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The Effect of Audit Firm Size on Audit Prices

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In a recent issue of *Journal of Accounting and Economics*, Francis,[1] developed a theory for determining the effect of audit firm size on audit prices (EAFSA). The present study offers an extension to his multivariable theory, which is otherwise viewed as an excellent attempt at presenting a realistic model of EAFSA. Further analysis of the data included in the present paper ranks the dominant variables and factors as (1) External audit fee (AFE), and Percentage of Assets (AST), and (2) Loss in last three years (LLS). In addition, this analysis reduces the multicollinearity and data redundancy of the original 11 variables by creating 6 less redundant factors from them. These new factors yield a EAFSA model of measurement with a fewer number of terms, a lower multicollinearity, and a multivariate normal distribution. The variable entitled Return on Investment (ROI) is ranked as the most subordinant, and most dependent, while (AFE) is ranked as the most dominant variable.

Key words—auditing, audit prices, audit firm size, audit fees, auditors, external audit fee

1. INTRODUCTION AND LITERATURE REVIEW

THE EFFECT OF AUDIT FIRM SIZE on Audit Firm Prices (EAFSA) impact on complex organizations continues to be a source of frequent managerial concern and frustration. One of the major sources of frustration in studying EAFSA is the multiplicity of associated variables and the inherent data redundancies. Some of the EAFSA relationships between audit firm size and audit prices depends upon competition in the market. Competition is difficult to objectively measure. One approach used market concentration by suppliers to proxy for competitiveness, this was done by Demsetz [8]. Buckley and O'Sullivan [4] indicated that Big Eight firms dominate the supply of audits to New York and American stock exchange companies. Pricing them will be a function of the level of collusion among the dominant firms as pointed out by Bain [2]. Simunac's [24] evidence is consistent with a competitive US auditing market. Informal evidence from the Cohen Commission (AICPA) [1] and other sources [3] also suggests that price competition occurs rather than collusion. Another factor closely allied with competition is the nature of auditing services themselves. The nature of auditing services has to do with audit quality as defined by [7] and reputation for audit quality based upon the perception of audit firm competence as studied by [25]. Libby [16] reports evidence that bank loan officers perceive differences in reputation and Shockley [22] indicates that perceptions of auditor independence are significantly different between large and small firms. Shockley and Holt [23] report a study in which perceptions of auditor reputation are differentiated within the Big Eight group. The final factor is that large accounting firms may experience scale economies in the audits of large companies [24]. This paper extends Simunac's tests of the effect of accounting firm size on audit prices. Francis has contributed greatly to the theory of

[1]The authors are indebted to Francis for his contributions to this study.

EAFSA. In particular, he has conducted a correlation analysis, focused on the relationship among EAFSA variables (Appendix A). Based on this correlation analysis, potential multicollinearity and skewed distributions, Francis has made the following assertion and comments:

> "The hypotheses are tested by use of the multiple regression equation of the audit fee function. Multiple regression ... states that observed audit fees are a function of both quantity and price. Therefore in order to make inferences about audit prices, it is necessary to control for the quantity of auditing supplied. A set of variables is used to control for audit quantity and a dummy variable (the experimental variable) is then used to represent audit firm size. Non-Big Eight firms are given a value of zero and Big Eight firms are given a value of one. The null hypothesis is that the regression coefficient of the audit firm size variable is not significantly different from zero."

Although the point at which multicollinearity becomes 'harmful' has not been statistically determined, it can certainly be harmful at some point [9, 17]. Since the harm of the present level of multicollinearity is unknown, it would be more advantageous to be statistically conservative, by trying to minimize the level of multicollinearity. Likewise, dealing with normally distributed variables is preferred to working with skewed variables. Thus, reducing multicollinearity and normalizing the distribution of the factors score should improve the overall statistical reliability of the EAFSA model. Accordingly, reducing the multicollinearity of this model and normalizing the distribution of its factors is one of the stated objectives of the present study.

2. PROBLEMS

The problems that emerge from the literature are rather complicated. One major problem which theorists have discussed extensively in the literature, is the multiplicity of EAFSA variables and their importance relative to each other. Dealing with so many variables is conceptually cumbersome. Moreover, this multiplicity of variables significantly raises the costs associated with the model design, data collection, and data processing, to the detriment of the overall cost/benefit analysis. These increased costs may also be detrimental to the use of the EAFSA model. The absence of an empirically tested rank-order among these variables is another part of this problem. Such ranking is particularly important for a EAFSA model which expresses the most subordinant and most dependent variable as a mathematical function of the remaining more dominant and more independent variables.

The second problem is multicollinearity, which is associated with the multiplicity of EAFSA variables. The problem related to multicollinearity is the redundancy among the EAFSA variables and their informational content. This is especially important whenever the model variables are expected to be independent of each other and contain no redundant information. Violating such assumptions will reduce the reliability of multivariate models which assume independence of variables [9, 17].

The third problem is the skewed distribution of the EAFSA variables, which leads to a potentially biased EAFSA model. This is especially relevant for multivariate methods using Ordinary Least Square (OLS) regression or Multiple Discriminant Analysis (MDA). Such OLS or MDA could be more effective if the EAFSA had a symetrical normal distribution.

3. OBJECTIVES

The objectives of this study are threefold. The first objective is to reduce the multiplicity of EAFSA variables. Thus, the initial 11 variables, which are somewhat redundant, will be replaced by fewer, non-redundant, factors, which will make up the modified EAFSA model. The second objective is to reduce the level of multicollinearity of the EAFSA factors. The third objective is to normalize the factor scores distributions for the modified EAFSA model. In sum, the objectives of this study involve ranking the variables, reducing the number of factors, their data redundancy, multicollinearity, and normalization of their distributions for the modified EAFSA model.

4. METHODS AND PROCEDURES

Orthogonal (uncorrelated) factor analysis is a statistical technique used in order to extract a set of common factors, with minimized multicollinearity, out of a set of variable scores. The methodology of principal component factor analysis has been chosen, since it can accomplish all of the objectives, reducing the data, ranking the variables, defining factors with minimized multicollinearity as well as normal distributions [5, 12, 15]. Assumptions concerning data structures inherent in factor analysis are similar to those in a correlation analysis [6]. Thus, assuming that Francis has met the required assumptions for his correlation analysis, one can perform a factor analysis without violating those assumptions.

Although the number of orthogonal factors is unknown, prior to conducting the factor analysis, the correlation matrix reveals that the number of factors will be fewer than the 11 original EAFSA variables. The mathematical formulation of factor analysis along with the orthogonal rotation of the axes ensures that the multicollinearity will be minimized. In addition, the application of factor score coefficients secures normally distributed factor scores with a mean score of 0 and a standard deviation of 1.00 [18].

5. THE HYPOTHESES

The hypotheses of this study can be stated as a null hypothesis and its related alternative hypothesis. Thus, the null hypothesis states that data reduction is impossible without a significant loss of information and multicollinearity is nonexistent. Thus, the number of the orthogonal factors will be equal to the number of original EAFSA variables (11). On the other hand, the alternative hypothesis states that the EAFSA variables are somewhat redundant, and, therefore, can be replaced by fewer less redundant factors, without a significant loss of information.

These hypotheses are formally stated as follows:

Null hypothesis—

$H(0)$; $a(i,j)$ are less than 0.3 for the EAFSA sample.

Alternative hypothesis—

$(H1)$; $a(i,j)$ are equal or greater than 0.3 for this sample, for $i = 1 \cdots n = 11$, and $j = 1 \cdots m < 11$.

where:

i = index for the number of variables;
j = index for the number of factors;
n = number of EAFSA variables;
n = number of EAFSA variables;
m = number of EAFSA factors;
$a(i,j)$ = orthogonal EAFSA factor loading coefficients.

If the null hypothesis is rejected in favor of the alternative hypothesis, then the Francis model can be restated in terms of orthogonal EAFSA factor with normally distributed scores instead of the original correlated and skewed variables scores [11, 18]. Consequently, the model will become less redundant as well as less biased and, therefore, more efficient as well as more reliable.

6. SAMPLE SELECTION AND DATA COLLECTION

Francis utilizes Big Eight accounting firms as a proxy for large auditors and non-Big Eight firms as a proxy for small auditors. The market studied is the Australian auditing services market over the period 1974–1978. The study revolves around two hypotheses to be tested. One is that audit firm size has no significant effect on audit prices in Australia. The other hypothesis is that there is not any significant price cutting of initial fees in Australia. A set of variables is used to control for audit quality and a variable is then used to represent audit firm size. The variables for this study were chosen after a thorough literature review and will incorporate Simunac's control variables and three additional control variables pertaining to liquidity and financial structure. Thirty companies were selected from each of the years 1974–1978 for a total sample of 150 companies. Companies were selected at random from the industrials listings of the Sydney stock exchange. Data were obtained from the companies' annual reports and the Investment Service of the Sydney Stock Exchange. This sample was sensitive to industry effects, therefore 14 observations were dropped from the original sample of 150 to produce a more homogeneous final sample of 136 companies. The final sample had 64 Big Eight auditors and 72 non-Big Eight auditors. The following variables, which are also factors in the EAFSA

Table 1. EAFSA Factor matrix using principal factor with iterations[a]

	Factor 1[c]	Factor 2[d]	Factor 3	Factor 4	Factor 5	Factor 6
(1) AFE[b]	0.88157	0.08457	−0.17190	0.07011	−0.03706	−0.05185
(2) AST	0.82482	0.14296	−0.29593	−0.13837	−0.10461	0.02319
(3) SUB	0.91455	−0.26093	0.27712	0.03509	0.07413	0.02135
(4) CAS	0.12635	0.35636	−0.00379	0.29362	0.36716	0.10326
(5) QRA	0.06331	0.34164	0.05457	0.41931	−0.01595	−0.12645
(6) EDR	−0.16386	−0.01310	0.07197	0.33393	−0.15732	0.12964
(7) ROI	0.05203	0.36117	0.29649	−0.23803	−0.08405	0.20917
(8) LLS	−0.13628	−0.29405	−0.41726	0.05035	0.29823	0.09763
(9) AOP	0.19158	−0.26874	0.28622	0.05760	0.15040	0.26579
(10) MYE	0.06124	−0.05895	0.30626	−0.10026	0.25545	−0.33825
(11) ACF	0.07842	−0.33672	0.06535	0.32717	−0.24799	−0.05759

[a]Coefficients greater than the absolute value of 0.3 are statistically significant [21].
[b]These variables have been defined by Francis.
[c]Factor 1 is a general factor, which loads highly on most variables. This may be simplified by axes rotation.
[d]Factor 2 tends to be bipolar, having both positive as well as negative coefficients. This may also be simplified by a rotation of the axes.

model, were defined, collected and recorded by Francis:

(1) External Audit Fees (AFE).
(2) Log 10 Assets (AST).
(3) Subsidiaries (SUB).
(4) Current Asset % (CAS).
(5) Quick Ratio (QRA).
(6) Equity–Debt Ratio (EDR).
(7) Return on Investment (ROI).
(8) Loss in Last three years (LLS).
(9) Audit Opinion rendered (AOP).
(10) Month year-end (MYE).
(11) Accounting Firm (ACF).

7. RESULTS AND DISCUSSION

The exploration of dominance is achieved by constructing a new set of dominant factors. Table 1 presents the new set of factors as described by a factor matrix, using the principal factor methodology with iterations. Since the principal component method had been applied, these new factors are exact mathematical transformations of the original data. This method is preferred since no particular assumptions are made about the structure of the variables [19]. Table 1 shows the initial solution of the principal component factor analysis. As expected from the literature, the substantial dominance of 6 factors over the original 11 EAFSA variables exists. In order to interpret these factors in the most meaningful way, the factor matrix has to be orthogonally rotated. This orthogonal (uncorrelated) rotation will lead to the terminal solution of this factor analysis.

The initial solution, in Table 1, extracted the orthogonal unrotated factors in the order of their eigenvalues, which depicts their dominance in relation to each other. These factors tend to be general and/or bipolar, therefore, is difficult to interpret them at the initial solution stage. Moreover, many EAFSA variables tend to load significantly on more than one factor (complex loadings), which inhibits a clear interpretation of the factors. Thus, naming and interpreting the factors is reserved for the terminal orthogonally rotated solution, which should be less bipolar and more simple.

Table 2 shows the EAFSA variables, communalities, factors, eigenvalues, percentage of variance (PCT of VAR) explained, and the cumulative percentage of variance. The 100% of explained variance supports the notion that the original 11 EAFSA variables can be expressed in terms of the new 6 factors, factor 1, 2, 3, 4, 5 and 6. Thus, it appears that substantial dominance exists, indicating significant potential for the reduction of data redundancy in the factors and their multicollinearity.

The terminal solution is presented in Table 3 as the Varimax Rotated Factor Matrix. This orthogonal rotation maximizes the difference between each pair of factor loadings. This rotation will also reduce the complexity and the bipolarity of the factor [20]. The values of the factor loading coefficients indicate the statistical significance of a variable contribution to each factor. Thus, the EAFSA variables, with statistically significant factor loadings (those which are greater than 0.3), are used to name and interpret the new EAFSA factors. Thus EAFSA the following name and interpretations have been assigned to the factors:

Factor 1—External Audit Fees and Log 10 Assets (AFE and AST).

Table 2. EAFSA variable communalities and factors eigenvalues

Variable	Communality[a]	Factor	Eigenvalue[b]	PCT of VAR	CUM PCT[c]
(1) AFE	0.82284	1	2.40859	47.3	47.3
(2) AST	0.81896	2	0.74554	14.7	62.0
(3) SUB	0.98846	3	0.64409	12.7	74.6
(4) CAS	0.37466	4	0.57843	11.4	86.0
(5) QRA	0.31577	5	0.42300	8.3	94.3
(6) EDR	0.18527	6	0.28880	5.7	100.0
(7) ROI	0.32853				
(8) LLS	0.38015				
(9) AOP	0.28743				
(10) MYE	0.29074				
(11) ACF	0.29566				

[a]The communality indicates the relative variable dominance, thus AFE is the most dominant among the EAFSA variables.
[b]The eigenvalue and the percentage of variance (PCT of VAR) explained, indicate the relative dominance of each EAFSA factor, thus factor 1 is the most dominant factor.
[c]The 100% cummulative percentage (CUM PCT) of the variance contained in the original 11 EAFSA variables has been explained by the 2 new EAFSA factors.

Factor 2—Loss in last three years (LLS).
Factor 3—Current Asset % and the Quick Ratio (CAS and QRA).
Factor 4—Audit Opinion rendered and Subsidiaries (AOP and SU).
Factor 5—Accounting Firm and the Equity Debt Ratio (ACF and ED).
Factor 6—Month Year-end (MYE).

Table 3 ranks the variables according to their dominance and independence. In order to interpret the information in Table 3, it is necessary to evaluate the factor loading coefficients. Therefore, upon examining the variables, it is evident that the single most dominant independent variable is AFE, since it has the largest factor loading coefficient of 0.89057, within factor 1. On the other hand, the table illustrates that the single most significant, subordinate and dependent variable is ROI, since it is the variable with the smallest difference between the absolute values of each significant pair of factor loadings, and loads high on more than one variable. In reference to factor 2, Table 3 indicates that LLS is the most significant dominant variable in factor 2, followed by ROI. However, since ROI loads high of other factors, we will consider LLS as the most dominant variable in factor 2, and ROI as the subordinant variable. This finding confirms several theoretical notions from the literature. First, the most dependent variable can be expressed as a function of the other more dominant factors as follows:

ROI = F(AFE and AST, LLS, CAS and QRA, AOP and SUB, ACF and EDR, MYE)**

Francis' findings indicate that a good linear fit was achieved with the model and the accounting firm size variable was significant. The sign of the coefficient was positive indicating higher audit prices for Big Eight firms. Francis' findings also support the conclusion that product differentiation was present in a competitive market structure. The observation of systematic price differences between large and small accounting

Table 3. EAFSA rotated factor matrix: A terminal solution

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
(1) AFE	0.89057[b]	0.02168	0.15358	0.05909	0.04468	0.01337
(2) AST	0.88717[c]	0.04519	0.00679	−0.03270	−0.12497	−0.17190
(3) SUB	0.77613	0.10249	−0.00332	0.51962	0.17605	0.27306
(4) CAS	0.06566	−0.13558	0.57564[b]	0.09172	−0.17108	−0.00624
(5) QRA	0.03941	0.13155	0.48882[c]	0.15859	0.18084	0.01035
(6) EDR	−0.19386	0.04335	0.15071	0.04540	0.29114[c]	−0.19044
(7) ROI[d]	−0.00834	0.49410[c]	0.03324	0.09120	−0.26412	−0.07165
(8) LLS	−0.07170	−0.58959[b]	−0.04216	0.05231[c]	−0.09593	−0.11697
(9) AOP	0.05562	0.00713	−0.02004	0.52522[b]	0.07481	0.04923
(10) MYE	−0.01619	0.04662	0.01148	0.06893	−0.04731	0.53027[b]
(11) ACF	0.05289	−0.07239	−0.06218	0.09205	0.52435[b]	−0.01620

[a]Largest absolute value in each line indicating the most significant factor loading coefficient for each EAFSA variable.
[b]Largest absolute value in each column indicating the single most dominant variable for factor naming and interpretation.
[c]Second largest absolute value in each factor column indicating the second most dominant variable for factor naming.
[d]Variable with the smallest difference between the absolute values of each significant pair of factor loadings (0.49410–0.26412) is the most subordinant, most dependent EAFSA variable.

Table 4. Factor score coefficients for normally distributed EAFSA scores

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
(1) AFE	0.44020	−0.10206	0.26610	−0.31228	0.08581	−0.08161
(2) AST	0.49415	0.02566	−0.16874	−0.22338	−0.27995	−0.30095
(3) SUB	0.09487	0.09105	−0.08719	0.67447	0.22476	0.39020
(4) CAS	−0.04074	−0.05788	0.44166	0.13981	−0.16108	0.00344
(5) QRA	−0.00088	0.08019	0.35546	−0.11650	0.17519	0.04235
(6) EDR	−0.02986	0.04209	0.10124	0.02965	0.18933	−0.17839
(7) ROI	−0.00906	0.36425	0.00532	0.10920	−0.19840	−0.09466
(8) LLS	0.02379	−0.46919	0.00431	0.10029	−0.09881	−0.07874
(9) AOP	0.02075	0.01361	−0.16450	0.50934	0.05580	0.03968
(10) MYE	0.06424	0.00437	0.02110	0.00327	−0.04005	0.45397
(11) ACF	0.05689	−0.01053	−0.07349	0.16425	0.43178	0.03602

[a]These regressions weights will be multiplied by the normalized observed scores for each variable, then the products will be added. This sum will become factor 1 with a normal distribution, a mean of 0 and a standard deviation equal to 1.

[b]The normalized score representing factor 2 will be computed in the same manner using the coefficients in the second column, etc.

firms' evidences product differentiation for large firms in the Australian services market. Finally, the evidence was inconsistent with price cutting of initial audit fees by either Big Eight or non-Big Eight firms in Australia. Also the possibility that an amount of lowballing is affected by future fee raising potential is not supported.

The factor-estimate matrix, in Table 4, is a supplement to the terminal solution. These factor estimate coefficients provide estimates of

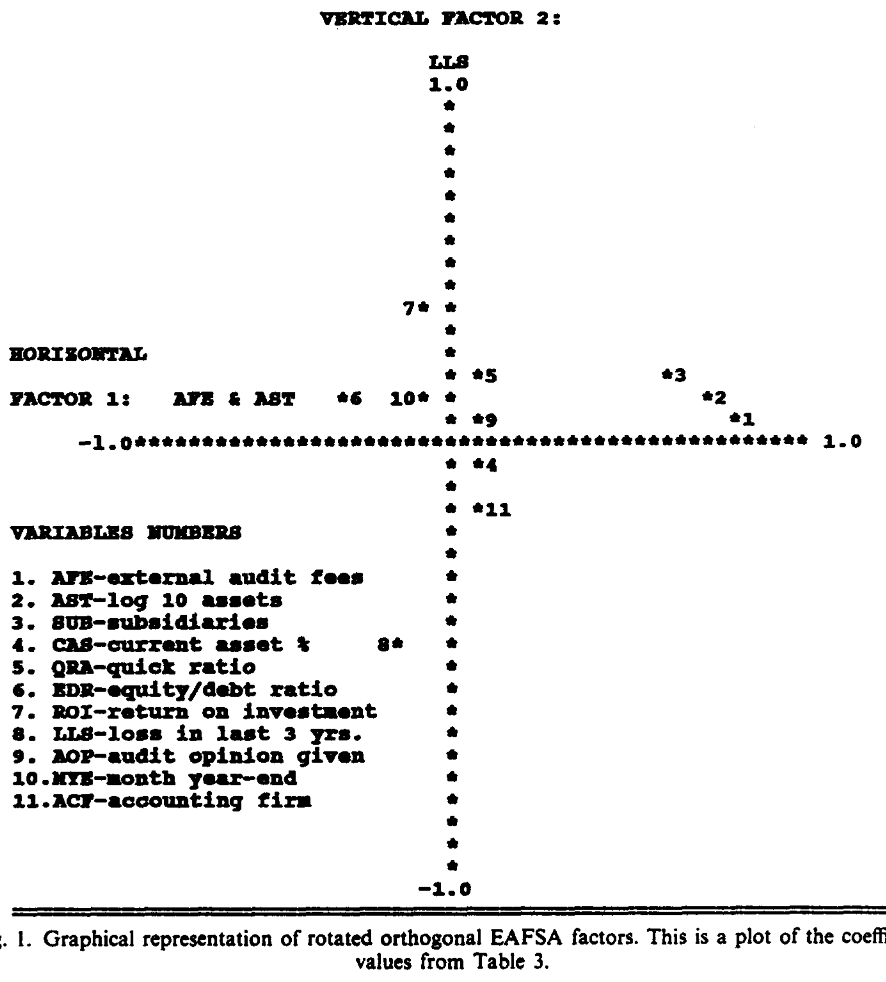

Fig. 1. Graphical representation of rotated orthogonal EAFSA factors. This is a plot of the coefficient values from Table 3.

the normalized factor scores from the observed standardized scores. This matrix consists of regression weights used for computing the new factor scores. The conversion of the 11 skewed variables into 6 normally distributed factors can be done by multiplying the factor estimate coefficients by the 11 variables scores. These 6 estimated factor scores combined into one score represent an EAFSA model of measurement, with a normal distribution, a mean of 0 and a standard deviation of 1.

The graphical description of the rotated orthogonal factors is shown in Fig. 1. The plot of the terminal solution points out the following:

(1) The relative distance of the variables (data points) from the two axes, which represent the two factors, factors 1 and 2.

(2) The direction of the variables in relation to the axes, that is whether they are either positive or negative.

(3) The clustering of variables and their positions, relative to each other, indicating the relationship between the factors.

Figure 1 shows the relationship between factor 1 (horizontal) and factor 2 (vertical). The plot presents variables 4, 5, 6, 9, and 10 close to the origin since it has small loading on both factors 1 and 2. The cluster of variables 1, 2, and 3 load highly on factor 1 (horizontal) and low on factor 2. In contrast, variable 8 loads highly on factor 2 and low on factor 1. This separation of the data point (EAFSA variables) clusters demonstrates graphically that these EAFSA factors are indeed uncorrelated or orthogonal [14].

By observing Fig. 1, one should notice that a rather weak correlation is reflected by the clusters of data points. If one were to draw a straight line through the middle of each cluster to the origin, then the two lines would be close to 90 degrees apart. An angle of 90 degrees between these imaginary lines, indicates the absence of any multicollinearity. Since the angle in this case is close to 90 degrees, the multicollinearity among these EAFSA factors has indeed been minimized, which was one of the stated objectives of this study.

8. SUMMARY

In summary, the hypothesis of redundancy, multicollinearity and skewed distribution have originally been introduced by the literature. This hypothesis has been confirmed by the present investigation of the correlation coefficients. Thus, the null hypothesis was rejected in favor of the alternative hypothesis. External Audit Fee (AFE) was ranked as the most dominant while the ROI turned out to be the most dependent variable. Subsequently, factor score coefficients have been computed, to enable the conversion of the 11 EAFSA variables into the 6 factors. These factor score coefficients can be used later as regression weights to create a weighted-average index which will describe EAFSA potential.

9. CONCLUSIONS

The conclusions of this study are that the work of Francis and other investigations of EAFSA can be conducted more efficiently using 6 factors rather than 11 variables. These 6 most dominant factors can be computed as composites of the most significant variables. These factors and variables can be ranked by their dominance relative to each other. Thus, factor 1 is the most dominant factor. Within this most significant factor, the most significant variable is AFE. While the most dependent, least dominant variable is ROI, which can be expressed as a function of the other most dominant EAFSE factor.

The conclusions of this study parallel the concluding remarks made by Francis which were as follows:

> "A regression model of the audit fee function was utilized to determine the effects of accounting firm size on audit fees in the Australian market... A good linear fit was achieved with the model and the accounting firm size variable was significant. The sign of the coefficient was positive, indicating higher audit prices for Big Eight firms... Results were consistent for both small and large auditee's, supporting that product differentiation was present in a competitive market structure. The observation of systematic price differences between large and small firms evidences product differentiation to large firms in the Australian audit service market... The evidence is inconsistent with the price cutting of initial audit fees by either Big Eight or non-Big Eight accounting firms in Australia."

10. IMPLICATIONS

The implication of this study is that the measurement index can be used for either cross sectional and/or time series analysis. For cross sectional analysis, one could compare the EAFSA scores of several different organizations, for a given period of time and rank-order them. Thus, one can identify the organization with the highest EAFSA potential. For time series analysis, one could compare a single organization's score over several periods of time and identify future trends.

Finally, this study may provide some background for the design of a path analysis. In such an analysis, the inter-relations among the variables can be further explored, based on the relative dominance of variables. ROI, the most dependent variable, can be expressed as a function of the EAFSA factors. Each of the factors can then be expressed as a function of its highest loading variables.

The positive effects of accounting firms' size on profitability, due to a thin spread of overheads etc. will induce mergers and acquisitions. Likewise the effect of size and the rendering of audit opinions increases exposure to risk and the probability of litigations against these firms.

APPENDIX A

EAFSA Correlation Coefficients Matrix[a]

Vars[b]	Var 1	Var 2	Var 3	Var 4	Var 5	Var 6	Var 7	Var 8	Var 9	Var 10	Var 11
Var 1	1.00										
Var 2	0.77	1.00									
Var 3	0.746	0.653	1.00								
Var 4	0.169	0.065	0.055	1.00							
Var 5	0.076	0.048	0.002	0.259	1.00						
Var 6	−0.124	−0.196	−0.123	0.034	0.102	1.00					
Var 7	−0.004	0.035	0.049	0.081	−0.010	−0.038	1.00				
Var 8	−0.099	−0.072	−0.122	0.044	−0.157	−0.03	−0.276	1.00			
Var 9	0.055	0.011	0.017	0.034	−0.077	0.018	−0.001	−0.012	1.00		
Var 10	−0.077	−0.096	0.035	0.025	−0.015	−0.108	−0.018	−0.099	0.03	1.00	
Var 11	0.07	−0.054	−0.089	−0.118	0.048	0.132	−0.168	0.002	0.067	−0.054	1.00

[a]From Francis [10].
[b]See Appendix B for full name

APPENDIX B

Key to Variable Numbers and Names

Var No.	Variable Name
Var 1	External Audit Fee (AFE)
Var 2	Log 10 Assets (AST)
Var 3	Subsidiaries (SUB)
Var 4	Current Asset % (CAS)
Var 5	Quick Ratio (QRA)
Var 6	Equity-Debt Ratio (EDR)
Var 7	Return on Investment (ROI)
Var 8	Loss in last three years (LLS)
Var 9	Audit Opinion rendered (AOP)
Var 10	Month Year-End (MYE)
Var 11	Accounting Firm (ACF)

APPENDIX C

Explanation of Key Terms

(1) ***Communality***—The communality is the percentage of the variables' variance which is contributing to their correlation with other variables. It is also the proportion of variance which one variable has in 'common' with the other variables.

(2) ***Eigenvalue***—The eigenvalue is the amount of total variance in the original data which is explained by a given factor. It shows the relative dominance or importance of a factor.

(3) ***Factorial complexity of variables***—Factorial complexity of variables is a measure of dependence and correlation of a given variable and the rest of the factors and/or variables. The factorial complexity of a variable is set by the number of factors on which it loads significantly (factor loading of greater than 0.3). Thus, a variable that loads significantly on two factors, has a factorial complexity of 2.

(4) ***Factor loading***—The factor loading is a coefficient of association between a variable and a factor. The factor loading's magnitude indicates the relative dominance of a variable compared to other variables, within a given factor.

(5) ***Factor scores***—Factor scores are the values of the factor. They are analogous to the values of the original variables. In contrast to variable scores, factor scores are computed from the original observed variable scores. Accordingly, factor scores are derived rather than observed. The derivations are done by the factor score coefficients.

(6) ***Index of measurement***—An index of measurements can be computed by a sum of factor scores. The index of measurement can be computed from raw data (unstandardized) or from standardized data. The score coefficients should be used for unstandardized data, while the varimax factor loadings should be used for the standardized data.

(7) ***Orthogonal factor (Empirical factor)***—A factor is a variable that is inferred and constructed from the observed (relatively high-loading) variables. Likewise, it is composed by grouping some of the original redundant input variables. Orthogonal factors are defined by rotating uncorrelated axes. In contrast, the axes of oblique factors are correlated.

(8) ***Theoretical factor***—A factor which is composed only according to theoretical arguments found in the literature. In contrast with an empirical factor which is composed not only according to theoretical arguments, but also through the statistical procedure of factor analysis.

(9) ***Variance explained (percentage of variance explained)***—The variance explains measures how much of the original variance of all the variables is represented by a single factor.

(10) ***Varimax rotation***—Varimax rotation describes the rotation of diametrically opposed axes that represent the factors. It is done in order to identify a set of factors such that each factor has a simple factorial structure. That is, some factor loadings are close to +1, or −1, and the rest are close to zero.

APPENDIX D

Factor Analysis Model Explanation

This initial solution, based upon the principal component model, can be compactly expressed as follows:

$$\begin{aligned} Z(J) = {} & (J, 1) * F(1) + A(J, 2) * F(2) \\ & + \cdots + A(J, I) * F(I) \\ & + \cdots + A(J, N) * F(N) + E(J) \end{aligned} \quad (1)$$

where

$Z(J)$ = original variable J scores in standardized form.
$A(J, I)$ = standardized multiple regression coefficient of variable J on factor I.
$F(I)$ = factor I scores replacing the original variable scores.
$W(J)$ = an error term which includes all scores of unexplained variables in variable J that are not accounted for by all the factors.
J = index for the variables: $1, 2, \ldots, N$.
I = index for the factors: $1, 2, \ldots, N$.
M = number of variables.
N = number of factors.

The communality describes the total variance of an original variable that is accounted for by a combination of all the common factors. It can also be stated as follows:

$$H(J)^{**}2 = \text{the sum of } A(I, J)^{**}2 \quad (2)$$

where

J = an index for variable J
I = an index for factor I.
$H(J)^{**}2$ = communality for variable J.
$a(I, J)^{**}2$ = factor loading of variable J on factor I squared.
$J = 1$.
$I = 1, 2, .., N$.
N = number of factors.

The eigenvalue is the amount of the total variance in the original data that is explained by a given factor. It shows the relative importance of this factor. The eigenvalue is calculated as the sum

of squared factor loadings (columns of the factor loading matrix) for each factor or by applying the formula (2)
where:

$J = 1, 2 \ldots, M$; and
$I = 1$.
M = number of variables.

The communality is used to compute the portion of explained variance contributed by each factor. The communality can be expressed formally as follows:

$$\text{Pct of var } F(I) = \text{Sum of } A(J, I)^{**}2/\text{Sum of } H(J)^{**}2 \quad (3)$$

where

I = an index for factor I.
J = an index for variable J.
Pct of var = percentage of variance in variables explained by $F(I)$.
$F(I)$ = factor score of factor I.
$(A(J, I)^{**}2$ = squared loadings for variable J on factor I.
$H(J)^{**}2$ = squared communality of J variables.
$J = 1, 2, \ldots, N$.
$J = 1, 2, \ldots, m$.
N = number of factors.
M = number of variables.

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