ELSEVIER

Journal of Banking & Finance 19 (1995) 45–60

Journal of BANKING & FINANCE

Financial ratio proportionality and inter-temporal stability: An empirical analysis

P.S. Sudarsanam, R.J. Taffler *

City University Business School, Frobisher Crescent, Barbican Centre, London EC2Y 8HB, UK

Received April 1991; final version received July 1993

Abstract

A major reason for the widespread use of the ratio transform in financial analysis is to control for company size. The primary condition for achieving size control is that the ratio numerator bears a strictly proportionate relationship with the denominator. This paper seeks to provide empirical evidence on how far commonly used financial ratios satisfy the proportionality condition and how serious violations of that condition are in practice, using the Box–Cox generalised functional form methodology. Twenty-four commonly used ratios are considered and separate analyses are conducted for six distinct industries and for a large pooled sample of over 500 companies. The inter-temporal stability of the relationship between ratio components across two years, from a low to a high point in a recent UK economic cycle, is also explored. The results show that the proportionality condition is not satisfied for any of the ratios examined. For half the ratios studied loglinearity is a better description of the ratio component relationship and this provides support for the use of the industry median in ratio analysis. The huge variation in the functional relationship of ratio components between one industry and another and over time indicates that great care is necessary in the use of financial ratios in inter-industry and inter-temporal comparisons.

Keywords: Ratio analysis; Size control; Proportionality; Median benchmark

JEL classification: M41

* Corresponding author. Tel.: (44) 171-477-8630. Fax: (44) 171-477-8648.

SSDI 0378-4266(94)00044-1

1. Introduction

One of the major reasons for using financial ratios in preference to raw accounting numbers is the need to control for the effect of size. For ratio transformation to achieve this, strict proportionality between the numerator and the size deflator must exist (Lev and Sunder, 1979). McDonald and Morris (1984; 1985) address certain aspects of this issue empirically using four ratios. They conclude that the proportionality condition is satisfied for some of the ratios for their utilities sub-sample but not for the more heterogeneous all-industry sample. Their study emphasises the need for examining the issue within individual industries as well as across industries. McLeay and Fieldsend (1987), reporting an indirect test of proportionality for a sample of French firms, reinforce this need.

Equally important is the question of whether the relationship between financial ratio numerators and deflators, proportionate or otherwise, is stable over time [1]. Since the relationship between the numerator and denominator in a financial ratio also reflects economy-wide events external to the firm it may change when these conditions vary. Inter-temporal instability in the ratio relationship will render ratio comparisons over time invalid. For example, in those years in which the proportionality condition is satisfied ratio transformation of raw variables is valid whereas in other years when that condition breaks down such transformation is inappropriate.

This study addresses empirically the above concerns about the validity of financial ratio analysis using a large sample of UK companies and a substantial sample of commonly used financial ratios. Its conclusions have practical implications for both univariate inter-firm financial ratio comparison and for multivariate financial ratio-based models.

This paper tests for the degree of conformity of 24 commonly used financial ratios with the assumptions underlying valid ratio transformation. Study of the distributional characteristics of financial ratios must be based on an understanding of the relationship between the ratio components (Tippett, 1990). Our focus is, therefore, on this underlying relationship. We employ the generalised Box–Cox transformation procedure to identify the underlying functional relationship between ratio components. To explore the industry factor, we separately investigate six distinct industry sub-groups. To help analysts choose among different size deflators, the relative merits of the three most commonly employed size measures are also specifically compared. This study, in addition, examines the temporal

[1] Fieldsend et al. (1987) have explored the proportionality and temporal stability issues but their study is limited to just one ratio. They also use a different methodology from that employed in our study.

stability of the underlying ratio relationships using data from two separate years representing, respectively, the low and high points in the economic cycle.

The results show that in none of the cases examined is the numerator-denominator relationship consistent with the proportionality assumption. However, in a substantial number of cases logarithmic transformation of the ratio components results in a proportionate relationship. Both results are consistent with the view that accounting ratios are in general unlikely to satisfy the proportionality condition and that for many accounting ratios the lognormal may be a better description of the underlying distribution (McLeay, 1986 and Tippett, 1990). The latter conclusion also lends support to the practice of using the ratio median, rather than the mean, as a measure of central tendency in ratio analysis.

The examined ratios do not exhibit the same functional relationship across different industry groups. Further, we observe a substantial variation in the functional relationship between ratio components over time suggesting that intertemporal ratio comparisons may be seriously flawed. Our results, therefore, call for circumspection in the use of simple and untransformed financial ratios by analysts.

2. Methodology

The implicit reason for employing financial ratios is to control for the effect of firm size and thereby measure the non-size related residual variation in the variable concerned either across companies or on a time series basis. For ratio transformation to achieve size control the numerator or financial variable transformed must bear a strictly proportionate relationship to the size deflator or ratio denominator (Lev and Sunder, 1979).

The proportionality condition requires the relationship between the ratio numerator and deflator to be of the form

$$Y = \beta' X \tag{1}$$

Lev and Sunder (1979) discuss potential sources of deviation from proportionality including non-homogeneity and non-linearity. When such deviations exist size deflation will still leave the resulting ratio a function of size. Non-linearity in the relationship between numerator and size deflator can, in theory, take a number of different forms and *ex ante* the true functional form is generally unknown. Further, if the ratio components are random variables the relationship between them will in the linear case be of the following form inclusive of an error term:

$$Y_i = \beta'' X_i + \epsilon_i \tag{2}$$

where $\mathrm{Var}(\epsilon_i) = k X_i^2$ and k is a constant. If the error term is homoscedastic or its heteroscedasticity is of a different form, valid ratio transformation for size control is not possible (Lev and Sunder, 1979).

In this study the existence of non-homogeneity and non-linearity is examined by fitting the following generalised functional form (GFF) equation:

$$Y_i^{(\Theta)} = \alpha + \beta X_i^{(\Theta)} + \delta_i \tag{3a}$$

where i refers to the i'th observation and $X^{(\Theta)}$ is a Box–Cox transformation (see Box and Cox, 1964), defined as:

$$X^{(\Theta)} = \begin{cases} (X^{\Theta} - 1)/\Theta & \text{if} \quad \Theta \neq 0 \\ \ln X & \text{if} \quad \Theta = 0 \end{cases} \tag{3b}$$

Under the Box–Cox procedure the transformation parameter, Θ, is estimated using a maximum likelihood method. The likelihood function for Equation (3a) is

$$L\max(\hat{\Theta}) = -n\log\hat{\sigma}_{\delta}(\Theta) + (\Theta - 1)\sum_{i=1}^{n}\log Y_i + C \tag{4}$$

where n is sample size, C is a constant and $\hat{\sigma}_{\delta}(\Theta)$ is the estimated regression residual standard error of Equation (3a) which is calculated after the power transformation (Lee, 1977). The optimum value of Θ is obtained by searching over a grid of values for Θ. Following the likelihood ratio method, an approximate 95% confidence interval for Θ can be obtained from the relationship in Equation (5):

$$L\max(\hat{\Theta}) - L\max(\Theta) < (1/2)\chi^2(0.05) = 1.92 \tag{5}$$

where the χ^2 statistic has one degree of freedom and $\hat{\Theta}$ is the maximum likelihood estimate of the hypothesised value of Θ. The 95% confidence region for Θ is used to determine the true functional form [2].

The value of $\hat{\Theta}$ indicates the functional relationship between Y and X. If $\hat{\Theta}$ is not significantly different from 1 the relationship is linear and if, additionally, α is not significantly different from zero (based on a Student's t-test), the relationship is proportionate. These two parameter values are required to satisfy the proportionality condition for valid ratio transform, Y/X, to control for the size effect. If $\hat{\Theta}$ is not significantly different from 0, the relationship between Y and X is loglinear. For other values of $\hat{\Theta}$, the relationship assumes more complicated non-linear forms. Thus both the linear and loglinear forms are special cases of the Box–Cox power transformation.

The Box–Cox transformation seeks to correct simultaneously for non-linearity between Y and X as well as for non-normality and heteroscedasticity in the error

[2] The Box-Cox GFF transformation has been employed in economics (Chang, 1977), finance (Lee, 1977; Fabozzi et al., 1980 and McDonald, 1983) and accounting (McDonald and Morris, 1985).

term, ϵ_i in Equation (2) (Zarembka, 1974) [3]. Following the power transformation, any model misspecification is tested for with the Durbin–Watson (DW) statistic [4].

2.1. Test of inter-temporal stability

Previous studies have examined the inter-temporal stability of financial ratios from different perspectives with regard to: ratio factor patterns (Pinches et al., 1973 and Ezzamel et al., 1987) and ratio models in bankruptcy prediction (Mensah, 1984; Izan, 1984 and Platt and Platt, 1990). Stability of ratios is, however, predicated upon the stability of the underlying functional relationship between the ratio components. For valid inter-temporal comparison of ratios, say, return on assets or sales margin over several years, the underlying proportionality relationship between ratio components must remain unaltered. This is certainly the tacit assumption of many analysts who employ accounting ratios for inter-temporal comparison purposes.

To test the validity of this implicit assumption, we identify the functional form of the relationship between ratio components using the Box–Cox power transformations for two different years at different points in the economic cycle. If the transformation parameter, Θ, is the same for both years we may infer that the functional form of the relationship is preserved.

2.2. Further tests of the loglinear relationship

When Θ in Equation (3a) is not significantly different from zero, the relationship is loglinear and Equation (3a) becomes:

$$\ln Y_i = \alpha + \beta \ln X_i + \delta_i \tag{6}$$

If $\beta = 1$ then,

$$\ln(Y/X)_i = \alpha + \delta_i \tag{7}$$

$$(Y/X)_i = \exp(\alpha + \delta_i) \tag{8}$$

Study of the lognormal is of particular interest from both empirical and theoretical perspectives. A number of studies have shown empirically that at least some accounting ratios are lognormally distributed (Deakin, 1976 in the US and McLeay, 1986 and Ezzamel and Mar-Molinero, 1990 for the UK). Tippett (1990) demonstrates, theoretically, that, if the ratio components are generated by either of two standard stochastic processes – a 'geometric' Brownian motion or an elastic random walk – the resulting ratio will not satisfy the proportionality assumption and will be lognormally distributed. Thus the lognormal appears to be a more

[3] This means that, if the transformation parameter $\Theta = 1$, the residuals of the linear form of Equation (3a) must be tested for heteroscedasticity of the form Var $(\delta_i) = kX_i^2$ where k is a constant.

[4] See Gujarati (1988, chapter 13) for a discussion of the DW statistic to test for model misspecification in general.

appropriate description of a ratio distribution. Lev and Sunder (1979) argue that when ratio components are lognormally distributed the resulting ratio distribution is also lognormal. A specific focus of this study is on whether the Box–Cox transformations yield a lognormal relationship.

The ordinary least squares estimate of α is the average of the logarithms of the ratios:

$$\alpha = 1/n \sum \ln(Y/X)_i \tag{9}$$

Thus an estimate of the characteristic value, $\exp(\alpha)$, is the geometric mean of the ratios (Fieldsend et al., 1987). For a lognormally distributed variable the geometric mean is also the median thus justifying the use of the median as the central tendency for ratios which are lognormally distributed. Use of ratios and that of the median as the benchmark can, therefore, be validated if β is not significantly different from one in Equation (3a). For those ratios whose components are loglinearly related we test whether β is indeed equal to one [5].

3. Data samples and variables

3.1. Ratio variables

The data used in this study is drawn from the EXSTAT computerised database of UK financial information provided by Extel Financial Ltd, London. The two test years selected for analysis are years ending the 15th of June 1981 and the 15th of June 1986 (hereafter referred to as 1981 and 1986) [6]. The 514 fully listed manufacturing companies with complete data for both these years represent the final sample. To test the hypotheses of interest, ratio selection is based on criteria of widespread use both in the financial literature and in practical financial analysis (Lev, 1974; Foster, 1986). Also, it is intended to achieve a broad representation of the various dimensions of corporate financial structure such as profitability, cash flow, activity, capital intensity, gearing and liquidity (Taffler and Sudarsanam, 1980; Chen and Shimerda, 1981; Bowen et al., 1987; Ezzamel et al., 1987). The sample ratios are listed in Table 1.

[5] It has been argued that accounting variables are likely to be lognormally distributed (Ijiri and Simon, 1977 and McLeay, 1986). In this study we have not tested for the lognormality of the ratio components but only for the loglinearity of the relationship between them. Where the components are not lognormal, loglinearity is unlikely to obtain.

[6] Barron (1986) indicates that 15th June is likely to be optimal for financial statement analysis of the kind dealt with in this study.

Table 1
List of ratios

1. WC/S	9. PB/TA	17. WC/NW
2. PB/S	10. CF/TA	18. PB/NW
3. CF/S	11. S/TA	19. CF/NW
4. NW/S	12. CA/TA	20. CA/NW
5. CA/S	13. QA/TA	21. QA/NW
6. QA/S	14. TD/TA	22. TD/NW
7. IN/S	15. TL/TA	23. TL/NW
8. WC/TA	16. IN/TA	24. IN/NW

Key and Definition
1. CF = Cash flow = Net income for ordinary shares + depreciation and amortisation.
2. WC = Working capital from operations = CF + provisions for deferred tax, doubtful debts, pensions and other provisions – associate company profits net of corporation tax + minority interests – government grants.
3. PB = Profit before interest and tax.
4. NW = Net worth = Ordinary shareholders funds – intangibles.
5. CA = Current assets.
6. QA = Quick assets = Current assets – inventory.
7. IN = Inventory
8. TD = All interest bearing debt including bank overdraft and capitalised finance leases.
9. TL = Total liabilities = long term + short term liabilities.
10. S = Sales, TA = Total tangible assets.

3.2. Data samples

Many studies (e.g. Frecka and Hopwood, 1983 and McDonald and Morris, 1985) use pooled samples of manufacturing companies. However, the industry construct is widely employed to facilitate inter-firm comparisons. The assumption is that firms within the same industry are homogeneous with regard to such economic factors as technology, supply and demand for inputs and outputs etc. relative to firms in other industries and that, by comparing firms within the same industry, the effects of such factors are held constant [7].

Because of the importance of the industry framework, separate analyses of six different industry samples are carried out in addition to that of the pooled, heterogeneous sample of all industries (termed here the ALL sample). The six industry groups analysed are those with a minimum of 25 member firms in the full sample of 514 companies to facilitate meaningful statistical inferences. The industries are: Engineering (ENGG), Construction (CONS), Electricals (ELEC),

[7] Sudarsanam and Taffler (1985) discuss the empirical evidence on industry homogeneity for the UK in terms of a number of these factors. See also Foster (1986, chapter 6).

Textiles (TEXT), Clothing (CLTH) and Breweries (BREW). The selection of industry groups is based on the London Stock Exchange Industrial Classification (SEIC) [8].

The Box–Cox transformation cannot be applied to observations with non-positive values. For this reason, the sample size is truncated in the case of the profitability numerators, WC (working capital from operations), PB (profit before interest and tax) and CF (cash flow), and the debt numerator, TD (total debt). Consequent loss of cases was small for most of the six industries [9,10].

4. Results

4.1. Functional relationship between ratio components

Tables 2 and 3 present estimates of the Box–Cox transformation parameter, Θ, for the two years 1981 and 1986. The estimates are first tested against the hypothesis of $\Theta = 1$ (the linear form) and it is rejected in every case [11]. They are then tested against the alternative hypothesis of $\Theta = 0$ for the loglinear relationship. The significance indicators in Tables 2 and 3 relate to this loglinear hypothesis. The tables also indicate whether the residuals from Equation (3a), conditional upon Θ, are normally distributed. The Durbin–Watson statistic is not significant at the 5% level except in a very small number of cases – 7.7% in 1981 and 3.6% in 1986 – thus confirming that the transformed equation is correctly specified (see Note 4 to Tables 2 and 3). The explanatory power of the Box–Cox

[8] Apart from ENGG (SEIC code 27), CONS (18) and CLTH (59) other industries are formed out of two or more closely related industries. Thus ELEC consists of Electrical (19) and Light Electronics (35); BREW of Breweries (45) and Wines and Spirits (46); TEXT of Cotton and Synthetic (60), Wool (61) and Miscellaneous Textiles (62). Such amalgamation is done to increase sample sizes.

[9] This truncation violates the assumption of normality concerning the residual distribution in Equation (3a). However, if the extent of truncation is small the Box-Cox transformation still provides a good approximation to the true functional form (see Judge et al., 1985, chapter 12). This truncation is a problem with profitability ratios especially in times of economic recession when negative values for the numerators, e.g. profit or cash flow, are more likely. Our results based on truncated data should be interpreted with this caveat in mind.

[10] The full sample is 514 but, with WC, PB, CF and TD, the sample size varies between 443 and 458. In ENGG, the complete sample is 54 and with the above four numerators it varies between 44 and 48. For the other five industry samples the complete samples (range for the above four numerators) are: CONS: 50 (44 to 46); CLTH: 29 (19 to 22); ELEC: 38 (30 to 34); BREW: 28 (27 to 28) and TEXT: 31 (24 to 27).

[11] Because of this any further test of residual heteroscedasticity is redundant and hence not carried out.

Table 2
Estimates of Box–Cox transformation parameter, Θ (1981)

	Industry													
	ENGG		CONS		CLTH		ELEC		BREW		TEXT		ALL	
NR		N		N		N		N		N		N		N
Panel A: Deflator = TA														
WC	0.00 *		0.21		0.46		0.16		0.24		0.18		0.15	n
PB	0.20		0.07 *		0.32	n	0.18		0.43		0.07 *		0.18	n
CF	−0.01 *		0.18		0.16 *		0.24	n	0.36		0.15 *		0.11	n
S	0.04 *		0.15 *		0.26 *		0.02 *		0.13 *		0.30		0.02 *	n
CA	0.35		0.07 *		0.47	n	0.24		0.10 *		−0.07 *		−0.03 *	n
QA	0.11		0.15 *		0.08 *		0.21		0.10 *		0.14 *		0.05	n
TD	0.12 *		0.16 *		0.24		0.28		0.23		0.02 *		0.21	n
TL	0.09 *	n	0.29		0.13 *		0.27		0.08 *	n	0.17		0.08	n
IN	0.22	n	0.15		0.66	n	0.10		0.14 *		0.07 *		0.07	n
Panel B: Deflator = S														
WC	−0.03 *		0.04 *		0.47	n	0.05 *	n	0.16	n	0.18		0.13	n
PB	0.15	n	−0.02 *		0.31		0.16	n	0.24		0.09 *		0.14	n
CF	−0.06 *		0.02 *		0.38 *		0.16	n	0.22		0.15 *		0.09	n
NW	−0.01 *		0.14 *		0.36	n	0.11 *		0.12 *		0.12 *		0.02 *	n
CA	−0.07 *		0.09 *		0.46		0.06 *		0.32	n	0.21 *	n	0.03 *	n
QA	0.05 *		0.13		0.21 *	n	0.08 *	n	0.23		0.20		0.07	n
IN	0.04 *		0.12 *		0.45		0.22		0.25	n	0.17 *		0.07	n
Panel C: Deflator = NW														
WC	0.05 *		0.23		0.40		0.24		0.14 *		0.19		0.13	n
PB	0.22		0.09 *		0.28		0.19		0.13 *		0.20 *		0.16	n
CF	0.02 *		0.25	n	0.28 *		0.26		0.19 *		0.20		0.10	n
CA	0.09 *	n	0.13		0.29	n	0.18		0.09 *	n	0.04 *		−0.02 *	n
QA	0.05 *		0.14 *		0.11 *		0.13		0.05 *		0.09 *		0.01 *	n
TD	0.06 *		0.13 *		0.24		0.27		0.17	n	−0.01 *		0.18	n
TL	0.03 *		0.24		0.17 *		0.18		0.07 *		0.08 *		0.06	n
IN	0.16		0.14	n	0.42		0.29	n	0.13 *		0.10 *		0.04	n

Notes:
1. NR = ratio numerator; for key to the codes see Table 1.
2. N = residual distribution; n means non-normal, otherwise it is normal (chi-square test of normality).
3. * Means Θ is not significantly different from zero at the 5% level.
4. The Durbin–Watson (DW) statistic was not significant at the 5% level except in the following cases:

Industry	*Significant*	*Indeterminate*	*Industry*	*Significant*	*Indeterminate*
ENGG	IN/TA	QA/TA,QA/NW	ELEC	–	CF/TA,WC/NW
CONS	TL/TA,CA/NW TL/NW	–	BREW	CA/TA,QA/TA CA/S, IN/S	QA/NW
CLTH	S/TA,CA/TA, QA/TA,TD/TA IN/S	NW/S,CA/S, TD/NW,IN/NW	TEXT,ALL	–	–

5. R^2 range is: ENGG (0.72 – 1.00); CONS (0.61 – 0.98); CLTH (0.29 – 0.98); ELEC (0.83 – 1.00); BREW (0.82 – 1.00); TEXT (0.72 – 0.99) and ALL (0.80 – 0.97).
6. Complete results are available from the authors.

Table 3
Estimates of Box–Cox transformation parameter, Θ (1986)

	Industry													
	ENGG		CONS		CLTH		ELEC		BREW		TEXT		ALL	
NR		N		N		N		N		N		N		N
Panel A: Deflator = TA														
WC	0.18		0.07 *		−0.41		0.09 *		0.15 *	n	0.24		0.13	n
PB	0.20		0.26	n	−0.11 *		0.18		0.25		0.26		0.18	n
CF	0.24		−0.02 *		0.25 *	n	0.04 *		0.17 *		0.25		0.14	n
S	0.06 *		0.20		0.34	n	−0.06 *		0.18		0.18 *		0.02 *	n
CA	0.29		−0.06 *	n	−0.09 *		0.20		0.21 *	n	0.06 *		−0.09	n
QA	0.06 *	n	0.26	n	−0.31		0.08 *		0.20 *		0.03 *		0.07	n
TD	0.16		0.19	n	0.32		0.06 *	n	0.22		0.39		0.17	n
TL	0.08 *		0.18		0.52		0.12		0.18 *		0.23	n	0.09	n
IN	0.16		0.05 *		0.18 *		0.16		0.22 *	n	−0.07 *		0.07	n
Panel B: Deflator = S														
WC	0.09 *		0.17		−0.10 *		0.05 *	n	0.14 *		0.17 *		0.13	n
PB	0.15		0.31		−0.02 *		0.16		0.20		0.20 *	n	0.17	n
CF	0.15		0.09 *		0.21 *	n	−0.00 *	n	0.16 *		0.18	n	0.13	n
NW	0.19	n	0.13 *		0.57		0.01 *		0.15 *	n	0.07 *		0.06	n
CA	0.04 *		0.19		0.09 *	n	−0.05 *		0.34		0.13 *	n	0.02 *	n
QA	0.07 *		0.20		−0.30		−0.02 *	n	0.35		−0.01 *	n	0.06	n
IN	0.07 *		0.17	n	0.46		0.11 *		0.31	n	0.18		0.10	n
Panel C: Deflator = NW														
WC	0.36		0.03 *	n	0.06 *	n	0.16		0.12 *	n	0.31		0.11	n
PB	0.22	n	0.21		0.33 *	n	0.19		0.19 *	n	0.48		0.17	n
CF	0.34	n	−0.02 *		0.27	n	0.15		0.16 *		0.27		0.13	n
CA	0.24	n	0.08 *		0.13 *		0.10 *		0.17 *	n	0.20		0.02 *	n
QA	0.27	n	0.20	n	−0.19 *		0.12		0.14 *	n	0.14 *		0.06	n
TD	0.13 *		0.17		0.35		0.07 *	n	0.18		0.31		0.16	n
TL	0.16	n	0.14		0.37		0.10 *		0.12 *		0.18		0.10	n
IN	0.20	n	0.09 *		0.29		0.10 *		0.20 *	n	0.14 *		0.07	n

Notes:
1. NR = ratio numerator; for key to the codes see Table 1.
2. N = residual distribution; n means non-normal, otherwise it is normal (chi-square test of normality).
3. * Means Θ is not significantly different from zero at the 5% level.
4. The Durbin–Watson (DW) statistic is not significant at the 5% level except in the following cases:

Industry	*Significant*	*Indeterminate*	*Industry*	*Significant*	*Indeterminate*
ENGG	CA/TA	–	ELEC	QA/TA	–
CONS	TL/TA,CA/NW, TL/NW	WC/NW,CF/NW	BREW	CA/S	CA/TA,QA/TA, QA/S,IN/S, QA/NW
CLTH	–	IN/S,CF/NW	TEXT	–	WC/TA
			ALL	–	–

5. R^2 range is: ENGG (0.55–1.00); CONS (0.67–0.98); CLTH (0.52–0.98); ELEC (0.74–1.00); BREW (0.79–0.98); TEXT (0.90–0.99) and ALL (0.76–0.97).
6. Complete results are available from the authors.

transformed regression models is also very high with R^2 significant at the 1% level or better in all cases (see Note 5 to Tables 2 and 3) [12,13].

From the above tables we observe that, in 48% of cases in 1981 and 45% of cases in 1986, the relationship between the ratio components is loglinear. In the remaining cases the relationship is neither linear nor loglinear [14].

4.2. Tests of the loglinear form

From Tables 2 and 3 we find that estimates of Θ, though statistically significantly different from zero, are fairly close to that value for several ratio components. This suggests that the loglinear form may provide a reasonable approximation to the underlying ratio relationship in such cases. Further, Section 2 above suggests that when the ratio components and the ratio are all lognormally distributed, the use of the ratio median as the central tendency requires that $\beta = 1$. To evaluate the sample ratios on this criterion, we fit the loglinear model to those ratios for which the loglinear is either the correct functional form (as indicated in Tables 2 and 3) or is a reasonable approximation (as described earlier). Adequacy of model specification and normality of the residual distribution are tested, respectively, using the Durbin–Watson statistic and the χ^2 test. Table 4 lists all the ratios for which the loglinear is a good fit and which also have a slope not significantly different from unity. In 67% of cases (covering six industries and two test years) loglinearity with a slope of unity provides an acceptable description of the underlying ratio component relationship.

4.3. Temporal stability of the functional relationship

Table 4 also shows that the loglinear relationship is not maintained across the two years in every case. We find only 49% of ratios (70 out of 144 in the six industries) with a consistent loglinear relationship. In the remaining cases the functional form varies from one period to another indicating instability in the ratio components' relationships.

[12] Due to space limitations, the R^2 statistic for each regression is not reported but only the R^2 range for each industry. R^2 values are mostly concentrated near the top end of the range with very few cases near the bottom.

[13] In estimating the GFF model parameters we have assumed that the ratio components are measured without error. This is probably unrealistic given the problems with accounting measurements. However, given the high R^2 of the regression models, the bias in parameter estimates may not be very serious (McDonald and Morris, 1985).

[14] When the transformation parameter Θ is significntly different from both 0 and 1 the ratio Y/X is still a function of size, X.

4.4. Choice of deflator

All the three deflators perform equally badly in terms of satisfying the proportionality condition. In terms of providing a more tractable framework for ratio analysis by permitting the use of the ratio median, TA (total assets), based on Table 4, does best with 69% of the cases (excluding ALL) for which the loglinear is acceptable. The corresponding figures for NW (net worth) and S (sales) are 67% and 62%. In terms of stability of the ratio relationship over time, with NW in 52%

Table 4
Ratios with loglinear component relationship

	Industry													
Ratio [1]	ENGG		CONS		CLTH		ELEC		BREW		TEXT		ALL	
	81	86	81	86	81	86	81	86	81	86	81	86	81	86
WC/TA	y [2]	y	y	y		y		y	y	y	y			
PB/TA			y		y	y	y		y	y	y			
CF/TA			y	y	y	y	y	y	y	y	y			
S/TA	y	y	y	y	y	y	y	y	y		y	y	y	y
CA/TA			y	y		y			y	y	y	y	y	
QA/TA		y	y		y	y	y	y			y	y		
TD/TA	y		y			y		y	y	y	y	y		
TL/TA		y		y	y	y	y		y	y		y		
IN/TA		y		y		y		y	y	y	y	y		
WC/S	y	y	y			y	y	y						
PB/S			y	y		y	y		y		y	y		
CF/S	y		y	y	y	y	y	y			y			
NW/S	y		y	y		y		y	y		y	y	y	
CA/S	y	y	y			y	y	y			y	y	y	y
QA/S	y	y	y		y	y	y	y	y		y	y		
IN/S	y	y	y	y		y					y	y		
WC/NW		y		y		y			y	y				
PB/NW			y	y	y	y			y	y	y	y		
CF/NW	y		y	y					y	y	y			
CA/NW	y		y	y		y	y	y	y	y	y		y	y
QA/NW	y		y						y	y	y	y	y	
TD/NW	y		y	y	y	y		y	y	y	y	y		
TL/NW	y		y	y			y	y	y	y	y	y		
IN/NW			y	y	y	y	y	y	y	y	y	y		
Consistency score [3]														
TA	2/9		4/9		5/9		3/9		7/9		5/9		1/9	
S	4/7		4/7		2/7		4/7		0/7		5/7		1/7	
NW	0/8		6/8		3/8		3/8		8/8		5/8		1/8	

Notes:
1. For key to the ratios and industries, see Table 1.
2. y means loglinearity provides a good fit and blank means otherwise.
3. Consistency refers to loglinearity holding in both years. The consistency score is the proportion of consistent ratios with the same deflator.

of cases the loglinear form is acceptable in both years. The corresponding figures for TA and S are 48% and 45%, respectively. It appears that while the performance of TA and NW is quite similar they both outperform S in terms of conforming to loglinearity.

Table 4 shows that the industry groups differ in terms of conformity with the loglinear form both across ratios and across time. They also differ in terms of the deflator which best ensures such conformity. For example, in BREW (Brewing), 7 out of 9 cases with TA and all 8 cases with NW satisfy the loglinear relationship in both years. In the same industry, with S, not a single ratio maintains a consistent loglinear relationship. The relative performance of the deflators in different industries is summarised at the foot of Table 4 ('Consistency score'). The conclusion must be that the choice of the deflator in ratio analysis is crucial and that the appropriate deflator is dependent on industry.

4.5. Problem of industry aggregation

Analysts often make judgments based on pooled multi-industry samples e.g. comparing a company's financial ratio with an economy-wide or stock market-wide ratio without questioning whether such industry aggregation is valid. Our purpose here is to contrast the results for individual industries with those for a pooled sample and to highlight the inappropriateness of using such heterogeneous samples in financial analysis.

The pooled manufacturing sample, ALL, performs worst of all the industry samples in terms of conformity with either the linear or loglinear functional form. Indeed, out of the 48 ratio cases (24 in each year), in only 9 (or 19% of) cases is the loglinear functional form acceptable and in no case is the linear the valid functional form (see Tables 2, 3 and 4). Even with these 9 cases, the loglinear form is consistently maintained over time only in three cases. This contrasts with the evidence for the separate industry groups discussed above.

This finding is consistent with the evidence reported by McDonald and Morris (1985) for their utility and all-industry samples. Using a similar GFF methodology to ours they find that homogeneity and linearity conditions are satisfied for their homogeneous sample of utilities, but not for their more heterogeneous all-industry sample. Given the wide variation among industries in terms of degree of satisfaction of the conditions for valid ratio transformation or for the use of the median as bench mark set out in Section 2, our results demonstrate that the analyst needs to pay careful attention to the industry construct in his or her use of financial ratio analysis.

5. Summary and conclusions

This study focusses on the validity of transforming accounting variables into financial ratios as is commonly done by financial analysts to control for company size. The assumption of proportionality implicit in such a transformation is examined for twenty-four common financial ratios formed with three widely employed deflators, Sales, Total Assets and Net Worth. The analyses are conducted for a pooled sample of 514 quoted UK industrial firms and for six distinct industry sub-samples for two separate years of data, 1981 and 1986. The identification of the underlying functional relationship between ratio components is carried out using the Box–Cox power transformation methodology.

Our results indicate that the relationship between ratio components is, generally, both non-proportionate and non-linear. In the majority of cases examined, loglinearity is a more valid description of that relationship. The evidence that most of our ratios exhibit loglinearity in component relationship suggests that they may be lognormally distributed. This is consistent with evidence from other studies that log transformation of accounting ratios improves their normality.

Further, perhaps not surprisingly, we find evidence of a substantial variation in the functional relationship between components of the same ratios across industries. This variation points to the danger in making inter-industry comparisons of company financial performance and condition using financial ratios and emphasises the need for analysts to be careful in their use of the financial ratio construct in practice. We also have evidence that the functional relationship of the ratio components changes over time within the same industry. While this is not altogether unexpected, it does imply that ratio transformation of the same variables may not be equally valid at different points in time. This has serious consequences for temporal comparisons of financial ratios.

Non-proportionality in component relationship may render the distribution of the resulting ratio skewed and non-normal (Barnes, 1982). Where such a ratio is an input to a statistical model requiring variable normality the validity of that model will be seriously weakened. Any understanding of the distributional characteristics of accounting ratios requires a thorough knowledge of the distribution of the ratio components and the stochastic processes which generate them (Tippett, 1990). In this paper we seek to shed some further light on the issue of ratio component distributions as a key to the behaviour of accounting ratios.

Acknowledgements

The authors wish to thank Ash Mahate for his excellent research assistance. The paper has benefited from the perceptive comments of two anonymous referees. Any remaining errors are the responsibility of the authors.

References

Barnes, P., 1982, Methodological implications of non-normally distributed financial ratios, Journal of Business Finance and Accounting 9 (1), 51–62.

Barron, M., 1986, Year-end heterogeneity in calculations of industry and economy averages of accounting numbers, Accounting and Business Research, Autumn, 275–284.
Box, G.E.P. and Cox, D.R., 1964, An analysis of transformations, Journal of the Royal Statistical Society, Series B, 26, 221–243.
Bowen, R.M., Bugstahler, D. and Daley, L.A., 1987, The incremental information content of accrual versus cash flows, Accounting Review LXII (4), Oct., 723–747.
Chang, H., 1977, Functional forms and the demand for meat in the United States, The Review of Economics and Statistics, Vol LIX, 355–359.
Chen, K.H. and Shimerda, T.A., 1981, An empirical analysis of useful financial ratios, Financial Management 15 (1), 51–60.
Deakin, E.B., III, 1976, Distributions of financial accounting ratios: some empirical evidence, Accounting Review, January, 90–96.
Ezzamel, M., Brodie, J. and Mar-Molinero, C., 1987, Financial patterns of UK manufacturing companies, Journal of Business Finance and Accounting 14 (4), 519–536.
Ezzamel, M. and Mar-Molinero, C., 1990, The distributional properties of financial ratios in UK manufacturing companies, Journal of Business Finance and Accounting 17 (1), 1–30.
Fabozzi, F.J., Francis, J.C. and Lee, C.F., 1980, Generalized functional form for mutual fund returns, Journal of Financial and Quantitative Analysis, XV, 5, 1107–1120.
Fieldsend, S., Longford, N. and McLeay, S., 1987, Industry effects and the proportionality assumption in ratio analysis: a variance component analysis, Journal of Business Finance and Accounting 14 (4), 497–518.
Foster, G., 1986, Financial Statement Analysis (Prentice Hall).
Frecka, T.J. and Hopwood, W.S., 1983, The effects of outliers on the cross-sectional distributional properties of financial ratios, Accounting Review 58 (1), 115–128.
Gujarati, D., 1988, Basic Econometrics (McGraw-Hill, New York, NY).
Ijiri, Y. and Simon, H.A., 1977, Skew Distributions and the Sizes of Business Firms (North-Holland, Amsterdam).
Izan, Y., 1984, Corporate distress in Australia, Journal of Banking and Finance 8, 303–320.
Judge, G.G., Hill, R.C., Griffiths, W.E., Lutkepohl, H. and Lee, T., 1985, Introduction to the Theory and Practice of Econometrics (John Wiley, New York).
Lee, C.F., 1977, Functional form, skewness effect and the risk-return relationship, Journal of Financial and Quantitative Analysis, March, 55–72.
Lev, B., 1974, Financial Statement Analysis (Prentice Hall).
Lev, B. and Sunder, S., 1979, Methodological issues in the use of financial ratios, Journal of Accounting and Economics 1, 187–210.
McDonald, W. and Morris, M.H., 1984, The statistical validity of the ratio method in financial analysis: an empirical examination, Journal of Business Finance and Accounting 11 (1), 89–97.
McDonald, W. and Morris, M.H., 1985, The functional specification of financial ratios: an empirical examination, Accounting and Business Research 15, Summer, 223–228.
McDonald, W., 1983, Functional forms and the capital asset pricing model, Journal of Financial and Quantitative Analysis 18 (3), 319–329.
McLeay, S., 1986, Student's t and the distribution of financial ratios, Journal of Business Finance and Accounting 13 (2), 209–222.
McLeay, S. and Fieldsend, S., 1987, Sector and size effects in ratio analysis: an indirect test of ratio proportionality, Accounting and Business Research 17, 66, 133–140.
Mensah, Y.M., 1984, An examination of the stationarity of multivariate bankruptcy prediction models: a methodological study, Journal of Accounting Research 22, 380–395.
Pinches, G.E., Mingo, K.A. and Caruthers, J.K., 1973, The stability of financial patterns in industrial organisations, Journal of Finance, May, 389–396.
Platt, H.D. and Platt, M.B., 1990, Development of a class of stable predictive variables: the case of bankruptcy prediction, Journal of Business Finance and Accounting 17 (1), 31–52.

Sudarsanam, P.S. and Taffler, 1985, Industrial classification in UK capital markets: a test of economic homogeneity, Applied Economics 17 (2), 291–308.

Taffler, R.J. and Sudarsanam, P.S., 1980, Auditing the board: a new approach to the measurement of company performance, Managerial Finance 5 (2), 127–147.

Tippett, M., 1990, An induced theory of financial ratios, Accounting and Business Research 21, 81, 77–85.

Zarembka, P., 1974, Frontiers in Econometrics (Academic Press, New York).