Analysing Corporate Insolvency in the Gulf Cooperation Council using Logistic Regression and Multidimensional Scaling

Abstract

Purpose: This paper examines corporate insolvency in the Gulf Cooperation Council (GCC) region for the period 2004-2011.

Design/methodology/approach: Financial ratio data on 56 matched pairs of insolvent and solvent firms are analysed using logistic regression with best-subset selection criteria to identify significant ratios, and prediction accuracy is tested on an *ex-ante* sample. The main dimensions of ratios, and the weights that firms attach to them, are examined using 3-way Multidimensional Scaling (MDS).

Findings: A parsimonious Logit model comprising one profitability, one leverage and two cash flow ratios has accuracy levels of 84.4% overall, 95.6% type I and 73.9% type II. Four financial-ratio dimensions are extracted from the MDS: (i) 'Non-strategic sales activities', (ii) 'Profitability and financial stability balance', (iii) 'Sales activities against capital conversion'; and (iv) 'Market value against cash generation'. Insolvent firms appear very specific and attach most salience to the 'Non-strategic sales activities' dimension; unlike solvent firms which attach more salience to the other three dimensions.

Practical Implications: Results indicate profitability ratios should be included in GCC insolvency classification models. It is suggested that firms' managers should focus less on non-strategic sales activities to reduce susceptibility to insolvency.

Originality/value: The study provides empirical evidence on insolvency in the GCC and introduces the application of 3-way MDS to insolvency research in the region.

Keywords: Gulf Cooperation Council, Corporate insolvency, Multidimensional Scaling, Cluster analysis, Logit, Probit, Financial ratio

1 Introduction

The stock exchange markets of the Gulf Cooperation Council (GCC) region (Bahrain, Saudi Arabia, Oman, Qatar and the United Arab Emirates) are important to the Middle East and North Africa (MENA). They constitute half of MENA's listed companies and three-quarters of the MENA region's market capitalisation (Rocha and Farazi, 2011). Beyond MENA, GCC economies contribute significantly to the global economy by investing their oil incomes abroad (Peeters, 2011); yet it was not until the 1980s that GCC countries began to regulate their stock markets (Al-Ajmi and Kim, 2012). GCC countries were only able to limit the negative effects of the 2008 global financial crisis by employing financial-sector support and countercyclical measures using the financial reserves they had accumulated during the oil price boom period of 2003-2008 (Khamis and Senhadji, 2010). The 2008 crisis revealed many vulnerabilities in the GCC region (Khamis and Senhadji, 2010). GCC financial markets are particularly vulnerable to firm insolvency (Uttamchandani et al., 2009); this is an international problem with high economic, financial and social cost (Warner, 1977, Altman, 2006, Lensberg et al., 2006, Brigham and Ehrhardt, 2010). It can impact on the investors or owners; creditors, employees and other stakeholders (Deakin, 1972, White, 1996, Morris, 1997, Moyer et al., 2008). Hence there is a need for research that can cast light on the susceptibility of GCC firms to insolvency. Such insight can aid investment decisions as well as offer a strategic guide to firms' managers.

There are important differences between the GCC and other major trading blocs, such as the European Union (EU) and the North American Free Trade Agreement (NAFTA). GCC economies remain highly dependent on oil, and are less diversified (Fasano and Zubair, 2003). GCC stock markets are less mature and, despite recent liberalisation measures, continue to be less liberal and not efficient in the weak form (Arouri et al., 2011, Al-Ajmi and Kim, 2012). The GCC financial and regulatory frameworks are less harmonised (Hussain et al., 2002), and the GCC is also culturally distant (House et al., 2004). Insolvency research evidence based on other regions may thus be misleading when applied directly to GCC firms: GCC context-specific research is required to examine both the commonalities and differences between GCC insolvency and other regions.

Compared to other regions, insolvency research in the GCC is relatively nascent, dating back to the 1990s, not the 1960s as in other regions. With the exception of Basheikh (2012) who applied logistic regression, the few studies that have been conducted have relied on Altman's (1968) Discriminant Analysis (MDA) technique, despite its restrictive assumptions. Second, although GCC studies have used a number of financial ratios to study insolvency (e.g. profitability, liquidity, leverage and activity ratios), they have not yet examined the valuable information generated by the operating cash flow, which, as shown by research in other contexts, is useful for predicting financial distress. There are thus three areas of weakness in GCC insolvency research: the volume of research is small; the scope of methodologies applied is narrow; and unlike other contexts, the predictive value of operating cash flow has not been examined. Focusing on firms listed on GCC stock markets between 2004 and 2011, this study hopes to contribute to the literature in these three areas. As well as logistic regression, we introduce the application of the multidimensional scaling (MDS) technique to insolvency research in the GCC context. MDS enables the visualisation of key differences between insolvent and solvent firms, increasing the depth of insight acquired (Neophytou and Molinero, 2004b). We also examine the predictive capacity of operating cash flow information in the GCC context.

The rest of this paper is structured as follows. In section two, we review the literature on financial failure in the GCC context as well as literature on financial failure prediction techniques, and we state our research questions based on this review. In section three, we describe the methods and the data used to answer the research question. In section four, we present the results. In section five, we discuss the implications of the results for investors and managers, before concluding the study.

2 Literature review and research questions

To predict insolvency, it is necessary to understand what causes it. Charan et al. (2002) argue that firms fail because they are poorly managed. Altman (1983) states that the overwhelming cause of an individual firm's failure is some type of managerial incompetence. Goudie and Meeks (1991) examine the extent to which macro-economic factors can be held responsible for the failure of large companies in turbulent exchange regimes. They conclude that factors that are beyond the control of the management, such as external macro-economic factors, often play a substantial role in failure and give results that offer a corrective to the wide spread notion that the prime cause of failure is bad management.

It is clear that environmental factors can instigate failure. For example, despite governments and their central banks infusing liquidity into the financial system via repurchase agreements and offering direct liquidity injections through long-term deposit schemes, the GCC region experienced many corporate failures following the financial crisis in 2008 (Khamis and Senhadji, 2010). The drop in oil prices in late 2009 was another shock. It resulted in the 'Dubai debt crisis', further weakening GCC capital markets (Khamis and Senhadji, 2010, Onour, 2010). Similarly, efficient markets reward or punish firms based on performance: Many studies conducted within the region have concluded that not all the GCC markets are efficient (Al-Khazali et al., 2007, Bley, 2011, Al-Ajmi and Kim, 2012). Failing, poorly managed firms can thus continue to operate without market censure until it is too late.

Environments being equal, however, weaker, less well-managed firms will exhibit poorer health. Financial ratios are important here: evidence shows that both the level (Chen and Shimerda, 1981) and trend over time (Neophytou and Molinero, 2005) of financial ratios can reveal the state of health of a firm. However, the relative importance of the ratios is not clear; studies differ in which ratios they consider significant (Chen and Shimerda, 1981, Barnes, 1987). This is true generally as well as, more specifically, in the GCC context. For example, in the GCC context, Hasabo (1987) suggested that total asset to ownership equity, shareholders equity to paid capital and profit from other operations to total profit are important; whereas Basheikh (2012) found return on investment, retained earnings to total assets, fixed assets to ownership equity, asset turnover and ownership equity turnover important.

Of the different types of ratios, the level of importance of cash flow ratios is perhaps the most unclear. Cash flow statements indicate a firm's cash receipts and payments from operational activities (CFA institute, 2009). The importance of the cash flow information as a predictive tool derives from the power of cash to enable a firm to meet its obligations and continue to operate (Gilbert et al., 1990). A number of studies have tested this hypothesis. As early as 1966, Beaver's research suggested that cash flow from operations to total debt ratio was very accurate at predicting failure a year before it occurred; and a number of studies since (Blum, 1974, Smith and Liou, 1979, Mensah, 1984, Aziz et al., 1988, Aziz and Lawson, 1989, Gilbert et al., 1990, Charitou et al., 2004) have concluded that cash flow ratios add explanatory power. Ward (1994) posited that cash flow information was more useful in some industries (mining, oil and gas) than others. Gombola and Ketz (1983), in one of the earliest studies to incorporate incremental operating cash flow, suggested that operating cash flow provides more information than that which exists in most other ratios. Similarly, Gentry et al. (1987) found that cash flow-based ratios can improve the scope and accuracy of prediction models; and Gilbert et al. (1990) who suggested that cash flow information can provide a more reliable means for assessing the financial health. Not all evidence is in agreement, however: Casey and Bartczak (1985) found that operating cash flow ratios have no incremental predictive power over accrual-based ratios. We were not able to find publications in the GCC context on the importance of cash flow ratios.

To summarise, then, studies in the GCC context are not only unclear on which ratios are important but have also yet to test the importance of cash flow information. Motivated by this gap, our first research question was thus:

RQ1: What are the significant predictors of insolvency in the GCC region; and do they include cash flow-based ratios?

A number of techniques for predicting insolvency with financial ratios have been developed over the last 50 years. The first was Beaver's (1966) single predictor, univariate model. Altman (1968) demonstrated the insufficiency of Beaver's single predictor model and proposed instead the multiple-predictor, Multiple Discriminant Analysis (MDA) technique. Regarded as seminal, Altman's (1968) MDA technique has been widely applied and further developed by a number of researchers (Deakin, 1972, Edmister, 1972, Wilcox, 1973, Blum, 1974, Libby, 1975). Despite its popularity, MDA has been criticised for a number of assumptions it makes (Edmister, 1972, Zavgren, 1983, Karels and Prakash, 1987). It has two key restrictive statistical assumptions (Balcaen and Ooghe, 2006): multivariate normality of financial ratios and equal variance-covariance matrices across groups - but research shows that both assumptions are often violated (Richardson and Davidson, 1983, Ezzamel et al., 1987, Laitinen and Kankaanpaa, 1999). The predictive accuracy of MDA can also be significantly reduced when optimal conditions for its application are not met by neglecting the prior probabilities of failure and not defining an accurate cut-off score (Edmister, 1972, Joy and Tollefson, 1975, Ohlson, 1980, Balcaen and Ooghe, 2006). To avoid some of the limitations of MDA, Ohlson (1980) introduced logistic regression: it does not require multivariate normality, or equality of variance-covariance matrices, and no assumptions are made about prior probabilities of failure (Ohlson, 1980, Zavgren, 1983).

There have been further methodological developments since since Ohlson (1980) including decision trees (Friedman, 1977); neural networks (Salchenberger et al., 1992, Coats and Fant, 1993); genetic algorithms (Varetto, 1998, Shin and Lee, 2002) and survival analysis (Lane et al., 1986, Luoma and Laitinen, 1991). Despite these advances, Altman's (1968) model has dominated GCC insolvency research (Aldeehani, 1995, AlShebani, 2006). Some studies have applied Altman's model in its original form (Aldeehani, 1995, AlShebani, 2006); others with minor modifications in terms of predictors (Abudelrahman, 2004, Basheikh, 2012). The exception is Basheikh's (2012) logistic regression application. We can argue thus that GCC insolvency research has been dominated by a very limited number of techniques.

The current study aims to contribute towards filling this gap by applying multidimensional scaling (MDS), a new approach and philosophy in GCC insolvency research. MDS is a multivariate visualisation technique that attempts to find a solution by locating objects in a spatial configuration or graphical representation (Kruskal and Wish, 1978, Schiffman et al., 1981). Although traditionally a social sciences approach, MDS has been applied in the accounting, finance and banking disciplines as an alternative to the more traditional statistical techniques when the data do not satisfy parametric assumptions (Moriarity and Barron, 1976, Emery et al., 1982). Mar

Molinero and Ezzamel (1991) extended MDS to insolvency research in the UK. It has been shown that the visualisation of the patterns in financial ratios that MDS offers can help identify the reasons behind firms' poor (or good) financial health (Mar-Molinero and Serrano-Cinca, 2001, Neophytou and Molinero, 2004b). It is this visualisation capability that makes MDS particularly useful in studying insolvency as it can provide insight on the level of similarity (or dissimilarity) between firms by visualising the distances between insolvent and solvent firms; or the level of similarity (or dissimilarity) between financial ratios. Applied in the latter regard, the key dimensions of financial ratios can be extracted and, subsequently, reasons behind a firm's financial health can be revealed by studying the relative salience that solvent and insolvent firms attach to the extracted financial ratio dimensions. Thus, based on these arguments, our second and third research questions were:

RQ2: What are the key financial ratio dimensions in the GCC?

RQ3: Relatively, what are the differences between solvent and insolvent firms in the salience they attach to financial ratio dimensions?

3 Methods

3.1 Sampling and data collection

Data on solvent and insolvent firms were gathered from DataStream^{TM}, financial statements and company websites. Categorising firm failure is crucial in all insolvency studies. Altman and Narayanan (1997) suggest the definition of failure in the literature varies 'depending on the inclination of the researcher or on the local conditions'. In this study, we adopted the legal definition of corporate failure in the GCC region. Under the law, in most GCC countries, firms are considered 'failed' if accumulated losses reach or exceed 75% of capital (Saudi Commerce Ministry, 1966, United Arab Emirate Ministry of Economy, 1984, Sultanate of Oman Ministry of Commerce and Industry, 1986, Ministry of Industry and Commerce Kingdom of Bahrain, 2002, State of Qatar Ministry of Economy and Commerce, 2002). The exception is the Kuwaiti system where the law mandates that a company increases its capital accordingly in order to continue trading if accumulated losses reach 25% of capital (Kuwait stock exchange, 2010).

As discussed above, external factors can trigger or exacerbate failure. So to examine the managerial (internal) causes of failure, it is now accepted practice to control for external influences by matching each sampled insolvent firm with an equivalent solvent firm, as shown in Appendix I. We matched firms using the most popular criteria in the literature (Mar Molinero and Ezzamel, 1991); (i) region, (ii) industry sector, (iii) comparable asset size, and (iv) financial year. Using data between 2004 and 2011, we found 56 matching pairs or 112 firms. For each insolvent firm (and matching solvent firm), financial data were collected for the year before failure. Table 1 shows the number of firms sampled in each sector by country. Also shown in brackets are the average asset values in US dollars (World Bank mid-year conversion rate) of the firms sampled in each sector and country. Our sample covers eight sectors: concurring with previous studies (Gilbert et al., 1990) banks, financial investment, insurance and real estate firms were excluded from the sample because of the different and unique nature of the financial reports in these sectors. In some sectors, there were a limited number of companies in the same country, so we matched firms by sector regardless of home country.

Table 1 Sample of insolvent/solvent firms by sector and country

Sample of Insolvent Firms: Sector by Country							
Sector	Country						
	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE	**Total**
Agriculture	0	1	8	0	3	2	**14**
Construction	0	4	2	0	0	1	**7**
Hotel and Tourism	1	3	1	0	0	0	**5**
Industrial Investment	0	0	2	0	6	1	**9**
Petrochemical Industries	0	3	0	0	0	0	**3**
Retail and Services	0	6	3	1	1	0	**11**
Telecommunications	0	0	0	0	1	0	**1**
Transportation	0	3	0	0	3	0	**6**
Total	**1**	**20**	**16**	**1**	**14**	**4**	**56**
Sample of Solvent Firms: Sector by Country							
Sector	Country						
	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE	**Total**
Agriculture	0	1	8	0	2	3	**14**
Construction	0	4	2	0	0	1	**7**
Hotel and Tourism	1	3	1	0	0	0	**5**
Industrial Investment	0	5	2	0	1	1	**9**
Petrochemical Industries	0	3	0	0	0	0	**3**

Retail and Services	0	6	3	1	1	0	**11**
Telecommunications	0	0	0	0	1	0	**1**
Transportation	0	5	0	0	1	0	**6**
Total	**1**	**27**	**16**	**1**	**6**	**5**	**56**

We selected 28 financial ratios according to Beaver's (1966) selection criterion, i.e. ratios most commonly and successfully used in prior studies (Beaver, 1966, Altman, 1968, Deakin, 1972, Elam, 1975, Gombola and Ketz, 1983, Mensah, 1983, Dambolena and Khoury, 2012). The financial ratios, shown in table 2, cover six major categories: profitability, leverage, liquidity, activity, operating cash flow and markets. As discussed earlier, we included cash flow ratios in order, for the first time, to examine their predictive significance in the GCC context. We did not include the ratio *EBITTA* (Earnings to total assets) because the calculation of this ratio closes resembles the rule used to classify firms as solvent or insolvent.

Table 2 Definition of Financial ratios and summary statistics by failure category

Description			Descriptive Statistics By (Firm) Failure Category					
Ratio Variable	Short Description	Formula	Ratio Mean		Standard Deviation		Coefficient of variation	
Type of Firm (S = Solvent; INS = Insolvent)			S	INS	S	INS	S	INS
EBITSEQ	Profitability - Return On Equity	Earnings Before Interest And Taxes/Shareholders' Equity	7.9	-0.5	57.6	2.8	727.7	-606.3
EBITCE	Profitability - Return On Capital Employed	Earnings Before Interest And Taxes/Capital Employed	5.9	-0.3	43.2	0.3	732.3	-104.7
EBITS	Profitability - EBIT Margin	Earnings Before Interest And Taxes/Sales	2.5	-6.1	17.7	38.5	697.5	-627.8
EBITTL	Profitability - Earing To Total Liabilities	Earnings Before Interest And Taxes/Total Liabilities	6	-0.4	42.9	0.6	714.4	-132.8
GPM	Profitability - Gross Profit Margin	Gross Profit/Sales	25.5	-23.5	19.2	230.3	75.5	-979.2
RETA	Leverage - Retained Earnings To Total Assets	Retained Earnings/Total Assets	0	-0.3	0.4	0.8	1572.2	-253.4
SETA	Leverage - Equity To Total Assets	Shareholders' Equity/Total Assets	53.6	39	26.4	37.6	49.3	96.3
SETL	Leverage - Equity To Total Liabilities	Shareholders' Equity/Total Liabilities	2.6	2	3.2	4.1	122.2	209.6
TLTA	Leverage - Total Liabilities To Total Assets	Total Liabilities/Total Assets	1.1	3.3	1.7	9.2	156.5	275.3
TLNW	Leverage - Total Liabilities To Net Worth	Total Liabilities/Net Worth[1]	4	4.5	4.9	13	122.7	286.7
SETD	Leverage - Equity To Debt	Shareholders' Equity/Total Debt	0.4	0.6	0.3	0.4	58.2	62.5
CR	Liquidity - Current Ratio	Current Assets/Current Liabilities	2.2	1.8	2.4	2.2	110.4	123
QR	Liquidity - Quick Ratio	(Current Assets - Stocks) / Current Liabilities	1.4	1.3	1.7	1.7	114.3	137.3
WCTA	Liquidity - Working Capital To Total Assets	Working Capital/Total Assets	-0.5	0	4.8	0.4	-928.6	-3538.9
IT	Activity - Inventory Turnover	Cost Of Sales/Inventory	8.9	14	13.3	47.7	148.7	340.4
TDS	Activity - Debt Ratio	Total Debt[2]/Sales	1.6	13	4.4	84	273.7	644.7

AT	Activity - Total Asset Turnover	Sales/Total Assets	0.6	0.6	0.5	0.7	83.4	111.5
SCA	Activity - Sales To Current Assets	Sales/Current Assets	1.6	1.5	1.1	1.2	72.3	79.4
SFA	Activity - Fixed Asset Turnover	Sales/Fixed Assets	1.9	2.6	2.9	6.8	153.5	261.6
SWC	Activity - Working Capital Turnover	Sales/Working Capital[3]	0.4	-6.5	15.2	75	3500.2	-1153
CFFOTA	Cash Flow - Cash Flow On Assets	Cash Flow From Operations/Total Assets	0.2	0	0.8	0.1	400.1	-336.5
CFFOS	Cash Flow - Cash flow on Sales	Cash Flow From Operations/Sales	12417.5	-328.2	92753.9	1651.4	747	-503.2
CFFOCL	Cash Flow - Cash Flow on Current Liabilities	Cash Flow From Operations/Current Liabilities	1.2	0.1	5.7	0.7	462.3	1184.3
CFFOTL	Cash Flow - Cash Flow on Total Liabilities	Cash Flow From Operations/Total Liabilities	0.7	0	3	0.4	425.6	1563
CFFONW	Cash Flow - Cash Flow on Net Worth	Cash Flow From Operations/Net Worth	0.2	-0.2	0.3	1	148.4	-520.7
TDCFFO	Cash Flow - Total Debt To Cash Flow Ratio	Total Debt/Cash Flow From Operations	3.2	81.1	5.2	512.9	161.8	632.8
MVOETD	Market - Market Value To Debt	Market Value Of Equity/Total Debt	7.8	6.6	12.9	17.6	165.3	267.3
MVOESE	Market - Market Value To Equity	Market Value Of Equity/Shareholders' Equity	1.9	1.7	1.4	5.3	76.9	312.7
[1] Net Worth= total Assets-total Liability [2] Total Debt=long-term Debt + short-term Debt + current portion of long-term Debt [3] Working Capital =Current Asset – Current Liabilities								

3.2 Data Analysis

Logistic Regression

We used Logistic regression or Logit model to address *RQ1*. We chose the Logit model because it satisfies a number of important criteria. First, it does not have restrictive distributional assumptions. This is important because, beyond predictive capacity, we are interested in the statistical significance of ratios: P-values may be incorrect when distributional assumptions are violated. Tests showed that all 28 financial ratio variables are non-normal, with the p-value of the *Shapiro-Wilk* statistic less than 0.001 in all cases. The *Mardia Skewness, Mardia Kurtosis and Henze-Zirkler* statistics also had p-values less than 0.001, confirming lack of multivariate normality. Group homogeneity tests also indicated (*chi-square* = 3018, *d.f.* = 406, p <.0001) that the covariance matrices of the insolvent and solvent firms cannot be considered equivalent. These results confirm that these financial ratio data are not suitable for MDA.

The second criterion is prediction accuracy: to be confident that the set of ratios found significant *does* contribute to 'good' predictions of GCC corporate insolvency, the prediction model must be 'good' overall. The performance of insolvency models is, typically, assessed by classification accuracy (Altman and Narayanan, 1997). Comparative studies suggest that Logit can perform at least as well as most other popular techniques: Whereas Charitou et al. (2004) ranked Logit second to neural networks (NN) and above MDA, Gloubos and Grammatikos (1988) found its overall accuracy on out-sample predictions higher than MDA, LPM (Linear probability model) and Probit. Laitinen and Kankaanpaa (1999) found Logit more accurate than five other popular techniques (including NN, recursive partitioning and MDA) in *ex-ante* predictions one year before failure occurred. Logit compares well even to more recent machine learning techniques such as Support Vector Machine (SVM) and Least Square Support Vector Machine (LSSVM); in personal credit classification comparisons, Zhu et al. (2013, p. 264)) ranked LSSVM first, logistic third and SVM fourth with their first test data. With their second test data, they ranked logistic first LSSVM fourth and SVM fifth.

The final criterion is interpretability: to address a lack in the literature, we wish to examine the significance of the effect of profitability ratios on insolvency in the GCC. Logit is highly interpretable (Steyerberg et al., 2001, Fedenczuk, 2003) as the estimated coefficients of the ratios can be translated directly into the effect of each ratio on the odds of insolvency. In contrast, a number of the techniques, namely NN, SVM and LSSVM, that sometimes perform better than Logit, are black box in nature and not interpretable (Doumpos et al., 2007, Han et al., 2013, Zhu et al., 2013). Classification trees are intuitive and interpretable but there is no evidence that they are more accurate than Logit: in Laitinen and Kankaanpaa (1999), overall, Logit outperformed Classification trees for all *ex-ante* predictions.

We ran the Logit model in SAS 9.2 setting the firm failure category as dependent (event = 'insolvent') and the 28 financial ratios as predictors. We partitioned the data into a training set covering the period 2004-2009 (33 pairs or 66 cases) and a test set covering 2010-2011 (23 pairs or 46 cases). To avoid overfitting, it is generally accepted that a Logit model should have at least 10 cases per predictor (Peduzzi et al., 1996). Thus, with 66 cases in our training data set, we should fit a model with no more than six predictors. We examined the literature for guidance on how to choose the optimal set of six predictors. We found seven corporate insolvency studies that have applied the Logit model using a data set of similar size. As shown in table 3, except for Basheikh (2012), all seven studies apply explicit selection criteria. Some (Gentry et al., 1985, Peel et al., 1986, Ward, 1994) choose the ratios discretionarily based on prior evidence or theory; others choose the ratios empirically using algorithmic stopping rules (Keasey and McGuinness, 1990, Charitou et al., 2004) or based on the results of prior analysis with other statistical techniques such as principal components analysis (PCA) (Canbas et al., 2005). As we stated earlier, we chose the 28 ratios under consideration based on evidence from the literature. So we could not re-apply this strategy to further narrow down the set of candidate ratios. Equally, we could not use PCA because, once combined into components, it is impossible to isolate the effect of individual ratios; we would have been unable to assert whether cash flow ratios are important in the GCC and thus address *RQ1* fully. Subsequently, we adopted the algorithmic approach; but unlike Charitou et al. (2004), and Keasey and McGuinness (1990), we did not use the stepwise, backward or forward criteria which have been shown to have a number of limitations (Steyerberg et al., 2001). Instead, we applied the best subset selection criterion using the SCORE option in SAS 9.2.

Table 3 Ratio selection strategies in logistic insolvency studies

Study Details	Estimation Data (Insolvent/Solvent)	Ratio Selection Criteria
Charitou et al. (2004)	25/25	Algorithmic: backward and forward criteria
Gentry et al. (1985)	33/33	Predetermined based on theory
Ward (1994)	14/37	Predetermined based on literature
Basheikh (2012)	18/38	No explicit criteria
Keasey and McGuinness (1990)	43/43	Algorithmic: stepwise criterion
Peel et al. (1986)	34/44	Predetermined based on literature
Canbas et al. (2005)	18/22	Step 1: ANOVA to select 12 'early warning ratios' Step 2: PCA of selected ratios

Based on Furnival and Wilson's (1974) branch-and-bound algorithm, the SCORE method estimates a specified number of models for each given number of predictors. It is not a fool proof approach: the selected subsets are unstable, particularly with small data sets. To enable the selection of the most robust subset, we conducted the selection process by borrowing some elements from Breiman's (1996) 'bagging' procedure. First, as we have explained, our model should have no more than six predictors; so we investigated only subsets with six predictors. Second, taking random samples with replacement, we created 1000 bootstrap replicates of the training data set, each being of equal size to the original sample. For each replicate, we then ran logistic regression entering all 28 financial ratios as predictors and specified that a single model (i.e. best fitting model with the highest likelihood score statistic) using six predictors should be estimated. Third, we tested the predictive performance of the most frequent (> 1%) subsets of the 1000 using the original training data set. We then evaluated the predictive performance of the most frequent subsets using the weighted value of the area under the curve (AUC) of the receiver operating characteristic curve (ROC), using each subset's frequency as the weight. Likened to the Gini coefficient (Thomas et al., 2002) and the Mann–Whitney–Wilcoxon test (Hanley and McNeil, 1982), the AUC is an important index for evaluating a model's ability to correctly forecast a dichotomous dependent with values ranging from 0.5 for a random classifier to 1 for a perfect classifier. Rather than as an absolute value measure, the AUC is most useful as a single number metric for comparing classification models as employed in this study.

Finally, using the subset with highest weighted AUC, we estimated the logistic regression model for the training data set. To validate the logistic model, we then used the estimated parameters of the significant ratios to score the test data set. As such we adopted a forecast validation test or out-of-sample, *ex-ante* test since our test data set is from a later period. According to Jones (1987), a forecast validation tests not only for overfitting which is likely to occur with in-sample validation but also the stationarity assumption, i.e. that relationship between ratios and failure holds over time. To further validate the results, we then re-ran the final model and validation test but this time using probit instead of logistic regression.

3-Way Multidimensional scaling with Hierarchical Cluster Analysis

To address the second and third research questions, we employed 3-way MDS (Kruskal and Wish, 1978) to extract the key dimensions of the 28 financial ratios because (i) MDS does not carry restrictive distributional assumptions such as normality, equal variance-covariance structures or independence of ratios, and (ii) we can measure the relative importance solvent and insolvent firms attach to the extracted financial ratio dimensions using 3-way MDS enabling us to examine differences between them. Using IBM SPSS 20, we conducted the 3-way MDS in four stages. First, we calculated Euclidean distance-based proximities among the 28 ratios. Second, to decide the number of dimensions to retain in the final solution, we adopted a strategy followed by similar studies (Neophytou and Molinero, 2004b, Chipulu et al., 2013) of independently establishing the dimensionality of the data *a priori* of the final three-way MDS. We iteratively submitted the proximity matrix for all sampled firms (solvent and insolvent) to MDS analysis using the *Proxscal* algorithm, each time extracting a different number of dimensions. We then used a scree plot of the normalised stress (a 'badness-of-fit" measure) for successive numbers of dimensions to judge optimal dimensionality. Third, we extracted the *individual* proximity matrices of the 28 financial ratios for solvent and insolvent firms; and entered them as inputs into three-way MDS model using the *Prefscal* algorithm (Busing et al., 2005), specifying that the number of dimensions decided in the second stage of the analysis be retained. The *Prefscal* algorithm began by extracting a common (to both types of firms) multidimensional space. Individual spaces for each type of firm were then extracted by rescaling (shrinking or extending) the common space along the dimensions based on the weight that each type of firm places on that dimension. We then used the re-scaling weights to examine the relative importance each type of firm (i.e. solvent or insolvent) attaches to each dimension. Finally, to support the interpretation of the MDS dimensions, we supplemented the MDS results by clusters of ratios obtained from an independently conducted hierarchical cluster analysis (HCA) (Gupta and Huefner, 1972, Neophytou and Molinero, 2004b). Based on Euclidean distance proximities among them, we clustered the 28 ratios using Ward's method, which we judged the most appropriate for this purpose because it leads to compact clusters by minimising cluster variance (Punj and Stewart, 1983)

The rationale behind our choice of 3-way MDS is that it reveals, as much as possible, the hidden structure in the data based on similarities among the financial ratios. This addresses *RQ2* and so other data reduction techniques such as PCA could have been applied instead. Recent examples of the application of PCA with financial ratios can be found in Min and Lee (2005) and Canbas et al. (2005). We chose 3-way MDS over other techniques for two reasons. First, by examining the weights that solvent and insolvent firms attach to the dimensions, we are able to address the third research question directly. This would have not been possible with a technique such as PCA without secondary analysis of the results. Second, it is thought that the dimensions arising from 3-way MDS are easier to interpret (than, say, PCA components) because the re-scaling of the common space using individual weights is strictly dimensional (Arabie et al., 1987).

4 Results

Logit Model Insolvency Prediction

Table 4 Training data predictive performance of most frequent best-six ratio sets

Set	Best-Six Ratios Set	N	%	AUC	Weighted AUC
1	*EBITCE, EBITTL, TLTA, CFFOTA, CFFOCL, TDCFFO*	69	6.9	0.989	68.2
2	*EBITCE, EBITS, EBITTL, SETL, TLTA, TDCFFO*	23	2.3	0.9651	22.2
3	*EBITCE, EBITTL, TLTA, CFFOTA, CFFOCL, CFFOTL*	23	2.3	0.9981	23
4	*EBITTL, TLNW, WCTA, CFFOTA, CFFOCL, CFFOTL*	21	2.1	0.9917	20.8
5	*EBITCE, EBITS, SETA, TLTA, TDCFFO, MVOETD*	19	1.9	0.9871	18.8
6	*EBITCE, EBITTL, TLTA, CFFOTA, CFFOTL, TDCFFO*	17	1.7	0.9761	16.6
7	*EBITTL, TLTA, TLNW, CR, CFFOTA, CFFOTL*	13	1.3	0.9752	12.7
8	*EBITTL, TLTA, TLNW, CFFOTA, CFFOTL, TDCFFO*	12	1.2	0.9752	11.7

The 1000 bootstrap replicates produced 497 unique sets of best-six predictors, indicating the uncertainty surrounding the predictive ability of the 28 ratios. Although most sets appeared only once, there were eight sets exceeding 1% frequency. As shown in table 4, the eight sets comprised 14 different ratios. Set 1 containing *EBITCE*, *EBITTL*, *TLTA*, *CFFOTA*, *CFFOCL* and *TDCFFO* was the most frequent, appearing thrice as much as the next most frequent set; and it performed best on frequency-weighted AUC of the ROC curve for the training data set. Inspection of table 4 suggests that beyond set 1, *EBITCE*, *EBITTL*, *TLTA*, *CFFOTA*, *CFFOCL* and *TDCFFO* also frequently appear in other best-six sets. Each of the six ratios is present in at least four of the other seven most frequent sets. There is hence a common pattern across the eight sets: except for sets 5 and 7, which respectively contain a liquidity and market ratio, the eight sets comprise ratios from the profitability, leverage and cash flow categories; however, there is no activity ratio in any of the eight sets. Thus, while the exact combination of best-six ratios is uncertain, it is likely profitability, leverage and cash flow ratios will offer more predictive value than liquidity, market, and, in particular, activity ratios.

The final training model fit statistics with *EBITCE*, *EBITTL*, *TLTA*, *CFFOTA*, *CFFOCL* and *TDCFFO* as predictors were good [Likelihood Ratio Chi-squared = 74.4, p-value < 0.0001; Pseudo R-square value (Nagelkerke) = 0.90], indicating that these six variables provide some explanation for firm insolvency. Table 5 shows the parameter estimates. Except for *EBITCE* and *TDCFFO,* the estimated coefficients of the ratios are significant at the .05 p-value level. The results suggest that higher levels of *TLTA* and *CFFOCL* will increase the likelihood of insolvency, whereas *EBITTL*, *CFFOTA and TDCFFO* will reduce it. Of these, *CFFOTA*, with the largest coefficient, is likely to have the greatest effect.

Table 5 Parameter estimates of predictors for insolvency

Parameter	**Description of Ratio**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > Chi Sq**
Intercept		-2.5	1.5	2.8	0.096
EBITCE	Profitability - Return On Capital Employed	-9.6	5	3.7	0.054
EBITTL	Profitability - Earing To Total Liabilities	-8	3.4	5.6	0.018
TLTA	Leverage - Total Liabilities To Total Assets	1.8	0.9	4.2	0.041
CFFOTA	Cash flow - Cash Flow On Assets	-78.2	35.6	4.8	0.028
CFFOCL	Cash flow - Cash Flow on Current Liabilities	11.5	5.3	4.7	0.03
TDCFFO	Cash flow - Total Debt To Cash Flow Ratio	-0.2	0.1	1.7	0.187

To validate the model, we then re-estimated the logistic regression with the four significant ratios, namely *EBITTL*, *TLTA*, *CFFOTA* and *CFFOCL* - as predictors and used the estimated parameters of the four predictors to score the test data set. The full results of this predictive logistic model are shown in Appendix II. The AUC of the ROC curve based on scoring the test data set was 0.97. This AUC value is very close to 1 (= perfect classification) and substantially greater than 0.5 (= random classifier). Thus, we can conclude that these four ratios can be used to predict insolvency of GCC firms before it occurs and that the cash flow ratios *CFFOTA* and *CFFOCL* may be useful predictors of insolvency in the GCC. The *ex-ante*, validation test shows that the model has 84.8%, 95.6% and 73.9% overall, type I and II classification levels of respectively.

The Probit model results are shown in Appendix III. They closely replicate the Logit results: the estimated parameters of the four predictors are very similar, and the two models have identical classification levels on the test data.

MDS Dimensionality

Figure 1 shows the scree plot from the *Proxscal* MDS models. There is no clear 'elbow' to indicate optimal dimensionality; however, this is not unusual in MDS. Experience shows that higher dimensions are increasingly harder to interpret as they account for more residual than common variance; and, typically, researchers trade-off the higher variance accounted for which comes with higher dimensionality in favour of lower dimensionality and higher interpretability (Neophytou and Molinero, 2004a, Chipulu et al., 2013). According to Kruskal and Wish (1978), an MDS configuration represents a 'good' fit when stress is 0.05 and is 'very good' at 0.01.

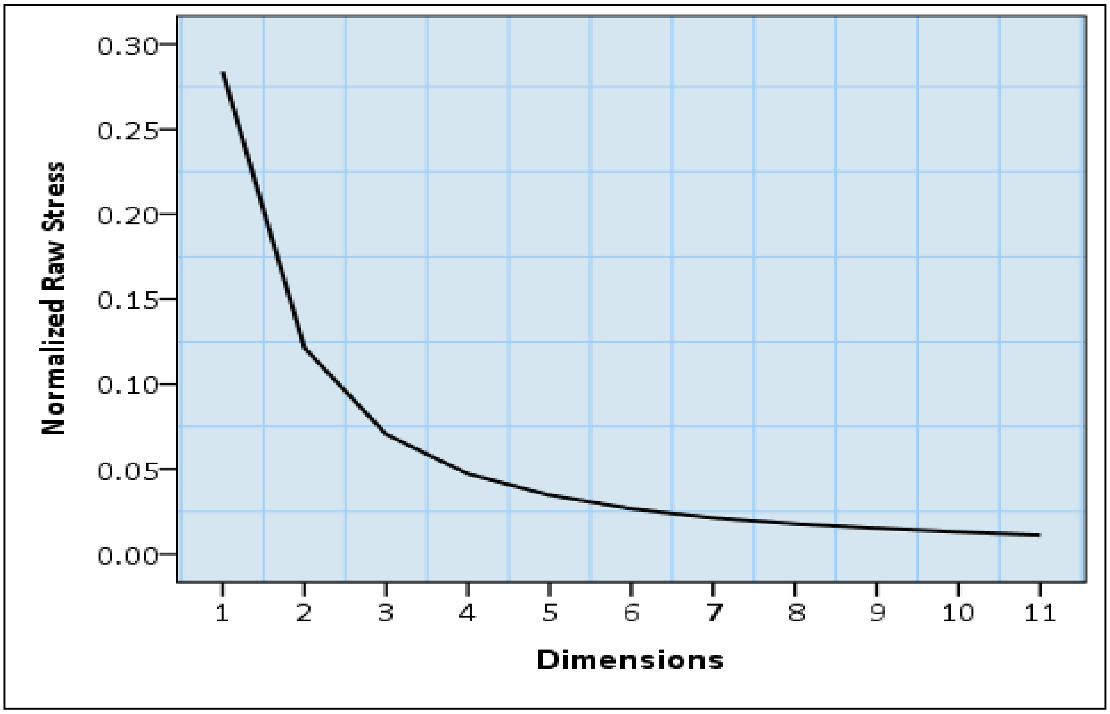

Fig.1 MDS Proxscal Models' Goodness-of-fit

In figure 1, model fit clearly improves between one and four dimensions when stress drops to 0.05 (a 'good' fit). After four, incremental improvements diminish and stress does not reach 0.01 even at 11 dimensions. This implies that at least 11 dimensions are required to obtain a 'very-good': yet each additional dimension after four improves fit only marginally. Therefore we decided to extract four dimensions as this represents the lowest dimension (and so highest interpretability) configuration that reaches a 'good' fit.

MDS Model Fit and Coordinates of Ratios

The final 3-way MDS model, retaining four dimensions, was a good fit for the data with a normalised stress value of 0.03, and accounted for 87% of the variance. Degenerate indices (DeSarbo's inter-mixedness = 0.22; Shepard's rough non-degeneracy = 0.76) were such that we can conclude the model is unlikely to be degenerate. Table 6 shows the dimensional coordinates of the financial ratios. The absolute value of a ratio's coordinate on each dimension is indicative of its level of association with that dimension. Ratios with very high absolute values can be used to interpret each dimension as they are the most representative of that dimension (Chipulu et al., 2013). In table 6, we have highlighted the ratios with large (absolute) value coordinates that we have used for this purpose.

Table 6 MDS dimensional coordinates of financial ratios

Financial Ratio	Description	Dim_1	Dim_2	Dim_3	Dim_4
CFFOS	Cash Flow - Cash flow on Sales	.750	-.268	1.049	.076
TDCFFO	Cash Flow - Total Debt To Cash Flow Ratio	.706	-1.171	.618	-.057
GPM	Profitability - Gross Profit Margin	.671	-.450	1.044	.212
TDS	Activity - Debt Ratio	.602	-1.058	-1.020	.144
SWC	Activity - Working Capital Turnover	.550	-.680	.595	.489
IT	Activity - Inventory Turnover	.344	-.722	.530	1.164
SETA	Leverage - Equity To Total Assets	.158	.427	.686	.536
EBITS	Profitability - EBIT Margin	.080	.086	-.089	2.213
MVOETD	Market - Market Value To Debt	-.462	-.577	.160	1.835
SETD	Leverage - Equity To Debt	-.676	-.824	-.327	1.899
TLNW	Leverage - Total Liabilities To Net Worth	-.740	-1.000	-1.156	.934
SFA	Activity - Fixed Asset Turnover	-.776	-.832	-.794	1.619
SETL	Leverage - Equity To Total Liabilities	-.973	-1.044	-1.126	.647
MVOESE	Market - Market Value To Equity	-1.002	-1.055	-1.261	.374
EBITSEQ	Profitability - Return On Equity	-1.051	.883	.392	-.096
SCA	Activity - Sales To Current Assets	-1.146	-1.183	-1.299	-.465
CFFONW	Cash Flow - Cash Flow on Net Worth	-1.187	-1.209	-1.336	-.903
CR	Liquidity - Current Ratio	-1.203	-1.182	-1.276	-.425
QR	Liquidity - Quick Ratio	-1.238	-1.222	-1.304	-.700
TLTA	Leverage - Total Liabilities To Total Assets	-1.246	-1.219	-1.339	-.909
AT	Activity - Total Asset Turnover	-1.251	-1.216	-1.351	-.857
RETA	Leverage - Retained Earnings To Total Assets	-1.260	-1.202	-1.303	-.917
EBITTL	Profitability - Earning To Total Liabilities	-1.262	1.265	.006	-.334
EBITCE	Profitability - Return On Capital Employed	-1.267	1.232	.069	-.281
WCTA	Liquidity - Working Capital To Total Assets	-1.276	-1.205	-1.323	-.942
CFFOCL	Cash Flow - Cash Flow on Current Liabilities	-1.276	-1.230	-1.327	-.924
CFFOTL	Cash Flow - Cash Flow on Total Liabilities	-1.291	-1.225	-1.334	-.969
CFFOTA	Cash Flow - Cash Flow On Assets	-1.294	-1.207	-1.315	-.982

HCA Clusters of Ratios

It is not possible to visualise the positions of the ratios in a four-dimensional (4D) space, so we created two-dimensional (2D) projections of the MDS configuration. However, as the true configuration is four-dimensional, distances between ratios in the 2D space can be misleading: two proximate ratios that therefore seem similar in, for example, dimensions 1 and 2, could actually be far apart in dimensions 3 or 4, and not as similar as they appear. It is important then to indicate on the 2D maps *overall* distances among ratios. One approach to this problem is to superimpose the 2D maps with a layer of the clusters obtained from HCA (Neophytou and Molinero, 2004b).

Table 7 HCA Cluster Membership

Cluster 1		**Cluster 2**	
SFA	Activity - Fixed Asset Turnover	*EBITTL*	Profitability - Earning To Total Liabilities
SCA	Activity - Sales To Current Assets	*EBITS*	Profitability - EBIT Margin
AT	Activity - Total Asset Turnover	*EBITCE*	Profitability - Return On Capital Employed
CFFOTA	Cash flow - Cash Flow On Assets	*EBITSEQ*	Profitability - Return On Equity
CFFOCL	Cash flow - Cash Flow on Current Liabilities		
CFFONW	Cash flow - Cash Flow on Net Worth	**Cluster 3**	
CFFOTL	Cash flow - Cash Flow on Total Liabilities	*TDS*	Activity - Debt Ratio
SETD	Leverage - Equity To Debt	*IT*	Activity - Inventory Turnover
SETL	Leverage - Equity To Total Liabilities	*SWC*	Activity - Working Capital Turnover
RETA	Leverage - Retained Earnings To Total Assets	*SETA*	Leverage - Equity To Total Assets
TLNW	Leverage - Total Liabilities To Net Worth	**Cluster 4**	
TLTA	Leverage - Total Liabilities To Total Assets	*GPM*	Profitability - Gross Profit Margin
CR	Liquidity - Current Ratio	**Cluster 5**	
QR	Liquidity - Quick Ratio	*TDCFFO*	Cash flow - Total Debt To Cash Flow Ratio
WCTA	Liquidity - Working Capital To Total Assets	**Cluster 6**	
MVOETD	Market - Market Value To Debt	*CFFOS*	Cash flow - Cash flow on Sales
MVOESE	Market - Market Value To Equity		

There were five stages in the HCA agglomeration schedule. There was a six-cluster solution at stage one comprising three multiple-ratio clusters; and three unattached ratios: *GPM*, *TDCFFO* and *CFFOS*. There were four clusters at stage two: the three multiple-ratio clusters merged into one large cluster; while *GPM*, *TDCFFO* and *CFFOS* remained unattached. *GPM* joined the large cluster at stage three, *TDCFFO* at stage four and *CFFOS* at stage five. Stage one thus represents the greatest cluster separation and so we decided to extract the six clusters at this level. Cluster membership is summarised in table 7. The schedule suggests the three larger clusters have more similarities among them than with *GPM*, *TDCFFO* or *CFFOS*. *GPM*, *TDCFFO* and *CFFOS*, particularly, are dissimilar to the other 25 ratios. They could be key indicators in that they carry unique information not shared by other ratios. We interpreted the three larger clusters as follows:

Cluster 1, the largest with 17 ratios, contains all the liquidity ratios, all but one of the leverage ratios and both market ratios; but *none* of the profitability ratios. This combination of ratios led us to interpret cluster 1 as an indicator of non-profitability-based **market valuation of financial stability;** and that the cash flow and activity ratios that are also in cluster 1 are closely related to market valuation of financial stability.

Cluster 2 contains only profitability ratios, which can be used to determine a company's ability to produce a return on investment. We believe this cluster represents **profitability**.

All except one of the ratios in cluster 3 are indicative of sales activity (*IT*, *SWC*, *TDS*). We believe this cluster represents **sales activities**, which is related to *SETA* (equity to total assets), the fourth ratio in the cluster.

Interpretation of ratio dimensions

Using the relative positions of the six clusters on the 2D MDS maps and the signs and sizes of dimensional coordinates of the ratios (table 6), we interpreted the four dimensions as follows

Dimension 1: 'Non-strategic sales activities'

Figure 2 shows the projection of the MDS structure in dimensions 1 and 2. MDS dimensions are extracted hierarchically based on variance accounted for, with the first dimension accounting for the most and the amount decreasing with each additional dimension. As such, dimensions 1 and 2 should capture a substantial amount of the pattern of similarities among ratios, closely mirroring the cluster patterns. It can be seen in figure 2 that this is the case. All six clusters occupy clear and distinct positions on the map. Cluster 3, an indicator of sales activities, is entirely on the right-hand side of dimension 1; as are the three unattached ratios *CFFOS*, *GPM* and *TDCFFO*, which - along with *TDS* - have the highest positive-valued coordinates on dimension 1. *CFFOS* measures cash generated from sales; *GPM* measures sales over costs. This suggests a need to maintain high sales activities to generate cash to cover financial obligations, where these obligations are reflected by the proximity of *TDCFFO* and *TDS*. In this case, however, the focus on sales activities is at the expense of profitability and financial stability as inspection of the left-hand side shows. The entire market valuation of financial stability cluster and most of the profitability cluster are on the negative side of dimension 1, indicating decreasing levels of both the markets' valuation of financial stability and profitability. This suggests a lack of long-term, strategic planning which is needed to ensure that sales activities not only generate profits but are conducted within a stable financial environment, engendering market value. Thus, we interpreted dimension 1 as an indicator of operational, **non-strategic focus on sales activities.**

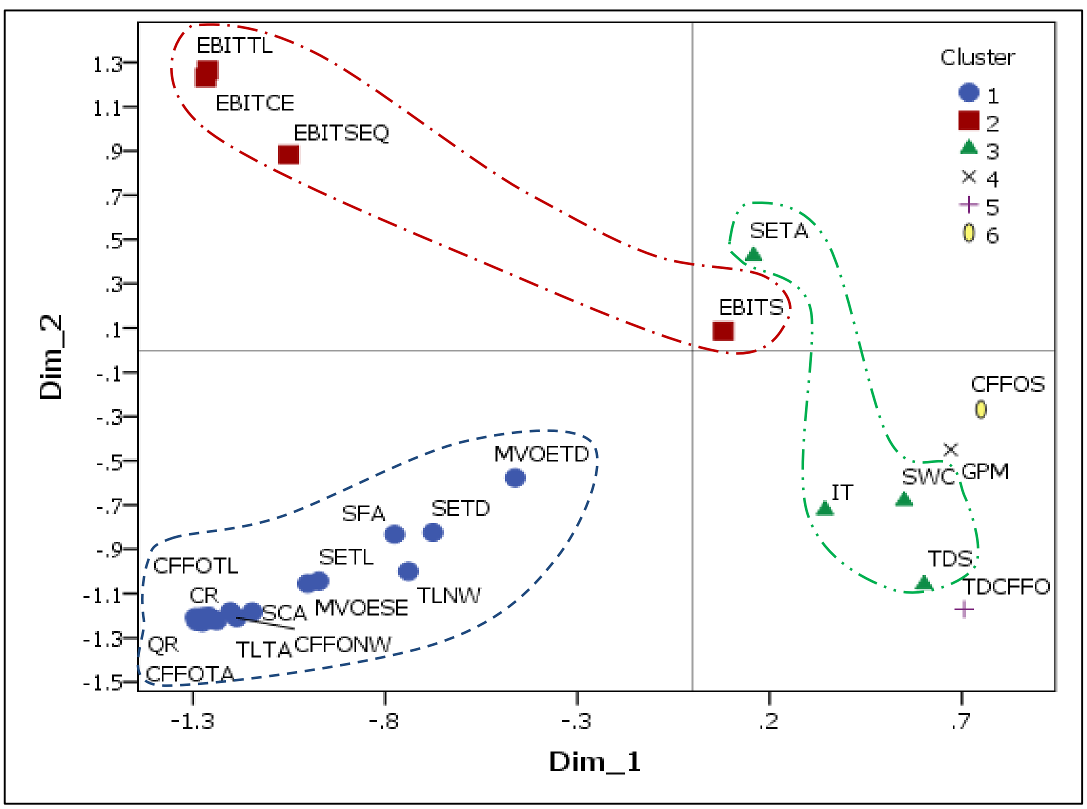

Fig. 2 MDS Dimensions 1 versus 2 and HCA Cluster

Dimension 2: ‘Profitability and financial stability balance’

Clusters 1 and 2 occupy different halves of dimension 2; whereas cluster 3 overlaps the two halves. The three ratios (*EBITTL, EBITCE and EBITSEQ*) with the highest positive valued coordinates on dimension 2 are all in cluster 2 (profitability). In contrast, cash flow over liabilities ratios (*CFFOCL, CFFOTL*) and the *quick ratio* (liquidity) and *TLTA* (leverage) have high negative coordinates on dimension 2. Together, these ratios indicate a firm’s ability to handle both its short- and long-term liabilities, i.e. financial stability. We interpreted dimension 2 to represent a balance between **profitability and financial stability**.

Dimension 3: ‘Sales activities against capital conversion’

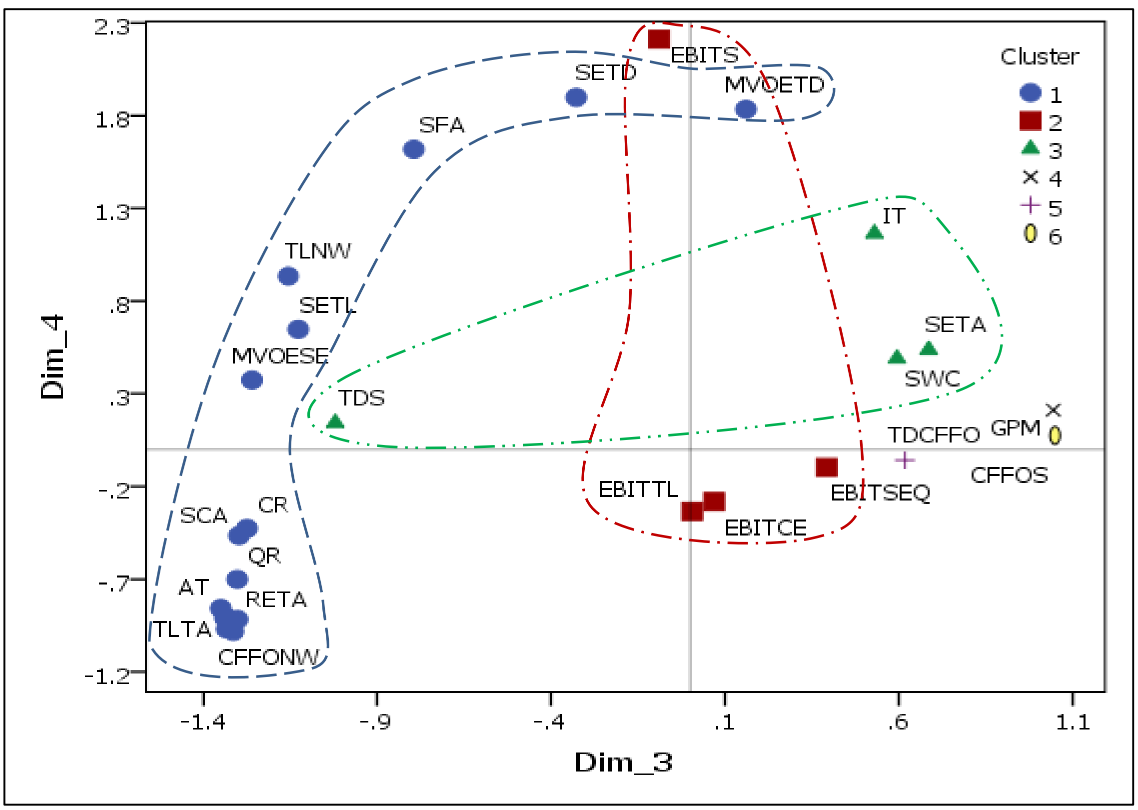

Fig. 3 MDS Dimensions 3 versus 4 and HCA Clusters

Figure 3 shows the projection of the MDS structure in dimensions 3 and 4. Unlike the dimensions 1 and 2 space, in this projection the clusters are not as compact and they overlap each other, i.e. they do not occupy clear and distinct areas of the map. These cluster transformations offer additional support for extracting a four-dimensional structure; they indicate that dimensions 3 and 4 offer extra insight (to 1 and 2) analogous to how regions in a country that are very similar in most aspects (for example geographical location, weather, population, etc.) may appear quite different when viewed in terms of urbanity and social deprivation.

On first inspection, based on the relative positions of the variables, dimension 3 appears very similar to dimension 1. Like 1, the ratios with high positive valued coordinates on dimension 3 - namely *CFFOS, GPM, DCFFO* - and most of the ratios in cluster 3 appear to indicate higher sales activities. Closer inspection, however, suggests noticeable differences. Whereas all the profitability ratios have large negative coordinate values on dimension 1, on 3 all profitability ratios have very small values, near zero. Dimension 3 does not appear to be strongly related to profitability. Similarly, it does not appear to be as strongly related to the market value and leverage ratios. Overall, unlike 1, the ratios on the negative side of dimension 3 do not give a clear indication of decreasing profitability and financial stability and, consequently, market-value. Rather, the two ratios with the highest negative valued coordinates, namely *AT* (total asset turnover) and *TLTA* (total liabilities to total assets); are, respectively, indicative of the efficiency in using own assets to generate sales and the effectiveness of using creditors' funds to acquire assets (Bragg, 2002, Megginson and Smart, 2005). This suggests the negative side of dimension 3 could be a reflection of return on capital. Thus, we interpreted dimension 3 as a balance between **sales activities against capital conversion**.

Dimension 4: 'Market value against cash generation' effectiveness

Dimension 4 transforms clusters 1 and 2 so that *EBITS*, a profitability measure from cluster 2, has a high positive-valued coordinate; and is located near cluster 1 ratios: *MVOETD* (market value to debt), *SETD* (equity to total debt), and *SFA* (fixed asset turnover). This combination of ratios indicates increasing efficiency in converting assets and debts into earnings and market value. In contrast, the ratios with the highest negative-valued coordinates are from the cash flow group (*CFFOCL, CFFOTL, CFFOTA),* indicating difficulties in generating cash from operations or inefficiencies in credit and cash collection. Therefore, we interpreted dimension 4 to indicate a balance between creating **market value against cash generation**.

Relative Importance of Ratio Dimensions

Table 8 shows the importance that 'solvent' or 'insolvent' firms ascribe to the four the four dimensions, how specific they are in attaching importance, and the importance (relative to other dimensions) of each dimension based on the amount of variance it accounts for. For each firm category, the dimensional weights can be used to compare the importance that firm category places on that dimension relative to the other three dimensions. For each dimension, dimension weights can be used to compare the importance that 'insolvent' firms attach to it relative to 'solvent' firms. The 'specificity' indicates the extent to which a source attaches weight to a specific dimension while overlooking others: values can range from zero for a source which regards *all* dimensions as equally important to one for a source which regards *only one* of the dimensions as important. An intuitive interpretation of specificity is that it captures the trade-off a source makes between focus on *one, some or all* of the dimensions: as emphasis on one or a few dimensions increases, lack of emphasis on the others may ensue. It can be seen thus that insolvent firms are very specific. They place a very large amount of weight on dimension 1; little or no weight on dimensions 2 and 3, and some weight on dimension four. In contrast, solvent firms are only moderately specific: instead of dimension 1 which appears unimportant to them, they place the most weight on dimension 2; and less, but still comparatively, much higher weights than insolvent firms on both dimensions 3 and 4. The importance values indicate that dimension 1 represents 40% of the overall variance extracted by the MDS structure. Since solvent firms appear to disregard this dimension, dimension 1 almost exclusively captures all the structural variations in ratios among insolvent firms, whereas the other three dimensions are more representative of solvent firms.

Table 8 Dimensional salience by firm failure category

Type of the Firm	Dimension				Specificity
	Dim_1	Dim_2	Dim_3	Dim_4	
Insolvent Firms	540.1	.0	8.2	104.9	.831
Solvent Firms	.1	444.6	350.6	204.5	.524
Importance	**.4**	**.3**	**.2**	**.1**	

5 Discussion

Above, after reviewing the literature, we concluded that, overall, no set of financial ratios is found to consistently predict firm failure. Rather, the set of ratios found significant varies by study (Altman and Narayanan, 1997). The results we have obtained from logistic regression modelling aimed at addressing our first research question (*RQ1*) - ***What are the significant predictors of insolvency in the GCC region; and do they include cash flow-based ratios?*** - mirror this synopsis of the literature. In our examination of six predictor subsets using 1000 bootstrap replications of the original training data set, we found that the 'best sets' varied considerably. Based on the premise that sets that appear with higher frequency are likely to be more robust, we examined the most frequent 'best sets'. We found that the sets were only marginally different in predictive performance, i.e. no set was unequivocally dominant. Given this uncertainty and lack of discriminability among sets, it is difficult to claim that one single set of ratios will consistently achieve high prediction performance, data changes notwithstanding. What our logistic regression appears to have uncovered is a general pattern: in the GCC context, ratios from the profitability, leverage and cash-flow groups are likely to contain insolvency predictive information.

Of the six predictors in the final Logit model, four, namely *EBITTL*, *TLTA*, *CFFOTA*, and *CFFOCL,* were significant. When we re-ran the prediction model using Probit regression, we were able to replicate the Logit results, confirming that the predictive capacity of these four ratios is not a mere artefact of the logistic model. Rather, it appears be a characteristic of the four ratios, which is independent of the predictive technique used. To assess how unique the significance of these four ratios is, we took a sample of 28 failure prediction studies for comparison. The 28 studies were selected to ensure representation of research over time (Beaver, 1966 to the present day), across locations and by classification techniques. Details of the 28 studies, including the significanc of the 28 ratios under consideration, are shown in Appendix IV. A count of number of occurrences of each ratio in the 28 studies suggests that the type of ratio most frequently reported significant is liquidity, having appeared first in the seminal studies of Beaver (1966) and Altman (1968). Our *not* finding any liquidity ratio to be significant is thus a contrast. This finding is not unusual, though: previous studies in the GCC such as Aldeehani (1995) and Basheikh (2012) did not find any liquidity ratio to be significant either. Perhaps liquidity ratios have lower predictive capacity in the GCC than elsewhere. We also did not find any activity or market ratio to be significant; but unlike liquidity, this type of ratio is rarely reported as significant in the literature, indicating low predictive capacity generally.

Based on theory (Gilbert et al., 1990) and empirical results elsewhere (e.g. Blum, 1974, Smith and Liou, 1979, Mensah, 1984, Aziz et al., 1988, Aziz and Lawson, 1989, Gilbert et al., 1990, Charitou et al., 2004) we posited that cash flow ratios should be of predictive value in the GCC context. The significance of *CFFOTA* and *CFFOCL* provides support for this postulate. Furthermore, *CFFOTA*, which has been reported significant in several other studies in different contexts (Shumway, 2001, Bose, 2006, Ravisankar et al., 2010) had by far the largest estimated effect. *CFFOCL*, also reported significant by Gilbert et al. (1990), had the second largest effect. These large cash flow ratio effects tend to support the argument that cash flow-based ratios may contain more predictive information than most other ratios (Gombola and Ketz, 1983). Consequently, the disregard of cash flow ratios seems to us a clear weakness in previous GCC insolvency research: cash flow-based ratios *should* be included when insolvency prediction models are constructed in the GCC.

The significance of *EBITTL* suggests that profitability is as good a predictor of insolvency in the GCC as it is in other contexts: *EBITTL* was also reported significant by Charitou et al. (2004) in the UK and Gloubos and Grammatikos (1988) in Greece. In the GCC, Basheikh (2012) found *EBITSEQ*, another profitability ratio, to be significant. Similarly, though it has the smallest estimated effect in our Logit model, *TLTA* is very often reported significant in the literature (e.g. Ohlson, 1980, Altman and Lavallee, 1981, Zmijewski, 1984, Zavgren, 1985, Gloubos and Grammatikos, 1988, Shumway, 2001, Charitou et al., 2004). We can hence conclude that leverage is as good a predictor of insolvency in the GCC as it is elsewhere.

The Logit model performed very well in the forecast validation test. As shown in table 9, the model accuracy levels are impressive even when compared to in-sample or ex-post validation results: It is well known that in-sample validation tends to over-estimate model performance (e.g. Hawkins, 2004); and it has been suggested that impressive ex-post classification rates can drop by 10% or more on *ex-ante* tests (Platt and Platt, 1990). Type I errors are considered much more costly than type II (e.g. Altman et al., 1977). It is good then that, like those of Altman (1968) and Charitou et al. (2004), the Logit model is better at classifying insolvency than solvency. We should also note that we partitioned the data such that the training data were for the period before and up to the onset of the 2008 financial crisis (2004-2009), whereas the test set data were post-crisis (2010-2011). The 2008 crisis is thought to have significantly affected the GCC economies including triggering the Dubai debt crisis (Khamis and Senhadji, 2010, Onour, 2010). Thus, the level of accuracy of the logistic model in correctly classifying firms after the 2008 financial crisis is notable given the potential confounding influence of the crisis.

Table 9 Comparative accuracy of a sample of insolvency studies

Study Details	Location of Study	Accuracy (%)		
		Overall	Type I	Type II
Current Study* **	**GCC**	**84.8**	**95.6**	**73.9**
Peel et al. (1986)***	United Kingdom	91.7	83.4	100
Charitou et al. (2004)***	United Kingdom	80.95	85.71	76.19
Gloubos and Grammatikos (1988)***	Greece	77.1	66.7	87.5
Ta and Seah (1988)**	Singapore	86.2	75	90.5
Keasey and McGuinness (1990)***	United Kingdom	63	56	70
Altman (1968)**	United States	85.5	96	79
Zavgren (1985)*	United States	82	89	76
Basheikh (2012)*	Saudi Arabia	83.8	83.3	84.2
*** out-sample, *ex-ante* ** out-sample, ex-post * in-sample				

Our second and third research questions were, respectively, ***What are the key financial ratio dimensions in the GCC?*** and ***Relatively, what are the differences between solvent and insolvent firms in the salience they attach to financial ratio dimensions?*** Rather than prediction, these two questions were aimed at generating insight as to why some firms might be more susceptible to insolvency than others. Using 3-way MDS supplemented by hierarchical cluster analysis, we found that, based on proximities, the 28 financial ratios under study can be reduced to four main dimensions. In order of decreasing importance (measured by the amount of the variance each dimension accounts for), the four dimensions were (i) ‘Non-strategic sales activities', (ii) 'Profitability and financial stability balance’, (iii) ‘Sales activities against capital conversion’, and (iv) ‘Market value against cash generation’. By examining the amount of weight each group puts on these four dimensions, we uncovered marked differences between solvent and insolvent firms. Insolvent firms place most weight on dimension 1 (‘Non-strategic sales activities') and very little on the other three. Solvent firms appear, by contrast, to disregard dimension 1 and place much more weight not only on dimension 2 ('Profitability and financial stability balance’) but also on dimensions 3 (‘Sales activities against capital conversion’) and 4 (‘Market value against cash generation’). This suggests that insolvent firms have a one-dimensional focus on ‘non-strategic sales activities’ (dimension 1), encapsulated in their high specificity value. Based on the relative positions of ratios in our MDS maps, we believe that the near-singular focus on ‘non-strategic sales activities’ by insolvent firms is likely a reactive, pragmatic stance dictated by a need to meet financial obligations. This inference is supported by the Logit results, which indicate that the level of cash relative to liabilities (*CFFOCL*) can significantly affect susceptibility to insolvency. Taking the multidimensional focus of solvent firms as exemplar, the MDS results imply, however, that focusing so exclusively on 'non-strategic sales activities'; while paying little regard to other dimensions, increases the risk of insolvency: it could harm profitability, put stability at risk and reduce market value. In other words, the implication for managers of firms in financial distress is to shift focus away from ‘non-strategic sales activities’ and much more on to 'profitability and financial stability balance’ and ‘sales activities against capital conversion', as solvent firms do. Likewise, managers of healthy firms should periodically evaluate strategy and, whenever signs of over-valuing 'non-strategic sales activities' are spotted, refocus on 'profitability and financial stability balance' and 'sales activities against capital conversion'.

Overall, we believe our results indicate some parallels as well as differences between insolvency in the GCC and in other regions. The Logit results confirm that financial ratios in general and cash flow ratios in particular can be used to detect firm's distress in the GCC as effectively as elsewhere. On the other hand, contrary to previous studies, the Logit results also indicate that liquidity ratios are not very good predictors of insolvency in the GCC. We note also that, in our MDS model, market value ratios are most strongly associated with the fourth dimension, which, based on amount of variance accounted for, is the least important of the four dimensions extracted. This may be a result of inefficiency in GCC markets (Arouri et al., 2011, Al-Ajmi and Kim, 2012); one of the key differences between the GCC and other major trading blocs such as NAFTA that we mentioned earlier. The implication for stakeholders, particularly investors, is that market values of GCC firms may not be as strongly associated with the financial health of the firms as they are in more efficient markets.

6 Conclusion

This study makes several contributions to the literature on corporate insolvency. To date, there has been relatively little research on insolvency in the GCC; and many of the existing studies have relied on Altman's model. This study breaks new ground by examining insolvency across the *whole* GCC, using multiple methodologies: a Logit model with a Probit model for extra validation, and a 3-way MDS model supplemented by Cluster Analysis. Thus, it extends the geographical coverage and methodological scope of corporate insolvency studies in the GCC. Beyond the GCC, as one of only a few studies to have conducted *ex-ante* validation, this study extends the *pool of countries* where validated insolvency classification models have been found. This is a worthwhile contribution in itself because we now have documented evidence of which ratios are likely to be good predictors of insolvency in, for example, the UAE. Arguably, however, the greatest contribution of this study is that, using MDS, it reveals the characteristic differences between solvent and insolvent firms, which we believe can aid managers of both types of firms take action to reduce susceptibility to insolvency.

We envisage a number of ways in which this research can be improved. Like other ‘developing’ (i.e. middle- and lower-income) regions, not only is the number of publicly listed companies in the GCC small but there is also very little data on insolvent firms because the stock markets are relatively nascent. Therefore, it will be valuable to re-model insolvency in the GCC as more data on insolvent firms emerge. Second, the GCC context has unique characteristics. This begs the question: to what extent are the structural differences between insolvent and solvent firms indicated by our MDS results idiosyncratic to the region? To examine this question, our forthcoming study will investigate whether or not the differences we have uncovered are generalisable, i.e. do similar structural differences exist between solvent and insolvent firms in other contexts such as the United Kingdom?

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Appendix I: Sample of Insolvent and Solvent Firms

Insolvent firms			Solvent Firms	
Companies	**size of Assets**	**year of failure**	**Companies**	**Size of Assets**
Middle East Specialized Cables Co	367,808	2011	Al hassan Ghazi Ibrahim	323,171
Ethihad Atheeb	563,439	2011	Etihad etisalat	10,000,180
Anaam	65,314	2006	Herfy Food Services	72,647
Saudi Fisheries Co	43,213	2005	Al Sharqiyah	38,049
Aseer Trading	882,461	2008	National co	130,075
Saudi Transeport Mobarad	47,065	2011	United international	267,459
Banader Hotels	26,624	2009	Bahrain Family	11,889
Medicare group	132,779	2006	Gulf international	589,687
Mushrif Trading Contracting	368,493	2008	Combined group	465,433
National Ind	466,163	2008	Mabanee co	854,885
Portland Cement	200,478	2008	United projects	159,474
National Ranges	476,852	2008	Kuwait cement co KSC	886,607
Human Soft Holding	44,510	2006	Safwan trading	47,797
Gulf franchising	40,776	2009	Hayat communi Holding	66,176
Nafais Holding	480,972	2009	Advanced technology	273,283
Sultan center food	1,085,362	2010	Gulf cable	1,143,807
Kuwait Cable Vision	21,041	2010	Automated systems co	37,162
Educational Holding	208,431	2010	Alsafat tec holding	211,376
Livestock transport and trading co	168,800	2011	Danah Al safat	183,004
Shuaiba Ind	62,469	2006	National metal	116,991
Heavy Eng and Ship Building	205,348	2006	Arabian pipes co	336,815
Equipment Holding	130,710	2009	Saudi steel pipe	261,634
Kuwait Founding	181,721	2011	Takween	215,259
Kuwait Pipe Ind and Oil Ser	824,718	2011	Saudi arabian mining	11,619,660
Mubarrad transport	101,403	2009	KGL logistics co	205,000
Jazeera airways	254,269	2009	Alafco Aviation	1,345,621
Refrigeration	79,103	2009	Saudi Public	484,156
City group	111,664	2011	National shipping	2,832,856
Kuwait Gulf Link Transport	694,379	2011	Agility Public	4,835,941

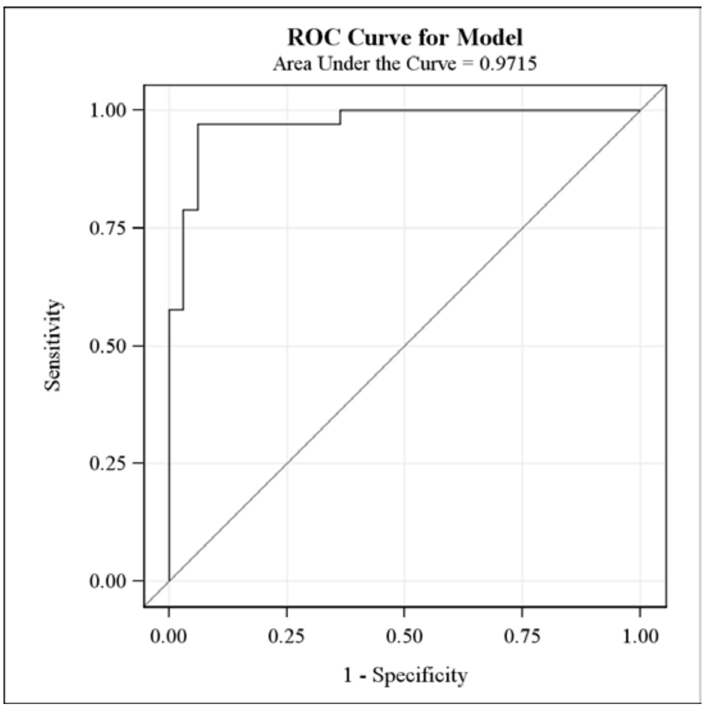
Ikarus Petroleum Ind	412,833	2008	Aref Energy	431,933
Gulf Petro Invest	198,903	2009	Al safat En. Holding	284,355
Independent Petro	1,516,646	2011	Boubyan Pet	1,535,243
IFA Hotels and Resorts	1,382,245	2010	Kuwait national	240,845
Kuwait Hotels	51,624	2010	Future Kid entertain	81,631
Mashaer Holding	255,200	2010	Kuwait resorts co	203,741
Oman Filters Ind	5,795	2006	Oman Chromite	6,032
National Aluminium pro	52,271	2008	Majan Glass	40,882
A Saffa foods	39,829	2005	Areej Vegtable Oils and Deriv	46,039
Oman National Dairy	13,287	2007	Omani Euro foods internaties	15,232
Sohar poultry	24,337	2007	Oman Refreshment	49,287
Dhofar Beverages and Food stuff	8,987	2008	Sweets of Oman	9,634
National beverages	20,624	2008	National Biscuit ind	20,534
National mineral water	31,976	2010	Oman Fisheries	43,974
Dhofar Fisheries	17,976	2011	Salalah Flour Mills	128,126
Oman Agriculture	15,521	2011	Oman Foods Ind	11,347
National Detergent	26,539	2005	Al Anwar ceramic	29,071
Cement and Gypsum Pro	5,289	2007	Al oula company saog	5,939
Al Jazeira services	61,742	2008	Oman investment	83,316
Oman international	5,976	2009	Computer stationery	12,384
National Hospitality	1,918	2010	Muscat Thread mills	6,468
Dhorar Tourism	213,497	2010	Gulf Hotels oman	86,771
United Foods	59,266	2008	Dubai Refreshments	97,729
Jeema mireral water	24,602	2010	Gulfa Mineral water and industrual prod	14,769
United Kaiparpa Dairies	48,977	2011	Food Products Co	58,773
National central cooling	2,101,698	2009	Arabtec Holding	2,482,415
Damas	1,101,044	2010	Arab heavy ind	62,881

Appendix II : Logit Prediction Model Results

R-Square	0.6281	Max-rescaled R-Square	0.8375

Testing Global Null Hypothesis: BETA=0			
Test	**Chi-Square**	**DF**	**Pr > ChiSq**
Likelihood Ratio	65.2891	4	<.0001
Score	40.8480	4	<.0001
Wald	13.5829	4	0.0088

Analysis of Maximum Likelihood Estimates					
Parameter	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	1	-0.7652	0.6856	1.2459	0.2643
EBITTL	1	-7.3046	2.1068	12.0208	0.0005
TLTA	1	0.7776	0.3726	4.3545	0.0369
CFFOTA	1	-55.5799	17.3161	10.3023	0.0013
CFFOCL	1	8.0985	2.5743	9.8969	0.0017



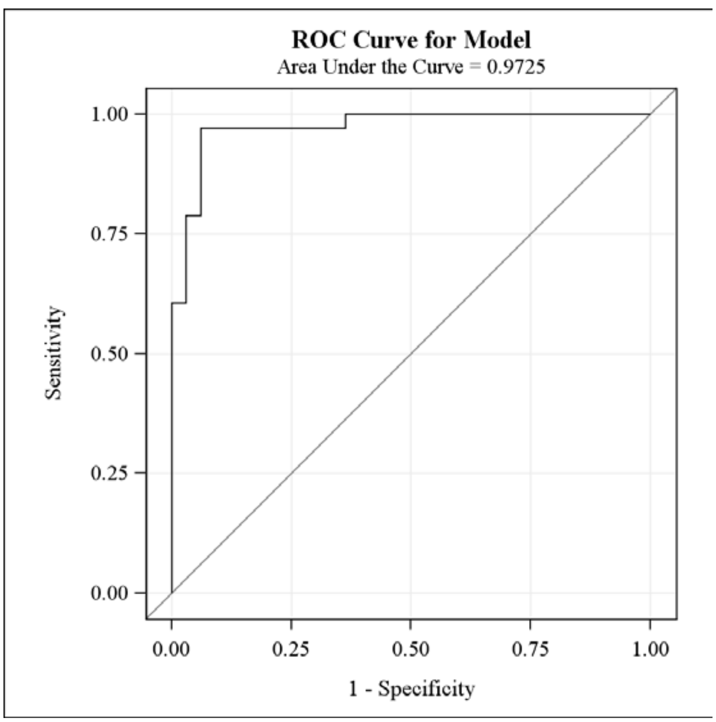
Classification Matrix				
		Observed Frequencies		**Total number**
		Solvent	Insolvent	
Predicted Frequencies	Solvent	17	1	18
	Insolvent	6	22	28
Total number		23	23	46

Appendix III: Probit Prediction Model Results

R-Square	0.6264	Max-rescaled R-Square	0.8352

Testing Global Null Hypothesis: BETA=0			
Test	**Chi-Square**	**DF**	**Pr > ChiSq**
Likelihood Ratio	64.9763	4	<.0001
Score	40.8480	4	<.0001
Wald	16.6675	4	0.0022

Analysis of Maximum Likelihood Estimates					
Parameter	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	1	-0.4884	0.3607	1.8327	0.1758
EBITTL	1	-3.9123	1.0173	14.7909	0.0001
TLTA	1	0.4518	0.1913	5.5763	0.0182
CFFOTA	1	-31.3039	8.7092	12.9194	0.0003
CFFOCL	1	4.5717	1.2904	12.5510	0.0004



Classification Matrix				
		Observed Frequencies		**Total number**
		Solvent	Insolvent	
Predicted Frequencies	Solvent	17	1	18
	Insolvent	6	22	28
Total number		23	23	46

Appendix IV: Significance of Financial Ratios Across Insolvency Studies

			Profitability					Leverage						Liquidity			Activity						Cash Flow						Market	
Details of Studies	Data Location	Method	EBITSEQ: Return On Equity	EBITCE: Return On Capital Employed	EBITS: EBIT Margin	EBITTL: Earing To Total Liabilities	GPM: Gross Profit Margin	RETA: Retained Earnings To Total Assets	SETA: Equity To Total Assets	SETL: Equity To Total Liabilities	TLTA: Total Liabilities To Total Assets	TLNW: Total Liabilities To Net Worth	SETD: Equity To Debt	CR: Current Ratio	QR: Quick Ratio	WCTA: Working Capital To Total Assets	IT: Inventory Turnover	TDS: Debt Ratio	AT: Total Asset Turnover	SCA: Sales To Current Assets	SFA: Fixed Asset Turnover	SWC: Working Capital Turnover	CFFOTA: Cash Flow On Assets	CFFOS: Cash flow on Sales	CFFOCL: Cash Flow on Current Liabilities	CFFOTL: Cash Flow on Total Liabilities	CFFONW: Cash Flow on Net Worth	TDCFFO: Total Debt To Cash Flow Ratio	MVOETD: Market Value To Debt	MVOESE: Market Value To Equity
Current Study	**GCC**	**Logit**				**X**					**X**												**X**		**X**					
Basheikh (2012)	Saudi Arabia	Univariate, MDA, Logit	X																X											
Ong et al. (2005)	Malaysia	Logistic												X					X	X										
Ravisankar et al. (2010)	International: Dot-Com Firms	Neural Networks						X															X	X						
Sori and Hasbullah (2009)	Singapore	Discriminant Analysis																						X						
Bose (2006)	International: Dot-Com Firms	Rough Sets						X															X							
Andreev	Spain	Neural			X											X														

(2006)		Networks																												
Charitou et al. (2004)	United Kingdom	Neural Networks, Logit				X					X														X					
Jones and Hensher (2004)	Australia	Logit, Multinomial Logit														X														
Shumway (2001)	United States	Hazard									X			X																
Sung et al. (1999)	Korea	MDA																					X			X				
Serrano-Cinca (1996)	International (Moody's Manual)	Neural Networks, Discriminant Analysis						X								X														
Back et al. (1996)	Finland	LDA, Logit, Genetic Algorithms												X	X															
Aldeehani (1995)	Kuwait	MDA																	X										X	
Ward (1994)	United States	Logit																				X								
Keasey and McGuinness (1990)	United Kingdom	Logit			X																									
Gilbert et al. (1990)	United States	Logit						X				X													X	X				
Gloubos and Grammatikos (1988)	Greece	Logit, Probit, LPM, MDA		X		X					X			X		X														
Ta and Seah (1988)	Singapore	MDA	X				X			X																				
Peel et al. (1986)	United Kingdom	Logit														X		X								X				

Zavgren (1985)	United States	Logit									X				X															
Zmijewski (1984)	United States	Probit									X																			
Ko (1982)	Japan	MDA			X																								X	
Altman and Lavallee (1981)	Canada	MDA									X			X					X											
Ohlson (1980)	United States	Logit									X					X														
Taffler (1982)	United Kingdom	MDA															X													
Deakin (1972)	United States	Univarite, MDA						X						X	X	X														
Altman (1968)	United States	MDA						X								X			X										X	
Beaver (1966)	United States	Univariate														X														
Total Number of Occurrences of Ratios			2	1	3	3	1	6	0	1	8	1	0	6	3	9	1	1	5	1	0	1	4	2	2	4	0	0	3	0