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Exploratory Modelling of Financial Reporting and Analysis Practices in Small Growth Enterprises

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Exploratory Modelling of Financial Reporting and Analysis Practices in Small Growth Enterprises

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This paper reports an exploratory study of statistical modelling of historical financial reporting and analysis in a sample of small growth enterprises. The study sought to identify those factors that determine whether particular financial reporting and analysis practices are undertaken, and to represent these explanatory factors in expressions that reflect their relative and combined influence. Dichotomous logistic regression is employed to model financial analysis and polytomous logistic regression is used to model financial reporting. The models developed seem moderately encouraging in terms of the statistical significance and predictive ability. The overall classification success for financial analysis is a modest 65 percent; but identifying users of financial ratio analysis is achieved with just below 90 percent accuracy. The overall classification success for a trichotomous financial reporting scale exceeds 70 percent; with anticipation of financial reporting at the highest level being as accurate as 90 percent. External validation of the models remains an important priority.

I. INTRODUCTION

The primary objective of this paper is to extend knowledge of historical financial reporting and analysis in small growth enterprises through statistical modelling of these practices using certain enterprise and owner-manager characteristics as independent variables. 'Modelling' is taken to mean system-

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atic identification of those factors that determine whether particular historical financial reporting and analysis practices are undertaken, and representation of these explanatory factors in an expression that reflects their relative and combined influence on the practices in question. Agresti (1984) justifies taking research based on mainly categoric data beyond mere reporting of measures of association on the grounds that modelling can expand and clarify associative findings, as well as add a predictive dimension.

A further objective of the paper is to exemplify exploratory or data analytic methodology in small enterprise research as a valid and insightful precursor to traditional confirmatory methodology. The research described relies on "simply and subjectively observing phenomena in their natural setting and deriving theories that fit the analysis of the data" (Abdel-Khalik & Ajinkya, 1979, p. 29). Such research:

- May rely on a relatively small, non-random sample.
- Can often be characterized as descriptive and/or associative, and without pretensions to causality.
- May employ non-parametric and distribution-free statistical methods, and possibly also techniques for structural escalation of data.

Reflecting a belief that this is a valid and acceptable approach to theory development, the exploratory research paradigm was recently supported in this journal by Petty (1991).

After reviewing previous research concerned with modelling of financial reporting and analysis in small enterprises in Section 2, the sample selection procedure and data collection methodology are described in Section 3. Characterization of historical financial reporting and analysis practices in the sample is outlined in Section 4. The paper goes on in Section 5 to describe selection of the modelling methodology employed, and in Sections 6 and 7 to detail findings of the modelling exercise. Concluding remarks on the outcomes of the research are made in Section 8.

II. REVIEW OF PREVIOUS RESEARCH

While some research has been undertaken to discover correlates with historical financial reporting and analysis practices in small enterprises (for example, an earlier stage of the present research described in McMahon and Davies (1991, 1992a,b and McMahon, Davies, & Bluhm, 1992), a thorough review of the literature has revealed that very little has been undertaken with the aim of modelling these practices. The only research of this kind discovered is described in Holmes and Nicholls (1989). The paucity of modelling studies of financial reporting and analysis practices in small enterprises is noted in that paper.

The modelling of financial reporting and analysis undertaken by Holmes and Nicholls (1989) is based on a three-way classification of financial information prepared or acquired at least annually by a sample of 928 Australian small enterprises:

- Statutory (ST)—predominantly returns required by government authorities.
- Statutory/Budget (SB)—ST plus operational and capital budgeting information.
- Statutory/Budget/Additional (SBA)—SB plus additional financial information such as cash-flow statements, breakeven analysis, production reports, interfirm comparisons and industry trends.

Holmes and Nicholls (1989) use logistic regression to develop an explanatory model from which the probability of a small enterprise preparing or acquiring the SBA level of financial information could be estimated, given the values of certain enterprise and owner-manager characteristics. Many possible models were tested involving a variety of independent variables selected by reviewing prior research and through exploratory data analysis. Using sensitivity analysis, the following model was found to have the best fit (predictive ability):

$$y = c + \sum_{i=1}^{7} a_i T_i + b_i TR + \sum_{i=1}^{6} d_i I_i + \sum_{i=1}^{5} e_i B_i + \sum_{i=1}^{2} f_i E_i + a$$

where y is the natural logarithm of the odds ratio $p/(1-p)$ in which p is the probability that a particular level of financial information (specifically SBA) will be prepared or acquired.

T_i represents sales turnover categories, $i = 1$–7.

TR indicates whether or not the owner-manager has sought management training since entering the enterprise.

I_i represents industry categories, $i = 1$–6.

B_i represents enterprise age under existing management categories, $i = 1$–5.

E_i represents numbers of employees categories, $i = 1$–2.

a is a stochastic disturbance term representing that part of y which is unexplained by the independent variables.

c, a_i, b_i, d_i, e_i and f_i are coefficients.

Holmes and Nicholls (1989) appear enthusiastic about the potential usefulness of their model. They identify the following possible applications:

- *Public accountants*—to predict the likely demand for financial information by small enterprises of different types in order to target market services, and also to provide more relevant and timely support to clients in the small enterprise sector.
- *Government policy-makers*—to assist in understanding the financial information needs of small enterprises so that government assistance, education and training programs, advice and counselling services, publications, etc. can be designed more effectively, made more relevant and targeted more accurately for specific user groups in the small enterprise sector.
- *Small enterprise owner-managers*—to ascertain the typical level of financial information prepared or acquired by competitors in the same industry and adjust their own demands accordingly.

III. SAMPLE SELECTION AND DATA COLLECTION

Sample selection began with a list of successful growth enterprises supplied by small enterprise support agencies situated in the northeast region of England. The list eventually contained 770 such enterprises after eliminating duplications. Each enterprise was mailed a brief questionnaire requesting temporal data on turnover and employment, and information on products/services and geographical area(s) of operation. There were 330 valid responses from enterprises engaged in manufacturing, wholesaling, retailing and service in a variety of industries.

A second list was constructed from the 330 responses in which enterprises were ranked on a combined index of growth rates in turnover and employment. Beginning with the highest ranked, and with a sample target of approximately 100, these enterprises were progressively contacted to arrange interviews. A refusal caused the next highest-ranked enterprise to be approached. The eventual size of the sample became 102 and it included all the more easily recognized small growth enterprises in the region. Interviewers were briefed Master of Business Administration students at Durham University Business School. Structured interviews were undertaken based on a schedule containing five questions on aspects of financial reporting and analysis (these are detailed in McMahon & Davies, 1992).

The sampling and data collection methodologies employed inevitably impose limitations on interpretation of results of the study. There is no assurance that the non-random final sample was representative of the original 770 enterprises, or indeed of small growth enterprises in the region as a whole. The inquiry was of a general, non-sectoral nature; and no attempt was made to match growth and non-growth enterprises. The accuracy and completeness of the data relied heavily on the skills of non-professional interviewers, and upon the cooperation of owner-managers interviewed. These considerations limit the internal and external validity of the study, and hence caution must be exercised in making generalizations based on its findings.

IV. FINANCIAL REPORTING AND ANALYSIS PRACTICES

A financial reporting index for each participating enterprise is based on responses to a question on how frequently (annually, semi-annually, quarterly, monthly, weekly, daily and never) certain historical financial reports (balance sheet, profit and loss statement, funds statement, cash-flow statement and "other statement") were usually prepared (see McMahon & Davies, 1991, 1992a,b and McMahon, Davies, & Bluhm, 1992 for details of the construction of the index). The index, designated FSINDEXF, has a maximum possible value of 5.000. The actual range for the study sample of 102 enterprises for this continuous variable is 1.428 to 5.000; with a mean of 3.637, a median of 3.582 and a standard deviation of 1.106. A grouped version of the continuous financial reporting index, designated FSINDEXG, was also constructed. This has the relative frequency distribution indicated in Table 1.

Financial analysis practice in the participating enterprises is represented by a dichotomous variable, designated FRATUSE, indicating whether financial ratios were used. Financial ratio analysis was employed by 61.8 percent of the 102 participants.

Table 1
Grouped Financial Reporting Index

FSINDEXF	*FSINDEXG*	*Percentage (n=102)*
0.000–2.499	1 (Low)	19.6
2.500–3.499	2 (Intermediate)	22.5
3.500–5.000	3 (High)	57.9
	Total	100.0

V. MODELLING METHODOLOGY

The criteria applied in selection of a modelling methodology for the study were as follows:

- The methodology needed to make minimal assumptions concerning sample selection and the distributional properties of variables employed. Exploratory data analysis had revealed statistically significant departures from normality at the $\alpha = 0.01$ level or better in all variables that could be tested using a Kolmogorov-Smirnov one-sample test.
- The methodology needed to be resistant to the influence of extreme values or outliers. Exploratory data analysis had revealed that certain continuous independent variables had a number of outliers. Outliers were not removed from the data set because this would result in an undesirable reduction in the size of the already small sample, and since all enterprises in the sample had passed the primary criteria of being independently owned and managed and having experienced significant growth.
- The methodology needed to handle both dichotomous and polytomous dependent variables which are either nominal or ordinal, and also dichotomous, polytomous (nominal or ordinal) and continuous independent variables.
- Given the usual computational complexities of statistical modelling, the methodology had to be accessible on the available statistical computer software package, SYSTAT.

Logistic regression (often abbreviated to 'logit') was selected for modelling historical financial reporting and analysis practices in the study sample.

Logistic regression has two main variants according to the nature of the dependent categoric variable:

- *Dichotomous dependent variable*—this is the most common form and in this study is used to model financial analysis practice.
- *Polytomous dependent variable*—referred to as multinomial logistic regression (sometimes abbreviated to 'multinomial logit' or 'multilogit'), this form is less well-known. In this study it is used to model historical financial reporting practice.

VI. MODELLING RESULTS FOR FINANCIAL ANALYSIS

The results of modelling the dichotomous dependent variable FRATUSE using logistic regression follow. FRATUSE has the value zero if financial ratio analysis is not in use, and the value one if financial ratio analysis is used. Findings of the earlier associative stage of the present research (see McMahon & Davies, 1991, 1992a,b and McMahon, Davies, & Bluhm, 1992) reveal that FRATUSE has a statistically significant association ($\alpha = 0.10$ or better) with the enterprise and owner-manager characteristics identified in Table 2. These were therefore trialled as independent variables in the models.

The generalized form of the multivariate logistic regression model with a dichotomous dependent variable and continuous independent variables can be expressed as follows:

$$\ln[\pi/(1-\pi)] = \phi + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon$$

where π is the probability that the value of the dichotomous dependent variable equals one.
$x_1, \ldots, x_n$ are independent variables which are at least interval scaled;
ϕ is a constant;
$\beta_1, \ldots, \beta_n$ are coefficients;
ε is a stochastic disturbance term representing that part of $\ln[\pi/(1-\pi)]$ which is unexplained by the independent variables.

Relatively straightforward adjustments can be made to this model when some of the independent variables are categoric. The parallels between this multivariate logistic regression model and the generalized form of the multivariate linear regression model are evident. However, three important differences should be noted.

Table 2
Independent Variables Trialled in Modelling Financial Analysis Practice

Characteristic	*Variable*	*Nature of Variable*
Financial Reporting	FSINDEXF	Continuous
Employment Now	EMPL90	Continuous
Owner-manager Inexperience Now	OMINNOW[a]	Dichotomous, nominal
Owner-manager Experience Now	OMEXNOW[a]	Dichotomous, nominal

Note: [a]In financial management.

1. The left hand side is not the dependent variable itself; but the so-called 'log odds' or 'logit' of the dependent variable.
2. The statistical properties of the residual or error term, ε, are quite different from those of the corresponding term in linear regression analysis.
3. Least Squares Estimation of unknown parameters in linear regression analysis was replaced with Maximum Likelihood Estimation in logistic regression.

The broad approach to logistic regression model building and evaluation employed in this study was that recommended by Hosmer and Lemeshow (1989). Following this procedure, a total of nine univariate and multivariate dichotomous logistic regression models of financial analysis practice were examined. Details of the most parsimonious multivariate model with acceptable explanatory power are presented in Table 3.

If the selected model is to be employed for anticipating whether financial ratio analysis is likely to be used in a particular small enterprise, given relevant enterprise and owner-manager characteristics, some assessment needs to be made of its reliability in terms of classification success. Classification is achieved by assigning each enterprise to the dependent variable category with the highest estimated probability according to the model. Preferably, the evaluation should be carried out using data other than that from which the model was developed. However, trials showed that the form of the logistic

Table 3
Model Selected for Financial Analysis Practice

		Bounds of Odds Ratio[a]		*Statistical Significance*[b]		*Derivatives*[c]	
						FRATUSE	
Fitted Model	*Odds Ratio*	*Upper*	*Lower*	*Parameter*	*Fitted Model*	*0*	*1*
−1.219				0.099[c]			
+0.419FSINDEXF	1.521	2.222	1.041	0.030[c]		−0.092	0.092
+0.898OMEXNOW	2.455	7.071	0.852	0.096[c]	0.026[c]	−0.197	0.197

Notes: [a]Bounds are 95 percent confidence limits.

[b] Probability for appropriate significance test. For individual parameters this is a Student's t-test. For fitted model this is a Likelihood Ratio (LR) test comparing "constant only" model with fitted model.

[c] Significant at $\alpha = 0.10$ or better.

Table 4
Classification Success for the Selected Model of Financial Analysis Practice

	Outcome	
Statistic	*FRATUSE=0*	*FRATUSE=1*
Observed Overall Percent	38.2	61.8
Percent Correctly Classified	28.2	87.3
Percentage Points Improvement	–10.0	25.5
Overall Percent Correctly Classified	64.7	

regression model of financial analysis practice was sensitive to the number of cases employed in its development. In view of this, and the limited size of the study sample, it was considered impracticable to base evaluation of the classification success of the selected model on a hold-out sample. Thus, the summary of classification success statistics presented in Table 4 is for the sample of 102 cases from which the model was derived.

Knowing that the statistics presented in Table 4 are likely to be optimistic reflections of the reliability of the model chosen, they might be described cautiously as fairly encouraging. For FRATUSE=1, the model appears to provide gains of approximately 25 percent over a corresponding "constant only" model, which assigns probabilities to every case equal to the observed proportions of the respective samples in each dependent variable category. However, the classification success is clearly asymmetric, with the anticipation of non-use of financial ratio analysis being approximately 10 percent worse than for a "constant only" model. On the basis of the null hypothesis that financial ratio analysis is not used, the Type I error (classifying a non-user as a user) is very high at 0.718. However, the Type II error (classifying a user as a non-user) is more acceptable at 0.127. The overall classification success of approximately 65 percent noticeably exceeds an arbitrary cut-off of being correct 50 percent of the time.

Ultimately, a judgement on the classification success of the model must be influenced by its application. To identify non-users of financial analysis so they can be encouraged to attend a training course or seek advice on this technique, the model would obviously be ineffective. However, it could be used with good effect to screen for owner-managers who have implemented comprehensive historical financial reporting systems, and who possibly have sufficient financial management experience to benefit from expertise in the analysis of their financial statements. A check would then need to be made to determine whether financial ratio analysis is used. If this is not so, then the owner-managers concerned might be a group with considerable latent interest in a relevant training program or professional counsel.

The final step in the Hosmer and Lemeshow (1989) procedure involves interpretation of the coefficients of independent variables in the logistic regression model of financial analysis practice. The purpose here is to draw practical inferences relating to the research problem from the estimated coefficients. This task focuses attention on the odds ratios and their confidence intervals for independent variables in the model, and also upon the derivatives for each independent variable. These are presented in Table 3.

Considering FSINDEXF first, the odds ratio approximates the multiplicative factor by which the likelihood of undertaking financial ratio analysis is altered by a change of 1.000 in FSINDEXF, statistically adjusted for the impact of OMEXNOW. Hence, it would appear that increasing the level of historical financial reporting in a small enterprise to the extent that FSINDEXF increases by 1.000 makes it around 1.5 times more likely that financial ratio analysis is used. The lower confidence limit of the odds ratio exceeds 1.000, again indicating that FSINDEXF is genuinely important in explaining whether financial ratio analysis is undertaken. The derivatives for FSINDEXF indicate that each increase of 1.000 in FSINDEXF will increase the probability of undertaking financial ratio analysis by around 0.1. The odds ratio for OMEXNOW suggests that providing an owner-manager with useful experience in financial management makes financial ratio analysis around 2.5 times more likely. The confidence bounds of the odds ratio are quite wide, implying that the outcome is far from certain. Nevertheless, the fact that the confidence interval for OMEXNOW is skewed to the right suggests that providing useful financial management experience is likely to be efficacious. The derivatives for OMEXNOW indicate that useful experience in financial management increases the probability of undertaking financial ratio analysis by around 0.2.

The broad implication of the model is that merely encouraging owner-managers to increase the extent and frequency of historical financial reporting on their enterprises is not likely to be as effective a strategy for improving financial management as doing this as well as providing necessary experience so that skills in financial analysis may also be acquired and used. This supports the widely held view that training and/or professional advice could supply much needed leverage to lift the general competency level in financial management amongst small enterprise owner-managers.

VII. MODELLING RESULTS FOR FINANCIAL REPORTING

Modelling historical financial reporting in the small growth enterprises used the polytomous dependent variable FSINDEXG which has possible integer values ranging from one to three. Previous findings (McMahon & Davies, 1991, 1992a,b and McMahon, Davies, & Bluhm, 1992) reveal that FSINDEXG has statistically significant associations ($\alpha = 0.10$ or better) with the enterprise and owner-manager characteristics identified in Table 5. These were therefore trialled as independent variables in the models.

In view of the ordinal nature of the dependent financial reporting variable FSINDEXG, and also Agresti's (1984) opinion on the desirability of retaining information contained in ordered data, it is appropriate to briefly contrast the treatments given nominal and ordinal dependent variables in polytomous logistic regression:

- *Nominal Scaling*—this is the simpler situation for which the normal approach is to specify k–1 logits as follows (assuming the reference group used is the highest, k):

  $\ln[\pi_j/\pi_k]$ for $j = 1, \ldots, k-1$

Table 5
Independent Variables Trialled in Modelling Financial Reporting Practice

Characteristic	*Variable*	*Nature of Variable*
Turnover Now	TURN90	Continuous
Employment Now	EMPL90	Continuous
Enterprise Age	AGEBUS	Continuous
Organizational Formality	FORMAL[a]	Polytomous, ordinal
Computer for Management	COMPUTER	Dichotomous, nominal
Computer for Financial Management	FINCOMP	Dichotomous, nominal
Strategic Thinking	STRATEGY[a]	Polytomous, ordinal
Formal Strategic Planning	EXTFORM	Dichotomous, nominal
Owner-manager Time	OMFMTIME[b]	Continuous
Employ Professionals	PROFESS	Dichotomous, nominal
Employ Managers	MANAGERS	Dichotomous, nominal
Employ Financial Specialist	FMSPEC	Dichotomous, nominal
Use Merchant Bankers Frequently	EXTADVM	Dichotomous, nominal

Notes: [a]On integer scale ranging from one (low) to five (high).
[b]In financial management.

This approach treats the dependent variable strictly as nominal, and any information contained in ordered values of the dependent variable is lost to the model.

- Ordinal Scaling—this situation is more complicated and can be approached in a number of ways, including the specification of k–1 "cumulative" logits as follows (again assuming the reference group used is the highest, k):

  $$\ln[\pi_{j+1} + \cdots + \pi_k)/(\pi_1 + \cdots + \pi_j)] \text{ for } j = 1, \ldots, k-1$$

  This approach recognizes the ordinal nature of the dependent variable, and any information contained in ordered values of the dependent variable is retained in the model.

In the present study, the second of these treatments would have been preferred for modelling historical financial reporting practice. However, in

Table 6
Model Selected for Financial Reporting Practice

Model Part[d]	*Fitted Model*	*Odds Ratio*	*Bounds of Odds Ratio*[a] *Upper*	*Lower*	*Statistical Significance*[b] *Parameter*	*Fitted Model*	*Derivatives*[c] *FSINDEXG* *1*	*2*	*3*
A	3.967				0.040[e]				
	–0.015EMPL90	0.985	1.003	0.967	0.102				
	+0.048AGEBUS	1.050	1.109	0.993	0.087[e]				
	–0.926FINCOMP	0.396	2.978	0.053	0.368				
	–1.144STRATEGY	0.319	0.816	0.124	0.017[e]				
B	4.881				0.048[e]				
	–0.081EMPL90	0.922	0.997	0.853	0.041[e]		0.000	–0.007	0.007
	–0.193AGEBUS	0.824	1.013	0.671	0.067[e]		0.010	–0.019	0.009
	–2.641FINCOMP	0.071	0.664	0.008	0.020[e]		–0.036	–0.220	0.256
	+0.186STRATEGY	1.204	2.991	0.485	0.689	0.000[e]	–0.132	0.046	0.086

Notes: [a]Bounds are 95 percent confidence limits.
[b]Probability for appropriate significance test. For individual parameters this is a Student's t-test. For fitted model this is an LR test comparing "constant only" model with fitted model.
[c]Derivatives are for whole model. These are rounded and, as shown, may not sum to zero.
[d] Model has two parts, one for each response level of dependent financial reporting variable FSINDEXG. Reference level is FSINDEXG=3.
[e] Significant at $\alpha = 0.10$ or better.

common with other commercially available computer software, the SYSTAT statistical package is unable to implement this form. As a result, the first treatment was used and FSINDEXG was regarded as a nominal variable.

In preliminary modelling trials of historical financial reporting practice, it became obvious that the influence of the independent variable COMPUTER would overshadow that of other explanatory variables, making interpretation of the resulting models problematic. The coefficients, significance statistics and other logistic regression measures for COMPUTER are strongly influenced by the fact that a high 89.2 percent of the small enterprises in the study sample reported using a computer for management purposes. It was therefore decided to restrict further modelling to data available for those enterprises that reported use of computers in management. This reduced the potential data set to 91; but it permitted a better view of the influence of other independent variables, including FINCOMP, which indicates whether or not computers were used in financial management.

Following the Hosmer and Lemeshow (1989) procedure, a total of 27 univariate and multivariate polytomous logistic regression models of historical financial reporting practice were examined. Details of the most parsimonious multivariate model with acceptable explanatory power are presented in Table 6.

In view of the limited size of the data set used to develop the model, it is impracticable to evaluate its classification success on a hold-out sample. Thus, the summary of classification success statistics presented in Table 7 is for the sample of 79 cases from which the model was derived.

Once again, the statistics presented in Table 7 might be described cautiously as fairly encouraging. The model appears to provide gains in the range 20 to 40 percent over a corresponding "constant only" model. The gain is greatest for the intermediate financial reporting level; although the classification success of the model is best for the highest level. The overall classifi-

Table 7
Classification Success for the Selected Model of Financial Reporting Practice

	Outcome		
Statistic	*FSINDEXG=1*	*FSINDEXG=2*	*FSINDEXG=3*
Observed Overall Percent	16.5	21.5	62.0
Percent Correctly Classified	23.1	58.8	89.8
Percentage Points Improvement	6.6	37.3	27.8
Overall Percent Correctly Classified	72.2		

cation success of just over 70 percent noticeably exceeds the arbitrary cut-off of being 50 percent correct. Thus, the model is reasonably good at specifying the level of historical financial reporting that is typically undertaken given the size and age of a small enterprise, the availability of computer facilities for the purpose, and the strategic orientation of its owner-manager(s). The model could therefore be used with good effect to screen for owner-managers who have not already implemented historical financial reporting systems seemingly appropriate to their circumstances. The owner-managers so identified might represent a group with potential interest in a relevant training program or professional counsel.

The final task of interpreting the coefficients of independent variables in selected logistic regression models of historical financial reporting practice focuses attention on relevant information presented in Table 6. Considering EMPL90 first, the odds ratios and derivatives suggest that increasing the size of an enterprise in terms of employment increases the likelihood of the highest level of historical financial reporting at the expense of the lowest and intermediate levels. Interestingly, the odds ratios and derivatives for AGEBUS suggest that the likelihood of the lowest and highest levels of historical financial reporting increase with enterprise age at the expense of the intermediate level. In other words, there appears to be some degree of polarization in historical financial reporting practice as small enterprises get older. The odds ratios and derivatives for FINCOMP suggest that the likelihood of undertaking historical financial reporting at the lowest or intermediate levels is substantially reduced if a computer is available for financial management purposes. However, the confidence bounds for the odds ratios are quite wide, indicating a relatively uncertain outcome. Finally, the odds ratios and derivatives for STRATEGY indicate that the likelihood of historical financial reporting at the intermediate and highest levels grows at the expense of the lowest level with increased strategic thinking on the part of the owner-manager(s). Again, the confidence bounds for the odds ratios are quite wide.

The broad implication of the selected model is that, as small enterprises get larger in employment terms, and survive longer, it becomes more likely that their owner-managers will install historical financial reporting systems that are comprehensive in terms of the number of financial statements obtained and the frequency of their preparation. This may be because the demands on an owner-manager are greater when there are more employees to oversee, and his or her primary role moves towards supervision of the work of others rather than direct hands-on involvement in the operations of the enterprise. It may also be due to greater managerial sophistication acquired by the owner-manager over time through experience and possibly training. It would seem, furthermore, that comprehensive historical financial reporting is more likely where a computer is available to facilitate this, and where the owner-manager has a strong strategic orientation. Thus, the situational and enabling factors identified in the model combine to explain observed financial reporting practice.

VIII. CONCLUDING REMARKS

It is difficult to assess the success or otherwise of this study of statistical modelling of historical financial reporting and analysis practices in small growth enterprises. In part, this is because there are virtually no studies of similar focus that can provide a benchmark for an acceptable level of accuracy in the classifications. Only some form of external validation can provide the final assurance for practical use of the models developed here for small enterprise support. Verification using a holdout sample or some other unrelated sample of small enterprises has not been possible. The overall size of the sample is very much at the lower limit of what can and should be used in a modelling exercise of this nature.

There is no guiding theory on financial reporting and analysis in business enterprises, be they large or small. The models proposed here may have value for the insights into financial management of small enterprises they provide, notwithstanding their limited classification success. They can, at the very least, be used as a basis for formulating testable hypotheses that may then be subjected to the full rigors of confirmatory research. This might in turn lead to the theoretical advances which are sorely needed if small enterprise scholarship in the area of financial management is to mature.

In the uncertain world of business, many argue that being correct more than half the time is an achievement. Against this standard, the overall classification success of approximately 65 percent for the financial analysis model, and in excess of 70 percent for the financial reporting model, appear encouraging. The higher levels of classification accuracy (around 90 percent) achieved for particular outcomes, such as financial ratio use and undertaking financial reporting at the highest level, seem to make use of the models for anticipating these outcomes compelling.

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