lying in this region, which are modelled by the normal distributions are likely to lead to spurious predictions.

The rationale for this investigation is to obtain for the various distributions of financial ratios defined by \( R_{ij} = \frac{X_{ij}}{Y_{ij}} \), the corresponding co-ordinates \( (\beta_{1ij}, \beta_{2ij}) \). By plotting the co-ordinates for several empirical cross-sectional samples of the same financial ratio, it is possible to identify the natural distributions that characterise these different financial ratios. Utilising the identified distributions for ratio modelling should ensure better performance of the resultant ratio models by the minimising the degree of spurious classification.

**Conclusions**

The paper has examined some considerations relating to the development of financial ratio models. The empirical evidence therefore indicates that the distribution of financial ratios conform to non-normality, which is caused by varying degrees of skewness and the existence of extreme outliers. This lack of conformity to the requirements of normality for a significant proportion of the financial ratios contained in the models, partly explains their inability to perform efficiently. Although the various improvement techniques considerably enhanced the normality of the data, their application to financial ratios significantly alters the natural distributions of these ratios. Any model estimated from such enhanced data therefore, cannot be relied on to achieve the degree of accuracy desirable for widespread adoption of ratio models in the industry.

In contrast to previous developments in ratio modelling, this paper advocates the investigation of the natural distributions of the financial ratios employed in estimating the models. It is possible to identify the different distributional characteristics by employing the \( (\beta_1, \beta_2) \) plane. This approach will not only conveniently model the outliers, but also provide a means to overcome the problem of non-normality that adversely affects the estimation of classification criteria employed with ratio models, which often cause spurious predictions.

**References**


