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Investigating Corporate Insolvency in the Gulf Cooperation Council: multiple-perspective studies

by

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ABSTRACT

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INVESTIGATING CORPORATE INSOLVENCY IN THE GULF COOPERATION COUNCIL: MULTIPLE PERSPECTIVE STUDIES

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This thesis focuses on the causes of corporate insolvency, and understanding the characteristics of insolvency risk in the Gulf Cooperation Council (GCC). Multiple studies are employed to address some of the gaps which have been identified in the literature. The first study analyses corporate insolvency in the GCC region between 2004 and 2011 using multiple methodologies: a Logit model, supplemented by a Probit model and a 3-way MDS model, which enables the visualisation of key differences between insolvent and solvent firms, supplemented by Hierarchical Cluster Analysis. The Logit regression with best-subset selection criteria suggests that profitability and leverage ratios, as well as cash flow-based ratios, can predict insolvency in GCC literature. MDS results indicate that insolvent firms attach most salience to the 'Non-strategic sales activities', unlike solvent firms which attach more salience to the other dimensions: 'Profitability and financial stability balance', 'Sales activities against capital conversion', and 'Market value against cash generation'. Hence, the results suggest that firms' managers should focus less on non-strategic sales activities to reduce susceptibility to insolvency. Taking a multilevel perspective, the second study attempts to contextualise the nature of corporate insolvency in the GCC, using samples of firms from the UK and the USA as comparators. MDS and cluster analysis reveal four dimensions of ratios across the samples: 'effectiveness of sales and cash-generating activities ', 'trade-off between debt management and cash generation/profitability', 'usage

of debt versus usage of own assets', and 'trade-off between profitability and cash-generating activities'. Unlike solvent firms, insolvent GCC firms appear very specific in the third dimension, 'usage of debt versus usage of own assets’, which did not appear as associated with macroeconomic variables. The third study is to examine the dynamic causal relationships among macroeconomic indicators of the corporate failure rate in the GCC region by using the Autoregressive Distributed Lag model (ARDL) bound test, which use quarterly dataset. These results provide evidence that oil prices in the GCC region combined with other macroeconomic indicators have an impact on the failure rate in the long-run equilibrium. In terms of the short-run, the ARDL model confirmed that the corporate failure rate is mainly determined by the previous period’s failure rate.

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DECLARATION OF AUTHORSHIP

I, Layla Khoja, declare that the thesis entitled *Investigating Corporate Insolvency in the Gulf Cooperation Council: multiple-perspective studies* and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research. I confirm that:

- this work was done wholly or mainly while in candidature for a research degree at this University;
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This thesis is dedicated,

To my Mother, with my love

To the soul and memories of my Father

Abbreviations

Chapter 1

GCC	Gulf Cooperation Council
MDA	Discriminant Analysis
UAE	United Arab Emirate
EU	European Union
NAFTA	North American Free Trade Agreement
MENA	Middle East and North Africa

Chapter 2

MDS	Multidimensional Scaling
EBITSEQ	Return On Equity
EBITCE	Return On Capital Employed
EBITS	EBIT Margin
EBITTL	Earning 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

PCA	Principal components analysis
ANOVA	Analysis Of Variance
AUC	The Area Under The Curve
ROC curve	Receiver Operating Characteristic (ROC) curve
HCA	Hierarchical Cluster Analysis
PCA	Principal Components Analysis
4D	Four-dimensional
2D	Two-dimensional

Chapter 3

UK	United Kingdom
USA	United States of America
MDM	Macro-industry Model
MLM	Multilevel Modelling
CATPCA	Categorical Principal Components Analysis

Chapter 4

ARDL	Autoregressive Distributed Lag model
ECM	Error Correction Model
S&P	Standard & Poor's 500 index
OLS	Ordinary Least Squares
AIC	Akaike Information Criteria
FR	Failure rate
KPSS	KPSS tests
INDEX	Stock Market Exchange Index
INFR	Inflation Rate
INR	Interest Rate
OILPR	Oil Prices
Δ	First Difference
In (FR)	Natural Log of Corporate Failure Rate
In (INDEX)	Natural Log of Stock Market Exchange Rate
In (INFR)	Natural Log of Inflation Rate
In (INR)	Natural Log of Interest Rate
In (OILPR)	Natural Log of Oil Prices

Chapter 1

Introduction

1.1 Overview

Insolvency is an issue that has a negative impact on the robustness and growth of every country's economy. Bernanke (1981) asserted that insolvency '*imposes net social costs, so that all agents have an interest in avoiding it'* (Bernanke, 1981, page.1). Corporate insolvency also has high economic financial cost (Lensberg, Eilifsen and Mckee, 2006; Altman, 2006; Gruber and Warner, 1977; Brigham and Ehrhardt, 2009). It can affect investors and owners, creditors and employees (Morris, 1997; Moyer, Mcguigan and Kretlow, 2008; Deakin, 1972; White, 1996), and the costs are even more widespread: most of its stakeholders suffer.

Thus, understanding the causes of corporate insolvency is an important research area. Academics and economists are encouraged to predict corporate failures by acquiring a better understanding of the causes and symptoms of corporate failures (Mckee and Lensberg, 2002). More effective prediction can help managers to understand how to prevent insolvency, or even help them improve corporate performance. Corporate failure can occur as a result of what happens within the firm, outside the firm, or combinations of both. In a business cycle the causes of insolvency vary. Timmons and Spinelli (1994) stated that the causes of corporate insolvency differ from industry to industry and from one company to another. Managerial incompetence is an example of a within-firm or micro factor. Charan, Useem and Harrington (2002) argued that firms fail because they are poorly managed. Altman (1983) stated that the overwhelming cause of firm failure is some type of managerial incompetence. Failing, poorly managed firms can thus continue to operate without market censure until it is too late. Economic downturn is an example of a macro-level factor. Goudie and Meeks (1991) examined the extent to which macro-economic factors can be held responsible for the failure of large companies in turbulent exchange regimes. They concluded that factors that are beyond the control of the management, such as external macro-economic factors, often play a substantial role in failure and gave results that offered a corrective to the widespread notion that the prime cause of failure is bad management. It is clear that environmental factors can instigate failure. Between the micro- and macro-levels, an industry-wide factor, such as government regulation targeting a specific product such as tobacco, can be considered as an example of a meso-level factor.

In insolvency literature, industry-wide factors, economic cycles and countries' legislation, together with microeconomic factors, have been introduced to measure the response of firms' financial strength. It seems reasonable to suggest that, to better understand corporate failure, we should study the effects of micro-, meso- and macro-level factors simultaneously; i.e. adopt a multilevel perspective (Kozlowski and Klein, 2000).

1.2 Microeconomic factors

Insolvency research mainly focuses on the impact of within-firm factors, and so can be categorised as micro-level. Financial ratios have played a significant role in evaluating the financial situation of a firm's performance. The earlier financial failure studies approved many ratios that were significant in predicting failure (Chen and Shimerda, 1981). Profitability, liquidity and solvency categories have been selected as the most significant groups in previous studies (Altman, Haldeman and Narayanan, 1977; Ohlson, 1980; Taffler, 1982). Nevertheless, there has been no agreement about the most significant financial ratios in the insolvency literature (Barnes, 1987; Chen and Shimerda, 1981).

Cash flow ratios information has been a controversial issue in insolvency studies. Blum (1974), Smith and Liou (1979), Lee (1982), Mensah (1984), Aziz, Emanuel and Lawson (1988), Aziz and Lawson (1989) and Gilbert et al. (1990) examined the usefulness of cash flow information in distinguishing between the failed and non-failed firms. They concluded that cash flow ratios add a remarkable explanatory power to the financial failure prediction models. On the other hand, some studies reported that the ability of the cash flow information to improve financial failure prediction models is limited (Casey and Bartczak, 1985). To date, there is no evidence that cash flow information has been included in the Gulf Cooperation Council (GCC) research.

By employing the usefulness of the financial ratios, researchers have developed several techniques and methodologies in the predicating of corporate insolvency studies. The first attempt was by Beaver (1966), who applied the univariate model by using a single predictor. Altman (1968) proved the insufficiency of Beaver's model and proposed the Multiple Discriminant Analysis (MDA) technique, by using multiple predictors instead. Despite the popularity of the MDA model, and its subsequent application by many researchers (Deakin, 1972; Edmister, 1972; Blum, 1974; Libby, 1975; Wilcox, 1973), the MDA has been criticised for a number of assumptions that it makes (Edmister, 1972; Zavgren, 1983; Karels and Prakash, 1987). Ohlson (1980) introduced logistic regression to avoid some of the shortcomings of MDA. Logistic regression 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). Since then, researchers have progressed several other methodologies, such as decision trees (Friedman, 1977), neural networks (Coats and Fant, 1993; Salchenberger, Cinar and Lash, 1992), genetic algorithms (Shin and Lee, 2002; Varetto, 1998), and survival analysis (Luoma and Laitinen, 1991; Lane, Looney and Wansley, 1986). To date, corporate insolvency studies in the GCC region have been dominated by a limited number of techniques, including the Multiple Discriminant Analysis (MDA) technique, which has been applied by (Alshebani, 2006; Aldeehani, 1995) and logistic regression application, used by Basheikh (2012). We can thus argue that a very limited number of techniques have dominated GCC insolvency research.

1.3 Macroeconomic factors

Corporate insolvency has been studied widely and successfully in microeconomic research through the use of financial ratios (Charan, Useem and Harrington, 2002). However, economists have proved that company failure corresponds also to macroeconomic factors (Bhattacharjee *et al.*, 2002; Liu, 2004). By using macroeconomic indicators, previous empirical studies show that company failure rate corresponded to macroeconomic developments in different contexts (Bhattacharjee *et al.*, 2004; Bhattacharjee *et al.*, 2009). Goudie and Meeks (1991) indicated that the widespread notion that the main cause of failure is not only bad management, but that macroeconomic factors also play an important role in larger firm failures.

Some of the macroeconomic indicators contribute successfully to determine corporate failure rate. The interest rate has proven to be the most significant indicator associated with corporate insolvency (Liu and Wilson, 2002; Liu, 2004; Ilmakunnas and Topi, 1999; Bhattacharjee *et al.*, 2009; Geroski and Machin, 1993; Sharma, 2001). Liu (2004) claimed that an increasing interest rate may lead to an upsurge in the number of corporate failures as it contributed to the higher cost of borrowing, thereby putting the company under financial pressure. Consequently, this increases the possibility of company bankruptcy indirectly affecting the company's profitability (Wadhwani, 1986; Liu, 2004; Halim *et al.*, 2009). As well as the inflation rate, the ability of consumers to buy goods or services is declining and may have a negative impact on the company's revenue as well as the total turnover (Halim, 2005). In order to reflect the stock market performance, the change in the Standard & Poor's Index of stock prices (S&P) has been examined for the listed companies (Altman, 1983; Fich and Slezak, 2008). Goudie and Meeks (1991) investigated how the exchange rate variation had an impact on the financial failure rate of UK companies in international markets. At the time of this study, macroeconomic factors on GCC failure rate have not been researched. However, it is necessary to examine the external environmental elements and factors in order to assess to what degree they affect insolvencies and capture the sensitivity of macroeconomic development (Shani, 1991; Guamundsson, 1995; Rose, Andrews and Giroux, 1982).

1.4 Industry sector impact

It is well known that portfolio distribution among various industrial sectors can help reduce the risk of industrial insolvency (Fabozzi, Gupta and Markowitz, 2002). Insolvency literature across the industry sector shows this as a significant factor (Lennox, 1999; Caves, 1998). The majority of the insolvency studies use this as one of the criteria to match between failed and non-failed firms (Altman and Narayanan, 1997; Aziz and Dar, 2006; Kumar and Ravi, 2007). However, few studies take into account the industry-level effects as a standardising ratio that uses either the industry mean (Fernandez (1988) or industry median (Platt and Platt, 1991; Altman and Izan, 1984).

The majority of studies do not explicitly model the effect of the industry sector. The evidence on how specific industry characteristics may impact insolvency is relatively sparse, although there are some exceptions to this general pattern. The 1972 study of Gupta and Huefner examined cluster patterns in financial ratios across different industry sectors. One of the most interesting studies in this area is that of Ward (1994), who specifically tested the hypothesis that the usefulness of cash flow-based information in predicting insolvency is industry-specific. Bhattacharjee *et al* (2003; 2004; 2009) came up with empirical evidence of the relationship between macroeconomic indicators, the firm size and the industry-specific factors with corporate failure rate. On the other hand, Hossari (2009) reported that the effect of industry-sector differences on corporate insolvency may be insignificant.

1.5 Impact of insolvency law

Legislation on bankruptcy codes is another factor that can impact on insolvency. Variances in insolvency rates have been observed before and after legislation within and across countries. Liu and Wilson (2002) and Liu (2004) introduced the impact of the United Kingdom's 1986 Insolvency Act on corporate failure rate examined in association with the macroeconomic determinants. Bhattacharjee (2004) also concluded that the UK bankruptcy code is less significant on bankruptcy hazard in an environment of macroeconomic instability. Compared with the reorganisation system discussed in US in form of Chapter 11, this system acts as a safe haven for insolvent firms during stable macroeconomic conditions, while permitting these firms to recover, or maybe to get acquired, in macroeconomic instability to reduce the hazard of bankruptcy. Swanson and Tybout (1988) provided evidence of the influence of applying the exchange rate regime in Argentina in 1978 to corporate failure rate.

Today, the impact of the insolvency regime in the GCC is difficult to address because the GCC governments have pondered on adequate measures and reform for the insolvency to be effective, quick and simple (Raghu, Pattherwala and Tulsyan, 2013) after the recent global financial crisis uncovered the lack of effective bankruptcy regimes (Uttamchandani, 2011), which contributed to the firms' bankruptcy in the region. In Kuwait, the Ministry of Commerce and

Industry presented a new Companies Law No. 25 of 2012, which is an essential development from the previous one issued in 1960 (Raghu, Pattherwala and Tulsyan, 2013). Dubai adopted a new concept, the "Reorganization code", into the law (Gine and Love, 2009) influenced by Chapter 11 in the US Insolvency Act. Recently, Saudi Arabia proceeded to issue a new bankruptcy law draft to supersede the 1930 law (improved upon in 1996) (Raghu, Pattherwala and Tulsyan, 2013).

1.6 Gulf Cooperation Council (GCC)

The Gulf Cooperation Council (GCC) was established in 1981 to support the economic integration of six countries: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the United Arab Emirate (UAE). 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 countries have homogeneity, for example between their economics, cultural structures and their financial infrastructures. In addition, GCC economies remain highly dependent on oil, and their economies are less diversified, especially Kuwait's economy, which shows 53% of the GDP based on the Petroleum production (Fasano and Iqbal, 2003; House *et al.*, 2004). Table 1.1 highlights the key characteristics of each of the GCC countries' economy. These countries also share common exposure to the oil market (Arouri, Lahiani and Nguyen, 2011; Maghyereh and Awartani, 2014). Saudi Arabia has shown the highest GDP, followed by U.A.E, contributing 46% and 24% respectively to the total GCC GDP. The countries with the highest growth rates in the region are Kuwait, at 6.1%, and Saudi Arabia, at 5.8%. The stock exchange markets of the GCC region are important to the Middle East and North Africa (MENA). They constitute half of MENA's listed companies and three-quarters of its market capitalisation (Rocha and Farazi, 2011). Beyond MENA, GCC economies contribute significantly to the global economy by investing their oil incomes abroad (Peeters, 2011). However, GCC countries did not begin to regulate their stock markets until the 1980s (Al-Ajmi and Kim, 2012). The GCC stock markets are less mature and, despite recent liberalisation measures, continue to be less liberal and inefficient in the weaker states (Al-Ajmi and Kim, 2012; Arouri, Lahiani and Nguyen, 2011).

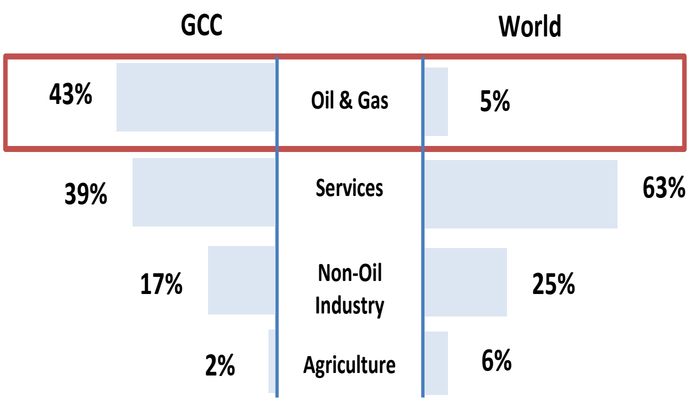
Table 1.1: Main characteristics of the GCC economies in 2012

	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	U.A.E.
GDP (Billion $)	30,36	183,21	78,28	189,94	733,95	383,79
GDP share in the GCC GDP (%)	2%	11%	5%	12%	46%	24%
GDP annual growth (%)	3.39	6.1	4.98	2.55	5.81	4.36
Petroleum production to GDP (%)	19.39	53.79	37.24	12.06	46.5	21.89
Inflation rate	2.75	2.91	2.91	1.86	2.88	0.66
Lending inters rate (%)	6.03	4.9	5.7	5.38	3.91	3.25
Population (Mill)	1,317	3,250	3,314	2,050	28,287	9,205
Market capitalization of the listed companies in stock market (Billion $)	16,06	97,09	20,10	126,37	373,37	67,95
Market capitalization of the listed companies in stock market to GDP (%)	52.91	53	25.68	66.53	50.87	17.70
Number of listed companies	43	189	124	42	158	102

Source: World Bank data 2012, IMF staff estimates data 2012

This thesis was conducted in the GCC for many reasons. *Firstly,* although GCC countries were able to limit the negative effects of the 2008 financial crisis by employing financial-sector support and counter-cyclical measures by using the reserves they had accumulated during the oil price boom period of 2003-2008 (Khamis and Senhadji, 2010), the crisis revealed the region's many financial vulnerabilities including, in particular, firm insolvency (Uttamchandani *et al.*, 2009). The drop in oil prices in late 2009 was another shock. It resulted in the 'Dubai debt crisis', further weakening the 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, Ding and Pyun, 2007; Al-Ajmi and Kim, 2012; Bley, 2011). This increases the economic, financial and social costs (Lensberg, Eilifsen and Mckee, 2006; Altman, 2006; Gruber and Warner, 1977; Brigham and Ehrhardt, 2009) and affects investors and owners, creditors, employees and other stakeholders (Morris, 1997; Moyer, Mcguigan and Kretlow, 2008; Deakin, 1972; White, 1996). Hence, there is a need for research that can cast light on the susceptibility of GCC firms to insolvency. Such insight could aid investment decisions, as well as offer strategic guidance to managers.

Secondly, this region plays a leading role in the world as the largest producer and exporter of oil and they possess approximately 50% of the world's reserves (Mohanty *et al.*, 2011). According to the Qatar National Bank (QNB) Report (2012), the GCC economies are dominated by the oil and gas sector. As shown in Figure 1.1, in 2010 the oil and gas sector represented only 5% of global GDP, but accounted for 43% in the GCC region. Hence, the GCC is becoming increasingly important in the world economy as a result of it holding 36% of the oil and 22% of the gas global reserves. However, it should be noted that GCC countries have integrated into the global economy through trade and by importing machinery and industrial products, mainly from Europe and the United States of America (USA), with total trade exceeding 393 billion US dollar in 2013, approximately 45% of the total number of imports worldwide (Economist Intelligence Unit, 2014).



Source: Qatar National Bank (QNB) report 2012

Figure 1.1: Economic sectors to World and GCC GDP

The Business environments in GCC countries are varied in terms of their outward orientation. Qatar and UAE are the most outwardly oriented countries in the region, while, in comparison, Saudi Arabia is considered to be a more conservative economy and less external-facing, due to its large domestic market and more restricted foreign investment. However, rapidly increasing liberalization of the restrictions on foreign capital inflow, and favourable Saudi market dynamics, indicates that there will be an increase in the growth of direct foreign investment by 2018 (Economist Intelligence Unit, 2014; Ugo and Iqbal, 2003). However, overseas firms face a limitation in the GCC exchange stock markets in terms of foreign ownership. But, recently in order to encourage foreign investment in the stock markets, GCC countries have been planning to increase the proportion of ownership by foreign equity firms in the GCC stock market. Qatar's has already increased the foreign ownership level up to 49%, while Saudi Arabia is on track to raise its overseas shareholdings in 2015 (Economist Intelligence Unit, 2014). Thus, this region is considered to be a promising business environment for foreign firms, especially with the GCC governments' efforts to develop the liberalization of foreign investment laws and to increase foreign ownership in the GCC stock market. Therefore, the foreign companies' investment in the GCC market may experience different business environments as well as variance of the commercial risks.

Thirdly, because of the unique characteristics of the GCC countries and the development of foreign investment laws, insolvency research evidence from other regions may be misleading when applied directly to GCC firms: GCC context-specific research was therefore required, to identify the commonalities and differences regarding insolvency between the GCC and other regions.

Fourthly, insolvency research focused on the GCC is relatively new, only dating back to the 1990s, whereas studies elsewhere began in the 1960s. Of the few studies of the GCC, most have relied on Altman's (1968) Discriminant Analysis (MDA) technique, despite its restrictive assumptions. One exception is Basheikh (2012), who applied logistic regression. Similarly, although a range of financial ratios have been used to study insolvency in the GCC (e.g. profitability, liquidity, leverage and activity ratios), the importance of cash flow-based ratios is yet to be examined, although research elsewhere suggests that cash flow information is useful for predicting financial distress. Thus, there are three areas of weakness in GCC insolvency research: the volume of research is small; the scope of the methodologies applied is narrow; and, unlike other contexts, the predictive value of operating cash flow has yet to be examined.

1.7 Structure of the thesis

The main focus of this thesis is to illuminate the characteristics of insolvency risk, by identifying the main factors associated with applying multiple methodologies in the GCC region. This thesis follows a three-paper approach. Table 1.2 illustrates the three research papers that have been developed from this thesis.

Table 1.2: List of research papers used in this thesis

Research paper	Publication
Research paper 1	"Analysing Corporate Insolvency in the Gulf Cooperation Council using Logistic Regression and Multidimensional Scaling" (Khoja, Chipulu and Jayasekera, 2014)
Research paper 2	"Compare and contrast: Contextualizing corporate insolvency in the GCC using the UK and the USA as comparators" (Khoja, Chipulu and Jayasekera, 2015)
Research paper 3	"The Impact of Macroeconomic Indicators on Failure rate in the Gulf Cooperation Council" (Khoja, Jayasekera and Chipulu, 2015)

Chapter 2, entitled "Analysing Corporate Insolvency in the Gulf Cooperation Council using Logistic Regression and Multidimensional Scaling", examines corporate insolvency in the GCC by introducing Multidimensional Scaling (MDS), in order to visualise the key differences between insolvent and solvent firms, as well as using logistic regression.

Chapter 3, entitled "Compare and contrast: Contextualising corporate insolvency in the GCC using the UK and the US as comparators", identifies the financial characteristics of solvent and insolvent GCC firms by applying multilevel analysis and using the UK and USA as comparators.

Chapter 4, entitled "The Impact of Macroeconomic Indicators on Failure rate in the Gulf Cooperation Council", examines the dynamic causal relationships among macroeconomic indicators on the corporate failure rate in the GCC region.

Chapter 5, entitled “Conclusions”, concludes the contributions of each research paper as well as the implication of these works. This chapter also presents the limitations of this work and recommends directions for future research.

Chapter 2

Study 1: Analysing Corporate Insolvency in the Gulf Cooperation Council using Logistic Regression and Multidimensional Scaling

Abstract

In this study, we examine corporate insolvency in the Gulf Cooperation Council (GCC) region between 2004 and 2011. The data comprises 28 financial ratio variables from 112 firms. We use Logit regression with best-subset selection criteria to investigate the predictive value of the ratios in the GCC context, particularly cash flow-based ratios. We also examine the main dimensions of the ratios, and the weights that firms attach to them, using 3-way Multidimensional Scaling (MDS). We find that a parsimonious Logit model with the profitability ratio *EBITTL*, the leverage ratio *TLTA* and the cash flow ratios *CFFOTA* and *CFFOCL* can predict insolvency, *ex-ante*, with 84.8%, 95.6% and 73.9% overall, type I and II accuracy, respectively. From MDS, we uncover four financial-ratio dimensions: (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. Therefore, the results imply that, to reduce susceptibility to insolvency in the GCC, managers should focus less on non-strategic sales activities.

2.1 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 its market capitalisation (Rocha and Farazi, 2011). Beyond MENA, GCC economies contribute significantly to the global economy by investing their oil incomes abroad (Peeters, 2011). However, GCC countries did not begin to regulate their stock markets until the 1980s (Al-Ajmi and Kim, 2012). Although GCC countries were able to limit the negative effects of the 2008 financial crisis by employing financial-sector support and counter-cyclical measures using the reserves they had accumulated during the oil price boom period of 2003-2008 (Khamis and Senhadji, 2010), the crisis revealed the region's many financial vulnerabilities including, in particular, firm insolvency (Uttamchandani *et al.*, 2009). Insolvency is an international problem with high economic, financial and social costs (Lensberg, Eilifsen and Mckee, 2006; Altman, 2006; Gruber and Warner, 1977; Brigham and Ehrhardt, 2009). It can affect investors and owners, creditors, employees and other stakeholders (Morris, 1997; Moyer, Mcguigan and Kretlow, 2008; Deakin, 1972; White, 1996). Hence, there is a need for research that can cast light on the susceptibility of GCC firms to insolvency. Such insight could aid investment decisions as well as offer strategic guidance to 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 Iqbal, 2003). GCC stock markets are less mature and, despite recent liberalisation measures, continue to be less liberal and inefficient in the weaker states (Al-Ajmi and Kim, 2012; Arouri, Lahiani and Nguyen, 2011). The GCC financial and regulatory frameworks are less harmonised (Hussain *et al.*, 2002), and the GCC is also culturally distant from the other major trading blocs(House *et al.*, 2004). Insolvency research evidence from other regions may thus be misleading when applied directly to GCC firms: GCC context-specific research is required to identify the commonalities and differences in insolvency between the GCC and other regions.

Insolvency research in the GCC is relatively new as it dates back only to the 1990s, whereas elsewhere studies began in the 1960s. Of the few studies of the GCC, most have relied on Altman's (1968) Discriminant Analysis (MDA) technique, despite its restrictive assumptions. One exception is Basheikh (2012), who applied logistic regression. Similarly, although a range of financial ratios have been used to study insolvency in the GCC (e.g. profitability, liquidity, leverage and activity ratios), the importance of cash flow-based ratios is yet to be examined, although research elsewhere suggests that cash flow information is useful for predicting financial distress. Thus there are three areas of weakness in GCC insolvency research: the volume of research is small; the scope of the methodologies applied is narrow; and, unlike other contexts, the predictive value of operating cash flow has yet to be examined. Focusing on firms listed in the 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, thus increasing the depth of insight acquired (Neophytou and Mar-Molinero, 2004). We also examine the predictive capacity of operating cash flow information in the GCC context.

The structure of the rest of this chapter is as follows. In section two, we review the literature on financial failure in the GCC context, the literature on financial failure prediction techniques, and then 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.

2.2 Literature review and research questions

To predict insolvency, it is necessary to understand its causes. Charan, Useem and Harrington (2002) argued that firms fail because they are poorly managed. Altman (1983) stated that the overwhelming cause of firm failure is some type of managerial incompetence. Goudie and Meeks (1991) examined the extent to which macro-economic factors can be held responsible for the failure of large companies in turbulent exchange regimes. They concluded that factors that are beyond the control of the management, such as external macro-economic factors, often play a substantial role in failure, and their study gave results that offered a corrective to the widespread 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, Ding and Pyun, 2007; Al-Ajmi and Kim, 2012; Bley, 2011). Failing, poorly managed firms can thus continue to operate without market censure until it is too late.

When Environments are equal, however, weaker, less well-managed firms will exhibit poorer health. Financial ratios are important here: both the level (Chen and Shimerda, 1981) and trend over time (Neophytou and Mar-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 (Barnes, 1987; Chen and Shimerda, 1981). 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 to be significant.

Of the different types of ratio, 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 predictive importance of the cash flow information derives from the power of cash to enable a firm to meet its obligations and continue to operate (Gilbert, Menon and Schwartz, 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 (Aziz and Lawson, 1989; Blum, 1974; Charitou, Neophytou and Charalambous, 2004; Gilbert, Menon and Schwartz, 1990; Mensah, 1984; Smith and Liou, 1979; Aziz, Emanuel and Lawson, 1988) 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 (1983a), in one of the earliest studies to incorporate incremental operating cash flow, suggested that operating cash flow provides more information than exists in most other ratios. Similarly, Gentry, Newbold and Whitford (1987) found that cash flow based ratios can improve the scope and accuracy of prediction models, and Gilbert, Menon and Schwartz (1990) suggested that cash flow information can provide a more reliable means for assessing 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 about the importance of ratios, but also they have 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?

Over the last 50 years, researchers have developed a number of techniques for predicting insolvency by using financial ratios. The first was Beaver's (1966) single predictor, univariate model. Altman (1968) demonstrated the insufficiency of Beaver's single predictor model. He proposed instead the multiple-predictor, Multiple Discriminant Analysis (MDA) technique. Regarded as seminal, Altman's (1968) MDA technique has been widely applied and enhanced by a number of researchers (Deakin, 1972; Edmister, 1972; Blum, 1974; Libby, 1975; Wilcox, 1973). 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. Research shows that both assumptions are often violated (Ezzamel, Mar Molinero and Beech, 1987; Laitinen and Kankaanpaa, 1999; Richardson and Davidson, 1983). 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 (Joy and Tollefson, 1975; Ohlson, 1980; Edmister, 1972; Balcaen and Ooghe, 2006). To avoid some of the limitations of MDA, Ohlson (1980) introduced logistic regression, which 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 other methodological developments besides logistic regression, including decision trees (Friedman, 1977), neural networks (Coats and Fant, 1993; Salchenberger, Cinar and Lash, 1992), genetic algorithms (Shin and Lee, 2002; Varetto, 1998) and survival analysis (Luoma and Laitinen, 1991; Lane, Looney and Wansley, 1986). Even so, Altman's (1968) model has dominated GCC insolvency research (Alshebani, 2006; Aldeehani, 1995). Some studies have applied Altman's model in its original form (Alshebani, 2006; Aldeehani, 1995), others with minor modifications in terms of predictors (Basheikh, 2012; Abudelrahman, 2004). The exception is Basheikh's (2012) logistic regression application. We can argue thus that a very limited number of techniques have dominated GCC insolvency research.

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, Reynolds and Young, 1981). Although traditionally a social sciences approach, MDS has been applied in accounting, finance and banking as an alternative to the more traditional statistical techniques when the data does not satisfy parametric assumptions (Emery, Barron and Messier, 1982; Moriarity and Barron, 1976). 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 Mar-Molinero, 2004). It is this visualisation capability that makes MDS particularly useful when studying insolvency. It can provide insight into the levels 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?

2.3 Methodology

2.3.1 Sampling and data collection

We gathered data on solvent and insolvent firms from DataStream™, and the financial statements and websites of the firms. Categorising firm failure is crucial in all insolvency studies. Altman and Narayanan (1997, p.2) suggested that the definition of failure in the literature depends *'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 (Ministry of Industry and Commerce Kingdom of Bahrain, 2002; Saudi Commerce Ministry, 1966; Qatar - Ministry of Economy and Commerce, 2002; Sultanate of Oman Ministry of Commerce and Industry, 1986; United Arab Emirate Ministry of Economy, 1984). The exception is the Kuwaiti system, where, under the law, to continue trading, a company must increases its capital accordingly if accumulated losses reach 25% of capital (Kuwait. 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. We matched the 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 generated between 2004 and 2011, we found 56 matching pairs or 112 firms. We present the sampled firms, which are detailed in Appendix A. For each insolvent firm (and matching solvent firm), we collected the financial data for the year prior to failure. Table 2.1 shows a breakdown of the sampled firms by sector and by country. Our sample covers eight sectors. As in previous studies (Gilbert, Menon and Schwartz, 1990), we excluded banks, financial investment, insurance and real-estate firms from the sample because of the unique nature of the financial reports in these sectors. There were a limited number of companies in the same country in some sectors, so we matched firms by sector regardless of home country. It should be noted that the GCC countries are considered to be an oil-based region. However, Table 2.1 shows three of Kuwait's firms from the Petrochemical Industries sector to be categorized as insolvent. (Senhadji *et al.*, 2010) and Beidas-Strom *et al.* (2011) reported that Kuwait was the GCC country most affected by the lower oil prices during the financial crisis, because it is the most dependant on the income from oil to support its other sectors.

Table 2.1: Sample of insolvent 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**

Consequently, Table 2.1 reflects the decline in the oil prices during the crisis, by showing Kuwait to have the highest number of insolvent firms in the sample. Moreover, unlike other GCC countries, the Table reveals three firms from the Petrochemical Industries to be insolvent. These three have been identified as becoming insolvent during the financial crisis period.

We selected 28 financial ratios according to Beaver's (1966) selection criterion, i.e. the ratios most commonly and successfully used in prior studies (Altman, 1968; Beaver, 1966; Dambolena and Khoury, 1980; Deakin, 1972; Elam, 1975; Gombola and Ketz, 1983a; Mensah, 1983). The financial ratios, shown in Table 2.2, cover six major categories: profitability, leverage, liquidity, activity, operating cash flow and markets. As discussed earlier, we included cash flow ratios in order to examine, for the first time, their predictive significance in the GCC context. We did not include the ratio EBITTA (Earnings to total assets) because the calculation of this ratio closely resembles the rule used to classify firms as solvent or insolvent.

2.3.2Data Analysis

2.3.2.1 Logistic Regression

A logistic regression model is one of the most popular and efficient methods used for binary classification and prediction in many fields, such as the social sciences and business, economic and finance research. It is a multiple regression to analyse the relationship between the categorical or dichotomous variable, as outcome and predictor or explanatory variables (Field, 2009) . Hosmer and Lemeshow (2004, p.1) stated that *"the main difference between the logistic regression and the linear regression is reflected both in the choice of parametric model and in the assumptions. Once this difference is accounted for, the methods employed in an analysis using logistic regression follow the same general principles used in linear regression".*

We used Logistic (or Logit) regression to address *RQ1.* This is because it satisfies a number of important criteria. Firstly, it does not have restrictive distributional assumptions. This is important because, beyond predictive capacity, we are interested in the statistical significance of ratios: violating distributional assumptions can cause p-values to be incorrect. Tests showed that all 28 financial ratio variables are non-normal, with the p-value of the *Shapiro-Wilks* statistic less than 0.001 in all cases. The p-values of the *Mardia Skewness, Mardia Kurtosis and Henze-Zirkler* statistics were also 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

Table 2.2: 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 - Earning 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

Table 2.2: Continued

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
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

Table 2.2: Continued

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
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

matrices of the insolvent and solvent firms cannot be considered equivalent. These results confirm that this financial ratio data is not suitable for MDA.

The second criterion is prediction accuracy: to be confident that the set of ratios found significant *does* contribute towards '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: Charitou, Neophytou and Charalambous (2004) ranked Logit second to neural networks (NN) and above MDA, Gloubos and Grammatikos (1988) found its overall accuracy on out-sample predictions to be 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 a test on personal credit classification performance, Zhu *et al.* (2013, p. 264) ranked LSSVM first, logistic third and SVM fourth. In the second test, they ranked logistic first, LSSVM fourth and SVM fifth.

The final criterion is interpretability: to address a lack of this in the literature, we wish to examine the significance of the effect of profitability ratios in the GCC context. 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 (Han, Han and Zhao, 2013; Doumpos, Zopounidis and Golfinopoulou, 2007; Zhu *et al.*, 2013). Classification trees are intuitive and interpretable, but there is no evidence that they are more accurate than Logit: Laitinen and Kankaanpaa (1999) found that, 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 over fitting, 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 dataset, 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 successfully applied the Logit model using a dataset of similar size. As shown in Table 2.3, with the exception of Basheikh (2012), all seven studies applied explicit selection criteria. Some (Gentry, Newbold and Whitford, 1985; Peel, Peel and Pope, 1986; Ward, 1994) chose the ratios discretionarily based on prior evidence or theory; others chose the ratios empirically, using algorithmic stopping rules (Charitou, Neophytou and Charalambous, 2004; Keasey and Mcguinness, 1990) or were based on the results of prior analysis with other statistical techniques, such as principal components analysis (PCA) (Canbas, Cabuk and Kilic, 2005).

Table 2.3: Ratio selection strategies in logistic insolvency studies

Study Details	Estimation Data (Insolvent/Solvent)	Ratio Selection Criteria
Charitou, Neophytou and Charalambous (2004)	25/25	Algorithmic: backward and forward criteria
Gentry, Newbold and Whitford (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, Peel and Pope (1986)	34/44	Predetermined based on literature
Canbas, Cabuk and Kilic (2005)	18/22	Step 1: ANOVA to select 12 ‘early warning ratios’ Step 2: PCA of selected ratios

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 say whether cash flow ratios are important in the GCC and thus address *RQ1* fully. Subsequently, we adopted the algorithmic approach, but unlike Charitou, Neophytou and

Charalambous (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.

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 as the selected subsets are unstable, particularly with small datasets. To enable the selection of the most robust subset, we conducted the selection process by borrowing some elements from Breiman's (1996) 'bagging' procedure. Firstly, as we have explained, our model should have no more than six predictors, so we investigated only subsets with six predictors. Secondly, taking random samples with replacement, we created 1000 bootstrap replicates of the training dataset, 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. Thirdly, we tested the predictive performance of the most frequent (> 1%) subsets of the 1000 using the original training dataset. We then evaluated the predictive performance of the most frequent subsets. To evaluate performance, we used the weighted value of the area under the curve (AUC) of the receiver operating characteristic curve (ROC), with each subset's frequency as the weight. Likened to the Gini coefficient (Thomas, Edelman and Crook, 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. AUC values range from 0.5 for a random classifier to one 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 the highest weighted AUC, we estimated the logistic regression model for the training dataset. To validate the logistic model, we then used the estimated parameters of the significant ratios to score the test dataset. As such, we adopted a forecast validation test or out-of-sample, *ex-ante* test since our test dataset 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 for the stationarity assumption, i.e. that relationship between ratios and failure that occurs 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.

It is well-known that, as with other models based on maximum likelihood estimators, logistic regression estimates suffer from bias. The level of bias increases as the sample size decreases (see for example Firth, 1993). In most contexts, our training dataset ($N = 66$) would be considered small. However, in the population, the proportion of insolvent firms tends to be small (e.g. Altman and Narayanan, 1997). Therefore, despite the likelihood of bias, corporate insolvency studies using logistic regression with sample sizes similar to ours are quite common (see Table 2.3). This may be because there are some mitigating arguments for applying logistic regression in this situation. Experiments show that the level of bias in the estimates is dependent on the type of independent variable and that bias is less severe for continuous variables (Nemes *et al.*, 2009). Financial ratios are continuous variables. Therefore, Nemes *et al.* (2009) imply that (i) there will be less bias in the estimated effects of financial ratios because they are continuous variables, and (ii) the effect of bias on the *relative importance* of the ratios indicated by the estimates should be insignificant because *all* financial ratios are of the same type of variable.

2.3.2.2 Three-Way Multidimensional scaling with Hierarchical Cluster Analysis

To address the second and third research questions, we employed 3-way MDS (Kruskal and Wish, 1978). Multidimensional scaling is a multivariate visualisation technique which attempts to find a solution by locating objects in a configuration or common map. (Schiffman et al. 1981; Kruskal and Wish 1978). This MDS spatial configuration may have interesting interpretations, because each dimension on the configuration has been systematically corresponded to the location of the objects' positions (financial ratios) in the space. Hence, each dimension reflects the characteristic of the item (firm) scale based on the similarity or dissimilarly between the pair of items (firms). Identifying these items' characteristics was the main point of using MDS technique (Kruskal, 1964).

MDS is also considered to be a data reduction technique (Strickert *et al.*, 2005). Cox and Cox (2000, p.1) defined MDS as "*the research for the low dimensional space, usually Euclidean, in which points in the space represent the objects, one point representing one object, and such that the distances between the points in the space match as well as possible, the original dissimilarities. The techniques used for the search for the space and the associated configuration of points form metric and nonmetric multidimensional scaling".*

Thus, we chose MDS because (i) it does not carry restrictive distributional assumptions, such as normality, equal variance-covariance structures or independence of ratios, and (ii) we could measure the relative importance that solvent and insolvent firms attach to the extracted financial ratio dimensions, thus enabling us to examine the differences between them. Using IBM SPSS 20, we conducted the 3-way MDS in four stages. Firstly, we calculated Euclidean distance-based proximities among the 28 ratios. Secondly, to decide the number of dimensions to retain in the final solution, we adopted a strategy followed by similar studies (Chipulu *et al.*, 2013; Neophytou and Mar-Molinero, 2004) of independently establishing the dimensionality of the data *a priori* to the final model. 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. Thirdly, we extracted the *individual* proximity matrices of the 28 financial ratios for solvent and insolvent firms and entered them as inputs into the 3-way MDS model using the *Prefscal* algorithm (Busing, Groenen and Heiser, 2005), specifying that the number of dimensions decided in the second stage of the analysis was to 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 that 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 with the results of an independently conducted hierarchical cluster analysis (HCA) of the ratios (Gupta and Huefner, 1972; Neophytou and Mar-Molinero, 2004). Based on the 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 was that it reveals, as much as possible, the hidden structure in the data, based on similarities among the financial ratios. This addresses *RQ2* and, had our requirements been limited to *RQ2*, we could have applied an alternative data reduction technique, such as Principal Components Analysis (PCA) instead. Recent examples of the application of PCA with financial ratios can be found in Min and Lee (2005) and Canbas, Cabuk and Kilic (2005). We chose 3-way MDS over other techniques for two reasons. Firstly, by examining the weights that solvent and insolvent firms attach to the dimensions, we were 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. Secondly, 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, Carroll and Desarbo, 1987).

2.4 Results

2.4.1 Logit Model Insolvency Prediction

The 1000 bootstrap replicates produced 497 unique sets of best-six predictors, indicating that there was uncertainty about the predictive ability of the 28 ratios. Although most sets appeared only once, eight sets appeared with more than 1% relative frequency. We show in Table 2.4 the eight sets. There are 14 different ratios in the eight sets. Set 1, containing *EBITCE, EBITTL, TLTA, CFFOTA, CFFOCL* and *TDCFFO,* was the most frequent. Set 1 appeared three times as much as the next most frequent set, and performed best on frequency-weighted AUC of the ROC curve for the training dataset. Inspection of Table 2.4 suggests that, besides set 1, *EBITCE, EBITTL, TLTA, CFFOTA, CFFOCL* and *TDCFFO* frequently appear in the other best-six sets. Each of the six ratios is present in at least four of the other seven most frequent sets. Hence, there is a common pattern across the eight sets in that, 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 that profitability, leverage and cash flow ratios will offer more predictive values than the liquidity, market, and, in particular, activity ratios.

Table 2.4: 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

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 dataset. The AUC of the ROC curve based on scoring the test dataset was 0.97.

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 2.5 shows the parameter estimates. Except for *EBITCE* and *TDCFFO,* the estimated coefficients of the ratios were 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 2.5: 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 - Earning 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

This AUC value is very close to one (= perfect classification) and substantially greater than 0.5 (= random classifier). Thus, we can conclude that these four ratios can predict insolvency of GCC firms before it occurs. We can also conclude 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, and types I and II classification levels, respectively. They closely replicate the Logit results: the estimated parameters of the four predictors are very similar, and the two models have identical classification levels for the test data.

2.4.2 MDS Dimensionality

Figure 2.1 shows the scree plot from the *Proxscal* MDS models. There is no clear ‘elbow’ to indicate optimal dimensionality. However, in MDS, this is not unusual. Experience shows that higher dimensions are increasingly harder to interpret as they tend to account for residual rather than common variance, and, typically, researcher trade-off the higher variance accounted for which comes with higher dimensionality in favour of lower dimensionality and higher interpretability (Chipulu *et al.*, 2013; Neophytou and Mar-Molinero, 2004).

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.

In Figure 2.1, the 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-fit’, yet each additional dimension after four improves the fit only marginally. Therefore, we decided to extract four dimensions as this represented the lowest dimension configuration (and so highest interpretability) that reached a ‘good’ fit.

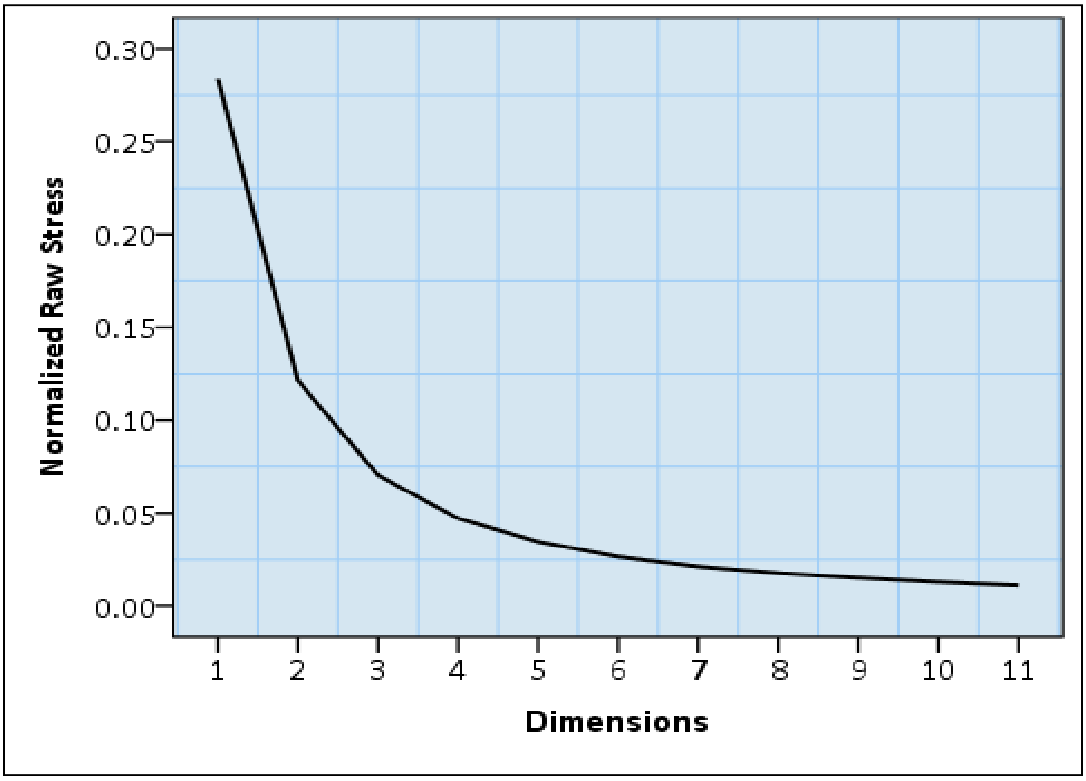


Figure 2.1: MDS Proxscal models’ goodness-of-fit

2.4.3 MDS Model Fit and Coordinates of Ratios

The final 3-way MDS model, retaining four dimensions, was a good fit for the data. It had 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 that the model is unlikely to be degenerate. Table 2.6 shows the dimensional coordinates of the financial ratios. The absolute value of a ratio’s coordinate for each

Table 2.6: 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

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 2.6, we have highlighted the ratios with large (absolute) value coordinates that we have used to interpret the dimensions.

2.4.4 HCA Clusters of Ratios

Since it is not possible to visualise the positions of the ratios in a four-dimensional (4D) space, 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 between ratios. One approach to this problem is to superimpose the 2D maps with a layer of the clusters obtained from the HCA (Neophytou and Mar-Molinero, 2004).

There were five stages in the HCA agglomeration schedule. At stage 1, there were three multiple-ratio clusters and three unattached ratios, namely *GPM, TDCFFO* and *CFFOS*. At stage 2, the three multiple-ratio clusters merged into one large cluster but *GPM, TDCFFO* and *CFFOS* remained unattached. *GPM* joined the large cluster at stage 3, *TDCFFO* at stage 4, and *CFFOS* at stage 5. We decided to extract the six clusters at stage 2, because stage 2 represents the greatest cluster separation. We show in Table 2.7 the ratios in each cluster. The agglomeration schedule we have described above suggests that the three larger clusters have more similarities among themselves than with *GPM, TDCFFO* or *CFFOS.* Because *GPM, TDCFFO* and, particularly, *CFFOS* 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. Because of this combination of ratios, we interpreted Cluster 1 as an indicator of non-profitability-based **market valuation of financial stability.** This interpretation also implies that because of the presence of the cash flow and activity ratios in Cluster 1, the market may use cash flow and activity ratios to evaluate financial stability. Cluster 2 only contains profitability ratios, which enable the determination of 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 are related to *SETA* (equity to total assets), the fourth ratio in the cluster.

Table 2.7: 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		

2.4.5 Interpretation of ratio dimensions

We used the relative positions of the six clusters on the 2D MDS maps and the signs and sizes of dimensional coordinates of the ratios (table 2.6) to interpret the four dimensions as follows:

Dimension 1: 'Non-strategic sales activities'

Figure 2.2 shows the projection of the MDS structure in dimensions 1 and 2. MDS dimensions were extracted hierarchically based on the variance accounted for, with the first dimension accounting for the most variance, 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. One can see in Figure 2.2 that this is the case: all six clusters occupy clear and distinct positions on the map. The entirety of Cluster 3, an indicator of sales activities, is on the right-hand side of dimension 1, as are the three unattached ratios *CFFOS*, *GPM* and *TDCFFO,* which, together with *TDS,* have the highest positive-valued coordinates in 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. The proximity of *TDCFFO* and *TDS* reflects such obligations. In this case, however, the focus on sales activities is at the expense of profitability and financial stability, as can be seen by inspecting the left-hand side of the map. The entire market valuation of financial stability cluster and most of the profitability cluster are on the negative side of dimension 1. This indicates decreasing levels of both the markets' valuation of financial stability and profitability, suggesting a lack of long-term, strategic planning to ensure that sales activities not only generate profits but also occur within a stable financial environment that engenders market value. Thus, we interpreted dimension 1 as an indicator of operational, **non-strategic focus on sales activities.**

Dimension 2: 'Profitability and financial stability balance'

Clusters 1 and 2 occupy different sides of dimension 2, whereas Cluster 3 overlaps the negative and positive halves. The three ratios (*EBITTL, EBITCE and EBITSEQ*) with the highest positive valued coordinates in dimension 2 are all in Cluster 2 (profitability). In contrast, the cash flow over liabilities ratios (*CFFOCL, CFFOTL*), the *quick ratio* (liquidity) and *TLTA* (leverage) have high negative coordinates in 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**

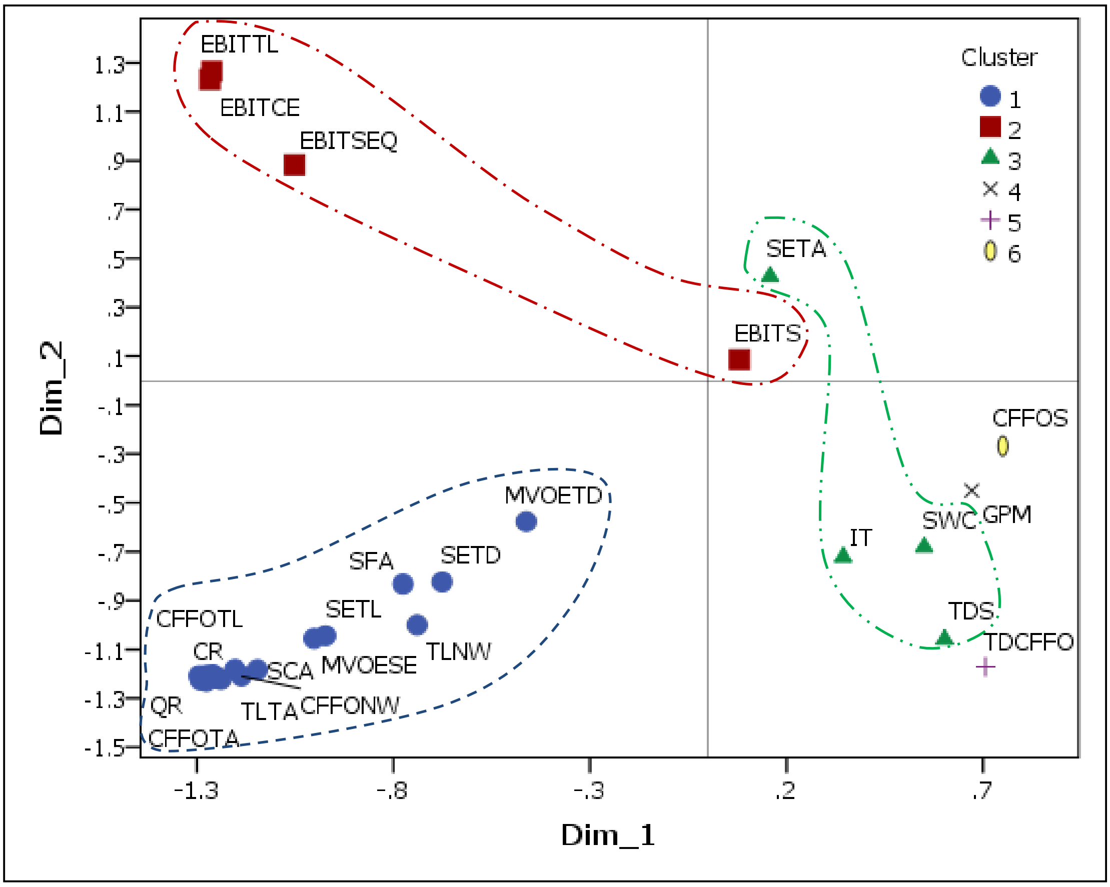


Figure 2.2: MDS Dimensions 1 versus 2 and HCA Cluster

Dimension 3: 'Sales activities against capital conversion'

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 value coordinates in dimension 3, namely *CFFOS, GPM, TDCFFO* 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 in dimension 1, in dimension 3 all profitability ratios have very small values, close to zero. Dimension 3 appears not to be strongly related to the profitability, market value and leverage ratios. Overall, unlike 1, the ratios in the negative side of dimension 3 do not give a clear indication of decreasing profitability and financial stability and, consequently, decreasing market value. Rather, the two ratios with the highest negative valued coordinates, namely *AT* (total asset turnover) and *TLTA* (total liabilities to total assets), respectively, indicate efficiency in using own assets to generate sales and effectiveness in using creditors' funds to acquire assets (Megginson and Smart, 2005; Bragg, 2012). Hence, the negative side of dimension 3 could be a reflection of return on capital. Subsequently, 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-value coordinate, and is located near the Cluster 1 ratios *MVOETD* (market value to debt), *SETD* (equity to total debt),

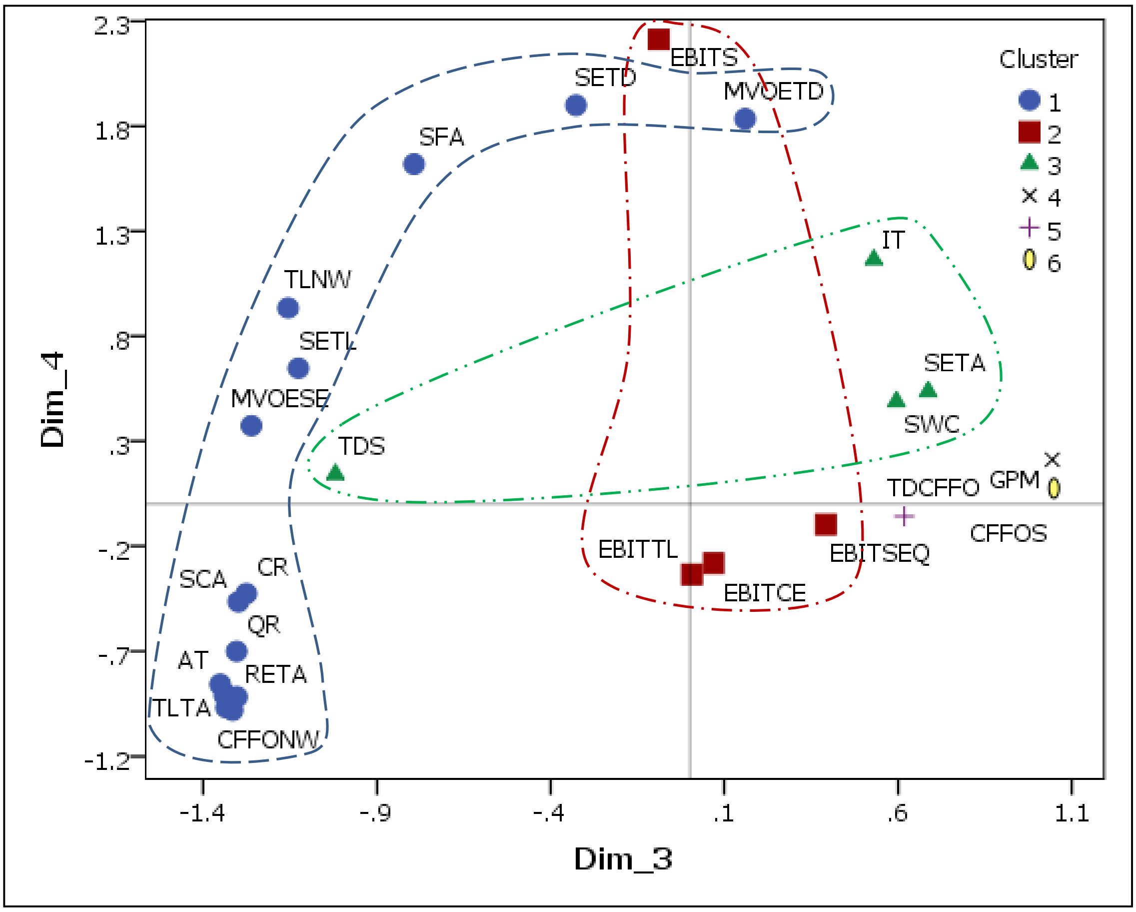


Figure 2.3: MDS Dimensions 3 versus 4 and HCA Clusters

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**.

2.4.6 Relative Importance of Ratio Dimensions

Table 2.8 shows the importance that solvent and insolvent firms ascribe to 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 indicate the importance that the category of firm places on that dimension relative to the other three dimensions. For each dimension, dimension weights indicate the importance that insolvent firms attach to it, relative to the case with solvent firms. The 'specificity' indicates the extent to which a source attaches weight to a specific dimension at the expense of other dimensions. Specificity 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 that a source makes between a focus on *one, some* or *all* of the dimensions: as the emphasis on one or a few dimensions increases, lack of emphasis on the others may ensue. We can thus see 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 4. In contrast, solvent firms are only moderately specific. Instead of dimension 1, which appears unimportant to them, solvent firms place the most weight on dimension 2. They place less, yet 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 2.8: 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	

2.5 Discussion

Above, after reviewing the literature, we concluded that, overall, no set of financial ratios can consistently predict firm failure. Rather, the set of ratios found to be significant varies according to different studies (Altman and Narayanan, 1997). This synopsis of the literature is mirrored by the results we obtained when we conducted Logit modelling in order to address the first research question (*RQ1*); namely, '***What are the significant predictors of insolvency in the GCC region; and do they include cash flow-based ratios?'*** For each of a 1000 bootstrap replicates of the training dataset, we estimated a set of the best-six predictors. We found that the composition of the best-six predictor sets varied considerably. Based on the premise that sets that appear more frequently are likely to be more robust, we examined the performance of the most frequent 'best-six predictor' sets; 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. Instead, our predictive logistic model results in Tables 2.9, 2.10 and Figure 2.4 appear to have uncovered a general pattern: in the GCC context, ratios from the profitability, leverage and cash flow groups are likely to contain insolvency predictive information.

Table 2.9 : Prediction logit model fit and parameter estimates

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

Table 2.10 : Classification matrix of logit prediction model

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

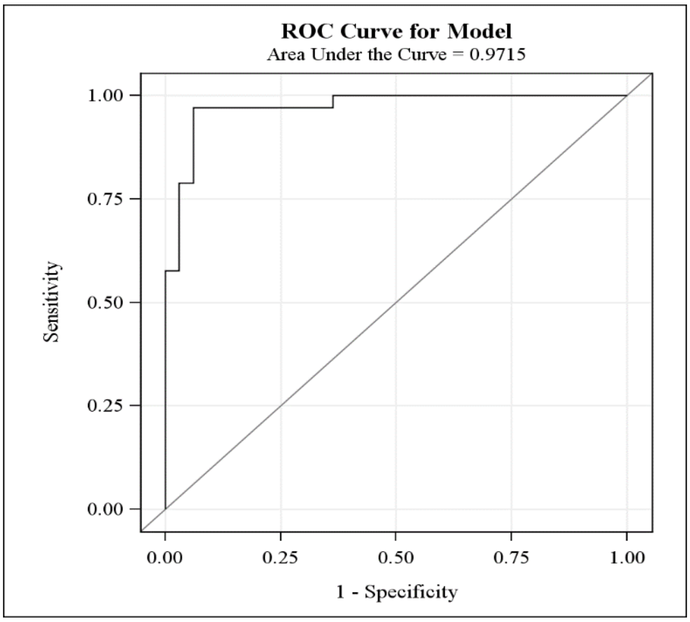


Figure 2.4: ROC curve for logit prediction model

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, and the Probit model results in Tables 2.11, 2.12 and Figure 2.5 confirm that the predictive capacity of these four ratios is not a mere artefact of the logistic model.

Table 2.11: Prediction probit model fit and parameter estimates

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

Table 2.12: Classification Matrix of logit prediction model

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

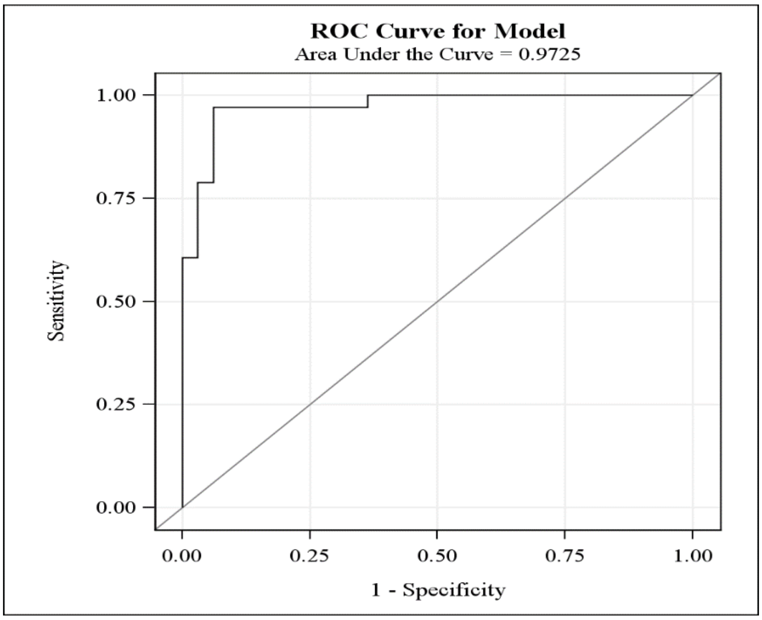


Figure 2.5: ROC Curve for Probit Prediction Model

Rather, it appears to 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, location (country) and classification technique. We present the details of the 28 studies, including the significance of the 28 ratios under consideration, in Appendix C. A count of the number of occurrences of each ratio in the 28 studies suggests that the type of ratio most frequently reported significant is liquidity, having first appeared in the seminal studies of Beaver (1966) and Altman (1968). It is notable, thus, that we have not found any liquidity ratio significant. This is not unusual, though: previous studies of the GCC, such as Aldeehani (1995) and Basheikh (2012), did not find any liquidity ratio significant either. Perhaps liquidity ratios have lower predictive capacity in the GCC than elsewhere. We also did not find any activity or any market ratio significant, but unlike liquidity, the literature rarely reports this type of ratio significant, indicating low predictive capacity generally.

Based on theory (Gilbert, Menon and Schwartz, 1990) and empirical results elsewhere (Aziz and Lawson, 1989; Blum, 1974; Charitou, Neophytou and

Charalambous, 2004; Gilbert, Menon and Schwartz, 1990; Mensah, 1984; Smith and Liou, 1979; Aziz, Emanuel and Lawson, 1988) 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 postulation Furthermore, *CFFOTA,* which has been reported significant in several other studies in different contexts (Bose, 2006; Ravisankar, Ravi and Bose, 2010; Shumway, 2001), had by far the largest estimated effect. *CFFOCL,* also reported significant by Gilbert, Menon and Schwartz (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, 1983a). Consequently, we think there is a clear weakness in previous GCC insolvency research, which has ignored cash flow ratios: cash flow-based ratios *should* be included in insolvency prediction models of 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, Neophytou and Charalambous (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, although it has the smallest estimated effect in our Logit model, *TLTA* is very often reported as significant in the literature (e.g. Altman and Lavallee, 1981; Charitou, Neophytou and Charalambous, 2004; Gloubos and Grammatikos, 1988; Ohlson, 1980; Shumway, 2001; Zavgren, 1985; Zmijewski, 1984). Hence, we can also 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 2.13, 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). Indeed, 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 to be much more costly than type II errors (e.g. Altman, Haldeman and Narayanan, 1977). It is good then that, like Altman (1968) and Charitou, Neophytou and

Charalambous (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 covered 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 2.13: 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, Peel and Pope (1986)***	United Kingdom	91.7	83.4	100
Charitou, Neophytou and Charalambous (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, the aim of these two questions was to generate insight as to why some firms are more susceptible to insolvency than others. Using 3-way MDS, supplemented by hierarchical cluster analysis, we found that the 28 financial ratios reduced to four main dimensions. In order of decreasing importance (measured by the amount of the variance each dimension accounted 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 put on these four dimensions, we uncovered marked differences between solvent and insolvent firms.

Insolvent firms placed most weight on dimension 1 (‘Non-strategic sales activities'). 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 this near singular focus on ‘non-strategic sales activities’ is likely to be a reactive, pragmatic stance, dictated by a need to meet financial obligations. Generally, the insolvent firms go through a perverse downward spiral. It seems that at the first sign of distress GCC insolvent firms concentrate on fire fighting and tighter working capital management, by cutting off strategic investments, such as market development. Balance sheet endogenity issues (where the market values and book values of a firm’s assets are interdependent) force the asset values of distressed firms to decline, thus reducing the level of collateral that could be used to raise funds. The decline in market values causes creditors to extend unfavourable terms, which further aggravates working capital issues. Hence, liquidity issues will force the firms to default on their obligations and cause the creditors to enforce the firm’s liquidation and recover whatever they can by selling the leftover assets at fire sale values. Because GCC firms do not have a reorganization route analogous to the US Chapter 11, the sole emphasis on dimension 1 at the expense of dimensions 2, 3 and 4 could be a critical issue. The Logit results, which indicate that the level of cash relative to liabilities (*CFFOCL*) can significantly affect susceptibility to insolvency, support this inference. Taking the multidimensional focus of solvent firms as a benchmark, 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, as it could harm profitability, put stability at risk and reduce market value.

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’). Regarding these dimensions, the solvent firms show their ability to invest their assets to finance the firms' activities, generate revenues and increase profitability. The efficiency of converting assets and debts into finance moves the firms' activities into profitability and a strong market value.

Knowledge of a firm's financial health is important to a number of stakeholders: managers, owners and investors, creditors, and other trading partners. Our logistic regression and MDS results indicate that financial ratios can be used to detect firm distress in the GCC as effectively as in other contexts. However, we believe they are most relevant to managers. The MDS results do suggest how managers of firms in financial distress can correct this situation, by shifting focus away from 'non-strategic sales activities' and focusing more on inverting assets with a better strategic sales activities plan to meet both the short and long term obligations, which will be less likely lead to insolvency. Likewise, this result is also instructive for managers of healthy firms, who should periodically evaluate strategy and, whenever signs of over-valuing 'non-strategic sales activities' are spotted, refocus on profitability and financial stability. Overall, we believe our results indicate some parallels, as well as differences, between insolvency in the GCC and in other regions. Equally, the insight revealed by our logistic regression results should be of importance to all stakeholders; the Logit results confirm that financial ratios in general, and cash flow ratios in particular, can detect firm 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. This empirical evidence should be of immediate use to all stakeholders of GCC firms, but more particularly to creditors, and for those to whom it is important to identify the company's ability to meet their claims and be aware of its long term solvency.

We also note that, in our MDS model, market value ratios are most strongly associated with the fourth dimension, which, based on the amount of variance accounted for, is the least important of the four dimensions extracted. This may be a result of inefficiency in GCC markets (Al-Ajmi and Kim, 2012; Arouri, Lahiani and Nguyen, 2011); 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 (market values) are in other, more efficient, markets.

2.6 Conclusion

This study contributes to the literature on corporate insolvency in a number of ways. To date, there has been relatively little research on insolvency in the GCC. Many existing GCC studies have relied on Altman's model. This study breaks new ground by examining insolvency across the *whole* GCC, extending the geographical coverage. It also increases the methodological scope of corporate insolvency studies in the GCC by applying multiple methodologies: a Logit model supplemented by a Probit model and a 3-way MDS model supplemented by Hierarchical Cluster Analysis. Beyond the GCC, as one of only a few studies to have conducted *ex-ante* validation, this study extends the *pool of countries* where researchers have developed and validated insolvency classification models. 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, we have revealed the characteristic differences between solvent and insolvent firms, which we believe can aid managers to take action to reduce susceptibility to insolvency.

We envisage a number of ways to improve this research. As in 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 about insolvent firms because the stock markets are relatively nascent. It will be valuable, hence, to re-model insolvency in the GCC as more data emerges. This will increase the prediction accuracy of the models. Secondly, the GCC context has unique characteristics. This begs the question, To what extent are the structural differences between insolvent and solvent firms that our MDS results indicate idiosyncratic to the region? To examine this question, our forthcoming study investigates 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?

Chapter 3

Study 2: Compare and contrast: Contextualising corporate insolvency in the GCC, using the UK and the USA as comparators

Abstract

Taking a multilevel perspective, in this chapter we attempt to contextualise the nature of insolvency in the GCC, using the UK and the USA as comparators. We calculate 28 financial ratios from the financial accounts taken between 2004 and 2012 of matched pairs of insolvent and solvent firms from the GCC (*N* = 116), the UK (*N* = 116) and the USA (*N* = 98). 3-way Multidimensional scaling (MDS) and cluster analysis reveal four common dimensions in ratios across the samples: 'effectiveness of sales and cash-generating activities ', 'trade-off between debt management and cash generation/profitability', 'usage of debt versus usage of own assets ' and 'trade-off between profitability and cash generating activities'. Unlike solvent firms, which diversify their efforts, insolvent firms are very specific; they place most weight on one of the dimensions and very little on the others. The macroeconomic variables - inflation, interest rates and the stock index - are significantly correlated with ‘effectiveness of sales and cash-generating activities’. Inflation is also correlated with ‘trade-off between debt management and cash generation/profitability’. We briefly discuss the implications of the results.

3.1 Introduction

Bankruptcy, according to Bernanke (1981), ‘*imposes net social costs, so that all agents have an interest in avoiding it*’ (Bernanke, 1981, page 1). When the entity going bankrupt is a corporation, the costs are even more widespread and most of its stakeholders suffer. Understanding the causes of corporate insolvency is thus an important research area. It can help managers understand how to prevent insolvency, or even help them improve corporate performance. Corporate failure can occur as a result of what happens within the firm, what happens outside the firm, or combinations of both. Managerial incompetence is an example of a within-firm or micro factor; economic downturn is an example of a national- or macro-level factor. Between the micro- and macro-levels, an industry-wide factor, such as government regulation targeting a specific product, such as has happened with tobacco, can be considered as an example of a meso-level factor.

It seems reasonable to suggest that to better understand corporate failure we should study the effects of the micro-, meso- and macro-level factors simultaneously; i.e. adopt a multilevel perspective (Kozlowski and Klein, 2000). However, most corporate failure studies are not multilevel (Goudie and Meeks, 1991); researchers tend to study each level discretely. The majority of studies are at the micro-level where, typically, researchers study the effects of within-firm factors within a single country while controlling for meso-level effects by, for example, matching firms by industry sector (see for example, Altman and Narayanan, 1997). Likewise, at the macro-level, studies tend to focus on the variance over time of macro-level variables within a single country (for example, Goudie and Meeks, 1991; 1992; 1998). In both these cases, the studies are limited because they are essentially single-level. By overlooking factors at other levels, a single-level study can only partially explain the phenomenon of insolvency because it tends to overlook cross-level interactions. Not only do firms affected by higher level factors, i.e. the meso- and the macro-, but the higher levels are themselves made up of firms as integral constituents. Thus, for example, the national economy impacts firms' activities; simultaneously, the activities of firms impact the national economy.

Therefore, the current study contributes to the literature by studying firm failure by taking a multilevel perspective (macro-level: macroeconomic indicators, meso-level: industry sector, micro-level: firm factors) which has been accorded limited attention in previous corporate insolvency researches. A multilevel perspective can tap into the sort of insight we cannot access via single-level studies. Moreover, many researchers have studied corporate insolvency in the course of individual studies of each country. In light of the added value of investigating the determinants of corporate failure across different contexts, this study adds to the existing literature a new pattern of studying the similarities and dissimilarities of the structures of insolvent and solvent firms contextual with other firms in different economies. This chapter develops a multilevel analysis of corporate insolvency by building on an earlier study by Khoja, Chipulu and Jayasekera (2014). Using financial ratios, Khoja, Chipulu and Jayasekera (2014) found some important differences between solvent and insolvent firms in the Gulf Cooperation Council (GCC). Notably, they found that, unlike solvent firms, insolvent firms appeared to attach a great deal of importance to ‘Non-strategic sales activities’. However, given the unique characteristics of the GCC, they were not able to say if such differences were idiosyncratic to the GCC or whether similar differences could be expected in other regions. In this paper, we extend that earlier work in two ways. Firstly, we extend the dataset to include not only solvent and insolvent firms in the GCC, but also in the United Kingdom (UK) and the United States of America (USA). This additional data enables us to put the nature of corporate failure in the GCC into perspective by comparing and contrasting it with that of firms in other regions. Secondly, this study will add to the existing literature a new dimension by adding macro-level variables. This allows us to examine how specific aspects of the macro environment may impact firm failure. Such information could be helpful to policy makers and managers of firms in managing the risk of insolvency. Rather than insolvency prediction, the main aim of this study is to contribute towards the body of knowledge about characterising insolvency at the firm level in different macro environments.

We begin the chapter by reviewing the literature on the different levels of study related to corporate insolvency research. Next, we state our research questions, which are based on our literature review. We then describe the data, the analysis and the findings. We conclude by discussing the implications of the results.

3.2 Literature and research questions

3.2.1 Impact of within-firm (micro-level) factors on insolvency

The majority of insolvency research focuses on the impact of within-firm factors, and so can be categorised as micro-level. Typically, researchers use financial ratios as proxies for the financial management of the firm. Ratios are popular perhaps, because one can easily calculate them from published accounts, whereas other data, such as qualitative information on the quality of management, is harder to obtain. It may also be because researchers have found most of the major categories of ratios significantly related to, and hence, highly predictive of, insolvency.

Among others, Ko (1982), Ta and Seah (1988) and Gloubos and Grammatikos (1988) reported profitability ratios to be significant, whereas Altman (1968), Deakin (1972), Ohlson (1980), Zmijewski (1984), Gilbert, Menon and Schwartz (1990) and Shumway (2001) reported leverage ratios as significant. Similarly, researchers such as Beaver (1966), Altman (1968), Deakin (1972), Peel, Peel and Pope (1986), Back, Laitinen and Sere (1996) and Jones and Hensher (2004) reported liquidity ratios as significant. Although early research tended to ignore them, cash flow-based ratios have also demonstrated predictive capacity in a number of studies, such as those of Ta and Seah (1988), Gilbert, Menon and Schwartz (1990), Sung, Chang and Lee (1999) and Ravisankar, Ravi and Bose (2010). In contrast, although both types appeared in Altman (1968)'s seminal study, neither activity nor market ratios have been widely reported as significant, bar a few exceptions, such as Taffler (1982), Peel, Peel and Pope (1986) and Aldeehani (1995), who reported activity ratios to be significant, and Ko (1982) and Aldeehani (1995), who reported market ratios as significant.

There is no doubt, then, that financial ratios are an important aspect of insolvency research, but what we learn about insolvency from each study depends on how the researchers approached the problem and the techniques they used. Some methods offer more insight than others. As computing power and speed have grown, machine-learning techniques, such as neural networks (Coats and Fant, 1993; Salchenberger, Cinar and Lash, 1992) and genetic algorithms (Shin and Lee, 2002; Varetto, 1998), have become more popular because they can classify insolvent and solvent firms very accurately. However, they are not interpretable and so offer no insight. In this regard, the more traditional statistical techniques, such as Logit regression (Ohlson, 1980; Peel, Peel and Pope, 1986; Zavgren, 1985), Probit regression (Gloubos and Grammatikos, 1988; Zmijewski, 1984), univariate analysis (Beaver, 1966; Deakin, 1972) and, to a lesser extent, Multiple Discriminant Analysis (MDA) (Altman, 1968; Sung, Chang and Lee, 1999; Ta and Seah, 1988), are more useful because one can interpret the results.

Unfortunately, statistical techniques are not without some limitations themselves. MDA, often the default baseline technique for evaluating other techniques (Altman and Narayanan, 1997), assumes that financial ratios are normally distributed and that the variance-covariance structures of insolvent and solvent firms are equivalent, but as Ezzamel, Mar Molinero and Beech (1987) show, both of these assumptions rarely hold up in practice. Logit and Probit regression models do not have the distributional assumptions of MDA, but both are prone to producing biased estimates, particularly in small-sample studies (Firth, 1993), which are quite common in insolvency studies (Khoja, Chipulu and Jayasekera, 2014). Given these problems, Mar Molinero and Ezzamel (1991) suggest Multidimensional Dimensional Scaling (MDS) as an alternative. A non-parametric technique, MDS has no distributional assumptions, unlike MDA. MDS is also not reliant on maximum likelihood estimates and so does not suffer from biases found in Logit and Probit regression. Furthermore, the visualisation philosophy of MDS allows for a richer, more intuitive insight into corporate insolvency.

Perhaps because of the precedent set by pioneers Beaver (1966) and Altman (1968), most micro-level research of insolvency is empirical rather than theoretical. Even so, a number of theories have been used or have been proposed to explain insolvency at the firm level. One stream of research applies Entropy theory to predict failure, based on changes in the structure of the balance sheets of firms (Booth, 1983; Lev, 1973). A second stream applies the Gambler's ruin theory: researchers posit that a failing firm will sell its assets to meet its losses until its net worth is zero: i.e. it is bankrupt (Morris, 1997; Scott, 1981). A third, much more popular, stream applies the cash management theory, which suggests persistent cash flow problems will eventually cause firm distress (Aziz and Lawson, 1989; Gilbert, Menon and Schwartz, 1990; Gombola and Ketz, 1983b; Aziz, Emanuel and Lawson, 1988).

3.2.2 Impact of macroeconomic factors on insolvency

Macroeconomic indicators, Liu (2004) claimed, have been neglected in the (largely) microeconomic analysis of corporate insolvency. Nevertheless, a number of macroeconomic factors have been found to affect insolvency. One such factor is the rate of inflation. Wadhwani (1986) suggested that inflation can create cash flow problems and cause bankruptcy; this is because imperfect credit markets fail to regulate debt levels with inflation. Both Turner, Coutts and Bowden (1992) and Liu and Wilson (2002) confirmed that inflation significantly impacts failure rates. Similarly interest rates have been shown to impact failure rates in a number of countries: by Rose, Andrews and Giroux (1982) in the United States, Desai and Montes (1982), Turner, Coutts and Bowden (1992), Young (1995), and Liu and Wilson (2002) in the United Kingdom, and Millington (1994) in Australia.

Oil prices may also be a relevant macroeconomic indicator, particularly in the GCC, where the oil and gas industries are prevalent. Platt, Platt and Pedersen (1994) found that adding oil prices as an independent predictor increased the classification accuracy of their prediction model.

3.2.3 Impact of industry sector and regulation on insolvency

Often, conditions across industry sectors can be, or appear to be, so disparate that it is common for investors to diversify their investments across a number of industry sectors in an attempt to minimise industry-specific risk of insolvency (see for example, Fabozzi, Gupta and Markowitz, 2002). Using standard econometric analysis, Lennox (1999) demonstrates that industry sector is an important factor in corporate insolvency. Similarly, Caves (1998) eports global patterns that suggest business failure rates differ across industry sectors. Based on this premise, typically, to control for industry-specific effects, insolvency studies match each insolvent firm sampled with its nearest neighbour among the population of continuing firms in the same industry (Altman and Narayanan, 1997; Aziz and Dar, 2006; Kumar and Ravi, 2007). A second, more refined, way to account for industry-level effects is by standardising ratios using either the industry mean (Fernandez (1988) or the industry median (Platt and Platt, 1991; Altman and Izan, 1984).

Since the majority of studies do not explicitly model the effect of industry sector, the evidence for how insolvency varies across different industries or how specific industry characteristics may impact insolvency is relatively sparse, although there are some exceptions to this general pattern. An early example is the study of Gupta and Huefner (1972), which examined cluster patterns in financial ratios across different industry sectors. One of the most interesting studies in this area is Ward (1994), who specifically tested the hypothesis that the usefulness of cash flow-based information in predicting insolvency is industry-specific. Overall, however, the effect of industry sector differences on corporate insolvency may be insignificant, as reported recently by Hossari (2009).

Another factor that can impact insolvency is legislation, particularly bankruptcy codes. Differences in insolvency rates have been observed before and after legislation within and across countries. According to Liu and Wilson (2002), the United Kingdom's 1986 Insolvency Act changed the character of the relationship between key macroeconomic indicators of insolvency and insolvency rates. Bhattacharjee *et al.* (2004) reported that the impact of macroeconomic instability on bankruptcy is less marked in the United States than in the United Kingdom, because USA firms facing bankruptcy are shielded from economic instability by Chapter 11. Beyond bankruptcy codes, other regulations have been shown to significantly impact insolvency. For example, Swanson and Tybout (1988) found that the exchange rate regime introduced in Argentina in 1978 caused a significant difference in firm failure before, and after, it was introduced, while Campbell *et al.* (2012) claimed that the size of the state government affected differences in failure rates across states in the United States.

3.2.4 A multilevel perspective on insolvency

The foregoing literature review suggests that insolvency is likely to be a multilevel phenomenon: conceptually, there are clear cross-level links among the factors, believed to be significant. For example, micro-level research suggests that insolvency can be predicted by profitability, leverage, liquidity and cash flow-based financial ratios. Hence, we can infer that any factor outside the firm, for example a macroeconomic condition, that can affect earnings, debt, equity or cash generation, will probably affect the risk of insolvency. Despite all this, only a few insolvency studies have taken a multilevel perspective.

In this regard, Goudie and Meeks (1991), Hossari (2009) and Bhattacharjee *et al.* (2004) are exceptional; they are among the few to have modelled insolvency taking a multilevel perspective. Goudie and Meeks (1991) predicted firm failure taking into account macroeconomic, industry- and firm-level effects. They used a two-stage approach: firstly, they predicted each company's financial accounts using a Keynesian economic model, the macro-industry model (MDM); they then predicted the company's insolvency using multivariate discriminant analysis based on the predicted accounts. (Hossari, 2009) applied multilevel modelling (MLM) to examine the effect of industry sector on the risk of insolvency among Australian firms, using financial ratios. Bhattacharjee *et al.* (2004) used macroeconomic variables, industry-effects and firm-level factors as inputs into a Cox Proportional Hazards model to examine the effect of macroeconomic instability and the insolvency legislation in the United States and the United Kingdom.

3.2.5 The research problem: Contextualising the nature of insolvency in the GCC

The majority of insolvency studies to date have used samples from the United States of America (USA), followed by the United Kingdom (UK) and other European countries (Kumar and Ravi, 2007). Despite a number of recent studies using samples from elsewhere (Khoja, Chipulu and Jayasekera, 2014; Maghyereh and Awartani, 2014), insolvency research in the Gulf Corporation Council (GCC) remains underdeveloped in comparison. Notably, Khoja, Chipulu and Jayasekera (2014) found that, in the GCC, insolvent firms appear to focus much more on 'non-strategic sales activities' than solvent firms, but having only sampled firms in the GCC, they were not able to state whether the differences were due to the intrinsic differences between failing and healthy firms, as opposed to the prevailing environment in the GCC, which is quite different from other regions. As Khoja, Chipulu and Jayasekera (2014, page.4) admit, '*there are important differences between the GCC and other major trading blocs*'. These include the GCC economies' dependency on oil (Fasano and Iqbal, 2003), and the GCC stock markets being less mature and less liberal, and inefficient in the weak form (Al-Ajmi and Kim, 2012; Arouri, Lahiani and Nguyen, 2011). In this study, thus, we propose two extensions to Khoja, Chipulu and Jayasekera (2014), which will enable us to isolate aspects that are representative of intrinsic differences between solvent and insolvent firms from those differences that are due to the GCC environment.

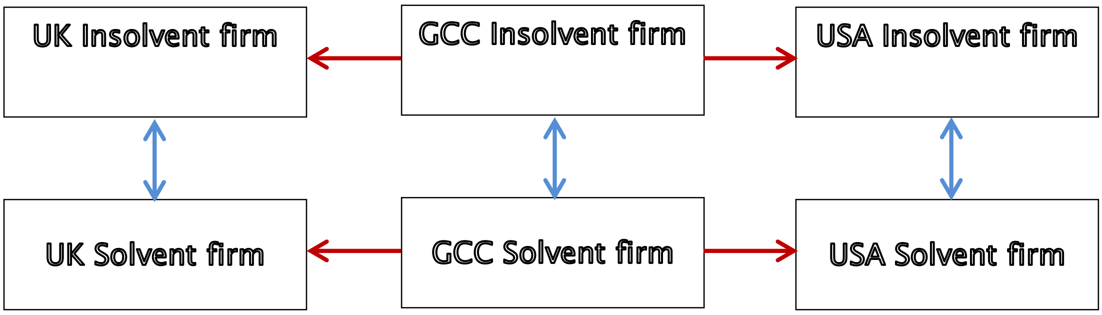


Figure 3.1: GCC insolvency vis-a-vis other regions: framework of comparisons

Firstly, we propose extending the samples of firms to include not just the GCC, but also the United States of America (USA) and the United Kingdom (UK). We examine a number of research questions based on the framework of comparisons shown in Figure 3.1. The first and second of the research questions arise from horizontal comparisons:

(RQ1): In what way are the financial structures of healthy firms in the GCC similar to those in the UK and the USA?

(RQ2): In what way are the financial structures of insolvent firms in the GCC similar to those in the UK and the USA?

RQ1 and RQ2 both address the notion of universal firm characteristics. Whereas RQ1 considers whether a solvent firm in the GCC has distinctive characteristics that would be readily recognised as those of a solvent firm elsewhere (such as in the UK and the USA), RQ2 considers the idea that insolvent firms in the GCC share identifiable characteristics with insolvent firms in other regions. In contrast, the third research question (RQ3) arises from the vertical following of from horizontal comparisons in Figure 3.1. It addresses the idea of universal *solvent v insolvent* differences. It considers whether differences observed between solvent and insolvent firms in the GCC would be readily observed between solvent and insolvent firms elsewhere, say in the UK or the USA; in other words, do the characteristics that differentiate a failing firm from a healthy one in the GCC remain unchanged elsewhere?

(RQ3): In what way are the differences observed between solvent and insolvent firms in the GCC similar to the differences observed between solvent and insolvent firms in the United States and the UK?

The second extension to Khoja, Chipulu and Jayasekera (2014) is that, in addition to firm-level data, we analyse the effect of macroeconomic factors, thus widening the perspective from single-level to multilevel. This multilevel perspective should enable us to understand how macroeconomic factors may be related to the factors that may define or influence the character of insolvency in the GCC, and whether comparable patterns can be expected elsewhere. Hence the fourth research (RQ4) question is:

(RQ4): How are macroeconomic factors related to characteristics that typify insolvency in the GCC and are the relationships comparable in the USA and the UK?

The USA and UK are ideal comparators for contextualising insolvency in the GCC for two reasons, *Firstly,* while little is known about insolvency in the GCC, arguably, given the larger body of research using samples from the USA and the UK (Kumar and Ravi, 2007), nowhere else is insolvency better understood than in those countries. The UK and the USA environments contrast sharply with the GCC. Relative to the GCC, the UK and USA stock markets are more mature, more efficient in the weak form and more liberal (Al-Ajmi and Kim, 2012; Arouri, Lahiani and Nguyen, 2011). Both countries' economies are also less dependent on oil and, hence, less sensitive to oil prices (Fasano and Iqbal, 2003). Furthermore, while similar to each other, the UK and the USA also differ from each other in important ways. They are geographically distant and they belong to different economic blocs: the UK is in the European Union, while the USA is in the North American Free Trade Agreement. They also have different legislations (see, for example, Bhattacharjee *et al.*, 2004). Hence, comparing the GCC to each country should give unique insights.

Secondly, on the trade side, the US and the UK have formed important investment and trade partnerships with the GCC, creating high level investment, which has reached 7.2% investment growth, compared to 2 % growth in the rest of the world. Large European and USA banks have set up in the GCC region, and other many projects have long been attractive to western firms in other industries, especially in the petroleum and real estate sectors (Economist Intelligence Unit, 2014). Thus, this region is considered to be a promising business environment for western firms, especially with the GCC governments' efforts to develop the liberalization of foreign investment laws and to increase foreign ownership in the GCC stock market. Thus, the western and USA companies' investment in the GCC market may experience different business environments as well as variance of the commercial risks, which can be reduced by understanding and determining the main corporate failure factors. These could be different from the predictors of bankruptcy in the western countries.

3.3 Data, analysis and results

3.3.1 Data

3.3.1.1 Sample of firms

We collected data on matched pairs of insolvent and solvent firms in the GCC, the UK and the USA for the period 2004 to 2012. To operationalise our main goal, which was to contextualise insolvency in the GCC using the UK and USA as comparators, we had to make like-for-like comparisons by holding important properties of firms constant across the different environments. Therefore, we categorised insolvency in the same way across the three countries. We did this by applying the Kuwaiti legal definition of insolvency, which defines a firm as insolvent when its accumulated losses reach 25% of its capital. We matched each insolvent firm with an equivalent solvent firm in the same country by industry sector and by comparable asset size. These matching criteria are those which are most widely used in the literature (Altman and Narayanan, 1997). For each pair of firms, we collected the financial data for the year prior to failure. For the GCC and the UK, we managed to find 58 matching pairs of firms, but we found only 49 pairs for the USA, due to the small number of insolvent firms in the Agriculture and Hotel and Tourism sectors. The sample of firms is displayed by sector and country in able 3.1.

Table 3.1: Sample of insolvent/solvent firms by sector and country

Sample of Insolvent Firms: Sector by Country				
Sector	Country			
	GCC	UK	USA	**Total**
Agriculture	15	15	7	**37**
Construction	7	7	7	**21**
Hotel and Tourism	5	5	4	**14**
Industrial Investment	9	9	9	**27**
Petrochemical Industries	3	3	3	**9**
Retail and Services	12	12	12	**36**
Telecommunications	1	1	1	**3**
Transportation	6	6	6	**18**
Total	**58**	**58**	**49**	**165**
Sample of Solvent Firms: Sector by Country				
Sector	Country			
	GCC	UK	USA	**Total**
Agriculture	15	15	7	**37**
Construction	7	7	7	**21**
Hotel and Tourism	5	5	4	**14**
Industrial Investment	9	9	9	**27**
Petrochemical Industries	3	3	3	**9**
Retail and Services	12	12	12	**36**
Telecommunications	1	1	1	**3**
Transportation	6	6	6	**18**
Total	**58**	**58**	**49**	**165**

3.3.1.2. Measures of within-firm conditions: financial ratios

To measure conditions at the firm level, we collected the financial statements of the firms from the database DataStream™ as well as from the firms' own websites. We used the financial statements to calculate the financial ratios. To be consistent with (2014), we calculated the 28 financial ratios that have been most widely and successfully used in the literature (Altman, 1968; Beaver, 1966; Dambolena and Khoury, 1980; Deakin, 1972; Elam, 1975; Gombola and Ketz, 1983a; Mensah, 1983). The 28 include activity, cash flow, leverage, liquidity, market and profitability ratios and they cover all six major categories of ratio. The descriptive statistics of the ratios in each country are presented in Table 3.2. Normality tests showed that none of the 28 ratios is normally distributed in any of the three countries; the *Shapiro-Wilks* statistic was significant at the 0.001 p-value level for all ratios.

Figure 3.2 is a graph that shows the differences in the mean values of the ratios between the GCC, and the UK and USA. For each ratio, we have calculated the differences of GCC mean less UK mean and the GCC mean less USA mean. Thus, positive values indicate that the GCC mean is greater than those of the UK or the USA; negative values indicate a lesser mean. In the graph, points close to the vertical axis represent small differences between the GCC and the UK, and points close to the horizontal axis represent small differences between the GCC and the USA.

In Figure 3.2, most of the ratios are located in a cluster around the origin, but a number of ratios show noteworthy mean differences. The largest difference observed is for the mean level of *MVOESE*, which is much smaller in the GCC than in the UK, unlike the USA where it is of similar magnitude to that of the GCC. The second biggest difference is for the mean value of the ratio *CFFOCL*: It is much smaller in the GCC than in the cases of both the UK and the US. The leverage ratios *SETL* and *SETA* present an interesting contrast, which may suggest important differences in levels of shareholders' equity over liabilities compared to shareholders' equity over assets. *SETL* has a much larger mean value in the GCC than is the case in both the UK and the US, whereas the mean for *SETA* is much smaller than both the UK and the US. The mean values of *GPM* (Gross Profit/Sales) and *IT* (Cost of Sales/Inventory) are also notably smaller in the GCC than they are in both the UK and the US. Similarly, the mean value of *AT* (Sales/Total Assets) is much smaller in the GCC than it is in the UK; it is also smaller than in the US, although not to the same extent.

Table 3.2: Summary statistics of financial ratios by country

Ratio	Category/Short Description	Formula	Ratio Mean			Standard Deviation		
			GCC	UK	USA	GCC	UK	USA
EBITSEQ	Profitability: Return On Equity	Earnings Before Interest And Taxes/Shareholders' Equity	3.8	-0.5	0.4	41.0	3.2	3.3
EBITCE	Profitability: Return On Capital Employed	Earnings Before Interest And Taxes/Capital Employed	2.9	-0.4	0.1	31.0	2.7	0.4
EBITS	Profitability: EBIT Margin	Earnings Before Interest And Taxes/Sales	-1.5	-0.8	0.0	29.0	5.7	0.2
EBITTL	Profitability: Earning To Total Liabilities	Earnings Before Interest And Taxes/Total Liabilities	2.8	-2.4	0.0	30.5	14.9	0.7
GPM	Profitability: Gross Profit Margin	Gross Profit/Sales	2.4	115.7	30.3	16.7	956.5	16.9
RETA	Leverage: Retained Earnings To Total Assets	Retained Earnings/Total Assets	1.5	-0.9	0.2	159.3	5.5	0.3
SETA	Leverage: Equity To Total Assets	Shareholders' Equity/Total Assets	2.0	52.0	35.6	10.7	158.6	26.7
SETL	Leverage: Equity To Total Liabilities	Shareholders' Equity/Total Liabilities	44.2	3.2	7.9	33.8	9.9	70.6
TLTA	Leverage: Total Liabilities To Total Assets	Total Liabilities/Total Assets	2.2	12.9	0.6	3.6	132.6	0.3
TLNW	Leverage: Total Liabilities To Net Worth	Total Liabilities/Net Worth	0.6	2.0	8.8	0.4	5.3	64.7
SETD	Leverage: Equity To Debt	Shareholders' Equity/Total Debt	2.2	40.0	6.1	6.6	232.8	36.2

Table 3.2: Continued

Ratio	Category/Short Description	Formula	Ratio Mean			Standard Deviation		
			GCC	UK	USA	GCC	UK	USA
CR	Liquidity: Current Ratio	Current Assets/Current Liabilities	4.2	2.8	1.7	9.7	5.5	1.0
QR	Liquidity: Quick Ratio	(Current Assets - Stocks)/Current Liabilities	1.9	49.2	1.1	2.3	503.5	0.8
WCTA	Liquidity: Working Capital To Total Assets	Working Capital/Total Assets	1.3	0.1	0.1	1.7	0.3	0.2
IT	Activity: Inventory Turnover	Cost Of Sales/Inventory	0.0	81.2	17.0	3.6	322.9	27.6
TDS	Activity: Debt Ratio	Total Debt/Sales	10.9	0.6	0.7	33.8	2.1	1.6
AT	Activity: Total Asset Turnover	Sales/Total Assets	7.0	88.4	1.0	57.9	935.2	0.7
SCA	Activity: Sales To Current Assets	Sales/Current Assets	0.6	2.9	3.7	0.6	2.1	3.5
SFA	Activity: Fixed Asset Turnover	Sales/Fixed Assets	1.8	11.9	3.4	3.9	42.6	7.9
SWC	Activity: Working Capital Turnover	Sales/Working Capital	2.7	4.2	-7.5	6.6	31.2	109.7
CFFOTA	Cash Flow: Cash Flow On Assets	Cash Flow From Operations/Total Assets	-2.9	0.0	0.1	52.7	0.4	0.3
CFFOS	Cash Flow: Cash flow on Sales	Cash Flow From Operations/Sales	0.2	-0.6	0.1	1.3	4.7	0.2
CFFOCL	Cash Flow: Cash Flow on Current Liabilities	Cash Flow From Operations/Current Liabilities	-144.52	-0.1	0.6	1144.6	1.6	0.7

Table 3.2: Continued

Ratio	Category/Short Description	Formula	Ratio Mean			Standard Deviation		
			GCC	UK	USA	GCC	UK	USA
CFFOTL	Cash Flow: Cash Flow on Total Liabilities	Cash Flow From Operations/Total Liabilities	0.6	-0.2	0.2	4.0	1.3	0.4
CFFONW	Cash Flow: Cash Flow on Net Worth	Cash Flow From Operations/Net Worth	0.4	0.3	-0.4	2.1	2.8	6.7
TDCFFO	Cash Flow: Total Debt To Cash Flow Ratio	Total Debt/Cash Flow From Operations	3.0	2.6	2.9	28.5	27.7	10.0
MVOETD	Market: Market Value To Debt	Market Value Of Equity/Total Debt	40.8	68.4	35.0	356.9	398.1	277.5
MVOESE	Market: Market Value To Equity	Market Value Of Equity/Shareholders' Equity	6.9	333.9	5.6	15.2	3481.5	33.0

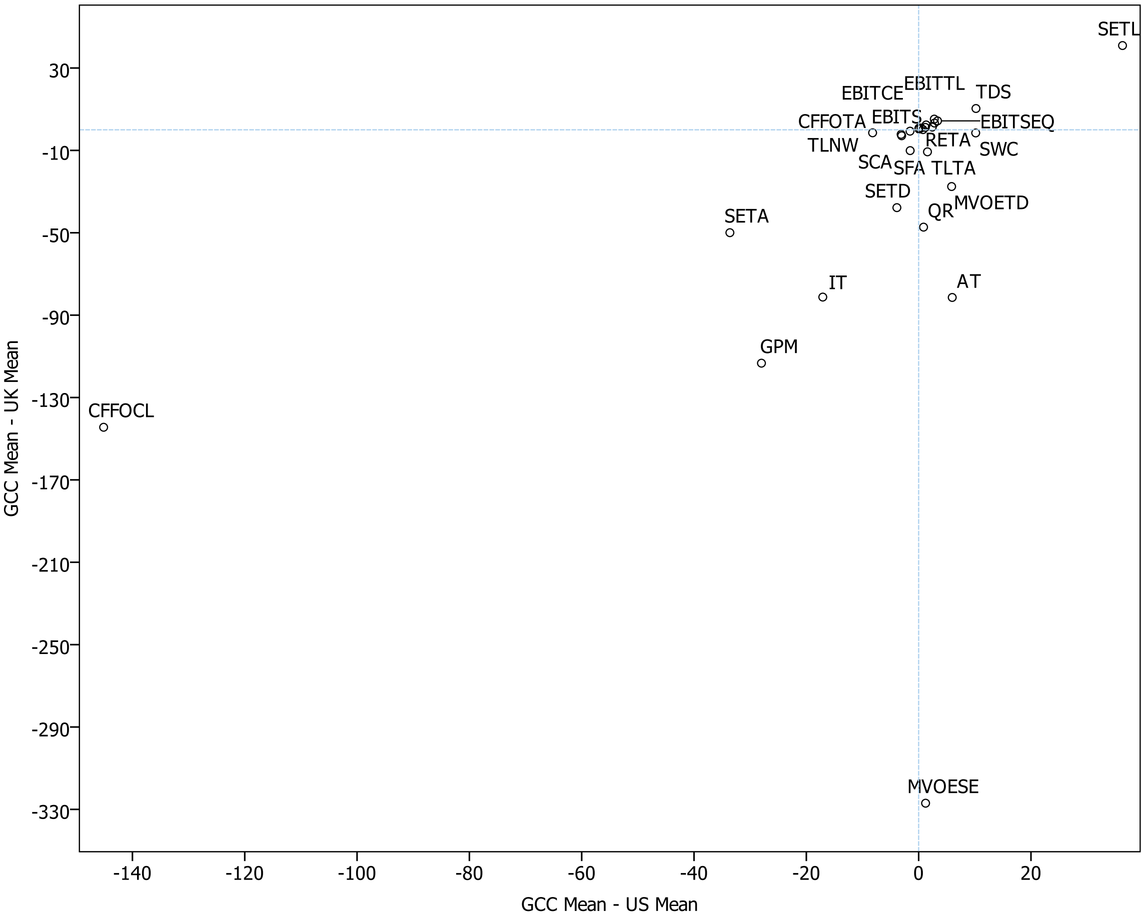


Figure 3.2: Differences in ratio means: GCC v UK, USA

3.3.1.3 Measures of macroeconomic conditions

To examine the influence of macroeconomic conditions, we collected data on the inflation rate, interest rate and oil price corresponding to the financial statement year for each pair of firms and the country of the firms. The literature suggests these macro variables may impact insolvency. We also collected data on the stock index to account for the size of index operating in each country at the time of failure. Table 3.3 shows the descriptive statistics of the macroeconomic variables. The stock index is clearly much smaller in the GCC than in the US and, to a lesser extent, the UK. Both inflation and interest rates are, on average, higher in the GCC than in the UK, although interest rates are more variable in both the UK and the USA than in the GCC. The oil price applies worldwide; there should be no differences across countries at a particular point in time. The observed differences in the summary statistics of oil price are due to the slight variations across the countries for the distributions of the years between 2004 and 2012 for which we collected data. Similar to the ratios, all the macro variables are non-normal, with the *Shapiro-Wilks* statistic significant at the 0.001 p-value level.

Table 3.3: Descriptive Statistics of Macroeconomic Variables

Factor	Mean			Standard Deviation			Coefficient of Variation		
	GCC	UK	US	GCC	UK	US	GCC	UK	US
Stock Index	26.7	784.2	319.7	137.6	417.0	1137.4	26.1	15.0	15.5
Inflation Rate	.3	.9	.5	3.1	0.9	1.4	71.4	32.7	58.3
Interest Rate	.4	.5	.4	0.9	2.1	1.5	16.9	82.3	33.0
Oil prices	6.1	1.5	9.1	26.9	30.5	30.0	31.3	37.5	33.7

3.3.2 Data analysis and results: 3-way Multidimensional Scaling

3.3.2.1 Rationale of 3-Way MDS

Like Khoja, Chipulu and Jayasekera (2014), we used 3-way Multidimensional Scaling (MDS) to address the research questions. MDS is a data reduction technique. The objective is to explain the greatest amount of the structure within a large amount of data using only a few key dimensions. MDS can be conducted with metric or non-metric variables (Kruskal, 1964; Kruskal and Wish, 1978) and, for this reason, it is often preferred over other data reduction techniques, such as factor analysis when all variables of interest are not at least interval scaled or do not satisfy distributional assumptions, such as normality. Typically, MDS involves the construction of a map based on similarities or proximities among data entities (cases or variables) from the given data such that entities with similar characteristics are located near to each other on the map. Hence, the structure within the data can be inferred by studying the loci of known entities on the map. 3-way MDS extends the analysis into a *third* way by examining data from different sources. Here the idea is that data from different sources can have a common structure (among the cases or variables), but also individual differences due to each source. For this reason, 3-way MDS is ideal for our purposes because we can study the similarities among the firms, but also the differences due to the source, i.e. type of firm (solvent, insolvent) from a specific country.

3.3.2.2 Number of MDS dimensions to retain

The first step in the MDS model was to determine dimensionality. Since the main objective of MDS is to represent the data structure using a small number of key dimensions, the number of dimensions retained should be much smaller than the number of entities in the data. Typically, it is no more than a handful. MDS dimensions, like components in Principal Components Analysis (PCA), are extracted hierarchically. The first few dimensions capture the majority of the variance in the data; they are the most meaningful and most interpretable. Higher dimensions, which capture less variance, are less important and less meaningful, and so harder to interpret, but the amount of variance explained increases in the number of dimensions retained. Therefore, deciding how many dimensions to retain is an important decision. In this study we adopted a method applied by Neophytou and Mar-Molinero (2004), Chipulu *et al.* (2013) and Khoja, Chipulu and Jayasekera (2014), where the dimensionality of the data is decided by an independent model *a priori* to the actual MDS model. We sampled the dataset to obtain five bootstrap replicates of it. Each replicate was equal in size to the original dataset. We then conducted categorical principal components analysis (CATPCA) of the 28 ratios for each replicate.

Figure 3.3 is a scree plot or 'elbow diagram' which shows the amount of variance explained by each dimension for each of the five CATPCA models. The overall shape in Figure 3.3 suggests a turn or 'elbow' at dimension 4: four dimensions may be sufficient to capture the majority of the structure in the data. However, the lines in Figure 3.3 are somewhat divergent, indicating that the exact dimensionality of the data is uncertain. Therefore, adopting a conservative approach commonly used in PCA (Neophytou and Mar-Molinero, 2004), we extracted an MDS configuration with six dimensions, but only interpreted the first four; we treated the last two dimensions as representing residual variation.

3.3.2.3 Three-way MDS procedure

The first step in the MDS was to split the data into the six data 'sources' representing each type of firm in each country, which are 'GCC-insolvent', 'GCC-Solvent', 'UK-Insolvent', 'UK-Solvent', 'USA-Insolvent' and 'USA-Solvent'. For each source, we calculated proximities among the 28 financial ratios using the Euclidean distance metric. As a result, there were six proximity matrices, one for each source. We then entered the six matrices as the inputs into the 3-way MDS model using the *Prefscal* algorithm (Busing *et al.,* 2005). The *Prefscal* algorithm first estimated a six-dimensional space common to all sources. Secondly, it rescaled the common space along each of the six dimensions, based on the weight each source places on that dimension. In other words, scale transformations were applied to the common space until the resultant space was a good fit for each individual source.

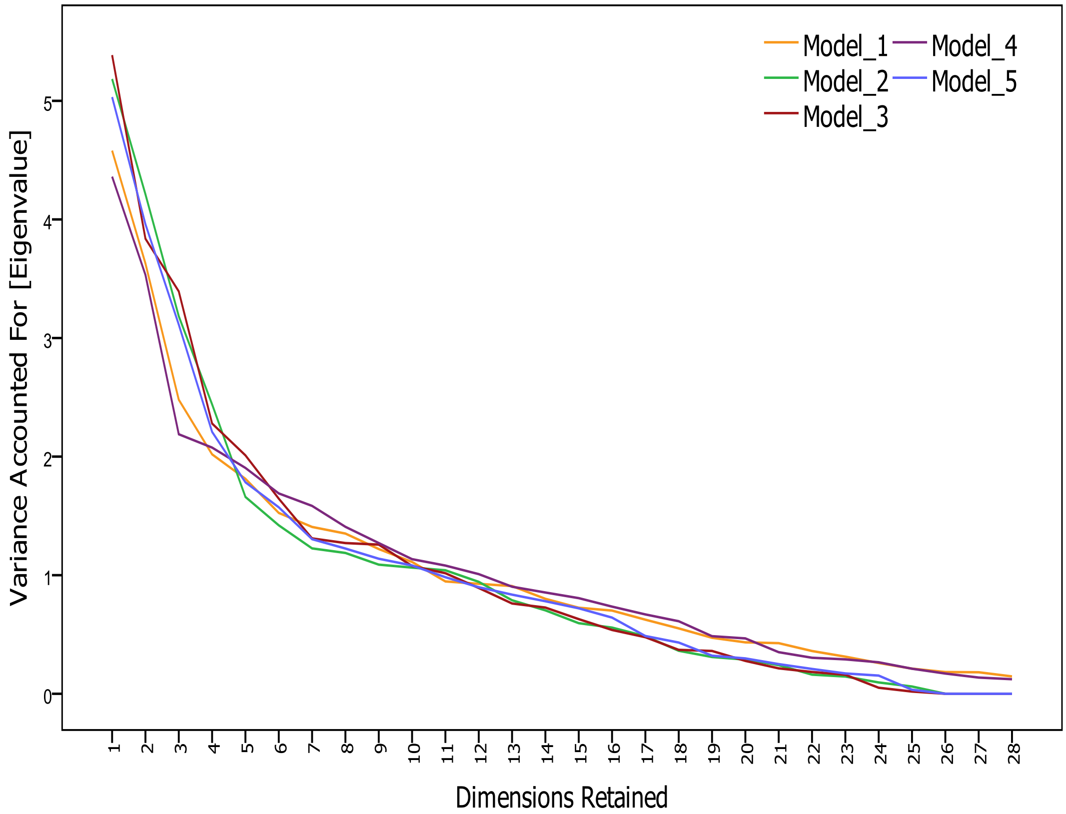


Figure 3.3: Variance accounted for per dimensions retained

The final 3-way MDS model fitted the data well. It accounted for 82% of the variance in the ratios. The normalised stress value was 0.05. The sum-of-squares of DeSarbo's Inter-mixedness Indices was 0.19 and Shepard's Rough Non-degeneracy Index was 0.76, which indicates that the extracted configuration is unlikely to be degenerate (Busing, Groenen and Heiser, 2005). Table 3.4 is a list of the coordinates of each ratio on the four MDS dimensions of interest.

Table 3.4: Coordinates of ratios on retained MDS dimensions

Name	Ratio Description	Dim_1	Dim_2	Dim_3	Dim_4
MVOETD	Market Value Of Equity/Total Debt	-0.642	0.6	0.704	-0.379
GPM	Gross Profit/Sales	-0.325	0.641	-1.181	0.28
SETA	Shareholders' Equity/Total Assets	-0.521	0.492	-0.929	-0.409
EBITS	Earnings Before Interest And Taxes/Sales	1.196	-1.319	0.087	-0.006
RETA	Retained Earnings/Total Assets	1.224	-1.313	0.593	-0.036
TDS	Total Debt/Sales	1.3	-1.268	0.335	-0.307
CFFOTA	Cash Flow From Operations/Total Assets	1.304	-1.319	0.465	-0.266
CFFOCL	Cash Flow From Operations/Current Liabilities	1.382	-1.201	0.75	0.107
MVOESE	Market Value Of Equity/Shareholders' Equity	0.86	0.633	-0.697	-0.444
CR	Current Assets/Current Liabilities	1.175	-0.946	-0.862	-0.792
IT	Cost Of Sales/Inventory	-0.576	0.483	-1.085	-1.446
CFFOS	Cash Flow From Operations/Sales	1.156	-1.302	-1.343	-1.15
WCTA	Working Capital/Total Assets	1.165	-1.292	-1.299	-1.317
CFFOTL	Cash Flow From Operations/Total Liabilities	1.15	-1.307	-1.332	-1.345
CFFONW	Cash Flow From Operations/Net Worth	0.782	-0.937	-1.412	-1.384
SETL	Shareholders' Equity/Total Liabilities	1.328	-1.142	0.192	0.636
EBITCE	Earnings Before Interest and Taxes/Capital Employed	0.897	-1.305	-1.29	0.906
EBITTL	Earnings Before Interest And Taxes/Total Liabilities	1.046	-1.323	-1.297	0.894
SCA	Sales/Current Assets	0.582	-0.986	-1.359	-1.425
AT	Sales/Total Assets	1.559	0.599	0.472	-1.143
TLTA	Total Liabilities/Total Assets	1.538	0.387	-1.111	-1.149
QR	(Current Assets - Stocks)/Current Liabilities	1.464	0.542	-1.299	-1.279
EBITSEQ	Earnings Before Interest And Taxes/Shareholders' Equity	0.679	-1.249	-1.078	0.818
TDCFFO	Total Debt/Cash Flow From Operations	-0.191	-0.952	0.246	-1.54
SFA	Sales/Fixed Assets	0.346	-0.844	-0.996	-1.42
TLNW	Total Liabilities/Net Worth	-0.401	-1.091	-1.411	-1.489
SWC	Sales/Working Capital	-0.386	0.179	-1.003	-1.212
SETD	Shareholders' Equity/Total Debt	-0.185	0.567	-0.866	-0.82

3.3.2.4 Hierarchical Cluster Analysis (HCA) of ratios

Once again, we followed the precedents set by Neophytou and Mar-Molinero (2004) and Khoja, Chipulu and Jayasekera (2014) in that we used hierarchical cluster analysis (HCA) to help us interpret the MDS dimensions. We used Ward's method to cluster the 28 ratios based on the Euclidean distances among them. We selected Ward as the clustering method because it produces compact clusters by minimising cluster variance (Punj and Stewart, 1983).

There were several stages in the HCA agglomeration schedule. We selected a five-cluster solution which appeared at the fifth stage. This was because we judged it to be the clearest solution. Table 3.5 is a summary of the contents of the clusters. Cluster 1 contains only the ratio *MVOESE;* Cluster 2 contains only *CFFOCL,* and Cluster 3 contains the activity ratio *AT* and the profitability ratio *GPM.* The presence of *AT* implies efficiency in generating sales from assets; *GPM* suggests efficiency in generating net revenues after accounting for cost of goods (Megginson and Smart, 2005). This combination, we believe, suggests that Cluster 3 is an indicator of **efficiency of sales activities.** Cluster 4 contains the three leverage ratios *SETD, TLTA* and *SETA,* the liquidity ratio *QR*, the activity ratio *IT* and the market ratio *MVOETD.* It is dominated by ratios which indicate a firm's ability to manage debt in such a way that it can maintain liquidity to finance its activities and accumulate market value, i.e. sustain day-to-day activities while growing in the long term. Therefore, we interpreted Cluster 4 as **operational and strategic debt management.** Cluster 5 is the largest. It contains 18 ratios, which cover all six ratio categories except market. Cluster 5 appears to represent nearly *all* measures of a firm's financial performance. Therefore, we labelled it **generic financial performance**.

3.3.2.5 Meaning of MDS dimensions

To enable visualisation and, hence, greater ability to see the structure in the data, we drew two-dimensional (2-D) maps of the MDS dimensions of the ratios using the coordinates in Table 3.4. This mapping approach is typical in MDS; see, for example, Neophytou and Mar-Molinero (2004). Figure 3.4 is a map of dimension 1 versus 2; Figure 3.5 is a map of dimension 3 versus 4.

Table 3.5: The contents of HCA ratio clusters

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

Since the dimensionality of the actual MDS configuration is higher than two, the relative locations of the ratios on the 2-D maps can be misleading (see, for example, Khoja, Chipulu and Jayasekera, 2014).

To help show the true overall distances among the ratios as well as aid interpretation, we added the five HCA clusters as an overlay on the MDS maps. In the same way that one would associate PCA components with high-loading variables, when interpreting each dimension, we paid the most attention to those ratios which have large (in absolute value terms) coordinate values on them; this is because those are the ratios that are most strongly associated with the dimension (see also Chipulu *et al.*, 2013).

In Table 3.4, we have highlighted the ratios we have used in this way. We interpreted the four MDS dimensions as follows:

Dimension 1: Effectiveness of sales and cash-generating activities

In Figure 3.4, clusters 3, 4 and 5 are all located on both the negative and positive sides of dimension 1. Therefore, none of the three clusters is, in itself, a clear pointer towards the meaning of dimension 1. However, one can see that *AT* (Sales/Total Assets), *TLTA* (Total Liabilities/Total Assets) and *QR* (Current Assets-Stocks)/Current Liabilities) have large, positive coordinates on dimension 1. *QR* reflects a firm's ability to use its liquid assets to meet short-term obligations (Robinson and Greuning, 2009); *AT* indicates how efficiently the firm can generate sales from its assets, and *TLTA* indicates how well the firm uses its creditors' funds to finance activities (Megginson and Smart, 2005; Bragg, 2012). *CFFOTA* (Cash Flow from Operations/Total Assets), *SETL* (Shareholders' Equity/Total Liabilities) and *CFFOCL* (Cash Flow from Operations/Current Liabilities) also have large, positive coordinate values on dimension 1. We believe this pattern of ratios represents a measure of how well a firm uses its assets and creditors' funds to generate sales and cash, and to maintain liquidity. A high level of cash or liquidity increases capacity to meet debt obligations: this may explain the large, positive coordinate of *TDS* (Total Debt/Sales). Thus, we interpreted dimension 1 to be an indicator of **effectiveness of sales and cash-generating activities**.

Dimension 2: Trade-off between debt management and cash generation/profitability

The proximity of clusters 3 and 4 on the positive side of dimension 2 in Figure 3.4 suggests this side of dimension 2 may represent a firm's effectiveness at managing debt, which may go hand in hand with efficient sales activities. Cluster 5 occupies most of the negative side of dimension 2. Given the generic nature of cluster 5, this provides no helpful guide *per se*. However, by inspecting Table 3.3, one can see that the ratios with the highest negative coordinates on dimension 2 are either indicators of profitability, namely *EBITS, EBITTL* and *EBITCE,* or cash flow measures, namely *CFFOTA, CFFOS and*

CFFOTL. Hence, we interpreted dimension 2 to be a **trade-off between debt management and cash generation/profitability.**

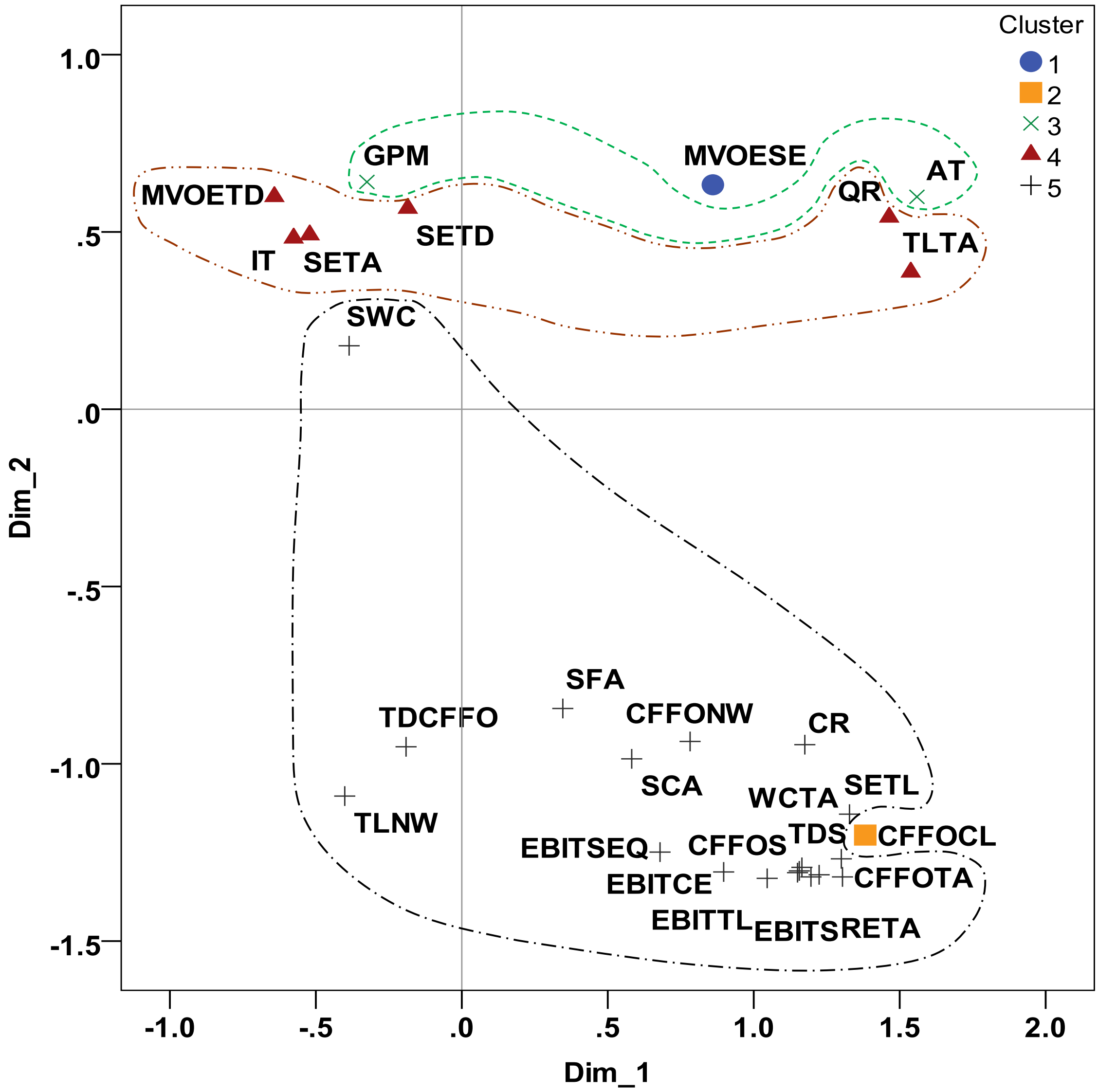


Figure 3.4: Map of dimension 1 versus dimension 2

Dimension 3: Usage of debt versus usage of own assets

Dimension 3 is similar to dimension 1 in that the location of the clusters is not very helpful in terms of interpreting the dimensions. Hence, as with dimension 1, we relied on the ratios with high coordinate values to interpret dimension 3. *CFFOCL* (Cash Flow from Operations/Current Liabilities) has the largest positive coordinate, followed by *MVOETD* (Market Value of Equity/Total Debt). Together, these two ratios suggest ability to generate cash and accrue market value from debt. In contrast, the two ratios with the largest negative coordinates *CFFONW* (Cash Flow from Operations/Net Worth) and TLNW (Total Liabilities/Net Worth) measure how well a firm uses its net worth. Dimension 3 appears to be a contrast between using debt, for example, to earn cash, as opposed to using a firm's own assets, i.e. its net worth. Therefore, we labelled dimension 3 **usage of debt versus usage of own assets.**

Dimension 4: Trade-off between profitability and cash-generating activities

As with dimensions 3 and 1, we interpreted dimension 4 by looking at the ratios with large coordinates. On the one hand, dimension 4 appears to be about profitability. The largest positive coordinates are for the profitability ratios *EBITCE* (Earnings before Interest and Taxes/Capital Employed), *EBITTL* (Earnings before Interest and Taxes/Total Liabilities) and *EBITSEQ* (Earnings before Interest and Taxes/Shareholders' Equity). On the other hand, the ratios with the large, negative coordinates are either indicators of cash generation, namely *TDCFFO* (Total Debt/Cash Flow from Operations), *CFFONW* (Cash Flow from Operations/Net Worth) and *CFFOTL* (Cash Flow from Operations/Total Liabilities), or indicators of activity; that is to say, *IT* (Cost Of Sales/Inventory), *SCA* (Sales/Current Assets) and *SFA* (Sales/Fixed Assets). We concluded, hence, that dimension 4 is a **trade-off between profitability and cash-generating activities.** We believe that this interpretation is consistent with the large, negative coordinate value of *TLNW* (Total Liabilities/Net Worth) on dimension 4: highly leveraged firms may be forced to generate large amounts of cash to meet their obligations, even at the expense of profitability.

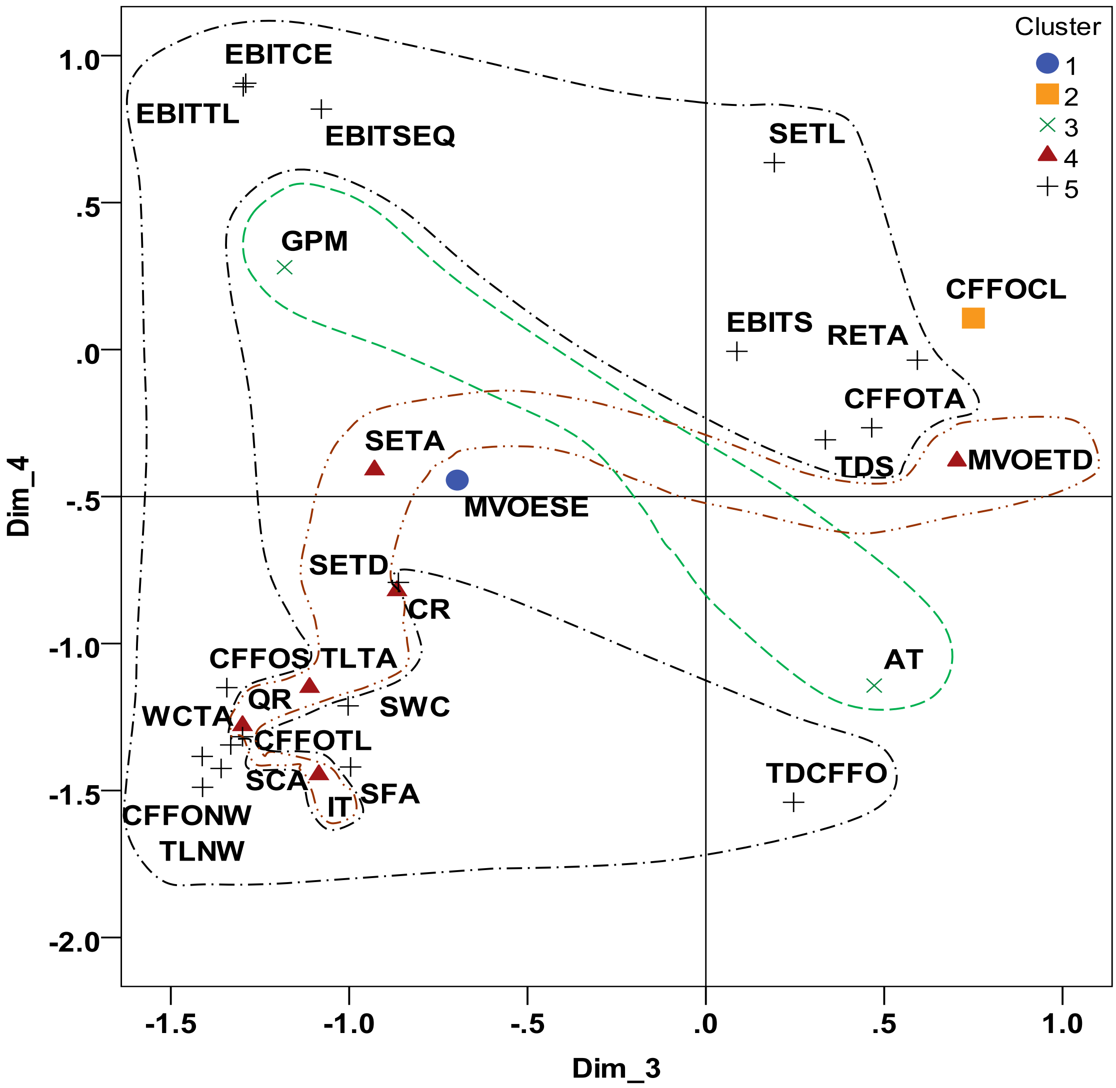


Figure 3.5: Map of dimension 3 versus dimension 4

3.3.2.6 Relative importance attached to MDS dimensions

We can infer the importance that each source attaches to the dimensions by studying the weights or re-scaling factors that are required to transform the common space into an individual space relevant only to each source. Table 3.6 is a summary of the importance weighting that each source attaches to each dimension and the overall relative importance of each dimension, which is determined by the amount of variance that each dimension accounts for. Table 3.6 also shows the specificity of each source. As explained by Khoja, Chipulu and Jayasekera (2014, page.19), 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*.'

We can observe some broad patterns from the data in Table 3.6. One is that insolvent firms are more specific than solvent firms. This is particularly pronounced in the USA and the GCC, where insolvent firms appear to disregard all but one of the dimensions. Another is that, based how much importance they attach to each dimension, GCC firms resemble USA firms more than UK firms.

We can also observe more particular patterns within these broad patterns. Insolvent firms in the GCC and the USA appear to attach low weight to dimension 1, unlike in the UK, where insolvent firms regard dimension 1 as having much more weight. Insolvent firms in the GCC attach much less weight to dimension 2 than those in the USA and, to a lesser extent, the UK. In contrast, insolvent firms in the GCC attach more weight to dimension 3 than those in the UK and, particularly, the USA. Insolvent firms are most alike in dimension 4, which they generally regard as being low weight.

Table 3.6: Importance attached to dimensions by sources

Source	Dimension				**Specificity**
	Dim_1	Dim_2	Dim_3	Dim_4	
GCC- (Insolvent)	3.0	18.4	1284.4	18.3	**0.9**
GCC- (Solvent)	1291.3	809.2	524.9	2.8	**0.4**
UK- (Insolvent)	1359.7	586.2	1.4	21.4	**0.6**
UK- (Solvent)	435.9	79.9	322.9	1288.8	**0.7**
USA- (Insolvent)	0.0	1400.4	0.0	0.4	**1.0**
USA- (Solvent)	1269.9	1010.6	331.3	313.4	**0.4**
Importance	**0.34**	**0.26**	**0.14**	**0.11**	

The patterns across solvent firms are different. Solvent firms are most alike in their regard for dimension 3 to which they generally attach moderate weighting. In dimension 1, solvent firms in the GCC attach about as much weight as those in the USA, and more weight than those in the UK. The pattern is somewhat similar in dimension 2; solvent firms in both the GCC and the USA attach more weight to dimension 2 than those in the UK but, unlike dimension 1, the USA weighting is clearly larger than that of the GCC. Solvent firms in the

GCC attach much less weight to dimension 4 than those in the USA and, particularly, the UK.

There is no consistent pattern in the weight differentials between insolvent and solvent firms. In this respect, UK and USA firms are more similar to each other than they are to GCC firms. The patterns of differences in weights in dimensions 2, 3 and 4 are the same across the USA and the UK two countries: insolvent firms place more weight on dimension 2 and less on both dimensions 3 and 4 than solvent firms do. This is the opposite to the GCC; in the GCC, insolvent firms place less weight on dimension 2 and more on both dimensions 3 and 4. The exception is dimension 1, which is regarded with more weight by insolvent firms than solvent ones in the UK, whereas the opposite is true in both the GCC and the USA. As such, while the GCC shares this one similarity with the USA in weight differentials, it does not share any similarity with the UK in any of the dimensions.

3.3.2.7 Property fitting: Relationship of macroeconomic conditions with MDS dimensions

The final step in the analysis was to examine the effects of macroeconomic variables on the four MDS dimensions in order to address Research Question 4. We did so using *Property fitting* or *Pro-fit*. Pro-fit is a method for fitting independent properties to the MDS configuration once it has been extracted, i.e. post-optimally. Typically, Pro-fit involves analysing how independent properties of interest are related to the MDS dimensions using correlation or regression analysis (see for example, Mar-Molinero and Mingers, 2006; Schiffman, Reynolds and Young, 1981).

There were two steps in the Pro-fit. Firstly, we calculated the proximity between each macroeconomic variable and each financial ratio using Kendall's Tau-b correlation coefficient. We chose Kendall's Tau-b because it is non-parametric and therefore suitable for the data which are non-normal. Secondly, we calculated the correlation (also using Kendall's Tau-b) between each macroeconomic variable and each of the MDS dimensions. We based this calculation on the proximity value for each ratio calculated in the first step and the coordinate value for that ratio on that MDS dimension (Table 3.4).

The results presented in Table 3.7 indicate that dimension 1, which we believe indicates the 'effectiveness of sales and cash-generating activities', is positively related to inflation and interest rates, and negatively to the stock index. Dimension 2, which we interpreted as the 'trade-off between debt management and cash generation/profitability', is negatively related to the inflation rate. The other two dimensions do not appear to be significantly related to any of the macroeconomic variables. The results also show that the price of oil is not related to any of the ratio dimensions.

Table 3.7: Correlations of macroeconomic variables with MDS dimensions

Macro Factor	Statistics	Dim_1	Dim_2	Dim_3	Dim_4
Stock Index	Coefficient	-0.571	0.193	-0.236	-0.18
	p-value	0	0.149	0.079	0.179
Inflation Rate	Coefficient	0.435	-0.316	0.135	0.18
	p-value	0.001	0.019	0.313	0.179
Interest Rate	Coefficient	0.582	-0.257	0.151	0.18
	p-value	0	0.055	0.26	0.179
Oil Price	Coefficient	0.207	-0.199	0.045	0.005
	p-value	0.123	0.138	0.737	0.968

3.4 Discussion

By comparing their means, we have found that there is no consistent pattern in how much bigger or smaller the financial ratios of firms in the GCC are than those of the UK or the USA. While the means of some ratios, e.g. *SETL*, are much larger in the GCC, and those of others, e.g. *CFFOCL*, are much smaller, most are not markedly different from those of the UK or the USA.

We have extracted four dimensions of ratios from 3-way MDS and Cluster analysis, which we have interpreted as 'effectiveness of sales and cash generating activities', 'trade-off between debt management and cash generation/profitability', 'usage of debt versus usage of own assets' and 'trade-off between profitability and cash-generating activities'. The dimensions differ from the ones Khoja, Chipulu and Jayasekera (2014) extracted but we are not surprised at this finding because our dimensions are common to firms in the

GCC, the UK and the US, whereas (Khoja, Chipulu and Jayasekera, 2014) focused *only* on firms in the GCC.

We posed four research questions. Firstly, ***in what way are the financial structures of healthy firms in the GCC similar to those in the UK and the USA?*** The results suggest the greatest similarity among solvent firms is that they appear to diversify their efforts; they are not very specific, in that they do not focus on only one, or predominantly one, of the four dimensions while overlooking the others. In terms of how much importance they place on specific dimensions, solvent firms in the GCC, the UK and the US are most similar in their regard for the third dimension, 'usage of debt versus usage of own assets', to which they all ascribe moderate levels of importance. It was found that solvent firms have the ability to use debt capital to increase profitability and liquidity. Higher levels of profitability and liquidity with lower levels of leverage indicate decreased risk insolvency.

On the other hand, there is little similarity in the levels of weight that solvent firms in the GCC, the UK and the US attach to the other three dimensions. The USA and GCC are more similar in terms of giving most weight to dimension 1, 'Effectiveness of sales and cash generation activities', as well as dimension 2, 'Trade-off between debt management and cash generation/profitability'. This clearly provides evidence of the similarly in the managerial styles between GCC and the USA in terms of using and managing their debt. Generally, in recent decades the GCC region has significantly developed by adopting similar managerial structures to the USA regarding knowledge exchange education. In the case of Saudi Arabia for example, this similarity in the managerial behaviour between Saudi and USA firms has been explained by the fact that since the 1950's most Saudi managers have been educated in the USA higher education system, which has led to the transfer of valuable knowledge to the Saudi firms (Marshall Hunt and At-Twaijri, 1996). Therefore, Multinational American firms in the oil, gas and petrochemical industries have imported their values into the GCC generally, and Saudi more particularly (Posner and Schmidt, 1984).

Secondly, ***in what way are the financial structures of insolvent firms in the GCC similar to those in the UK and the USA?*** Unlike solvent firms, insolvent firms appear to be very specific: in the GCC they appear to focus mainly on the 'usage of debt versus usage of own assets', while in the USA, they appear to focus only on the 'trade-off between debt management and cash generation/profitability'. Insolvent firms in the UK, which are the least specific, appear to attach most weight to 'effectiveness of sales and cash-generating activities'. Thus, although they all equally disregard the fourth dimension, 'trade-off between profitability and cash-generating activities', the aspects they consider most important, as captured by the MDS dimensions, differ between the GCC, the UK and the USA. Insolvent GCC firms struggle to generate profit using their own resources; rather, they finance their operations by borrowing and accumulating debts. This also suggests that specificity extends to the given macro environment: we cannot assume that the aspects which are most symptomatic of insolvency in the UK or the USA will be reliable identifiers of insolvency in the GCC.

Thirdly, ***in what way are the differences observed between solvent and insolvent firms in the GCC similar to the differences observed between solvent and insolvent firms in the United States and the UK?*** From the preceding discussion, we can conclude, as Khoja, Chipulu and Jayasekera (2014) did, that insolvent firms are much more specific than solvent firms. This shows the low level of the efficiency of operations and investment quality and it appears that they have difficulty in managing assets to generate a profit, which is also confirmed by (Aldeehani, 1995). In terms of the polarity of differences, i.e. whether insolvent firms regard a particular dimension to have more weight than solvent firms do, or vice versa, the GCC appears to have very little in common with the USA and, in particular, with the UK.

Finally, we asked: ***how are macroeconomic factors related to characteristics that typify insolvency in the GCC, and are the relationships comparable in the USA and the UK?*** Consistent with other studies (Desai and Montes, 1982; Liu and Wilson, 2002; Millington, 1994; Rose, Andrews and Giroux, 1982; Turner, Coutts and Bowden, 1992; Young, 1995), we found significant relationships between the dimensions of ratios and the macroeconomic variables. The results suggest that inflation, interest rates and the stock index are significantly related to dimension 1, ‘effectiveness of sales and cash generating activities’. Inflation is also related to dimension 2, ‘trade-off between debt management and cash generation/profitability’. Since neither insolvent firms in the GCC nor those in the USA consider dimension 1 as important, the observed correlations imply, by overlooking dimension 1, that insolvent firms in the GCC and the USA may also be overlooking the macroeconomic factors which are associated with dimension 1.

Overall, our results suggest that differences (or similarities) between firms in the GCC and those in the UK and the USA are much more nuanced than straightforward. This has one clear implication for creditors, investors and competitors: applying findings from, or applying models calibrated in, the USA or the UK to the GCC is likely to produce misleading conclusions. The financial health of firms should be examined *in situ* within the ‘local’ macro environment. There is also a clear implication for managers of firms: paying most of one’s attention to one aspect of financial performance appears to increase the risk of insolvency.

3.5 Conclusion

At the time of writing, we know of no other study that has attempted to examine similarities and differences in the financial structure of firms in the GCC versus those in the UK and the USA. In this respect, this study makes a unique contribution: by adopting a multilevel approach, we now have some indication of what those similarities/differences are. The current study also contributes to the corporate insolvency literature by increasing the pool of evidence about the character of insolvency in the GCC, which is sparse compared with other contexts.

As is typically the case in corporate insolvency research, this study suffers from the lack of a large population of failed firms to draw upon. Future research could improve on it as more records of failed firms become available in the GCC. Researchers could extend the multilevel analysis so that it incorporates the effect of macroeconomic changes over time; they would then be able to examine how time-dependent patterns, such as business cycles, may impact the nature of insolvency in the GCC. With more data, they could also make the MDS model more robust by partitioning the dataset into training and validation sets: they could use the training set to extract the dimensions as we have done, and then validate the meaning of the dimensions using the validation set. In this study, although we matched insolvent and solvent firms by industry sector, we have not directly analysed the effect of industry sector, so another way the study could be improved upon is by analysing how differences across industry sectors may be influential.

Chapter 4

Study 3: The Impact of Macroeconomic Indicators on Failure Rate in the Gulf Cooperation Council

Abstract

In this paper we examine the dynamic causal relationships among macroeconomic indicators and the corporate failure rate in the GCC region. Macroeconomic indicators have been collected quarterly from 2000 to 2013 for the GCC region and analysed by using the Autoregressive Distributed Lag model (ARDL) bound test. We find that in the GCC region, oil prices, combined with macroeconomic indicators, impact the failure rate in the long-run equilibrium. In terms of the short-run, the ARDL model confirmed that the corporate failure rate is mainly determined by the previous period's failure rate.

4.1 Introduction

Corporate insolvency has been studied widely in microeconomic research by successfully using financial ratios (Charan, Useem and Harrington, 2002). Researchers believe that the microeconomic causes have significant association with a firm's weaknesses that can be attributed to managerial problems. However, Macro-economists have also proved that company failure corresponds to macroeconomic factors, such as interest rate (Desai and Montes, 1982; Liu, 2004) and inflation rate (Bhattacharjee *et al.*, 2004). Additionally, there are other studies that apply the effect of the bankruptcy codes along with macroeconomic factors to the failure rate (Bhattacharjee *et al.*, 2004; Song and Meeks, 2009). Regardless of the fact that macroeconomic theory has been paid less attention than microeconomic studies in this field (Goudie and Meeks, 1991), microeconomic studies provide several econometrics techniques, such as a Cox Proportional Hazards model (Bhattacharjee *et al.*, 2004), the macro-industry model (MDM) (Goudie and Meeks, 1991), to identify the effect of the macroeconomic indicators only in the short-run relationship among variables. The studies that have been designed to investigate the macroeconomic determinants of corporate failures in long- and short-run equilibrium are *very rare.* Among them are the works of Liu and Wilson (2002) and Liu (2004), which used the error correction model (ECM), and Halim *et al.* (2009), which applied the Autoregressive Distributed Lag (ARDL) model.

Thus, this paper attempts to provide econometric theoretical and empirical insights into the dynamic causal relationships among macroeconomic indicators of the corporate failure rate in the long- and short-run equilibrium in the Gulf Cooperation Council (GCC) region. Analysis of corporate insolvency studies is narrow and limited in the GCC literature; GCC research has focused mainly on testing the financial ratios by using alternative methods: multiple discriminant analysis (MDA); logistic regression (Basheikh, 2012; Khoja, Chipulu and Jayasekera, 2014); and the Multidimensional Scaling Model (MDS) (Khoja, Chipulu and Jayasekera, 2014). Testing the effect of the macroeconomic enviroment has been neglected in this region. To the best of our knowledge, no research has been conducted on the impact of the macroeconomic environment on the financial rate in GCC studies.

We apply the ARDL co-integration approach which has been developed by Pesaran, Shin and Smith (2001) for three reasons. Firstly, to determine the association between the macroeconomic variables and the corporate failure rate for short- and long-run equilibria. Secondly, the ARDL model does not request the same order of integration (Pesaran, Shin and Smith, 2001). Finally, the ARDL technique is a powerful test in terms of examining small-sample datasets (Tang and Nair, 2002; Halim *et al.*, 2009). We assume that this study will be of importance to managers and companies' owners, economists, and financial analysts. We also posit that this study can assist policymakers to adopt strategies that will reduce the levels of insolvency risk and cost.

The paper is structured as follows: the second section reviews the macroeconomic literature. The third section outlines the econometric method to uncover the effects of the macroeconomic indicators on the failure rate of firms. In the fourth section, we report and discuss the short- and long-run relationships among the variables. In the final section, the paper summarises the work with concluding remarks.

4.2 Literature review

The majority of financial failure studies have investigated intensively the causes of corporate failures in the microeconomic environment. Beaver (1966) employed a univariate model, i.e. using a single predictor variable, to predict financial failure. Altman (1968) used multiple-predictor variables by applying multiple discriminant analysis (MDA) to overcome the limitations in Beaver's model. The MDA technique is a popular technique in the corporate insolvency literature (Deakin, 1972; Taffler and Tisshaw, 1977; Casey and Bartczak, 1985), but logistic regression was introduced by Ohlson (1980) to address the limitations of MDA. Logistic regression does not require multivariate normality of the independent variables or equal dispersion matrices, and no assumptions are made for the distribution of financial ratios or prior probabilities of failure (Ohlson, 1980; Zavgren, 1983; Peel, Peel and Pope, 1986). More recently studies and academic research have developed a more statistically advanced method rather than applying the one of the traditional statistical techniques, such as the Probit model (Gentry, Newbold and Whitford, 1987; Lennox, 1999), Instead, artificially intelligent expert system models (AIES) have been applied, including Genetic Algorithms (Mckee and Lensberg, 2002), Neural Networks (Salchenberger, Cinar and Lash, 1992; Coats and Fant, 1993; Wilson *et al.*, 1995). By comparing the global literature with the GCC literature, the GCC area only has a limited number of insolvency studies (Khoja, Chipulu and Jayasekera, 2014; Maghyereh and Awartani, 2014).

Despite the fact that a firm's financial failure is fundamentally a microeconomic phenomenon, the probability of the failure can also be impacted by the whole economic environment in which the firms are operating (Levy and Bar-Niv, 1987). The fluctuations in economic indicators and the business cycles can be developed by analysing and determining the corporate failure factors (Levy and Bar-Niv, 1987). Bernanke (1981, p.157) stated that *"costly bankruptcy and asset illiquidity bring a distinctly Keynesian flavor to the analysis of recession"* According to the Keynes theory, demand for each industry's products has been identified based on the supply and demand schedules for industries, which indicate that if the failure rates getting higher in the upstream (buying) industry, it might be a reason to increase the failure rate in the downstream (selling), by reducing the selling industry's product demand (Platt, Platt and Pedersen, 1994). By using macroeconomic indicators previous studies have shown that company failure rate corresponded to the macroeconomic developments in different contexts (Bhattacharjee *et al.*, 2004; 2009). Macroeconomic indicators contribute differently to corporate failure rate, i.e. empirical results have found a positive relationship between failure rate and the interest rate (Desai and Montes, 1982; Hudson, 1986; Turner, Coutts and Bowden, 1992; Geroski, Machin and Walters, 1997; Liu and Wilson, 2002; Bhattacharjee et al., 2004), as well as the inflation rate (Wadhwani, 1986; Bhattacharjee *et al.*, 2004) and the exchange rate (Goudie and Meeks, 1991; 1992; 1998), unlike the growth of money stock (Desai and Montes, 1982), and profit (Hudson, 1986; Turner, Coutts and Bowden, 1992), which have a negative relationship with failure rate.

Desai and Montes (1982) provided the first evidence of the relationship between the failure rate and macroeconomic factors: the money stock and the interest rate in the period 1945-1980 in the UK. They proved that the monetary variables are significant when identifying the corporate failure rate. Altman (1983) and Fich and Slezak (2008) provided evidence of the impact of the Standard & Poor's 500 index of stock prices (S&P) on the aggregate of the failure rate. By using the polynomial-distributed lag method, Hudson (1986) determined that the main external cause for the failure rate was the real interest rate. Wadhwani (1986) found that there is a strong significant relationship between a high level of the inflation rate and increasing corporate failure rate, as evidenced by declining stock market prices in the UK listed companies during the period 1964-1981. Goudie and Meeks (1991) also showed the relationship between the macroeconomic factors and the failure rate by applying macro and micro models to the large listed UK companies which failed between 1979 and 1983. They also found that the exchange rate variation had an impact on the financial failure rate of UK companies in international markets. Bhattacharjee *et al.* (2003; 2004; 2009) came up with empirical evidence of the relationship between macroeconomic indicators, the firm size and the industry-specific factors with corporate failure rate by applying risk hazard regression models; they also found higher failure rate and lower acquisitions in periods of high macroeconomic instability. However, there are some other studies have been done to develop the bankruptcy models in different industries, such as the oil and gas industries, which have added a specific independent predictor, i.e. oil prices, which has been associated with this specific industry more than others. Oil prices have been successfully used only in these studies as a proxy of the income of the oil and gas firms, and they reveal that increases in the oil price supposes a decrease in the probability of a firm's failure. Platt *et al.* (1994) developed a bankruptcy early warning model by using oil prices as an external factor to predict the corporate insolvency of firms in the oil and gas industries. In the same way, the motivation for examining the oil price in this paper comes from the natural economy of the GCC region, which considers the six countries of the GCC to be an oil-based region. Thus, the first research hypothesis is:

(RH1): The oil prices have an impact on the company failure rate in GCC countries

The Keynes (1935) theory is primarily concerned with equilibrium states which are consistent in both short run and long run equilibria (Hansson, 1985). The theoretical part of this paper hypothesizes that the macroeconomic factors have a negative and positive impact on the failure rate of firms. Few previous studies have provided evidence of this rationale. Liu and Wilson (2002) and Liu (2004) developed their econometric models by examining the macroeconomic determinants, in short-run and long-run behaviours, of the failure rate in the UK. Further, they also investigated the influence of the Insolvency Act 1986 by using the Error Correction Model (ECM). The result shows that the failure rate is associated with macroeconomic indicators in both the long- and short-runs. The Insolvency Act 1986 also shows its impact on the UK corporate failure rate. Following the same lines as this study, Halim *et al.* (2009) examined the long- and short-run relationships between the failure rate and the Malaysian macroeconomic indicators by employing the Autoregressive Distributed Lag model (ARDL) bound test, which test is applicable for regressors which have mixed integrated order. The results show that the Malaysian failure rate has long-run equilibrium with lending rate, GDP and the inflation rate. Regarding the GCC studies, to the best of the author's knowledge, at the time of writing there are no studies in this area that examine the impact of macroeconomic factors on GCC failure rate; hence, this study addresses this gap in the literature by answering the following research hypotheses:

(RH2): There is a long-run dynamic among macroeconomic indicators and corporate failure rate in the GCC.

(RH3): There is a short-run dynamic among macroeconomic indicators and corporate failure rate in the GCC.

Bankruptcy code is another factor that has been examined together with macroeconomic factors in corporate insolvency studies (Bhattacharjee *et al.*, 2004; Song and Meeks, 2009). Variances in insolvency rates have been observed before and after legislation within and across countries. Liu and Wilson (2002) and Liu (2004) introduced the impact of the United Kingdom's 1986 Insolvency Act on corporate failure rate, and explored it in association with the macroeconomic determinants. Bhattacharjee (2004) also concluded that the UK bankruptcy code is less significant as a bankruptcy hazard in macroeconomic instability than that of the impact of Chapter 11 in the United States during periods of macroeconomic instability. Swanson and Tybout (1988) provided evidence of its influence when applying the exchange rate regime in Argentina in 1978 to the corporate failure rate. At present, the impact of the insolvency regime in the GCC is difficult to address because the GCC government introduced adequate measures and reforms for instances of insolvency which are effective, quick and simple (Raghu, Pattherwala and Tulsyan, 2013) after the recent global financial crisis uncovered the lack of effective bankruptcy regimes, (Uttamchandani, 2011) which had contributed to firms' bankruptcy in the region. In Kuwait, the Ministry of Commerce and Industry presented a new Companies Law No. 25 of 2012, which is an essential development from the previous one which was issued in 1960 (Raghu, Pattherwala and Tulsyan, 2013). Dubai adopted a new concept, the "Reorganization code" in the law (Gine and Love, 2009) influenced by Chapter 11 of the US Insolvency Act. Recently, Saudi Arabia proceeded to issue a new draft bankruptcy law to supersede the 1930 Law (improved upon in 1996) (Raghu, Pattherwala and Tulsyan, 2013).

4.3 Methods

4.3.1 Sampling and data

In order to evaluate the impact of the macroeconomic indicators on the corporate failure rate, quarterly data was collected for all the GCC countries

(Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the United Arab Emirates) covering the period from 2000:1 to 2013:4, which identified 56 observations during the period, as shown in Table 4.1. The corporate failure rate was calculated as a ratio to indicate the number of failed firms in each specific quartier in relation to the total number of GCC listed firms under the legal framework which governs the companies system in the GCC. The shareholding company is considered to have failed - and must be delisted from the stock market - when 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; Qatar - Ministry of Economy and Commerce, 2002). This study uses the macroeconomic factors which the literature has recorded as having a significant impact on the failure rate. We calculated the average for each of the indicators in order to consider the countries as one region over the same period. The *lending interest rate* was chosen to measure the cost of borrowing. Thus, the interest rate is considered to be the leading indicator for corporate financial failures (Liu, 2004). The *GCC MSCI Global Equity Index* was chosen as a proxy to measure the stock market performance at the time of the failure. All these factors were obtained from the Thompson Financial DataStream. The *inflation rate* was chosen to measure consumers' purchasing power and the company's profitability, which was collected from the Bloomberg database. *Oil prices* were selected as a proxy of the GCC economic income. This factor was collected from the OBEC database.

Table 4.1: Descriptive statistics of macroeconomic factors

Variable	N	Mean	Std. Dev.	Min	Max
Failure rate (FR)	56	.0045	.0059	0	.035
MSCI Global Equity Index (INDEX)	56	2.96	2.79	-.76	10.92
inflation rate (INFR)	56	7.34	1.29	5.219333	10.31
interest rate (INR)	56	62.50	33.49	17.97	138
Oil prices (OILPR)	56	4192.68	1789.71	1674.22	7992.99

4.3.2 Main econometric model

The estimating equation represented below was used to test the effect of the macroeconomic indicators on the corporate failure rate:

$$\ln(\mathrm{FR})_t = \alpha_0 + \beta_1 \ln(\mathrm{INDEX})_t + \beta_2 \ln(\mathrm{INFR})_t + \beta_3 \ln(\mathrm{INR})_t + \beta_4 \ln(\mathrm{OILPR})_t + \varepsilon_t \quad \textbf{(1)}$$

where $\ln(\mathrm{FR})_t$ is the natural log of corporate failure rate, $\ln(\mathrm{INDEX})_t$ is the natural log of stock market exchange index, $\ln(\mathrm{INFR})_t$ is the natural log of inflation rate, $\ln(\mathrm{INR})_t$ is the natural log of interest rate, $\ln(\mathrm{OILPR})_t$ is the natural log of oil prices, the parameter of α_0 is the intercept, and ε_t is the random error at time. In this study, equation (1) can be derived as a long-run equilibrium of the corporate failure rate.

Theoretically, the GCC MSCI Global Equity Index (INDEX) represents and reflects the performance of the stock market. Altman (1983), provides evidence of the impact of the Standard & Poor's 500 index of stock prices (S&P) in the US 1951-1978 with the aggregate of the failure rate. According to this, the coefficient of the price ratio β_1 should be negative. The inflation rate (INFR) reflects the relationship between the consumers' purchasing power and the company's profitability. Altman (1983) and Wadhwani (1986) stated that countries' governments believe that an increasing level of inflation has an unfavourable impact on a country's real economy. Consequently, the coefficient of the inflation rate (β_2) is expected to be positive. The lending interest rate (INR) should have a positive impact on the failure rate, as increasing the lending interest rate indicates increases in the cost of borrowing, which has a negative impact on a firm's profitability and raises the possibility of firm bankruptcy (Wadhwani, 1986; Liu, 2004; Halim *et al.*, 2009). Thus, the coefficient of the lending interest rate (β_3) is expected to be positive. As indicated by Platt *et al.* (1994), oil prices can be used as an external factor to predict the corporate insolvency of firms in the oil and gas industries. Therefore, we expected that the coefficient of the oil prices (β_4) would be negative.

4.3.3 ARDL approach and Results

In this paper we explored the dynamic relationship between macroeconomic variables and the corporate failure rate by using the Autoregressive distributed lag (ARDL) method, which was developed by Pesaran, Shin and Smith (2001). The ARDL model is a time series regression model, which includes a lagged value of the dependent variable (as a Autoregressive), as well as multiply lags (distributed lag) to the one or more explanatory variables (Stewart and Gill, 1998; Stock and Watson, 2012). The main advantages of the ARDL model over the other co-integration methods is that the ARDL model is very flexible to apply to variables that have a different order of integration; they can only be purely I(0), purely I(1), or mutually integrated (Pesaran, Shin and Smith, 2001).

As discussed earlier, there are few studies that have investigated the macroeconomic determinants of corporate failures in the long- and short-run equilibrium, such as Liu and Wilson (2002); (Liu, 2004), by using the Error Correction Model (ECM) and that of Halim *et al.* (2009) which applied ARDL. We use the ARDL co-integration approach developed by Pesaran, Shin and Smith (2001) for several reasons: (i) The error correction model integrates examination of the short-run equilibrium with the long-run relationship without losing the information about the long-run relationship (Shrestha and Chowdhury, 2007), (ii) the ARDL model contains one simple linear transformation of the ECM model (Banerjee *et al.*, 1993; Shrestha and Chowdhury, 2007) and, (iii) the ARDL technique is a powerful test in terms of testing small-sample datasets (Tang and Nair, 2002; Halim *et al.*, 2009).

Figure 4.1 shows the ARDL method progress steps which started with estimating ordinary least squares (OLS) after selecting the maximum order of lags by using the Akaike information criteria (AIC). Then an F-statistic was used to test the long-run equilibrium of the model. Following that, to determine the appropriateness of the ARDL model, we conducted a diagnostic test - the serial correlation of the model - by using the Breucsh-Godfrey serial correlation test, and the stability of the model by using CUSUM (Pesaran, Shin and Smith, 2001). In the last stage, a short run of variables was examined by applying the condition error correction model and the general-to-specific procedure. The general-to specific-procedure, and the reduction procedure continually eliminated the highest non-significant variables (Stock, 1987).

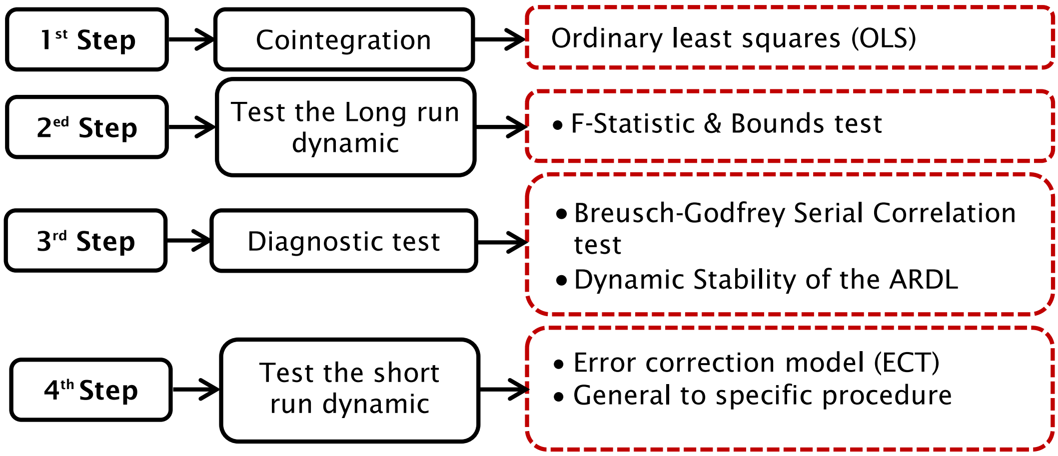


Figure 4.1: ARDL Model progress steps

4.3.4 Unit root

The main concern in time-series analysis is the stationarity of the economic data. The nature of economic time series data generally has been assumed to be non-stationary (Engle and Granger, 1987), because it is characterized by a "random walk", which means that this value of the period is equal to the last period's value and to the random walk (Kennedy, 2003). Thus, the stationarity of the economic data must be tested, and then the non-stationary is such that the differencing will create a stationary condition. *Kennedy (2003, p. 326) "A variables is said to be integrated written I(d), if it must be differenced d times to be made stationary. Thus a stationary variable is integrated of order zero, written I(0), a variable which must be differenced once to become stationary is said to be I(1), integrated of order one, and so on".*

Thus, this study tests the stationarity of the variables by using the Augmented Dickey–Fuller test by Dickey and Fuller (1979), which is the most commonly used unit root test in empirical studies, performs relatively well when applied to linear time series. the Phillips–Perron unit-root test by Phillips and Perron (1988) for the natural lag of the variables. Hasan (2010, p. 238) said *"It is well known that the Augmented Dickey-Fuller (ADF) and Phillips-Perron unit root tests have low power in rejecting the null of a unit root and are prone to size distortion".* The ARDL method assumed that the regressors are on a different order of integration. In order to use the ARDL method to examine the long-run and short-run relationships between the failure rate and the macroeconomic variables, we have to ensure that the variables are not integrated of order two (Pesaran, Shin and Smith, 2001).

Table 4.2: Unit root tests

Variable's name	Intercept				Trend			
	Level		First difference		Level		First difference	
	t-statistic	5% Critical Value	t-statistic	5% Critical Value	t-statistic	5% Critical Value	t-statistic	5% Critical Value
Augmented Dickey–Fuller test								
FR	-4.1	-2.93	-7.37	-2.93	-4.72	-3.4	-7.32	-3.49
INFR	-1.73	-2.93	-5.8	-2.93	-1.97	-3.49	-5.75	-3.49
INR	-0.59	-2.93	-522	-2.93	-1.14	-3.49	-5.2	-3.49
OILPR	-1.21	-2.93	-6.52	-2.93	-3.07	-3.49	-6.5	-3.49
INDEX	-1.54	-2.93	-5.45	-2.93	-1.35	-3.49	-5.5	-3.49
Phillips–Perron unit-root test								
FR	-26.47	-13.32	-54.48	-13.32	-31.14	-19.85	-54.60	-19.84
INFR	-5.59	-13.34	-42.36	-13.33	-8.02	-19.89	-42.43	-19.87
INR	-0.65	-13.34	-36.98	-13.33	-2.6	-19.89	-36.1	-19.87
OILPR	-2.8	-13.34	-48.17	-13.33	-17.08	-19.89	-48.19	-19.87
INDEX	-3.12	-13.34	-39.18	-13.33	-3.68	-19.89	-39.72	-19.87

Notes: Hypothesis of unit root has been rejected by MacKinnon critical values at the significance level of 5%. Unit root test includes intercept or trend.

The results in Table 4.1 show that all the macroeconomic variables are non-stationary at the level; rather they are integrated of order one, except for failure rate (FR) which shows stationarity in 5% critical value in intercept and trend. KPSS tests also confirm our Augmented Dickey–Fuller and Phillips–Perron unit-root results. We accepted the null hypothesis at 10% significance level, while the rest of the variables in the same level were rejected.

4.3.5 Cointegration

The unit root was tested for all the macroeconomic variables to ensure that the variables were not integrated in more than I(1) in order to apply the autoregressive distributed lag (ARDL) bounds testing approach to co-integration (Pesaran, Shin and Smith, 2001). Recent Co-integration literature provided the solution to determining the long run and short run relationship between multiple predictors with different orders of integration (Choudhry, Hassan and Papadimitriou, 2014). The ARDL bounds test (Pesaran, Shin and Smith, 2001) could be applied by using Ordinary Least Squares (OLS). The results are shown in Table 4.2, based on the following estimated equation:

$$\Delta \ln(\mathrm{FR})_t = \alpha_0 + \delta_1 \ln(\mathrm{FR})_t + \delta_2 \ln(\mathrm{INDEX})_t + \delta_3 \ln(\mathrm{INFR})_t + \delta \,\mathrm{In}(\mathrm{INR})_t + \delta_5 \ln(\mathrm{OILPR})_t + \sum_{i=1}^{p} \alpha_{i1} \Delta \ln(\mathrm{FR})_{t-i} + \sum_{i=1}^{p} \alpha_{i2} \Delta \ln(\mathrm{INDEX})_{t-i} + \sum_{i=1}^{p} \alpha_{i3} \Delta \ln(\mathrm{INFR})_{t-i} + \sum_{i=1}^{p} \alpha_{i4} \Delta \,\mathrm{In}\,(\mathrm{INR})_{t-i} + \sum_{i=1}^{p} \alpha_{i5} \Delta \,\mathrm{In}(\mathrm{OILPR})_{t-i} + \varepsilon_t \quad \textbf{(2)}$$

where In(FR) is the natural log of corporate failure rate, In(INDEX) is the natural log of stock market exchange index, In(INFR) is the natural log of inflation rate, In(INR) is the natural log of interest rate, In(OILPR) is the natural log of oil prices, the parameter of α_0 is the intercept; Δ is first difference, and ε_t is the random error at time. We decided to choose lag 1 for the conditional ARDL model based on Akaike information criteria (AIC) given by selection-order criteria (see Table 4.3).

Table 4.3: ARDL model by ordinary least squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.132114	4.040527	-0.527682	0.6006
In(FR(-1))	-0.886342	0.169322	-5.234643	0.0000
In(INDEX (-1))	-0.370608	0.449457	-0.824569	0.4144
In(INFR (-1))	0.015686	0.127922	0.122623	0.9030
In(INR (-1))	0.612701	0.918791	0.666856	0.5086
In(OILPR (-1))	-0.214753	0.382946	-0.560793	0.5780
Δ In(IFR (-1))	0.336513	0.147731	2.277881	0.0280
Δ In(INDEX (-1))	0.211415	0.935980	0.225875	0.8224
Δ In(INFR (-1))	0.085736	0.154868	0.553608	0.5829
Δ In(INR (-1))	-3.646663	4.360669	-0.836262	0.4079
Δ In(OILPR (-1))	-0.067671	0.682906	-0.099093	0.9215
R-squared	0.432824			
Adjusted R-squared	0.294488			
Durbin-Watson stat	1.837731			

The first part of this equation which contains $\delta_1, \delta_2, \delta_3, \delta_3, \delta_4, \delta_5$ represents the long-run dynamic of the model. The null hypothesis is $\mathrm{H0}: \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$, which indicates no long-run relationship among the variables. We conducted a bounds test by adopting the approach taken by Pesaran, Shin and

Smith (2001) to test this hypothesis. The second part of the equation, which includes $\alpha_{i1}, \alpha_{i2}, \alpha_{i3}, \alpha_{i4}, \alpha_{i5}$, examines the short-run relationship among the variables by developing the condition error correction dynamic of the model.

Table 4.4: Selection-order criteria

lag	LL	LR	df	P	FPE	AIC	HQIC	SBIC
0	-151.923				.000288	6.03549	6.10742	6.22311
1	72.5196	448.88	25	0.000	1.3e-07*	**-1.63537***	-1.20379*	-.50965*
2	97.1867	49.334	25	0.003	1.4e-07	-1.62257	-.831347	.44125
3	112.249	30.125	25	0.220	2.2e-07	-1.24035	-.089489	1.76156
4	132.818	41.138*	25	0.022	3.0e-07	-1.06992	.440582	2.87009

4.3.6 Estimation of long-run relationship

Returning to equation 2, in the third step of the ARDL approach, we tested the long-run equilibrium among the variables. Based on the ARDL technique, the result reveal evidence of the cointegration between macroeconomic indicators and failure rate, which suggest a long-run equilibrium relationship among the underlying variables.

Table 4.5: Estimated long-run coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.078717	3.933490	0.274239	0.7851
ln(INDEX)	-0.246777	0.434078	-0.568508	0.5723
ln(IINFR)	0.004436	0.119775	0.037039	0.9706
ln(INR)	-0.894595	0.904764	-0.988761	0.3276
ln(OILPR)	-0.671422	0.359738	-1.866422	0.0680
R-squared	0.230877			
Adjusted R-squared	0.168092			
Durbin-Watson stat	1.184784			

Table 4.5 presents the estimated long-run coefficients of the ARDL model, and the results show that only the oil price is statistically significant at 10%. F-statistics were calculated to examine the long-run relationship among the variables by using the Wald test developed by Pesaran, Shin and Smith (2001). By conducting F-statistics for combined significance of the lagged level of the independent variables, the null hypothesis is that there is no co-integration $H0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$. If the value of the F-statistic exceeds the upper critical bounds value, then the null hypothesis is rejected, while it is accepted if

the F-statistic is lower than critical bounds value. However, the co-integration is inconclusive if the F-statistic is found between the critical bounds value (Pesaran, Shin and Smith, 2001). We assumed that all the variables in the second part of the equation were co-integrated in order one. In this case, the calculated F-statistics are presented in Table 4.6 by showing higher value than the upper-bound critical value (4.01) at the 5% level. This implies that the null hypothesis of no co-integration between the variables has been rejected. The co-integration results show that there is a long-run relationship among the variables, which means that the independent variables move together with the failure rate as a dependent variable.

Table 4.6: F-statistics for testing long-run relationship

Test Statistic	Value	Df	Probability
F-statistic	5.883886	(5, 41)	0.0003
Chi-square	29.41943	5	0.0000
Lower-bound Critical value at 5%	2.86		
Upper-bound Critical value at 5%	4.01		

4.3.7 Diagnostic test

The ARDL model fits well with R^2 = 43%. However, to ensure the appropriateness of our model, we applied the diagnostic test against serial correlation by using the Breusch-Godfrey Serial Correlation LM Test. The ARDL model and bounds test required that the model should be serially independent in the same lag which has been chosen in equation (2) (Pesaran, Shin and Smith, 2001). The result shows the Prob. F (.28) and Prob. Chi-Square (0.23) at more than the 5% level, meaning that we cannot reject the null hypothesis and that this model does not have a serial correlation. Moreover, the CUSUM of the square represented in Figure 4.2 has been used to confirm the stability of our model. This figure shows an absence of the coefficients instability because the plot of the CUSUM appears within the 95% confidence interval of parameter stability.

Table 4.7: Breusch-Godfrey Serial Correlation LM Test

F-statistic	1.163688	Prob. F(1,40)	0.2872
Obs*R-squared	1.470029	Prob. Chi-Square(1)	0.2253

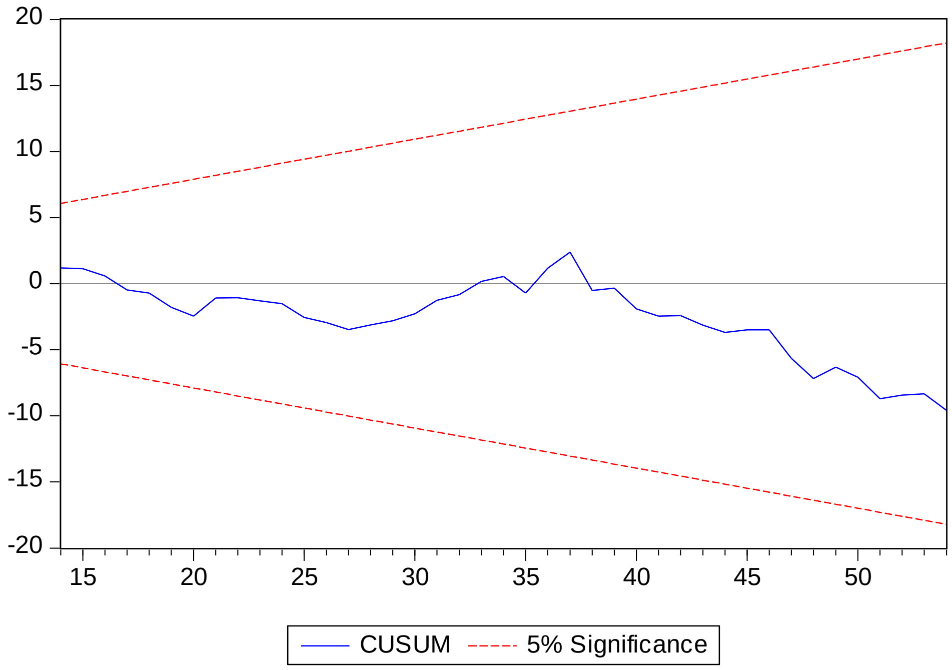


Figure 4.2: Stability of the ARDL Model

4.3.8 Estimation of short-run relationship

In this study we found evidence of the long-run dynamic among the variables. As a final step of the ARDL model, we estimated the long-run co-integration with the corresponding condition of the error correction model (ECM). This indicates the speed of adjustment for the long-run equilibrium after a short disturbance (Waliullah *et al.*, 2010; Belloumi, 2014). Unrestricted ECM of the ARDL equation is represented as:

$$\Delta \ln(\mathrm{FR})_t = \alpha_0 - \alpha\, \mathrm{ECM}_{t-1} + \sum_{i=1}^{p} \alpha_{i1}\, \Delta \ln(\mathrm{FR})_{t-i} + \sum_{i=1}^{p} \alpha_{i2}\, \Delta \ln(\mathrm{INDEX})_{t-i} + \sum_{i=1}^{p} \alpha_{i3}\, \Delta \ln(\mathrm{INFR})_{t-i} + \sum_{i=1}^{p} \alpha_{i4}\, \Delta\, \mathrm{In}\,(\mathrm{INR})_{t-i} + \sum_{i=1}^{p} \alpha_{i5}\, \Delta\, \mathrm{In}(\mathrm{OILPR})_{t-i} + \varepsilon_t \quad \mathbf{(3)}$$

In the above equation, $\alpha\, \mathrm{ECM}_{t-1}$ replaces the first part of equation (2) which represents the long-run equilibrium. The rest of the equations represent the short-run.

The results of the ECM model depicted in Table 4.8, (ECM_{t-1}) show a statistically significant and high negative coefficient (-0.87), which indicates that 87% of the volatilities from the previous period of time have converged to the long-run equilibrium in a recent time period. The T-statistic (-5.288) shows higher than the lower (-2.86) and upper (-3.99) bounds tests, which were developed by Pesaran, Shin and Smith (2001). The results show that the failure rate has a long-run relationship, and confirm the bound test co-integration results. In terms of the short-run, only the difference lagged of the failure rate has a significant impact on itself, while all of the macroeconomic factors show no significant impact in the short-run on the corporate failure rate.

Table 4.8: Error correction model for the selected ARDL model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.021975	0.105537	-0.208219	0.8360
ECM(-1)	-0.874196	0.165295	**-5.288707**	0.0000
Δ ln(FR(-1))	0.341156	0.144573	2.359750	0.0227
Δ ln(INDEX(-1))	-0.118227	0.851953	-0.138772	0.8902
Δ ln(INFR(-1))	0.073183	0.140430	0.521135	0.6048
Δ ln(INR(-1))	-2.700965	3.892498	-0.693890	0.4913
Δ ln(OILPR(-1))	0.130631	0.618118	0.211337	0.8336
R-squared	0.399252			
Adjusted R-squared	0.319152			
Durbin-Watson stat	1.816119			

To confirm the previous result, this study applied the general-to-specific procedure. This method, also called the reduction procedure, continually eliminated the highest non-significant variables (Stock, 1987) to uncover only the most significant variables. Table 4.9 reports the results of the general-to – specific procedure.

Table 4.9: ARDL model: general-to-specific procedure

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.009942	0.089450	-0.111140	0.9120
ECM (-1)	-1.319811	0.231404	-5.703483	0.0000
Δ ln(FR(-1))	0.813973	0.187645	4.337829	0.0001
R-squared	0.400343			
Adjusted R-squared	0.375867			
Durbin-Watson stat	1.870584			

The results corroborate that there is no statistical significance for the macroeconomic variables in the short-run, except the differences lagged for the failure rate itself. The ECM (-1) shows a statistically significant and high negative coefficient (-1.31) which confirm also the co-integration among the macroeconomic indicators.

4.4 Discussion

After reviewing the insolvency literature, we concluded that various external factors have impacted on the corporate failure rate from one economy to another. The purpose of the paper was to examine the impact on the long- and the short-run dynamics in the GCC region. Our research hypotheses have been answered based on analysis of macroeconomic factors by applying ARDL to estimate the quarterly data from 2000:1 to 2013:4 periods. Based on the results, the first research hypothesis, ***(RH1): The oil prices have an impact on the company failure rate in GCC countries.,*** has been answered. The results show that the oil prices, combined with other macroeconomic indicators, have an impact on the failure rate in the long-run equilibrium in the GCC region. This is an expected result due to the oil –based nature of the GCC economy[1]. From the experience of the recent financial crisis, increasing the oil revenue during the oil prices boom from 2003-2008 limited the negative impact of the global financial crisis by using large GCC governments' fiscal surpluses to employ countercyclical measures and to increase liquidity in the financial sector (Khoja, Chipulu and Jayasekera, 2014). Consequently, credit growth and asset prices rose and GCC governments paid more attention to boosting non-oil sectors (Arvai, Prasad and Katayama, 2014). However, when this situation reversed in 2008, and the oil price dropped to US$49.79 per barrel from US$ 110.01 (OPEC, 2013), the region faced many financial vulnerabilities, notably

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[1] In 2010, the oil and gas sector represented only 5% of global GDP, while accounting for 43% of the GDP in the GCC region.

increasing leverage, limited liquidity (Arvai, Prasad and Katayama, 2014) and firm insolvency (Khoja, Chipulu and Jayasekera, 2014). Arvai, Prasad and Katayama (2014) posited that the movement of the GCC economic cycle, together with the oil price cycle (see appendix C), also helped to increase the confidence of the consumers and the investors in the financial market.

In response to the second research hypothesis ***(RH2): There a long-run dynamic among macroeconomic indicators and corporate failure rate in the GCC.,*** as expected, and based on the Keynes theory, the ECM coefficient with negative value (-0.874) and being statistically significant, confirms the existence of the long-run equilibrium among the corporate failure rate and macroeconomic factors. Hence, an *ECM* coefficient of -0.874 indicates that 87% of the change from the previous period of time converged to the long-run equilibrium in the recent period of time. This could indicate that dynamic changing of the economy has an impact on the failure rate in the long-run. Morley (2006) posed the assumption that economic growth collaborates mainly with other macroeconomic indicators in the long-run relationship, more so than in the short-run relationship.

Our findings detected different results to those from other regions relating to the research hypothesis ***(RH3): There a short-run dynamic among macroeconomic indicators and the corporate failure rate in the GCC.,*** the changes in the corporate failure rate attract different macro economical approaches in the GCC region. From our results we can construe that none of the macroeconomic factors is significant, indicating that there is no short-run dynamic among the macroeconomic factors and the failure rate, while the interest rate, for example, shows as the most significant factor in other regions such as the UK (Desai and Montes, 1982; Liu, 2004), and Malaysia (Abdullah *et al.*, 2008). The explanation for that comes from the unique characteristics and tightness of the policy frameworks in this region, where fixed exchange rate regimes and the independence of monetary policy in GCC counties are limited. Moreover, GCC governments apply macro-prudential policy in order to reduce the risk of system-wide distress (Arvai, Prasad and Katayama, 2014). All this has exerted control on the impact of the macroeconomic factors to increase the failure rate in the GCC, unlike the cases in other regions. However, the model confirmed that the corporate failure rate is significantly determined by the previous period's failure rate. We expect that investors' behaviour plays a role in this case. Hence, the reaction of investors has been described as an individual decision, which is grounded in behavioural decision theory (Deegan and Unerman, 2006). It seems that investors distrust investment in the GCC markets that previous to the current period they wanted to invest in when the failure rate is high in a particular period, because they expect that the current period will also suffer from a high a failure rate, and vice versa. For example, in 2009, when the *Dubai World* in UAE was granted a restructuring agreement by the government, the investors' confidence index rose. Furthermore, the lack of investor sentiment and the conservative policy followed by investors can be associated with the herding behaviour that took place in the economic downturn in the GCC region (Arvai, Prasad and Katayama, 2014). Thus, the implication of understanding investors' behaviour is to improve the decision-making process of analysts, economists. Furthermore, this study is of practical importance to policymakers as it enables them to gain a better understanding of the role of oil prices and macro-prudential policy in strengthening the financial system's resilience to shocks in the long-term.

4.5 Conclusion

This paper examined the dynamic causal relationship among several macroeconomic variables and corporate failure rate in the GCC region for the period 2000-2013. It is the first attempt to examine the impact of the long- and the short-run equilibria in the region by applying the ARDL model. The influence of oil prices, combined with other macroeconomic factors, has proven to be significant in the long-run equilibrium. However, in the short-run equilibrium, the previous period's failure rate is the determinant of corporate failure rate. Based on these results, the significance of the various macroeconomic indicators from one economy to another leads to the conclusion that corporate failure reacts differently in different external environments and relates to each unique characteristic of each economy. However, this result can be improved upon by extending the dataset and examining the impact of changes in legislation on the failure rate, which was difficult to observe in this study because the insolvency regimes that have been introduced have been developed since the recent global financial crisis. It would be useful to study the impact of the bankruptcy laws as an external indicator, together with macroeconomic indicators, in the GCC region in future studies. We believe this study can assist analysts, economists and firms' managers in understanding the impact of the investors' behaviour on failure rate. Additionally, we hope that it will caution policymakers to consider the role of the volatility of the oil prices and to incorporate it into the decision-making process.

Chapter 5

Conclusion

5.1 Overview

In this chapter the aim of the thesis will be presented, together with the conclusions reached. The study focused mainly on analysing corporate insolvency in the GCC region, and on identifying the main micro and macro-economic factors associated with it, by applying multiple methodologies: Multidimensional Scaling, Cluster analysis, logistic regression supplement by Probit analysis and an economic model, the Autoregressive Distributed Lag model (ARDL) bound test, which have not been used previously in the GCC region.

Analysing corporate insolvency is essential for the GCC region for many reasons. Firstly, GCC firms are particularly vulnerable to firm insolvency, as reflected by the recent financial crisis (Uttamchandani et al.,2009). Secondly, based on the unique characteristics of the GCC region, previous insolvency research evidence conducted in other regions may thus be misleading when applied directly to GCC firms. Finally, insolvency research in the GCC is relatively new and limited in terms of the use of such methodologies as were used in this study.

Brief outlines of the main findings and the implications of each study's aims and questions (as detailed in Chapters two, three and four) are presented in this final chapter. Moreover, this chapter highlights the unique contributions of the research to the corporate insolvency literature, together with its implications. In addition, this chapter presents the limitations of this research and identifies several directions for future study.

5.2 Chapter 2: Study 1: Analysing Corporate Insolvency in the Gulf Cooperation Council using Logistic Regression and Multidimensional Scaling

By focusing on the impact of within-firm factors at the micro-level, the second chapter of this thesis analysed the structure of corporate insolvency and provided empirical evidence of insolvency in the GCC region, which is comparatively scarce. Examining the managerial causes of failure was done by matching each sampled insolvent firm with an equivalent solvent firm, to reach

56 matching pairs, or 112 firms, between 2004 and 2011, based on the most popular criteria in the literature: region, industry sector, comparable asset size, and financial year. The most common and successful 28 financial ratios were collected for both pairs of the sample (insolvent and solvent firms) for the year prior to failure for eight sectors in the GCC stock markets. This financial data covered six major categories: profitability, leverage, liquidity, activity, and markets, as well as operating cash flow ratios, in order, for the first time, to examine their predictive significance in the GCC context.

By using financial ratios, Logit regression with best-subset selection criteria was applied to investigate the predictive value of these ratios in the GCC context. Moreover, Chapter 2 examined the main dimensions of these ratios, and the weights that firms attach to them, using 3-way Multidimensional Scaling (MDS) and cluster analysis. The parsimonious Logit model with the profitability ratio *EBITTL*, the leverage ratio *TLTA* and the cash flow ratios *CFFOTA* and *CFFOCL* provided evidence of being able to predict corporate insolvency in the region, *ex-ante*, with 84.8%, 95.6% and 73.9% overall, and type I and II accuracy, respectively.

The MDS result uncovered four financial-ratio dimensions: (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 appeared to behave very specifically by attaching most salience to the 'Non-strategic sales activities' dimension. It appears that at the first sign of distress GCC insolvent firms concentrate on fire fighting and tighter working capital management, by cutting off strategic investments. As a result, the asset values of distressed firms are forced to decline, which reflects negatively on the level of collateral that could be used to raise funds. Hence, liquidity issues will force the firms to default on their obligations. The Logit results, which indicate that the level of cash relative to liabilities (*CFFOCL*) can significantly affect susceptibility to insolvency, support this inference. Taking the multidimensional focus of solvent firms as a benchmark, 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, as it could harm profitability, put stability at risk and reduce market value. This is unlike solvent firms, which attached more salience to the other three dimensions. Regarding these dimensions, the solvent firms show their ability to invest their assets to finance the firms' activities, generate revenues and increase profitability. The efficiency of converting assets and debts by finance moves these firms' activities into profitability and strong market value. The findings suggest that they could aid managers of firms under threat of insolvency to take action to reduce susceptibility to insolvency, by shifting the focus away from 'non-strategic sales activities' and much more towards 'profitability and financial stability balance' and 'sales activities against capital conversion', as solvent firms do. Furthermore, market value ratios were ranked the least important of the four dimensions extracted from the MDS model. The corresponding 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 (market values) are in other, more efficient, markets.

This study contributes to the corporate insolvency literature by extending the range of methodologies through the use of financial ratios: a Logit model supplemented by a Probit model and a 3-way MDS model supplemented by Hierarchical Cluster Analysis. In addition, this study has conducted *ex-ante* validation and, as one of the few studies to have done so, this study thus extends the *pool of countries* where researchers have developed and validated insolvency classification models. This is a worthwhile contribution in itself, because we now have documented evidence about which ratios are likely to be good predictors of insolvency in, for example, the United Arab Emirates (UAE). However, the main contribution of this study is the use of the MDS model, which reveals the characteristic differences between solvent and insolvent firms. Also, this study examines the predictive capacity of operating cash flow information in the GCC context for the first time.

5.3 Chapter 3: Study 2: Compare and contrast: Contextualising Corporate Insolvency in the GCC using the UK and the USA as Comparators

The third chapter developed a multilevel analysis for a better understanding of corporate insolvency, by studying the effect of managerial incompetence as an example of a micro-level factor, as well as examining the economic downturn as an example of a macro-level factor, to uncover how specific aspects of the macro-environment may impact on firm failure. Between the micro- and macro-levels, an industry-wide factor, was considered, as an example of a meso-level factor. A multilevel perspective was utilized in this chapter to contextualise insolvency in the GCC, using the UK and USA as comparators, and to make like-for-like comparisons, by holding important properties of firms constant across the different environments.

In order to measure conditions at the micro-level, 28 financial ratios were calculated from the financial statements of the firms, taken from the period 2004 to 2012. Each insolvent firm was matched with an equivalent solvent firm in the same country, by industry sector and by comparable asset size for the year prior to failure. For both the GCC and the UK, 58 matching pairs of firms were found, but only 49 pairs were found for the USA, due to the small number of insolvent firms in the Agriculture and Hotel and Tourism sectors. Macroeconomic conditions were identified by using macroeconomic indicators: the inflation rates, interest rates and oil prices in corresponding financial years for each pair of firms and the country of the firms. These were used together with the Stock Index, which took into account the size of the index operating in each country at the time of failure. 3-way Multidimensional Scaling (MDS) was applied to address the research questions, because MDS is a data reduction technique which can help to explain the greatest amount of the structure within a large amount of data using only a few key dimensions.

The 3-way Multidimensional scaling and cluster analysis revealed four common dimensions of ratios across the samples: 'effectiveness of sales and cash-generating activities', 'trade-off between debt management and cash generation/profitability', 'usage of debt versus usage of own assets ' and 'trade-off between profitability and cash generating activities'.

The results suggest the greatest similarity among the GCC, the UK and the US solvent firms appeared in the third dimension, ‘usage of debt versus usage of own assets’, to which they all ascribe moderate levels of importance. It was found that solvent firms have the ability to use debt capital to increase profitability and liquidity. Higher levels of profitability and liquidity with a lower level of leverage indicate decreased risk of insolvency. On the other hand, there is little similarity in the levels of weight that solvent firms in the GCC, the UK and the US attach to the other three dimensions. However, the US and GCC are more similar in terms of giving the most weight to dimension 1, ‘Effectiveness of sales and cash generation activities’, as well as dimension 2, ‘Trade-off between debt management and cash generation/profitability’, which clearly provides evidence of the similarity of managerial styles in the GCC and the US through the knowledge and the value placed on education in both countries. Unlike solvent firms, insolvent firms appear as being very specific; in the GCC they appear to focus mainly on the ‘usage of debt versus usage of own assets'; in the USA, they appear to focus only on the ‘trade-off between debt management and cash generation/profitability’. Insolvent firms in the UK, which are the least specific, appear to attach most weight to ‘effectiveness of sales and cash-generating activities’. Thus, insolvent GCC firms struggle to generate profit using their own resources; rather, they finance their operations by borrowing and accumulating debts. This also suggests that specificity extends to the given macro environment: we cannot assume that the aspects which are most symptomatic of insolvency in the UK or the USA will be reliable identifiers of insolvency in the GCC.

The macroeconomic variables - inflation, interest rates and stock index - were significantly correlated with ‘effectiveness of sales and cash-generating activities’. Inflation was also correlated with ‘trade-off between debt management and cash generation/profitability’. The results of this chapter illustrate that the financial structure of firms in the GCC is much more nuanced than the comparatively straightforward nature of firms in the UK and the USA.

Thus, the implication for creditors, investors and competitors is that applying findings from models calibrated in the US or the UK to the GCC is likely to produce misleading conclusions. The financial health of firms should be examined *in situ* within the ‘local’ macro-environment. There is also a clear implication for managers of firms: paying most of one’s attention to only one aspect of financial performance appears to increase the risk of insolvency.

Such information could be helpful to policy makers and managers of firms in managing the risk of insolvency. However, rather than insolvency prediction, the main aim of the study in Chapter 3 was to contribute to the body of knowledge characterising insolvency at the firm level in different macro-environments. The unique contribution of this study is to indicate what those similarities and differences are, by using the MDS model. Another contribution of this study is to the corporate insolvency literature, by increasing the pool of evidence regarding the characteristics of insolvency in the GCC, which is scant, by using a multilevel perspective.

5.4 Chapter 4: Study 3: The Impact of Macroeconomic Indicators on Failure Rate in the Gulf Cooperation Council

To the best of the author's knowledge, this chapter is the first attempt to examine the dynamic causal relationship between several macroeconomic variables and the corporate failure rate in the GCC region using the quarterly data from 2000:1 to 2013:4 periods. The main contribution of this study is to indicate the impact of the long- and the short-run equilibrium in the region by applying the ARDL Model bound test to the GCC region. The findings, based on Keynes theory, provided empirical evidence which showed that the changing dynamics of the economy has had an impact on the failure rate in the long-run equilibrium: 87% of the change from the previous period of time converged to the long-run equilibrium in recent times. Also, the findings suggested that oil prices, combined with the other macroeconomic indicators, are significantly important for the long-run equilibrium. Based on the results, the significance of the various macroeconomic indicators from one economy to another leads us to conclude that corporate failure reacts differently to external environments and relates to the unique characteristics of each economy. This study believes that these findings will aid policymakers with regard to the survival of firms in financially distressed and financially-driven business cycles.

Moreover, the results of Chapter 4 construed that none of the macroeconomic factors was significant, indicating that there is no short-run dynamic among the macroeconomic factors and the failure rate, which was not the case in other regions. The explanation for this comes from the unique characteristics and tightness of the independence of monetary policy frameworks in this region and the role of the GCC governments, which apply macro-prudential policies in order to reduce the risk of system-wide distress (Arvai, Prasad and Katayama, 2014). However, the findings show that the earlier period's failure rate was the determinant of corporate failure rate. The model confirmed that the corporate failure rate was significantly determined by the previous period's failure rate, which may indicate that a lack of investor sentiment and the conservative policies followed by investors can be associated with the herding behaviour that took place in the economic downturn in the GCC region (Arvai, Prasad and Katayama, 2014). Thus, the implications for understanding investors' behaviour is to improve the decision-making processes of analysts, economists and firms' managers. Furthermore, this study is of practical importance to policymakers, as it enables them to gain a better understanding of the role of oil prices and macro-prudential policy in strengthening the financial system's resilience to shocks in the long-term.

5.5 Limitations and future research

By considering analysis of corporate insolvency in GCC in this thesis, some limitations have been highlighted which indicate areas for further research directions.

Firstly, as is typically the case in corporate insolvency research, this study suffers from the lack of a large population of insolvent firms to draw upon, as the number of publicly listed companies in the GCC region is a low; this is because the stock markets in the GCC region are relatively young. Because the GCC region has unique characteristics, re-modelling insolvency in the GCC with more data about insolvent firms, and comparing the financial structural differences between solvent and insolvent firms within other developed (see Chapter 3) and developing countries needs further investigation. Additionally, with more data, future researchers could also make the MDS model more robust by partitioning the dataset into training and validation sets; the training set could be used to extract the dimensions, as was done in chapter 3, and then the meaning of the dimensions could be validated using the validation set.

Secondly, in this thesis (in Chapters 2 and 3) firms were matched by industry sector. However, the impact of the sectors has not been examined directly, because industry sectors in the GCC stock markets suffer from low numbers of firms. With more firms in each industry sector, the multilevel analysis could be extended to analyse how differences across industry sectors maybe of importance when determining a firm's health. With more data, the effect of macroeconomic changes over time could then be used to examine how time-dependent patterns, such as business cycles, may impact the nature of insolvency in the GCC.

Thirdly, in the corporate literature, corporate insolvency rates have been observed before and after changes in legislation within and across countries, which was difficult to observe in this study because the insolvency regime has being modernised since the recent global financial crisis. It will be better to further study the impact of the bankruptcy code together with macroeconomic indicators in the GCC region in future studies.

Appendix A
Sample of Insolvent and Solvent Firms in Chapter 2

Table A. 1: Sample of insolvent and solvent firms

Insolvent firms			Solvent Firms	
Companies	Size of Assets M$	Year of failure	Companies	Size of Assets M$
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

Table A.1: Continued

Insolvent firms			Solvent Firms	
Companies	Size of Assets M$	Year of failure	Companies	Size of Assets M$
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

Table A.1: Continued

Insolvent firms			Solvent Firms	
Companies	Size of Assets M$	Year of failure	Companies	Size of Assets M$
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 B
Significance of Financial Ratios Across Insolvency Studies in Chapter 2

Table B. 1: 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: Earning 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, Huang and Tzeng (2005)	Malaysia	Logistic												X					X	X										
(Ravisankar, Ravi and Bose, 2010)	International: Dot-Com Firms	Neural Net						X															X	X						
Sori and Hashullah (2009)	Singapore	Discriminant Analysis																						X						
Bose (2006)	Int. Dot-Com Firms	Rough Sets						X															X							
(Andreev, 2006)	Spain	Neural Net			X											X														

Table B.1: Continued

Details of Studies	Data Location	Method	Profitability					Leverage						Liquidity			Activity						Cash Flow						Market	
			EBITSEQ: Return On Equity	EBITCE: Return On Capital Employed	EBITS: EBIT Margin	EBITTL: Earning 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
Charitou, Neophytou and Charalambous (2004)	United Kingdom	Neural Net,Logit				X					X															X				
Jones and Hensher (2004)	Australia	Logit, Multinomial Logit														X														
Shumway (2001)	United States	Hazard									X			X																
(Sung, Chang and Lee, 1999)	Korea	MDA																					X			X				
Serrano-Cinca (1996)	International (Moody's Manual)	Neural Net, Discriminant Analysis						X								X														
Aldeehani (1995)	Kuwait	MDA																	X										X	
Ward (1994)	United States	Logit																				X								

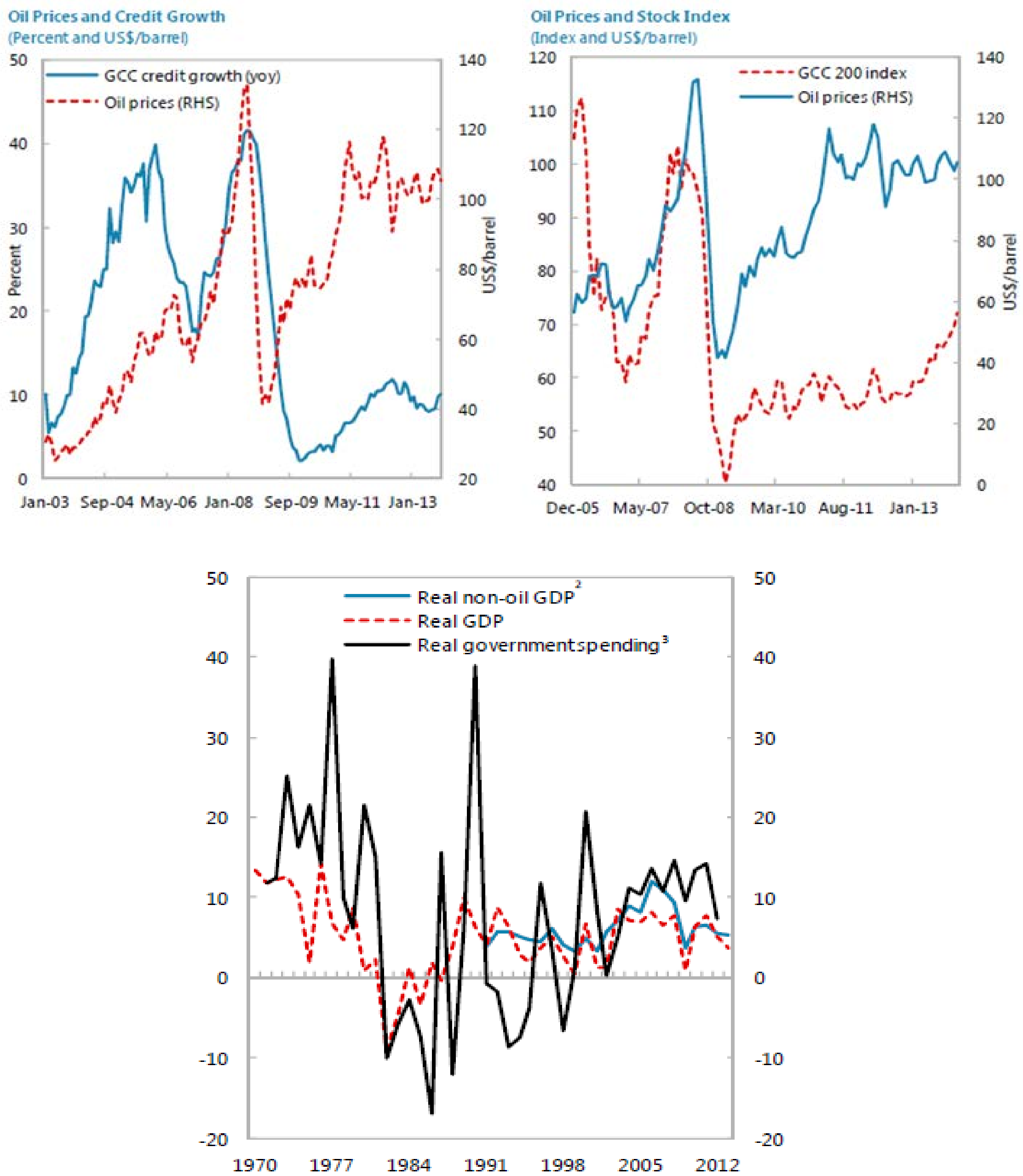
Table B.1: Continued

			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: Earning 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
(Keasey and Mcguinness, 1990)	United Kingdom	Logit			X																									
Gilbert, Menon and Schwartz (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, Peel and Pope (1986)	United Kingdom	Logit														X		X								X				

Table B.1: Continued

			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: Earning 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
Zavgren (1985)	United States	Logit									X				X															
Zmijewski (1984)	United States	Probit									X																			
Ko (1982)	Japan	MDA			X																								X	
Altman and Narayanan (1997)	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												X		
Altman (1968)	United States	MDA						X								X			X										X	
Beaver (1966)	United States	Univariate														X												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

Appendix C
Oil prices and GCC economic cycle in Chapter 4



Sources: Macroprudential policy in the GCC countries report (2014) cited from Country authorities; WEO and Bloomberg.

Figure D. 1 : Oil prices and GCC economic cycle

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