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Late financial distress process stages and financial ratios: Evidence for auditors' going-concern evaluation

ABSTRACT

The present study adds to our understanding and knowledge of financial distress predictions regarding the usefulness of financial ratios in the late stages of the financial distress process. The study contributes to previous research by generating information concerning: (1) the behavior and usefulness of single financial ratios in short-term financial distress prediction when the effect of each different financial distress process stage is considered; (2) the effects of recognition of the financial distress process stage on the financial distress prediction model. The time horizon for prediction is less than one year, and the empirical data consist of financial statement information from 106 distressed firms undergoing reorganization and their matched counterparts for 2003–2007. To analyze the effects of the specific distress process stage, the sample has been divided into two groups according to the date of application for reorganization: the first group of businesses applied for reorganization between 1 and 182 days after the closing of accounts, and the second group between 183 and 365 days after that point. The study findings provide evidence that the financial distress process stage affects the classification ability of single financial ratios and financial distress prediction models in short-term financial distress predic-

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tion. The study shows that the auditor's GC task could be supported by paying attention to the financial distress process stage. The implications of these findings for auditors and every stakeholder of business firms are considered.

Key words: *financial distress process***,** *going concern evaluation, financial ratios, classification accuracy and reorganization*

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1. INTRODUCTION

The basic assumption in preparing financial statements is that a business is considered as a going concern (GC). This means that the business will usually be in operation for the following 12 months or for the following accounting period. If a business is a GC, the risk that it will enter liquidation in the foreseeable future is very small. If there is a considerable risk that the company will not be in business at the end of the following fiscal year, an auditor should report a GC opinion, which is one of the most difficult tasks an auditor faces (Martens et al. 2008). To justify a GC opinion, material uncertainties about the business must exist. If the auditor does not issue a GC opinion and the business encounters financial difficulties within the subsequent fiscal year, the auditor risks being held responsible to the stakeholders for the financial consequences of not having issued a GC opinion. The most severe forms of financial difficulties in business are reorganization and bankruptcy, because in both cases stakeholders can suffer considerable financial losses.

Recently the number of distressed companies filing for reorganization and bankruptcy has significantly increased. Auditors and all stakeholders in businesses are aware of the very severe worldwide economic crisis. In other words, there is concern about auditors' awareness of matters relating to the consideration of applying the going-concern assumption when preparing financial statements. Furthermore, businesses are faced with the challenge of evaluating the effect of the credit crisis and economic downturn on the entity's ability to continue as a going concern. Questions have been raised as to whether such effects on the entity ought to be described or otherwise reflected in the financial statements. Those are the key messages in the international newsletter "AUDIT Considerations in respect of Going Concern in the Current Economic Environment", issued by The International Auditing and Assurance Standards Board (IAASB) in January 2009. In the light of the current situation, our study provides evidence of the challenging nature of the auditor's task of determining whether a company is a GC and the related assessment of the severity of financial distress the company might experience in the coming year. Several reasons underpin the decision to undertake the current research.

First of all, while the GC assessment reflected by financial distress has a long history, most of the previous research has focused on the needs and points of view of creditors. In other words, this focus has led researchers to extend the time span underlying the failure prediction as much as possible. The importance of the time span in distress prediction models is emphasized by the instability of financial ratios (Balcaen and Ooghe 2006: 74), and in order that their predictive ability may be maintained, distress prediction models require that the relationships between predictors are stable over time. However, the statistical significance of financial ratios will change at different stages, and this implies that optimal cross-sectional models vary for different stages (see e.g. Zavgren 1983; Zavgren and Friedman 1988). Accordingly, the optimal models for creditors differ from those for auditors and moreover, the quicker the changes in the financial situation of the distressed firm happen, the greater the need for a short-term model (Laitinen 1991). This study is one of the first attempts to consider auditors' support requirements for short-term predictions, and it thus shifts the emphasis from the previous creditor-based long-term financial distress predictions to auditor-based short-term predictions.

Second, previous studies have mainly based their empirical analysis on an auditors' GC evaluation, and little seems to be known about statistical models to support auditors' GC decision-making. There is evidence that the GC decision is a complex task that has comprehensive consequences for both the business being audited and the auditors, who are likely to welcome any systems that may support them in making the decision (Louwers 1988; Martens *et al.* 2008).[1] An auditor's GC evaluation can be viewed as a two-stage process: First a judgment stage in which the auditor forms an initial opinion about the client's financial distress or stability, and second a decision stage in which the auditor finally decides on the type of report to issue (Asare 1992). Taking this into consideration, this study presents evidence of the first stage of GC evaluation to support auditors' decision-making and uses the GC concept in the context of the financial distress process. The use of a corporate distress model may help the auditor identify high-risk firms in the planning stages of the audit and assist the auditor in planning specific audit procedures aimed at evaluating the appropriateness of a GC opinion (Koh and Brown 1991).[2]

1 The assessment of an entity's ability to continue as a GC is the responsibility of the entity's management, and the role of the auditor is to consider the appropriateness of applying the GC assumption. However, the task of commenting on the GC assumption goes somewhat beyond the traditional role of the auditors, which is to verify historical transactions and check the existence of inventory etc. In sum, in comparison with other reporting requirements, GC reporting involves a large degree of subjectivity.

2 Furthermore, International Standard on Auditing (ISA) 570 establishes the relevant requirements and guidance with regard to the auditor's consideration of the appropriateness of management's use of the GC assumption and auditor reporting.

Finally, it has been stated that when studying auditors' decision-making, the samples of very distressed businesses (such as those in the bankruptcy process) and viable firms should be considered separately. This is because the auditors' decision-making problems are different in very distressed and viable firms respectively (Martens *et al.* 2008; Hopwood *et al.* 1994). In earlier financial distress research, the different groups compared in classifications have traditionally consisted of bankrupt and viable firms. This is due to a creditor-based approach where the main purpose is to identify a bankrupt firm to avoid losses from defaults. Typically, bankrupt firms have been very deeply distressed before the event. However, in an auditor-based approach this kind of setting cannot be justified. As a result, rather than focusing on bankrupt firms, the current article uses empirical data from reorganization firms.

To conclude, the present study adds to our understanding and knowledge of financial distress predictions regarding the usefulness of financial ratios in the late stages of the financial distress process. Our contribution to the previous literature is to provide an alternative to the classic long-term financial distress prediction that is based on the creditor-based approach. Hence, our study builds on previous research by generating information concerning: (1) the behavior and usefulness of single financial ratios in short-term financial distress prediction when the effect of each different financial distress process stage is considered; (2) the effects of recognition of the financial distress process stage on the financial distress prediction model.

The paper is organized as follows: Following this introduction of the motivation behind the study and its purpose, the second section includes a short review of earlier studies followed by a definition of the research hypotheses. In addition, a short description of the Finnish reorganization process is presented. The third section details the data and statistical methods of the empirical analysis before the empirical results are presented and discussed in the fourth section, and finally, the last section presents the findings of the study and limitations of the approach. Several suggestions for further research are also presented.

2. REORGANIZATION AND FINANCIAL DISTRESS

2.1. Earlier studies

The present study focuses on the financial distress concept; in this context, traditional financial distress prediction research has focused on failed and non-failed firms one to five years prior to the event, and the fundamental issue has been the same in almost every study: to distinguish between financially viable and financially distressed firms as early in the financial distress process as possible. In this research, Altman's Z model (Altman 1968), the ZETA model (Altman, Haldeman and Narayanan 1977), Ohlson's (1980) logit model, and Zmijewski's (1984) probit model are well-known early models. Later, a number of novel statistical estimation methods for distress modeling have been suggested: the artificial neural network (ANN) model (Altman, Marco and Varetto 1994; Tam and Kiang 1992), Bayesian network models (Sarkar and Sriram 2001; Sun and Shenoy 2007), and data envelopment analysis (DEA) (Cielen, Peeters and Vanhoof 2004). Moreover, it is argued that a mixed logit model outperforms a standard binary logit model in financial distress prediction (Shumway 2001), and hazard models are applied (Shumway 2001; Beaver, McNichols and Rhie 2005).

There are many different approaches to improving the performance of the statistical models. Indeed, in spite of the existence of a theory, the predictors of financial distress prediction models are mainly chosen on empirical grounds (Balcaen and Ooghe 2006). However, Beaver (1966), Altman (1986), Scott (1981), Jones (1987), Karels and Prakash (1987), Laitinen and Kankaanpää (1999), and Balcaen and Ooghe (2006) indicate financial determinants of financial distress (bankruptcy) on theoretical and empirical grounds. Dimensions supported by bankruptcy theory and related empirical evidence are leverage, profitability, liquidity, cash flow, and size (Scott 1981; Jones 1987; Laitinen 1991). Furthermore, research shows that it is possible to predict bankruptcy with relatively high (classification) accuracy at least 5 years before the event when financial ratios are used as predictors (Beaver *et al.* 2005). Accordingly, a large number of financial distress prediction models are traditionally based on the systematic deterioration of financial ratio values (Beaver 1966; Beaver *et al.* 2005), since as firms move closer to the event of financial distress, they take on more unusual characteristics (Salehi 2009).

However, failing firms may have different financial distress processes since the first symptoms and the timing of financial symptoms vary between financially distressed firms (Laitinen 1991; D'Aveni 1989). In other words, it is obvious that all failing firms do not behave in the same way in terms of financial ratios, and accordingly the identification of specific processes may considerably improve understanding of the financial distress prediction (Laitinen 1991). Indeed, in the financial distress prediction, financial indicators will maintain their significance throughout the process, but as the symptoms of financial distress become more apparent, the relative significance of the indicators may diminish (Laitinen 2005). As a result, a situation has arisen where the usefulness of distress prediction models is limited due to the instability of models (Balcaen and Ooghe 2006: 74). To maintain their predictive ability, traditional prediction models require that relationships between predictors remain stable over time. In addition, they are stationary, which implies a stable relationship between the event measure and predictors. However, the statistical significance of predictors will vary in different years prior to distress (Zavgren 1983; Zavgren and Friedman 1988; Laitinen 2005). This means that one single cross-sectional model cannot be optimal for every year.

Different stages of the financial distress process have been identified (see e.g. Laitinen 1991). These stages can be summarized as follows:

1. Early stage
   – financial statements indicate decreased profitability
2. Late stage
   – financial statements indicate decreased profitability and increased leverage
3. Final stage
   – financial statements indicate decreased profitability, increased leverage and decreased liquidity

The current study focuses on stages 2 and 3, the late and final stages.

Zavgren and Friedman (1988: Table 2) outline the significance of different predictors in their models estimated separately for five years prior to failure (but post filing for bankruptcy). The evidence shows that the operating performance ratios (inventory turnover and capital turnover) were significant 4–5 years prior to failure but not in subsequent years. The short-term liquidity ratio was significant only in years 1–3, while the debt ratio (financial leverage) was significant in each of the five years. The profitability ratio (return on investment) was not statistically significant in any year. The insignificance of profitability has also been noted by Ohlson (1980). This evidence indicates that it is important to pay attention to the time span allowed for prediction when developing a model. In order to study this phenomenon empirically we identify different financial distress process stages to find out whether financial ratios (univariate analysis) and financial prediction models (multivariate analysis) in short-term financial distress prediction are affected by the different stages (univariate analysis).

For these analyses, the following research hypotheses are proposed:

H1: the financial distress process stage affects the prediction ability of a single financial ratio in short-term predictions (Univariate analysis)
H2: the financial distress process stage affects the statistical financial distress prediction model in short-term predictions (Multivariate analysis)

To conclude, this study generates new evidence for financial distress prediction research by testing whether the explanatory power of alternative ratios and models based on these ratios differs in short-term prediction when the effect of the stage of financial distress process is considered. In these analyses, we apply univariate analysis, stepwise logistic regression, and a Z-test to test the two research hypotheses.

2.2. The reorganization process in Finland

In Finland, the reorganization proceedings of a business are stipulated by the Reorganization of Enterprises Act (REA) (47/1993; amendments up to 247/2007 included) that came into force on

8 February 1993. The legislation sets out that reorganization proceedings may be undertaken in order to rehabilitate a distressed debtor's viable business, to ensure its continued viability, and to facilitate debt arrangements. In the proceedings, a court may approve a restructuring program with instructions regarding measures on the activities, assets and liabilities of the debtor as provided by the Act (247/2007). Consequently, the main objective of the REA is to assist the recovery of a business having temporary financial difficulties but otherwise being financially viable. Furthermore, reorganization proceedings may be instigated to avoid bankruptcy. When the application for reorganization has been filed with the court, the business can be protected from creditor demands. If the business does not get court approval for reorganization, it may be declared bankrupt under the Finnish Bankruptcy Act (FBA). Therefore, reorganization proceedings may be a way of avoiding bankruptcy liquidation, at least temporarily, even if the business is unviable (Laitinen 2009).

The application for reorganization proceedings may be filed by the debtor or a creditor or several creditors jointly, but not, however, by a creditor stating a claim which is contested in terms of its basis or its amount or a claim that is otherwise unclear, or by a party for whom the insolvency of the debtor would probably cause financial loss on a claim, on grounds other than partnership or shareholding. Reorganization proceedings may be commenced if:

1. At least two creditors whose total claims represent at least one fifth of the debtor's known debts and who are not related to the debtor file a joint application with the debtor or declare that they support the debtor's application;
2. The debtor faces imminent insolvency; or
3. The debtor is insolvent and no other outcome ensues from the application of section (247/2007).

In the Act, insolvency is defined as being other than a temporary inability of the debtor to repay its debts when they become due, and the definition of imminent insolvency is that the debtor is at risk of insolvency. Reorganization proceedings are not to be commenced if the debtor is insolvent and it is probable that the reorganization program will not remedy the insolvency or prevent its occurrence for more than a short period (247/2007).

REA has enabled the recovery of thousands of distressed businesses. In total, during the years 1993–2007, 4842 reorganization petitions were filed (Statistics Finland). In the research period 2003–2007 respectively 332, 317, 269, 302, and 306 petitions for reorganization were filed. The data used in this study only include limited companies that are not publicly traded and which have published financial statements. Thus, all non-incorporated companies which are not obliged to publish financial statements have been excluded.

The majority of businesses filing for reorganization do not recover. On average, the court approves about 60 % of the applications for reorganization, and of those applications about 75

% lead to an approved restructuring plan. Many of these businesses, however, are unsuccessful in implementing the reorganization plan and go bankrupt during the program. Reorganization statistics show that on average only 50–60 % of the businesses prove able to carry out the reorganization plan successfully. Consequently, the failure rate of reorganization firms is high (Laitinen 2009:186).

3. EMPIRICAL DATA AND STATISTICAL METHODS

3.1. Empirical data

3.1.1. Sample of firms

The data used in this study include published annual financial statements of private Finnish limited companies relating to the research period, which stretches over the accounting years 2003–2007. The sample consists of 106 businesses that filed a petition for reorganization and 106 viable businesses that did not register public payment defaults during the period in question. Furthermore, every reorganization business is matched with a viable business in terms of industry, size (i.e. total assets), and accounting period. In this way, the effects of size, industry, and accounting period (business cycles) have been eliminated from the results (see Beaver 1966). The number of reorganization businesses in the population is very small compared to the number of viable businesses. This means that using equal groups of reorganized and viable businesses leads to an oversampling of reorganization businesses. This oversampling may lead to a choice-based bias in the results. However, this bias is relatively weak and does not appear to affect the statistical inferences (Zmijewski 1984). The data include financial statements (income statement and balance sheet) and the date of the petition filed for reorganization proceedings. The financial statements are gathered from the last accounting year prior to the petition being filed. This study includes all available limited companies that filed an application for reorganization during the research period in the current dataset obtained from the largest Finnish credit information company Suomen Asiakastieto Oy for research purposes (see http: www.asiakastieto.fi).

3.1.2. Descriptive statistics

Tables 1 and 2 present the descriptive statistics of the sample. Table 1 shows the industrial distribution of the sample companies in this study. This distribution is the same for reorganization and viable companies because of paired sampling. The proportion of industries such as electricity, gas, steam, and air conditioning supply is 31.13 %. Furthermore, a majority of the companies represent industries such as construction and wholesale and retail trade with shares of 21.7 % and 19.81 %, respectively. The size distribution in the sample is presented in Table 2. The size of a company is estimated using the amount of its total assets, and this gives the same distribution for reorganization and viable companies. The majority of the companies have total assets of between EUR 100,000 and EUR 1 million. Only a few companies in the sample have total assets of over EUR 10 million. Thus, the size distribution is skewed by including only a few large companies.

TABLE 1. Industry classification of the sample companies.

Industry	Amount	%
Electricity, gas, steam, and air conditioning supply	66	31.13
Construction	46	21.70
Wholesale and retail trade	42	19.81
Transportation and storage	18	8.49
Administrative and support service activities	12	5.66
Accommodation and food service activities	10	4.72
Professional, scientific, and technical activities	8	3.77
Information and communication	6	2.83
Mining and quarrying	2	0.94
Other service activities	2	0.94
Total	212	100.00

TABLE 2. Size distribution of the sample companies.

Balance sheet	Amount	%
0–99,999 €	22	10.38
100,000–499,999 €	70	33.02
500,000–999,999 €	56	26.42
1–5 million €	46	21.70
6–10 million €	12	5.66
over 10 million €	6	2.83
Total	212	100.00

3.2. Financial distress process and financial ratios

In this study, the effect of the stage of the financial distress process is analyzed by classifying the sample into two parts according to the period extending from the last closing of accounts to the filing of the petition for reorganization. This time period varied in the sample firms between 1 and 365 days. While the financial statement and auditor’s report must be completed no later than 4 months after the closing of accounts, for an auditor it is less challenging to study GC problems during the four months immediately following the closing of the accounts. The two following months are easily foreseeable because of the short time period, and accordingly the most challenging months are the last six months of the fiscal year. However, the auditor needs to consider the going-concern assumption for the entire fiscal year. Even though the first six months of the fiscal year are less challenging compared to the last six months, they must also be carefully analyzed for professional reasons. As a result we have divided the accounting period into two equally long periods, and the main issue is whether there are differences in the information content of alternative financial ratios between these two sub-samples. The companies that filed their application for reorganization in the first six months (i.e. 1–182 days after the date of the last financial statements) are considered as being in the final stage of the distress process at the time of the last closing of their accounts. This sub-sample is here called Group 1 (final stage). Correspondingly, companies that filed their application for reorganization in the last six months (i.e. 183 – 365 days after the date of the last financial statements) were considered as being in the late but not final stage of the distress process at the time of the last closing of their accounts. This sub-sample is called Group 2 (late stage). The cut-off point of 182 days was selected because of a need to divide the accounting period into two equal time periods. Group 1 includes 45 reorganization and viable companies, and Group 2 includes 61 of each.

The selection of financial ratios in this study is based on a long history of prior studies. In most studies, financial ratios are classified according to the dimensions they measure, and the choice of financial variables (predictors) is related to the symptoms of financial distress. The traditional classification of financial ratios encompasses three broad classes: profitability, solidity, and liquidity. In most previous studies this set of financial dimensions has been used to design a model leading to the best classification or prediction result. Consequently, this study also uses those three traditional dimensions (profitability, liquidity and solidity) as its preferred explanatory variables. They have been found to be the most successful predictors of company failure in earlier research (Zmijewski 1984; Karels and Prakash 1987; Chen *et al.* 2006; Balcaen and Ooghe 2006). However, the significance of the profitability ratios has been questioned especially in the models for the last stages of distress (Zavgren and Friedman 1988; Ohlson 1980). In addition to the traditional financial ratios, the company's growth may serve as an important indicator of failure (Laitinen 1991; Laitinen and Laitinen 2004: 242–244). Together with profitability, growth is the main determinant of income finance that may have a significant effect on the likelihood of financial distress. In many cases, financial distress is caused by growth that is too strong compared to profitability. Therefore, the present study includes a measure of company growth.

This study also reviews previous going-concern studies (see Appendix 1) and lists all the traditional financial ratios that have been used to predict financial distress. The number of previously used financial ratios was huge. In our study we included financial ratios that represented the three focused financial dimensions (profitability, liquidity, and solidity) and which had given the best results in previous studies. In all, six liquidity ratios, three profitability ratios, and two solidity ratios were selected. In addition, percentage change in net revenue was selected to measure growth. The twelve financial predictors are presented in Table 3.

TABLE 3. Financial ratios used in the present study.

Liquidity
Quick ratio (Liquid assets/Current liabilities) **Current ratio (Current assets/Current liabilities)** **Working capital/total assets** **Operating cash flow (OCF) ratio (Cash flow from operations/Total liabilities)** **Net working capital % (Net working capital/Revenue)** **Accounts payable turnover ((Accounts payable/Purchases) *365))**
Profitability **Return on invested capital, ROI (Net income + financial expenses + taxes/Invested capital)** **Return on equity, ROE (Net income/Average equity)** **Return on assets, ROA (Net income/Total assets)**
Solidity
Net worth/Total liabilities **Total debt ratio (Total liabilities/Total assets)**
Growth
Change in revenue (Change in revenue/Revenue in the beginning)

Table 4 presents descriptive statistics of the independent variables for reorganization and viable companies in the sample. Panel A shows statistics for the reorganization companies in Group 1. This group includes 45 companies that filed reorganization petitions between 1 and 182 days after the date of the last financial statements (the annual closing of accounts). These ratios thus describe the financial situation of companies in the final stage of the financial distress process (the period before filing is less than six months). Panel B shows statistics for the distressed companies in Group 2. This group includes 61 companies that filed reorganization petitions between 183 and 365 days after the date of the last financial statements. These companies are in the very late but not final stage of the financial distress process at the point of the last financial statement. Finally, the last panel C lists statistics for the viable companies and records 106 observations. These viable companies did not experience registered (official) payment defaults during the research period of this study.

When comparing the descriptive statistics across panels A, B, and C in Table 4 it can be observed that there are differences in the statistics between the distressed and the viable companies. In addition, panels A and B show obvious differences in the statistics between distressed companies (i.e. Group 1 and Group 2). The reorganization companies in Group 1 tend to show lower or poorer figures for profitability, liquidity, solidity, and growth than do the companies in Group 2. This is intuitively reasonable, since the companies in Group 2 may be categorized as 'healthier' than those in Group 1. The time lag between the date of the last financial statements and the event of filing the petition for reorganization is longer for the companies in Group 2 than for those in Group 1. These results overall support our expectations regarding the effect of the stage of distress process on the financial ratios. The financial ratios of the companies in Group 1 have deteriorated more than have those of the companies in Group 2. Thus, at the date of the annual closing of accounts, the companies in Group 2 are not yet in the final stage of the distress process. Moreover, there are remarkable differences in the financial ratios between the distressed companies (Groups 1 and 2) and the viable companies (panel C). The statistics of the financial ratios in panel C on average refer to good performance in the group of viable companies.

TABLE 4. Descriptive statistics.

Panel A. Summary statistics for distressed companies, Group 1 (n = 45 observations)

Variable	Mean	Minimum	Maximum	Median	Std.dev.
LIQUIDITY					
Quick ratio	0.4	0	2.5	0.3	0.4
Current ratio	0.6	0.1	1.6	0.6	0.4
Working capital/Total assets	6%	–77%	62%	7%	33%
OCF ratio	–18%	–66%	14%	–13%	19%
Net working capital %	–21.50%	–109.40%	21%	–16.60%	23.20%
Accounts payable turnover	441days	15 days	7753 days	125 days	1315 days
PROFITABILITY					
ROI	–37%	–204%	26%	-31%	44%
ROE	–20%	–101%	14%	-17%	23%
ROA	–46%	–274%	11%	-21%	60%
SOLIDITY					
Net worth/Total liabilities	–24%	–87%	60%	-24%	31%
Total debt ratio	158%	63%	768%	127%	114%
GROWTH					
Change in revenue	7%	-65%	335%	-6%	63%

Group 1: 1–182 days from the financial statement to the restructuring application

Panel B. Summary statistics for distressed companies, Group 2 (n= 61 observations)					
Variable	**Mean**	**Minimum**	**Maximum**	**Median**	**Std.dev.**
LIQUIDITY					
Quick ratio	0.7	0	10.4	0.5	1.3
Current ratio	1	0.1	10.4	0.8	1.3
Working capital/Total assets	14%	–102%	79%	14%	31%
OCF ratio	7%	–71%	586%	1%	77%
Net working capital %	–9.17%	59.30%	27.10%	–7.20%	19.47%
Accounts payable turnover	288days	0days	3145days	88days	618days
PROFITABILITY					
ROI	–9%	–98%	53%	–0.50%	30%
ROE	–4%	–56%	48%	–0.30%	19%
ROA	–13%	–218%	100%	–5%	37%
SOLIDITY					
Net worth/Total liabilities	19%	–121%	1629%	–4%	212%
Total debt ratio	123%	6%	700%	99%	88%
GROWTH					
Change in revenue	45%	–47%	1308%	11%	174%
Group 2: 183–365 days from the financial statement to the restructuring application					

Panel C. Summary statistics for healthy companies (n=106 observations)					
Variable	**Mean**	**Minimum**	**Maximum**	**Median**	**Std.dev**
LIQUIDITY					
Quick ratio	2.3	0.1	25.6	1.3	2.9
Current ratio	3	0.3	29.1	1.7	4
Working capital/Total assets	25%	–54%	99%	21%	25%
OCF ratio	39%	–73%	271%	21%	61%
Net working capital %	39.43%	–34.70%	955%	15.70%	114%
Accounts payable turnover	53days	5days	417days	34days	64days
PROFITABILITY					
ROI	20%	–42%	164%	17%	29%
ROE	14%	–41%	124%	13%	21%
ROA	8%	–50%	65%	9%	16%
SOLIDITY					
Net worth/Total liabilities	257%	–104%	6059%	77%	687%
Total debt ratio	54%	2%	119%	56%	27%
GROWTH					
Change in revenue	58%	–100%	4593%	8%	449%

3.3. Statistical modeling approach and method

To test our hypotheses, we analyze the twelve financial ratios of Group 1 and Group 2 separately against the ratios of their viable matched pairs. We use matched pairs because the aim is to mitigate the effects of industry, size, and accounting period, but also to give the same weight to reorganized and viable companies in statistical analyses. Although the number of reorganization companies in the population is small compared to that of viable companies, the misclassification cost of a reorganization company (Type 1 error) is extremely high compared to that of a viable company (Type 2 error). This fact gives support to the use of equal sample sizes for the groups. For statistical analyses, a large number of previous studies have used a logistic regression (LR) analysis to test the GC predictor variables (see Appendix 1). According to Kuruppu *et al.* (2003), statistical models such as probit and logit analyses, which are types of conditional probability models, provide a good evaluation of the probability of when the auditor's client might fail. Therefore, in the present study, binary univariate LRA based on conditional (default) probability is applied when testing Hypothesis 1. In the same way, multivariate LRA is used to test Hypothesis 2. The equal group sizes result in a cut-off probability of reorganization of 50%. Technically, this situation is desirable since LRA assumes that midranges of probability are more sensitive to changes of values in independent variables to minimize the grey area (the area of ignorance).

LRA can be used to describe the relationship between a response variable and one or more explanatory variables. Therefore, cause-effect relationships are reflected in regression analyses, and the purpose is to examine how well the independent variable (financial ratios) explains the dependent variable (probability of reorganization). Logistic regression analysis does not require independent variables to be multivariate normal or groups to have equal covariance matrices, contrary to what is the case in linear discriminant analysis. This analysis creates a score, a logit L, for every company by weighting the ratio of independent variables. It is assumed that the independent variables are linearly related to L. The score is used to determine the probability of membership of a group where the reorganization probability is computed. The logistic curve determines the probability of the occurrence of the event as follows:

$$\text{Probability of reorganization (p(i,X))} = \frac{1}{1+e^{-L}} = \frac{1}{1+e^{-(b_0+b_1x_1..+b_nx_n)}} \tag{1}$$

where b_i ($i = 0,1,\ldots, n$) are the regression coefficients and n is the number of independent variables x_i ($i = 0,1,\ldots, n$).

In the univariate analysis to test Hypothesis 1, every financial ratio is tested separately by LR to establish its ability to classify businesses into reorganization and viable companies. In the multivariate analysis to test Hypothesis 2, a stepwise LR analysis is applied to test which variable or combination of variables is significant in their ability to discriminate between reorganization and viable companies. The LR models are estimated by the maximum likelihood method in SAS, and the significance of the coefficients is tested by the Wald test statistic. The strength of association is assessed by the standard Nagelkerke's R-Square (R^2) test. Nagelkerke's R^2 applied here is a modification of the Cox and Snell R-Square test, and consequently, R^2 measures the strength of association. R^2 describes how well the regression equation fits the data. The goodness of fit of the model is also tested by the Hosmer-Lemeshow Chi-square test. This test divides the predicted probabilities into deciles and then computes a Chi-square to compare predicted and observed frequencies. A higher *p*-value indicates a good fit to the data. In fact, this is a test of the linearity of the logit. The performance of the financial ratios and the LR models being predicted, the rates of correct classification are calculated. In addition, the ROC (Receiver Operating Characteristic) curve is used to assess the accuracy of the multivariate models.

To ensure stability of the financial ratios it is essential that their information content remain unchanged during the whole post-accounting period (from 1 to 365 days after the closing of accounts). This stability was assessed by the Z-test to test the differences between the correct classification rates for the sub-periods (1–182 days and 183 – 365 days). The Z-test is determined for the two groups as follows:

$$Z = \frac{p_1 - p_2}{\sqrt{p\,(1-p) \times (\frac{1}{n_2} + \frac{1}{n_2})}}, \text{ where}$$

$$p = \frac{n_1 p_1 + n_2 p_2}{n_1 + n_2}$$

p_1 = correct classification rate for Group 1

p_2 = correct classification rate for Group 2

n_1 = size of the Group 1

n_2 = size of the Group 2

The *p*-value of these statistics is the observed level of significance of the difference between the correct classification rates in Groups 1 and 2.

4. RESULTS

4.1. Logistic regression results for the financial ratios (univariate analysis)

The first research hypothesis (Hypothesis 1) suggests that the financial distress process stage affects the prediction ability of single financial ratios in short-term predictions (univariate analysis). Table 5 presents the estimated results of the univariate LR analysis for each of the twelve financial ratios.

In these analyses, a model is estimated for each financial ratio to predict the probability of a reorganization petition being filed. The estimation results in the table show that most financial ratios can be used to predict reorganization in both Groups 1 and 2. In general, financial ratios have high classification rates to discriminate between viable and distressed companies correctly. In addition, it can be ascertained that when the time distance to the event of filing the petition is only 1–182 days in Group 1, the correct classification rates are higher than in Group 2 when the distance to the event is longer (183–365 days). This result again demonstrates that the previously discussed reckoning of financial distress process stages is rational, and to sum up, the findings support the criteria of late and final stages. According to significantly higher correct classification rates for liquidity ratios, the companies in Group 1 are clearly at a later stage of financial distress

TABLE 5. Results from the logistic regression analysis based on individual financial ratios.

Liquidity	$R^2(1)$	$R^2(2)$	p(1)	p(2)	Correct1	Correct2	p
Quick ratio	0.55	0.29	<.0001	<.0001	83.3 %	74.6 %	0.064*
Current ratio	0.67	0.29	<.0001	<.0001	82.2 %	78.7 %	0.264
Working capital/ Total assets	0.17	0.03	0.0024	0.1023	62.2 %	54.1 %	0.119
Operating cash flow ratio	0.61	0.10	<.0001	0.0141	85.6 %	77.0 %	0.059*
Net working capital %	0.62	0.46	<.0001	<.0001	85.6 %	73.0 %	0.014**
Accounts payable ratio	0.34	0.27	0.0003	0.0009	74.7 %	74.5%	0.487
Profitability	$R^2(1)$	$R^2(2)$	p(1)	p(2)	Correct1	Correct2	p
Return on invested capital	0.67	0.29	<.0001	<.0001	84.4 %	70.5 %	0.009***
Return on equity	0.67	0.27	<.0001	<.0001	83.3 %	73.8 %	0.049**
Return on assets	0.70	0.22	<.0001	0.0002	86.7 %	76.2%	0.028**
Solidity	$R^2(1)$	$R^2(2)$	p(1)	p(2)	Correct1	Correct2	p
Net worth/Total liabilities	0.76	0.23	<.0001	0.0011	88.8 %	76.2 %	0.010**
Total debt ratio	0.77	0.68	<.0001	<.0001	87.8 %	87.7 %	0.491
Growth	$R^2(1)$	$R^2(2)$	p(1)	p(2)	Correct1	Correct2	p
Change in revenue	0.0171	0.0032	0.3073	0.6114	55.6 %	43.0 %	0.035**

(1) = Group 1, 1–182 days from the date of financial statements to the reorganization petition vs. matched viable companies (n = 90 observations)
(2) = Group 2, 183–365 days from the date of financial statements to the reorganization petition vs. matched viable companies (n = 122 observations)
R^2 = the goodness of fit, p = p-value, Correct = correct classification
***), **), and ***) denotes the significance at the 0.10, 0.05, and 0.01 levels, respectively.**

(i.e. the final stage) than companies in Group 2. This can also be observed from the higher correct classification rates across all twelve ratios without exception.

The main interesting feature of Table 5 is found in the *p*-value (the rightmost column), which refers to the changes between the examined sub-groups and equates to the first hypothesis of the present study. The findings indicate that financial distress process stages have an effect on the classification ability of financial ratios. The *p*-values in the table show that only four of the twelve ratios (i.e. current ratio, working capital/total, accounts payable ratio, and total debt ratio) retain their classification ability at the same level irrespective of the stage of financial distress process. Most of the ratios lose their classification ability to a statistically significant extent when the prediction time span increases from 1–182 days (final stage) to 183–65 days (late stage). This result provides strong empirical evidence of the acceptance of our first research hypothesis that the financial distress process stage affects the prediction ability of single financial ratios in short-term predictions.

The last column in Table 5 illustrates that out of the liquidity ratios included in the study, the current ratio, the working capital to total assets ratio, and the accounts payable turnover did not change their predictive ability to any statistically significant extent when the financial distress process moved from the late stage to the final stage. It can be noted from the correct classification rates that each of these ratios improves its classification accuracy when the time span is shorter; however, the difference in accuracy does not statistically differ from zero. Thus, the financial distress process stage in this analysis does not statistically affect the prediction ability of these ratios. In addition, it can be observed from the last column in Table 5 that the quick ratio, the operating cash flow ratio, and the net working capital ratio do not maintain their classification ability when the temporal distance to the event increases. They lost their ability to statistically significantly classify at the levels of 0.10, 0.10, and 0.01, respectively. Thus, they will provide a significantly less reliable prediction about the event when the time before filing the petition is between 183 and 365 days rather than between 1 and 182 days.

It is worth noting that all three profitability ratios lose their classification ability when the time span of the prediction increases from the 1–182 day range to the 183–365 day range. Indeed, according to the last column in Table 5, profitability ratios lost their ability to classify to any statistically significant extent when the prediction time span increased. According to the column labeled ‘Correct2’, the return on investment capital (ROI) gives the most inaccurate classification when the time span is 183–365 days or when the late stage of the distress process is considered. It loses its classification ability at a significance level of 0.01 whereas the return on equity and the return on assets lose their classification ability at a significance level of 0.05. It can thus be concluded that the predictive ability of all three profitability ratios in the present analysis is affected by the financial distress process stages.

In the final stage of the financial distress process the two solidity ratios tested performed very well, and the classification accuracy was almost 90 percent. However, in the late but not final stage of the process the classification accuracy of the net worth to total liabilities decreased dramatically by over 10 percent at the 0.05 significance level. The total debt ratio also shows relatively good performance in the late stage when compared to the net worth to total liabilities ratio. It maintains its classification ability well when the time distance to the event increases from 1–182 days in the final stage to 183 – 365 days in the late stage. The change in revenue ratio reflecting the growth of a company performs poorly in both stages of the financial distress process. Even though the accuracy of growth was not much better than 55 % in classification during the final stage of the financial distress process, it still loses its ability to classify statistically significantly at a level of 0.05 when the time span increases.

4.2. Stepwise logistic regression results (multivariate analysis)

The second research hypothesis suggests that the financial distress process stage affects the statistical financial distress prediction model in short-term prediction (multivariate analysis). Accordingly, the present study investigated stepwise logistic regression analysis, i.e. automatic variable selection via a stepwise process, to select the most significant set of predictors that are most effective in predicting the probability of reorganization in both financial distress process stages. Table 6 presents estimated results for the stepwise LR model when predicting the reorganization event on the basis of all 12 financial ratios included in the study. Indeed, in the stepwise LR analysis the variables are individually added to the logistic regression, and after entry of each variable, each of the included variables is tested to see if the model would be more effective if the variable were excluded. The main purpose of this is to remove insignificant variables from the model before adding a significant variable to it, and so to ensure that the final variables included in the model are the most significant predictors. The process of adding more variables into the model ends when all of the variables have been added into the model and when it is not possible to make a statistically significant better model using any of the predictors not yet included.

In Table 6, panel A describes the regression results for Group 1 where the companies are in the final stage of the financial distress process. The best combination to measure the probability of filing a reorganization petition is based on the current ratio and the operating cash flow to total liabilities ratio. These financial ratios both measure the liquidity of the firm. The most significant coefficient is found for the operating cash flow to total liabilities ratio with a Wald statistic of 10.5. However, both of these ratios equally dominate the information contained in the model. The Nagelkerke R-square for the model is 0.88, which is very good. The Hosmer & Lemeshow test also indicates a good overall model fit to the data (linearity of the logit).

Panel B describes the stepwise LR results for Group 2 where companies are in the late but not final stage of the financial distress process. For this model, the –2 Log likelihood is higher and the Nagelkerke R^2 slightly lower. In addition, the Hosmer & Lemeshow test also indicates a weaker overall model fit to the data with a *p*-value of 0.4086. The best model to predict the probability of reorganization includes three financial ratios. The model first includes the accounts payable turnover ratio measuring the liquidity of the company; however, the other two ratios in the model, the total debt ratio and the net worth to total liabilities, measure the company's solidity. The most significant coefficient is found for the total debt ratio with a Wald statistic of 17.4. This financial ratio clearly dominates the information contained in the model, but in addition the net worth to total liabilities has a very significant parameter with a Wald statistic of 12.8.

The estimation results for the whole sample are shown in Panel C of Table 6. In this analysis all reorganized companies and their matched viable pairs are included in the sample data. The –2 Log likelihood is again high and the Nagelkerke R^2 is low at 0.77; and furthermore, this ratio is the lowest of all the models presented in Table 6. However, the Chi-square associated with the Hosmer & Lemeshow test indicates an improved fit to the data compared to the results in panel B when the *p*-level for it is 0.94. There are now four significant financial ratios included in the model: the current ratio, the total debt ratio, the return on total assets, and the net worth to total liabilities ratio. The most significant coefficient is found for the total debt ratio with a Wald statistic of 28.9. It is obvious that this financial ratio is the dominant power in the model. Furthermore, the net worth to total liabilities ratio has quite a high power with a Wald statistic of 14.1. These two most powerful ratios measure the solidity of the company. The current ratio (a liquidity measure) and the return on assets ratio (a profitability measure) are both statistically significant with Wald statistics of 6.3 and 6.7, respectively.

To conclude, the study findings are consistent with the previously discussed criteria of late and final stages of the financial distress process. In Group 1, liquidity ratios tend to be the most significant predictors, which supports the criteria of the final stage of distress process, whereas in Group 2, solidity ratios are found to be the most dominant predictors, which support the criteria of the late stage of distress process. Finally, when the effect of financial distress stage is not considered, the best model to predict the financial distress includes liquidity, solidity, and profitability ratios.

The classification accuracies of the estimated stepwise LR models are presented in Table 7. The binary classification accuracy is estimated for the leaving-one-out data using the Lachenbruch validation method. It is observed that all three regression models for Group 1, Group 2, and Group 1 and 2 together (the pooled group) perform well in the sample of viable and reorganization companies with correct classification rates of 90.5 %, 90.0 %, and 85.6 % respectively. As expected, the model estimated for the final stage (Group 1) has the highest classification accuracy.

TABLE 6. Stepwise logistic regression model for the restructuring probability.

Panel A. Results for the Group 1 (n = 90 observations)				
Model summary			**Hosmer & Lemeshow Test**	
–2 Log L	**Nagelkerke R^2**		**Chi-square**	***p*-value**
116.258	**0.8814**		**2.3148**	**0.9698**
Parameters of the regression model				
Variable	**Coefficient**	**STD**	**Wald**	***p*-value**
Current ratio	**4.2628**	**1.6104**	**7.0066**	**0.0081**
OCF/Total liabilities	**19.1156**	**5.9031**	**10.4861**	**0.0012**
Panel B. Results for the Group 2 (n = 122 observations)				
Model summary			**Hosmer & Lemeshow Test**	
–2 Log L	**Nagelkerke R^2**		**Chi-square**	***p*-value**
151.181	**0.8082**		**8.2586**	**0.4086**
Parameters of the regression model				
Variable	**Coefficient**	**STD**	**Wald**	***p*-value**
Accounts payable ratio	**–0.0148**	**0.00531**	**7.7300**	**0.0054**
Total debt ratio	**–18.2662**	**4.3816**	**17.3790**	**< .0001**
Net worth/Total liabilities	**–1.0230**	**0.2856**	**12.8324**	**0.0003**
Panel C. Results for the Group 1 and Group 2 together (n = 212 observations)				
Model summary			**Hosmer & Lemeshow Test**	
–2 Log L	**Nagelkerke R^2**		**Chi-square**	***p*-value**
267.620	**0.7663**		**2.8120**	**0.9456**
Parameters of the regression model				
Variable	**Coefficient**	**STD**	**Wald**	***p*-value**
Current ratio	**1.3096**	**0.5192**	**6.3628**	**0.0117**
Total debt ratio	**–10.7996**	**2.0085**	**28.9118**	**< .0001**
Return on total assets	**5.1393**	**1.9783**	**6.7484**	**0.0094**
Net worth/Total liabilities	**–1.5092**	**0.4021**	**14.0870**	**0.0002**

Group 1 = 1–182 days from the date of financial statements to the reorganization petition vs. matched viable companies (n = 90 observations)
Group 2 = 183–365 days from the date of financial statements to the reorganization petition vs. matched viable companies (n = 122 observations)

TABLE 7. Classification accuracy of the LR models.

	Healthy companies	Restructuring companies	Correct, %
Group 1	**45**	**45**	**90.5**
Group 2	**61**	**61**	**90.0**
Entire sample	**212**	**212**	**85.6**

The differences in the classification accuracy again support the idea that our reckoning of financial distress process stages is rational.

Figures 1, 2, and 3 illustrate the ROC curve for both sub-samples, Group 1 and Group 2, and for the entire sample. The x-axis shows the percentage of viable companies where reorganization was incorrectly predicted when the cut-off value changed. The y-axis describes the percentage of companies where reorganization was correctly predicted. In figure 1 the ROC curve for Group 1 is presented. The area under the ROC curve (AUC) is 0.98, which refers to a very high accuracy in classification and gives an accuracy ratio (AR) of 0.97 (value of 1 refers to a perfect model). The curve shows that almost 90 % of the reorganization companies were correctly predicted to become so when approximately 0 % of the viable companies are incorrectly classified as reorganization companies.

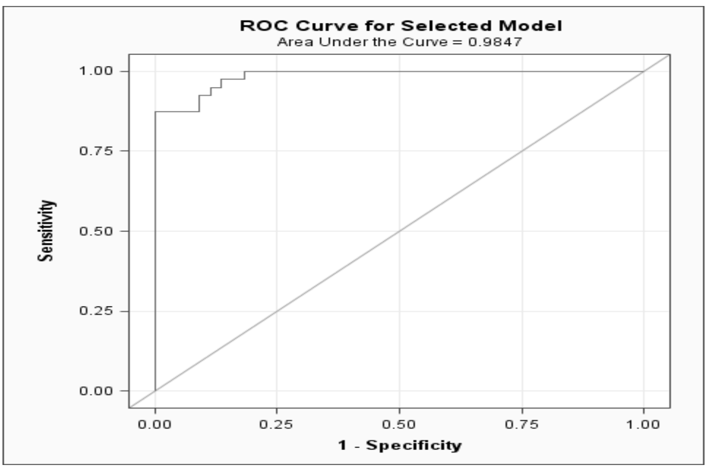

FIGURE 1. The ROC curve for estimated restructuring probability (Group 1).

Figure 2 illustrates the ROC curve for Group 2. The area under the ROC curve is 0.97, which is also very good and indicates a high accuracy classification with an AR of 0.94. However, the ROC curve indicates graphically in this case that only close to 50 % of the reorganization companies are correctly classified when approximately 0 % of the viable companies are incorrectly classified as reorganization companies. This percentage of Group 1 was about 90%, which means that the difference in classification is remarkable although the difference in AR is not very significant. Figure 4 presents the ROC curve for the total sample. The AUC of the ROC curve is about 0.95 – lower than the AUC in Group 1 and Group 2. However, this value indicates highly accurate classification with an AC of 0.91, and the curve shows about 60 % accuracy in classification of the reorganized companies when none of the viable companies is misclassified.

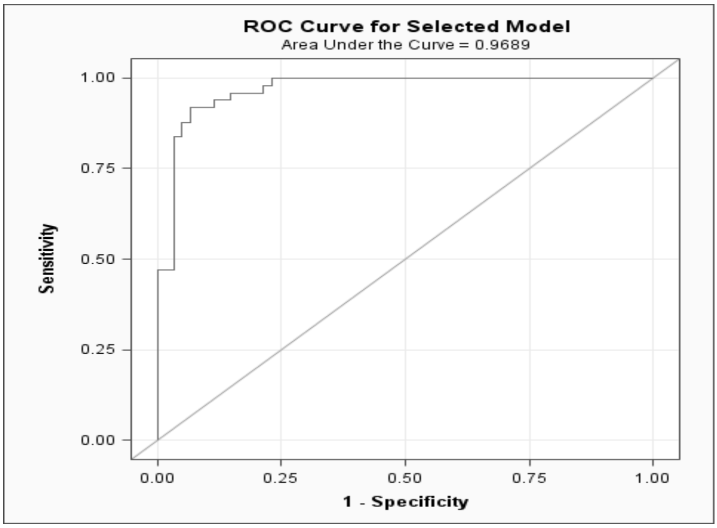

FIGURE 2. The ROC curve for estimated restructuring probability (Group 2).

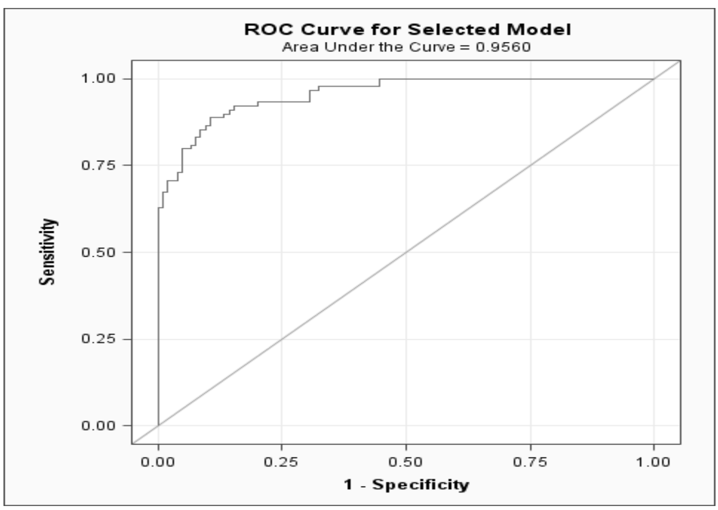

FIGURE 3. The ROC curve for estimated restructuring probability (Group 1 and Group 2).

In summary, the results of the stepwise LR analysis strongly support our second research hypothesis (Hypothesis 2) suggesting that the financial distress process stage at which a company is found affects the (optimal) statistical financial distress prediction model in short-term predictions. In Group 1, where companies are at the final stage of the financial distress process, the LR model included two liquidity ratios, the current ratio and the operating cash flow per total liabilities ratio. In Group 2, where companies are at the late but not final stage of the financial distress process, the resulting LR model consisted of three ratios, the accounts payable turnover (liquidity), the total debt ratio (solidity), and the net worth to total liabilities ratio (solidity). For the whole sample, where the financial distress stage was not considered, the LR model included four ratios, namely the current ratio (liquidity), the total debt ratio (solidity), the return on total assets (profitability), and the net worth to total liabilities (solidity). The resulting ROC curves show that these models lead to different results in classifying reorganization and viable companies. Thus, the results provide strong empirical evidence for the acceptance of our second research hypothesis, since the models projected for different stages of the distress process differed and focused on different financial dimensions. These results have obvious implications that are discussed in more detail below.

5. SUMMARY AND CONCLUSIONS

This study was motivated by the recognition of the fact that the GC decision task faced by auditors is a complex and demanding one. This task has been widely discussed in previous research, and the need for information to support auditors' decision-making has been documented in several studies (Martens *et al*. 2008). Nevertheless, previous research on the topic has mainly examined the elements of an auditor's decision-making process. This study contributes to the previous research by generating information to support auditors' challenging decision-making. The purpose of the present study is to investigate the effect of the financial distress process stages on financial ratios and financial distress prediction models in short-term GC predictions.

The study focuses on auditors' information needs when planning the research framework. First, the results of previous research suggests that in studies of auditors' decision-making samples of distressed and viable companies should be kept separate, because the issues affecting an auditor's decision-making are different from one case to the next (Martens *et al.* 2008; Hopwood *et al*. 1994). Consequently, we included viable companies as well as companies that have temporary financial difficulties but have not failed in our data set to meet this condition. In this framework, companies with temporary financial difficulties are represented by those that have filed a petition for reorganization. These reorganization companies can be regarded as having more in common with viable companies than with those in financial distress that eventually go bankrupt.

Secondly, instead of predicting qualified audit opinions, this study concentrates on financial ratios and their usefulness in supporting auditors' going-concern evaluations. Previous research indicates that financial ratios have an explanatory power to distinguish financially distressed firms from viable companies between 5 years and 1 year prior to the event. Instead of working on a comparison of financial ratios during this extensive time period, we examined the latter stages of the financial distress process during the last accounting period of a company, so mimicking auditors' short-term GC decision-making.

The study results indicate that the financial distress process stage has an effect on the classification ability of financial ratios. Liquidity ratios such as the quick ratio, the operating cash flow ratio, and the net working capital ratio lost their ability to classify to any statistically significant extent when the distance from the date of closing of accounts to the date of filing a reorganization petition increased. In other words, when companies moved away from the final stage of the distress process to the late but not final one, liquidity ratios lost their predictive ability. Along the same lines, the three profitability ratios, one of the solidity ratios (the net worth to total liabilities), and the rate of growth lost their predictive ability when the time span of the prediction increased.

This study also applied stepwise logistic regression analysis to select the most significant variables for predicting the probability of reorganization in both financial distress process stages. The results indicate that when the period between the date of the last financial statements and the date of filing a reorganization petition is extended, the best explanatory variables also change. When the reorganization event is very close and the financial distress process is in its final stage, the financial ratios that measure a company's liquidity tend to be the most significant predictors. When the time to the reorganization event is extended, solidity ratios are found to be the best predictors. Moreover, when the effect of the financial distress stage was not considered, solidity ratios tended to be the most significant measures, but liquidity and profitability ratios also mattered.

To conclude, our study has implications for general understanding of the behavior of financial ratios during the late stages of a financial distress process. According to the IAASB's newsletter 2009, the IAASB is concerned about matters relevant to the consideration of the use of the going-concern assumption in the preparation of statements in the current environment. Our study findings indicate that the auditor's GC task could be supported by paying attention to the financial distress process stage. In sum, certain changes in the financial ratios indicate at which stage the firm is. If the company's financial statement indicates that in addition to decreased profitability (early stage) and increased leverage (late stage) also the liquidity (final stage) is poor, the company should be considered to be at the final stage. However, it is possible that a GC opinion should not be issued by the auditor if the business is not at risk of liquidation during the next fiscal year. To avoid the increased risk of being held responsible to the stakeholders for the financial consequences of not having issued a GC opinion when needed, or on the other hand having issued one without justification, an auditor should, as part of the decision-making process, examine liquidity ratios when the company is at the final stage. The decision to issue a GC opinion will then be based on the auditor's evaluation and judgment of the adequacy of the company's liquid assets for the next fiscal year.

The current study is limited in several ways, and the empirical results have uncovered important research directions for the future. First, the empirical research in recognizing different financial distress processes can highlight the changes in the ability of financial ratios to classify viable and non-viable businesses at different financial distress process stages. In this study we have not made any assumptions concerning different financial distress processes but concentrated only on the two last stages of the process. Accordingly, a further study focusing on more than just two stages of the financial distress process seems merited. Second, we were only able to include a limited amount of financial dimensions and financial ratios in the analysis. The careful examination of different financial distress processes will probably expand the necessary set of financial dimensions and financial ratios to be examined. This research would be very relevant, especially due to its potential to support GC evaluations made by auditors. Finally, the present study has been unable to investigate the outcome of businesses filing a reorganization application, the study findings are based on a relatively small sample of reorganization companies, and the paper lacks the information on ownership structure that might have an effect on the ability to continue as a going concern in the face of financial difficulties. ■

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APPENDIX 1. Literature table of previous studies on going-concern prediction (Martens** et al. **2008; Kuruppu** et al. **2003)

Study	Sample	Technique	Sampling
Altman & McGough (1974)	Bankrupt: 33 Non-bankrupt: 33	MDA	Other
Altman (1983)	Failed: 40	MDA	Other
Mutchler (1985)	Going concern: 119 Distressed: 119	MDA	Balanced
Levitan & Knoblett (1985)	Going concern: 32 Non-going concern: 32	MDA	Matched
Menon & Schwartz (1987)	Bankrupt: 89 Going concern: 37 Non-going concern: 52	Logit	Other
Dopuch et al. (1987)	Qualified: 275 Non-qualified: 411	Probit	Other
Koh & Killough (1990)	Failed: 35 Non-failed: 35	MDA	Other
Mutchler & Williams (1990)	Going concern: 87 Distressed: 612 Healthy: 1171	Logit	Other
Bell & Tabor (1991)	Qualified: 131 Non-qualified: 1217	Logit	Other
Koh & Brown (1991)	Failed: 40 Non-failed: 40	Probit	Other
Chen & Church (1992)	Going concern: 127 Distressed: 127	Logit	Matched
Hopwood et al. (1994)	Bankrupt: 134 Distressed: 80 Healthy: 80	Logit	Other
Carcello et al. (1995)	Bankrupt: 446 Going cocern: 231 Non-going concern: 215	Logit	Other

Study	Sample	Technique	Sampling
Raghunandan & Rama (1995)	Bankrupt: 175 Going concern: 90 Non-going concern: 85 Non-bankrupt: 362 Going concern: 105 Non-going concern: 257	Logit	Other
Cornier et al. (1995)	Failed: 138 Non-failed: 112	Logit MDA RP	Other
Mutchler et al. (1997)	Bankrupt: 208 Going concern: 107 Non-going concern: 101	Logit	Other
Carcello et al. (2000)	Going concern: 52 Distressed: 264	Logit	Other
Carcello & Neal (2000)	Going concern: 83 Distressed: 140	Logit	Balanced
Reynolds & Francis (2000)	Going concern: 224 Distressed: 2215	Logit	Balanced
Geiger & Raghunandan (2001)	Bankrupt: 365 Going concern: 198 Non-going concern: 167	Logit	Other
Behn et al. (2001)	Going concern: 148 Distressed: 148	Logit	Matched
Geiger & Raghunandan (2002)	Bankrupt: 117 Going concern: 59 Non-going concern: 56	Logit	Other
DeFond et al. (2002)	Going concern: 96 Distressed: 1158	Logit	Other
Geiger & Rama (2003)	Going concern: 66 Distressed: 66	Logit	Matched
Gaeremynck & Willekens (2003)	Terminated firms: 114 Continued firms: 114	Logit	Matched
Geiger et al. (2005)	Bankrupt: 226 Going concern: 121 Non-going concern: 105	Logit	Other
Carey & Simnett (2006)	Going concern: 66 Distressed: 493	Logit	Other