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INCORPORATING COMPLEMENTARY RATIOS IN THE ANALYSIS OF FINANCIAL STATEMENTS

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Abstract – Ratios are routinely used for extracting information from accounting reports. However, ratios present only part of the information available and can be easily complemented provided that information-technology facilities are accessible. This study infers the functional form of the information discarded by ratios. Then it develops extensions of ratios incorporating the discarded information, showing examples of their use and discussing the benefits obtained. Extensions of ratios seem promising as a facility attached to computerized databases of accounting reports. The concepts developed here are a step toward a more technology-supported analysis of financial statements.

Keywords: Financial statement analysis, Ratios, Accounting databases, Neural networks.

INTRODUCTION

Accounting reports are an important source of information for managers, investors, and financial analysts. Ratios are the usual instruments for extracting this information. They are supposed to remove the effect of size from accounting variables and to highlight noteworthy features of the firm, such as profitability or liquidity. Foster (1986) offers a detailed discussion of ratios in the analysis of financial statements.

Ratios present only part of the available information. In the first instance, ratios discard information regarding the size of the firm being analysed, thus allowing the comparison with other firms of different sizes, or with the same firm in previous periods. However, size is not the only piece of information discarded by ratios. They also discard information from which the effect of size has been removed.

This study infers the functional form of the *size-free* information discarded by ratios. Then it discusses its usefulness, showing that this information, being complementary to ratios, may be valuable for financial analysis. The consideration of both the ratio and the complement leads to extensions of ratios. Based on them, graphical representations of accounting features are developed and examples of their use in the analysis of financial statements are given. The last section of the paper uses a particular kind of Neural Network, the Self-Organized Map (Kohonen, 1986), to scan and discretize graphical representations. It also explains how this discretization is the first step toward automating the financial diagnosis of firms.

Computer-supported databases of accounting reports are widely employed in the analysis of financial statements (Board, Pope, & Skerratt, 1991; Dixon & Franks, 1992). These databases are oriented toward data manipulation: selecting, sorting, report generation. Other processing facilities are rudimentary, comprising the computation of a few ratios and industry averages. The concepts developed here are technology-oriented as their implementation requires more extensive use of graphical and processing power available. We expect to show that a thorough exploring of possibilities offered by the computerized support of accounting databases and a better understanding of the statistical characteristics of accounting data, lead to more accurate and easy analysis.

THE COMPLEMENT OF A RATIO

This section shows that, given two raw items, y and x, to be used as the numerator and the denominator of a ratio, the whole size-free information contained in them can be expressed in terms of the ratio itself, y/x, plus a complementary ratio. We also point out, based on the way some ratios are used in practice, that such a complementary ratio is likely to be valuable for financial analysis.

The size-free information contained in two raw items

Accounting raw items, as found in databases containing annual reports of firms, can be viewed as statistical variables. Each firm is a case. For a given item, for example, Fixed Assets or Sales, a collection of reports from the same year forms a cross-sectional sample.

Recent studies on the statistical characteristics of raw items have brought to light two facts. First, the probability density function governing raw items tends to be lognormal. Second, items belonging to the same report share most of their variability because the effect of size they share is prevalent (McLeay, 1986; Trigueiros, 1991). Therefore, the variability of logarithms of raw items x_i belonging to the same report, should be explained as the effect of size, σ, present in all of them, plus some extra variability, ε_i, particular to each raw item. That is, item i is explained as

$$\log x_i = \mu_i + \sigma + \varepsilon_i \tag{1}$$

The μ_i are expected values of $\log x_i$. After removing the effect of size, the variability remaining in item i is ε_i. Notice that ε_i is the logarithm of a ratio in which the denominator is the statistical effect of size and the numerator is the deviation of item i from the industry average. Such ratio reflects the proportion to which item i differs from the expected in firms of that size. That is, the ε are size-free Sales, Working Capital, and so on. An ε_i larger than zero denotes an item i larger than expected.

Assessing the statistical effect of size

The ε could be useful for the analysis of financial statements as they convey size-free information in the same way ratios do. However, in order to isolate every ε, it is first necessary to estimate the overall effect of size, the σ, so as to be able to subtract it from the log of each item. Unfortunately, σ cannot be directly estimated. One possible way of circumventing this problem consists of using, instead of σ, a traditional proxy for size such as Total Assets or Sales. However, σ obtained in this way contains spurious variability, the one specific to the used proxy. A more accurate alternative consists of building, inside each report, averages of a few positive-valued items. In this way, the variability particular to each item, ε, is seif-smoothed so that only the common one remains. Applying Eq. (1) to M raw items, x_i, $i = 1, M$, extracted from the same report

$$\log x_1 - \mu_1 = \sigma + \varepsilon_1$$
$$\log x_2 - \mu_2 = \sigma + \varepsilon_2$$
$$\vdots$$
$$\log x_M - \mu_M = \sigma + \varepsilon_M$$

and averaging, we obtain:

$$\sigma = \frac{1}{M} \sum_{i=1}^{M} (\log x_i - \mu_i) - \frac{1}{M} (\varepsilon_1 + \varepsilon_2 + \cdots + \varepsilon_M).$$

Since an average of independent random deviates tends to zero with $1/M$,

$$\sigma \approx \frac{1}{M} \sum_{i=1}^{M} (\log x_i - \mu_i) \tag{2}$$

for large enough M. Both ε and σ are logs of proportions, independent of scale and unit of measure. σ estimates, on a log scale, the proportion to which the size of firms is larger or smaller than the industry average. Equation (2) can be interpreted as a means of performing the task opposite to ratios. Ratios conceal size in raw items thus revealing deviations from size. Equation (2) conceals deviations from size thus revealing size.

In practice, raw items are not equally adequate to extract size. Sales, Wages, Current Assets mainly reflect size. Inside industries, their particular variability is small. Inventory, EBIT, or Funds Flow have more variability of their own. Finally, Fixed Assets, Working Capital, and especially Long-Term Debt, have large variability of their own. Items for estimating σ using Eq. (2) should have small variability of their own and their ε should not be correlated. Otherwise, a larger M may be required.

Assessing the complementary information discarded by ratios

Since any pair of raw items, $\{x, y\}$, conveys two-dimensional information and ratios are just one variable, when ratios are used instead of their components some information is discarded. Not only information about size, ratios also discard size-free information, potentially interesting for financial analysis. Given Eq. (1), the information conveyed by the ratio y/x can be written on a logarithmic scale as the subtraction of two deviations from the expected in firms of that size:

$$\text{since} \quad \begin{array}{l} \varepsilon_y = \log y - \mu_y - \sigma \\ \varepsilon_x = \log x - \mu_x - \sigma \end{array} \quad \text{then} \quad \varepsilon_y - \varepsilon_x = \log \frac{y}{x} - \mu_{y/x}. \tag{3}$$

Let us define two Cartesian coordinates in which the ε_y are measured along the Y-axis and the ε_x along the X-axis. All the size-free information conveyed by two items, y and x, about one firm, will be represented by a point, $\{\varepsilon_y, \varepsilon_x\}$, in this coordinate system. Now we rotate this system 45° anti-clockwise: we apply the transformation H to each pair $\{\varepsilon_x, \varepsilon_y\}$ or to a matrix D containing many of these pairs in rows, as in Eq. (4).

$$D' = DH \qquad \text{with} \qquad H = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}. \tag{4}$$

We obtain new coordinates in which the X-axis measures $\varepsilon_y - \varepsilon_x$ and the Y-axis measures $\varepsilon_y + \varepsilon_x$. As seen in Eq. (3), $\varepsilon_y - \varepsilon_x$ is, on a log scale, the information conveyed by the ratio y/x. Since the new Y-axis is orthogonal to the axis assessing the information conveyed by the ratio, we can be sure that all the information not accounted for by the ratio will be contained in $\varepsilon_y + \varepsilon_x$. That is, of all the size-free information contained in raw items x and y, $\varepsilon_y + \varepsilon_x$ conveys the one discarded by the ratio y/x.

It is easy to see that, on an ordinary scale, the information in $\varepsilon_y + \varepsilon_x$ is assessed by the new ratio $x \times y/s^2$. We call this new ratio the complement of y/x. Its denominator, s^2, is the squared effect of size ($\sigma = \log s$), estimated as suggested in Eq. (2) or in other way. Ratios y/x and $x \times y/s^2$ show two orthogonal aspects of a unique, two-dimensional, observation.

The role of complementary ratios in ratio analysis

We now discuss whether complementary ratios contain interesting information. Ratios remove the effect of size from their components. However, this removal can be accomplished in two different ways (Lev & Sunder, 1979):

- Explicitly, when the denominator of the ratio is selected so as to reflect size (Total Assets is a typical choice). Ratios explicitly removing size are meant to measure whether a particular raw item is large or small when compared with size. The complementary ratio devised in this study ($x \times y/s^2$ or, on a log scale, $\varepsilon_y + \varepsilon_x$) removes the effect of size explicitly.
- Implicitly, when the denominator of the ratio is selected so as to produce a desired contrast with the numerator. Ratios implicitly removing size are meant to measure whether a particular raw item is large or small when compared with other raw item, irrespective of its proportion to size. In this study we refer to the usual ratio (y/x or, on a log scale, $\varepsilon_y - \varepsilon_x$) as removing the effect of size implicitly.

Though, in practice, no sharp separation exists between both functions, some ratios are clearly meant to remove size explicitly, while the majority do it implicitly. For example, in the two ratios Working Capital to Total Assets and Current Assets to Current Liabilities, the former assesses liquidity by comparing Working Capital with a proxy for size, while the latter compares short-term assets with short-term liabilities, regardless of size. That is, financial analysts select some ratios because they perform tasks similar to those accomplished by the complementary ratio $x \times y/s^2$. When practitioners use ratios whose denominator is meant to explicitly reflect size, they are probably trying to assess, in a less accurate way, the information contained in complementary ratios. From this we conclude that complementary ratios might convey, in some cases, useful information.

However, we do not claim a universal fitness for the complementary ratio. On statistical grounds, where ε_y is correlated to ε_x, then the above decomposition of information becomes less attractive as correlation means redundancy. On practical grounds, the reasons leading to the pairing of some ratios are often based on different considerations. For example, the Interest Cover ratio is used together with Financial Structure ratios. These two pieces of information are complementary on grounds of financial analysis, not because of being orthogonal. Finally, it is also obvious that ratios meant to explicitly remove size will not benefit from pairing with their complement.

TWO-DIMENSIONAL REPRESENTATIONS OF RATIOS

This section explores a specific question: when the complementary ratio turns out to be useful, to what extent is it interesting to gather in a unique observation two ratios – y/x and $x \times y/s^2$ – instead of using each of them separately? Is there anything to be gained by using bivariate information instead of their two separated pieces?

Bivariate information can be more revealing than the examination of two ratios separately. First, because two dimensions increase specificity: trajectories are more accurate and easy to interpret than simple time-histories. Second, because bivariate distributions of accounting information are difficult to describe functionally. Therefore, instead of analysing complementary ratios separately, practitioners should privilege the analysis of bivariate representations provided by scatterplots and other graphical instruments. Nowadays, these facilities are not out of reach as most of the data practitioners work with is computer-supported.

The rotated residual plot (RRP)

The Rotated Residual Plot (RRP) is a scatterplot in which the X-axis measures, on a log scale, deviations of y/x from the industry average. For conveniently selected y and x, this axis is supposed to capture a financial feature of the firm such as liquidity or profitability. The Y-axis measures deviations of $x \times y/s^2$ from the industry average, that is, the joint deviation of y and x from the expected in that industry, in firms of that size. The RRP is just a 45° anti-clockwise rotation of a scatterplot of ε_y with ε_x. As seen, Eq. (4), this rotation leads to a new X-axis assessing $\varepsilon_y - \varepsilon_x$ (which is the deviation of $\log y/x$ from average) and a new Y-axis assessing $\varepsilon_y + \varepsilon_x$ (which is the deviation of $\log(x \times y/s^2)$ from average).

Cross-sectional ratio analysis is based on the magnitude of deviations of ratios from values expected for a given industry. Industry averages are important only in that they are needed for calculating such deviations. In the RRP, only deviations from averages are plotted and, when showing data from several years, each year is mean-adjusted separately. This procedure accounts for overall economic trends affecting one whole industry. Such trends, if not accounted for, introduce fluctuations in ratio norms, thus making it misleading to compare ratios in different years.

Figure 1 shows the diagnostics to infer from locations in the RRP. As usual, the term *feature* refers to characteristics of firms as reflected by financial statements: liquidity, profitability, financial structure, and so on. Ratios are supposed to capture features. In this sense, the diagnostics provided by the RRP are as follows:

When the position of a firm is near "A," both the feature we are assessing and its magnitude when compared with the size of the firm are near the expected in that industry. For example, in the case of liquidity, this position means that the proportion of Current Assets to Current Liabilities is near the average and these items are also in the usual proportion to the size of the firm.

When the position of a firm is along the "B" line, the feature we are assessing is near

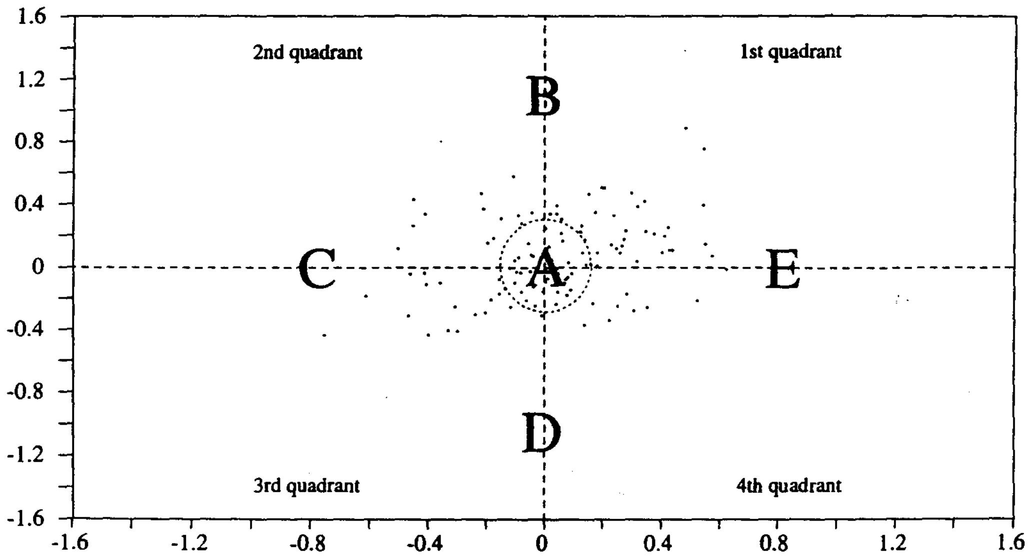

Fig. 1. Financial analysis based on the location of firms in the Rotated Residual Plot. The X- and Y-axes measure logs of percent deviations from expected. Each dot is a firm.

the expected, but its magnitude is larger than expected in firms of that size. For example, the proportion of Current Assets to Current Liabilities is near average, but these items are larger then expected in firms of that size.

Positions along "C" denote a magnitude of the feature near expected given the size of the firm but the feature itself is below expected. Continuing with liquidity, this position corresponds to Current Assets falling short of the expected proportion to Current Liabilities but these items being in balance with size.

Positions along "D" show that the feature itself is near expected but its magnitude, given the size of the firm, is small. For example, the liquidity of a firm might agree with the norm but both Current Assets and Current Liabilities are smaller than expected in firms of that size.

Positions along "E" show that the magnitude of items conforms with the industry average in the case of firms of that size but their proportion is above expected. For example, there is an excess of short-term assets over short-term liabilities, even when the items reflecting liquidity are in balance with the size of the firm.

Positions between axes induce a combination of two of the above diagnostics. For example, when the position of firm is between line "C" and "D," both the feature and its magnitude given the size of the firm are below expected. This is frequent when assessing profitability and it means firms too big for the generated earnings.

How to build the RRP

We extracted from the Micro-EXSTAT database (Extel Ltd, UK; see Board et al., 1991) all the reports of firms belonging to the Food Manufacturing industry in the UK during the period 1983–1987. Then two items were selected from these reports: *EBIT* (Earnings Before

Interest and Tax) and *NW* (Net Worth, the shareholder's equity and reserves). These items are the components of a profitability ratio measuring the percent profit generated by the firm's unit value, thus showing the efficiency of the firm's worth.

After selecting the two components of the ratio, we applied to each of them the symmetric log transformation recommended by Snedecor and Cochran (1965).

$$\begin{aligned} x &\mapsto \log x, && \text{for } x > 0 \\ x &\mapsto -\log|x|, && \text{for } x < 0 \\ x &\mapsto 0, && \text{for } x \approx 0. \end{aligned} \tag{5}$$

The transformed items were then mean-adjusted separately by year, for the period 1983–1987. Notice that, in the case of *EBIT*, the positive and the negative observations were mean-adjusted separately. This is the common practice in ratio analysis, based on the fact that profits and losses are two different populations and should not be mixed in the same sample. Accordingly, the negative-*EBIT* firms were placed in the third quadrant of the RRP, away from the positive-*EBIT* ones, as shown in Fig. 4. Foster (1986) and Lev and Sunder (1979) offer a more detailed discussion of this practice.

The estimated size, $\sigma = \log s$, was obtained by averaging the logs of several raw items, as explained in Eq. (2). In this example we used

$$\begin{aligned} \sigma = 1/6(&\log \text{Sales} + \log \text{Wages} \\ &+ \log \text{Number of Employees} + \log \text{Debtors} \\ &+ \log \text{Current Liabilities} + \log \text{Current Assets}). \end{aligned} \tag{6}$$

Prior to their use in Eq. (6), log items were mean-adjusted year by year.

Next, for all the firms in the Food Manufacturing industry, we calculated the Y and X coordinates of firms in the RRP, in the same way for positive and negative-EBIT observations. If

$$\varepsilon_{ebit} = \log EBIT - \overline{\log EBIT} - \sigma, \qquad \text{and} \qquad \varepsilon_{nw} = \log NW - \overline{\log NW} - \sigma,$$

then the two axes of the RRP are:

$$Y = \varepsilon_{ebit} + \varepsilon_{nw} \qquad \text{and} \qquad X = \varepsilon_{ebit} - \varepsilon_{nw}$$

$\overline{\log EBIT}$ and $\overline{\log NW}$ are the industry averages of log items. The RRP is just a scatterplot showing, for a given industry, positions of firms according to X and Y.

The above calculations could be performed as a facility attached to databases of accounting reports. Then available graphical facilities would accomplish the implementation of the RRP as an instrument of analysis.

How to use the RRP

After building the RRP, four firms were selected from the set used above and their profitability was examined using both the ratio *EBIT* to *NW* and the corresponding RRP. Figures 2 and 3 display the trajectories of these firms in the RRP and also the time-histories of the ratio *EBIT* to *NW* and $\sigma = \log s$. The time-histories are on the left side and the RRP is on the right side of the figures. The marks on the RRP refer to years. For example, "4" means 1984. The description is complemented with Table 1.

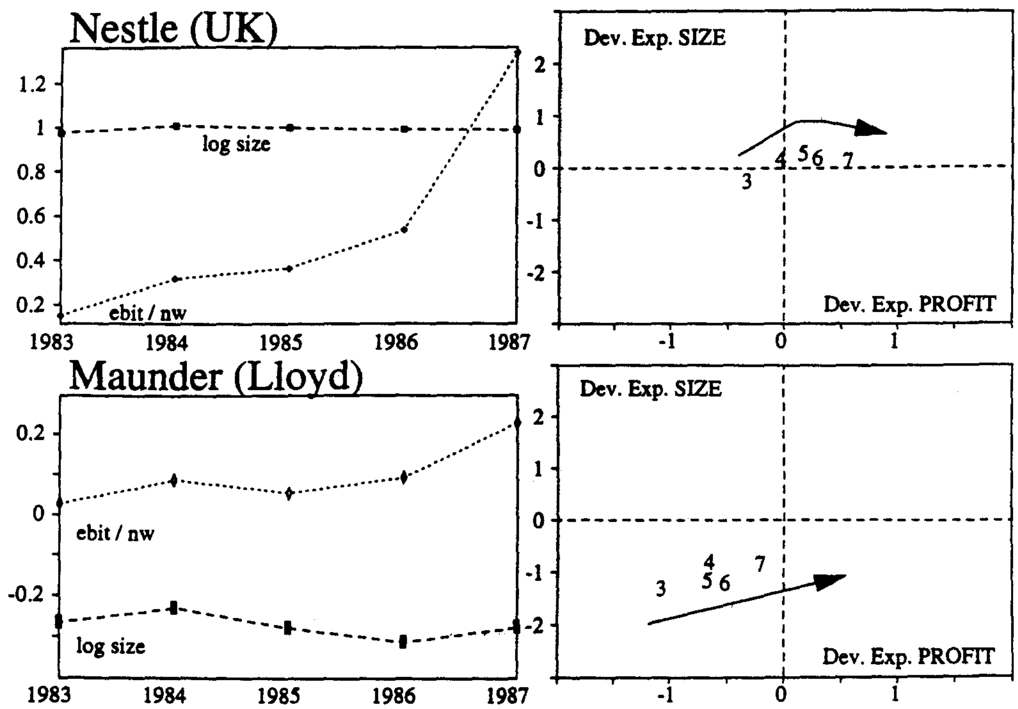

Fig. 2. On the left, *EBIT/NW* and σ during 5 years. On the right, the trajectory drawn in the RRP during the same period. Marks 3 to 7 refer to 1983 to 1987.

The nearer a firm is to the centre of the RRP the less it diverges from the industry average. In the RRP the *X*-axis measures, on a log scale, percent deviations from the average profitability in the Food Manufacturing industry. The *Y*-axis measures, on the same scale, how Earnings and Net Worth, jointly considered, diverge from expected in firms of that size. The first quadrant of the RRP contains firms with both Earnings and Net Worth above expected given the size of the firm. The second quadrant means Net Worth above expected but Earnings below expected and so on.

Table 1. *EBIT/NW* and σ (1983–1987) for four firms

	Mean-Adjusted Log Size (σ)					EBIT to New Worth Ratio				
Company	1983	1984	1985	1986	1987	1983	1984	1985	1986	1087
Campbell Frozen Foods Ltd.	−0.24	−0.24	−0.25	−0.15	−0.16	0.218	0.232	0.227	0.100	0.064
Lovell (G.F.) Plc.	−1.09	−1.11	−1.18	−1.15	−1.16	−0.01	−0.03	0.020	0.138	−0.12
Mauder (Loyd) Ltd.	−0.26	−0.23	−0.27	−0.31	−0.27	0.026	0.073	0.053	0.091	0.227
Nestle Holdings (UK) Plc.	0.975	1.005	0.998	0.991	0.988	0.152	0.310	0.366	0.538	1.336

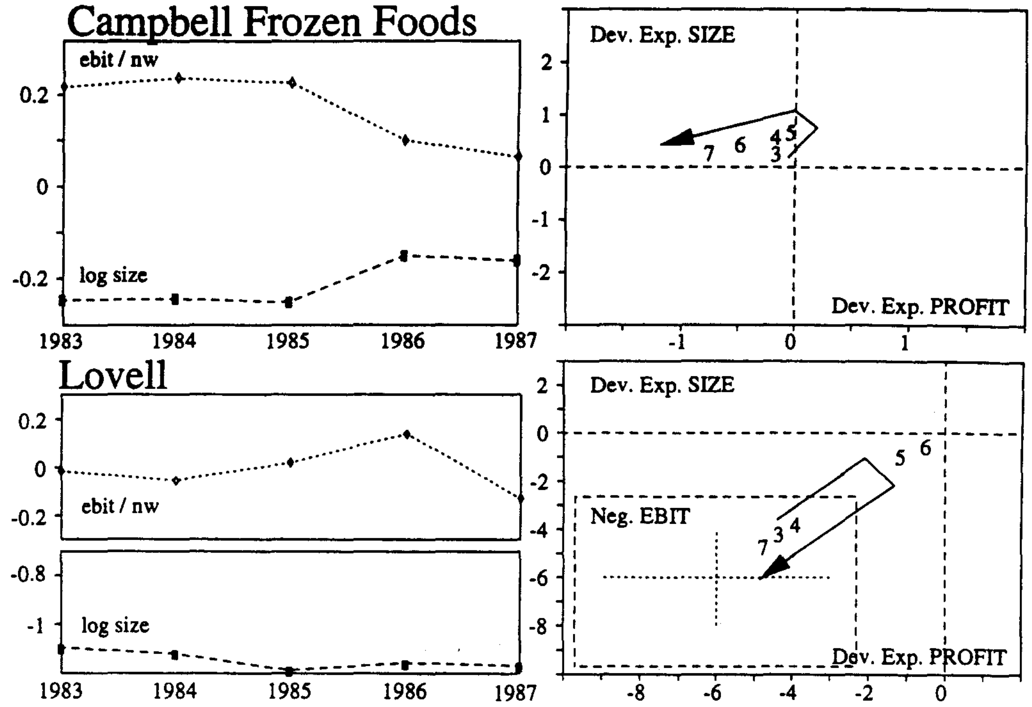

Fig. 3. On the left, *EBIT/NW* and σ during 5 years. On the right, the trajectory drawn in the RRP during the same period. Marks 3 to 7 refer to 1983 to 1987.

In this example, the desirable position in the RRP is along the positive *X*-axis, as far away as possible from the origin. The distance to the origin depicts an advantage in profitability against the industry. Trajectories parallel to the *Y*-axis depict firms growing in capital and earnings but not efficiency. Nestle (UK) and Maunder (Lloyd), both in Fig. 2, show a trend towards efficiency. The first firm is large. During the period 1983–1987, it improved from profitability near the industry average to above it. Its Net Worth was kept at level with size. The second firm is small. It recovers from profitability below the average and oversized, to a new position near average.

Campbell Frozen Foods (Fig. 3) is losing profitability against the industry. The whole of the trajectory lies in the upper two quadrants of the RRP, which means an excess of Net Worth. The second quadrant explicitly means that the firm's Net Worth is not producing the profits expected in the Food Manufacturing industry. Figure 3 also shows one firm having negative and positive-*EBIT*. G.P. Lovell, despite being a small firm, is oversized for its Net Worth and for the profits it generates.

Benefits from using the RRP

When comparing the ratio with the RRP, it is clear that the former only conveys part of the available information. The RRP is more specific as it also refers to the values expected in firms of that size. For example, the profitability of Nestle (UK) increased during the period. The RRP says as much but also points out that such gain was obtained purely by an increase in efficiency. The proportion of Net Worth and Earnings to size was kept near the industry average. The RRP explained more clearly where the competitive advantage of this firm came from.

Unfavourable positions were more clearly ascertained by the RRP as problems in size, not just in efficiency. During the initial 3 years of the period, Campbell Frozen Foods faced an increase in the proportion of Net Worth to size. Since *EBIT* also increased in the same proportion, the *EBIT* to *NW* ratio was blind to this anomaly and only denounced the ensuing plunge in efficiency.

Finally, in the RRP it is easy to compare the position of a firm with others or with previous periods, since all measures are carried out against the industry average.

AUTOMATING THE ANALYSIS

This section uses Self-Organized Maps to discretize the positions and trajectories of firms drawn in the Rotated Residual Plot. It further explains how this technique can be a step toward the automation of ratio analysis.

Statistical models are often used to describe functional relationships. For example, regressions aim at describing relationships that are linear. However, in some cases it is desirable to describe entire distributions, not just relationships. The statistical models able to describe distributions are known as maps. The reasons for using maps can be twofold: either the information regarding positions of observations in distributions is relevant and must be preserved, or the density of observations draws a shape that cannot be described by functions.

Both such reasons lead to the use of maps as a way of modelling the RRP. As stressed before, each zone of the RRP is assigned a financial diagnostic. It is the fact that a firm lies in a particular zone that is important for the analysis. Also, the RRP often exhibits irregular shapes. For example, when studying profitability or flow of funds, it is frequent to observe a comet-like shape, that is, a regular density of observations around the origin, except in the third quadrant where a bivariate tail develops. Such shape is difficult to describe by functional models.

How to build self-organized maps

Self-Organized Maps (Kohonen, 1986) are fast and simple Neural Networks able to reproduce an original density distribution using a small number of classes. They consist of a lattice of "nodes," each of them containing its own set of adjustable coefficients, known as "weights." In the j^{th} node, a set of weights $W_j = w_{j1}, w_{j2}, \ldots, w_{jM}$ links to a corresponding set of "input" or independent variables $X_k = x_{k1}, x_{k2}, \ldots, x_{kM}$ containing information on firm k. Each node's "output," o_j, is a function of both input and weights: $o_j = f(X, W)$. It is required that this $f(X, W)$ assesses some form of similarity between W and X. A frequently used $f(X, W)$ is the Euclidean distance:

$$o_j = \sqrt{\sum_{i=1}^{M} (x_i - w_{ji})^2}.$$

The building of the map takes place as follows: all the nodes are supplied with the same input, extracted at random from the available firms. Then the node with the largest output is found. This node is the one whose weights show greater similarity with the presented firm. Next, a neighbourhood is defined around this node and the weights of all nodes inside it are updated or "rewarded" in a way that makes them more similar to the firm they identified. For example, the new value of a weight, w_{ji}, linking variable i to a rewarded node j, can be updated in this way:

$$w_{ji}^{t+1} = w_{ji}^{t} + \eta \times (x_i - w_{ji}^{t})$$

in which t and $t + 1$ denote a sequence and η is a small increment. The nodes out of this neighbourhood receive no rewarding. The procedure is repeated for all the firms in the sample and then again and again. At length, the position of firms in the RRP is mirrored by the position of the nodes (as in Fig. 4) because their weights become similar to some supplied input. The result is a mapping of the firm's input variables onto a few classes, defined by neighbourhoods of nodes.

Interpreting self-organized maps

In the case of the RRP, the input variables are logs of ratios and their complement: $X = \{\varepsilon_y - \varepsilon_x, \varepsilon_y + \varepsilon_x\}$. We refer to nodes as pairs of integers $\{m,n\}$. m is the counter of rows in the lattice and n is the counter of columns. Since each node "covers" a neighbourhood, the map will be able to identify, for each new firm, the pair $\{m,n\}$ representing a given node. Where a firm's input lies in the neighbourhood of such node, it "fires" the node, that is, it causes the node to exhibit the largest output.

Figure 4 refers to the examples given in the last section. It shows the positions, after the building of the map has finished, of a lattice of nodes superimposed to the density of observations in the RRP. Straight lines link nodes that are neighbours. The discretization performed by the map allows the assigning of a financial diagnostic to each region of the RRP. In fact, since each node acquires a mapping quality, its firing has a precise meaning on financial analytic grounds. This is because each region of the mapped RRP also has a precise meaning. For example, if a firm is shown to a Self-Organized Map and it fires node {2,5}, then this firm conforms with the industry norm, both in efficiency and in size,

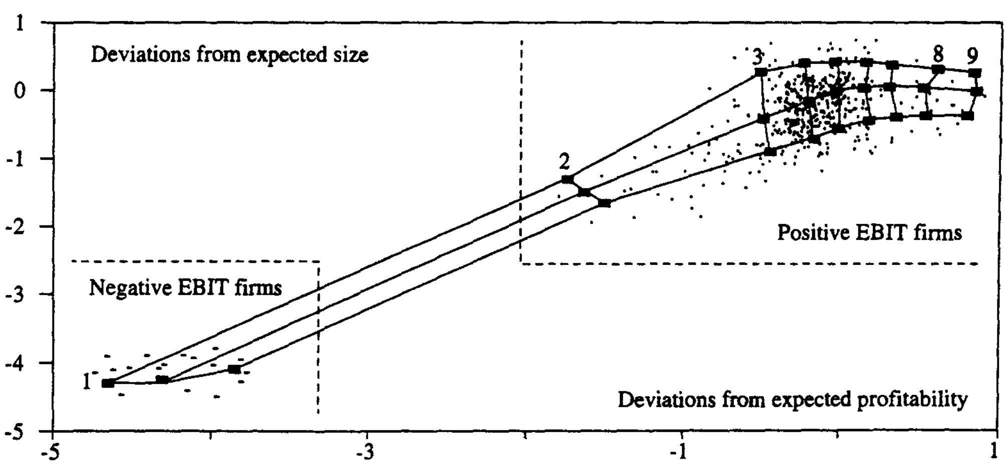

Fig. 4. Lattice of 3 × 9 nodes superimposed to the RRP.

as the neighbourhood of node {2,5} is the central region of the RRP. Thus it is now possible to build a table of correspondence relating each node to profitability and to its magnitude inside the firm.

Since the RRP uses mean-adjusted log values and the basis of each diagnostic is the extent to which each observation differs from this average, it follows that the table of correspondence between nodes and financial features is expected to be as robust as the median is, regarding changes in the variability of statistical distributions of ε_y and ε_x (Laurent, 1963). Therefore, after building a map for a given industry, it is not likely to be necessary to adjust it frequently.

After showing this tool a sequence of variables representing the same firm during several years, it outputs the corresponding sequence of fired nodes. This output sequence defines a trajectory in the discrete space of the lattice of nodes. Figure 5 presents three of these trajectories. Based on tables of correspondence and on the increments observed in m and n, it would be easy to build an expert system for automatically interpreting these trajectories. The table of correspondence can be more or less detailed. If, in our example, a larger number of nodes were used in the n dimension, then we would get more specific, albeit less robust diagnostics.

CONCLUSIONS

The recent development in information technology has had a fundamental impact on the way the analysis of financial statements is carried out. For example, computer-supported databases are routinely used for comparing reports of firms with other reports or with industry norms. However, these databases are not using all the possibilities offered by their support. The results of this study suggest that a better understanding of the statistical characteristics of accounting information, together with a thorough exploring of possibilities

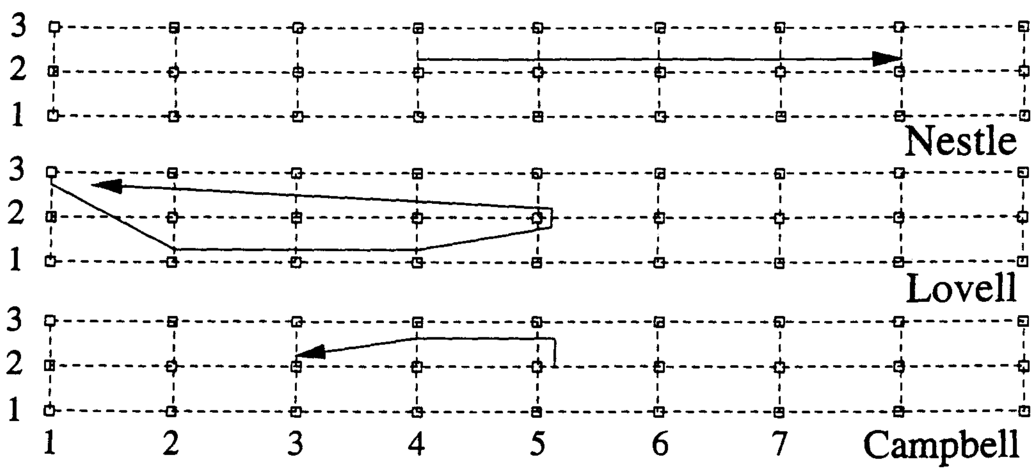

Fig. 5. Lattices of nodes showing trajectories of firms in the discrete space. Integer $m,m = 1,9$ is the row counter and integer $n,n = 1,3$ is the column counter.

offered by the computerized support of accounting databases, leads to more accurate and easy to interpret analysis.

We have shown that the size-free information discarded by the ratio y/x is the ratio $y \times x/s^2$, s being an estimated size. We also studied the potential interest of such a complementary ratio in financial statement analysis. We outlined two kinds of questions that ratios are called upon to answer. Then noticing that complementary ratios seem to answer one of these questions, we concluded that they convey, in some cases, information useful to analysts.

Complementary ratios seem to apportion interesting information about the strategic position of firms. They capture deviations from expected given the size of the firm. For example, profitable firms may, nevertheless, use more capital than expected, thus being at a disadvantage. An increase in capital and earnings leading to the same efficiency as before, may be damaging where not in balance with the size of the firm. Complementary ratios trace size-related anomalies that ordinary ratios fail to recognize. In other words, complementary ratios provide a measure of size-efficiency, against which the pure efficiency can be confronted.

Another feature of complementary ratios that might be interesting is that, by using them, practitioners can focus on two raw items reputed as important for the analysis, knowing that they assess all available information. This probably would contribute to avoiding the use of too many ratios.

In this study we also asked to what extent is it useful to gather ratios and their complements in a unique observation. We remarked that the consideration of both the ratio and its complement can improve, in some cases, the specificity of the analysis and we described a graphical tool, the Rotated Residual Plot (RRP), allowing the study of trajectories. The drawing of trajectories reveals a certain behaviour valuable for financial analysis and less explicit when solely using time histories of ratios.

The RRP is a different, yet familiar, way of analysing accounting reports. It is different from ratios in that it conveys two pieces of information at a time. But it is based on the same principles: the proportion of one component to the other is supposed to capture features of the firm and the value expected for the industry sets the norm. This tool is not a departure from traditional ratio analysis. Rather, it is its natural extension. All the expertise of ratio analysts can be directly implemented on the RRP. We think that the RRP, when attached to computerized databases of accounting reports, could be an intuitive way of analysing financial statements as it would not require from practitioners the development of new skills. Besides, the RRP takes full advantage of the widespread graphical power of computers and it is also suited for machine learning.

Self-Organized Maps can be used to assign financial diagnostics to regions of the RRP. Neural Networks have been the object of increasing regard. They are local and parallel in structure, which makes them ideal for implementation on future machines. They are also robust, allowing the relaxing of assumptions about the data. Recently, Serrano, Martin, and Gallizo (1993) used Self-Organized Maps to reduce the dimension of several ratios onto a simple lattice. Trippi and Turban (1993) depict applications of Neural Networks in Finance.

The implementation of the RRP as a facility permanently attached to databases of accounting reports requires an effective use of existing information technologies. The development of these technologies has presented the accounting profession with an opportunity to take full advantage of more computationally demanding tools. The impact of the resulting decision support systems is necessarily a matter of conjecture. But the RRP is promising enough to deserve a closer look, namely by observing its acceptance amongst practitioners and empirically testing its benefits.

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